

ULRR

An evaluation of technical efficiency in Irish nursing homes

Item Type	Thesis
Authors	Ni Luasa, Shiovan
Download date	2026-04-10 16:05:07
Item License	https://creativecommons.org/licenses/by-nc-sa/1.0/
Link to Item	https://hdl.handle.net/10344/9526



**An Evaluation of Technical Efficiency
in Irish Nursing Homes**

by

Shiovan Ni Luasa

A Thesis Submitted to The Kemmy Business School, University of Limerick
In Fulfilment of the Requirements of the Degree of Doctor of Philosophy

Supervisors:

Dr Marta Zieba and Mr Declan Dineen

**Submitted to the University of Limerick,
July 2020**

An Evaluation of Technical Efficiency in Irish Nursing Homes

Shiovan Ni Luasa

Abstract: The evaluation of technical efficiency (TE) and its determinants in the Irish nursing home (INH) care provision is an important research area for a number of reasons. First, Ireland's population is ageing quickly, and it is the increase in the 'oldest' old that is going to be the most dramatic. Second, all of the nursing homes (NHs) examined in this research – both public and private – are in receipt of a quasi-subsidy by the state; and third, Irish policy-makers have moved away from the traditional public provision of nursing home (NH) care in favour of incentivising private delivery. As the costs of long-term care (LTC) are expected to increase considerably as the population ages, the estimation of technical efficiencies is essential in assessing whether NHs can utilize their resources more efficiently in order to reduce their costs of care. This research is the first attempt to investigate the efficiency of nursing home services using Irish data.

This thesis measures and appraises TE in 38 public and 72 private (including voluntary) LTC units in Ireland using detailed primary data which were collected via face-to-face interviews for the years 2008-2009. The analysis is input-oriented and hence looks at the amount by which inputs can be proportionally reduced, while holding output constant. Here output is given by the number of total patient days, while inputs are measured as medical staff, non-medical staff and the number of beds in a NH unit. This research also considers a case-mix adjusted efficiency model. The outcomes of this model are compared with the standard approach which does not adjust for the severity cases of patients. A comprehensive set of environmental variables are employed to investigate their effect as potential determining factors of efficiency in Irish long-stay facilities. Investigating the factors driving productive efficiency can assist policy-makers in explaining the possible managerial slack in the INH sector. Conventional determinants are included such as ownership, size and age along with other firm characteristic variables, together with output characteristics of NHs such as the HMD rate, chain status, and numerous quality related factors.

Using a primary dataset for INHs, this study applies a conventional DEA model to identify technical and scale inefficiencies. Then, both the homogenous bootstrap (HB) and the two-stage double bootstrap (DB) DEA methods are employed to obtain confidence intervals for the bias-corrected DEA scores. This research compares the obtained mean technical and scale efficiency scores, and the distribution of these scores for both public and private (and voluntary) NHs, and also for other subsamples of NHs, such as chain and non-chain private homes, and urban and rural units. To examine the impact of potential TE determinants, this thesis applies alternative semi-parametric two-stage methods, such as Tobit regressions and the DB DEA model. Crucially, the DB DEA integrates the effects of TE determinants as explanatory variables in estimating the true efficiencies. Hence, the DB DEA method affords bias-corrected DEA scores after controlling for the effects of the efficiency factors. However, none of the two-stage approaches account for data noise. Hence, a fully parametric SFA input-distance function is estimated, which controls for data noise and allows us to obtain unbiased TE estimates and parameters of the determining variables.

The findings of this thesis suggest that the conventional DEA model overestimates both the technical and scale efficiency of NHs in comparison to the semi-parametric (HB and DB) DEA methods. The SFA method fails to deliver valid results when output is measured as total patient days, because of convergence issues, which might be due to the small data sample and the cross-sectional nature of the data. INHs are only 52% to 58% technically efficient on average, and these estimates are based on our preferred estimation method, the DB DEA. Hence, NHs in Ireland are considerably inefficient as they could reduce the usage of resources by 42 to 48 % in order to be technically efficient. INHs are also only 89% scale efficient. The scale efficiency (SE) is higher than the TE, inferring that the productivity of INHs will result to a greater extent from pure TE improvement rather than SE. This result coincides with another finding that smaller NHs are more technically efficient than larger homes. Importantly, the private NHs are more technically efficient than public units. However, case-mix as measured by the high-max dependency rate of residents has a negative effect on TE and it is higher in public NHs. While the ratio of medical to non-medical staff, and the labour to capital ratio have positive effects on the TE of INHs, there is a trade-off between TE and other quality factors, such as staffing levels and staff flexibility. Overall, the analysis of factors which explain the TE of long-stay facilities in Ireland is important given that these units are considerably inefficient.

Declaration of Originality

No portion of the work referred to in this thesis has been submitted in support of an application for another degree or qualification of this or any other university or institute of learning.

I declare that the thesis represents the results of my own work. Following normal academic conventions, I have made due acknowledgements of the work of others. The work has been completed with a total word count of 81,976 excluding the references and the final appendix.

Copyright Statement:

Copyright in text of this thesis rests with the author. Copies (by any process) either, in full or of extracts, may be made only in accordance with instructions given by the author.

Signed: _____

Shiovan Ni Luasa

Acknowledgements

First and foremost, I wish to thank and acknowledge my supervisors, Dr Marta Zieba and Mr Declan Dineen. Their expert guidance, support, and help has been unwavering in my journey to complete this Doctorate. I am forever indebted to you both for sharing your knowledge and expertise with me, and for diligently and caringly mentoring me through this journey. Together with your example and the skills that you have empowered me with, I am encouraged to make a difference in society and it is my fervent wish to achieve that.

Thanks also to current and past members of the Department of Economics and the Kemmy Business School. I am grateful for the opportunities I received, the positive encouragement and the kind words. My admiration and respect has grown over the years for each one of you and, as I reflect on my journey in UL, I feel privileged to have been associated with this University.

Also thank you to my friends within and outside UL. Your constant support, your positive comments or the unsaid word, inspired me to keep going. I hope I can give to others in the same way you have given to me.

Thank you too to my fantastic Mayo/Clare family – Sarah Jane, Mary and Kieran. Your direction and wise words have helped me stay en-route while at the same time enjoying myself. I love our wide-ranging chats and countless cups of Lyons tea (should have been Barry's!).

Do mo mhuintir fein – Mam, Seán agus Micheál – mile, mile buiochas le haghaidh an taciocht a thug sibh dom i rith mo shaol. As I reflect on all you have done for me, Ronaldinho sentiments come to mind: “my family is everything”. I am what I am thanks to my mother, my father, and my brothers – because they have given me everything.

So, *gurbh maith agat* for being my family through the ups and downs of life.

Table of Contents

Abstract:	ii
Declaration of Originality	iii
Acknowledgements.....	iv
Table of Contents.....	v
List of Tables	x
List of Figures	xii
List of Appendices	xiv
List of Abbreviations	xv
Chapter One: Introduction	17
1.1 Introduction	17
1.2 Rationale and Motivation for the Study	18
1.3 Research Questions and Objectives	21
1.4 Background and Framework for Analysis	22
1.5 Contribution of the Study.....	28
1.6 Thesis Structure.....	32
1.7 Conclusion.....	34
Chapter Two: Theoretical Framework and Previous Research	36
2.1 Introduction	36
2.2 Farrell’s Efficiency Measures in the NHs Literature	37
2.2.1 Technical Efficiency (TE) in the NH Sector.....	41
2.2.2 Allocative Efficiency and Economic Efficiency.....	45

2.3	Scale Efficiency.....	48
2.4	Determinants of NH Efficiency.....	50
2.5	Efficiency Measurement Methods	66
2.5.1	The Non-Parametric Techniques	66
2.5.2	Parametric Approach	70
2.6	Conclusion.....	76
Chapter Three: The Nursing Home Sector in Ireland.....		78
3.1	Introduction	78
3.2	Care Policy	79
3.2.1	Informal and Formal Care.....	80
3.2.2	The Stakeholders of Residential Care.....	87
3.3	Residential Care Sector	88
3.3.1	Long-Term Care Bed Capacity 1998 - 2017.....	89
3.3.2	The NH Environment.....	92
3.3.3	Profile of the Resident	97
3.3.4	Ireland's Aging Population	105
3.3.5	The Cost of Care	111
3.3.6	Future NH Capacity	122
3.4	Conclusions	124
Chapter Four: Methodology.....		125
4.1	Introduction	125

4.2	Data Envelopment Analysis	129
4.2.1	The CRS DEA Model	130
4.2.2	The VRS DEA Model.....	132
4.2.3	Scale Efficiency Measurement in the DEA	133
4.2.4	Homogenous Bootstrap DEA Model	135
4.3	Two-Stage Semi-Parametric Methods	136
4.3.1	Two-Stage Ordinary Least Squares Model.....	137
4.3.2	Two-Stage Tobit Model.....	138
4.3.3	Two-Stage DB DEA Model.....	140
4.4	Stochastic Frontier Analysis	142
4.4.1	Stochastic Production Function	143
4.4.2	Stochastic Input Distance Function	144
4.5	Dataset.....	148
4.5.1	Data Gathering	148
4.5.2	Questionnaire	150
4.5.3	The Fieldwork and Final Dataset.....	152
4.6	Definition and Measurement of Variables	153
4.6.1	Output Variable.....	154
4.6.2	Input Variables.....	155
4.6.3	Ownership and Conventional Characteristics	160
4.6.4	Output-Characteristic Variables.....	166

4.6.5	Summary Statistics for Output and Inputs	170
4.6.6	Summary Statistics for Efficiency Determining Variables.....	171
4.7	Conclusion.....	176
4A	Appendix	179
Chapter Five: Estimating Technical Efficiency		180
5.1	Introduction	180
5.2	Conventional DEA Model Results	182
5.3	Homogenous Bootstrap DEA Model Results.....	190
5.4	Double Bootstrap DEA Model Results	196
5.5	Comparison of the Three DEA Methods	202
5.6	Stochastic Frontier Analysis	205
5.7	Conclusions	208
5A	Appendices	211
Chapter Six: Determinants of Technical Efficiency		214
6.1	Introduction	214
6.2	Choice of Method Used.....	216
6.3	Semi-parametric DB DEA Results.....	218
6.3.1	Ownership.....	220
6.3.2	Conventional characteristics	221
6.3.3	Output Characteristics.....	223
6.4	OLS and Tobit Regression Results	231

6.4.1	Model diagnostics	231
6.4.2	Comparison of results	233
6.5	Marginal Effects	238
6.6	Parametric SFA Results	242
6.7	Summary of Key Findings	244
6.8	Conclusions	249
6A	Appendices	251
Chapter Seven:	Conclusions	256
7.1	Introduction	256
7.2	Summary and Discussion	256
7.3	Contributions	261
7.3.1	Theoretical Contributions	261
7.3.2	Empirical Contributions	262
7.3.3	Methodological Contributions	266
7.3.4	Policy Contributions	267
7.4	Limitations of the Study and Suggestions for Future Research	272
7.5	Final Conclusions	273
References	275
Final	Appendix: Questionnaire.....	284

List of Tables

Table 2-1	Previous evaluations of efficiency in the NH sector.....	39
Table 2-2	Definition of Quality according to Donabedian’s Structure-Process-Outcome Framework and its Applications in Efficiency Literature.....	55
Table 2-3	Previous evaluations of case-mix in the NH Sector.....	60
Table 3-1	Private NH Growth 2007 – 2010.	92
Table 3-2	Percentage distribution of residents at 31 December 2017 by age in years.....	99
Table 3-3	Percentage share of elderly people by age in HSE regions.	107
Table 3-4	Long-term beds and population aged 65+ per bed in 2014.	108
Table 3-5	Population projections of ‘65 + age cohort’ and projections of LTC beds.....	109
Table 3-6	Comparative public expenditure on LTC as a % of GDP and by <i>type of care</i> (2010).	114
Table 3-7	Public expenditure on LTC and HC.....	115
Table 3-8	Weekly cost of care in euros in a shared nursing home room.	116
Table 3-9	Labour costs in NHs.....	118
Table 3-10	Replacement costs in a nursing home.	120
Table 3-11	Gross investment in a nursing home.	120
Table 4-1	Comparison of Estimation Methods	128
Table 4-2	Previous evaluations of two-stage methods of the determinants of TE in the NHs sector.	138
Table 4-3	Data collection and data sample.	150
Table 4-4	Final dataset	153
Table 4-5	Formal qualifications of nurses in private and public NHs.	158
Table 4-6	Efficiency Model Specifications.....	159
Table 4-7	Percentage of private, voluntary and public NHs by location.	161
Table 4-8	Percentage of private and public NHs by <i>size</i>	163
Table 4-9	Efficiency Determining Variables.	165
Table 4-10	Summary Statistics for Output and Inputs in the DEA and SFA models.	174
Table 4-11	Summary Statistics of Potential Efficiency Determining Variables.....	175
Table 5-1	Conventional DEA Model Results.....	188
Table 5-2	Mean Comparison Tests for Conventional DEA Results.	189
Table 5-3	Frequency Distribution of Efficiency (VRS DEA) of the Different Samples.	189
Table 5-4	The Nature of Returns to Scale Obtained from NIRS DEA Model.....	190

Table 5-5	HB DEA Model Results.....	194
Table 5-6	Mean Comparison Tests for Homogenous Bootstrap (HB) DEA Results.....	195
Table 5-7	Frequency Distribution of Homogenous Bootstrap Efficiency (VRS DEA)...	195
Table 5-8	Double Bootstrap DEA Results.	200
Table 5-9	Mean Comparison Tests for Double Bootstrap (DB) DEA Results.	201
Table 5-10	Frequency Distribution of DB DEA Efficiency (VRS DEA).....	201
Table 5-11	Correlation Matrix of CRS and VRS TE Scores of the different DEA methods.	204
Table 6-1	Models Applied to Estimate Efficiency Determinants.	216
Table 6-2	Double Bootstrap VRS DEA Estimates of the TE Determinants.	229
Table 6-3	Double Bootstrap CRS DEA Estimates of the TE Determinants.	230
Table 6-4	Tobit regression results for VRS DEA TE scores.	236
Table 6-5	Comparison of Marginal Effects of Efficiency Determinants for VRS Technology.....	241
Table 6-6	Key findings for efficiency determinants.	247

List of Figures

Figure 1-1	Conceptual Framework.....	25
Figure 2-1	Input-Oriented TE.....	43
Figure 2-2	Scale Efficiency.....	49
Figure 2-3	The Stochastic Frontier Approach (SFA).....	73
Figure 3-1	Continuum of Care in Irish Formal Care Services.....	86
Figure 3-2	Mix of Public, Private and Voluntary Beds 1998 –2017.....	90
Figure 3-3	Percentage of Public, Private and Voluntary Beds 1998 -2017.....	91
Figure 3-4	Level of residents’ dependency (as % of total patient) from 2005 – 2014.....	100
Figure 3-5	Percentage of residents in “Low”, “Medium”, “High” and “Max” dependency.....	102
Figure 3-6	Percentage of residents in ‘Low-Medium’ and ‘High-Maximum’ dependency 2000 – 2014.....	103
Figure 3-7	Proportion of high-maximum dependency residents and proportion of patients 85+ in all homes.....	104
Figure 3-8	Proportion of high-maximum dependency residents and patients 85+ in.....	104
Figure 3-9	Proportion of high-maximum dependency residents and proportion of patients 85+ in private NHs.....	105
Figure 3-10	People aged 65+ as a % of total population: Ireland and EU average,.....	108
Figure 3-11	Population projections for ‘85+ age cohort’.....	110
Figure 3-12	Funding of the NHSS scheme 2010 – 2015.....	113
Figure 3-13	Average weekly price of private nursing home care by county at the end of December 2014.....	117
Figure 3-14	Estimated Future Cost of Resident Care - € Million.....	122
Figure 4-1	Methodology of Study.....	127
Figure 4-2	An Input-Oriented DEA model.....	131
Figure 4-3	The Input Distance Function (IDF) and TE.....	145

Figure 4-4	Distribution of Irish private-voluntary NHs in % of state-contracted beds.....	149
Figure 4-5	Distribution of INHs in relation to number of beds.....	162
Figure 5-1	Kernel Density Functions of Conventional DEA and HB DEA TE Scores. ...	196
Figure 5-2	Kernel Density Functions for Conventional DEA and DB DEA.	202
Figure 5-3	Distribution of VRS TE scores in % for all three DEA methods across all homes.....	203
Figure 5-4	Distribution of SE scores in % for all three DEA methods across all homes..	205

List of Appendices

Appendix 4A-4-1	The Double Bootstrap DEA Procedure used in Algorithm #2 of Simar and Wilson (2007; 2011).	179
Appendix 5A-5-1	Conventional DEA scores obtained by using different measurement of labour inputs and by <i>including HMD rate</i> as an input.....	211
Appendix 5A-5-2	Conventional DEA scores obtained by using different measurement of labour inputs and by <i>excluding HMD rate</i> as an input.	211
Appendix 5A-5-3	Kernel Density Functions of Conventional DEA, Homogenous Bootstrap and Double Bootstrap DEA TE Scores.	212
Appendix 6A-6-1	Correlation matrix of potential efficiency determinants.....	251
Appendix 6A-6-2	Tobit regression results for CRS DEA scores.....	252
Appendix 6A-6-3	OLS regression results for VRS DEA scores.....	254
Appendix 6A-6-4	Estimates of the Input distance Function and the determinants of TE.	255

List of Abbreviations

Activities of Daily Living	ADL
Allocative Efficiency	AE
Banker, Charnes, Cooper	BCC
Centre for Ageing Research and Development	CARDI
Central Statistics Office	CSO
Certified Nurse Aides	CNAs
Charnes, Cooper and Rhodes	CCR
Confidence Interval	CI
Constant Returns to Scale	CRS
Cost Efficiency	CE
Data Envelopment Analysis	DEA
Data Generating Process	DGP
Double Bootstrap	DB
Decreasing Returns to Scale	DRS
Decision-Making Unit	DMU
Department of Health and Children	DOHC
Department of the Taoiseach	DOT
Deterministic Frontier Approach	DFA
Diseconomies of Scale	DOS
Economic & Social Research Institute	ESRI
Economies of Scale	EOS
Efficient Unit Isoquant	EUI
European Union	EU
Gross Domestic Product	GDP
Health-care	HC
Health-care Attendant	HCA
Health Information Quality Authority	HIQA
Health Service Executive	HSE
High-Maximum Dependency	HMD
Home Care Package	HCP
Homogenous Bootstrap	HB
Horwath Bastow Charleton	HBC
Increasing Returns to Scale	IRS
Independent Living Unit	ILU
Input Distance Function	IDF
Input Orientation	IO

Irish Nursing Home	INH
Labour Capital	L-C
Licenced Practical Nurse	LPN
Lower Bound	LB
Local Health Manager	LHM
Long-Term Care	LTC
Marginal Effect	ME
Medical to Non-Medical Staff	M-NM
Most Productive Scale Size	MPSS
National Treatment Purchase Fund	NTPF
Non-Increasing Returns to Scale	NIRS
Nursing Home	NH
Nursing Homes Ireland	NHI
Nursing Homes Support Scheme	NHSS
Ordinary Least Squares	OLS
Organisation for Economic Cooperation and Development	OECD
Overall Economic Efficiency	OE
Output Orientation	OO
Registered Nurse	RN
Republic of Ireland	ROI
Revenue Efficiency	RE
Scale Efficiency	SE
Skilled Nursing Facilities	SNFs
Stochastic Frontier Analysis	SFA
Structure Process Outcome	SPO
Technical Efficiency	TE
Technically Optimal Productive Scale	TOPS
United Kingdom	UK
United States	US
University of Limerick Research Ethics Committee	ULREC
Upper Bound	UB
Variable Returns to Scale	VRS
Variance Inflation Factor	VIF
World Health Organization	WHO

Chapter One: Introduction

1.1 Introduction

The opening chapter of this thesis aims to present the focus, rationale, and motivation for the study, along with the research questions and objectives, theoretical framework, and contribution to knowledge. The extended ageing of populations is substantially changing health-care needs since an increasing number of citizens will require long-term care (LTC) in the coming decades. This change has stirred a sense of societal urgency to understand and evaluate the economic performance of nursing homes (NHs). In terms of performance indicators, this research focuses on technical efficiency (TE); herein defined as the ability of the firm to produce at the optimal production frontier attainable given the available resources (physical inputs) and production technology. LTC, which can be provided at home, in the community, in assisted living facilities, or in NHs, is one of the fastest growing areas of health-care. Since nursing home (NH) care provision is the most expensive of the LTC services, it is imperative that their performance is evaluated to establish whether such firms are utilizing their limited resources in an optimal manner. Therefore, in order to appropriately evaluate the technical efficiencies (TEs) of Irish nursing homes (INHs), this thesis applies an holistic multivariate modelling approach by integrating three types of potential determinants in estimating and explaining TE. Figure 1-1 presents the conceptual framework outlining this research, and the three categories of variables which frequently influence TE: namely, (1) ownership status; (2) nursing home characteristics; and (3) quality indicators. Moreover, the study employs a spectrum of non-parametric to fully parametric techniques which enable the overall research to yield important theoretical, methodological, empirical, and policy insights into the estimation and determinants of TE in INHs.

The majority of LTC beds across Europe are provided by state NHs; entities, which according to the somewhat meagre literature available on the topic (Kooreman 1994; Bjorkgren *et al.*

2001), are wholly inefficient. In contrast, both public and private NHs provide care to the elderly in the US; and the latter is considered more efficient (Nyman and Bricker 1989; Ozcan *et al.* 1998). Very little remains known about performance efficiencies in relation to Ireland's NH industry providers, with Ni Luasa *et al.* (2018) the only relevant research published to date. As such, this thesis presents the first efforts to evaluate efficiency and the drivers of efficiency for INHs.

Section 1.2 outlines the rationale and motivation for this study and is followed by the research questions and objectives in Section 1.3. Section 1.4 delineates the theoretical framework underpinning this investigation, while Section 1.5 discusses how TE is measured in extant NHs efficiency literature. Section 1.6 outlines the theoretical, empirical, methodological, and policy contributions of this study. Section 1.7 elaborates on the overall thesis structure, and Section 1.8 offers a number of summative remarks.

1.2 Rationale and Motivation for the Study

As the challenges and total costs of financing LTC are forecast to rise in tandem with the extended life-expectancy of populations in most developed countries, a proper estimation of TEs is now essential to assess whether NHs could utilize their resources more efficiently to reduce their costs of care. In the context of the fiscal constraints facing the Irish exchequer, efficiency and 'value for money' are increasingly dominant considerations in relation to all areas of public spending, including health-care. Taxpayers, policymakers, regulators, and indeed, society as a whole, require assurance that long-term health-care services are being efficiently provided. Additionally, and in keeping with any other public or private enterprise which receives public funding, nursing home performance should be measured by the extent to which the units meet the goals set by public authorities. Public enterprises are non-profit firms wherein objectives such as the provision of local employment, quality services (which can operate at the expense of efficiency), and equity matters, may take precedence over profit

considerations. According to Perelman and Pestieau (1988), the only objective for which no mitigating circumstances can be invoked in both public and private firms is in the pursuit of TE. The advantage of TE measurement is that it is based on physical inputs and outputs: therefore, no behavioural assumptions of cost minimization or revenue maximization are required. Rosko *et al.* (1995) reasoned that managers in both for-profit and non-profit NH facilities can pursue self-enhancing objectives (e.g. excess staff, travel, slack time, etc.) which increase inputs and costs, and hence reduce efficiency. The same authors concurred with property rights theorists who purport that profit as a strong incentive to monitor can restrain this type of behaviour and give rise to efficient operation of for-profit firms. However, previous studies have found significant, albeit occasionally contradictory results, regarding the impact of ownership on efficiency in the LTC sector. This is noteworthy as the NHs investigated in this research operate in a market which is less than fully competitive, since they all receive some degree of funding from the State.

This research is of importance to a wide range of stakeholders, including NH operators, government bodies, regulators, policy makers, and the general public, for four key reasons. Firstly, Delellis and Ozcan (2013) noted the urgency of defining and estimating efficiencies so that NHs may utilize their resources more efficiently and reduce care costs which are expected to increase dramatically as the US population ages. Ireland's population is also ageing quickly, and the increase in the 'oldest' old will be most dramatic. The 65+ and 85+ age cohorts are forecast to increase by 38% and 46% respectively in the years 2011-2021 (BDO 2014: 22): a growth is expected to accelerate into the future. This means that more long-stay beds will be required, and the projected surge in demand expected to present severe challenges for the supply of INH care services. In short, such resources are finite. Thus, achieving greater effectiveness and efficiencies in resources use will increasingly become the dominant considerations to ensure INHs can meet the future demand. Secondly, the INH market serves

as an interesting case as it is comprised of a cross-section of public, private and non-profit (voluntary) providers. This is unusual in a European context, where most care homes are publicly owned. In 2007, about 36% of all private and voluntary INHs received a fixed/block contract per bed to supply some of their bed capacity to the State: the present sample of non-public facilities is drawn entirely from these homes. For these private-voluntary long-stay care units which are compared with the public NHs in this study, such payments are not tied to bed use or occupancy. In effect then, all of NHs examined in this research, whether public and private, are in receipt of varying levels of quasi-subsidy from the State, and thereby cushioned from the market imperatives of minimizing costs and producing efficiently. However, identifying best practice and identifying the scope for improvement in organizational performance is now vital given the projected increases in the elderly population. Thirdly, since the late 1990s, Irish policymakers have moved away from the traditional public provision of nursing home care in favour of incentivizing private delivery through the provision of capital allowances. This had been expected to lead to greater efficiencies, effectiveness, and responsiveness to consumer relative to public provision. Yet, within a short period of time, the private sector's share of total long-stay beds capacity had doubled to 80%; raising the question of whether such a policy is justified in terms of the productive performance of INHs. Finally, given that vulnerable elderly people reside in these facilities, there is heightened social concern that efficiency considerations also satisfy quality outcomes. Taxpayers, government, and citizens as a whole have an understandable interest in ensuring that the considerable national resources devoted to INHs services are used efficiently.

In particular, patterns of firm inefficiency might well suggest that public resources could be better used elsewhere in the economy, or that more outputs could be generated within NH services without the burden of additional resources. More alarmingly, inefficiency could

undermine public support for the tax funding of care services: a critical component of health-care given that the number of elderly people will increase sharply in the next decades.

1.3 Research Questions and Objectives

Building on the motivation and rationale of this research, the thesis addresses three principal research questions:

1. *How to appropriately measure TE for the NH sector in Ireland?*
2. *What are the determinants of TE in INHs?*
3. *Are private NHs more technically efficient than public homes in Ireland?*

These research questions inform the following key research objectives:

- To validate the robustness of our TE estimates, this study applies a broad spectrum of methods to measure TE in the INH sector
- To estimate scale efficiency in INHs
- To identify environmental factors which could influence the TE in INHs
- To investigate the impact of these determinants on TE
- To categorize the environmental factors into conventional and output-characteristic variables
- The pooled sample is divided into the following subsamples:
 - Private and public NHs
 - Private chain and non-chain facilities
 - Urban and rural units

This study examines the impact of the environmental variables on TE for these groups

- This research particularly focuses on the effects of ownership and various quality indicators in determining TE

1.4 Background and Framework for Analysis

This thesis measures and appraises TE since it does not require any behavioural assumptions of the NHs and it is also the dominant measure of efficiency in the NHs literature (Chattopadhyay and Ray 1996; Borge and Haraldsvik 2009; Chang and Cheng 2013). Furthermore, Figure 1-1 illustrates that this research uses an input-oriented TE approach, assesses if, and by how much, capital and labour inputs can be reduced while producing the same level of output. As the output of the NHs in this study is defined as total patient days, it is assumed that NH managers can better control inputs than outputs. Input-oriented TE has also been widely used in empirical studies of the NH sector (e.g. Nyman and Bricker 1989; Nyman *et al.* 1990; Fazel and Nunnikhoven 1992; Chattopadhyay and Heffley 1994; Kooreman 1994; Ozcan *et al.* 1998); Bjorkgren *et al.* 2001; Laine *et al.* 2005a; Wang and Chou 2005; Borge and Haraldsvik 2009; Garavaglia *et al.* 2011; Chang and Cheng 2013; DeLellis and Ozcan 2013).

In the TE models estimated in this thesis, the production process of the care unit is identified, whereby the output of the NH is measured as the total patient days, while the inputs are measured as the medical staff, non-medical staff, and the number of beds in the facility. Along with these input variables, this research also includes the high-maximum dependency (HMD) rate of the NH residents as an additional input. This index represents a proxy for case-mix and provides for the application of a case-mix adjusted efficiency model. Moreover, to elucidate the heterogeneity evident in the performance of the NHs, this study employs an holistic multivariate modelling approach, whereby a wide range of possible TE determinants are considered. It is important to note that while the efficiency determinants are neither inputs nor outputs in the production process of a NH unit, they can influence the distance from the

efficient production frontier, and hence affect the TE of the NH firms. As Figure 1-1 illustrates, these determinants are classified into three categories¹ as follows:

1. **Ownership:** Public provision of NH care versus private or for-profit delivery
2. **Nursing home characteristics:** For example, size, location, age, case-mix, whether the unit is part of a chain (for private or for-profit homes)
3. **Quality variables:** Including the ratio of medical to non-medical staff and labour to capital, staff levels, staff flexibility, staff turnover, and the proportion of single rooms

With respect to ownership status, the literature exploring efficiency in the US (e.g. Nyman and Bricker 1989; Nyman *et al.* 1990; Fazel and Nunnikhoven 1992; Ozcan *et al.* 1998) demonstrates that for-profit care facilities attain higher TE scores than public nursing counterparts. This aligns with the property rights theory, which postulates that for-profit homeowners' exclusive rights to the income generated result in incentives to gauge input productivity. By contrast, in Europe, most LTC beds are provided by the non-competitive public sector and non-pecuniary goods are consumed at the expense of efficiency. Since the question of whether ownership status affects the efficiency of the NH has not been widely considered, this research adds to the debate by evaluating whether private NHs are more efficient than public facilities in Ireland. It is interesting to note that while studies such as those of Crivelli *et al.* (2002) in Switzerland and Wang and Chou (2005) in Taiwan, found public NHs to be just as cost efficient as private units, others such as that of Garavaglia *et al.* (2011) in Italy, concluded that public NHs were less efficient than private facilities.

Figure 1-1 also demonstrates that other NH characteristics such as the size, location, and age of the home, may impact the TE of the firm. For example, while larger care facilities can

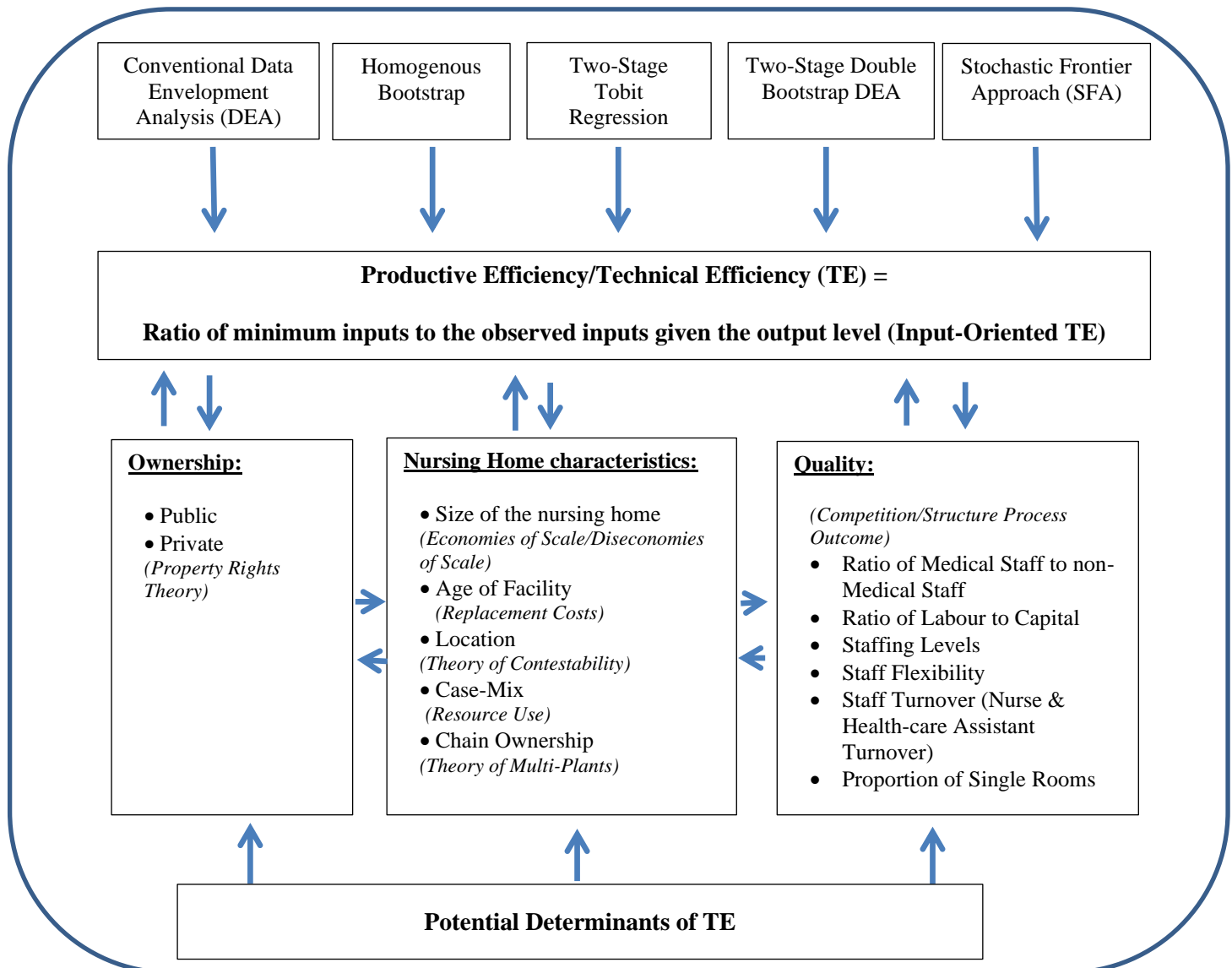
¹ Alternatively, these factors can be classified into conventional determinants and output characteristics of the nursing home.

achieve cost savings through bulk-purchasing, large-scale operations can experience lengthier decision-making processes due to greater levels of staff hierarchy and indistinct areas of responsibility. Older NHs can expect higher costs base as capital inputs need to be replaced. Moreover, facilities located in urban areas may experience greater competition than those in rural areas, which means that the former may be more efficient due the market forces. The quality determinant of the present study adheres to the structural dimension of quality of care as defined by Donabedian (1988). Hence, for the purposes of this enquiry, NH quality is measured via a number of indicators which are highlighted in Figure 1-1. Increased competition can improve efficiency and enhance quality by allocating resources where they are likely to be most valuable. On the other hand, competition could ameliorate organizational efficiency performance, but quality may fall. Thus, this research explores the correlation between TE and quality which has been only marginally addressed in previous studies in the field. This is important as consumers of NH services demand both efficient and high-quality outcomes at the same time.

The conceptual framework of analysis in Figure 1-1 presents the approaches used in this study to estimate TEs in the INH sector, along with the variables which may determine TE. This figure also illustrates the interactions between the explanatory and the dependent variables. It is evident that this research employs a spectrum of methods; from the non-parametric conventional DEA and semi-parametric two-stage DEA approaches, to the fully parametric SFA. This study initially applies these methods to the pooled sample wherein public and for-profit facilities face the same production frontiers. However, since it is widely accepted that these groups face divergent technological goal orientations, this study also streams the data into the following subsamples: public and private homes; private chain and non-chain facilities; and urban and rural units. The research begins by using the conventional DEA technique to estimate TEs in INHs, since this is the dominant approach to efficiency measurement across

the NH literature. This method was used to estimate TEs in the USA by Nyman and Bricker (1989); Nyman *et al.* (1990); Fizel and Nunnikhoven (1992); Kleinsorge and Karney (1992); Chattopadhyay and Heffley (1994); Chattopadhyay and Ray (1996); Ozcan *et al.* (1998); DeLellis and Ozcan (2013); by Kooreman (1994) for the Netherlands; Bjorkgren *et al.* (2001) and Laine *et al.* (2005a) for Finland; Borge and Haraldsvik (2009) for Norway; Garavaglia *et al.* (2011) for Italy; and Wang and Chou (2005) and Chang and Cheng (2013) for Taiwan.

Figure 1-1: Conceptual Framework



The DEA facilitates the measurement of scale efficiency (SE) as it enables the estimation of both constant returns to scale (CRS) and variable returns to scale (VRS) TEs. The approach has been criticised in that it implicitly assumes that the distance between an observed firm and

the efficient technology boundary or frontier exclusively reflects inefficiency. In fact, this distance is composed of two discrete parts: inefficiency; and noise. The DEA approach does not allow for data noise caused by omitted input or output variables or because the observed input-output data may be subject to measurement error. Since it follows that data noise could bias estimation, the present research employs robust bootstrap methods to validate the non-parametric DEA scores and to integrate the effects of potential determinants in estimating the true efficiencies.

Developed by Simar and Wilson, the homogenous bootstrap (1998, 2000) and the two-stage double bootstrap (2007, 2011) techniques are regularly used to obtain confidence intervals for bias-corrected DEA scores. In addition, the application of the double bootstrap (DB) approach affords 'true' DEA TE scores following adjustment for the effects of the environmental variables, as well as providing estimates of the parameters of these efficiency determinants. Interestingly, to date, the bootstrap methods have had few applications in the NHs efficiency literature: only Garavaglia *et al.* (2011) and Borge and Haraldsvik (2009) have previously implemented these procedures. Nonetheless, as the bootstrap methods are based on the DEA TE scores, they do not account for statistical noise in the data. Conversely, the econometric stochastic frontier analysis (SFA) approach clearly separates and incorporates error terms representing both statistical noise and inefficiency. Thus, SFA controls for data noise, allowing unbiased TE estimates to be obtained and parameters of the determining variables identified. Again, relatively few NH studies have applied this technique to the parametric estimation of efficiency. These include Hoffler and Rungeling (1994); Vitaliano and Toren (1994); Anderson *et al.* (1999); Crivelli *et al.* (2002); Knox *et al.* (2007); and Farsi *et al.* (2008).

While selecting an appropriate method to measure the TE of LTC facilities is an essential first step, identifying the determinants of efficiency is also imperative as these offer insights into improving the performance of the NH unit. This study applies two-stage semi-parametric DEA

techniques as well as the fully parametric SFA method to identify the determinants of efficiency. In the two-stage approaches, non-parametric DEA efficiency estimates drawn from the first stage are regressed on a vector of efficiency determinants in a parametric analysis in the second stage. In this research, ordinary least squares (OLS) and Tobit regression techniques are used in the second stage. The latter is appropriate given that the DEA TE scores are confined to a range between 0 and 1, while the former approach provides valuable information as to the fit of the model. However, both approaches rely on conventional methods for inference. Simar and Wilson (2007; 2011) asserted that conventional inference methods fail to give valid inference due to the fact that in the second-stage, true efficiency remains unobserved and must be replaced with DEA estimates of efficiency which are serially correlated by construction and are also biased.² In light of this, the present study employs the two-stage DB DEA procedure to obtain unbiased estimates of the parameters of our posited determining variables. However, since this technique does not account for statistical noise, the methodology is further extended to apply the fully parametric SFA approach to identify the determinants of TE.

Dataset of the Study

To date, Ni Luasa *et al.* (2018) is the only published study to evaluate the efficiency of NH services using Irish data. Hence, this research is based on unique, and detailed, primary data which were collected via face-to-face interviews with NH managers throughout the Republic of Ireland (ROI) during the period 2008-2009. While the dataset is cross-sectional and represents a snapshot of the NH industry in Ireland at a particular point in time, the depth and richness of the information gathered provides unique insights into the NH environment: an area that has thus far been neglected in studies of economic performance. While a certain amount of time has elapsed since the dataset was collated, it is held that the issues facing the INH sector

² The efficiency score is a point estimate without a probability distribution around it as required by the Tobit method or any other parametric regression technique. Using the DEA point estimates in a second stage analysis may cause biased and inconsistent estimates of the parameters of the explanatory/ determining variables.

remain the same; although now even more acute due to a lack of investment. The intervening years have seen the impact of the Global Financial Crisis. Ireland was one of the worst affected economies and the ensuing austerity measures resulted in stringent reductions in public expenditures across all services, including health-care. In addition, the empirical results from this research should be considered a starting point in relation to the evaluation of TE in INHs: this marks the start of a conversation that future investigations can add to and develop further. The findings in this study afford a benchmark against which future efficiency performance can be compared. Meanwhile, as a standalone study, the estimates from this investigation provide valuable information for a range of stakeholders, including Government and policymakers, on how INHs are utilizing their resources relative to other counterparts in their industry. Such a reference point is critical, given the challenges ahead for the LTC sector in Ireland, including NH services, and the immense policy imperative to provide for an increasingly elderly population and the additional resources needed to meet future demands for LTC beds.

1.5 Contribution of the Study

The pursuit of efficiency in health-care provision has become a key consideration as expenditure on health-care systems accounts for a sizeable proportion of Gross Domestic Product (GDP), and is increasing. Indeed, almost every developed country is faced with a population which is getting older and commensurate increase in resources that will be needed to meet this challenge. Since LTC services and supports for elderly people is one of the fastest growing areas within health-care, significant demands continue to be placed on the NH sector to meet the care needs of the older population. However, to date, INHs have been comparatively neglected as a focus for economic research, and there have been no studies examining efficiency of the Irish LTC units. This study therefore makes important contributions in the area of efficiency evaluation in relation to NHs, and the Irish case, in particular. As such, this research is of importance to a wide range of stakeholders, including the NH operators,

policymakers, taxpayers and indeed, society as a whole. This investigation extends the efficiency performance literature in 4 ways; (1) theory, (2) empirics, (3) methods and (4) policy as detailed below:

(1) Theory

The previous studies which evaluated efficiency in NH care provision were located in US care homes (Ozcan *et al.* 1998; DeLellis and Ozcan 2013), European NHs (Borge and Haraldsvik 2009; Garavaglia *et al.* 2011) and Asian facilities (Wang and Chou (2005; Chang and Cheng 2013). Thus, there is an interesting lacuna in the literature in terms of Ireland, which is an unusual mix of public and private firms. This thesis addresses the gap by integrating a comprehensive set of three types of potential determinants in estimating and explaining TE in an holistic multivariate modelling approach. As shown in Figure 1-1, this study proposes that TE is determined by:

1. whether care is delivered by public or private facilities
2. the NH unit's inherent characteristics
3. certain quality indicators

In particular, this investigation focuses on the effects of ownership and various quality indicators in determining TE. This representation is derived from the classification of the determinants into conventional characteristics and output-characteristic variables. These conventional factors are common to firms in any sector, and include *inter alia* ownership status of the facility, size, location, and the age, of the NHs. On the other hand, objective output-characteristic variables specific to the NH sector include the dependency rate or case-mix, chain versus non-chain status for private homes, and quality-related factors. To reiterate, this research measures quality through Donabedian's (1988) structural dimension of quality of care, and includes such indicators as the proportion of single rooms and a number of labour management variables.

Integrating such an extended set of variables redresses a number of gaps in the existing NHs literature by providing novel insights into: (a) the non-clinical factors that affect inefficiency; (b) the relationship between quality and efficiency which has been only marginally addressed in prior efficiency studies; and (c) the status of private chain versus non-chain NHs as a relatively recent phenomenon in the care industry. In addition to developing and testing an holistic multivariate modelling approach, this study is novel in its treatment of case-mix in modelling efficiency.

Herein, the case-mix indicator is incorporated as both an input in the production process and a likely determinant of TE. This game-changing approach differs from previous research, where ‘case-mix’ was deemed as either an output or an environmental factor in determining TE, and thus delivers further understanding in the area of efficiency evaluation in the extant literature.

(2) Empirics

This research is the first attempt to evaluate TE in INHs. As such, the empirical analysis of two key questions provides rich information to a wide range of stakeholders. Firstly, the results reveal whether INHs are utilizing their limited resources optimally. This is important as it highlights whether future challenges can be met given the current efficiency performance of the INH care system. Secondly, the findings determine whether private NHs are more efficient than public homes; thus offering guidance to policymakers on which ownership model is best placed to provide the LTC bed capacity to meet future needs in Ireland. As research in this area remains largely neglected outside of the US, the present study tackles this looming policy imperative and advances knowledge in the field. Moreover, the empirical evidence provides a more comprehensive understanding of the factors that determine the efficiency performance of INHs. This is crucial as it may explain managerial slack and extend knowledge of the determinants that drive inefficiency. Finally, the results afford interesting insights into the

quality-efficiency relationship: a subject that has attracted scant research interest in studies of efficiency in the NH sector.

(3) Methods

In order to estimate TE and its determinants, the present study applies methods ranging from non-parametric to parametric, and thus makes a number of noteworthy methodological contributions. This research is distinctive and meritorious in that it does not just present a method, but treats of a methodology and examines the robustness of the model results across a range of approaches.

While conventional DEA is the dominant method in the literature to estimate TEs, this research goes beyond this approach to employ homogenous and double bootstrap techniques to vouchsafe the reliability of the non-parametric conventional DEA TE scores. Bootstrap methods have rarely been applied in NHs studies. As such, this thesis extends the efficiency literature in this arena. In addition, this research itself is novel in that it adopts a range of two-stage semi-parametric approaches to identify the determinants of TE: namely, two-stage OLS regression and two-stage Tobit regression; and two-stage DB DEA. This permits direct comparison of the statistically significant drivers of TE across the different approaches. To the best of the researcher's knowledge, this is the first attempt to compare the determinants of TE across the semi-parametric methods. A further valuable contribution of this study is the unique and detailed primary dataset used which curates an in-depth understanding of INHs: an industry where no significant economic research has occurred to date.

(4) Policy

This research makes unique and beneficial contributions to policy in three distinct ways. Firstly, given that all care homes in this investigation are in receipt of limited public funds and the empirical findings reveal that INHs are inefficient, it arguably behoves policymakers to consider the introduction of performance measurement. This policy strategy could increase the

productivity of the care homes and assist the identification of top performing care facilities. This could serve as a best practice tool for other NHs, motivating managers to consider how care is delivered and to address weak points in the system. Additionally, improved communication between management and employees could be enabled by an improved understanding of their firm's efficiency performance. In a national context, the promotion of efficiency measurement could foster public interest in resource use in the delivery of public services; thereby encouraging society to assess performance and whether the industry is in a position to meet future challenges.

Secondly, this study finds that private NHs are more productively efficient than their public sector counterparts. As such, this investigation provides valuable evidence to corroborate the efficacy of public policy instruments to develop private care provision to achieve efficiency objectives in the use of taxpayer funds. Finally, the findings in this research foreground beacons of good practice; wherein efficiency and quality outcomes can be simultaneously achieved across the NH sector. These results are of great importance. The central challenge for both practitioners and policymakers is to ensure that high quality of care is delivered, and that the pursuit of productive efficiency in the NH industry is maintained.

1.6 Thesis Structure

Chapter Two presents a review of the literature on efficiency in the NH sector to elucidate how efficiency is analyzed and measured in this industry. Moreover, it highlights the research gaps this study aims to address. The literature shows that input-oriented TE is the most widely applied measure of efficiency in NH studies, primarily because it is not necessary to specify a behavioural assumption of cost minimization or revenue maximization. In addition, the chapter reviews the various determinants of efficiency in extant NH literature, and discusses the range of methods in relation to estimating efficiencies and the impact of efficiency determining factors.

Chapter Three presents an overview of the NH sector in Ireland. The Irish LTC system is discussed, and formal ROI care services which comprise home helps, home care packages, and residential care, positioned within it. The primary focus of the chapter is residential care as NHs located within this setting. Key stakeholders are identified, and the chapter considers future bed capacity needs, a profile of the residents, and the cost of care. It is clear that the INH sector will need to considerably increase its long-stay bed capacity to meet the projected surge in demand. According to ‘Population and Labour Force Projections 2016-2046’ (CSO, 2013), the number of people aged 65 and over in Ireland is expected to rise by 167%: from 532,000 in 2011 to over 1.4 million by 2046. Perhaps more significantly, the cohort requiring the highest level of care, those aged 85 and over, is growing more rapidly, and is forecast to accelerate into the future. This poses severe challenges for the supply of INH care services.

Chapter Four discusses the wide spectrum of methods applied throughout this research to estimate the TEs and to identify the determinants of TE in INHs. In order to validate the robustness of the TE estimates, this study employs a full range of methods from non-parametric conventional DEA, to semi-parametric two-stage approaches, to the fully parametric SFA. In addition, this chapter describes the primary dataset on which this research is based, and includes the design of the questionnaire, pilot-testing, and the overall data gathering process. The chapter also outlines the variables used to measure the inputs and outputs of production in this study and the potential efficiency determining variables included in the model. The chapter concludes by presenting summary statistics for the output and inputs variables and for the efficiency determinants.

Chapter Five is the first of two empirical chapters. In this chapter, a full spectrum of methods is applied to estimate the input-oriented TE scores for the sample of INHs and the sub-samples. The chapter therefore presents estimates for the following approaches: Conventional Data Envelopment Analysis (DEA); Homogenous Bootstrap (HB) DEA; Two-Stage Double

Bootstrap (DB) DEA; and Stochastic Frontier Analysis (SFA). In addition, this study measures SE as it may be that while the NHs are technically efficient, the scale of operations is not optimal.

Chapter Six presents the results for the estimated effects of the potential determinants of TE for all NHs and for the subsamples using two-stage semi-parametric and fully parametric methods. This chapter builds on Chapter Five wherein estimates of the TEs for INH units are analyzed. A number of two-stage semi-parametric approaches are applied as follows: OLS with conventional DEA scores; OLS with HB DEA scores; Tobit regression with conventional DEA scores; Tobit regression with HB DEA scores; and Two-Stage Double Bootstrap DEA. Importantly, the double bootstrap model integrates the effects of the efficiency determinants as explanatory variables in estimating the true TEs. Hence, this method affords accurate estimates of the parameters of the efficiency determinants, as well as bias-corrected DEA TE scores following controlling for the effects of efficiency factors. Moreover, the marginal effects of the determinants are obtained since it is vital to estimate the magnitude of the effects of the efficiency determining variables on TE. However, as previously mentioned, none of the two-stage approaches account for data noise. Hence, this study prioritizes the fully parametric SFA method which controls for data noise and enables unbiased TE estimates and parameters of the determining variables to be obtained. Finally, the efficiency factors which have a consistent effect on TEs in NHs across the different methods are identified to reinforce the robustness of the results.

Chapter Seven presents the findings and important contributions of this study, while noting the limitations and offering suggestions for future research.

1.7 Conclusion

The conspicuous dearth of research relating to the estimation of efficiencies in INHs, as well as the limited application of different methods in all long-term care TE studies, came to light

during a review of the NHs efficiency literature. Most prior studies in this area have relied on the conventional DEA approach, and few have applied bootstrap techniques or SFA. The main aim of this thesis, therefore, is to redress this gap by providing theoretical, methodological, empirical, and policy insights into the estimation of TE in the NH sector in Ireland. This research considers how to appropriately measure the TEs of NHs, and applies a comprehensive set of potential determinants in estimating and explaining TE with particular emphases on the type of ownership as well as quality factors. This study, therefore, contributes to the NHs efficiency literature in terms of validating the robustness of estimates across different methods, and in providing policy insights into the factors governing TE.

Chapter Two: Theoretical Framework and Previous Research

2.1 Introduction

This chapter presents the theoretical foundations of this study and a review of the literature pertaining to the evaluation of the efficiency in the NHs sector. To this end, the chapter will firstly review the Farrell's efficiency measures in the NH sector, with the main focus on TE. Farrell (1957) defined the TE of a firm as the ability to produce at the optimal production frontier attainable given the available resources and production technology. Technical efficiency can also be regarded as the productive efficiency since it involves the measurement of physical units of inputs and outputs. While TE is the most commonly applied concept of efficiency in the NH sector, allocative efficiency (AE) involves the measurement of input or output prices, and thus a combination of the two can be used to calculate the overall economic efficiency of a nursing home. Since it is clear that some technically efficient NHs do not operate at an optimal scale, scale efficiency (SE) is another important extension of the analysis of TE which is considered in the NH literature.

This research aims, not only to measure TE, but also to discuss the potential determinants of TE proposed in the relevant literature. Such determinants are neither input nor output factors in the production process, but those which may influence the production frontier and affect the organizational performance of the firm. A review of the literature indicates that possible determinants of efficiency can be divided into external and internal factors. External determinants are beyond the control of the management, and include such factors as the ownership, location, or the age of the NH unit; the internal factors, such as the quality or size of the nursing home, are controlled to a varying degrees by management.

Determinants of efficiency are particularly important from policy perspectives as they may account for sources of inefficiencies across the NHs sector. Thus, an appropriate examination

of efficiency determinants could assist a wide range of stakeholders such as nursing home operators, government bodies, and other policymakers, in illuminating possible managerial slack in the INH sector. This chapter will also interrogate the relevant methods used to estimate or measure the TE within the NH sector. The most significant analytical techniques that have been applied in the efficiency literature on the NHs include the non-parametric data envelopment analysis (DEA) and the parametric stochastic frontier analysis (SFA). Both techniques have been applied in the NH literature to various extent and using different modifications.

Section 2.2 discusses the NHs efficiency by reviewing the Farrell's (1957) efficiency measures and considering their applications in the NH sector. The SE concept as a further extension of the TE is discussed in Section 2.3, while Section 2.4 presents the various efficiency determining variables which have been used in the NH literature. Section 2.5 presents the two main efficiency measurement methods (DEA and SFA) that are mostly employed in the NH literature, and it also critically assesses the strengths and limitations of each approach. Section 2.6 concludes the chapter.

2.2 Farrell's Efficiency Measures in the NHs Literature

Measuring efficiency is a complex concept since any definition of efficiency rests on numerous assumptions, such as the objective of the firm, measurement and definition of variables used, and the inclusion of the case-mix and quality variables as other important factors affecting the performance of the NH sector.

The concept of efficiency was firstly proposed by Farrell (1957), who drew upon the work of Debreu (1951) and Koopmans (1951) to define a simple measure of firm efficiency. Farrell's (1957) proposition maintained that the efficiency of the firm comprises two core components: namely, TEs and AEs. TE involves physical quantities of inputs and outputs, whereas, from an input-oriented perspective, AE involves selecting that mix of inputs that produces a given

quantity of output at minimum cost, given their respective input prices and the available production technology. The product of both technical and allocative efficiencies determine the total economic (cost or revenue) efficiency.³

Table 2-1 presents the relevant research on efficiency evaluation conducted for the NH sector to date. Such literature is extremely sparse, and to the author's knowledge, the empirical works and findings outlined in this table are the only relevant studies which apply the efficiency measurement in the NHs sector. Table 2-1 also demonstrates that the TE is the pre-eminent form of efficiency measured in this industry, although some studies also measured the allocative or economic efficiency of the sector (see Nyman and Bricker 1989; Nyman *et al.* 1990; Fizel and Nunnikhoven 1992; Chattopadhyay and Heffley 1994; Kooreman 1994; Ozcan *et al.* 1998; Bjorkgren *et al.* 2001; Wang and Chou 2005; Borge and Haraldsvik 2009; Garavaglia *et al.* 2011; Chang and Cheng 2013; DeLellis and Ozcan 2013; and Ni Luasa *et al.* 2018). The choice of the efficiency measure, as already noted, is largely dictated by the objective of the NH unit, such as output maximization, input minimization or cost minimization. Secondly, it will depend on the measurement and definition of variables used. The measurement of allocative or economic efficiency can pose serious practical difficulties, particularly for the NHs research, wherein data on input and output prices are not always readily available. The following section considers TE, AE, the overall economic efficiency and application of these efficiency measures in the NHs literature:

³ Farrell (1957) refers to 'total economic efficiency' as 'overall efficiency' or 'overall productive efficiency'.

Table 2-1: Previous Evaluations of Efficiency in the NH Sector

Author(s)	Technique	Country and sample	Output variable	Average efficiency and other findings
Garavaglia, Lettieri, Agasisti and Lopez (2011)	DEA (CRS and VRS), – input-oriented TE; homogenous bootstrap model.	40 Italian NHs (six public and 34 private facilities), over a 3-year period.	Case-mix, extra nursing hours and out-of-pocket charges	Mean TE scores is between 0.78 and 85. Quality of care is positively related to efficiency.
Hoffler and Rungeling (1994)	SFA (cost frontier) - CE	1079 NHs in the U.S. for the year 1985.	Skilled inpatient days; intermediate inpatient days and ‘other’ inpatient days.	For-profit homes have lower costs relative to non-profit homes.
Kleinsorge and Karney (1992)	DEA TE (output-oriented)	22 NHs in Kansas	Total patient days; State inspection score; Decubiti-free days care; operating income.	The NHs are found to be fully efficient with a score of 1.0.
Knox, Blankmeyer, Stutzman (2007)	SFA (Cobb Douglas)	Panel data of Texas NHs for 1999 and 2002	Number of Patient days.	Average Efficiency Scores 0.80-0.92. Non-profit facilities are notably less productive than facilities operated for profit.
Kooreman (1994)	DEA (CRS and VRS) – input-oriented TE	292 Dutch NHs.	Number of patients by care needs.	Average efficiency score 0.87
Laine, Finne-Soveri, Bjorkgren, Linna, Noro, Hakkinen (2005)	DEA (CRS) – input-oriented TE	114 public health centre hospitals and residential homes in Finland.	Total inpatient days adjusted by case-mix.	Mean TE 0.72.
Ni Luasa, Dineen, Zieba (2018)	DEA (CRS and VRS) – input-oriented TE, and SE,	39 public and 73 private INHs	Total patient days. Case-mix taken into account in the second-stage analysis.	Mean TE 0.61 (with TE of 0.62 for public homes and 0.623 for private homes), mean SE 0.88
• Nyman and Bricker (1989). • Nyman, Bricker and Link (1990)	DEA (CRS) – input-oriented TE	195 NHs in Wisconsin (U.S.) for the year 1979.	Patients by care needs.	Average efficiency score was 0.89. For-profit NHs are significantly more efficient than the not for profit NHs.
Ozcan, Wogen, and Mau (1998)	DEA – input-oriented TE.	Uses a 10% national sample of 324 skilled nursing facilities in the United States	Total inpatient days of <i>medicare</i> and <i>medicaid</i> clients; Total private-pay inpatient days.	The average efficiency of the for-profits is 0.840 and for the non-profits is 0.803. For-profit and medium skilled nursing facilities are more efficient than non-profit and low-skilled units.
Vitaliano and Toren (1994)	SFA (cost frontier) - CE	164 Skilled Nursing Facilities and 443 combination skilled and health related facilities during 1987 and 1990.	Patient days.	Average CE 71% No change in efficiency between 1987 and 1990, and it does not vary between for-profit and not-for profit homes.
Wang and Chou (2005)	DEA (CRS and VRS) – input-oriented TE	53 Long-Term Care Institutions in Taiwan.	Number of residents; Number of quality outputs (e.g. accreditation of professional review committee; and accident rate)	Average Efficiency VRS TE score of 0.77.

Table 2-1:continued

Author(s)	Technique	Country and sample	Output variable	Average efficiency and other findings
Anderson, Lewis and Webb (1999)	Bayesian SFA (stochastic production frontier model).	653 NHs, United States nation-wide for the year 1995.	Number of patients admitted.	For-profit homes have much higher mean efficiency scores than the non-for-profit homes, with TE scores of 0.90 and 0.73, respectively.
Björkgren, Häkkinen and Linna (2001)	DEA (CRS and VRS) – input-oriented TE, SE, AE and CE.	64 NHs in Finland collected for the year 1995.	Case-mix adjusted patient days.	The mean CE was 0.77 for model 1 and 0.74 for model 2. The means of the TE scores were 0.85 and 0.87 and the means of AE were 0.86 and 0.89. Larger units operated more efficiently than smaller units.
Borge and Haraldsvik, (2009)	DEA (CRS and VRS) – input- and output-oriented TE; double bootstrap model.	Each local government area and the national level efficiency potential.	Number of patients by service.	The mean TE score is 0.84 (for input-orientation) and 0.85 (for output-orientation).
Chang and Cheng (2013)	DEA (CRS and VRS) – input-oriented TE	132 NHs in Taiwan during 2004-2009.	Number of residents; Number of falls; Number of times the resident uses emergency services.	The average TE is 0.90.
Chattopadhyay and Heffley (1994)	DEA (CRS and VRS) – input - oriented TE.	140 NHs from Connecticut, USA during the year 1982-83	Total patient days.	The mean efficiency score for non-profit homes is 0.71 compared to 0.92 for-profit homes.
Chattopadhyay and Ray (1996)	DEA (CRS, VRS and NIRS) –output-oriented TE	140 NHs from Connecticut, USA during the year 1982-83	Total patient days.	The mean level of TE was 0.80 for non-profit homes and 0.94 for-profit homes. The mean levels of scale efficiency are 0.96 for no-profit homes and 0.97 for those operating for profit.
Crivelli, Filippini, and Lunati (2002)	SFA (cost frontier) – CE and SE.	Cross Sectional Data of 886 NHs. Data given by the Swiss Federal Statistical office and its' for the period 1998.	Total patient days.	The mean CE was 0.79 (or 0.21 for cost inefficiency)
DeLellis and Ozcan (2013)	DEA (CRS and VRS) – input-oriented TE	10% of random sample of U.S. NHs	Number of <i>medicare</i> residents; Number of <i>medicaid</i> residents; Number of other residents.	The average efficiency was 0.87, with a statistically significant higher average efficiency for NHs in urban areas; in counties with a higher level of competition, higher average income, or higher number of home health agencies, and in not-for-profit and governmental facilities. Mostly favourable quality outcomes were found for efficient NHs.
Farsi, Filippini, Lunati (2008)	SFA (cost frontier) - CE	356 NHs in Switzerland, operating over the period from 1998 to 2002	Total patient days.	The mean CE for the final model used was 0.92 (or 0.081 for cost inefficiency).
Fizel and Nunnikhoven (1992)	DEA (CRS – input-oriented TE)	163 Michigan NHs in USA, of which 104 are for-profit and 59 are non-profit homes.	Total patient days for skilled and intermediate-care patients.	Average efficiency 0.655. Chain homes have higher average efficiency scores (0.705) relative to independent operators (0.622).

Note: TE = technical efficiency, AE = Allocative Efficiency, SE = scale efficiency, CE = cost efficiency. The table also draws partly on information presented in Iparraguirre and Ma (2015). The studies are presented in alphabetical order.

2.2.1 Technical Efficiency (TE) in the NH Sector

As shown in Table 2-1, TE is the most common measure of efficiency or productive performance in the NHs literature. According to Farrell (1957), TE⁴ reflects the ability of a firm to obtain the maximum output from a given set of inputs or the ability of using minimum inputs for a given level of output. Furthermore, the previous efficiency literature distinguishes between input-oriented (IO) TE, and output-oriented (OO) TE. The input-oriented TE involves minimizing inputs while maintaining a given level of output. In other words, the input-oriented (IO) TE informs by how much can input quantities be proportionally reduced without changing the output quantities produced. In contrast, an output-oriented (OO) TE measures the proportional expansion of output quantities for the given level of inputs employed and within the possible production possibilities set (Coelli *et al.* 2005).⁵

Coelli *et al.* (2005) maintained that the owner of the firm selects the orientation based on which quantities of inputs or outputs they have most control over. Table 2-1 confirms that the majority of studies estimate IO TE for the NHs and that the definition of an output-oriented TE is somewhat scarce in the NHs literature.⁶ This may be attributable to the fact that the manager of the LTC facility has a greater control of the inputs relative to the outputs since the output of the nursing home is generally defined as the number of patients per period of time or the total patient days.

Thus, it is generally assumed that NH facilities aim to reduce their inputs while maintaining a given level of output in order to be fully technically efficient. The following subsection will briefly outline the theoretical definition of IO TE, as it is also assumed in this research as an

⁴ Farrell (1957) also refers to the ‘technical efficiency’ as ‘productive efficiency’.

⁵ The exact exposition of the OO TE is presented in Coelli *et al.* (2005).

⁶ Nyman and Bricker (1989); Nyman *et al.* (1990); Fazel and Nunnikhoven (1992); Chattopadhyay and Heffley (1994); Kooreman (1994); Ozcan *et al.* (1998); Bjorkgren *et al.* (2001); Laine *et al.* (2005a); Wang and Chou (2005); Borge and Haraldsvik (2009); Garavaglia *et al.* (2011); Chang and Cheng (2013); DeLellis and Ozcan (2013).

appropriate orientation for the NHs sector. The second subsection will discuss the application of IO TE in the relevant efficiency literature of the LTC provision.

Input-Oriented (IO) TE for NHs

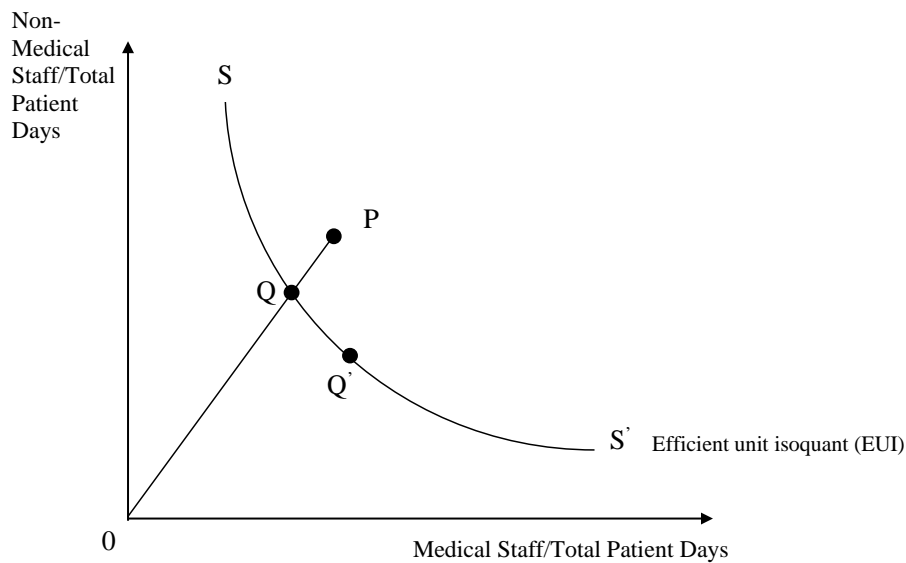
Figure 2-1 illustrates Farrell's (1957) conceptualization of an IO TE measurement using a constant returns to scale (CRS) assumption of technology.⁷ The graph presents a simplified IO TE model for the NHs which assumes that one output is produced using two inputs. Therefore, the figure uses a CRS technology, and the SS' shows an efficient unit isoquant for two inputs, X_1 and X_2 , denoted by medical and non-medical staff respectively, and one output, Q , as measured by the number of patient days. Knowledge of the isoquant of fully efficient firms enables measurement of TE. Since the production frontier of fully efficient firms is not known in practice, this is estimated from observations on a sample of firms in the industry concerned.⁸

Along the frontier SS', represented by the unit isoquant, the increased usage of one input, medical staff (X_1), necessitates a decrease in the use of the second input, non-medical staff (X_2), in order to maintain the same level of output (the total patient days). All NHs being on the SS' isoquant (or optimal frontier) are technically efficient. All homes located above the curve are inefficient, meaning that they must proportionally reduce their medical and non-medical staff for a given level of output in order to become technically efficient.

⁷ The constant returns to scale CRS technology implies that the nursing homes produce at the optimal scale, and this assumption can be relaxed using the VRS assumption which will be explored in Section 2.3. Farrell also discussed the extension of his method, so as to accommodate more than two inputs, multiple outputs, and the non-constant returns to scale technology.

⁸ The estimation of the production frontier using both non-parametric and parametric methods are discussed in section 2.5.

Figure 2-1: Input-Oriented TE



In Figure 2-1, the nursing home indicated by point P is technically inefficient as it is not on the production frontier. The nursing home needs to reduce its use of medical and non-medical staff, given a fixed amount of total patient days, in order to move to a feasible and technically efficient production point such as that adopted by nursing home Q. In view of this, nursing home Q becomes the target point for nursing home P. Hence, if a given firm uses quantities of inputs defined by point P to produce one unit of output, the technical inefficiency of that firm is the distance QP, which is the amount by which all inputs could be proportionally reduced to achieve a technically efficient production at point Q. This is usually expressed by the ratio QP/OP . Equivalently, the TE, of a nursing home P is represented by the following ratio:

$$TE = OQ/OP \quad \text{Eq. 2.1}$$

The TE score accordingly shows the ratio of the minimum inputs which could be used relative to the actual inputs used. The TE score takes a value between 0 and 1, and provides an indicator of the degree of TE of the nursing home P. A value of 1 implies that the home is fully technically efficient. As noted earlier, the point Q is technically efficient because it lies on the efficient isoquant and $TE=OQ/OQ=1$. The greater the distance OP from the frontier (if $OP>OQ$),

the smaller the TE will be. On the other hand, the distance OP will move toward 0 if the nursing home is becoming more technically efficient.

Application of TE in the NH Sector

As previously noted, the literature on the estimation or measurement of TE in the NH sector is very limited; highlighting a significant lacunae in the research for this sector. It is also observed that the majority of research regarding the estimation of the IO TE has taken place in the USA. Perhaps, the most important US study was that of Ozcan *et al.* (1998) which used a sample of 10% of all skilled nursing facilities in the USA and found their IO TE levels of 0.84 for the for profit homes, and 0.80 for the non-profit homes. A similar approach was used more recently by DeLellis and Ozcan (2013) who estimated an average TE score of 0.87 for US NHs, using a random sample of 10% for all NHs in the USA. The latter finding suggests that these institutions needed to reduce their inputs, such as the number of full time equivalent of registered nurses; licenced practical nurse; nurses' aides and number of beds by an average of 13%, while achieving the same level of output (as measured by the number of residents) in order to become technically efficient. On the other hand, Fazel and Nunnikhoven (1992) found that Michigan NHs to have a much lower mean TE score of 0.66, indicating these homes must reduce their inputs by 34% while maintaining a given level of output and to achieve the full TE. Chattopadhyay and Heffley (1994) estimated an input-oriented TE for 140 NHs and found the TE score ranging between 0.71 for profit and 0.92 for non-profit homes, respectively. Nyman and Bricker (1989) and Nyman *et al.* (1990) used the data on Wisconsin NHs in the US, and found that their TE score is about 0.89.

Overall, the results of those US studies were comparable as the calculated TE were at similar level as those studies which applied more robust samples (see Ozcan *et al.* 1998; DeLellis and Ozcan 2013). Similarly, Asian efficiency studies of the NH sector, such as those of Wang and Chou (2005) and Chang and Cheng (2013) estimated input-oriented TEs for the NHs in Taiwan.

The findings of both studies concurred that the inputs of these facilities (i.e. the number of doctors; the number of registered nurses, the number of other personnel and the number of beds) should be decreased between 10 and 13%, while achieving a given level of output and to ensure full TE. In the European context, Kooreman (1994) found Dutch NHs to have an average input-oriented TE score of 0.87; indicating that these homes must reduce their labour inputs by 13% in order to achieve full TE. Whereas Garavaglia *et al.* (2011) found that Italian NHs have an average IO TE scores ranging between 0.78 and 0.85, Laine *et al.* (2005a) demonstrated that Finnish NHs have an average TE score of 0.72. In Norway, Borge and Haraldsvik (2009) found a mean TE of 0.85 for public care facilities. Most recently, Ni Luasa *et al.* (2018) estimated the TE for 110 private, public and non-profit NHs in Ireland and found an average TE of 0.62. These results indicate that INHs are relatively inefficient. In fact, they could decrease their inputs by 38% and still produce the same level of output, as measured by patient days, in order to be fully technically efficient.

Table 2-1 confirms that the estimation of OO TE is also rather sparse in the efficiency literature in the NH sector. Kleinsorge and Karney (1992) found that all 22 Kansas NHs are technically efficient and are producing at optimal output. On the other hand, Chattopadhyay and Ray (1996) suggest that the output (as measured by total patient days) of Connecticut non-profit homes must further increase by 20% to achieve optimal performance. Similarly, Borge and Haraldsvik (2009) noted that Norwegian NHs outputs, as measured by the number of patients by service, must be expanded by 15% to achieve full TE.

2.2.2 *Allocative Efficiency and Economic Efficiency*

Allocative efficiency (AE) is derived from a cost-minimizing perspective or a revenue-maximizing perspective; noting that in both cases a producer must firstly be technically efficient in order to be allocatively efficient. From the cost-minimizing perspective, allocative

efficiency⁹ reflects the ability of a producer to use the inputs in optimal proportions, given their respective prices, and which, together with the input-oriented TE can be combined to obtain the economic efficiency, defined as the cost efficiency (CE). Conversely, from the revenue-maximization perspective, AE represents the ability of a producer to maximize revenue given the respective output prices, which combined with the output-oriented TE, will define an economic efficiency as the revenue efficiency (RE).¹⁰ Table 2-1 outlines the previous evaluations of efficiency in the NH sector and illustrates that the measurement of AE and economic efficiencies is rather sparse. In fact, none of the studies estimated the AE from the revenue-maximization perspective. This is mainly due to the assumption that the revenue maximization in the NH sector can be difficult to justify when the output of the long-term facility is usually measured in terms of total patient numbers or total patient days. Therefore, most of the studies which estimated allocative or economic efficiency for the NH sector defined these measures from the cost-minimization perspective: the assumption being that the NHs will minimize costs given their respective input prices. The application of cost and allocative efficiencies is still very rare in the literature on the NHs due to the fact that the exact data on the input prices are seldom available for this sector. For instance, Bjorkgren *et al.* (2001) estimated TE, AE, and CE, for the 64 Finnish NHs, by using official salary statistics for different types of labour¹¹ and assumed the costs of capital were the same for all NHs.

They found an average CE score of 0.74 for Finnish NHs, which according to this definition was the product of two components: the mean TE, which ranged between 0.85 and 0.87; and the average AE which ranged between 0.86 and 0.89. The estimated CE was between 0.74 and 0.77, suggested these care homes were cost inefficient and should reduce costs by 26 to 23%. Cost inefficiency was attributed to technical and allocative inefficiencies, as these care facilities

⁹ Farrell (1957) also refers to allocative efficiency as price efficiency.

¹⁰ As the focus of this research is on TE, the theoretical descriptions of AE, CE and RE are not discussed in the detail here, and these efficiency concepts are graphically outlined and discussed in Coelli *et al.* (2005).

¹¹ In Finland, wages are centrally negotiated, and the variation in wage levels between facilities is small.

were allocatively inefficient by 11-14% and technically inefficient by 13-15%. In the USA, On the other hand, Vitaliano and Toren (1994) estimated the cost efficiencies of New York NHs by measuring the cost of capital using the total reported property expenses divided by the gross square feet of each care home, and by incorporating the wage costs of registered nurses (RNs) and aides in the estimation of AE. These authors found that the average CE estimate of 0.71 did not vary significantly for New York facilities between 1987 and 1990, nor did it not vary between for-profit and not-for profit homes. Interestingly, this finding is in contrast to those of Crivelli *et al.* (2002) and Farsi *et al.* (2008) who estimated the CEs of Swiss NHs. Both studies found private NHs to be more cost-efficient than public institutions, although Farsi *et al.* (2008) acknowledged a narrowing of the efficiency gap between private and public NHs.

AEs and CEs have not been previously analyzed in the the INHs literature as it is difficult to ascertain the behavioural assumption of the cost minimization for the Irish long-term care sector; mainly because INHs comprise a combination of public, private, and voluntary care homes as further discussed in Chapter Three. Pestieau and Tulkens (2006) emphasized the difficulty in assessing the performance of public firms owing to the multidimensional objectives of public enterprise, including efficiency considerations, equity, and full employment goals. Studies by Frech (1985) and Alchain and Demsetz (1972) suggested that the different structures of property rights conveyed by different institutional arrangements inevitably impact the efficiency of the NH industry.

Private NHs owners have exclusive rights to the income generated, with the resulting incentive to monitor inputs and to produce efficiently (Fizel and Nunnikhoven 1992). By contrast, in public NHs the owner's property rights to income are attenuated and non-pecuniary goods are consumed at the expense of efficiency and wealth. Nyman and Bricker (1989) purport that non-profit firms are constrained to spend their entire budget, at least in the long-run; a situation which can generate the use of more inputs or inputs with higher prices than it is necessary to

achieve a certain level of output. Such arguments would suggest that the behavioural assumption of cost minimization or revenue maximization may not be appropriate for public NHs. Nevertheless, various studies rightly acknowledge the fact that even if the public NHs have different objectives (such as the quality and other non-pecuniary goals), they should still aim to minimize the usage of inputs and minimize costs by the given level of output and quality.

2.3 Scale Efficiency

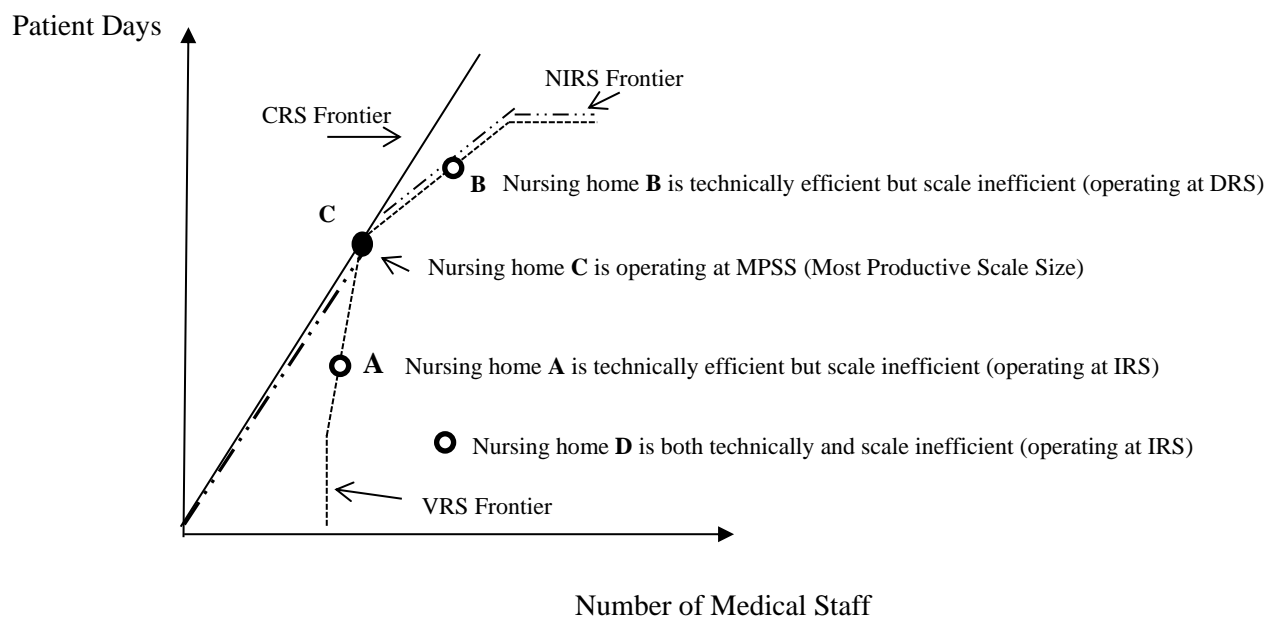
As previously stated, Farrell (1957) assumes that the technology exhibits constant returns to scale (CRS) in measuring TE. However, this assumption is only appropriate when all NHs are operating at optimal scale. In contrast, variable returns to scale (VRS) technology permits the estimation of a ‘pure’ efficiency score: in other words, one which is devoid of scale efficiency (SE). Figure 2-2 illustrates the concept of SE for the NHs using a production technology with one input (medical staff) and one output (total patient days). The identification of TEs under both VRS and CRS technologies can be used to derive the SE scores. Following Färe *et al.* (1998), the input-orientated measure of SE for a nursing home operating at a given input vector, x , and an output vector, q , is defined as:

$$\text{Scale efficiency} = SE = \frac{d_i(x, q|VRS)}{d_i(x, q|CRS)} = \frac{TE_{CRS}}{TE_{VRS}}$$

Figure 2-2 demonstrates that when the nursing home is operating at the CRS frontier, the CRS and VRS TE scores will be equal, and the firm deemed to be scale efficient. A difference between the CRS and VRS TE scores indicates that a nursing home is scale inefficient; which infers that the care home is operating at increasing returns to scale (IRS) or decreasing returns to scale (DRS). In Figure 2-2, nursing home A is technically efficient but is scale inefficient as it is operating at IRS, while nursing home B is technically efficient but scale inefficient as it is operating at DRS. In other words, these facilities are technically efficient but not scale efficient. Moreover, to identify the nature of scale economies, a non-increasing return to scale frontier

model (NIRS) can be employed as illustrated in the same figure¹². Additionally, nursing home D is located away from both CRS and VRS frontiers; implying that it is both technically inefficient and scale inefficient, and is operating at IRS. On the other hand, when a firm is both technically and scale efficient, it will produce using the CRS technology, and the production will occur at the point where the average productivity of the observed input-mix attains a maximum. This corresponds to point C in Figure 2-2, wherein the nursing home is operating at its most productive scale size (MPSS).¹³ This is to say that the NH unit is both technically and scale efficient (Coelli *et al.* 2005). Additionally, if a firm is not scale efficient, TE_{crs} will be always smaller than TE_{vrs} , as it does not disentangle the SE. Hence, TE_{crs} provides a measure of the overall or aggregate productivity improvement that is possible, if the firm is able to alter its scale of operation.

Figure 2-2: Scale Efficiency



Source: Own illustration based on Coelli *et al.* (2005, p.174)

¹² Section 4.2.3 discusses the NIRS Frontier Model to indicate whether a nursing home operates at IRS or DRS.

¹³ The MPSS can alternatively be referred to as the technically optimal productive scale (TOPS).

Table 2-1 confirms that very few studies estimate SE for NHs. For example, Bjorkgren *et al.* (2001) evaluated the relationship between optimal production size and the actual size of the unit by plotting SE scores against the size of the care facilities¹⁴. These authors found that scale inefficiencies occur in Finnish NHs of less than 30 beds and concluded that larger NHs in Finland operated more efficiently than smaller units. In contrast, Crivelli *et al.* (2002) found 50% of Swiss NHs to be characterized by IRS and strongly recommended they increase in size in order to reach optimal size. These authors noted that the MPSS could be reached with 88 beds. In the US, Chattopadhyay and Ray (1996) found 54% of Connecticut NHs to be scale inefficient, noting that 18% are categorized by IRS and 36% by DRS. Additionally, they concluded that non-profit homes are more scale inefficient than the for-profit homes. With regard to INHs, only Ni Luasa *et al.* (2018) have recently estimated the scale efficiency for those units and indicated that only 4% of all NHs are scale efficient, as they are operating at CRS and the vast majority of both public and private NHs is operating at the IRS indicating that these facilities should expand further and gain economies of scale. On the other hand, some care homes may be too large; leading to slow decision-making and inefficient performances. However, the authors acknowledged that their findings with regard to the SE are preliminary and a fuller examination of scale economies of the INHs should be conducted in the future. The present thesis attempts to address this lacuna in the literature.

2.4 Determinants of NH Efficiency

Identifying the relevant factors that affect TE can assist a wide range of stakeholders in accounting for possible managerial slack in NHs. In turn, recognizing the drivers of efficiency enables homes to improve their performance and can lead to a reduction in public expenditures on NH services. While efficiency determinants¹⁵ are not the traditional inputs or outputs in the

¹⁴ As measured by the number of beds.

¹⁵ Alternatively, they are referred to later in this thesis as the environmental factors or efficiency determining variables.

production set,¹⁶ they might nonetheless influence the production frontier and the TE of the nursing home in turn. Diverse measurement techniques are available to control for the impact of efficiency determinants as discussed in Section 2.5. In contrast to the inputs and outputs, the main difference of these variables lies in the fact that they are not routinely included in the derivation or estimation of TE. However, Table 2-1 underlines the wide range of determinants which have been applied to evaluate their effect on efficiency in the NH sector¹⁷ as discussed below.

- *Ownership*

The most common variable of interest is the ownership status of a NH unit. The effect of ownership on efficiency largely originates in the US nursing home research as this market structure is a mix of public and private LTC homes. Accordingly, an overview of the NH studies in Table 2-1 illustrates that for-profit units are more technically efficient than the public homes. For example, Ozcan *et al.* (1998) found that certain private NHs achieve levels of TE which are 0.86 times higher than the most efficient non-profit units. Nyman and Bricker (1989), Nyman *et al.* (1990), Fazel and Nunnikhoven (1992) and Chattopadhyay and Heffley (1994) similarly concluded that private facilities have significantly higher TE scores than the public facilities. The theoretical rationale for greater efficiency of for-profit firms arises from property rights theory as private NHs maximize profit and minimize costs. For-profit home-owners have exclusive rights to income generated, with the resulting incentive to monitor input productivity. Non-profit care facilities espouse different behavioural objectives than profit firms, such as, for example, equity and employment goals. Thus, non-profit providers choose non-pecuniary

¹⁶ Chapter 4 discusses inputs and how they are defined in this study.

¹⁷ The focus of this review will be on the impact of the various determinants on efficiency of the nursing homes but not on how these factors have been estimated. These determinants can be estimated using both parametric and non-parametric techniques which will be explored in detail in Section 2.5.

benefits at the expense of wealth as owner's property rights to income are attenuated (Alchain and Demsetz 1972).

Since the most European NHs are publicly owned, the issue of the effect of ownership status on efficiency has not been widely considered in this context. Nonetheless, a small cohort of studies, such as that conducted by Crivelli *et al.* (2002), found public NHs are just as cost efficient as private units. This challenges Farsi and colleagues' (2008) conclusion that Swiss private care homes are more cost efficient than public facilities. In the Asian context, Wang and Chou (2005) claimed that ownership did not impact upon the TE performance of private and public NHs in Taiwan. Such findings counter property rights theory which purports that for-profit homes are inherently more efficient than non-profit homes. Garavaglia *et al.* (2011) found public NHs in the Lombardy region to be less efficient than their private counterparts, while Ni Luasa *et al.* (2018) undertook the only such study to date on the effect of the ownership on INHs efficiency. While they found that the private NHs have significantly higher TE scores than the public NHs, their findings were not conclusive when the effect of ownership was examined in the second-stage regression analysis. As such, this thesis contributes and extends the debate on the effect of ownership on TE of NHs. This is particularly important in the context of Ireland given the mixed ownership structure of the LTC home units.

- *Chain Affiliated NHs and Independent Units*

Only cursory attention has focused on the effect that chain ownership might have on nursing home efficiency. Chains are based on a multi-plant structure: the objective of each is to link together the production plans of several plants which are part of an integrated firm and achieve near optimal results on performance measures (Bhatnagar *et al.* 1993). Nursing home chains are a group of firms which share a uniform mission statement and comparable organizational policies and procedures (Kleinsorge and Karney 1992). Efficiencies in multi-plant firms arise from the need to only make a single investment in research and development; while in contrast,

two or more independent firms, must each make independent investments. Additionally, multi-plant firms can shift resources within the firm in response to adverse shocks or improve the firm performance by the sharing of services or bulk-purchasing (Bernard, 2007). Chains can also increase their efficiency through a firm-wide 'learning curve'. By specializing in a narrow product array and increasing the rate of output per firm relative to an independent firm, a specialist chain nursing home may hone technical expertise at a much faster rate than an independent home. On the other hand, as more and more firms become part of the chain, the lines of authority and responsibility become less clearly defined, leading to coordination problems, untimely decisions, and less efficient performances.

The growth of chains is interesting because it underlies the rise of an organizational norm that is coming to dominate in the service industry. For example, Martin and Jerome (2016) noted that the three largest chain operators (Korian-Medica, Orpea, and DVD) accounted for 45% of the 20% of profit beds in the French LTC environment, compared to 33% in 2007. Nonetheless, the existing theoretical and empirical literature in NHs is largely silent on the issue of firm performance in terms of multi-plants versus independent operators. Knox *et al.* (2001) maintained that chain facilities are significantly more efficient than independent units when both technical and allocative efficiencies are considered. Furthermore, these authors rejected Anderson and colleagues' (1999) advice that mergers with and subsidies from chain facilities be discouraged. Fizel and Nunnikhoven (1993) posited that the significant multi-plant economies which exist with multi-plants suggest the growth of chain ownership may offer promise for an NH sector which is hampered by rapidly escalating costs. In contrast, Martin and Jerome (2016) found that cost efficiencies decrease with the number of facilities in the chain. This research contributes to the limited extant literature with respect to the impact private chain homes may have on efficiency relative to private non-chain care facilities. As will be discussed in Chapter Three, private chain homes are now an area of rapid development in

Ireland despite the lack of established empirical evidence to support the efficiencies of this type of organizational form.

- *Quality*

The passive consumer of the past has been replaced by the quality-sensitive consumer; a trend which has compelled health-care managers to include quality in strategic decision-making processes. Since quality is therefore another potentially important determinant of TE, achieving the correct balance between efficiency and quality is paramount for NH services in a society that demands efficient outcomes and appropriate quality. Unfortunately, strategies to assure and improve quality of formal LTC can come at the expense of efficiency. The ensuing ‘trade-off’ resting on the intensity of competition among NH providers is addressed in a number of prior studies. Effective competition typically requires a number of preconditions to be met: not least, the existence of multiple providers, the easy entry and exit of providers, and data on the prices and quality of providers (EC, 2015). However, such preconditions are seldom fully met in the health-care sector; suggesting that high quality outcomes and efficient outcomes may not be achieved simultaneously. Providers of care may respond to greater competition not by reducing the price of the service, but by increasing the quality, assuming it costs the provider less to gain additional customers by increasing quality than by lowering the price. In view of this, quality competition is often associated with higher investment in technical or medical equipment and accommodation aspects of care, and less commonly aligned with improvements in technical aspects of quality (Propper *et al.* 2004). In fact, these care items are least likely to be properly judged by patients in comparison with the availability of certain items of equipment or the luxury of the building. Furthermore, investing in easily observable aspects of quality is consistent with the profit-maximizing rationales, since they ostensibly play the most important role in the demand for the elderly care.

Table 2-2: Definition of Quality according to Donabedian’s Structure-Process-Outcome Framework and Applications in Efficiency Literature

Dimensions of Care	Description	Application
Structure	<p>Structure includes all of the factors that affect the context in which care is delivered. This includes the physical facility, equipment, and human resources, as well as organizational characteristics such as staff training and payment methods. These factors control how providers and patients in a health-care system act and are measures of the average quality of care within a facility or system. Structure is often easy to observe and measure and it may be the upstream cause of problems identified in process.</p>	<p>(1) Nyman and Bricker (1989); (2) Garavaglia <i>et al.</i> (2011); (3) Laine <i>et al.</i> (2005b); (4) Martin and Jerome (2016) (5) Ni Luasa <i>et al.</i> (2018), Dineen <i>et al.</i> (2019), Zieba <i>et al.</i> (2020)</p>
Process	<p>Process is the sum of all actions that make up health-care. These commonly include diagnosis, treatment, preventive care, and patient education but may be expanded to include actions taken by the patients or their families. Processes can be further classified as technical processes, how care is delivered, or interpersonal processes, which all encompass the manner in which care is delivered. According to Donabedian, the measurement of process is nearly equivalent to the measurement of quality of care because process contains all acts of health-care delivery. Information about process can be obtained from medical records, interviews with patients and practitioners, or direct observations of health-care visits.</p>	<p>(1) Nyman and Bricker (1989); (2) Kooreman (1994); (3) Anderson <i>et al.</i> (2003); (4) Zhang <i>et al.</i> (2008); (5) Rosko <i>et al.</i> (1995); (6) DeLellis and Ozcan (2013) (7) Shimshak <i>et al.</i> (2009)</p>
Outcome	<p>Outcome contains all the effects of health-care on patients or populations, including changes to health status, behaviour, or knowledge as well as patient satisfaction and health-related quality of life. Outcomes are sometimes seen as the most important indicators of quality because improving patient health status is the primary goal of health-care. However, accurately measuring outcomes that can be attributed exclusively to health-care is very difficult. Drawing connections between process and outcomes often requires large sample populations, adjustments by case mix, and long-term follow ups as outcomes may take considerable time to become observable.</p>	<p>(1) Kleinsorge and Karney (1992); (2) Shimshak <i>et al.</i> (2009); (3) Laine <i>et al.</i> (2005b)</p>

In relation to the effect competition has on quality and efficiency in the NH studies, DiGiorgio *et al.* (2014) and Garavaglia *et al.* (2011) concurred the literature only “marginally addresses” quality of care, while the empirical evidence drawn from hospitals is mixed. Propper *et al.*

(2004) observed that more competition drove down the quality but enhanced the efficiency in English hospitals. In contrast, Croes *et al* (2018) found that competition leads to improved quality and efficiency. DiGiorgio *et al.* (2014) and Garavaglia *et al.* (2011) also agreed that efforts to accurately measure quality within the formal LTC settings is a complex issue. Despite this, Garavaglia *et al.* (2011) provided perhaps the most comprehensive and systematic examination of the impact of quality on efficiency in the NH sector.

To do so, they divided quality into three broad aspects of care according to Donabedian's (1988) classification: Details of the Structure; Process, and Outcome (SPO), classifications are presented in Table 2-2, which also demonstrates that most studies focus on process-oriented measures of quality. For example, Kooreman (1994) applied four process-related variables to measure quality of care: the presence of a patients' council; the presence of a council of patient's relatives; the presence of a procedure to handle complaints; and the presence of unrestricted visiting hours. All such quality variables had a negative effect on TE, but only a weakly significant effect on efficiency in the NHs.

Delellis and Ozcan (2013) used process-related dimension of quality indicators, such as rates of catheter use, physical restraints, bowel and bladder incontinence, pneumonia and influenza vaccinations, depression, unplanned weight change, pressure sores, and bedfast residents, to interrogate the relationship between quality and TE. Their empirical results revealed largely favourable quality outcomes for efficient NHs; indicating that higher efficiency in NHs is not invariably achieved at the expense of quality. Zhang *et al.* (2008) also employed process-related measures of quality (number of deficiencies issued in a facility) but found a negative association between quality and efficiency. Conversely, Rosko *et al.* (1995), who measured the quality of care by pressure ulcer rates, catheter use rates, and restraint use, established no link between quality and efficiency for 461 NHs located in Pennsylvania.

Nyman and Bricker (1989) evaluated the relationship between quality and TE in Wisconsin NHs by applying structural and process-oriented measures of quality. As structural measures, the authors used the proportion of Medicaid patients and the average number of empty beds but found no significant effects of these variables on TE. As a process-related measure, the authors used the number of deficiencies issued to the facility and found that this variable was significantly linked to lower efficiency scores in non-profit homes only. Similarly, Laine *et al.* (2005b) found no effect of quality on TE in Finnish care facilities using the three structural quality measures of the proportion of registered nurses, the proportion of rooms with own toilet, and the proportion of single rooms.

A small number of NH efficiency studies incorporated measures of quality into their efficiency analysis via staff indicators which can be classified as structural measures according to Table 2-2. For example, Martin and Tiphaine (2016) observed that the ratio of nursing auxiliary staff to total staff members had a positive link with costs whilst the ratio of skilled nurses and physicians to total staff had an insignificant effect on total costs. Similarly, Laine *et al.* (2005a) included staffing levels as a proxy for quality and found a negative association between quality and TE. Garavaglia *et al.* (2011) included extra nursing hours as a structural dimension of quality of care, and used it directly as an input in the production process, but found no differences in the obtained TE scores when comparing with the standard non-adjusted TE scores. In the context of Ireland, Ni Luasa *et al.* (2018) used one proxy indicator of quality using the qualification of nurses with ‘a diploma in gerontology’ and found that this quality indicator significantly decreases TE in the NHs. However, in their more recent papers, the same authors examined a much wider spectrum of quality variables that could affect the efficiency of the NHs in Ireland (see Dineen *et al.*, 2019 and Zieba *et al.*, 2020 in Table 2-2). The research presented in this thesis also contributes to the very limited efficiency literature which evaluates the relationship between quality and efficiency using the data on INHs. This study employs a

novel approach to measuring the structural elements of quality by utilizing non-clinical indicators which include labour management factors, since care services are inherently labour-intensive.

- *Case-mix*

Case-mix is a critical element of care services. It is concerned with placing care beneficiaries into clusters, where members of the cluster share similar care needs; inferring these care recipients use a similar amount of care. Thus, case-mix is aligned with resources use. For instance, facilities which accommodate individuals with higher care needs require more staff and additional resources to meet them. This can have a knock-on effect on the efficiency of the nursing home. In contrast, care homes housing residents with lower care needs require fewer resources which may facilitate more efficient outcomes.

Table 2-3 shows that the case-mix is incorporated into the efficiency model by employing a variety of measures in the NH studies. For example, Nyman and Bricker (1989) and Kooreman (1994) used average patient-days as a proxy for case-mix. Patients with longer patient days may require more resources because they represent chronic cases that do not improve. This could negatively impact the efficiency performance of the care facility. Another indicator of case-mix is the age profile of residents used by Nyman and Bricker (1989), Nyman *et al.* (1990), Kooreman (1994), and Ni Luasa *et al.* (2018), since once again, older residents might have greater resource requirements relative to younger patients.

The empirical finding regarding the link between efficiency in the NHs and the case-mix is also mixed. Both Nyman and Bricker (1989), and Kooreman (1994) detected no significant impact of case-mix on TE when using the proxy measures of case-mix such as the proportion of patients over 85 years of age and the average length of stay. The authors therefore concluded that these two variables may be poor proxies for the case-mix of patients. Similarly, Ni Luasa *et al.* (2018) and Dineen *et al.* (2019) concurred that the proportion of INHs residents aged 85

and above does not significantly affect the TEs of the home units. Nyman and Bricker (1989) and Fazel and Nunnikhoven (1992) also found that when skilled nursing facilities (SNF) increase their proportion of patients, efficiencies fall as greater resources are assigned to the care needs of such residents.

Table 2-3 presents alternative measures of the case-mix, such as the level of dependence or the Activities of Daily Living index (ADL), as applied by Nyman and Bricker (1989), Nyman *et al.* (1990), Fazel and Nunnikhoven (1992), and Chattopadhyay and Heffley (1994). The institutional classification used by Chattopadhyay and Heffley (1994) of the number of patients with decubiti, disability, dementia, and long-term medications was used by Nyman *et al.* (1990). Nyman *et al.* (1990) used a total array of 10 indicators to account for case-mix differences in Iowa NHs. The authors found the percentage age of patients deemed ‘confused’ and that the average number of medication times per patient had a significant influence on efficiency.

Moreover, Zieba *et al.* (2020) used the high-max dependency (HMD) rate which is predicated on the proportion of residents with high-maximum dependency to total residents in a nursing home. It is argued that inflated proportions of high-maximum dependency patients require more labour and capital inputs resources, which can result in lower TE. However, it is equally reasonable to infer that NHs with higher dependency levels of patients might become more technically efficient as they learn to use their resources more effectively over time.

Table 2-3: Previous Evaluations of Case-mix in the NH Sector

Author	Indicators of Case-Mix	Stage of Analysis	Effect on Efficiency
Nyman and Bricker (1989)	<ul style="list-style-type: none"> • Proportion of Skilled Nursing Facilities (SNF) patients • Proportion Patients over 85 • Average Length of Stay 	<ul style="list-style-type: none"> • Determinants of nursing home efficiency 	<ul style="list-style-type: none"> ○ Increases in the SNF patients reduce efficiencies. ○ Other proxy measures of case-mix were insignificant.
Fizel and Nunnikhoven (1992)	<ul style="list-style-type: none"> • %age of skilled beds 	<ul style="list-style-type: none"> • Determinant of efficiency 	<ul style="list-style-type: none"> • Increases in skilled nursing care results in lower efficiency scores
Chattopadhyay and Heffley (1994)	<ul style="list-style-type: none"> • ADL Index 	<ul style="list-style-type: none"> • Used as an output variable to compute efficiency scores 	<ul style="list-style-type: none"> • n/a
Kooreman (1994)	<ul style="list-style-type: none"> • Proportion of patients over 85 • Length of Stay 	<ul style="list-style-type: none"> • Determinants of efficiency 	<ul style="list-style-type: none"> • Both measures are insignificant
Rosco <i>et al.</i> (1995)	<ul style="list-style-type: none"> • Case Mix Index • Live discharge rate per bed per year • Proportion of facility residents over the age of 85 • Proportion of facility residents classified as confused 	<ul style="list-style-type: none"> • Determinants of efficiency 	<ul style="list-style-type: none"> • Case Mix Index positively influences the efficiency score • Live Discharge Negatively affects the efficiency score • Remainder of measurements of case mix are insignificant
Borge and Haraldsvik (2009)	<ul style="list-style-type: none"> • Share of residents in NHs 90 years and above 	<ul style="list-style-type: none"> • Determinant of efficiency 	<ul style="list-style-type: none"> • Insignificant effect on efficiency
Garavaglia <i>et al.</i> (2011)	<ul style="list-style-type: none"> • Revenues for a nursing home • %age of patients relative to lower severity SOSIA classes 	<ul style="list-style-type: none"> • Output measure. • Determinant of efficiency 	<ul style="list-style-type: none"> • Insignificant effect on efficiency
Dulai (2018)	<ul style="list-style-type: none"> • Case-mix index 	<ul style="list-style-type: none"> • Utilized in the first-stage of DEA as an output variable 	<ul style="list-style-type: none"> • n/a
<ul style="list-style-type: none"> • Ni Luasa <i>et al.</i> (2018) • Dineen <i>et al.</i> (2019) 	<ul style="list-style-type: none"> • The case-mix is measured as the proportion of residents over the age of 85. 	<ul style="list-style-type: none"> • Utilized in the second-stage analysis 	<ul style="list-style-type: none"> • Insignificant effect on efficiency
Nyman <i>et al.</i> (1990)	<ul style="list-style-type: none"> • Average ADL score • Turnover rate of patients • % patients with decubiti/catheter • % patients bedfast • % patients over 85 • % male patients • % confused patients • % restrained patients • Mediations times per patient 	<ul style="list-style-type: none"> • Determinants of the efficiency score 	<ul style="list-style-type: none"> • Only the %age of patients deemed “confused” and the average number of medication times per patient” had a significant influence on efficiency
Zieba <i>et al.</i> (2020)	<ul style="list-style-type: none"> • High-Max dependency ratio (HMD) measured as the proportion of high and maximum dependency residents 	<ul style="list-style-type: none"> • The HMD ratio is included both in the efficiency model as one of the inputs and in the second-stage analysis as one of the efficiency determinants. 	<ul style="list-style-type: none"> • The HMD ratio highly significant and has a negative effect on TE of the NHs.

It is also noted that there is little agreement on or evidence of how to best include the case-mix variable in the measurement of TE for the NHs in the extant efficiency literature. While a number of studies include the case-mix variable as the production variable (input or output) to compute the efficiency score (Garavaglia *et al.* 2011; Chattopadhyay and Heffley 1994), the majority of studies include case-mix as a determinant of TE in the second stage analysis only. This study extends the debate on the impact of case-mix on efficiency. Like Zieba *et al.* (2020) then, rather than an either/or approach, this research incorporates the case-mix variable in an holistic manner. As such, this variable is included both as an input variable to obtain TE scores for INHs and as an efficiency determinant, and the results are compared to the standard approach.¹⁸

- *Occupancy Rates*

Occupancy rates are another factor that can influence the performance of the nursing home. While higher occupancy rates can generate greater demand for resources, low occupancy rates can result in falling efficiencies. By measuring the occupancy rate by the number of patients in the home on a given day divided by the actual number of beds, Nyman and Bricker (1989) and Nyman *et al.* (1990) found that as occupancy increased and NHs were more likely to reach their target level as regards staffing. Conversely, those with lower occupancy fell below their targets; suggesting that overstaffing leads to declining efficiencies. Furthermore, Rosko *et al.* (1995) maintained that low occupancy rates revealed that the supply of places exceeded demand; thereby implying that vigorous competition strategies should be pursued to attract additional residents and improve the efficiency performance of the home. Ozcan *et al.* (1998) defined high NHs occupancy rates as 95.8% and above, and purported that facilities with such occupancy rates were 2.09 times more likely to be efficient. Sexton *et al.* (1989) concluded that

¹⁸ Further details on the methods used to estimate both efficiency and the efficiency determinants are discussed in section 2.5 of this chapter and the entire methodology applied in this thesis is provided in Chapter 4.

rises in occupancy generated a corresponding fall in efficiency due to potential overcrowding within the care facility.

- *Affiliations*

Since certain synergies can occur when a nursing home is affiliated with a hospital, the efficiency performance of the home may be ameliorated through interaction and/or cooperation between the two organizations; such as, for instance, the sharing of medical staff or non-clinical personnel duties across the care facility and hospital. Kooreman (1994) noted that NHs affiliated to specific hospitals could increase efficiency by an exchange of resources. In contrast, Nyman and Bricker (1989) maintained that NHs could lose efficiency as hospital administrators were not necessarily familiar with the operations of NHs. While Kooreman (1994) also noted that NHs may have dedicated affiliations, such as Catholic or Protestant dominations, no specific influence on efficiency was determined.

- *Age of Facility*

Friedman and Shortell (1988) purported that the age of the facility leads to increased costs due to the depreciation of premises. In the context of the NH sector, the literature on the effect of building age on efficiency is limited to the only one published study of Martin and Jerome (2016). The authors of this study observed that the age of NH facilities may increase costs and decrease the CE, since the NHs need to bear depreciation expenses. On the other hand, the ageing factor of the NH also provides an opportunity for learning by doing for nursing staff which could induce cost savings. Nonetheless, these authors concluded that the ageing of such facility exerted a negligible effect on cost inefficiency. As a result, the research in the present thesis contributes to the existing literature, no studies in Ireland or elsewhere appear to have examined the effect of age on TE.

- *Size*

The size of an individual firm could have significant impact on efficiency (Jacobs *et al.* 2006; Coelli *et al.* 2005); with numbers of beds used as the most frequent means to calculate size. The effects of size on technical or CE is related to the scale economies presented in Section 2.3. The size of the nursing home will not only determine the scale economies, however, but also the TE or CE of the firm. If the nursing home is small, there may be certain advantages to the production as better and more effective overview of the processes might be in place. In contrast, however, larger NHs can utilize a more effective division of labour which might result in higher TEs, but also in higher CEs due to the scale economies. However, rapid or excessive growth of the firm, can result in slower and less effective decisionality. As such, it is paramount to examine the impact of this important NH characteristics on the efficiency in the NHs sector.

The empirical findings regarding the effect of the size variable on efficiency are somewhat limited and mixed. For example, Ozcan *et al.* (1998) underscored the minimal correlation between size (as measured by in-patient beds) and efficiency, while contrastingly, Filippini (1999) demonstrated the existence of economies of scale for most outputs which suggested that Swiss NHs increase their size to become more cost efficient. Nyman *et al.* (1990) determined that size exerts a positive impact on efficiency up to a threshold of 170 beds. The authors further contended that larger firms could expect efficiency gains due to labour specializations, but that at some point, diseconomies of scale could set in due to the complexities of effectively and efficiently managing a larger facility. While Nyman and Bricker (1989), Chattopadhyay and Heffley (1994), and Ni Luasa *et al.* (2018) revealed a similar positive link between size and efficiency, Sexton *et al.* (1989) identified a negative correlation between size and efficiency owing to potential congestion within the care facility. This thesis also widens the debate in relation to the impact of 'size' on TE in the INHs. As previously noted, it is therefore essential

to determine the optimal size of the home to maximize TE and potentially minimize costs; particularly in light of the challenges ahead in the INHs environment.

- *Income of Area*

The environmental variable ‘income of area’ may also be an important determinant of efficiency. Rosko *et al.* (1995) observed that more affluent areas demonstrate a greater demand for amenities and services, which requires more resources. This, in turn, may detract from the efficiency of the nursing home. Conversely, as income levels decrease, demand for NH places become more price-sensitive. As NHs compete for patients in terms of cost, price competition may yield to more efficient outcomes. Interestingly, Iparraguirre and Ma (2015) attempted to capture income poverty among people aged 60 and over in the UK by using the number of guarantee credit beneficiaries¹⁹. Their empirical evidence confirmed that areas with a greater number of beneficiaries generated improved performances within the care homes.

- *Reimbursement Policy*

Another important determinant that can influence the efficiency of the nursing home is the reimbursement policy of the facility. Nyman and Bricker (1989) noted that care facilities which are retrospectively reimbursed for costs incurred²⁰ and/or given a certain return on capital, have no reason to minimize costs as even the profits of profit-maximizing firms cannot be increased in this way. On the contrary, homes in this environment are more likely to maximize the status or managerial slack which promotes the inefficient use of resources. On the other hand, NHs who face a fixed *per diem* payment have more incentive to minimize costs; possibly leading to improved efficiencies. Crivelli *et al.* (2002) noted that NHs in the cantons of Geneva and Wallis

¹⁹ The guarantee credit element of the pension credit tops up a pensioners’ weekly income to a guaranteed minimum level.

²⁰ Sometimes referred to as cost-per-case transaction

receive a fixed contribution from the State which incentivizes them to provide efficient care services.

- *Location*

The inclusion of the location determinant is based on the theory of contestability. Perfectly competitive markets characterized by perfect information and freedom of entry and exit, result in the best possible outcomes for both buyers and sellers. It follows then, that as competition in the marketplace becomes more intense, prices decline, market power falls, profit levels approach the ‘normal level’ and prices become closer to the minimum point of average costs curve, implying that the efficient outcomes are being achieved (Miller, 1996). In the context of health-care, however, many of these conditions are not met due to serious market issues, such as barriers to entry and/or imperfect information (Goddard, 2015), and competition may not yield pareto-optimal outcomes. The empirical literature evaluating the effect of competition in the NH sector is limited. Nyman and Bricker (1989) and Nyman *et al.* (1990) considered location as a determinant of NH efficiency to control for any competition effects among rival firms on their efficiency scores. These authors concluded that homes located in urban areas would experience greater competition relative to those in non-urban environments. Higher wage expectations in urban settings were deemed a significant cost factor; implying fewer labour inputs would be used and the efficiency scores would be higher in urban areas. Nonetheless, these authors found that TE decreased in for-profit homes in urban areas. Similarly, Fazel and Nunnikhoven (1992) included an urban/ rural dummy to capture the effect of concealed factors, including the possible quality of labour. Chattopadhyay and Heffley (1994) used dummy variables to represent counties with low population densities and percentages of the population living in urban areas compared to other counties, to control for ‘market characteristics’. Both studies concluded that location did not exert a significant effect on efficiency. This research contributes to the efficiency literature in relation to the effect

contestability has on efficiency in the INHs, by utilizing location as a possible determinant of TE.

2.5 Efficiency Measurement Methods

According to Farsi *et al.* (2008), Chattopadhyay and Ray (1996), and Worthington (2004), the literature on measuring efficiency in the NH industry dates back to the 1980s. In the earlier econometric studies, the estimated relation reflected an average (based on best-fit) rather than an efficient or frontier cost function. Thus, inefficiencies were confounded with pure random shocks. For this reason, over the last two decades, the literature on the NH sector has shifted towards a more appropriate approach to the measurement of efficiency. Jacobs *et al.* (2006) posited that methods to measure efficiency can be divided into two broad categories: namely, non-parametric; and parametric techniques. Both approaches rest on the assumption of an optimal frontier which is not known in reality: since the production technology is not known, the efficient frontier must be estimated from the sample data. However, there are fundamental differences between both approaches when estimating the optimal frontier and measuring the gap between the actual production of the firm and the efficient frontier. Section 2.5.1 therefore considers non-parametric approaches such as data envelopment analysis (DEA) and its modern extensions to account for some of the shortcomings of this approach, while Section 2.5.2 presents a stochastic frontier analysis (SFA) as the pre-eminent form of the parametric approach to estimating efficiency.

2.5.1 The Non-Parametric Techniques

Data envelopment analysis (DEA) is a non-parametric method which uses a linear programming technique to construct a non-parametric piece-wise surface over the data (Jacobs *et al.* (2006). Efficiency measures are then calculated relative to this surface. On the basis of an assumed input orientation, the NH units which use the fewest inputs in producing a given level of output are identified by constructing a non-parametric piecewise-linear convex frontier

from the sample data. The TE for each NH unit is then calculated relative to this surface. A nursing home is deemed technically efficient with regard to inputs usage if it lies on the frontier (isoquant) and the distance from this frontier is solely due to inefficiency. Conversely, the parametric SFA approach as delineated in the next subsection, estimates production or cost functions using a maximum likelihood method which assumes that deviation from the frontier is due to statistical noise and inefficiency. Clearly then, parametric methods attempt to determine the absolute economic efficiency of organizations against an imposed benchmark, whereas non-parametric methods seek to evaluate the efficiency of an organization relative to other organizations in the same industry (Jacobs *et al.* 2006).

It is stressed that all efficiency measures assume that the production or cost frontier of the fully efficient firms (in this case, NHs) are known. However, as this is seldom the case, the frontier must be estimated using sample data by constructing a non-parametric piecewise-linear convex frontier, such that the ‘best’ firms will define the efficient production. All other firms are considered to be technically inefficient if they are not located on the frontier. In the case of input-oriented TEs, the frontier will be represented by an isoquant, with all firms on the isoquant utilizing a minimum amount of inputs given a fixed amount of outputs.²¹

The piecewise-linear convex hull approach to frontier estimation had been considered by only a few authors in the two decades since the initial publication of Farrell’s preposition in 1957. While Boles (1966), Shephard (1970), and Afriat (1972) concurred that mathematical programming methods could achieve the task, the method did not receive widespread attention until Charnes *et al.* (1978) first coined the term ‘data envelopment analysis’ (DEA). In their paper, the authors proposed a DEA model which both inherited an input orientation and assumed

²¹ Similarly, in the case of output-oriented technical efficiencies a firm will be efficient if placed on the production possibility frontier, which means that all firms are maximising their outputs given a certain level of inputs.

constant returns to scale (CRS)²². Subsequent papers, such as that of Färe *et al.* (1983), and Banker *et al.* (1984), considered alternative sets of assumptions, in which variable returns to scale (VRS) models²³ were proposed.

The Table 2-1 elucidation of previous evaluations of efficiency in the NH sector confirms DEA to be the dominant approach to efficiency measurement in the LTC provision. For example, DEA was used to estimate TEs in the USA by Nyman and Bricker (1989), Nyman *et al.* (1990), Fazel and Nunnikhoven (1992), Kleinsorge and Karney (1992), Chattopadhyay and Heffley (1994), Chattopadhyay and Ray (1996), Ozcan *et al.* (1998), and DeLellis and Ozcan (2013). Its application in the context of Europe is similarly widespread: for instance, Kooreman (1994) applied DEA in Dutch LTC facilities; Bjorkgren *et al.* (2001) and Laine *et al.* (2005a and 2005b) utilized it in Finnish municipalities, Borge and Haraldsvik (2009) in Norway; and Garavaglia *et al.* (2011) in Italy. More recently, Wang and Chou (2005) and Chang and Cheng (2013) have applied DEA in the Taiwanese NHs context, and Ni Luasa *et al.* (2018) also utilized the model to estimate efficiencies for the INHs.

One notable advantage of DEA is that while it incorporates the use of multiple inputs and outputs in the estimation of efficiency, it does not impose any functional form restrictions on the data. Nevertheless, the DEA method has attracted criticism for the implicit assumption that all of the distance between an observed firm and the optimal frontier for the efficient firms reflects inefficiency. In fact, the distance of an observation from the efficient boundary reflects both inefficiency and noise because the observed input-output data might be subject to measurement error or noise in the data due to omitted input or output variables. To overcome this limitation, the homogenous bootstrap procedure can be employed to validate the conventional DEA TE scores. The homogenous bootstrap (HB) can be applied as a robustness

²² Sometimes the DEA CRS model is referred to as the CCR model.

²³ Sometimes the DEA VRS model is referred to as the BCC model.

check for the conventional DEA TE estimates. Introduced by Simar and Wilson (1998; 2000), this technique corrects for any bias in the conventional DEA efficiency scores and estimates confidence intervals (CIs) for them. Throughout the extant NHs efficiency literature, only Garavaglia *et al.* (2011) have previously implemented the HB procedure. Nevertheless, this approach fails to take account of the determinants of efficiency.

Adjusting for Efficiency Determinants in Non-Parametric Methods

The term ‘efficiency determinants’ relates to factors which could influence the efficiency of a nursing home: as previously explained, these are neither real inputs or outputs. To reiterate; typical examples of efficiency determining variables which obtain to the NH literature include ownership, location, occupancy, size, and age of the nursing home, case-mix, quality, and governmental regulations. A number of previous DEA studies, including those of Nyman *et al.* (1990), Fazel and Nunnikhoven (1992), Kooreman (1994), Ozcan *et al.* (1998), Wang and Chou (2005), and Garavaglia *et al.* (2011), have employed a two-stage approach wherein non-parametric DEA efficiency estimates from the first stage are regressed on a vector of efficiency determinants in a parametric analysis in the second stage.

This approach, referred to as a two-stage semi-parametric method, combines both the non-parametric and parametric methods. The above studies typically used either ordinary least squares (OLS), or Tobit or logistic regression techniques in the second stage, and relied on conventional methods for inference. However, Simar and Wilson (2007; 2011) asserted that regardless of the second-stage regression technique employed, conventional inference methods fail to provide valid inferences in the second-stage, as true efficiency remains unobserved and must be replaced with DEA estimates of efficiency which are serially correlated by construction and biased. Therefore, Simar and Wilson (2007) developed a two-stage DB DEA procedure to investigate the effects of these environmental variables in the second stage, which not only enables robust estimation of the parameters of efficiency determinants, but also re-

estimates the bias-corrected efficiency scores to take account of the efficiency determining variables. To the researcher's knowledge, only Borge and Haraldsvik (2009), Iparraguirre and Ma (2015), and more recently, Ni Luasa *et al.* (2018), have employed this technique to examine the impact of determinants on efficiency.

However, two-stage semi-parametric approaches do not control for noise which reflects all events outside the producer's control and may impact the production process resulting in non-robust estimates of efficiency. As a result, the next subsection introduces stochastic frontier analysis (SFA): a parametric method which assumes that any deviation from the frontier is composed of two parts: one representing inefficiency; and the other, statistical noise.

2.5.2 *Parametric Approach*

The stochastic frontier analysis (SFA) approach is an econometric (parametric) technique. In contrast to non-parametric techniques, SFA recognizes not only the technical inefficiency component of the firm, but also the fact that random shocks beyond producers' control may affect the production output or inputs of production.

The parametric method assumes that the production or cost frontier of the efficient nursing home is known. However, as this is not normally the case in practice, this frontier must be estimated from sample data by fitting a parametric function to the data. Thus, production functions can be specified, or alternatively cost functions can be identified, if the data on input prices are available. Identifying a production technology infers an output-orientation and it is generally preferred when a firm produces one output only from many inputs. To estimate input-oriented efficiencies, an input-distance function approach²⁴ can be employed which includes multiple inputs and outputs in the efficiency model.

²⁴ Debreu (1951) introduced distance functions, although Sheppard (1963) expanded upon this work. Distance functions are closely related to production frontiers and the basic idea underlying distance functions involves radial contractions and expansions in defining these functions. Distance functions allow one to describe a

Table 2-1 highlights that very few studies employed the SFA methods for the NHs sector. For example, Hoffler and Rungeling (1994), Vitaliano and Toren (1994), Crivelli *et al.* (2002), and Farsi *et al.* (2008) focused on estimating cost frontiers, whereas Anderson *et al.* (1999) and Knox *et al.* (2007) estimated production functions using the SFA framework. Moreover, to estimate efficiency and its determinants using the parametric SFA, it is important to note that the assumption of certain functional form restrictions, including the linear, Cobb-Douglas, Quadratic, Translog, Generalized Leontief, and Constant Elasticity of Substitution functions. Coelli *et al.* (2005) advised that when deliberating between the various forms, preference should be given to functional forms that are: (a) flexible; (b) linear in the parameters²⁵; and (c) parsimonious. Moreover, Griffin *et al.* (1987) suggested that the final choice of functional form may depend on four criteria: (1) the function may be deemed appropriate if the maintained hypotheses implies it is useful; (2) the data availability (and the availability of computing resources) influences the functional form; (3) the specific data properties (i.e. goodness of fit) may affect the choice of the functional form; (4) the econometric estimation method plays an important role by the choice of production function²⁶.

The historical development of the parametric approach to the estimation of efficiency commenced with Aigner and Chu (1968) who considered a Cobb-Douglas production frontier of the form:

$$\ln q_i = \beta_0 + \beta_1 \ln x_i - u_i \quad \text{Eq.2.2}$$

where q_i is the output of firm i ; x_i is the input of firm i ; and u_i is a non-negative random variable associated with technical inefficiency. This parametric approach was considered

production technology without the need to specify a behavioural objective (cost minimisation or profit maximisation). Parametric estimation of an output-distance function is also possible for multiple output technology and assuming an output-oriented TE.

²⁵ At first glance, the Cobb-Douglas and translog functions appear not to satisfy this property. However, taking the logarithms of both sides yields functions which are both linear in the parameters. Thus, the parameters of Cobb-Douglas and translog functions can also be estimated in a linear regression framework.

²⁶ For example, some functional forms do not permit parameter estimation by linear least squares and some cannot be used in simulation or optimization procedures.

deterministic since, like the non-parametric DEA, all deviations from the frontier were assumed to be the result of inefficiency; inferring that no account was taken of the possible influence of measurement error and other noise upon the frontier. Thus, this deterministic parametric approach, also referred to as ‘deterministic frontier approach’ (DFA), has exactly the same disadvantage as the non-parametric DEA.

To overcome the limitation of the DEA, Aigner *et al.* (1977), Meeusen and Van Den Broeck (1977) proposed the introduction of another random variable representing statistical noise. As such, the proposed SFA stochastic production frontier is identical to the model in Eq.2.2 except that a symmetric random error, v_i , is added to account for the statistical noise. Thus, the adjusted model takes on the following form:

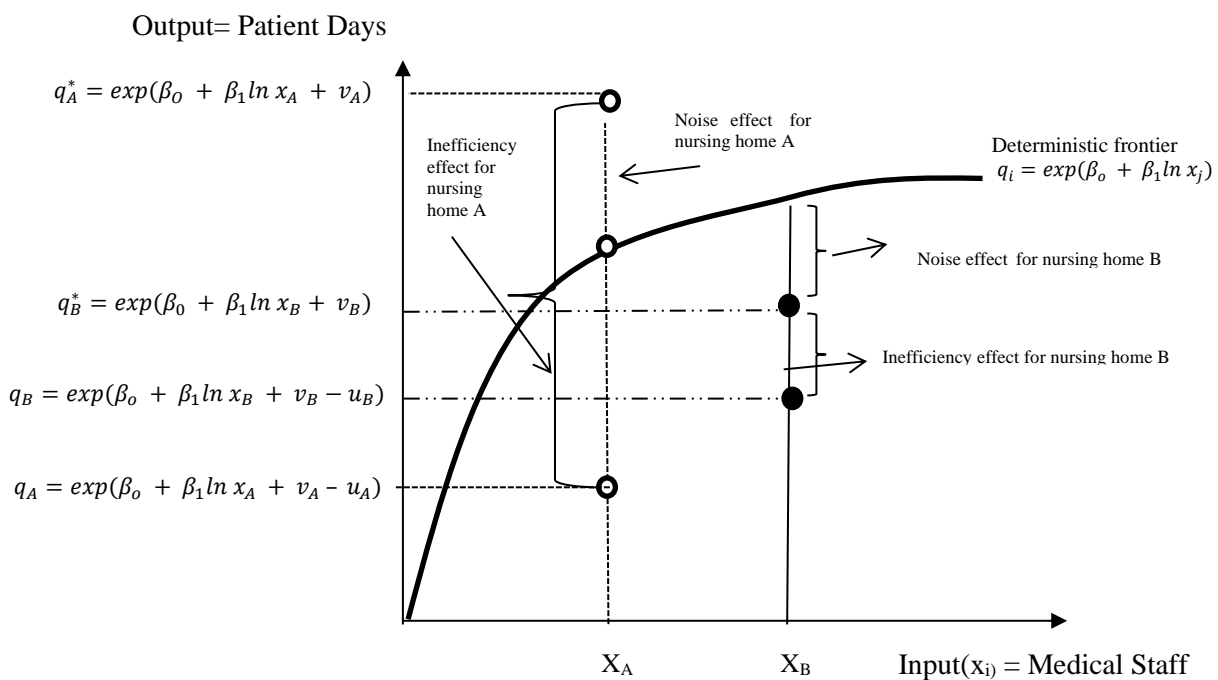
$$\ln q_i = \beta_0 + \beta_1 \ln x_i + v_i - u_i \quad \text{Eq. 2.3}$$

where q_i is the output of firm i ; x_i is the input of firm i ; v_i is the random error of firm i , which can be positive or negative; and u_i is a non-negative random variable associated with technical inefficiency’.

In Figure 2-3, Eq.2.3 is graphically presented as where the input and output levels of two firms (e.g. nursing home A and B) are also highlighted. The deterministic component of the frontier model is also depicted in this figure to reflect the existence of diminishing returns to scale. Nursing home A uses the level of medical staff, X_A , to produce patient days, q_A , while nursing home B uses the level of medical staff, X_B , to produce patient days, q_B . The observed output of unit A is represented by $q_A = \exp(\beta_0 + \beta_1 \ln x_A + v_A - u_A)$. If there were no inefficiency effects for nursing home A (if $u_i = 0$), the stochastic production frontier equals: $q_A^* = \exp(\beta_0 + \beta_1 \ln x_A + v_A)$. The diagram shows that the frontier output for nursing home A lies above the deterministic part of the production frontier only because the noise effect is positive (i.e., $v_A > 0$). In respect of nursing home B, the frontier output lies below the

deterministic part of the frontier because the noise effect is negative (i.e., $v_B < 0$). Therefore, the random error, v_i can be positive or negative and so the stochastic frontier outputs can vary about the deterministic part of the model, $\exp(x_i \beta)$. Figure 2-3 also demonstrates that the deterministic approach the inefficiency of nursing home A is underestimated as the noise is positive. Clearly then, in disregarding the noise, the deterministic approach will overestimate TE of the nursing home A. On the other hand, the inefficiency of nursing home B is overestimated in the deterministic frontier (i.e. not controlling for noise which is negative), and hence the TE will be overestimated for the nursing home B.

Figure 2-3: The Stochastic Frontier Approach (SFA)



Source: Coelli *et al.* (2005), p.244

In the SFA framework, the TE of the above firm is obtained by the ratio of observed output for the i -th firm, relative to the potential output, defined by the stochastic frontier function, given the input vector, as follows:

$$TE_i = \frac{q_i}{\exp(x_i \beta + v_i)} = \frac{\exp(x_i \beta + v_i - u_i)}{\exp(x_i \beta + v_i)} = \exp(-u_i) \quad Eq. 2.4$$

Eq.2.4 measures an output-oriented TE which is defined by the ratio of the output of the *i*-th firm relative to the output that could be produced by a fully efficient firm and using the same input vector. This TE measure again takes a value between 0 and 1 as defined in Section 2.2.

The efficiency studies in Table 2-1 which employ SFA, focus on the estimation of an SFA production function or an SFA cost function. Those studies, in particular, confirmed that the for-profit homes have higher TE scores than the public homes. For instance, Anderson *et al.* (1999) found that the for-profit homes have a TE score of 0.90 relative to non-profit homes which have a score of 0.73. Similarly, Knox *et al.* (2007), who constructed a stochastic production frontier model to compute the efficiencies in the US NH market, confirmed that the non-profit facilities were less productive than the for-profit NHs in Texas in the years 1999 and 2002. Hoffler and Rungeling (1994) also estimated CEs and found that for-profit homes have lower costs relative to non-profit homes. However, Vitaliano and Toren (1994) concluded that CEs do not vary between for-profit and not-for profit homes in New York. In Europe, Crivelli *et al.* (2002) found an average CE of 0.79 for 886 Swiss NHs; meaning they needed to reduce their costs by a further 21% to achieve full efficiency. Conversely, Farsi *et al.* (2008) cost function estimates of 356 NHs in Switzerland between 1998 and 2002, concluded these homes were achieving almost optimal performance at an average CE equal to 0.92.

The application of an SFA framework is rare in the existing nursing home literature; the main drawback being that this method requires the functional form to be specified, which is not the case in the non-parametric DEA framework. Nevertheless, as an econometric technique, SFA incorporates randomness (or statistical noise) and inefficiency; acknowledging that the random error term reflects all events beyond the control of the organization in terms of mis-specifications of the production or cost function, or basic measurement errors.

Summary and Comparison of Estimation Methods

Jacobs *et al.* (2006) referred to the lack of consensus in the literature regarding ‘the best method’ to estimate TE for the NHs. As previously mentioned, one important feature of DEA is that it does not impose a functional form upon the frontier of the investigated firm, as is requisite for the SFA. Furthermore, estimations of an SFA production function can pose serious practical difficulties, particularly in cases where organizations produce multiple outputs. A more convenient functional form alternative is the cost function since this permits a single dependent variable, namely the cost, to be estimated as a function of several outputs. If a firm can assume cost-minimizing behaviour, the cost function is usually the dual of the production function, making the two approaches equivalent. In fact, and as shown to Table 2-1, several relevant studies, including those of Hoffler and Rungeling (1994), Vitaliano and Toren (1994), Crivelli *et al.* (2002), and Farsi *et al.* (2008), have estimated cost functions. On the other hand, in the estimations of efficiency, DEA models incorporate multiple output and input production processes with ease. For instance, Kooreman (1994) purported that “four output²⁷ types better reflect NH output than a single measure” (p.306). Similarly, Borge and Haraldsvik (2009) incorporates seven measures of output²⁸ in their measurement of TE of Norwegian facilities.

Finally, small sample sizes do not prevent the application of DEA, but within all parametric estimation processes, the smaller the sample size, the more imprecise SFA estimates are likely to be (Banker *et al.* (1993). Moreover, in estimating efficiencies and the likely efficiency determinants which may influence the efficiency performance of the firm, SFA estimates the frontier using a maximum likelihood method which assumes that any deviation from the frontier is composed of two parts: one representing randomness (or statistical noise); and the

²⁷ The author distinguishes between physically disabled patients and patients with psycho-geriatric disability, as well as between full-care and day care patients in his measurements of output in his DEA.

²⁸ Output is measured by nursing homes, permanent residents; nursing homes, short-term residents; nursing homes, single bedrooms; home based care, practical help; home based care, nursing; home based care, practical help and nursing; number of mentally handicapped.

other, inefficiency. The random error term reflects all events outside the control of the organization, but also misspecification of the functional form or simply the measurement error. In contrast, the DEA approach implicitly assumes that all of the distance between the observed firm and frontier reflects inefficiency. As a result, the DEA efficiency estimates may be biased. Nonetheless, in order to vouchsafe the robustness of these scores, bootstrapping procedures may be employed as previously noted by Simar and Wilson (1998; 2000; 2007; 2011). These recent extensions of DEA which have been but rarely used in the literature for the NHs, are applied here as a means to holistically evaluate both the efficiency and the efficiency determinants in this sector.

2.6 Conclusion

This chapter elucidated the theoretical framework utilized to evaluate efficiency in the NH sector and to review the relevant literature on efficiency for the formal LTC providers. The technical, allocative, and economic efficiency concepts of Farell (1957) were presented and the application of these measures throughout the extant literature was discussed. It is clear that input-orientated TE is the most useful and favoured form of performance evaluation in the LTC sector, primarily because TEs prioritize the employment and production of physical units of inputs and outputs. As such, they inhere no behavioural assumptions of cost minimization or revenue maximization issues which are difficult to justify for this sector.

Importantly, the examination of the literature revealed a gap in the NH sector which this thesis addresses by evaluating TEs for the INHs. As labour and capital resources are clearly limited, an evaluation of TEs is important for a wide range of stakeholders including NH operators, government bodies responsible for running the public nursing entities, and lastly, for the taxpayers. Indeed, as Ireland's population ages, more and more LTC beds will be required, indicating that greater efficiencies in resource use will be critical to meeting future demand. As such, TE evaluation is important for both private and public (or non-profit) NHs, which will

need to allocate their resources effectively despite the different behavioural objectives their management might have. The review of literature also suggested the potential determinants of TE which may explain how to improve TE and/or how to reduce the costs of NHs: a significant issue as the ageing population continues to grow.

Finally, this chapter also outlined and discussed the various estimation techniques and their application across extant literature to measure NH efficiency. Methods included the non-parametric DEA approach and its contemporary semi-parametric extensions using the HB and DB DEA, and a fully parametric SFA method. The DEA is the most commonly applied method to estimate efficiency in the NH sector, since it does not impose a functional form on the investigated NHs compared to SFA. Furthermore, while NHs can be technically efficient, their scale of operations may not be optimal. The analysis in this chapter concluded that the examination of SE in the current literature for the NHs is conspicuously scarce, and that employing both CRS and VRS TEs facilitates the estimation of SE in the NH sector.

Chapter Three: The Nursing Home Sector in Ireland

3.1 Introduction

The examination of efficiency and its determinants in relation to the nursing home (NH) industry is an important research area due to the fact that the European population is aging increasingly rapidly while the labour force continues to decline (Gill *et al*, 2013). The rise in the ‘oldest’ old that is most dramatic, with Ireland serving as a particularly interesting case since its population in this age group is rising quickly. In fact, Irish 65+ and 85+ age cohorts are forecast to increase by 38% and 46% respectively in the years 2011-2021 (BDO, 2014: 22); a growth projected to accelerate into the future. Moreover, NHs account for 83% of overall public expenditure on LTC provision in Ireland, with the balance attributed to informal care (DG ECFIN, 2012). While the current capacity of 30,674 beds in Irish long-stay units meets the present needs of the elderly population, sweeping challenges face Irish society going forward if the trend in public expenditure on LTC continues to increase. In 2014, the direct cost of long-term residential care to the Irish exchequer was estimated to be in the region of €975m, and is projected to exceed €1.2 billion by 2021;, and rise to €2 billion by 2041 (BDO, 2014: iii). Clearly then, future NH care costs will significantly add to total government expenditure on health services. In the context of the fiscal pressures facing the Irish exchequer, the efficiency of long-stay care provision and ‘value for money’ are increasingly dominant considerations.

In the past, stay-at-home women provided LTC to elderly members of the Irish family. However, recent dramatic changes throughout Irish society has given rise to increased demand for residential care services, includes NHs. While the Irish State has traditionally provided NHs services through public NHs, owing to the 1998 introduction of capital allowances, the role of the State has been regulated to a secondary source of LTC beds with the private nursing home providing 80% of all LTC beds at present. Interestingly, Nursing Home’s Ireland claim the cost

of care is considerably less in private NHs, and affords better value for money to the Irish exchequer which generally subsidizes care in such facilities.

In light of Ireland's aging population, and, in particular the strong growth in the cohorts of the population whose care needs have been independently assessed as requiring long-term residential care, future bed capacity within both private and/or public NH sector need expand to keep pace with growing demand. However, many challenges prevail, not least, uncertainty as to whether existing state funding arrangements will continue and/or be increased to match the acute care needs of the future elderly population. In the light of limited resources, it is crucial for the State to achieve efficiency in the delivery of both public and private NHs services to ensure future needs of the elderly can be met.

This chapter therefore reviews the Irish nursing home (INH) sector. Section 3.2 presents the care policy which dominates the LTC environment, while Section 3.3 provides an overview of the residential care sector including past, present, and future trends of bed capacity in public and private homes, the NH environment and typical resident; the cost of care and future NH capacity. Section 3.4 offers concluding remarks.

3.2 Care Policy

As the older population increases and escalates, it is essential that LTC policy reflects the demands and needs of the elderly citizens. With the average population across the island of Ireland growing older, the fundamental issue of how to provide and pay for care in the home and in residential settings is becoming more pressing. It is therefore imperative that a strategy for providing LTC for an ageing population is devised and implemented. Understanding exactly what the demand for care will be is a major part of this. Stated Irish Government policy supports older people to live in dignity and independence in their own homes and communities for as long as possible, and where this is not possible, to support access to quality long-term residential care. This policy approach was renewed and developed in the partnership

agreement, Towards 2016 (DOT, 2006). Elderly People or “*Older Persons are regarded as those in the population who are 65 years or more*” (INHS Organization 1999, p.3) and the future development of LTC thus lies within the remit of community-based care. However, there will always be a need to provide long-stay residential care in public and private facilities for some older people.

3.2.1 Informal and Formal Care

Long-term care in Ireland can be categorized into two broad areas: informal and formal care. Informal care entails caring for the elderly person without any financial return. In the past, more often than not, the elderly person resided with the family, or was within close distance whereby the daughter or daughter-in-law or extended family and friends could keep a close eye on the person. This informality was once a prominent feature of Irish society as the social fabric encouraged community spirit and “care for one another”. In addition, the propensity to care was also supported by the Irish social fabric at that time, in that female participation rates in the labour market were relatively low and social mobility was limited. However, by 2012 the CSO highlighted the provision had changed owing to significant socio-economic developments in Irish society which include increased female participation rates in third level education and the labour market, and the migration of young women to urban centres. Moreover, while care-giving is mentally and emotionally challenging, it remains associated with low recognition: something that today’s generation prefer to yield to trained professionals.

In Ireland then, formal care services entail formal structures and processes whereby key professional such as nurses and health-care assistants are engaged by the State to care for an elderly person, either in their own home, or in a dedicated care facility.

Informal Care

Informal care was more common in former times in Ireland. It entailed the elderly person living with the person who took the family farm or living close by to extended family and friends.

The primary advantages were that the elderly individual remained independent, self-governing, and autonomous, while at the same time enjoying safety and the company of loved ones, whilst living in their own community. Moreover, family members within the 'home' were in a position to observe and support if the senior person became unwell, or a welcome neighbour would call frequently and detect anything amiss. However, Irish society is changing and evolving; more women have entered the workforce and increasing urbanization has attracted more young adults towards the cities. This means elderly parents are left now behind with few if any family members to care for them in their declining years. Moreover, with increasing distance times from the original family home and the time pressures of the modern world, young adults may see less of their elderly parents. This can result in increased isolation and loneliness, which can lead to ill-health, depression, and mental anxiety. Additionally, contemporary Irish family configurations may imply less support to the older generations. As a result, alternative ways of caring for the elderly are now being considered in Ireland, such as the hiring of a professional caregiver, or the purchasing of NH services, which may be subsidised by the State. These forms of caring are in complete contrast to informal care whereby no formal financial arrangements were required or arranged, and most care was provided on the basis of goodwill and adherence to the concept of 'community'.

Formal care

According to CARDI (2012) formal care services in the ROI encompass home helps, home care packages, and residential care. Home help and home care packages fall under the auspices of community services, while residential care (NH services) are arranged through institutional care. Ideally an elderly person would initially utilize the continuum of care via community services. Then, in due course, and when deemed inappropriate by key health-care professionals, older people would graduate to NH care services. In reality, however, this seamless process cannot always be pursued, and various other configuration of Irish formal care may come into to play.

Home helps

The concept of ‘home help’ has been in existence for several decades in Ireland; albeit in a less formalized manner. The development of a structured and remunerated home help (and other iterations of home care²⁹) assists older people to continue residing in the community by providing domestic services such as cleaning, shopping, doing laundry, and making meals for the elderly person who lives in their own home. Home help is supplied by publicly employed staff, community and voluntary organizations, or private sector agencies. Individuals apply for home help services through the local public health nurse and an assessment of need is carried out to determine their suitability. The services are either directly provided the Health Service Executive (HSE), or through HSE arrangements with other care organizations (Pierce, Fitzgerald, & Timonen, 2010).

Home help services are financed through general taxation, although some older people receiving home help may be asked to make contributions towards the services depending on their private means and/or locality (Timonen *et al.* 2006). Interestingly, there is some evidence that the actual number of hours of home help per client has reduced materially over the years. In 2000, the figure was estimated at eight hours per client per week (Mercer Ltd 2002), but 2016 HSE targets suggests a figure of a little over four hours per client per week. This decrease raises the question of the adequacy of provision at an individual level and may point to the apparent increase in the use of short 15/30-minute home care visits: a trend that has attracted much negative criticism, particularly in the UK (Campbell, 2015). In short, between 2008 and 2012, the number of hours delivered by home help dropped by approximately 20% (from 12.6m hours in 2008 to 9.89m hours in 2012) (Care Alliance Ireland, 2016).

²⁹ See discussion on Home care Packages (HCPs).

Home Care Packages (HCPs)

The home care supports or home care packages (HCPs) scheme is the other formal provision by which the State supports older people with care needs living in their own home. Home care packages, introduced in 2006, represents an attempt to reduce the hospital and residential LTC of older people and is defined by the HSE as consisting of “community services and supports which may be provided to assist an older person, depending on their individual assessed care needs, to return home from hospital or residential care or to remain at home”. Such home care packages may consist of nursing, home help, or respite care³⁰ depending on the needs of the applicant (Health Service Executive, 2015). Each HCP is therefore tailored to the needs of the individual based on their medical condition and the level of care required. Moreover, the HCP can consist of a combination of direct services, which can be provided by public agencies or purchased from private and voluntary agencies, and through cash payments, to enable the recipient to purchase their own care.

Each HSE Area has responsibility for the operation of the scheme within the resources allocated for it in that area. In reality, this means that levels of service or support given under an HCP vary in different parts of the country depending on the local population, individual needs, who is available to deliver services, and the demand for the scheme. However, the scheme is not means tested, and there is no charge or contribution for the services provided. Like home help, HCPs are not established in law and inconsistent provision exists. When an elderly person applies for an HCP, the HSE carries out a Care Needs Assessment. to evaluate overall health-care needs, social circumstances, identify the level of care currently in effect, and determine whether additional supports are needed. In order to be allocated an HCP, the

³⁰ Respite care may involve providing alternative family or institutional care for an elderly person in order to enable the carer to take a short break, a holiday or a rest. It can cover very short-term respite, for example, a carer for an evening, or a much longer arrangement for a holiday. Schemes of respite care are sometimes called ‘breakaway’ or ‘friendship’ schemes.

assessment must confirm that enhanced levels of service/support are required. In cases that find that additional services/supports are not needed, the application for a HCP is refused.

At the end of 2014, 13,057 older people were in receipt of a home care package. Over 18,500 home care packages were provided throughout the year, benefitting approximately 3% of the 65+ population. A further 190 older people benefited from more intensive home care packages. A total of 60% of all home care packages are provided by private contracted to deliver these services by the HSE.³¹ The remaining 40% of home care packages are directly provided by the HSE and through voluntary organizations on their behalf.

Notwithstanding that Irish care policy advocates that older people should be supported to live in their communities for as long as possible, Donnelly *et al.* (2016) found that “despite a 25% increase in the population of those aged 65 years and over and a near 30% increase in the population of those 85 years and over in the last seven years, there has been nearly a 2% decrease in the number of people receiving support, from 64,353 people receiving home help and HCP in 2008 to 63,245 people in 2015” (p.12). This suggests the reality may be somewhat different from the policy direction.

Residential Care

In Ireland, formal care incorporates both community services and residential care. Ideally, when an older person engages with the service, home help and HCPs should be considered first, and residential care only as the elderly person becomes frailer and more dependent. This continuum of care as outlined in Figure 3-1 is central to the most recent care policy document (*The Years Ahead: A Policy for The Elderly*). However, given that home help and HCPs have no statutory basis and evenly delivered, combined with the system of state subsidy for residential care³², in practice, the elderly population seem to gravitate towards residential care

³¹ The delivery of HCPs has been tendered out by the HSE since 2013, and a number of private providers have been approved to provide this service on behalf of the HSE.

³² Discussed in section 3.3.5.

(Wren *et al.* 2012). At present, there are three types of residential LTC institutions available in ROI: public; private; and voluntary NHs. All entities provide both limited and long-stay beds. Limited beds obtain to residents whose intended length of stay is less than three months: in other words, short-term beds. In contrast, LTC beds are suitable for residents whose intended length of stay is equal to or greater than three months. Whilst care facilities provide both types of beds, NHs primary focus on long-term beds informs the remit of this study. Public NHs are owned, financed, and operated by the State. At present, they refer to HSE Extended Care Units³³ and HSE Welfare Units³⁴: public institutions which devolved from the ‘workhouse’³⁵ era. Today they provide 20% of overall capacity of LTC beds; down from 48 % in 1998 (O’Shea, 2002).

Private NHs are run as a business for the care and maintenance of dependent persons. These homes, which are established and run by private individuals or companies in the private sector on a profit-making basis are the most rapidly growing sector of residential care at present. Voluntary Homes are run by charitable non-profit-making organizations in which patients are not maintained for the personal profit of the proprietors. Such entities, which include all NHs run by religious orders and lay charitable organizations, generally provide accommodation for older people who are in need of long or short-term care for medical or other reasons. Whilst the importance of short/limited beds is acknowledged, the focus of this research is upon LTC beds only. More generally, however, INHs are classified into two groups: namely, ‘public’; and ‘private and voluntary’ homes. Some commentators have suggested that private homes are

³³ These institutions generally provide accommodation for older people who are in need of care for medical reasons

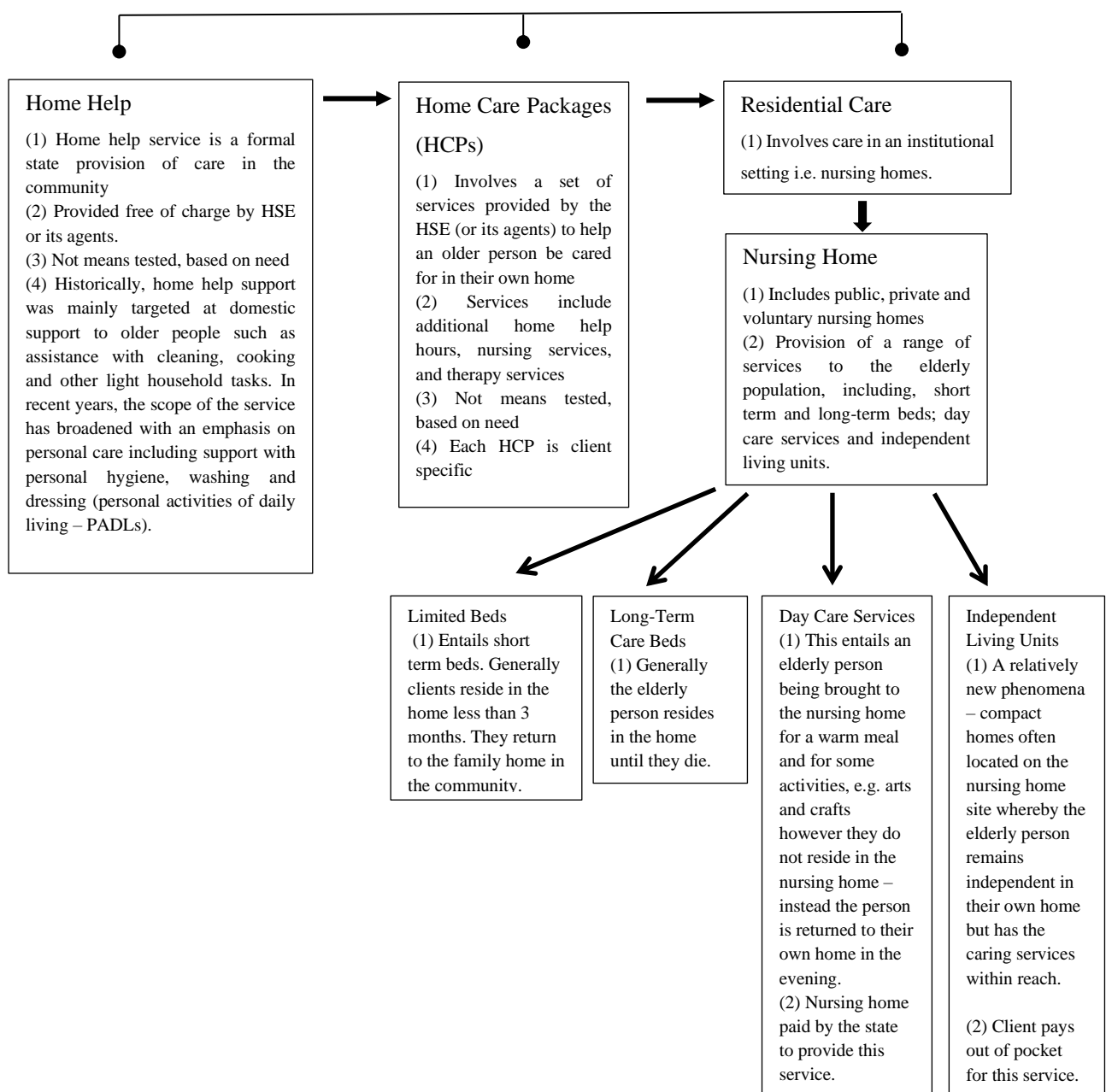
³⁴ These institutions generally provide accommodation for older people who are in need of long or short-term care for medical or other reasons.

³⁵ In 1703 the House of Industry’s Act and the Poor Law act of 1838, resulted in the provision of 130 workhouses, intended to house the old and infirm, the poor and destitute (O Loughlin 1999).

The first Dáil Eireann (1918) committed to dismantling the Poor law system, closed many workhouses and re-titled those that remained County Homes. Country homes provided shelter for the poor, the old and the infirm however the stigma of the ‘workhouse’ remained. As we move forward in history county homes were ‘re-branded’ to include such titles as district hospitals, welfare homes and geriatric homes (the remit of the ‘home’ broadened to include medical services).

more efficient than public facilities as commercial entities operate with a view to maximizing profit and minimizing cost in contrast to public units who may have multiple goals, such as the employment of local citizens and community service (Rosko *et al*, 1995). Whilst this debate has widely examined in the US NH literature (Nyman and Bricker 1989; Nyman *et al*. 1990; Fazel and Nunikhoven 1992), to date, there has been very little comparison in the efficiency of private and public NHs in the ROI.

Figure 3-1: Continuum of Care in Irish Formal Care Services



3.2.2 *The Stakeholders of Residential Care*

This section outlines the key stakeholders involved in residential care in order to elucidate into the various role and functions of the necessary agents in the delivery of NH care services. LTC (LTC) in Ireland is primarily organized and financed by Government. The Department of Health and Children (DOHC) is responsible for the formulation and orientation of policy related to formal care services. Currently, the overarching aim of LTC policy is community provision which supports an older person to remain living in their home or an appropriately similar community-based accommodation, and only be transferred to an institutional environment when community residences are no longer suitable. Interestingly, this policy perspective has had its roots in official government reports from the 1960s³⁶ to the current report *The Years Ahead: A Policy for the Elderly* (Working Party on Services for The Elderly, 1988). However, in reality, elderly people are shifting towards residential care, possibly owing to state subsidies which are only available for this sector.

The Health Service Executive³⁷ (HSE) is responsible for delivering NH services throughout four regional areas: namely, Dublin Mid Leinster; Dublin North East; the Southern Region; and the Western Region. While historically, the delivery of LTC services was undertaken through public institutions, the role of the State has moved from doing everything themselves, towards managing, monitoring, and regulating contracted care providers. ‘Other providers’ include the private and voluntary NHs which provide more than 80% of all LTC beds in Ireland at present.

As the representative body of private and voluntary NHs, Nursing Homes Ireland (NHI) plays an influential and key role within the Irish health-care sector. NHI engages with State bodies,

³⁶ Care of the Aged Report (Government of Ireland, 1968)

³⁷ The ‘HSE’ was established in Jan 2005 and emanated from 7 regional Health Boards and a Regional Health Authority. It presently manages and annual budget of over €15billion (<http://www.hse.ie/eng/about/>) and employs 140,000 personnel to deliver a vast array of health services including long-term care programmes (<http://www.hse.ie/eng/staff/>)

health stakeholders, and representative organizations for older persons and wider society, to influence and shape policy, and to inform debate surrounding the care of older persons. The Health Information and Quality Authority (HIQA) has been tasked with the registration, monitoring, and inspecting of all residential care homes since 1st July 2009.³⁸ The main goal during inspection is to meet as many people as possible, including residents and families, staff, the person in charge, and a representative of the service provider. This yields insights into the running of the nursing home and facilitates evaluations of the quality of care given: in particular, whether residents are involved in the running of the centre. As such, residents, relatives, and the general public, may now access information regarding public and private homes as all homes are now inspected against the National Quality Standards for Residential Care Settings for Older People in Ireland, and regulated under the Health Act 2007; the Health Act 2007 (Registration of Designated Centres for Older People) Regulations 2009, Health Act 2007 (Care and Welfare of Residents in Designated Centres for Older People) Regulations 2009 and amendments, to ensure all homes are safe and residents cared for properly. This new policy direction in monitoring and regulating all public and private providers of NH services is deemed fair and equitable as it ensures all suppliers a level field to compete for the delivery of services. Perhaps more to the point, compliance³⁹ ensures quality services are delivered for the elderly.

3.3 Residential Care Sector

Given the choice, most older people would prefer to live in their own homes and communities than reside in a nursing home. Unfortunately, while a number of some services available to support older generations to continue doing so, such as home help and HCPs, resources are limited and vary depending upon where the elderly person resides. Interestingly, Care Alliance Ireland (2016) noted an 8% deficit of publicly-funded home care hours in community care

³⁸ Prior to July 2009, only private facilities were subject to inspection and it was undertaken by the DOHC.

³⁹ As per www.hiqa.ie, 4050 corrective actions have been suggested by the inspection team to ensure standards are being met.

resulting in elderly people considering other care options such as NH services. Moreover, this sector is regulated⁴⁰ and receives considerable state subsidies relative to community services.⁴¹ The NH market has seen profound changes over the years from when the Irish State provided the majority of long-term beds to the current situation where private NHs are the dominant players in this environment. Additionally, this sector is incurring significant challenges as the Irish population ages. More long-term beds will be required to meet the needs of the increasing 65+ cohort suggesting that significant capital investments must occur in private, voluntary, and/or public homes. In the context of the budgetary constraints of the Irish State, rising health-care costs must be curtailed and value for money realized in the delivery of NH services, whether private or public.

3.3.1 Long-Term Care Bed Capacity 1998 - 2017

There are three formal categories of NHs in the ROI: namely: ‘for profit’; ‘not-for-profit’; and ‘public’ or private, voluntary, and public units respectively. In 2014, there were 310 private NHs, 41 voluntary (or not-for-profit) homes, and 96 public long-stay institutions and facilities in Ireland.⁴² Voluntary NHs include homes run by charities or those run by religious orders for their retired nuns and priests. More generally, however, INHs are classified into two groups: ‘public’ and ‘private and voluntary’ NH sectors; each providing limited and long-term beds. However, it is reiterated that the present study focuses on long-stay care, and does not include limited stay patients.

Traditionally, public NHs were the dominant setting for long-term residential care in Ireland: these have now been replaced by privately owned and operated-units. Between 1998 and 2011,

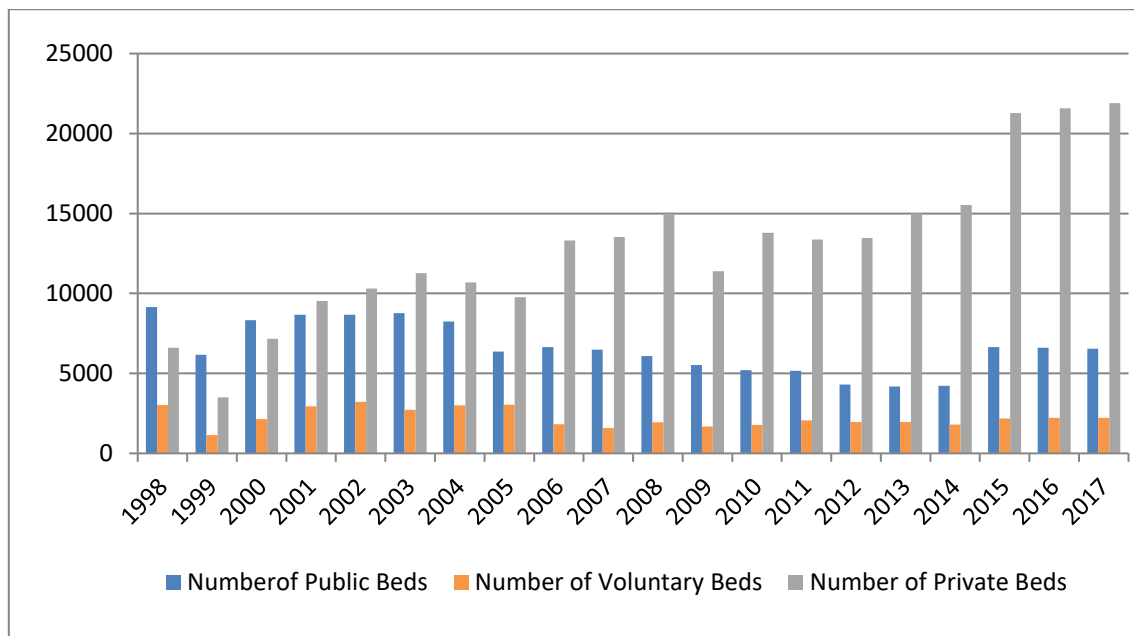
⁴⁰ Home Help and HCPs is not regulated, and no specific standards have been formulated to ensure a quality service is being delivered to the client.

⁴¹ Section 3.35 discusses the nursing home support scheme (NHSS) which is available for nursing home care only. In contrast, should an elderly person want to reside in their own home – no fair deal exists for them. Instead, the Health Service Executive (HSE) provides a very limited amount of home help to the elderly person in the home, however no financial resources are transferable to this sector of care.

⁴² The most recent annual survey of long-stay units (2017) no longer collates the number of units in the ROI. Instead, it focuses on the number of beds.

the government offered capital allowances to the NH care market to stimulate private supply. It was held that this policy initiative would lead to greater efficiencies, effectiveness, and responsiveness to consumer needs than could have realized through continued direct government provision of NH services. Canniffe (1999) suggested that investments in private NHs became a legitimate way of reducing exposure to income tax for middle to high income tax-payers. Resultantly, a secular trend has been the rapid increase in private sector beds provision as a proportion of total long-stay beds. Figure 3-2, demonstrates that the number of private beds doubled from 6,609 to 13,375 between 1998 and 2011. In 1998, the State provided 9,138 public beds: 48% of the country’s LTC beds. However, by 2001 the public sector was relegated to the role of secondary player in the NH care market, and by 2017, private and voluntary NHs provided 80% of the overall long-stay beds capacity of 30,674, with the remainder supplied by public units.

Figure 3-2: Mix of Public, Private and Voluntary Beds 1998 –2017⁴³

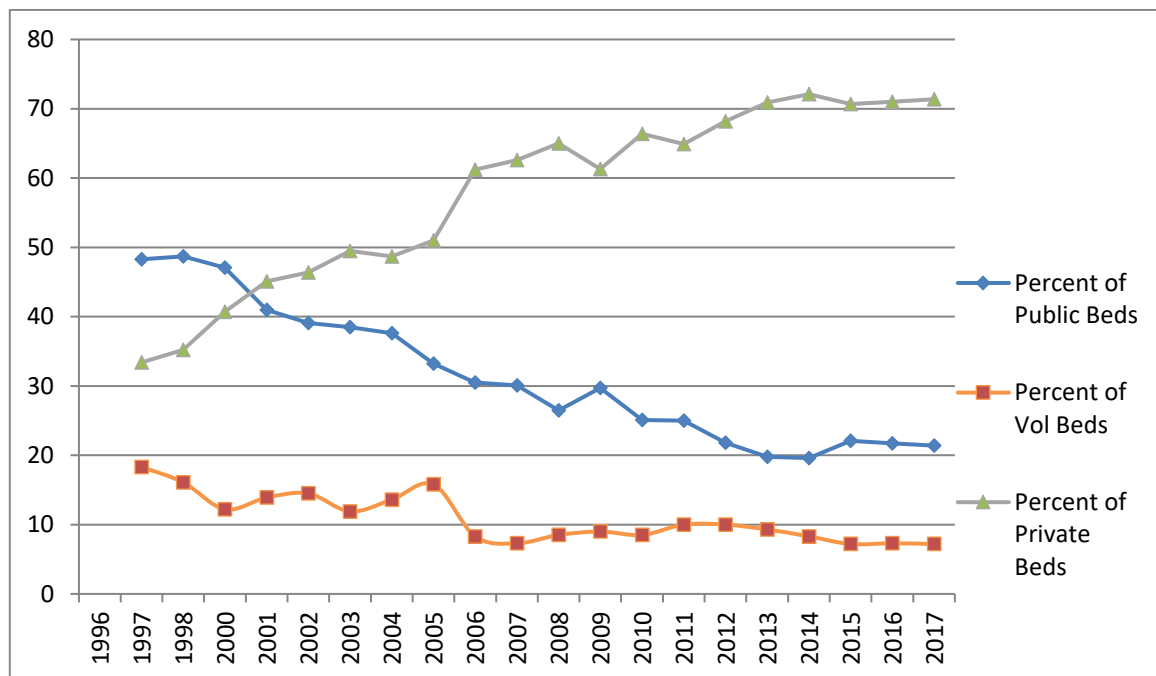


Data source: Annual Survey of Long Stay Units, Department of Health and Children

⁴³ Data from 1998 – 2014 was collated by the information unit of the DOHC. Data from 2015-2017 was collected by HIQA.

According to Nursing Home Ireland (NHI) the growth of private NH beds has taken place across most regions⁴⁴. Figure 3-3 illustrates that the percentage of private beds increased significantly between 1998-2017. In fact, the graph underscores how private NHs doubled their long-term bed capacity in the marketplace during this timeframe. Moreover, Table 3-1 reinforces the substantial strides private nursing home made in terms of bed capacity during the 2007-2010 period. Overall, total private bed capacity increased by 9% with most areas increasing their number of beds in the marketplace relative to 200: for instance, the Mid-Western Area increased its number of private beds from 1,788 to 2,086 between 2007-2010. Similarly, the South Western area increased its LTC beds in private NHs by 20.1%. Surprisingly, however, the East Coast saw no change in their overall bed complement while the North Western area experienced a decline.

Figure 3-3: Percentage Public, Private and Voluntary Beds 1998 -2017⁴⁵



Data source: Annual Survey of Long Stay Units, Department of Health and Children.

⁴⁴ They caution that the information captured in their survey is reported by reference to the HSE areas that existed prior to the introduction of new administrative structures within the HSE in 2005.

⁴⁵ Data from 1997-2014 was collated by the Information Unit of DOHC. Data from 2015-2017 is collated by HIQA.

Table 3-1: Private NHs Growth 2007 – 2010

HSE Area	Number of Beds 2010	Number of Beds 2007	% Change between 2007 and 2010
East Coast Area	2,447	2,447	0.0
Northern Area	1,964	1,763	11.4
South-Western Area	2,219	1,848	20.1
Midlands Area	1,218	1,035	17.7
Mid-Western Area	2,086	1,788	16.7
North-Eastern Area	1,769	1,746	1.3
North-western Area	945	1,033	-8.5
South-Eastern Area	2,322	2,153	7.8
Southern Area	2,730	2,428	12.4
Western Area	2,890	2,642	9.4
Total	20,590	18,883	9.0

Data source: Annual Survey of Private NHs 2009/2010, Horwath Bastow Charleton

3.3.2 *The NH Environment*

Whilst public, private, and voluntary institutions provide the same care to the elderly, the various facilities differ in their orientations. Private homes are commercial units which seek to maximize profit and minimize costs. In contrast, public facilities are non-profit entities in where profit goals are replaced by a range of multidimensional objectives (Pestieau and Tulkens 2006). Such goals may include enhanced amenities and quality services, and employment of local citizens. Likewise managers in public homes may pursue self-enhancing objectives (for example, excess travel or recruitment of additional staff) which may increase costs and reduce efficiency in contrast to private homes whereby profit motives create a strong incentive to monitor and refrain from these types of behaviour. Other differences emerge between private and public facilities other than the motivations of the firm as indicated by the following overview of the key characteristics of public and private homes.

Years in Operation

Public facilities largely date from the days of the ‘workhouse’⁴⁶, and many people perceive residence in these formidably imposing, gloomy, and “grey” buildings as undesirable due to historic associations with poverty and shame. While many such institutions are more than 100 years old, the average age of a public facility is 72 years, and despite their vintage, all public units aim to ensure that safe and quality care is delivered to residents. Since the publication of the ‘*National Quality Standards for Residential Care Settings for Older People in Ireland*’ (HIQA, 2016), public homes seek to ensure that first-class care underpins the ethos of care delivery. However, DiGiorgio *et al.* (2014) and Garavaglia *et al.* (2011) concurred that measuring quality in LTC is fraught with complexity⁴⁷. Nonetheless, public homes acknowledge the critical importance of instantiating a comprehensive set of high standards to guide providers in the delivery of optimal levels of care. Moreover, inspections⁴⁸ ensure that appropriate governance and leadership affords safe services and person-centred quality care. The most recent document, ‘*National Quality Standards for Residential Care Settings for Older People in Ireland*’ (HIQA, 2016) further promotes continual improvement in the quality and safety of the residential services provided to people living in residential care.

In contrast, private NHs are often modern, bright institutions and therefore perceived more favourably than public homes. The capital allowance introduced by the Irish Government in 1998 stimulated the supply of private facilities, ultimately enabling private homes to become the majority provider of LTC beds in the Irish market. Interestingly, the 2009/2010 NHI annual survey of private NHs found that the average duration of operation for a private facilities to be 17.5 years. Indeed, realtors DTZ Sherry Fitzgerald (2015) have observed that institutional

⁴⁶ See Chapter 1.

⁴⁷ See Chapter 2 for additional discussion on quality of care in the previous literature and Chapter 4 for how quality of care is measured in this study.

⁴⁸ Undertaken by the Health Information and Quality Authority (HIQA), however prior to July 2009 only private facilities were subject to inspection and this was undertaken by the Department of Health and Children (DOHC).

investors wish to purchase modern contemporary NH facilities in response to the aging Ireland population; suggesting the net value of private homes may rise going forward.

Bedroom Type

Single en-suite rooms are the most common form of bedroom type available for residents in private NHs. Over half of private homes surveyed in 2009/2010 offered rooms of this type. In contrast, the dominant bedroom formations in public NHs are multiple occupancy rooms where up to six residents may reside. However, that the volume of rooms with multiple occupancy has decreased in recent years, as NHs faced risk of closure due to the revised physical environment standards introduced by HIQA in 2009. These required that NH facilities built after July 2009 to comply with a number of different stipulations, including a minimum of 80% of residents to be accommodated in single en-suite rooms and a maximum of two residents to occupy shared rooms. The six-year grace period for NHs built prior to 2009 to meet these new standards came to an end in July 2015. The HSE estimated that approximately 90% of the available long-stay public beds did not meet the HIQA standards for physical environment, with a total of €834 million investment necessary to achieve compliancy with the stricter standards (DTZ Sherry Fitzgerald, 2015).

Further amended standards issued in 2016⁴⁹ specify that “where multi-occupancy bedrooms exist, there are no more than four residents accommodated in each bedroom” (p.40). This means that the public NH sector will need considerable investment to upgrade and improve their accommodations. To date, the NHI has estimated the average capital cost of NH compliance with the HIQA upgrades to be approximately €579,000.

Trends in New Facilities

The gap between the demand and supply of NH beds in Ireland is increasing. The LTC sector is facing significant challenges to meet the expected demand for beds. Compared to their public

⁴⁹ National Quality Standards for Residential Care Settings for Older People in Ireland (HIQA, 2016).

counterparts, private NHs are relatively new entities. As such, they have better opportunities to design their NH services around the present and future needs of the older generation. Services include specialized facilities such as Alzheimer and Dementia Units, and Independent Living Units (ILUs). As Irish public NHs originated in 1701, the provision of services tends to focus on the traditional role of caring in the NH environment with the addition of day care services. Again, this service provides a revenue stream to the home and compliments NH services. The following details the new trends evident in the care facilities.

Specialised Facilities

Given that private NHs are a relatively new addition to the sector, they have tailored their services according to the needs of the market. For example, the Alzheimer's Society of Ireland purport that 55,000 people are currently living with dementia in the ROI⁵⁰ and forecast this figure to rise to increase to more than 104,000 by 2036. It is reasonable to assume that greater numbers of people living with this condition will intensify demand for care in dedicated care units. In fact, the most recent survey of private NHs⁵¹ found that 21% of respondents provided dedicated dementia care units within their NHs facilities and regard them as a significant area of growth within their business model. Such specialized facilities enable the home to charge additional monies to engage expertise personnel with specific skill sets on site. The provision of specific dementia units remains comparatively limited across public NH sector and would require substantial investment and resources to cater for the needs of the residents.

Day Care Services

Both public and private NHs provide day care services to the elderly which provide an important revenue stream to the facility. The range of services available varies widely and can include any or all of the following: transport to and from day centre within the nursing home; chiropody; meals; health monitoring; art and crafts; and other social programmes. Day care

⁵⁰ www.alzheimer.ie

⁵¹ Annual Private Nursing Home Survey 2009/2010, Horwath Bastow Charleton.

services are provided on a variable basis throughout the country: some directly by the HSE; and others in conjunction with private and voluntary NHs. The general ethos of day care services is to assist older people to continue living in their communities and to promote independent living.

Day centres providing medical care are less widely available. Access is by referral and eligibility conditions vary from area to area, with means tests applying in some cases. In fact, there are no definitive regulations for day centres which gradually evolved as an alternative to hospital and residential care facilities for older people. In their report on private NHs, Horwath Bastow Charleton (2009/2010) noted the average rate charged for the provision of such services as €64.00 per day. Owing to data limitations it is unclear what financial allocation public homes receive in their budgets in relation to the provision of this service.

Contract Beds

Contract beds are another source of revenue for private NHs, through which the State enters into agreements with the private sector to provide care in private NHs for eligible residents (O'Shea, 2002). In 2007, about 36% of all private and voluntary NHs received a fixed/block contract per bed to supply an agreed volume of their overall bed capacity to the State. In such cases, the Health Services Executive (HSE) pays the full cost of a private NH bed. Typically, contract beds are 'purchased' on a block contract basis, whereby the private facility receives a fixed payment from the State regardless of the severity of a resident's care needs or whether the bed is occupied at all times.

The number of contract beds, and hence the degree of funding varies across private units, and again, there are no clear regulations inscribing the HSE's governance of such arrangements. The purchase of contract beds in private facilities occurs when public NHs do not have sufficient capacity or the specific skill-set to offer care in particular cases. While private NHs can appeal to the State for additional funding should the case-mix of an individual resident

change, there is no guarantee that this will be forthcoming. Thus, it is imperative that the private facility negotiates a contract that anticipates both the present and future costs of resident care. Ideally, private providers of care would prefer to supply contract beds on a 'cost by case' basis. However, given that the State has limited resources and pursues value for money objectives in the delivery/purchase of health services, most LTC beds continue to be contracted on a fixed funding basis.

Independent Living Units

Independent living units (ILUs) are often associated with private NHs as they located on the NH site. ILUs offer one-, two- or three-bedroom accommodation in a village environment. They are suitable for older people who are actively independent and able to care for themselves. The purpose of ILUs is to make day-to-day life a little easier, thereby enabling residents to live independently for as long as possible. Thus, landscaping and housekeeping services, meal preparation, security surveillance, and a variety of social activities and events, are provided by personnel from the care facility. While a nurse may occasionally call to check the health needs of a specific resident, ILUs do not generally provide on-site medical assistance or nursing care. In essence, ILUs are not hands-on care communities since residents are mainly in good health. Rather, the units focuses on elder non-health matters, such as personal safety and well-being.

3.3.3 Profile of the Resident

In evaluating the efficiency of NHs and assessing the determinants that impact upon the efficiency performance of public, private and voluntary NHs it is important to consider the people who actually live in these facilities. Evidence from the United States indicates that 70% of NH residents are women of which 75% are aged 75 years and above. Research findings in Britain also indicate that the elderly in residential care are more likely to be women. The purpose of this section is to provide an overview of the residents in INHs: who these residents are; and their level of independence. This is imperative since care plans and care management

strategies must be devised and implemented with the elderly person at the centre of the decision-making process in order to ensure quality NH services are delivered.

Gender

Wren (2009) indicates that 4.8% of people aged 65+ are in public, private and voluntary NHs. Since women enjoy longer life expectancy than men, it follows that two thirds of these are women. In 2010, the life expectancy of men was set at 77.9 years, and is expected to rise to 85.1 years by 2046. Women's current life expectancy is 82.7 years and expected to be 88.5 years by 2046. While over two-thirds of all NH patients are aged 80+, 77.1% of all long-term beds are supplied to women. In short, and in line with gender life expectancy ratios, 65.4% of patients in long-stay beds are women and 34.6% are men (DOHC, 2013).

Age

In 2003, 66.3% of all residents were 80 years of age or above. Just 14 years later, 70% of residents are 80 years or more. Table 3-2 demonstrates there are now greater numbers of residents in the oldest age categories compared to previous years. This shift directly impacts core resources, as this age cohort consumes more health services relative those under 80 years of age. Furthermore, the older the person, the more complicated their case-mix is likely to be. This again results in the necessity for increased inputs which can lead to lower efficiency performances. In light of this, private NHs could potentially 'cherry pick' residents with less complicated ailments and resource demands relative to people aged 80+. However, empirical evidence indicates that public and private NHs have an equitable share of residents of 80 years or more; at 71.7% and 73%, respectively. Of some note, however, is the percentage of residents of less than 64 years of age who reside in public and private NHs (4.15%; 4.45%) given that care policy (*The Year Ahead: A Policy for The Elderly*) states that low to medium dependency residents should reside in the community setting with appropriate supports.

Table 3-2: Percentage Distribution of Residents at 31 December 2017 by Age in Years

Category	Under 40	40-64	65-69	70-74	75-79	80-84	85-89	90-94	95+	Total
Public	0.5	7.8	6.8	14.3	27.1	44.6	52.7	32	14.2	200.0 ⁵²
Private	0.4	8.5	7.1	13.7	24.1	38	51.1	40.5	16.5	200.0 ⁵³
All	0.4	5.2	4.2	7.6	12.7	20.5	24.7	17.9	6.9	100.0

Data source: Annual Survey of Long Stay Units, Department of Health and Children (2017).

Dependency

Clinical personnel in INHs utilize a very simplistic approach to case-mix classification throughout service planning and funding procedures for aged residential care. On entering a home, the individual is streamed into one of the four dependency categories: low; medium; high; and maximum. The annual surveys of Long Stay Units use the following definitions for the various groupings of dependency:

- **Low Dependency:** persons who need some support in the community and more independent residents in residential accommodation who require little nursing care. They are usually independently mobile, but may use a walking stick and have difficulty managing stairs.
- **Medium Dependency:** persons whose independence is impaired to the extent that they require residential care because appropriate support and nursing care required cannot be provided by the community. Mobility is impaired to the extent that they require supervision or a walking aid.
- **High Dependency:** persons whose independence is impaired to the extent they require residential care but are not bedbound. They may have a combination of physical and mental disabilities, may be confused at times, and be incontinent. They may require a walking aid and physical assistance to walk.

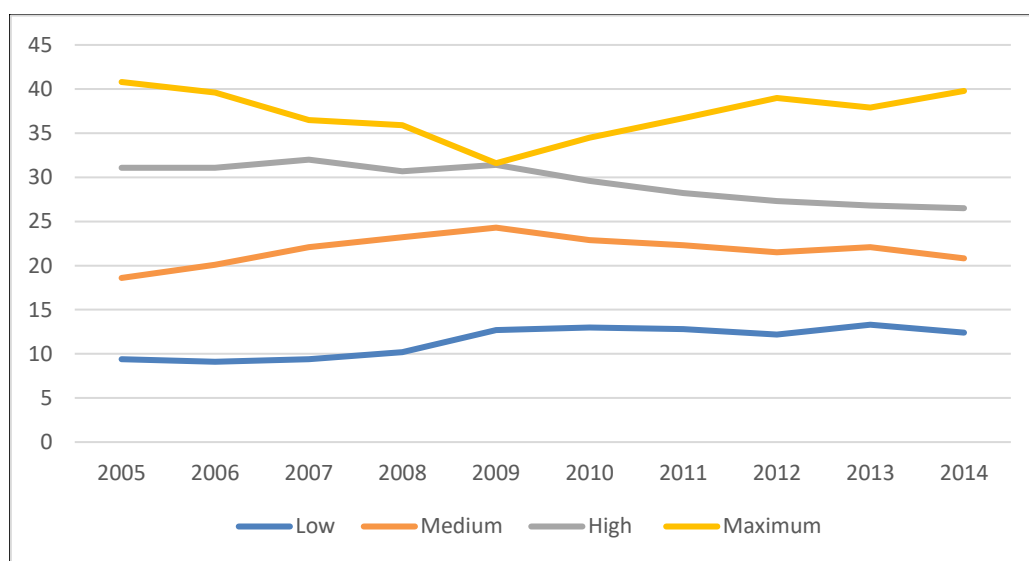
⁵² Includes both HSE residential care centres and welfare homes.

⁵³ Incorporates both voluntary and private nursing homes.

- **Maximum Dependency:** persons whose independence is impaired to the extent that they require nursing care. They are likely to be bedbound, require assistance with all aspects of physical care, and may be ambulant but confused, disturbed, and incontinent.

Nursing homes traditionally accommodated individuals who had low care needs due to limited supports in the extended family or for medico-social reasons. However, since Irish care policy now advocates that such people should remain living in the community, elderly people with low and medium dependency needs could be supported in their home environment with adequate home care packages and supports. Illustrating the trends in dependency over 2005-2014⁵⁴ Figure 3-4 confirms that no dramatic reductions have occurred in the low-medium dependency groupings over this period. This result is unexpected given the objectives of *The Year Ahead: A Policy for The Elderly*.

Figure 3-4: Level of Residents' Dependency (as % of total patients) 2005 – 2014



Data source: Annual Survey of Long Stay Units, Department of Health and Children (2014)

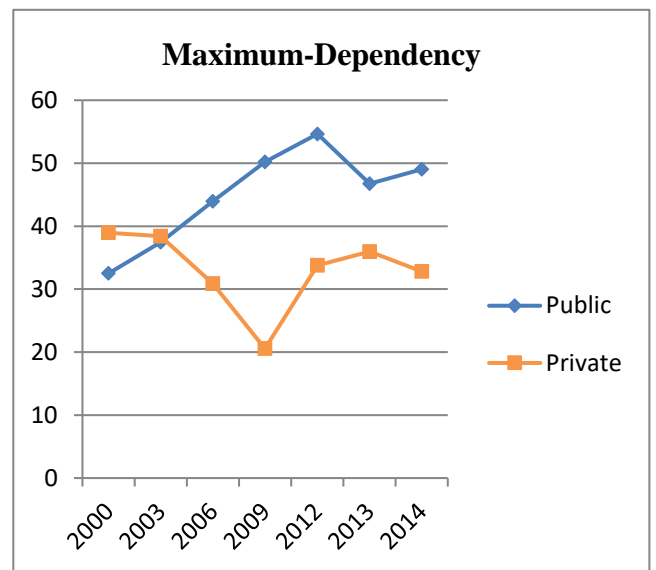
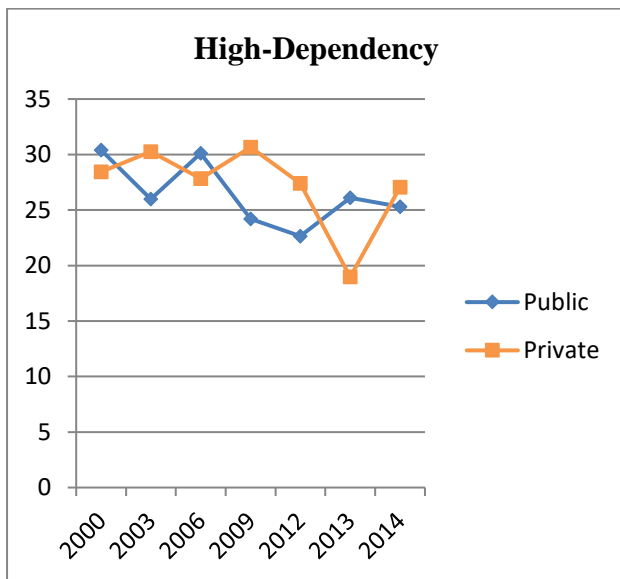
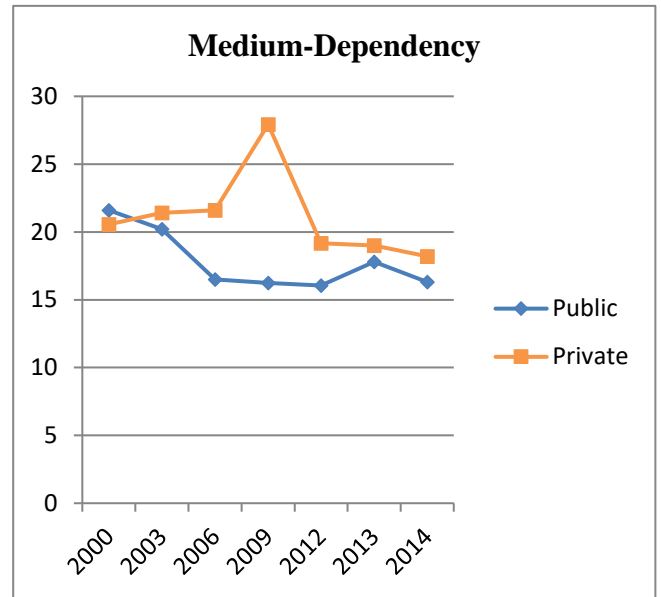
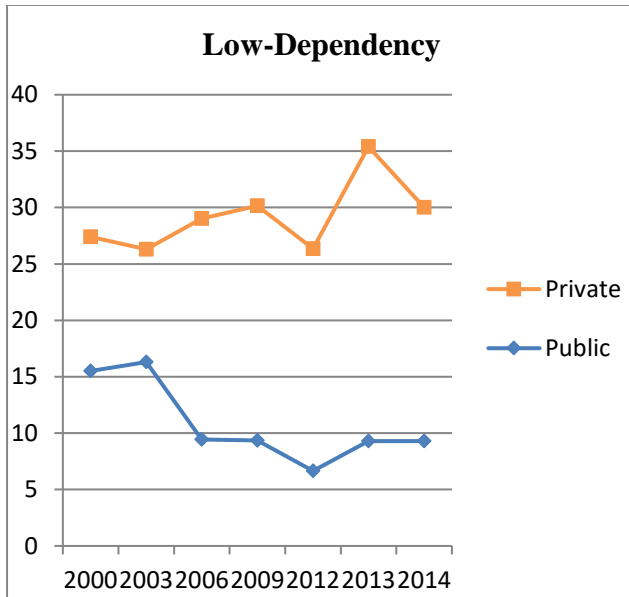
Nonetheless, an interesting pattern emerges from an assessment of the ‘low-medium high-maximum dependency’ patterns according to the key providers of NH care (public and private NHs). The Figure 3-5 illustrates the ‘low’, ‘medium’, ‘high’ and ‘maximum’ dependency patterns in public and private NHs for the period 2000-2014, and shows that public NHs have

⁵⁴ Current annual long-stay statistics (2015-2017) no longer collate information dependency levels.

reduced their 'low-dependency' residents by 40% over this timeframe, while private homes have increased their volumes of elderly people with 'low dependency' by 73.9% during the same period. This outcome suggests that private nursing facilities are maximizing their profits as low-dependency patients consume fewer resources relative to high-dependency residents. Moreover, Figure 3-5 indicates that since 2003, public NHs have a higher proportion of 'maximum-dependency' residents compared to private facilities, with the greatest difference evidenced in the 2009, whereby the ratio of maximum-dependency clients in public homes relative to private NHs was at 2.5:1. Maximum-dependency individuals have greater care needs relative to other dependency levels, meaning more NH services are required, leading to rising costs and lower efficiency performances for these homes.

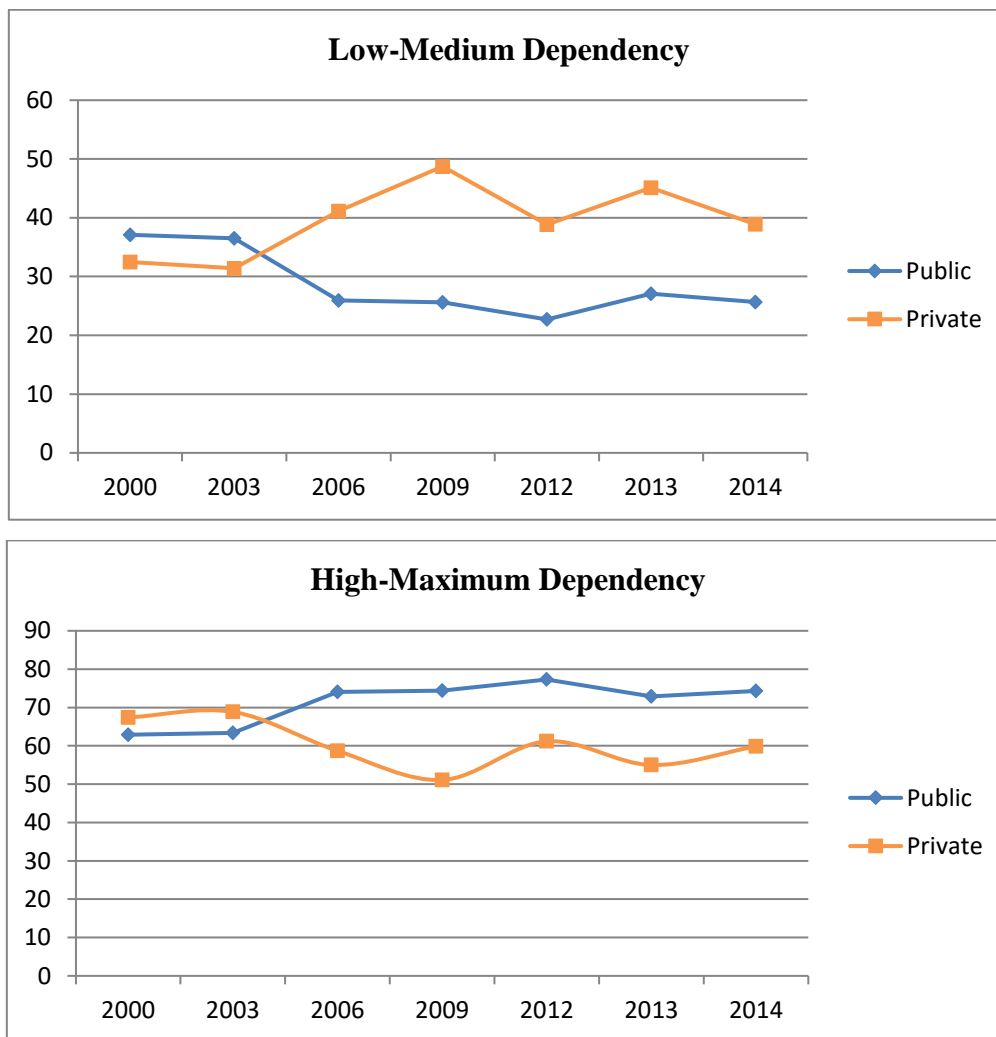
Figure 3-6 illustrates that the combined percentages of 'low medium' dependency and 'high maximum' percentages reveals a public NHs decrease of 'low medium' dependency clients by 30.8% in the period 2000-2014, while at the same time increasing their 'high-maximum' dependency residents by 18.2%. The consequences of this shift are that more medical and non-medical staff are employed in the home as the care needs of 'high-maximum' dependency residents are greater than the medium-low dependency patients. By contrast, in the same period, private NHs increased their percentage of 'low-medium' dependency clients by 19.8% while simultaneously decreasing their 'high-maximum' percentage of clients by 11.1%. This change suggests that less clinical personnel are required as this skillset is not demanded because of less acute residents; thus allowing the home to reduce its cost base, enhance its profit levels, and improve its efficiency performance.

Figure 3-5: Percentage 'Low', 'Medium', 'High' and 'Max' Dependency Residents in Public and Private NHs 2000 -2014



Data source: Annual Surveys of Long Stay Units, Department of Health and Children

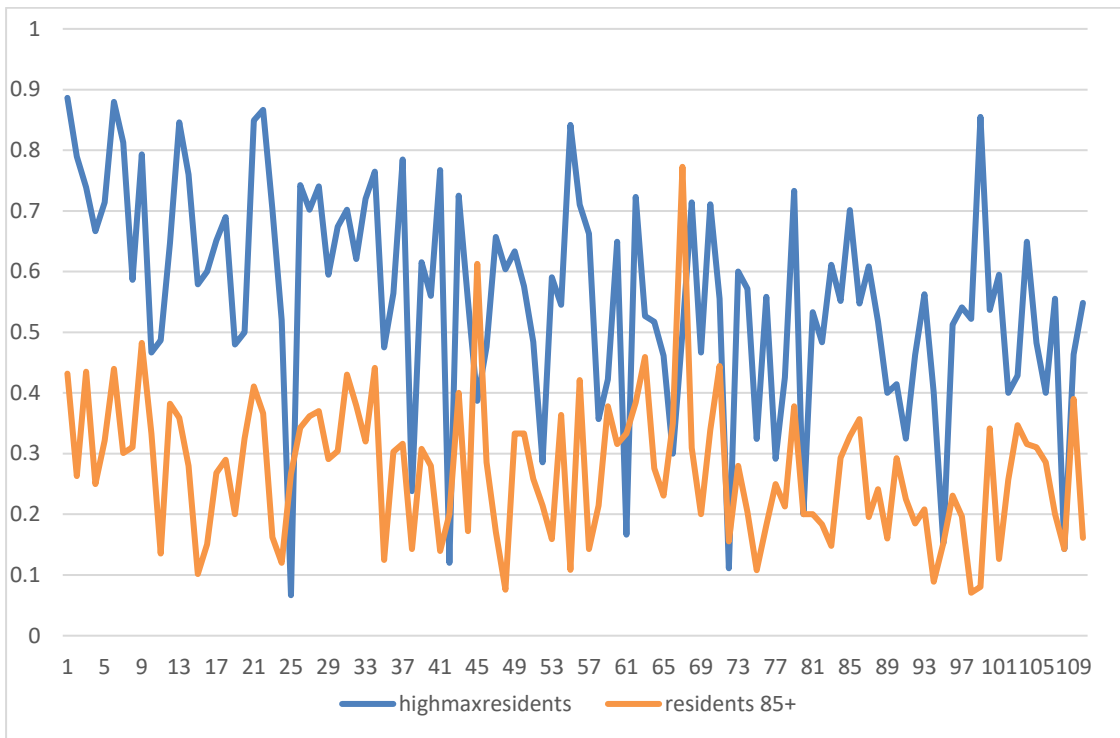
Figure 3-6: Percentage Age of 'Low-Medium' and 'High-Maximum' Dependency Residents 2000 – 2014



Data source: Annual Surveys of Long Stay Units, Department of Health and Children

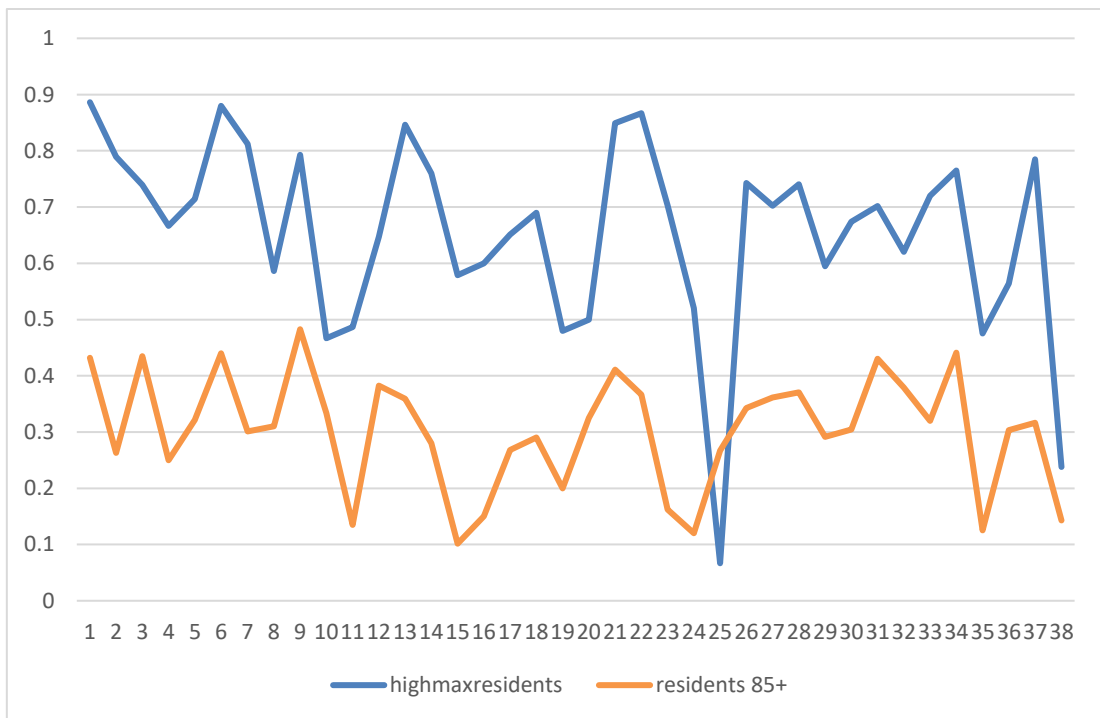
The care demands of patients are critically important for the resource requirements of a nursing home. Older patients might have greater resource needs than younger patients. To test for this effect in INHs, the proportion of high and maximum dependency residents in INHs against the proportion of residents that are 85 years or more was mapped. As Figure 3-7 confirms, no overlap was found between these two variables. Indeed, the correlation result of 0.274 indicates there is little or no relationship between both these factors.

Figure 3-7: Proportion of High-Maximum Dependency Residents / Patients 85+ in All Homes



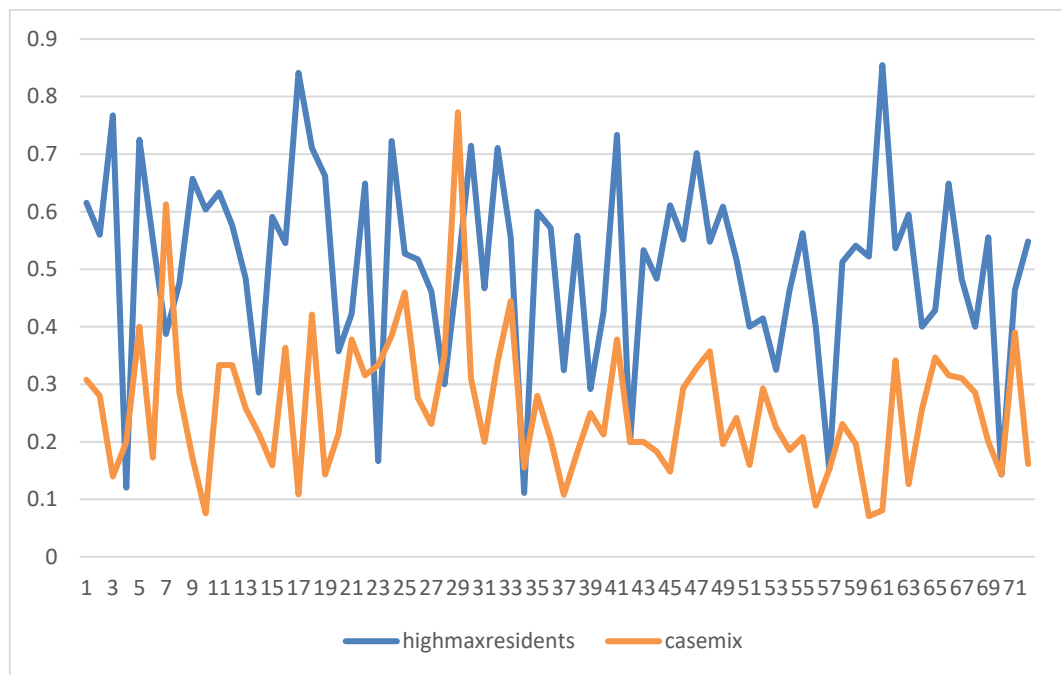
Source: Primary dataset on INHs, 2007-2008

Figure 3-8: Proportion of High-Maximum Dependency Residents/ Patients 85+ in Public NHs



Source: Primary dataset on INHs, 2007-2008

Figure 3-9: Proportion of High-Maximum Dependency Residents/Patients 85+ in Private Nursing Homes



Source: Primary dataset on INHs, 2007-2008

As previously discussed, public homes have a higher percentage of high-maximum dependency residents relative to private facilities. Anecdotal evidence suggests that public facilities accommodate a greater proportion of patients that are 85+ relative to private units. Thus, the evaluation of the relationship between these two variables in public NHs shown in Figure 3-8 reveals a pattern for these two indicators. Likewise, the correlation result of 0.568 indicates a ‘relatively’ strong link between the proportion of high-maximum dependency residents and residents who are 85+ in public NHs. Conversely, Figure 3-9 demonstrates that private homes present no relationship between these variables and the result of the correlation coefficient (0.070) supports this outcome.

3.3.4 Ireland’s Aging Population

Unlike comparable European countries where more integrated models of older care services and supports exist, the Irish model of care for elderly people remains underdeveloped. This is reflected in limited intermediate/or step-down options which effectively places significant demands on the NH sector to meet the care needs of the older population. While at 13.0%, the

share of persons aged 65+ in the total population in Ireland is the lowest of the EU member states and well below the wider European average of 19.4%, Ireland's elderly population is increasing rapidly and this rate of growth is projected to continue well into the future. According to official projections,⁵⁵ the number of people aged 65 and over in Ireland will rise by over 1% between 2016 and 2021, and will grow by a further 17% in the period 2021-2026. This age cohort is forecast to increase by 167%, from 532,000 in 2011 to over 1.4 million by 2046. In 2010, only 17% of public expenditure on LTC provision in Ireland was allocated to the home-care packages to support the elderly person to reside in their own home, with the balance spent on residential facilities. However, given this dominance of formal residential facilities in LTC of the elderly, an increasingly older Irish society translates increased demand for NH places.

The key determinant of need for LTC is influenced by the size and age of the older population and associated levels of disability and dependence. However, actual demand for long-term care in any setting is also influenced by additional factors, including socio-economic determinants such issues of social isolation and the availability of alternative forms of care for older people. This following section presents an overview of current and future trends in the Irish elderly population and elaborates in future demands for NH services.

Current Trends

According to the 2011 Census, Ireland's population grew by approximately 8% between 2006 and 2011. In the same period, the number of people aged 65+ rose by 14.4% from 467,926 in 2006 to 535,393 in 2011. In short, 11.7% of the 2011 Irish population was aged 65 or older. However, as Table 3-3 illustrates, there are significant regional variations: from 10.5% in Dublin North East to 13% in the Western Region.

⁵⁵ Population and Labour Force Projections 2016-2046 (CSO, 2013).

Interestingly, in terms of absolute numbers, the Southern Region has the largest number of people aged 65 (146,189) with Dublin North East having the lowest (107,225).

Table 3-3: Percentage (%) Share of Elderly People by Age in HSE Region

Region	65-69	70-74	75-79	80-84	85 and Over	Total	Total Number Over 65	Over 65+ as % of total population in the region
	%	%	%	%	%	%	total	%
Dublin Mid-Leinster	32.6	24.5	19.0	13.1	10.8	100	141,521	10.7
Dublin North-East	32.6	24.9	19.2	12.9	10.5	100	107,225	10.5
South	32.5	24.7	19.2	13.0	10.7	100	146,189	12.6
West	32.1	24.0	18.9	13.3	11.6	100	140,458	13.0

Source: CSO (2011)

The consequences of an aging population can be significant as more older people will require more long-term beds. Table 3-4 presents the ratio of long-term beds relative to the population aged 65+. Interestingly, the NHI estimated there were 20.2 people aged 65+ as a proportion of the quantity of LTC beds in 2014. However, this figure came in significantly higher in the NHI region of Dublin North at 26.7, followed by 24.5 in the North-West, and 21.1 in the South-East. However, the lowest figures were recorded in the West and the Dublin-Wicklow regions, at 17.5 and 17.7, respectively. However, DTZ Sherry Fitzgerald (2015) point out that regional variations in demand and supply do not necessarily reflect an imbalance in the provision of NHs but rather factors such as the availability of home care or other community-based services in the region.

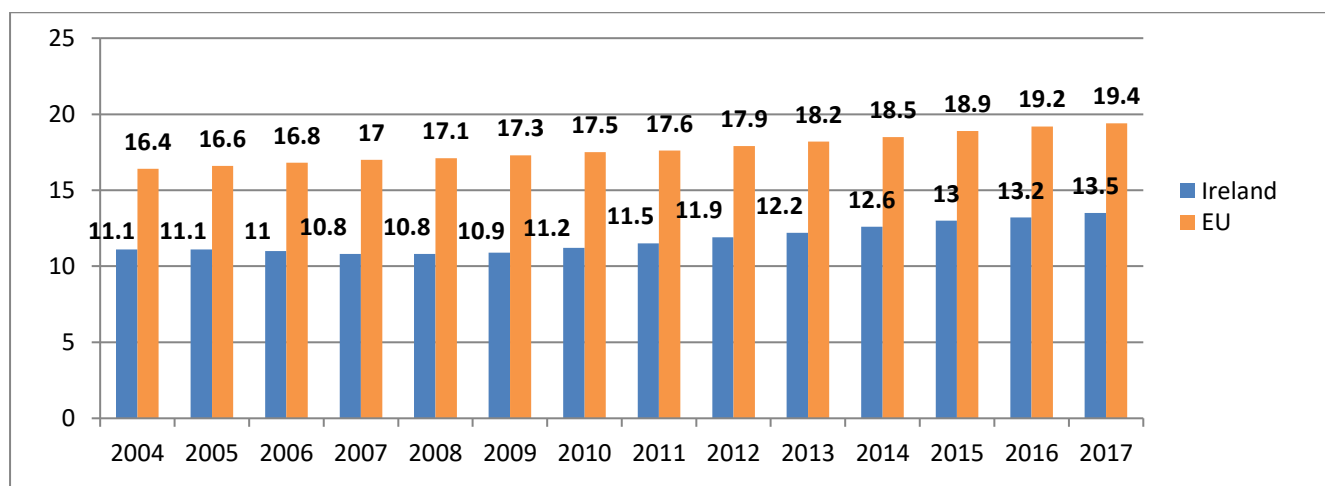
Table 3-4: Long-Term Beds and Population Aged 65+ Per Bed in 2014

Region	Population 65+ (estimate)	Public Beds	Private/Voluntary Beds	Total Beds	Population 65+ per bed
Dublin North	68,572	351	2,220	2,571	26.7
North-West	38,309	622	942	1,564	24.5
South-East	68,331	897	2,339	3,236	21.1
Dublin-Kildare	68,240	867	2,471	3,338	20.4
North-East	50,171	524	2,007	2,531	19.8
Midlands	34,274	403	1,336	1,739	19.7
Mid-West	51,399	429	2,219	2,648	19.4
South	89,592	1,416	3,270	4,686	19.1
Dublin-Wicklow	54,643	480	2,599	3,079	17.7
West	63,070	667	2,939	3,606	17.5
State	586,601	6,656	22,342	28,998	20.2

Source: DTZ Sherry Fitzgerald 2015 (p.6)

Increased life expectancy, improved prevention and treatment of illnesses, and better housing conditions, have all contributed to raising the age profile of Ireland’s population. Whilst Ireland’s share of persons aged 65 or older in the total population is less than the European average of 19.4% and the lowest of the EU Member states at 13%, Figure 3-10 confirms that Ireland’s elderly population increase has clear repercussions for NH services going forward. It is likely that more care homes and LTC beds will be demanded as the population ages and that costs will dramatically rise in this sector.

Figure 3-10: People aged 65+ as a % of Total Population: Ireland and EU Average 2004-2017



Source: Long Stay Activity Statistics (2017), p.7.

Another critical aspect of current demographic trends is that the number of people 80 years or above is also steadily rising. This has stark consequences for health services as this age-group generally exhibit higher dependency levels, increased frailty, and more complex needs, meaning that additional resources such as medical and non-medical staff will be needed; generating rising costs for NH care. Between 2006 and 2011, the number of people aged 80 years or more increased by 14% and is likely to increase in the years ahead.

Future Trends in Ireland' Aging Population

According to official projections,⁵⁶ the number of people aged 65 and over in Ireland will rise from 532,000 in 2011 to almost 1.4 million by 2046. In other words, the total 65+ population is estimated to increase by 167% in this period. The consequences of an increasingly elderly Irish society will be an commensurate increased in demand for NH places, given the fact that very little step-down options are available. Moreover, with increased female participation rates and other societal changes, such as a shift towards urbanization, it is less likely that older people will be cared for by the extended family; resulting in demand for residential care. Department of Health and Children commentators anticipate that 4 to 4.5 % of the projected population of the '65+ age cohort' will require long-term beds. With a current capacity at 30,674 beds, Table 3-5 demonstrates that more must be commissioned to meet future demand: indeed, existing provision will need to increase twofold to meet anticipated demand in 2046.

Table 3-5: Population Projections of '65+ Age Cohort' and Projections of LTC Beds

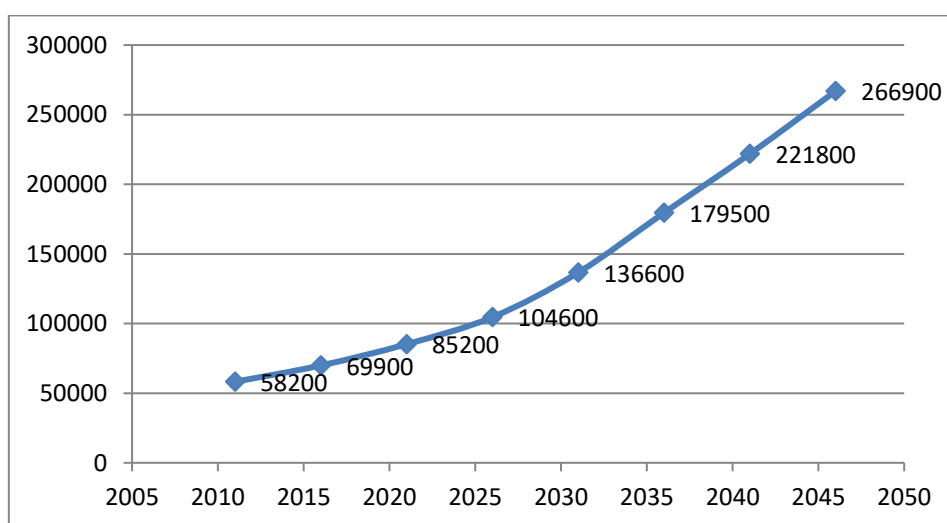
Year	Population Projections for '65+ Age cohort'	Projections of Long-Term Beds Required	
		4 %	4.5 %
2021	731,900	29,280	32,940
2026	854,900	34,200	38,470
2031	991,000	39,640	44,590
2036	1,131,100	45,240	50,900
2041	1,276,300	51,050	57,430
2046	1,419,300	56,770	63,870

Source: CSO (April 2013)

⁵⁶ Population and Labour Force Projections 2016-2046 (CSO, 2013).

A further issue of population ageing is the progressive ageing of the older population itself. In short, the relative matter of the very old is growing at a faster pace than any other age stream of the EU’s population. The EU population share of those aged 80 years is projected to more than double between 2015 and 2080; from 5.3% to 12.3%. Similarly, in Ireland, the cohort which requires the highest level of care, those aged 85 and above, is growing rapidly and is predicted to rise by a staggering 458% between 2011 and 2046. Figure 3-11 demonstrates that 69,900 of the Irish population are presently aged 85+, representing 1.4% of the overall population. However, by 2046, 4% of the Irish population will be aged 85 years or more. The consequences of this population change will be increased demand for health and NH services for an age cohort which utilizes four times more health services than an elderly person under 85 years of age. Moreover, with the attendant increases in chronic illnesses such as Alzheimer’s and Dementia⁵⁷, future demand for public and private NH places is expected to rise significantly. An aging population means greater use of service utilization and rising health-care costs. Furthermore, with residential care being largely financed by public finances, additional bed projections indicate more public funding will be needed for this LTC sector.

Figure 3-11: Population Projections for ‘85+ Age Cohort’



Source: CSO (2013)

⁵⁷ Current estimates are 48,000 people with Alzheimer’s Dementia however by 2046 this will have increased to 153,157 (Irish Times – 29th July 2014).

3.3.5 *The Cost of Care*

One of the most notable features of Ireland's changing demographics is the pace at which the population is ageing; specifically, the rate of growth in the older age cohorts, and in particular, those in the 85+ category. The implication of these changes is that more NHs care services are urgently needed, resulting in additional costs for society as the NH sector is primarily financed by the exchequer. According to Wren *et al.* (2012), care for older people cost the DOHC €1 billion in 2006 and €1.6 billion in 2011. With the increasing demands of an aging population these costs will grow significantly. While the Mercier Report (2002) predicted that residential care will cost €663m by 2021, rising to €1 148m by 2031, some commentators expect that costs of NH care to rise even further. With finite available resources then, it is imperative that they are expensed efficiently to ensure value for money is attained to meet future residential needs of the Irish elderly. The following section therefore reviews the funding model which underpins INHs and compares the cost of care in Ireland to its international counterparts. The section specifically focuses on the price of public, private, and voluntary NHs, since anecdotal suggests that private and voluntary homes are actually less expensive than public institutions. Finally the projected costs of Irish care facilities going forward given the projected increases in the Irish elderly population is fully evaluated.

Funding of NH Care in Ireland

The NHs Support Scheme (NHSS), or the 'Fair Deal' as it is commonly referred to, is the Irish mechanism which funds the cost of long-stay care for the majority of NH residents. The scheme first came into effect in October 2009 and replaced the various prior systems of support; namely, subventions for the elderly in private NHs or long-stay charges for those in public NHs and contract beds.⁵⁸

⁵⁸ The systems that existed prior to the introduction of the NHSS were acknowledged as being inequitable. There were vastly different levels of support available to residents in the public system and residents in the private system. Individuals who obtained a public bed were charged a maximum of up to 80% of the State Pension (Non-Contributory) towards the cost of their care. In contrast, individuals who availed of a private nursing home bed

The NHSS/Fair Deal provides financial support for persons who have been independently assessed as requiring long-term residential care. It is predicated on the core principles that LTC be affordable, and that a person should receive the same level of State support whether they choose a public or private nursing home. Applicants approved for NHSS funding undergo an income and assets assessed to determine the level contribution to be made to the cost of their long-term residential care and the level of State support, if any. A key feature of the scheme is resident choice. Once an applicant has been approved for the scheme, they are free to choose any public or registered private nursing home covered under the scheme; thereafter entering into a contract for care with their preferred provider.

While the HSE administers the scheme and facilitates the payment to individual NHs, the National Treatment Purchase fund (NTPF) is the official body which negotiates the maximum charges of “approved” private and voluntary NH operators for long-term services to residents in receipt of state support. Interestingly, the NTPF has no role in setting or negotiating prices for public facilities. The maximum prices paid to public facilities is set by the HSE, laid before the *Oireachtas*, and published on the HSE website.⁵⁹ It is also important to note that the NHSS provides financial support towards the cost of the standard components of NH care which are:

- Nursing and personal care appropriate to the level of care needs of the person
- Cost of bed and board
- Basic aids and appliances necessary to assist the person with the activities of daily living
- Laundry service

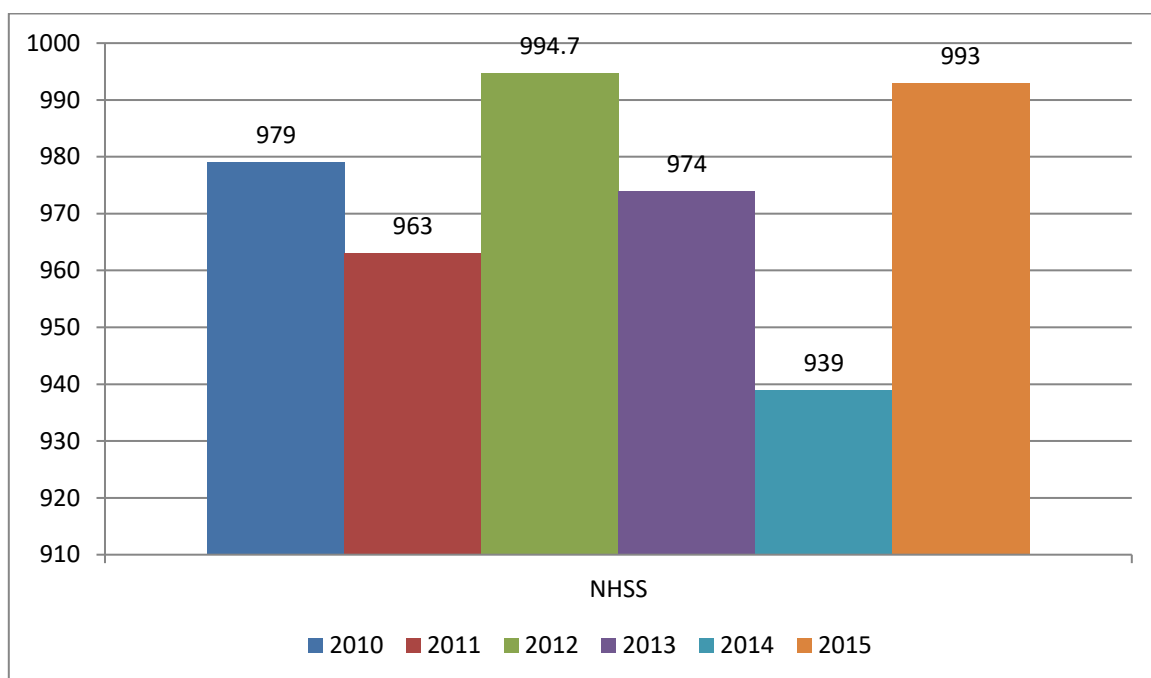
Eligibility for other schemes, such as the medical card scheme or the drugs payment scheme, is unaffected by participation in the NHSS or residence in a nursing home. Funding for the NHSS is annually determined by the *Oireachtas* and the HSE may not exceed their budgetary

may have been entitled to a level of subvention, based on their means, but otherwise were obliged to meet the full cost of their nursing home care.

⁵⁹ <https://hse.ie/eng/services/list/4/olderpeople/nhss/costs.html>

allocation. Figure 3-12 shows that the Irish State has increased funding to the NHSS by 1.5% since 2010: it is likely additional funding will be needed to be allocated to this scheme given future demand for NH beds. The BDO (2014) estimate that the annual cost of funding this scheme is expected to exceed €1.2bn by 2021, and €2bn by 2041. Thus, with limited public resources, achieving greater efficiencies will be paramount in order to meet future demand for NH care services:

Figure 3-12: Funding of the NHSS Scheme 2010 – 2015



Source: Department of Health and Children (2015), p.20

Public Expenditure in EU Countries

Table 3-6 compares public expenditure on LTC as a percentage of GDP and by type of care for selected EU countries in 2010. Ireland spends 1.1% of its GDP on LTC provision: only 17% of which is allocated to community supports like home-care packages to support the elderly person to reside in their own home, with the balance spent on residential facilities. Sweden, on the other hand, invests more of its GDP on LTC provision than any other EU country; with roughly half of this funding allocated to community services for the elderly. It is also important to note that Sweden had 7.5% of its population aged 65+ in residential LTC institutions in

2009, compared to 4.5% in Ireland and 3.4% in Germany (BDO, 2014: 3). Given the projected increases in its elderly population, it is likely that Ireland will soon be spending appreciably more on LTC provision. In fact, the BDO estimate that NH expenditure will increase by 67% between 2021-2041. Clearly then, in light of budgetary constraints and limited public resources, achieving much improved efficiencies will be critical to ensure future NH services can be met for the growing elderly population.

Table 3-6: Comparative Public Expenditure on LTC as a % of GDP and Type of Care (2010)

Country	Public Expenditure on LTC as % of GDP	Community Supports (%)	NHs (%)
Sweden	3.8	52	48
Netherlands	3.8	48	52
Portugal	0.3	76	24
Czech Republic	0.8	74	26
Ireland	1.1	17	83
Lithuania	1.2	59	41
Germany	1.4	61	39
EU – 27	1.8	58	42

Data source: DG ECFIN (2012)

Moreover, the correlation between public expenditure on health-care (HC) and on LTC is unclear. As shown in Table 3-7, some relatively low-spenders on LTC are big-spenders on HC. For instance, Portugal’s public expenditure on HC as a percentage of GDP is 24 times greater than its spend on LTC. Similarly, the Czech Republic public expenditure on HC as a percentage of GDP is nine times greater than its spend on LTC. On the other hand, while Sweden spends twice the amount of public expenditure on LTC relative to the European average, it only allocates 7.48% of public expenditure to HC.

Table 3-7: Public Expenditure on LTC and HC

Country	Public Expenditure on LTC as % of GDP	Public Expenditure on HC as % of GDP
Sweden	3.8	7.48
Netherlands	3.8	6.99
Portugal	0.3	7.15
Czech Republic	0.8	6.89
Ireland	1.1	7.27
Lithuania	1.2	4.93
Germany	1.4	8.00

Data source: DG ECFIN (2012)

The Price of Care in Irish Private and Public NHs

At the end of 2014, the average weekly cost of care in a public facility was €1,390 compared to €893 in a private or voluntary facility (DOHC, 2015a). Whilst public NHs are ostensibly more expensive than private units, the headline price differential in the average cost of care between public and private facilities of approximately 58% may be attributable to public greater requirements for public units to comply with regulation regarding staffing levels, staff qualifications, pay agreements, and statutory time-off and holiday allocations. In any event, the actual price of care has no direct impact on the resident, since the resident's contribution is determined according to their means and is independent of their choice of nursing home. The weekly cost of long-term residential care in each approved nursing home is published on the HSE website. Table 3-8 highlights that the average weekly cost of care in public homes is 49% more expensive than private and voluntary NHs. Additionally, the median of public homes is 52% higher than private and voluntary homes and equates to €1358.5. In reality, this merely indicates that 50% of public homes charge more than €1358.5 and 50% charge less. Likewise, there is significant variation in the cost of care with a minimum figure of €700 in private and voluntary homes compared to €140 in public facilities. Similarly, the maximum amount charged for care in public facilities is 308% more than the maximum amount charged in private and voluntary care homes.

Table 3-8: Weekly Cost of Care in a Shared NH Room (in Euros)

NHs	Observations	Mean	Median	Std. Dev.	Min	Max
Private/Voluntary	434	938.97	895	135.60	700	1325
Public	112	1395.41	1358.5	406.87	140	4082

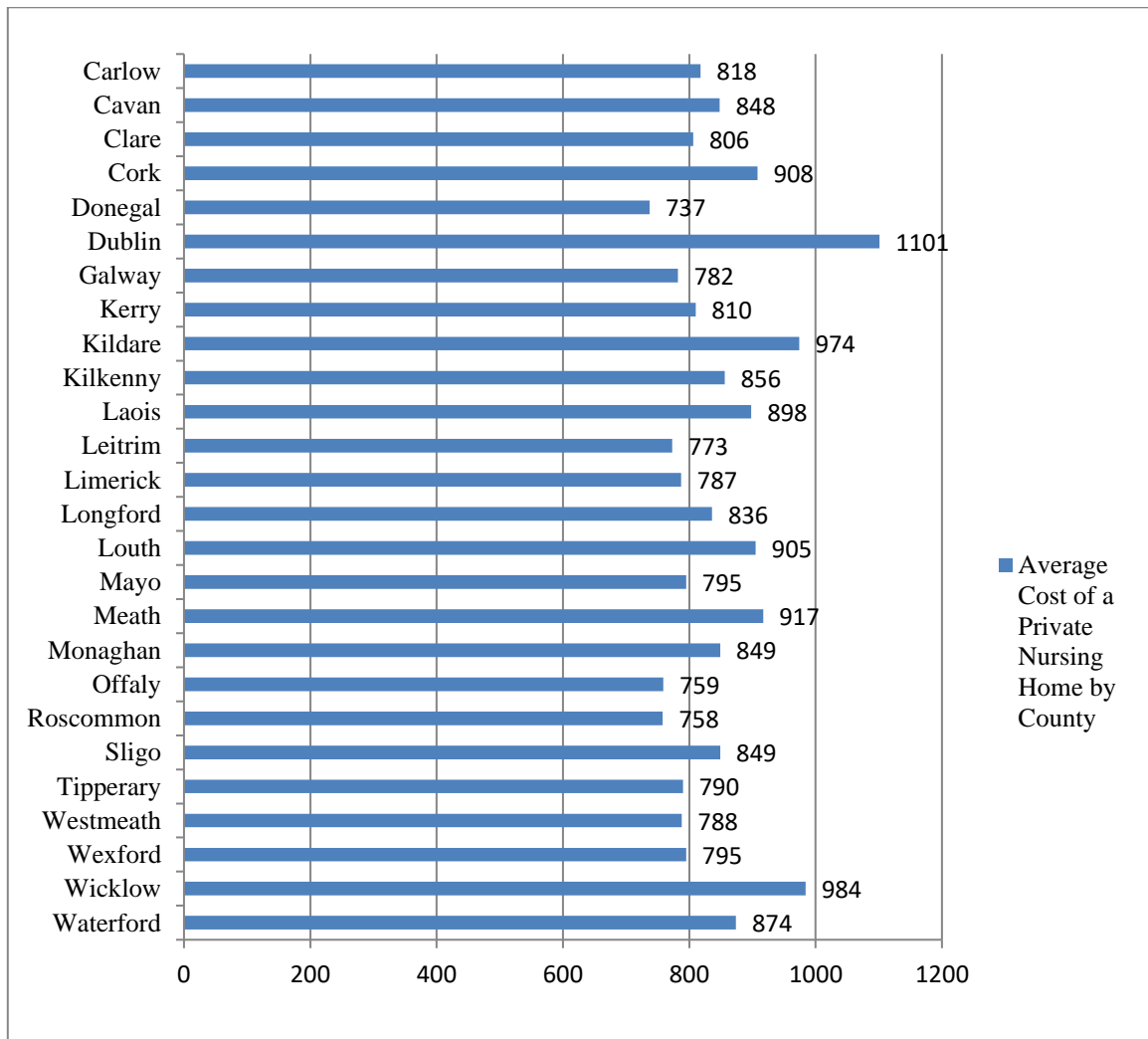
Source: <http://hse.ie/eng/services/list/4/olderpeople/nhss/costs.html>

Whilst the cost of care in public NHs is apparently more expensive than that of private and voluntary NHs, this can be misleading. The higher cost of care in public NHs may align with superior quality of public care provision. DiGiorgio *et al.* (2014) and Garavaglia *et al.* (2011) emphasized that previous efficiency studies “marginally address quality of care” and stress the complexities inherent in measuring quality in LTC. In fact, several taxonomies have been proposed to classify the measures of quality as discussed in Chapter Two. While all professions and organizations experience some turnover, private and voluntary NHs have higher turnover rates of medical and non-medical staff relative to public facilities. Cullen (2016) noted that profit-orientated homes often lose staff to better-paid HSE jobs. This arguably compromises private homes ability to care for patients in terms of quality of care available, loss of continuity of care, loss of skills, and local knowledge of the resident. This study found that 54% of nurses had left private and voluntary homes for work in public sector NHs; perhaps resulting in deficient service quality as a result of overworked staff. The cost of care in public NHs may also be more expensive relative to private care facilities due to the case-mix of the resident. The case-mix describes the characteristics of a patient which determines the intensity of care. Having greater volumes of high and maximum dependency clients necessitates more staff due to the more acute care needs of the resident which in turn adds to the cost of care.

Figure 3-13 presents the 2014 average weekly costs of care in private and voluntary NHs by county. Donegal was found to be the least expensive area; with a care cost is €737 per week. This is not surprising since supply exceeds demand in this region. By contrast, the most expensive region for care is Dublin; with a care cost of €1101 per week. However, Dublin is a

unique case which must contend with the highest premises costs in the country. Also, due to greater competition for medical and non-medical personnel relative to other regions in Ireland, labour and operating costs are also significantly higher in the Irish capital.

Figure 3-13: Average Weekly Price of Private NH Care by County - End Of December 2014



Source: Review of the NH Support Scheme (2015a, p.47)

The BDO (2014) reported that the cost of care consists of labour costs, building costs, capital costs, and operating costs. The following discusses each of these categories.

Labour Costs

Labour costs are the single largest cost component in the operation of a nursing home. The data collected by Horwath Bastow Charleton (HBC) in their Annual Private NH Survey 2009/2010, found that labour costs accounted for 61.5% of turnover in private and voluntary NHs in

Ireland. The higher labour costs of public homes are due to the combination of different skill-mixes, pay arrangements, and other benefits. Public NHs generally employ higher nurse staffing ratios than private and voluntary facilities. Moreover, public long-stay residential centres are obliged to apply public service rates of pay and conditions of employment for all staff. These include statutory paid sick-leave and maternity leave, which may or may apply to private and voluntary environments.

McEnery (2007) noted that labour costs of INHs are higher in Dublin compared to areas outside of Dublin due to greater competition for personnel resulting in higher wages and costs for the care home. McEnery (2007) maintained the labour costs associated with the different staffing resources should be provided to an efficient 50 bed nursing home in line with standards of international best practice⁶⁰. Table 3-9 demonstrates that administration and reception staff earn 31% more in Dublin than elsewhere in the ROI. Similarly, maintenance earn 22.5% more in Dublin. However, nurses only earn 4% more in Dublin compared to peers throughout the rest of Ireland.

Table 3-9: Labour Costs in NHs

Staff Level	Average Rate Per Hour – Greater Dublin Area (€)	Average Rate Per Hour – Outside Dublin Area (€)
Health-care Attendant	258.67	241.57
Nurses	186.12	178.78
Chefs & Cooks	20.57	19.45
Cleaning & Domestic	50.91	45.25
Administration & Reception	27.58	21.11
Maintenance	8.43	6.88
Management	37.61	30.55
Total	589.89	543.59

Source: McEnery (2007, p.10)

⁶⁰ The rates of remuneration for this staff are the rates applicable in the market at the current time, based on the detailed review of the audited accounts of 16 nursing homes and cross referenced to data from the private nursing home survey 2006.

INH labour costs are higher than those in their international counterparts. For example, Laing and Buisson (2011) noted that total staff costs for a nursing home typically averaged 56% of revenue in the UK. This lower cost, relative to the comparable figure in Ireland, may be accounted for by the fact that on average care and NHs in the UK are larger (average of 50 beds) than their Irish counterpart, and therefore provide greater opportunity to realize and achieve economy of scale benefits.

Building Costs

Building and maintenance costs are often a function of the age of the nursing home. According to BDO (2014) building and maintenance costs account for approximately 5-6% of a NH total income, but vary depending on the age of the property. As Ireland's private NH bed-stock is relatively new compared to public NHs, this effectively maintains lower costs in these facilities. Conversely, many public homes are more than 100 years of age and equipped with large multiple-bed rooms. As such, significant investment and upgrading is required to meet existing standards and regulations and enable premium quality care services to be delivered to the elderly generation.

McEnery (2007) stressed the need to properly factor the cost of renewals as some equipment, such as a catering kitchen, has an estimated lifespan of 10 years. He went on to estimate comparative replacements costs for a number of assets in the Dublin and non-Dublin region. Table 3-10 shows the total estimated replacement cost of the assets in a nursing home located outside of Dublin. As expected, the total cost of €4,500,000⁶¹ was significantly less than the replacements costs of a Dublin home which came in at €4,865,000.

⁶¹ This figure is based on the detailed review of the audited accounts of 16 nursing homes and cross referenced to data from the private NH survey 2006.

Table 3-10: Replacement Costs in a Nursing Home

Asset Type	Estimated cost 000s€
Buildings	3,650
Plant & Machinery	400
Furniture and Fittings	400
Technology Equipment	50
Total	4,500

Source: McEnery (2007, p.11)

Capital Costs

NH capital costs in the UK account for between 25-31% of total revenue. These costs will vary in line with building and equipment costs, and with land prices which can be the most difficult to measure. McEnery (2007) attempted to estimate the capital costs of a nursing home located in the Dublin area and outside of the greater Dublin area⁶². Table 3-11 shows the gross investment in a nursing home is 25% more in the greater Dublin area than beyond of the greater Dublin area. This is hardly surprising given that land is a finite resource and is 200% more expensive in the greater Dublin area than elsewhere in the ROI. Furthermore, McEnery (2007) recommended a nursing home operator/owner to seek a 10% return on capital employed: this translates into a weekly cost per resident of €293 to cover financing cost and profit to the operator. For provincial locations, the corresponding amount is €235 per resident per week:

Table 3-11: Gross Investment in a Nursing Home

Description	Greater Dublin Area	Outside Greater Dublin
	€'000,000	€'000,000
Development and Fit-Out	4.865	4.5
Land	2.0	1.0
Gross Investment	6.865	5.5

Source: McEnery (2007, p.13)

⁶² Rates are based on a detailed review of the audited accounts of 16 nursing homes and cross referenced to data from the private nursing home survey 2006.

Operating Costs

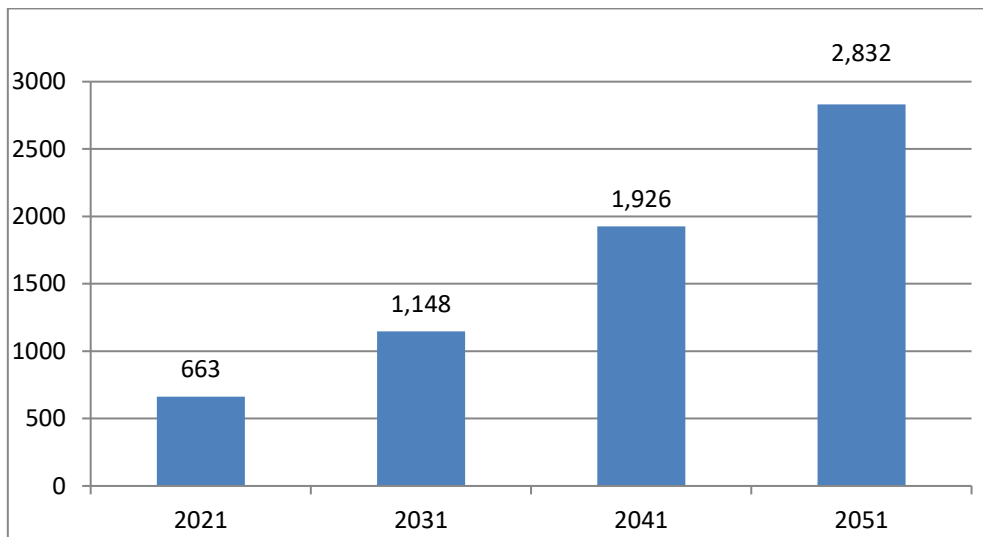
This category of expense covers current overheads and expenses associated with the operation of a nursing home other than staffing, building, and financing costs. McEnery (2007) originally suggested a weekly charge of €108 per week to cover overheads and operating costs⁶³. However, this figure is likely to increase due to the new standards imposed by introduction of the HIQA standards in July 2009. The annual license fee of €190.00 per bed also imposes a significant burden on the operator of a private or voluntary home. Moreover, Culliton (2010) calculated that the figure spent on implementing the HIQA standards per home has averaged €77,872 to date, or €35.1 million across the 450 voluntary and private NHs; resulting in significantly inflated operation costs for the care facility. How much the State has invested in upgrading their public facilities to comply with HIQA standards is less clear. Nonetheless, it is evident that significant funding would be required to bring these care facilities up to standard.

Projected Future Costs

An ageing population generates greater general service utilization and rising health-care costs. With residential care being largely financed by public monies, the dramatic projected increase in the demand for long-stay beds means that considerably more funding will be required for the LTC sector (Wren *et al.*, 2017). Figure 3-14, derived from the Mercer Report (2002), purports that the estimated future costs of residential care will increase by 327% between 2021 and 2051. Given the backdrop of Ireland's recent economic crisis, the projected surge in the elderly population most in need of LTC and attendant ramping-up of funding demands on the exchequer within the context of stricter budgetary discipline at national level within the EU, it is imperative to identify the determining factors that affect the TEs of INHs to ensure optimal use of limited public resources and to meet future demands.

⁶³ Based upon 16 audited accounts of nursing homes in 2006.

Figure 3-14: Estimated Future Cost of Resident Care - € Million



Source: Mercer Report (2002, p.22)

3.3.6 Future NH Capacity

Long-term NH care in Ireland is provided through a combination of public and private provision, with the public sector providing about 20% of beds and the private sector delivering the remaining bed capacity. At the end of 2017, the DOHC advised that there were approximately 30,674 long-stay beds available across public and private NHs. Going forward, it is clear additional capacity is necessary as the population ages. However, public and private facilities face arduous challenges in providing this additional bed-stock.

Public Nursing Home Capacity

Although there are currently 6,551 long-term residential care beds available in the public system, an extraordinary number of facilities do not meet HIQA standards. While some progress has been made in maintaining and upgrading existing public bed-stock so that it is HIQA compliant, considerable work is still required which will entail substantial capital costs. Cullen (2013) observed that public NHs were at a crossroads and unsure of direction due to the credit squeeze and policy uncertainties.

In addition to the pressing urgency to upgrade and maintain existing public capacity, there is also a need for additional public sector capacity if Government wishes the public sector to

maintain its current presence within the NH market. There may be important policy reasons for maintaining a strategic presence, such as the need to ensure that the State is not wholly dependent on private operators. A policy which inscribes the continuation of circa 20% of all nursing home capacity in the public sector will necessitate a commensurate increase in its supply of long-term beds. Table 3-5 indicates that by 2026, 38,470 beds will be needed for the elderly population. In light of this, public NHs must increase their capacity by approximately 1,143 with an associated capital cost for the provision of these beds.

Private NH Capacity

Private and voluntary NHs currently provide 80% of long-term beds in Ireland. However, given projected demographic trends, it is evident that the supply gap in the sector and NH places will need to be bridged over the next 20 years to meet the demands of an aging population (DOHC, 2015b). An analysis of planning permissions for NH developments reveals that between January and November 2015, a total of 27 planning permissions were granted for NHs in Ireland. More than half of the permissions were granted for extensions and conversions to existing facilities, while permissions granted for new developments accounted for 37% of the total costs (DTZ Sherry Fitzgerald, 2015).

Whilst these developments are clearly welcome, considerably more will need to be done to meet the increasing numbers of elderly people that will require NH services. Meantime, the existing price-setting model of the Fair Deal is regarded as the single greatest barrier to entry to private investors due to low rates, and the non-alignment of payments to the dependency levels of residents. Furthermore, NHI has suggested that both private and voluntary NHs should be given guarantees of future NHSS funding and advanced price agreements, since these incentives would stimulate supply and reduce the uncertainty of the marketplace.

3.4 Conclusions

This chapter provided a detailed overview of the NH sector in Ireland. While traditionally, public NHs provided the majority of LTC beds, since the introduction of capital allowances in 1998, private suppliers have become the dominant provider. NHs provide both LTC and limited term beds. This study focuses on the former only. At present public, private, and voluntary, care facilities provide 30,674 LTC beds to the aging population. However, the numbers of the Irish elderly are increasing rapidly and projected to accelerate dramatically in the future. This means that more LTC beds will be needed in the NH environment, resulting in increasing costs for the Irish State. Nevertheless, where this excess capacity will be drawn from remains unclear, as public NHs currently require significant capital investments to upgrade facilities in compliance with HIQA standards. Moreover, private NHs are at a crossroads due to the concerns regarding the future funding of the Fair Deal model in addition to future price agreements.

Given these uncertainties, it is imperative to determine whether private NHs are more efficient than public homes since empirical data might highlight which organizational structure is optimizing their limited resources. This is crucial given that more long-term beds will be required in the future given Ireland's population is aging. Chapter Four therefore presents the wide array of methods ranging from non-parametric to parametric techniques employed in this study to estimate the TEs of public and private care homes and to identify the TE determinants.

Chapter Four: Methodology

4.1 Introduction

This chapter presents the strategies used to estimate TE and identify the efficiency determinants of INHs. As such, it provides the background and framework for the empirical work delineated in Chapters Five and Six. The chapter will firstly discuss the methodology and the empirical models used to estimate both efficiency and potential efficiency determining variables. In addition, this chapter outlines the primary data for NHs used for this research and elucidates the dataset collation process. Building on these, the chapter will then delineate the variables used to define the inputs and outputs of the efficiency model, and the variables used to define the potential efficiency determinants.

To reiterate; the present study seeks to estimate the TE for all NHs and subsamples such as public and private homes, private chain and non-chain facilities, and urban and rural homes. In light of this, the broad spectrum of methods is also applied; ranging from non-parametric conventional or traditional DEA to a parametric SFA input-distance function (Figure 4-1). The primary rationale for the application of conventional DEA is its simplicity and flexibility, as no functional form restrictions for production technology are required. Moreover, as noted in Chapter Two, DEA is the dominant method to measure TE throughout the NH literature, and incorporates measuring efficiency by using multiple outputs and multiple inputs.⁶⁴ Furthermore, the distinction between CRS and VRS DEA models is possible which facilitates the estimation of scale efficiencies.

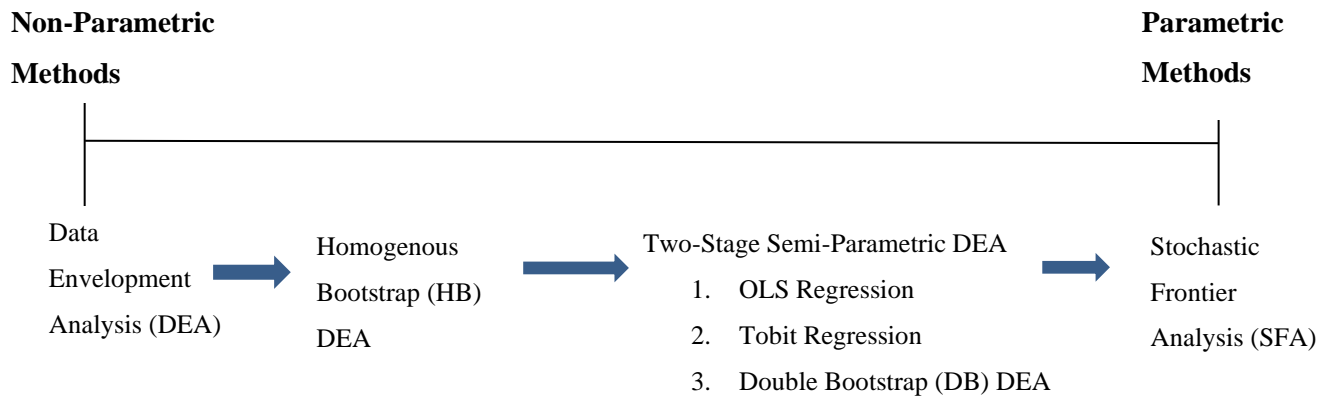
The main criticism of conventional DEA is the implicit assumption that the distance between the subject firm and the optimal isoquant or frontier represented by efficient firms, reflects

⁶⁴ In the SFA framework, an output or an input distance functions could be applied to allow for multiple outputs and inputs, but the results are often highly unstable and can cause severe multicollinearity issues, as discussed further in chapters 5 and 6 of the thesis.

inefficiency. In fact, the distance of an observation from the efficient boundary actually reflects both inefficiency and noise. This is because the observed input-output data may be liable to measurement error, or noise in the data due to omitted input or output variables. Bootstrapping techniques provide an attractive alternative to conventional DEA in order to illustrate the sensitivity of DEA efficiency estimates to variations in sample composition. The first bootstrapping approach, the homogenous bootstrap (HB) method developed by Simar and Wilson (1998; 2000), corrects for any bias in the conventional DEA TE scores using simple random sampling with replacement and obtains the confidence intervals (CIs) for them. Thus, the HB DEA approximates the properties of the sampling distribution of an estimator. In the NHs efficiency literature, only Garavaglia *et al.* (2011) have previously implemented this bootstrapping procedure. The second bootstrapping approach is the two-stage double bootstrap (DB) DEA also proposed by Simar and Wilson (2007; 2011). This two-stage semi-parametric approach not only produces robust ‘pseudo estimation’ of the parameters of the efficiency determinants, but also re-estimates the TE scores to adjust for the values of these efficiency determining variables to give unbiased efficiency estimates.

Since such bootstrapping techniques estimate bias-corrected TEs by dealing with sample variability, they provide an indication of the degree to which the efficiency estimates are likely to vary when a different sample is randomly selected from the population. However, they do not seek to account for random noise arising from measurement or specification errors. In other words, in both conventional and bootstrapping DEA methods, all variations in firm performance are attributed to inefficiencies only. In view of the inherent drawbacks of these approaches, the final method applied in this research to estimate TE in the INHs sector is the stochastic frontier analysis (SFA). This parametric technique assumes the distance from the frontier is composed of two parts: one representing statistical random noise; and the other inefficiency. This method requires the mathematical functional form of production technology as will be explored later.

Figure 4-1: Methodology of Study



In the next step, this study evaluates the determinants of TE. Thus, after the efficiency scores for INHs are obtained, the two-stage semi-parametric and parametric techniques are employed. Figure 4-1 demonstrates that this study commences with two-stage ordinary least squares (OLS), whereby in the first step the TE scores are obtained using DEA and then in the second stage, these scores are regressed on a vector of efficiency determinants using the OLS multivariate regression analysis. While OLS produces very useful model diagnostics, a two-stage Tobit regression is preferable as the TE scores are censored between 0 and 1. Both OLS and Tobit regressions are applied to both the conventional and HB DEA TE scores. Moreover, as Simar and Wilson (2007; 2011) pointed out, the efficiency score is a point estimate without a probability distribution around it, as is required by the Tobit method or any other parametric regression technique. Therefore, using these DEA point estimates in a second stage analysis may generate biased and inconsistent estimates of the parameters of the explanatory variables. In order to overcome this limitation, this research applies the two-stage DB DEA approach which both enables the estimation TE determinants and ‘adjusts’ the TE scores to take account of these efficiency determining variables.

While these two-stage semi-parametric methods identify the environmental factors of TE, it is acknowledged that these DEA methods overlook the potential of data adulteration by noise:

semi-parametric techniques cannot account for it. In order to overcome this shortcoming, the present research employs a parametric SFA which controls not only for statistical noise and inefficiency, but also for the determinants which can be directly estimated as factors affecting the variance of inefficiency. Table 4-1 provides a summary of the key similarities and differences of the estimation methods applied in this research.

Table 4-1: Comparison of Estimation Methods

	Accounts for biasness	Accounts for noise	Assumption about functional form	Allows for multiple outputs	Vulnerable to small sample Size
Non-Parametric (incorporating bootstrapping procedures)	✓	no	no	✓	no
Parametric	✓	✓	✓	not easily	✓

In order to estimate the TEs of INHs and identify their determinants, the dataset was collated via face-to-face interviews with NH managers in the Republic of Ireland throughout 2008-2009. In estimating input-oriented TEs, this research is concerned with how far the input vector can be proportionally reduced while maintaining the output vector fixed. Output is measured as total patient days, while inputs are measured as medical staff, non-medical staff, and the number of beds in each NH unit. This study also incorporates the high-maximum dependency rate of NHs residents as a proxy variable for case-mix, which is directly included in the linear programming of DEA model and in the SFA framework. Furthermore, not only is the case-mix included in the production model as a discretionary input, but also as an efficiency determining variable. To the author's knowledge this is the first study since Garavaglia *et al.* (2011) to examine the case-mix using this holistic approach. Moreover, the present study employs an extensive set of additional explanatory variables to investigate TE in the Irish long-stay facilities.

Section 4.2 of the chapter presents the non-parametric DEA employed in this research to estimate TE and elucidates the HB DEA. Section 4.3 presents an outline of the two-stage

semi-parametric methods applied to identify the potential determinants of TE. Given that both conventional and semi-parametric DEA methods do not account for noise, Section 4.4 presents SFA input distance function employed in this thesis. Section 4.5 discusses the data sample used and the processes involved in acquiring the primary dataset of this research. Section 4.6 presents the output and input variables of the efficiency model along with the efficiency determinants. The summary statistics of all the variables is also presented. Section 4.7 concludes the chapter with summative remarks.

4.2 Data Envelopment Analysis

As Figure 4-1 demonstrates that the non-parametric DEA is the initial estimation strategy employed in this study to estimate the TE's of INHs and their subsamples. There are three reasons for choosing the DEA method as opposed to SFA which is the pre-eminent parametric approach. Firstly, no specification of a functional form is required for the DEA method in contrast to SFA technique wherein the choice of functional form, such as a production function for an output-oriented TE or an input distance function for an input-oriented TE, is essential. The estimation of an input distance function may pose serious practical difficulties, such as multicollinearity between inputs and output variables, and issues of convergence, particularly with small data sample sets. In light of this, the estimation of TE of all NHs and relevant subsamples commences with the employment of the original DEA, called here also 'conventional' DEA model.

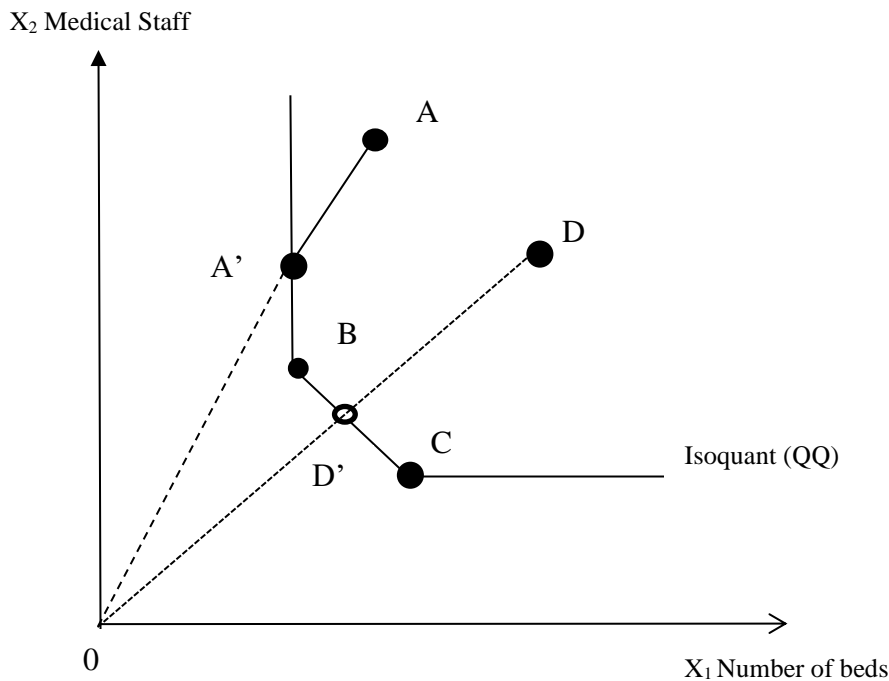
The conventional DEA method firstly assumes constant returns to scale (CRS); inferring that all NHs are operating at their most technically optimal and productive size. In contrast, the variable returns to scale (VRS) DEA model is applied to estimate a 'pure' TE, which is devoid of scale efficiency (SE). Employing both CRS and VRS DEA allows estimations of the SEs of the NH facilities. This is important as some facilities may be technically efficient but not scale efficient; meaning that these facilities must adjust their scale of operation to reach their most productive scale.

4.2.1 The CRS DEA Model

This research applies a DEA approach which seeks to estimate the input-oriented TEs of the NHs, which can also be referred to as the decision-making units (DMUs). Firstly, this study applies the CRS DEA model which was introduced by Charnes et al. (1978) and who also proposed an input orientation to measuring TE which assumes that all LTC homes are scale efficient.

As the production frontier of the fully efficient NHs is not known, the optimal frontier, represented in this case by the isoquant, must be estimated using to the sample data using the DEA linear programming technique. The DEA constructs a non-parametric piecewise-linear convex frontier (Jacob *et al.* 2006) by identifying NH units which use the fewest inputs in producing a given level of output. Figure 4-2 represents the efficient NHs by points A' , B , D' and C , which form the best practice 'isoquant or frontier' (QQ) by connecting these points with piecewise linear segments. A nursing home is considered technically efficient, with regard to its inputs usage, if it lies on the frontier (isoquant). The efficiency of every other nursing home is measured relative to the efficient isoquant (QQ). For example, the efficiency estimate of a hypothetical nursing home D is calculated as the ratio of minimum input use (OD') to actual input use (OD), or alternatively it is expressed as: $1 - D'D/OD$. Therefore, this nursing home is considered to be technically inefficient since it lies above the frontier implying excessive input usage of both labour (medical staff) and capital (the number of beds) relative to organisation D' which would be a target for a nursing home D . Therefore, the input-oriented TE score of nursing home D is less than 1. This indicates that nursing home D must reduce its inputs (X_1 and X_2), given its current levels of patient-days, to the optimal level of the target which is a firm D' , in order to become technically efficient. In short, all TE scores range from 0 to 1. A TE score of 1 implies that the nursing home is on the frontier and it does not need to reduce the quantity of its inputs for a given level of output. A TE score less than 1 implies that the nursing home is technically inefficient and must reduce its inputs to become efficient.

Figure 4-2: An Input-Oriented DEA Model



Input-oriented (IO) CRS DEA Model in Envelopment Form

An IO DEA approach is specified in this study on the assumption that NHs have more control over their use of inputs than their level of output which is defined as total patient days. Following Charnes *et al.* (1978), IO TE is estimated under CRS DEA model using the linear programming method in envelopment form. The present research assumes that there are data on N inputs and M outputs for each of the I nursing homes which are the decision-making units (DMU's). For the i -th nursing home these are represented by the column vectors of inputs, x_i , and outputs, q_i , respectively. The $N \times I$ input matrix, X , and the $M \times I$ output matrix, Q , represent the data for all I NHs. Thus, the linear programming model in the envelopment form to obtain the TE score of nursing home i for a given time period is presented as follows:

Eq. 4.1

$$\begin{aligned}
 & \text{Min } \theta_i (\theta, \lambda) && \text{subject to:} \\
 & - q_i + Q\lambda \geq 0 && \text{where } i = 1, 2 \dots n \text{ nursing homes} \\
 & \theta_i x_i - X\lambda \geq 0 \\
 & \lambda \geq 0 \\
 & TE_i = \theta_i
 \end{aligned}$$

where θ_i is the TE score for each i 'th nursing home and λ is an $I \times I$ vector of constants. This model aims to keep the output level constant while reducing the input level. If θ_i is equal to 1, then the current level of inputs cannot be reduced proportionately, indicating that the nursing home i is producing on the DEA frontier and that the nursing home is technically efficient. However, if θ_i is less than 1, then the nursing home i is inefficient, meaning that it can proportionately reduce its level of inputs to achieve the same level of output.

4.2.2 The VRS DEA Model

The CRS DEA model is common to the NH literature. For instance, Borge and Haraldsvik (2009); Garavaglia *et al.* (2011); Chang and Cheng (2013) estimated efficiencies under the CRS assumption, implying that there is a proportional relationship between the inputs and outputs, and that NHs are scale-efficient. However, in practice, NHs may operate at sub-optimal scales. As such, the application of a CRS DEA model might yield TE estimates which are confounded by scale efficiency (SE) effects. In light of this, Färe *et al.* (1983) and Banker *et al.* (1984) proposed adjusting the DEA model for variable returns to scale (VRS) to permit the calculation of TEs devoid of these SE effects.

Input-oriented VRS DEA Model in Envelopment Form

To estimate an IO TE which is devoid of SE, this study applies the VRS DEA model. To account for VRS, the CRS DEA linear programming problem presented in Eq. 4.1 is extended by adding the convexity constraint $I1'\lambda = 1$ as proposed by Banker *et al.* (1984). Using the same notations as before, the VRS DEA in envelopment form for NH unit i becomes as follows:

$$\begin{aligned}
 \text{Eq. 4.2} \quad & \text{Min } \theta_i (\theta, \lambda) && \text{subject to:} \\
 & - q_i + Q\lambda \geq 0 && \text{where } i = 1, 2, \dots, n \text{ nursing homes} \\
 & \theta_i x_i - X\lambda \geq 0 \\
 & I1'\lambda = 1 \\
 & \lambda \geq 0 \\
 & TE_i = \theta_i
 \end{aligned}$$

where all variables and notations have the same meaning as in *Eq. 4.1*. The additional constraint ($I1'\lambda = 1$) ensures that an inefficient nursing home is only ‘benchmarked’ against units of a similar size, whereas in CRS DEA, a nursing home may be benchmarked against firms which are substantially larger or smaller. In fact, the VRS specification has been widely applied in the estimation of efficiency in relevant literature since the 1990s, including that of Kooreman (1994), Chattopadhyay and Heffley (1994), Chattopadhyay and Ray (1996), Bjorkgren *et al.* (2001), Wang and Chou (2005), and DeLellis and Ozcan (2013).

Since the present research estimates IO TE using both CRS and VRS DEA models, it is possible to estimate the SEs of INHs. This is vital as a number of care facilities may not be at their most productive scale size (MPSS), and will need to adjust their scale of operation accordingly.

4.2.3 Scale Efficiency Measurement in the DEA

By employing both CRS and VRS DEA models to measure TE, scale efficiency (SE) may also be obtained. While the CRS is predicated on the assumption that all NHs are operating at an optimal scale, the VRS DEA specification facilitates the calculation of TE devoid of SE effects. To calculate the SEs, the TE scores under VRS and CRS are compared. Should there be a difference between TE scores under VRS and CRS, it may be said that nursing home *i* is experiencing some form of scale inefficiency. The three concepts are linked in the following way:

$$TE_{it}^{CRS} = TE_{it}^{VRS} \times \text{Scale Efficiency} \quad \text{Eq. 4.3}$$

Thus, to obtain the SE of nursing home *i*, the CRS TE score of nursing home *i*, is divided by the VRS TE score of nursing home *i* as follows:

$$SE_i = \frac{TE_i^{CRS}}{TE_i^{VRS}} \quad \text{Eq. 4.4}$$

The SE result is bound between 0 and 1, with an SE score of 1 inferring that the home is scale efficient, and scale inefficient if the index is less than 1. The measurement of SE is somewhat limited in the efficiency literature in the NH sector; and while Chattopadhyay and Ray (1996)

found that for-profit homes are more scale efficient than non-profit homes, Bjorkgren *et al.* (2001) recommended that Finnish NHs adjust their size to ensure scale efficiency is reached. There are currently no empirical studies to indicate whether Irish public, private or voluntary NHs are operating at their most productive scale size: a gap this study seeks to address.

The drawback of the SE calculation is that it does not indicate whether a nursing home is operating in the area of IRS, which would imply the scale of operation of a nursing unit is too small, or whether DRS exist, which would imply it is too large. In order to properly identify the nature of the scale inefficiencies besides VRS DEA then, a further VRS DEA model with *non-increasing returns to scale* (NIRS) is applied.

The NIRS DEA in Envelopment Form

If the nursing home is scale inefficient, this study can also obtain the nature of returns to scale using the non-increasing returns to scale (NIRS) DEA model (see Figure 2-2). To obtain the NIRS TE scores, the constraint proposed by Färe *et al.* (1983, 1985) can be added, by substituting the $I1'\lambda = 1$ in the VRS DEA model (Eq. 4.2) with $I1'\lambda \leq 1$, as follows:

$$\begin{array}{ll}
 \text{Eq. 4.5} & \text{Min } \theta_i (\theta, \lambda) \quad \text{subject to:} \\
 & - q_i + Q\lambda \geq 0 \quad \text{where } i = 1, 2 \dots n \text{ nursing homes} \\
 & \theta_i x_i - X\lambda \geq 0 \\
 & I1'\lambda \leq 1 \\
 & \lambda \geq 0 \\
 & TE_i = \theta_i
 \end{array}$$

The NIRS DEA TE scores (TE_i^{NIRS} for nursing home *i*) are compared with the TE estimates from both the VRS model and CRS models. When the NIRS and CRS measures are equal to one another but differ from the VRS measure, IRS holds at the corresponding efficient projection on the VRS frontier. On the other hand, if the VRS and NIRS measures are equal but differ from the CRS measure, diminishing returns to scale ($TE_i^{VRS} = TE_i^{NIRS}$) holds at the relevant point on the VRS frontier. If the VRS and CRS are equal than the firm is scale efficient

but might be still technically inefficient. The NIRS, CRS and VRS TE measures will coincide and be all equal to one at an MPSS (most productive scale size) as illustrated in Figure 2-2. This infers that the nursing home is both technically and scale efficient.

4.2.4 Homogenous Bootstrap DEA Model

Next, this research employs the homogenous bootstrap (HB) approach proposed by Simar and Wilson (1998; 2000) to validate the sampling distribution of conventional TE scores obtained through a non-parametric DEA method. As one of the first bootstrapping techniques as outlined in Figure 4-1, it corrects for any bias in the DEA by deriving ‘pseudo-estimates’ from random sampling procedure. The application of the homogenous bootstrapping method to evaluate efficiency in LTC provision is rather sparse with the exception of Garavaglia *et al.* (2011). While the conventional DEA method only gives a point estimate of TE scores, bootstrapping enables a confidence interval to be created around the TE score.

As previously noted, bootstrapping involves randomly selecting thousands of ‘pseudo samples’ from the observed set of sample data. ‘Pseudo estimates’ are then estimated from each of these samples which ultimately form an empirical distribution for the TE scores which is used to approximate the true underlying sampling distribution of the estimator. In this way, an empirical sampling distribution is constructed for the DEA TEs of the NH units. The bias in the DEA efficiencies can then be estimated and 95% confidence intervals can be built using this empirical distribution. This study repeatedly samples from the obtained CRS and VRS DEA efficiency scores obtained in linear programming given by Eq. 4.1 and Eq. 4.2. Thus, the research firstly obtains the conventional CRS and VRS DEA TE scores for each nursing home $i=1,2,3,\dots,n$ as follows:

$$\hat{\theta}_1, \hat{\theta}_2, \hat{\theta}_3, \dots, \hat{\theta}_n \quad \text{Eq. 4.6}$$

Next, the bias corrected estimates of TE of nursing home i ($\tilde{\theta}_i$) are obtained:

$$\tilde{\theta}_i = \hat{\theta}_i - \widehat{bias}_i \quad \text{Eq. 4.7}$$

Further derivations are detailed in Simar and Wilson (1998; 2000) and the estimations are performed in R using the FEAR software package of Paul Wilson (2008). According to Coelli *et al.* (2005) this method is relatively robust with regard to the chosen bandwidth of the confidence intervals.

While the HB DEA technique is a useful way of illustrating the sensitivity of the TE estimates to variations in sample composition, and thus tests the robustness of the conventional TE scores by deriving the bias-corrected TE scores and confidence intervals (CIs), it does not account for noise or the determinants of TE. To overcome this drawback, the second bootstrap technique employed in this thesis is the two-stage DB DEA method as one of the two-stage semiparametric techniques which details are presented in the next section. This method will estimate bias-corrected TE scores while simultaneously adjusting for the effects of potential efficiency determining variables.

4.3 Two-Stage Semi-Parametric Methods

This study employs two-stage semi-parametric methods to identify the determinants of TE. This is crucial since identifying the environmental factors that affect the TE of the nursing home educates rich insights into improving the productivity of the NHs. The present study applies the following two-stage semi-parametric methods:

- Two-stage Ordinary Least squares (OLS) regression model
- Two-stage Tobit regression model
- Two-stage Double Bootstrap DEA (DB DEA) model

Table 4-2 reveals that the two-stage OLS model has been applied in a number of prior studies (Nyman and Bricker 1989; Fazel and Nunnikhoven 1992; Chattopadhyay and Heffley 1994; Wang and Chou 2005) whereby the TE scores are estimated in the first stage and regressed on potential determinants of TE using OLS regression in the second stage. While this method is relatively straightforward to apply, the two-stage Tobit regression model is preferred as the

efficiency scores are censored between 0 and 1. Similarly, in this model the TE are estimated in the first step and regressed in the second step on a series of environmental variables using Tobit regression. However, Simar and Wilson (2007; 2011) assert that whichever the second-stage regression technique is employed, conventional inference methods fail to give valid inference. This is because true efficiency remains unobserved in the second step and must be replaced with DEA efficiency scores that are not random, and thus serially correlated by construction and biased. Accordingly, Simar and Wilson (2007; 2011) devised the two-stage DB DEA model which provides the bias-corrected coefficients of the efficiency determinants, in addition to bias-corrected TE scores which are adjusted by the values of the efficiency determining variables. To the best of the researcher's knowledge, only Borge and Haraldsvik (2009) have previously applied the DB DEA method in evaluating the determinants of TE in the NH sector.

4.3.1 Two-Stage Ordinary Least Squares Model

In this study, the determinants of TE are identified using the two-stage ordinary least squares (OLS), reflecting previous DEA studies as illustrated in Table 4-2. This model entails a two-step approach, whereby the first step estimates the TE scores using DEA, and the second stage regresses these estimates on a vector of efficiency determinants in a parametric analysis. Estimations are performed in STATA 14 and the following presents the two-stage OLS regression model:

$$TE_i = \beta_0 + \beta_1 Z_{i1} + \beta_2 Z_{i2} + \dots + \beta_p Z_{ip} + \varepsilon_i \sim N(0, \sigma^2) \quad \text{Eq. 4.8}$$

where TE_i is the technical efficiency score; Z_{ip} are the potential determinants of TE of nursing home i ,⁶⁵ β_0 is the intercept; $\beta_1, \beta_2, \dots, \beta_p$ are the slope coefficients of the estimated efficiency determining variables, and ε_i is the error term, which is normally distributed with 0 mean and

⁶⁵ Details of these efficiency determining variables are presented in Section 4.6 of this chapter.

constant variance. Specifically, this research utilizes two different dependent variables when employing the two-stage OLS model as follows:

- OLS regression on conventional DEA scores;
- OLS regression on HB DEA scores.

Whilst the two-stage OLS regression model is the best-known of all regression techniques and also provides a convenient model diagnostics (such as goodness of fit, or F-test of overall significance of the model), Coelli *et al.* (2005) cautioned that a frequent proportion of the efficiency scores are equal to 1, and that the OLS regression could predict scores greater than 1. Therefore, these authors favoured a Tobit regression which can better account for limited dependent variables.

Table 4-2: Previous Evaluations of Two-Stage Methods of Determinants of TE in NHs Sector

OLS	Logistic Regression	Probit	Tobit	Double Bootstrap DEA
Nyman and Bricker (1989)	Ozcan <i>et al.</i> (1998)	Kooreman (1994)	Kooreman (1994)	
Nyman <i>et al.</i> (1990)	Nyman <i>et al.</i> (1990)		Garavaglia <i>et al.</i> (2011)	
Fizel and Nunnikhoven (1992)			Borge and Haraldsvik (2009)	Borge and Haraldsvik (2009)
Chattopadhyay and Heffley (1994)	Chattopadhyay and Heffley (1994)		Rosko <i>et al.</i> (1995)	
Wang and Chou (2005)			Chang and Cheng (2012) Dulai (2018)	

4.3.2 Two-Stage Tobit Model

Given that the TE scores are limited between 0 and 1, the two-stage Tobit model was applied to identify the determinants of TE. Borge and Haraldsvik (2009), Garavaglia *et al.* (2011), and Dulai (2018) also employed this approach to evaluate the environmental factors of TE. In the first stage, the TE scores are estimated using DEA, while in the second non-parametric DEA,

efficiency estimates are regressed on a wide array of determinants ($Z_{1,\dots,p}$) using the parametric non-linear Tobit model.⁶⁶ The two-stage Tobit model takes the following form:

$$TE_i^* = z_i' \delta + \varepsilon_i \sim N(0, \sigma^2) \quad Eq. 4.9$$

where TE_i^* is the unobserved latent variable of nursing home i which satisfies the classical linear model assumptions in that it has a normal, homoscedastic distribution with a linear conditional mean, and z_i is the vector of exogenous and fully observed regressors (here the potential efficiency determinants), ε_i is the error term which is normally distributed with 0 mean and constant variance. Furthermore, Eq.4.9 implies that the observed variable TE_i is equal to the latent variable, TE_i^* , when $TE_i^* \leq 0$ and $TE_i^* \geq 1$, inferring this is a two-limit Tobit model, as the efficiency scores have a lower and upper limits simultaneously:

$$TE_i = \begin{cases} TE_i^* & \text{if } 0 < TE_i^* < 1 \\ 0 & \text{if } TE_i^* \leq 0 \\ 1 & \text{if } TE_i^* \geq 1 \end{cases} \quad Eq. 4.10$$

This study estimates the following two-stage Tobit models:

- Tobit regression with conventional DEA scores as the dependent variable;
- Tobit regression with HB DEA scores as the dependent variable.

The maximum likelihood estimation method is applied to estimate the parameters of the statistical model. Nonetheless, the Tobit model is a non-linear method, inferring it cannot quantify the effect the potential efficiency determining variables have on TE without applying marginal effects analysis. Therefore, the present research derives the marginal effects in order to estimate the unit changes in TE scores due to a one-unit change in the relevant explanatory variables (i.e. efficiency determinant).

⁶⁶ The Tobit model can also be referred to as the censored regression model or the limited dependent variable model.

4.3.3 Two-Stage DB DEA Model

This research employs an alternative two-stage method to identify the determinants of TE, which is referred to as the two-stage DB DEA model. This method was introduced by Simar and Wilson (2007; 2011) who argued that the two-stage methods (wherein nonparametric DEA efficiency estimates from the first stage are regressed on a vector of efficiency determinants in a parametric analysis in the second stage) take no account of the underlying data-generating process (DGP), casting doubt on the meaning of the produced estimates to explain TE. The authors also highlighted that the efficiency scores are point estimates without a probability distribution around it, as required by parametric regression techniques. However, using these point estimates in a second stage analysis may cause biased and inconsistent estimates of the coefficients of the explanatory variables.

Conversely, the DB DEA procedure not only enables robust estimation of the parameters of efficiency determinants, but also re-estimates the bias-corrected TE scores to take account of these efficiency determining variables. The application of this technique is rather limited in the efficiency literature in the NH sector, with the exception of Borge and Haraldsvik (2009), who studied the effect of three key determinants of efficiency in public homes in Norway, and Iparraguirre and Ma (2015), who evaluated efficiency in the provision of social care for older people in England.

To estimate the bias-corrected DB DEA TE scores and their determining factors, this research adopts the Algorithm 2 formulated by Simar and Wilson (2007). While the technical detail of the algorithm is presented in Appendix 4A-4-1, the following presents the main steps of the algorithm which is performed to the dataset in R using the rDEA package in line of Simm and Besstremyannaya (2015).

Firstly, the 'naive' or conventional input-oriented CRS and VRS DEA TE scores are estimated for each nursing home i by solving the DEA linear programming problems provided in *Eq.4.1*

and Eq.4.2, as before. Thus, in the first stage the conventional CRS and VRS DEA TE scores are obtained for each nursing home $i = 1,2,3,\dots,n$ as follows:

$$\hat{\theta}_1, \hat{\theta}_2, \hat{\theta}_3, \dots, \hat{\theta}_n \quad \text{Eq. 4.11}$$

Secondly, the truncated regression for each case is run, where the reciprocals of the original CRS and VRS DEA TE scores for each nursing home i are regressed on the vector of potential efficiency determining variables. The computations are performed in terms of Shepard's (1970) technical inefficiency definition which is the reciprocal of TE score ($\hat{\theta}_i$).⁶⁷ The truncated regression is run twice. The first stage of the truncated regression model is given by the following equation:

$$\frac{1}{\theta_i} = f(Z_{i1}, Z_{i2}, \dots, Z_{ip}) + \varepsilon_i \sim N(0, \sigma^2) \quad \text{Eq. 4.12}$$

where θ_i is the TE obtained in Eq. 4.11 as before and $1/\theta_i$ is the reciprocal of TE score. The explanatory variables (Z_{i1}, \dots, Z_{ip}) are the efficiency determinants which are discussed in Section 4.6 in this chapter, and ε_i is the error term, which is normally distributed with 0 mean and constant variance. After obtaining the results from the truncated regression model given by Eq. 4.12, a bootstrapping procedure is applied to correct for the bias problem in the original DEA scores. First, empirical distributions are obtained by taking L1=100 drawings of residuals from a truncated normal distribution. The truncated regression model is then re-estimated for each drawing to estimate the bias-corrected reciprocals of TE scores ($1/\tilde{\theta}_i$). Furthermore, the DEA TE scores are obtained by adjusting the input values for the ratio of original DEA TE estimates to bias-corrected DEA TE scores.

In the second stage of truncated regression model, this study re-runs the truncated regression model; this time with the bias-corrected and adjusted by efficiency determinants, reciprocals

⁶⁷ Hence, $1/\theta$ ranges from one (indicating a full TE) to infinity (indicating full inefficiency).

of efficiency scores, that is: $1/\theta_i^*$, as the dependent variable, and with the explanatory variables as given in Eq. 4.12. The second stage is presented in Eq. 4.13:

$$\frac{1}{\theta_i^*} = f(Z_{i1}, Z_{i2}, \dots, Z_{ip}) + \varepsilon_i \sim N(0, \sigma^2) \quad \text{Eq. 4.13}$$

In the second truncated model given by Eq. 4.13, L=2000 drawings of residuals are taken from a truncated normal distribution. The truncated regression model is re-estimated for each drawing. Following this, a set of robust coefficients of environmental variables is estimated in the truncated regression of the reciprocal of θ^* score on environmental variables (i.e. after the second loop). The lower and upper bounds for β -coefficients are also obtained. The robust DB DEA CRS and VRS TE scores are further used to derive equally robust SE scores according to the definition of scale efficiency as elucidated in Section 4.2.3.

As previously discussed, the DB DEA remains a semi-parametric or deterministic approach to measuring the bias-corrected TEs, since all variations in firm performance are attributed to inefficiencies only. In other words, the DB DEA does not control for random error (or noise) which reflects all events outside the producer's control and may affect the production process resulting in non-robust estimates of TE and its determinants. In light of this, the next step of this research considers the stochastic frontier analysis (SFA) as a parametric method which assumes that any deviation from the frontier is composed of two parts: one representing inefficiency; and the other statistical noise. This method allows for noise and to thus obtain unbiased parameters of both the efficiency term and the determinants of efficiency in one step procedure.

4.4 Stochastic Frontier Analysis

Figure 4-1 illustrates the parametric Stochastic Frontier Analysis (SFA) as the final estimation strategy employed in this research to estimate input-oriented TE and its determinants. The primary rationale for applying this method is to redress the main drawback of the DEA methods which do not account for random error. As originally proposed by Aigner *et al.* (1977), SFA is

applied to estimate an efficient production or cost functions, assuming that any deviation from the technology (frontier) is composed of two parts: one representing randomness (or statistical noise); and the other inefficiency. The random error term reflects all events outside the control of the organization, but also mis-specification of the production or cost function, or measurement errors. The main drawback of the approach rests on its requisite assumption of the production technology. As such, a functional form must be specified which is not the case with the DEA framework.

The few studies which have used the parametric methods in the NHs literature have typically focused on the estimation of stochastic frontier cost functions (e.g. Hoffler and Rungeling 1994; Vitaliano and Toren 1994; Anderson *et al.* 1999; Crivelli *et al.* 2002; Farsi *et al.* 2008; Martin and Jerome 2016). Unusually then, Knox *et al.* (2007) study opted to examine output-oriented (OO) TE by estimating SFA Cobb-Douglas production function.

In terms of this research, estimating a cost frontier was not possible owing to difficulties in justifying the behavioural assumption of cost minimization for INHs and in obtaining reliable information on their costs of inputs. On the other hand, the stochastic production function allows for the estimation of an OO TE. This study attempts to measure an input-oriented (IO) TE. As such, in order to relax the constraint of the single-output production function, the concept of an input-distance function is applied. To the best of the researcher's knowledge, with the exception of a few hospital-based studies (e.g. Rodriguez-Alvarez *et al.* (2004), no efficiency studies on the NH sector have employed the concept of an input distance function (IDF) to date. The following provides a brief overview of the stochastic production function and presents the stochastic IDF model which is applied in this study.

4.4.1 Stochastic Production Function

As previously mentioned, the SFA rests on specification of a functional form of the production frontier. While this study is unable to estimate cost function due to the aforementioned

difficulty in assuming cost minimization for public NHs, a specification of a production function allows the estimation of an output-oriented TE. Chapter Two (Figure 2-3) outlined the simple model of the production function using one output and one input case. This model could be extended to include more inputs which would enable the estimation of an output-oriented TE for the sample of NHs. It is noted that while the production (and also cost) functions can be specified using various functional forms, the simplest and the most common functional form applied in many applications is the Cobb-Douglas function. However, this functional form imposes certain restrictions on the production structure, such as non-varying returns to scale and unitary elasticity of substitution. Therefore, to account for the non-standard features of production technology associated with the NH care, a flexible functional form is preferred such as the translog (logarithmic transcendental) function formulated by Christensen *et al.* (1973) and which have been applied by Filippini (1999) and Criveli *et al.* (2002) to estimate the cost functions for the NHs sector.

To reiterate: this research does not apply the concept of a production function to estimate the TE for INHs as this research estimates an input-oriented TE. The concept of an input-oriented TE is applied as the managers of the examined NHs do not have control over their output in terms of total patient days, but they can adjust their inputs usage. Thus, to estimate an input-oriented TE in the parametric SFA analysis, this study applies the concept of a stochastic IDF.

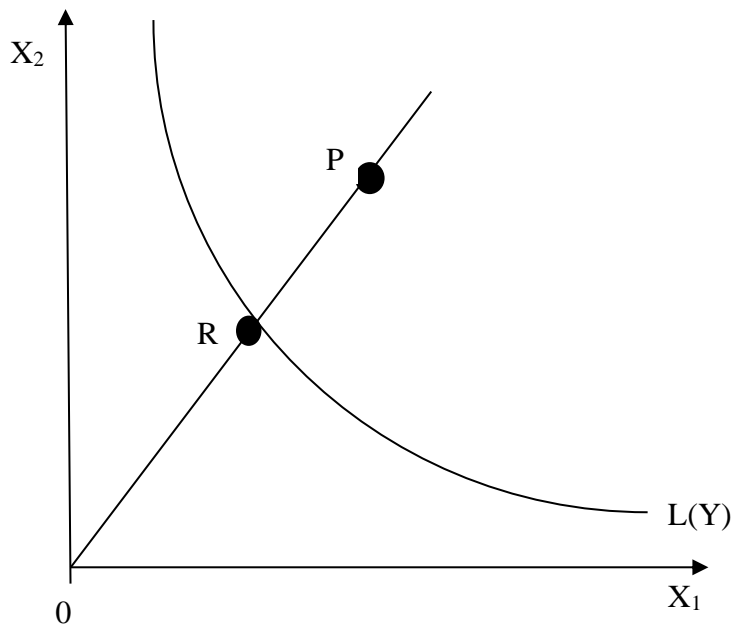
4.4.2 *Stochastic Input Distance Function*

The primary rationale for focusing on SFA input-distance function (IDF) as opposed to the SFA production function, is the possibility to investigate how far the input vector may be proportionally reduced while holding the output vector fixed. As a result, the IDF also allows us to compare the empirical results of SFA with the TE estimates of the input-oriented DEA model presented earlier. Moreover, the IDF can easily accommodate multiple inputs and outputs: a key advantage compared to the stochastic production function which imposes constraints on the production technology such as a single-output production process.

Furthermore, the IDF is not predicated on the assumption of cost minimization: a prerequisite for the cost function does not obtain in this case owing to the inherent uncertainty of the behavioural objective function of public NHs.

The IDF is the reciprocal (inverse) of Farrell's input-oriented TE. Figure 4-3 demonstrates that TE is equal to OR/OP whereas the IDF is equal to OP/OR (alternatively referred to as ρ -parameter). In other words, the input distance function is an inverse of the factor by which the usage of inputs could be contracted, while still remaining on the isoquant for the given level of output. Hence, ρ is the input-oriented inefficiency which the managers of the NHs will want to minimize:

Figure 4-3: The Input Distance Function (IDF) and TE



One output and four inputs are here used to estimate the TE for INHs, details of which are provided in Section 4.6. Following Kumbhakar *et al.* (2015), expressing output and inputs in natural log values, the translog IDF can be written as:

$$\ln D_I = \beta_0 + \sum_{j=1}^J \beta_j \ln X_{ij} + \sum_{m=1}^M \gamma_m \ln Y_{im} + \frac{1}{2} \sum_{k=1}^K \sum_{l=1}^L \beta_{kl} \ln X_{ik} \ln X_{il} + \frac{1}{2} \sum_{m=1}^M \sum_{n=1}^N \gamma_{mn} \ln Y_{im} \ln Y_{in} + \frac{1}{2} \sum_{k=1}^K \sum_{m=1}^M \delta_{km} \ln X_{ik} \ln Y_{im} \quad \text{Eq. 4.14}$$

where D_I is the input distance term; X_{ij} and Y_{im} denote the input j and output quantities m for the nursing home i , respectively. This research imposes homogeneity restrictions by normalizing the distance term and the inputs in Eq. 4.14, by dividing each term by one of the inputs (Kumbhakar *et al.* (2015), and hence we obtain the translog IDF of the following form:

$$\begin{aligned}
-\ln X_{li} = & \beta_0 + \sum_{j=2}^J \beta_j \ln X_{ij}^* + \frac{1}{2} \sum_k^K \sum_l^L \beta_{kl} \ln X_{ik}^* \ln X_{il}^* + \sum_{m=1}^M \gamma_m \ln Y_{im} + \frac{1}{2} \sum_m^M \sum_n^N \gamma_{mn} \ln Y_{im} \ln Y_{in} + \\
& + \frac{1}{2} \sum_k^K \sum_m^M \delta_{km} \ln X_{ik}^* \ln Y_{im} + v_i - \ln D_I
\end{aligned} \tag{Eq. 4.15}$$

Furthermore, by replacing the negative log of the distance term $\ln D_I$ with the inefficiency term u_i (which is independently and identically distributed half-normal random variable with a 0 means and a scale parameter σ_u^2), and adding the standard noise term, v_{it} (which is independently and identically normally distributed with 0 mean and constant variance), the translog IDF can be estimated using the stochastic form as follows:

$$\begin{aligned}
-\ln X_{li} = & \beta_0 + \sum_{j=2}^J \beta_j \ln X_{ij}^* + \frac{1}{2} \sum_k^K \sum_l^L \beta_{kl} \ln X_{ik}^* \ln X_{il}^* + \sum_{m=1}^M \gamma_m \ln Y_{im} + \frac{1}{2} \sum_m^M \sum_n^N \gamma_{mn} \ln Y_{im} \ln Y_{in} + \\
& + \frac{1}{2} \sum_k^K \sum_m^M \delta_{km} \ln X_{ik}^* \ln Y_{im} + v_i + u_i
\end{aligned} \tag{Eq. 4.16}$$

where v_{it} is the statistical noise term with 0 mean and constant variance, and $u_{it} \geq 0$ is a non-negative one-sided inefficiency term which follows a half-normal distribution, so that $u_{it} \sim N^+(0, S_u^2)$. The parameters of the model in Eq. 4.16 are estimated by maximum likelihood (ML) and the inefficiency term is computed using the technique of Jondrow *et al.* (1982), so that $E[-u_i | v_i - u_i]$. Furthermore, Aigner *et al.* (1977) parameterized the log-likelihood function for this half-normal model in terms of $\lambda^2 = \sigma_u^2 / \sigma_v^2$ and $\lambda^2 = \sigma_u^2 / \sigma_v^2 \geq 0$. Where $\lambda = 0$, there are no technical inefficiency effects and all deviations from the production frontier are due to noise.

Kumbhakar *et al.* (2015) noted that the SFA estimates of TE often depend on model specification and distributional assumptions of the inefficiency term (u_i). Vitaliano and Toren (1994) further observed that the half-normal distribution of (u_i) is most widely assumed in the applied efficiency measurement literature. However, alternate distributional assumptions include the half-normal truncated above 0, the exponential distribution, and the gamma distribution of the inefficiency term.

Modelling the Determinants of Efficiency within SFA

To evaluate the determinants of TE, the efficiency determinants Z are included as heteroscedastic variables in the inefficiency function by directly parameterizing the variance of the inefficiency (u_i):

$$\sigma_{ui}^2 = \exp(\delta' z_i) \tag{Eq. 4.17}$$

where; z_i is a vector of efficiency determining variables (Section 4.6), which influence the inefficiency (u_i) and hence TE_i of nursing home i and δ is a vector of unknown parameters to be estimated. One advantage of the specification given by *Eq. 4.17* is that it facilitates the estimation of the inefficiency effects simultaneously as a single-stage procedure, together with the parameters of the IDF SFA model. This procedure has an advantage over the alternative two-stage methods presented earlier in this chapter, in that the first stage involves the estimation of a conventional frontier model with the Z -variables omitted, and the second stage involves regressing these predicted technical efficiencies on the Z -variables. The two-stage procedures would generate inconsistency in the assumptions regarding the distribution of the inefficiency since the estimates of u_i would be biased by the omission of Z -variables in the first step regression.

Furthermore, controlling for (in)efficiency determinants in the SFA method is important, since unlike the classic linear model in which heteroscedasticity affects only the efficiency and not their consistency of the estimators, ignoring the observed heteroscedasticity in u_i may lead to

biased estimates of both TE and the production function parameters (Kumbhakar and Lovell 2000; Kumbhakar *et al.* 2015). It should also be noted that similar to OLS and the Tobit two-stage regressions, the estimations for the SFA IDF are performed in STATA and computations undertaken in terms of an *inefficiency* (u_i), meaning the sign of the coefficient of the determinant is the opposite when evaluating it in relation to its effect on TE.

4.5 Dataset

To measure the TE of INHs and to identify the efficiency determinants using a wide spectrum of methods, this research uses a novel and rich primary dataset derived from NHs in Ireland between 2008 and 2009 through the medium of a face-to-face interview with the NH manager. The next section outlines the various preparation stages necessary to ensure accurate and relevant collection of data for the final data sample, up to and including the actual fieldwork and the final dataset used.

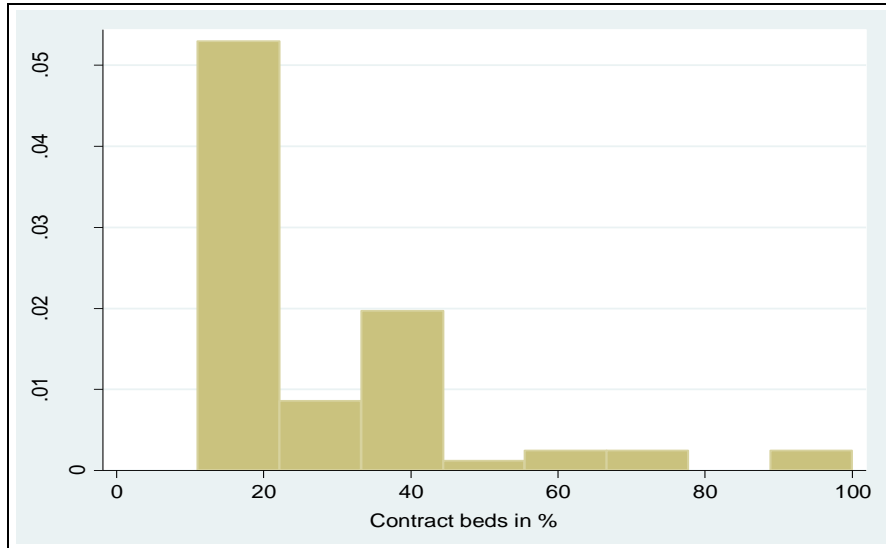
4.5.1 Data Gathering

This research focuses on public NHs as well as the private and voluntary NHs which provide long-stay care only under contract to the Irish State. All NHs examined are either fully or partially funded through the exchequer. In 2007 a parliamentary question (29365/07) was submitted in order to identify the private and voluntary long-stay units from which the State purchases care and the ensuing reply specified the name of each nursing home and the number of contract beds which the unit supplied.

The population of INHs with public and State-contracted beds was divided into 125 public, 151 private and six voluntary units. Thereafter, the population of 157 private and voluntary NHs was filtered by through a threshold inclusion criterion, whereby 10% or more of a unit's total beds provision were State-contracted. Figure 4-4 demonstrates that the share of contract beds is below 50% for the vast majority of private and voluntary NHs in this research: the average share is 27%. Since these units are more private or profit-orientated, their TE levels

were expected to differ significantly compared to the public homes which are fully subsidized by the State.

Figure 4-4: Distribution of Irish Private/Voluntary NHs - % of State-Contracted Beds



Data source: Primary dataset on INHs, 2007-2008

The collection of the data sample is presented in Table 4-3. Following permission to undertake this research was approved at Assistant Director of Nursing level, Local Health Managers (LHMs) were contacted to discuss NH access. The LHMs stipulated that 51 named public homes could not be approached due to privacy considerations related to the “medico-social status of the residents”. Thus, the ‘effective’ population was reduced to 74 public and 106 private and voluntary units. All 180 NHs were contacted, and a total of 59 public, 90 private, and three voluntary units, agreed to partake in this research and comprised the final sample. Cross-sectional data were then collated from July 2008 to September 2009 via face-to-face interviews. In fact, a very high response rate was achieved relative to the effective population: with 59 out of 74 public NHs (80%), and 93 out of 106 private and voluntary units (88%) participating in the survey.

Table 4-3: Data Collection and Data Sample

Population/ sample	Public NHs	Private and voluntary NHs with contract beds
Overall population	125	157
Effective population	74	106
Final sample	59	93
Response rate	80%	88%

Source: Primary dataset on INHs, 2007-2008

Face-to-face interviews were chosen as opposed to telephone surveys, postal, or internet surveys, for a number of fundamental reasons. Firstly, following a number of ‘informal conversations’ with different stakeholders across the NH industry, the researcher came to believe that interpersonal engagement would ultimately generate better quality results. Being present at ‘the interview’ with the NH operator also provided opportunities for the researcher to clarify any concerns participant felt in addressing a question. Moreover, it enabled the interviewer to observe how questions were responded to. Additionally, it allowed the NH manager to actually meet the researcher, which was reported to be extremely important by several contributors⁶⁸ since it made the process ‘feel real’ to them. In addition, participants admitted that presence of the researcher on-site allayed some of their fears and reassured them that the data would not be utilized for unintended purposes⁶⁹. This was a particularly sensitive issue due to the negative media coverage which the sector had attracted as a result of the ‘Leas Cross Scandal’⁷⁰.

4.5.2 Questionnaire

The questionnaire which guided the interview between the NH manager (who was often the owner of private homes) and researcher, is available in the Final Appendix to the thesis. Two

⁶⁸ Nursing home managers stated that they have previously been requested to engage in postal surveys however they noted that they preferred ‘one on one contact’.

⁶⁹ The researcher had a letter from the University of Limerick stating that the data from the survey will be utilized for research purposes only.

⁷⁰ An investigation program revealed elderly abuse and sub-standard living conditions in a nursing home in North County Dublin using bogus clinical staff to film the environment of the home – www.health.gov.ie/wp-content/uploads/2014/03/leascross.pdf

broad objectives unpinned its design: firstly, it was imperative that the layout was simple and fluid so as to encourage the participant to engage and commit to the process; and secondly, it was critical that responses were accurate, so that quality and worthwhile information could be shared. With this mind, the schedule comprised questions relating to the following topics:

1. The general environment of the nursing home
2. The Staff
3. Services provided to the Client
4. The Resident.

The questions were derived from an extensive review of the NH literature which highlighted the key issues that warranted investigation. For example, efforts to estimate TE of INHs led to formulation of questions: 1, 8, 9, 18, 19, 36 and 39; whereas efforts to evaluate the determinants of TE informed questions: 4, 6, 13, 14, 15, 23, 37, 41 and 46. In addition, a series of open-ended and closed questions were devised to elicit rich insights into the NH sector. Thus, questions 16 and 24 encouraged the respondent to share ‘their views, thoughts and experiences’ as to why clinical staff left the organization, while in contrast, questions 28 and 30 limited the response of the participant.

Prior to the conducting the interviews, ethical approval was obtained from Kemmy Business School Research Ethics Committee (KBS REC) in University of Limerick. Pilot-testing was also undertaken at 10 ROI NHs across the Southern and Western Regions. The pilot sample comprised five public NHs and five private and voluntary homes which had contracted 1% or more of their LTC beds to the State. All homes were asked to part-take in the research by formal, written invitation, and a convenient time subsequently arranged for the researcher to visit each home. The face-to-face interviews generally took place in the morning, with one during the afternoon. However, occasionally, due to unforeseen events, such as a death of a resident or an unannounced visitor to the nursing home, it was necessary to re-schedule events.

Similarly, the face-to-face interview took longer than the allocated 45 minutes slot owing to managers need to take important calls or confer with staff. Whilst these interruptions and delays were sometimes challenging, the experiences proved invaluable as they were often repeated during the actual fieldwork.

The questionnaire itself was generally well-received. Questions relating to the characteristics of the home, the staff, the services, and the residents were welcomed, while the ‘grouping of topics’ kept the conversation flow on-track and encouraged respondents to ‘easily’ re-engage with the process following any interruptions. Nonetheless, the pilot process shed light on the need for certain minor adjustments to the questionnaire in order to elicit the most reliable and precise data possible. For example, salary requests were categorized as opposed to actual figures and some percentage figures were requested as opposed to actual figures. Subsequently, preparations for the fieldwork commenced.

4.5.3 The Fieldwork and Final Dataset

As shown in Table 4-3, the effective population comprised 74 public NHs and 106 private and private-voluntary homes with contract beds. Accordingly, all facilities were initially contacted by postal mail inviting them to participate in the research process. This was followed by a phone call to make the appropriate arrangements for the interview which took place throughout 2008-2009. As a number of managers declined to take part on the basis of pressures of work, unsuitable timing, fear of being involved, and so on, the final sample consisted of 59 public NHs, 90 private homes, and three voluntary units. Each of the ensuing face-to-face interviews had its own ebb and flow, and took between 60 and 110 minutes. There were occasional delays owing to a death or a new admission in the home. However, rescheduled appointments overcame these difficulties. Following each interview, the researcher documented her experience of the ‘process’ and recorded the issues challenges facing the INH industry according to the NH managers.

Final Dataset

It is noted that although the final data sample consisted of 59 public and 93 private, and private voluntary homes, the actual number of NHs investigated in the empirical part of the thesis was reduced as 40 NHs failed to provide the output variable (total patient days). In addition, two NHs failed to provide data on non-medical staff. As a result, all 42 NHs had to be excluded from the final analysis. Details on the missing responses are provided in Table 4-4. The final number of observations used for the efficiency models presented in the empirical part of the thesis then totalled 110 NH units. This comparatively small sample supports the value of non-parametric DEA and semiparametric two-stage DEA methods to measure TE for these homes, since estimating the parametric SFA IDF could lead to numerous estimation problems as documented and discussed in Chapter Five.

Table 4-4: Final Dataset

Sample/No. observations	Public NHs	Private and voluntary NHs with contract beds	Total
Final Data Sample	59	93	152
Missing observations for output variable (total patient days)	20	20	40
Missing observations for labour input variable (non-medical staff)	1	1	1
Final number of observations used in efficiency models	38	72	110

It should also be noted that private NHs and private-voluntary nursing homes are clustered together into one single group 'private NHs', since only three NHs of this type were included in the final dataset for the empirical analysis.

4.6 Definition and Measurement of Variables

This section defines the output and input variables used to estimate input-oriented TE and presents the potential determinants of TE employed in this study. The efficiency determinants

are divided into conventional factors and ‘output characteristics’ variables. The firms’ conventional characteristics include *ownership*, *location*, *age*, and *size*.

On the other hand, objective output-characteristic variables are specific to the nursing home sector, such as *case-mix*, and *chain status*, and numerous additional factors which might impact the quality or labour management of NHs. Finally, the summary statistics of output, inputs, and the efficiency determining variables are also presented.

4.6.1 *Output Variable*

The definition of the relevant output of the LTC facilities is essential to properly estimate TE for the NH sector. However, as the definition and measurement of output is an enduring topic in the health economics literature, it is noted that conceptual output in terms of improved health status, or even the more general improved quality of life, is difficult to measure (Kooreman 1994). Furthermore, the concept of ‘value-added’ as a result of engaging with the ‘service’ has proved more challenging in the health-care market because of the much greater heterogeneity of service users and intrinsic measurement difficulties. A fundamental issue is that it is rarely possible to observe a baseline: for example, the health or quality of life status which would obtain in the absence of nursing home intervention. Additionally, the ‘care’ outcome of NHs is difficult to measure. Castle and Ferguson (2010) alluded to the inability to adequately realize what quality of care *is* in the context of care facilities. Whilst there is a general acceptance that certain clinical quality indicators exist to measure quality of care, such as the number of falls of a resident, the authors emphasized the inherent ambiguity of ‘care’ per se. One solution to this challenge is to measure output on a more ‘quantifiable basis’ (Hollingsworth, 2003).

The studies on performance measurement in the health sector employ quantifiable output measures which include the number of discharges, in-patient days, emergency visits, or days in intensive care (Hofmarcher *et al.* 2002). Similarly, the NH literature reflects the use of quantifiable indicators of output.

Delellis and Ozcan (2013) observed that the number of patient days in a home or the number of residents are the predominant measures of output used. As such, this research defines the output of a NH unit as total patient days. This measure has been applied in other NH efficiency studies, including that of Fazel and Nunnikhoven (1992), Chattopadhyay and Heffley (1994), Chattopadhyay and Ray (1996), Bjorkgren *et al.* (2001), Borge and Haraldsvik (2009) for DEA, and Hoffler and Rungeling (1994), using the SFA method. Furthermore, this study adjusts total patient days for case-mix, using the high-max dependency rate as defined below.

It is noted that all DEA models specified in this chapter (i.e. the conventional DEA, HB DEA and DB DEA), employ the output variable as measured by the total patient days. However, this research was unable to apply this output measure in the SFA framework as the maximum likelihood function did not converge, an issue which is further elucidated in Chapters Five and Six. Therefore, an alternative output variable for the SFA IDF model was utilized; namely ‘the total patient days per resident’ which can be denoted as the average length of stay.⁷¹

4.6.2 *Input Variables*

A commonly used classification of inputs involves five categories (see Coelli *et al.* 2005): namely, capital (K); labour (L); energy (E); material inputs (M); and purchased services (S). The construction and use of data according to these categories in productivity measurement is sometimes referred to as the KLEMS approach. The latter three categories of inputs are often aggregated to form a single ‘other input’ category. However, specifically in NH studies (Hollingsworth 2003; Wang and Chou 2005; Dervaux *et al.* 2006; Hollingsworth 2008; Chang and Cheng 2013), input variables are mainly measured in terms of capital and labour as the basic inputs of a production function.

⁷¹ This measure is only used to compare the robustness of the SFA results with semiparametric two-stage methods in chapter 6 at the same time acknowledging that this variable will be only an approximation of the actual output produced in the nursing homes.

In addition to employing standard capital and labour inputs in the efficiency model, this research also includes a further type of input which accounts for case-mix in the NHs. In alignment with the earlier work of Fazel and Nunnikhoven (1992), this study assumes that NHs with a more severe case-mix composition of patients require more resources than NHs with lower case-mix. In consequence, failure to control for case-mix in the efficiency model generate underestimations of the TE scores of such NHs. It should also be noted that this research incorporates the case-mix both as an input variable and as an efficiency determinant⁷². To the researcher's knowledge, this procedure has only once been previously applied to NHs by Garavaglia *et al.* (2011).⁷³

Furthermore, and as previously discussed, this research measures an IO TE, as managers of INHs can alter the input combinations but usually have no control over patient days (the output). In this research, private NHs can adjust the case-mix clientele of the home to maximize profits whereas public NHs have less discretion over this variable. Nevertheless, public NH managers can indirectly control for case-mix in the home by suggesting the skills set of the personnel may not be able to meet the complex needs of the individual.

Capital Input

Capital in the NH sector is difficult to measure as it is a durable input. Unlike labour inputs which are utilized in the production process within a specific accounting period, capital assets are purchased in one period and used in the production process throughout the life of the asset or until it is replaced by a new asset. In principle, an efficiency model should use the capital flow consumed in the current period as a production input. However, as information on capital flow is difficult to obtain in the NH sector (and also in other health-care sectors), this study approximates the capital input by using the number of beds available in the NH unit. This measure has been employed in other NH efficiency studies including that of Ozcan *et al.*

⁷² The case-mix is also discussed in section 4.6.4 below as one of the potential determinants of efficiency.

⁷³ These authors used case-mix both as an output variable and as a determinant of TE.

(1998), Bjorkgren *et al.* (2001), Laine *et al.* (2005a), Wang and Chou (2005), and Delellis and Ozcan (2013). Furthermore, data for the NH sector in Ireland has shown that managers are able to significantly increase or decrease beds capacity over consecutive years. Chapter Three highlighted how, between 1998 and 2011, the Irish Government provided capital allowances in the NH care market to stimulate private supply. It is no coincidence that this period witnessed a trend in the rapid rise in private sector beds provision as a proportion of total long-stay beds (Figure 3-3). Moreover, the private and voluntary NH units in Ireland with State-contracted beds are incentivized to increase their capital investment in order to receive higher public funding. Therefore, this research asserts that including the number of beds in the production model as a proxy capital input is important in the Irish case.

Labour Inputs

Labour constitutes a major component of the total expenditure on inputs in many enterprises and is considered one of the primary inputs of NH care. In spite of this, very little attention is usually devoted to the measurement of labour, and the quantity of the labour input is normally measured using a single aggregate variable.⁷⁴ For the purposes of this research, the labour inputs are measured by the number of staff employed in each NH unit, using the primary and secondary inputs of medical staff and non-medical staff, respectively. The former is measured by the number of full-time nurses, while the latter is measured by the number of full-time health-care attendants.⁷⁵ Among the efficiency studies which have used medical staff (full-time equivalents) as an input in their DEA models are Nyman *et al.* (1990), Ozcan *et al.* (1998), Bjorkgren *et al.* (2001), Laine *et al.* (2005a), and Delellis and Ozcan (2013).

⁷⁴ The most commonly used measures of labour input in the general efficiency literature are the number of persons employed, the number of man-hours, the number of full-time equivalent employees, the deflated wages and salaries.

⁷⁵ In the preliminary stage of this research, to test the sensitivity of the results in relation to the labour measures used, the researcher substituted the number of staff with the salaries of full-time nurses and the salaries of health-care attendants for the primary and secondary inputs, respectively. The preliminary DEA results were very similar to those obtained using the full-time employees which are used for all the models presented in this thesis.

Nurses can attain formal qualification in clinical care delivery; sometimes to postgraduate level. In addition, their pivotal role is given legal standing in Ireland’s Health Act 2007, which stipulates that a nursing home has a nurse on the premises at all times. The literature suggests that nurses can affect patient outcomes, thus highlighting their contribution in the care delivery process (Aaronson *et al.* 1994; Blegen *et al.* 1998; Harrington *et al.* 2000). Nurses are supported in the care delivery process by health-care attendants who undertake non-clinical duties. Having a professional qualification, such as Diploma in Gerontology, provides the nurse with a competency and unique skill set that could lead to improved delivery of efficient care. Table 4-5 demonstrates that nurses in the Irish public NHs are more skilled in the care of the elderly as approximately 75% of NHs in the sample employ nurses with a formal qualification in the care of elderly compared to only 23% of private nursing units.

Table 4-5: Formal Qualifications of Nurses in Private and Public NHs

	No. Obs.	%	No. Obs.	%
	<i>Private NHs</i>		<i>Public NHs</i>	
‘Yes’ to Dip.in Gerontology	21	22.58	44	74.58
‘No’ to Dip. In Gerontology	70	75.27	14	23.73
Don’t Know	2	2.15	1	1.69
Total	93	100.00	59	100.00

Source: Primary dataset on INHs, 2007-2008

Non-medical personnel also have a significant impact on the daily care of the patients, including the quality of care provision. The inclusion of both primary and secondary labour measures facilitates assessment of their relative importance in the efficiency of NH care provision in Ireland. In light of this and depending on how the labour input is defined, the present study employs three alternative model specifications as follows:

- *Model 1:* labour is measured solely by the number of medical staff in the unit
- *Model 2:* labour is measured by the number of non-medical staff only
- *Model 3:* includes both medical and non-medical staff variables

In each of the model specifications, output is defined as total patient days, capital is proxied by the number of beds, and the case-mix is measured by the proportion of high-maximum dependency rate of NH residents. Table 4-6 summarizes the three model specifications.

Table 4-6: Efficiency Model Specifications⁷⁶

Input / Output Variable	Description	Model 1	Model 2	Model 3
Output	Total patient days	yes	Yes	yes
Labour (Primary Input)	Medical staff	yes	No	yes
Labour (Secondary Input)	Non-medical staff	no	Yes	yes
Capital Input	Number of beds	yes	Yes	yes
High-maximum dependency (HMD) rate	Proportion of high -maximum dependency residents	yes	Yes	yes

High-Max Dependency Rate (HMD)

Case-mix index is one of the widely used approaches to capture heterogeneity in resource requirement in health-care though the measurement of the intensity of care and service required for each resident. As noted in Table 2-3, various indices are used to measurement of case-mix; such as average patient days, the age structure of residents, proportion of SNF, and the average number of ADLs. In relation to INHs, health-care professionals apply a needs assessment when an elderly person enters the nursing home which determines their dependency level of *low*, *medium*, *high*, or *maximum*. This study uses the high-maximum dependency rate (HMD) rate as a proxy variable for the case-mix indicator in the efficiency model.

To derive the HMD rate, the total number of individuals categorized as ‘high’ or ‘maximum’ dependent are divided by the total number of residents in the home. As previously established in Chapter Three, it is reasonable to assume that residents with complex needs require more inputs. As such, failure to control for this dependency will underestimate TE scores of these

⁷⁶ While the empirical results of Chapters 5 and 6 refer to *Model 3* owing to its inclusion of all inputs, reference is also made to *Models 1* and *2* in order to illustrate how the TE performance of the facility can differ depending upon the choice of the labour input.

homes, while that of other homes will be overestimated. A review of the case-mix efficiency studies in Chapter Two also indicates that levels of dependency have been employed as a proxy for case-mix by Nyman *et al.* (1990) and Chattopadhyay and Heffley (1994).

4.6.3 *Ownership and Conventional Characteristics*

This study applies a comprehensive set of efficiency determining variables to explain TE of INHs. These determinants are categorized into two groupings: (1) ownership and conventional (firm's) characteristics; and (2) output characteristics of NHs. The main factors of interest in the first group are: *ownership, size, location, and age* of the nursing home, while those of the second group include the *HMD rate, chain-status, and structural dimensions of quality* defined as objective output characteristics of the NHs as discussed in the next subsection. All potential efficiency determining variables applied in the empirical models in this study are summarized in Table 4-9.

Ownership

Table 4-9 indicates that *ownership* is the first conventional determinant of TE of this research. The mixed ownership structure of INHs enhances the need for the debate on whether private NHs are more technically efficient than public facilities. Table 4-7, reveals that private NHs constitute 59.21% of the overall sample with the voluntary home sample share equal to just 1.97%, and the public NH share equal to 38.82%. The dominance of the private care facilities is hardly surprising given that they provide 80% of LTC beds and that the capital allowances introduced in 1998 stimulated their supply. However, Table 4-7 underscores that private and public NHs are distributed relatively equally among the different regions in Ireland.

Table 4-7: Percentage of Irish Private, Voluntary, and Public NHs by Location

NHs	South	West	Dublin- North East	Dublin-Mid Leinster	Total
Private	26.7	22.2	21.1	30	100
Voluntary	33.3	33.3	0.00	33.4	100
Public	30.5	20.3	17	32.2	100
All Homes	28.3	21.7	19.1	30.9	100

Source: Primary dataset on INHs, 2007-2008

This study also examines the effect of ownership in three ways. Firstly, TEs are estimated for the pooled sample of all private and public NHs. Then, a *for-profit dummy* variable is introduced with a value of 1 assigned to private (including voluntary) nursing facilities, and with a value of 0 assigned to public NHs. A similar approach was applied by Chattopadhyay and Heffley (1994) and Nyman and Bricker (1989), whereas Ozcan *et al.* (1998) estimated the pooled sample of all homes and examined the differences in the mean values of TE using the mean comparison tests.

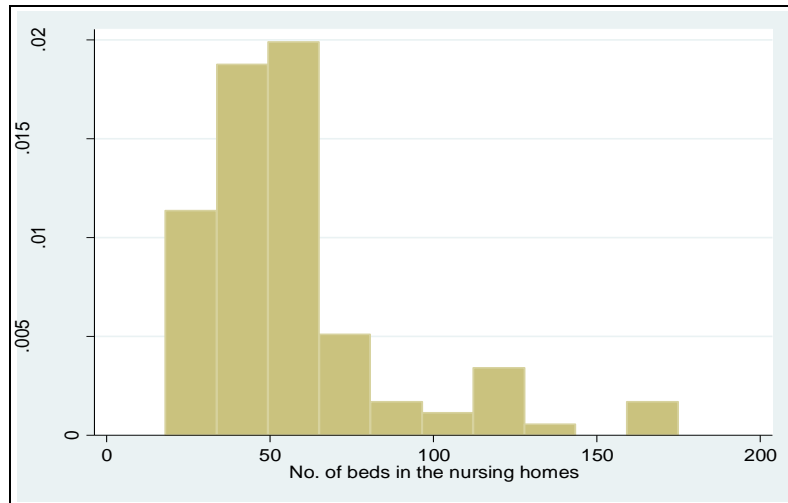
Secondly, this research assumes that private and public NHs use different technologies and that their efficient frontiers or isoquants should be examined separately. Therefore, the sample is split into private and public NHs, the TE scores are estimated for the respective groups separately, and the results are compared. Thirdly, as all private NHs in the sample supply at least 10%+ of their total bed capacity to the State on a fixed contract basis, this research also investigates the effect of *share of contract beds* on TE of those facilities. Based on previous empirical evidence, for-profit homes are expected to be more technically efficient than the public units. On the other hand, given the complicated funding structure of the Irish private-voluntary NHs, this assumption might not hold in this case.

Size

Size of the NH facility is considered another conventional determinant of TE which has been used in previous studies on NHs (e.g. Kooreman 1994; Ozcan *et al.* 1998; Chattopadhyay and Ray 1996; Filippini 2001). In keeping with these studies, the size variable in this research is

approximated by using the number of beds in the NH unit. Figure 4-5 indicates that most of the NHs in the sample of Irish long-stay units have less than 100 beds at their disposal and the mean is centred around 50 beds.

Figure 4-5: Distribution of INHs in Relation to Number of Beds



Data source: Primary dataset on INHs, 2007-2008

Therefore, the sample is divided into three size categories of: size_1 (0-49 beds); size_2 (50-99 beds); and size_3 (100+ beds). Interestingly, as most of the INHs in the sample are small and medium-sized units, with almost 90% of all units having less than 100 beds, there may be a reason to assume that many of these facilities are operating in the range of IRS and experiencing decreasing average costs. These homes should increase size to achieve optimal scale, and at this point TE would be equal to SE. Nyman *et al.* (1990) found that size has a positive impact on efficiency up to a threshold of 170 beds. In contrast, Wang and Chou (2005) found that size had a negative association with efficiency. However, these authors employed a different classifications of size⁷⁷: namely, ‘small’ equalled less than 100 beds, medium equalled 100-499 beds, and large implied 500+ beds. Therefore, the exact effect of the size variable is difficult to predict in advance.

⁷⁷ In the Wang and Chou (2005), the ‘small’ category equalled less than 100 beds, the ‘medium’ one equalled 100-499 beds and the ‘large’ category implied greater than 500 beds.

Table 4-8: Percentage of Private and Public NHs by Size

NHs	0-49 beds	50 – 99 beds	≥100 beds	Total
Private	45.6	46.7	7.7	100
Voluntary	66.7	0.00	33.3	100
Public	50.9	30.5	18.6	100
All Homes	48.0	39.5	12.5	100

Source: Primary data sample on INHs, 2007-2008.

Table 4-8 illustrates that the majority of public NHs (50.9%) have less than 49 beds, compared to private NHs (45.6%). However, in the group of 50-99 beds, the percentage share of private homes (46.7%) is greater than that of public facilities (30.5%); while in the ‘100+ beds’ group, the proportional share of public homes is higher again than of the private NHs. Table 4-8 further illustrates that 48% of all NHs are small units, whereas 39.5% of homes have between 50 and 99 beds, and only the remaining 12.5% of public, private and voluntary homes have 100+ beds.

Location

Location is deemed another possible conventional determinant of TE and is measured by two alternative indicators. Firstly, following Kooreman (1994) and Ozcan *et al.* (1998), the regional differences in TE of INHs are investigated. The ‘*region*’ variable is divided into the four distinctive areas defined by the Health Service Executive (HSE) who provide elderly services nationwide in Ireland. These areas are ‘South’, ‘West’, ‘Dublin Mid-Leinster’ and ‘Dublin North East’. Thus, four regional dummies are constructed wherein ‘West’ is the reference category. As the latter area has excess supply of LTC beds, it might have a different effect on TE than other regions.

Additionally, DeLellis and Ozcan (2013) noted that NHs have higher average TE scores if they are located in locations with increased competition. Thus, this study applies an alternative dummy variable for location which equals 1 for Dublin (capital city) and 0 otherwise. Dublin represents a special case compared to other regions and cities in Ireland as 50% of all NHs examined in this study are indeed located in Dublin area. *A priori*, it is possible that NHs

located in Dublin are more technically efficient than NHs operating in other areas, resulting from greater competition for medical and non-medical personnel relative to other regions in Ireland, which leads to higher labour costs in Dublin. Consequently, as wage rates increase, NH managers might react by using their labour inputs more efficiently (Zinn 1993; Rosko *et al.* 1995).

Urban

This research evaluates whether the ‘*urban*’ area could be a likely determinant of TE for INHs. The ‘urban’ indicator variable equals 1, if the nursing home is located in a county with a population of 25,000 or more and 0 otherwise. A similar variable representing an urban versus rural differences was included by Nyman and Bricker (1989) to examine the potential effects of intensity of competition among rival firms on the NH efficiency. Although these authors had no expectations regarding the sign of the urban’s coefficient, they found that TE decreased in for-profit homes that were exclusively located in urban areas. Similarly, Nyman *et al.* (1990) included an urban variable to determine whether the nursing home was located in a county with 25,000 inhabitants or more. This dummy variable was expected to act as a proxy for a market wage variable which indicated that NHs could exhibit higher efficiency in urban areas, not because they were more efficient *per se* but rather because they substituted away from labour inputs due to relatively high wages. Fizek and Nunnikhoven (1992) similarly included an urban/rural dummy to capture the effect of unobserved regional differences and they found this environmental factor to be insignificant:

Table 4-9: Efficiency Determining Variables

Variables	Description	Hypothesized effect on TE
Conventional Determinants		
For-profit dummy*	1 = the nursing home has a private ownership, 0 otherwise (used only for pooled data)	+/-
State contract beds	% share of contract beds in private NHs (used only for the sample of private NHs).	+/-
Size	Categorical variable: Size_1=0–49 beds; Size_2 = 50–99 beds; Size_3 ≥ 100 beds (dichotomized in the final analysis)	+/-
Urban	1 = if the nursing home is situated in an urban centre, 0 otherwise	+
Location	1 = if the nursing home is located in Dublin, 0 otherwise	+
Age	Age of the nursing home facility in years	+/-
Output Characteristics		
HMD rate	The proportion of high maximum dependency residents in the nursing home	+/-
% single rooms	The number of single rooms as a proportion of total beds available in the NH facility (in %)	-
Staffing Level	The ratio of full-time equivalent nurses (FTE) per 1,000 adjusted inpatient-days.	-
Staff Flexibility	The ratio of nurses that were classified as part-time to full-time nurses.	+/-
M-NM ratio	The ratio of medical staff (nurses) to non-medical staff (HCA).	+/-
L-C ratio	The ratio of labour to capital which is the ratio of full-time nurses to the number of beds available in the nursing home.	+/-
Nurse turnover	The proportion of nurses that left the NH organization in 2007 (in %)	+/-
HCA Turnover	The proportion of health-care attendants that left the organization in 2007 (in %)	+/-
Chain Status	1 = Private Chain Nursing Home, 0 otherwise	+/-

* Ownership is used for the pooled sample analysis only.

Age

The last *conventional* determinant of TE in this research is *age*. This is measured by the number of years in operation. Friedman and Shortell (1988) argued that the age of the facility leads to increased costs due to capital depreciation. Similarly, Martin and Jerome (2016) observed that

new buildings may increase costs, since NHs needed to bear depreciation expenses. On the other hand, nursing home ageing provides an opportunity for learning by doing for nursing staff which could induce cost savings. Nonetheless, these authors concurred that the ageing of a facility had an insignificant effect on cost inefficiency.

This study incorporates age as a likely determinant of TE. The descriptive statistics in Table 4-11 below also indicate that public NHs premises are older than private nursing facilities, owing to the former being repurposed ‘workhouse era’ buildings. This suggests that public facilities have less up-to-date capital inputs which may drive down technical efficiencies. On the other hand, older homes may provide a chance for medical and non-medical staff to be more innovative and creative which may improve their efficiencies. Therefore, the exact effect of an age variable on TE scores cannot be predicted *a priori*.

4.6.4 Output-Characteristic Variables

Table 4-9 confirms that the output characteristics of NHs relate to case-mix, the chain status of the unit, and structural dimensions of quality. The latter variables primarily focus upon the labour management factors.

HMD Rate as the Case-Mix

In this research, case-mix is considered both as an input in the input-oriented TE model and as an efficiency determinant which may explain TE. As previously noted, case-mix is evaluated using the high-max dependency (HMD) rate which is measured as the proportion of residents with ‘high-maximum’ dependency to total residents in a nursing home. Table 2-3 also demonstrates that the HMD rate has been widely used as a determinant of efficiency in other studies. The trends in this variable were also extensively discussed in Chapter Three for the public and private NHs over the period 2000-2014. Figures 3-5 and 3-6 illustrated that the percentage share of residents with high-maximum dependency (HMD rate) was considerably higher in the public than private NHs, and that over time, this share has increased for the public

NHs and decreased for the private nursing units. It is therefore reasonable to infer that higher proportions of high-maximum dependency patients in the nursing home require more resources (labour and capital inputs) which might result in lower TE. However, it is equally possible to argue that NHs with higher dependency levels of patients might become more technically efficient as they learn to use their resources more effectively over time.

Chain Status

Chain ownership refers to a group of NHs in contrast to a single operation, which is referred to as a ‘non-chain’ home. A group of homes can engage in bulk-buying and a sharing of labour and capital resources which could lead to better efficiency outcomes relative to single operators (Fizel and Nunnikhoven, 1993). On the other hand, decision-making may be slowed and more bureaucratic in a group of homes which can impact the TE performance of chain homes. In Ireland, only private NHs can have chain or non-chain status, and in this study, private homes with chain status are assigned a value of 1, and private non-chain facilities a value of 0.

Structural Quality Variables

This research includes a vector of output-characteristic variables that are structural factors according to Donabedian’s (1988) definition of quality of care (Table 2-2). The first structural quality indicator is the proportion of *single rooms* on offer in each nursing home, followed by further quality factors that are held as pertinent labour management variables.

- *Single Rooms*

Following Laine *et al.* (2005b), the first structural quality indicator is the percentage of *single rooms* on offer in each nursing home as the proportion of total beds. This study assumes that patients accommodated in a single room enjoy greater freedom and privacy which might positively influence their perception of quality. This research could conversely assume that this quality variable could exert a negative impact on TE, since locating beds in single rooms intensified usage of available resources.

- *Labour Management Variables*

The literature on quality in Chapter Two suggests that skilled nursing can affect patient outcomes; thus highlighting professional nurses' contribution to the delivery of quality of care (Aaronson *et al.* 1994; Blegen *et al.* 1998); Harrington *et al.* 2000). Given the available data, this research examines the impact of nurses on TE using five different structural quality factors, related to the employment of nurses: namely, *staffing level*; *staff flexibility*; *ratio of medical staff to non-medical staff*; *ratio of labour to capital*; and *staff turnover*.

- *Staffing Level*

This variable is measured as the ratio of full-time equivalent (FTE) nurses per 1000 adjusted inpatient-days. If the home experiences an increase in staffing levels, the facility may be less technically efficient as additional labour inputs are required, but on the other hand, the quality perception of a patient might increase.

- *Staff Flexibility*

The second variable used which captures the effect of nurses as a structural dimension of quality is '*staff flexibility*' which is measured as the ratio of part-time medical staff to full-time nurses. According to US Healthcare Financing Administration (2000), NHs which employ fewer full-time health-care professionals per patient are less able to improve the quality of care for their patients. Part-time personnel can be less familiar with the daily routines of the residents and therefore not as engaged in the organization, resulting in declining quality. Falling quality may be associated with increasing TE as fewer full-time medical personnel may be demanded. However, on the other hand, falling quality might decrease TE as part-time nurses will not be as experienced or productive as full-time medical staff.

- *Ratio of Medical to Non-Medical Staff*

The third variable capturing the structural quality of nurses used in this research is the ratio of medical to non-medical staff (*M-NM ratio*). This is measured as the ratio of full-time nurses to health-care assistants. A higher *M-NM* ratio suggests higher quality since nurses have more

advanced expertise in the caring process than health-care attendants. However, this might indicate falling TEs if more nurses are employed relative to health-care attendants as more resources might be used. On the other hand, this research could argue that having more nurses in contrast to health-care attendants could lead to more efficient outcomes.

○ *Ratio of Labour to Capital*

The fourth variable capturing the quality of nurses is the labour-capital ratio (*L-C ratio*) which is measured as the proportion of full-time nurses to the number of beds available in a nursing home. *A priori*, it is likely that more nurses per bed increases quality, but on the other hand, it also increases labour inputs which may reduce TE. However, these resources may be more productive and effective relative to other staff members, which could result in higher TEs.

○ *Staff Turnover*

Finally, this study uses staff turnover variables as additional structure-oriented measures of quality; namely the nurse turnover and the health-care attendant (HCA) turnover rates as detailed in Table 4-9. Nurse turnover is defined as the percentage of nurses who left the nursing home in 2007, whereas HCA turnover is defined as the percentage of care attendants that left the organization in the same year.

According to Castle (2006), the high staff turnover rates in NHs is not a recent phenomenon. Cohen-Mansfield (1997), and Halbur and Fears (1986) have documented average turnover rates for registered nurses, licensed vocational nurses, and certified nurse aides (CNAs), ranging between 55% and 75%, or even reaching 100% for CNAs. Moreover, a large number of studies (Castle and Engberg 2005; Bostick *et al.* 2006) purport that high turnover rates are associated with poor quality of care. In contrast, low levels of turnover may increase quality as they reflect the adjustment of an organization to its workforce and vice versa; ensuring that those who remain employed are suited to the job and the work environment (Brannon *et al.* 2002). In their study of Rhode Island NHs, Spector and Takada (1991) found the lower turnover rates of health-care professionals to be positively related to patients' higher functional

improvements. Thus, this research could expect that lower turnover rates could be connected with higher quality. Also, this study could expect that staff who remain with the organization are familiar with the patient, the culture of the nursing home, and the general day-to-day running of the facility which could improve the TEs of the care unit. Equally, however, low turnover rates can lead to stagnation and lower staff productivity. In turn, a high turnover rate may lead to increases in innovation and competition resulting in increasing TEs.

4.6.5 Summary Statistics for Output and Inputs

Table 4-10 presents the descriptive statistics of output and inputs variables for all NHs and their subsamples of public and private homes, private chain and non-chain homes, urban and rural homes. The NHs in the sample produced on average 54,500 total patient days, with a minimum of 16,200 days for private homes and approximately 7,920 days for public NHs. The maximum output is 165,900 total patient days for public NHs. Moreover, the mean value of total patient days is slightly higher for private NHs than for public nursing units. On the other hand, focusing on private chain and non-chain NHs the average value of total patient days is higher in non-chain homes relative to chain homes. With regard to urban and rural areas, the mean value of patient days in urban regions is equal to 66,325 compared to 46,616 in rural districts.

With regard to labour inputs, 15 nurses are employed on average in a public nursing units, compared to nine nurses in private homes. Moreover, the ratio of medical to non-medical personnel (M-NM ratio) in private-voluntary homes is approximately 1:2 in contrast to 1:1 in public homes which suggests that substitution may be occurring between medical and non-medical staff in private units. Consequently, this could influence their TE levels. Additionally, the M-NM ratio is also examined further as one of the output characteristics. In relation to private chain and non-chain homes the mean value of medical personnel is approximately the same for both types of NHs. However, the average number of health-care attendants (HCAs) is slightly higher in non-chain homes compared to private chain homes. With regard, to urban

and rural homes, the former averages twice the number of nurses employed in rural homes. Moreover, the ratio of medical to non-medical personnel in rural homes is almost to 1:2 which indicates that the substitution could be occurring between nurses and HCAs.

As for the capital input, the average number of beds provided in all NHs is 57; whereas this number is slightly higher for public and urban homes. In relation to HMD rate, Table 4-10 shows that the mean HMD rate in public NHs is equal to 0.66 compared to 0.51 in private facilities. Furthermore, private non-chain homes average a higher HMD rate than the private chain homes, which aligns with the discussion in Chapter Three. This could be attributable to the fact that private non-chain homes provide care to all types of residents, compared to chain homes which often specialize in specific types of care. Finally, urban and rural homes show a similar average proportion of ‘high-maximum dependency’ residents.

4.6.6 Summary Statistics for Efficiency Determining Variables

Table 4-11 presents the descriptive statistics of the potential efficiency determining variables⁷⁸ and demonstrates substantial differences in variables between private and public NHs. More than half of the NHs examined in this study are private (or profit-oriented) units (see *for-profit* dummy). Moreover, on average, 27% of beds in private homes are State-contracted. Although the size between private and public NHs is very similar on average, 47% of private NHs are medium-sized units (*size_2* with 50-99 beds) as opposed to 29% of public nursing units that are large homes with 100+, as indicated by variable *size_3*. However, most of the public NHs (58%) belong to the smallest size category with less than 50 beds (i.e. *size_1*). With regard to the *age* variable, public NHs tend to have been in operation considerably longer (66 years on average) than the private units (14 years). The majority of public NHs are located in the *Dublin Mid Leinster* Region while 57% of private NHs are located in Dublin region. With

⁷⁸ For convenience reasons, determinants are split into continuous variables, displaying their respective means, and into categorical/dichotomous variables which display the % share of NHs for which the particular characteristics are present.

regard to the *urban* variable, the distribution among private and public NHs is relatively similar. The HMD rate is higher in public NHs than in private homes, and the statistics is consistent with the discussion of trends in the residents' dependency levels in Chapter Three (Figures 3-5 and 3-6).

In terms of *staff turnover*, private homes demonstrate considerable non-retention of personnel compared to public homes. In fact, nurse turnover rates are four times that of public facilities. Similarly, 30% of HCAs leave private facilities compared to only 9% in public homes. These high turnover rates may have adverse implications for the quality of care process and for the pro-efficient smooth running of the homes.

In terms of *staffing level* and *staff flexibility*, *L-C* ratio, and the *M-NM* staff ratio, all these indicators are higher on average in public NHs than in private units. A higher level of *staff flexibility* indicates that public NHs employ more part-time nurses than private homes. A higher *L-C* and *M-NM* ratio further indicates the public NHs employ more professional medical staff (nurses) relative to the number of beds and the non-medical staff, respectively. On the other hand, there is a higher proportion of *single rooms* in private homes (49%) compared to public units (15%). Whereas public homes were built in the past for 4-6 bed wards, private facilities are relatively new and offer more single bedrooms than shared rooms.

In relation to efficiency determinants for private chain and non-chain homes specifically, the summary statistics in Table 4-11 offer revealing insights into this 'group'. Firstly, private chains are a relatively recent phenomenon as the average age of chain homes is nine years compared to 19 years for non-chain homes. Secondly, the majority of private chain homes are located in *Dublin North East* and *Mid-Leinster* compared to non-chain homes where 65% of these are located in the *South* and *West*. Table 4-11 also confirms that medical and non-medical turnover rates are higher in chain units than in the non-chain homes. This divergence might reflect the challenges of the staff being transferred between the non-chain homes. Moving

between the care facilities requires the staff members to familiarize themselves with the norms and culture of the new unit, which could generate an additional staff workload in the short to medium term. Moreover, the ratio of part-time nurses to full-time nurses, as measured by the staff flexibility ratio variable, is greater in non-chain homes (0.996), as compared to 0.445 in chain facilities. Since the option of re-deploying staff to other units of the home is not possible in a sole business, the likelihood of part-time work may be greater in non-chain homes relative to chain homes. Moreover, private non-chain homes average a higher HMD rate compared to non-chain homes. This could have repercussions on the TE of these homes, as greater inputs are required to meet the care needs of elderly people.

Table 4-10: Summary Statistics for Output and Inputs in DEA and SFA Models

Variable	All homes	Public	Private	Private Chain	Private Non-Chain	Urban	Rural
Output = total patient days							
Mean	54,500	51,052	56,320	49,767	61,562	66,325	46,616
Std Dev	32,884	38,871	29,378	24,197	32,287	36,893	27,482
Min	7,920	7,920	16,200	16,200	16,200	17,940	7,920
Max	165,900	165,900	148,000	125,430	148,800	165,900	148,800
Primary Labour = the number of medical staff							
Mean	11.463	15.289	9.444	9.687	9.25	15.204	8.969
Std Dev	11.268	16.946	5.772	6.166	5.508	15.976	5.320
Min	1	1	1	3	1	1	1
Max	82	82	30	30	29	82	29
Secondary Labour = the number of non-medical staff							
Mean	19.227	19.92	18.861	17.406	20.025	21.886	17.454
Std Dev	11.596	13.567	10.493	7.716	12.248	13.409	9.927
Min	2	3	2	5	2	4	2
Max	61	61	50	45	50	61	50
Capital Input = the number of beds in a nursing home							
Mean	56.98	58.02	56.430	55.968	56.8	66.5	50.636
Std Dev	30.83	40.757	24.352	22.161	26.247	38.895	22.165
Min	18	18	22	27	22	22	18
Max	175	175	128	120	128	175	128
HMD rate as case-mix = the proportion of high-maximum dependency residents							
Mean	0.559	0.655	0.508	0.495	0.517	0.555	0.561
Std Dev	0.180	0.170	0.164	0.142	0.180	0.193	0.171
Min	0.066	0.066	0.111	0.111	0.12	0.111	0.066
Max	0.886	0.886	0.854	0.733	0.854	0.880	0.886
No. of observations (NHs)	110	38	72	32	40	44	66

Table 4-11: Summary Statistics of Potential Efficiency Determining Variables

Variable and description		All homes	Public	Private	Private Chain	Private Non-Chain	Urban	Rural
Indicator (dummy) Variables								
Ownership (1=Private, 0 = Public)	%	65.45	n/a	n/a	n/a	n/a	61.36	68
Size_1 (0–49 beds)*	%	48.18	57.89	43.05	40.62	45	40.90	53.03
Size_2 (50–99 beds)	%	40.90	28.94	47.22	50.00	45	40.90	40.90
Size_3 (≥ 100 beds)	%	10.90	13.15	9.72	9.37	10	18.18	6.06
Southern region	%	29.09	21.05	33.33	28.12	37.5	25	31.81
Western region*	%	20.90	15.78	23.61	18.75	27.5	11.36	27.27
Dublin North East region	%	17.27	21.05	15.27	25.00	7.5	20.45	15.15
Dublin Mid Leinster region	%	32.72	42.10	27.77	28.12	27.5	43.18	25.75
Location (1=Dublin and 0 otherwise)	%	50	36.84	56.94	46.87	65	36.36	59.09
Urban (=1 if population ≥ 25,000 and 0 otherwise)	%	40	44.73	37.50	37.50	37.5	n/a	n/a
Chain	%	n/a	n/a	44.4	n/a	n/a	27.27	30.30
Continuous Variables								
Share of contract beds	mean	n/a	n/a	26.86	27.94	26.01	54.95	50.25
Age of premises	mean	32.30	66.23	14.40	8.75	18.92	36.54	29.48
HMD rate (proportion of high-maximum dependency residents)	mean	0.559	0.655	0.508	0.495	0.517	0.555	0.561
% single rooms	mean	37.29	14.73	49.19	50.15	48.42	35.09	38.75
Staffing level	mean	0.229	0.302	0.191	0.200	0.183	0.220	0.236
Staff flexibility	mean	1.341	2.457	0.751	0.445	0.996	1.255	1.397
Labour to capital (L-C) ratio	mean	0.191	0.243	0.163	0.169	0.157	0.204	0.181
Medical to non-medical (M-NM) ratio	mean	0.627	0.780	0.546	0.546	0.545	0.717	0.566
Nurse turnover in %	mean	30.81	11.44	41.03	49.14	34.54	31.58	30.299
HCA turnover in %	mean	22.93	9.34	30.10	33.75	27.19	22.52	23.211
No. NHs		110	38	72	32	40	44	66

Notes: * denotes the reference category

4.7 Conclusion

This chapter presented the wide spectrum of methods applied in this research to estimate the TEs of INHs and to identify the relevant efficiency determinants which explain the inefficiencies of this sector. The first estimation strategy employed in this study was conventional DEA. As a non-parametric method, DEA does not rest on assumptions about the functional form of the production technology of the investigated NHs and their subsamples. Moreover, it is the predominant orientation in the efficiency studies of the NH sector. Nevertheless, it is limited by an implicit assumption that all of the distance between an observed firm and the frontier reflects inefficiency. However, the distance of an observation from the efficient boundary actually reflects both the inefficiency and noise. This is because the observed input-output data could be subject to measurement error, or there could be noise in the data due to omitted input or output variables.

Therefore, bootstrapping approaches provide an attractive alternative to the conventional DEA approach. The homogenous bootstrap corrects for any bias in the original DEA efficiency scores and CIs for them, approximating the properties of the sampling distribution of an estimator. The two-stage DB DEA approach not only produces robust ‘pseudo estimation’ of the parameters of the efficiency determinants, but also re-estimates the TE scores to adjust for the values of these efficiency determining variables to give unbiased efficiency estimates.

However, while these bootstrapping techniques estimate bias corrected TEs by dealing with sample variability, they do not attempt to account for random noise, which may arise from measurement or specification error. In view of this, the final method employed in this study to estimate TE is the SFA. This parametric technique assumes the distance from the frontier is composed of two parts: one representing statistical noise; and the other inefficiency.

In order to evaluate the determinants of TE, this study employs two-stage semi-parametric and parametric methods. The first semi-parametric technique applied in this research is the two-stage OLS approach, whereby the TE scores are estimated by DEA in the first stage, and in the second stage these estimates are regressed on a comprehensive range of efficiency determining variables. Given that the TE estimates are censored between 0 and 1, two-stage Tobit regression is accordingly applied. Nevertheless, according to Simar and Wilson (2007; 2011), these conventional inference methods fail to give valid inference due to the fact that in the second-stage, true efficiency remains unobserved and must be replaced with DEA estimates of efficiency, and these are serially correlated by construction, and are also biased. To control for this drawback, this research employs the two-stage DB DEA which enables robust estimation of both TE and the corresponding TE determinants. Nonetheless, these semi-parametric methods still fail to recognize that the primary dataset is subject to random error. To overcome this limitation, the SFA IDF method is applied which not only controls both for statistical noise and inefficiency, but it also allows unbiased parameters of both the efficiency term and the (in)efficiency determinants to be estimated.

However, because the final sample used in the empirical part of this thesis is rather small at just 110 observations of NHs, estimating the parametric SFA IDF might be deemed vulnerable or infeasible in this case. This indicates the need to apply the non-parametric DEA or semiparametric two-stage DEA methods to measure TE and efficiency determinants of INHs. These empirical issues will be further explored in the Chapters Five and Six.

Additionally, this chapter presented and described the primary dataset of this research, including the data gathering process, the data sample used, the design of the questionnaire, the pilot-testing, the fieldwork conducted, and the final dataset. The chapter further delineated the definition and measurement of output and inputs in the NHs. While output is measured as total patient days, inputs are measured as medical staff, non-medical staff, and the number of beds

in the NH unit. The research also included as an additional input the high-maximum dependency (HMD) rate in the NHs. This index represents a proxy for a case-mix and ensures application of a case-mix adjusted efficiency model. The sample of NHs is also divided into different subsamples to evaluate the TE of these facilities: namely, public and private NHs, private chain and non-chain facilities, and care homes located in urban and rural areas.

This chapter considered a comprehensive set of potential determinants of efficiency, some of which have been previously examined in the NHs literature. On other hand, other determinants applied in this thesis are novel variables, such as the HMD rate which is a proxy for case-mix, or certain quality factors (e.g. *medical to non-medical staff* or *staff flexibility*). Furthermore, the determinants of the present study are divided into conventional factors and output-characteristic variables. The conventional factors are common to a firm in any sector, and these factors include, among others, ownership, size, location, and the age of the nursing home. Output-characteristic variables are specific to the NH sector and include HMD rate, chain versus non-chain status, and other numerous quality-related factors. The quality factors relate to structural quality and include single bedrooms, and various labour management factors.

Chapter Five is the first of two empirical chapters in which the full spectrum of methods is applied to the entire dataset. These methods range from non-parametric to parametric techniques to estimate the input-oriented TE of INHs.

4A Appendix

Appendix 4A-4-1 The Double Bootstrap DEA Procedure used in Algorithm #2 of Simar and Wilson (2007; 2011).

Using the original sample of data, estimate the input-oriented DEA TE scores $\hat{\theta}_i$ s ($i = 1, \dots, n$)

- 1 Obtain estimates \hat{B} in the truncated regression $0 < \hat{\theta}_i = z_i B + \varepsilon_i \leq 1$ using $m < n$ observations, when $\hat{\theta}_i < 1$
- 2 Loop over the next four steps (i-iv) $L_1=100$ times to obtain a set of bootstrap estimates $B = \{\hat{\theta}_{ib}^*\}_{b=1}^{L_1}$, $i=1, 2, 3, \dots, n$
 - i. For each $i=1, \dots, n$ draw ε_i from $N(0, \hat{\delta}^2)$ with left truncation at $-z_i \hat{B}$ and right truncation at $1 - z_i \hat{B}$
 - ii. Compute $\theta_i^* = z_i \hat{B} + \varepsilon_i, i = 1, \dots, n$
 - iii. Set $x_i^* = x_i \hat{\theta}_i / \theta_i^*$ and $y_i^*, i = 1, \dots, n$
 - iv. Using x_i^* and y_i^* , estimate $\hat{\theta}_i^* (i = 1, \dots, n)$ using the DEA estimator
- 3 For each ($i = 1, \dots, n$), compute the bias-corrected estimates $\tilde{\theta}_i$ using the bootstrap estimates in B and the original estimates $\hat{\theta}_i$
- 4 Estimate the truncated regression of $\tilde{\theta}_i$ on z_i to obtain estimates \tilde{B}
- 5 Loop over the next three steps (i-iii) $L_2=2000$ times to obtain a set of bootstrap estimates $\Delta = \{\tilde{B}^*\}_{b=1}^{L_2}$
 - i. For each $i = 1, \dots, n$, draw ε_i from $N(0, \tilde{\delta}^2)$ with left truncation at $-z_i \tilde{B}$ and right truncation at $1 - z_i \tilde{B}$
 - ii. Compute $\theta_i^{**} = z_i \tilde{B} + \varepsilon_i, i = 1, \dots, n$
 - iii. Estimate the truncated regression of θ_i^{**} on z_i , yielding estimates \tilde{B}^*
- 6 Use the bootstrap values in Δ and the original estimates \tilde{B} to construct confidence intervals for each element of B . The $(1-\infty)$ confidence interval for B_j is constructed by finding values $a_{\infty/2}$ and $b_{\infty/2}$ such that $\Pr\{-b_{\infty/2} \leq (\tilde{B}^*_j - \tilde{B}_j) \leq -a_{\infty/2}\} \approx 1-\infty$

Chapter Five: Estimating Technical Efficiency

5.1 Introduction

This chapter is the first of the two empirical chapters which detail the full spectrum of non-parametric to parametric methods applied to estimate the input-oriented (IO) TE scores of INHs. Building on this, Chapter Six then identifies the determinants that influence the TE scores of the examined homes.

In estimating input-oriented TE, this research interrogates how far the input vector can be proportionally reduced while holding the output vector fixed. While output is measured as the total patient days, inputs are measured as the medical staff, non-medical staff, and the number of beds in the NH unit. This research also includes as an additional input the high-maximum dependency (HMD) rate of the NH residents. This index represents a proxy for a case-mix and ensures application of a case-mix adjusted efficiency model. The study also divides the sample of NHs into the different subsamples of public and private NHs, private chain and non-chain facilities, and care homes located in urban and rural areas, to evaluate the TE of these facilities. In order to estimate the TE scores of Irish care homes across a full spectrum of methods the following techniques are employed:

- Conventional DEA
- Homogenous Bootstrap DEA (HB DEA)
- Two-Stage Double Bootstrap DEA (DB DEA)
- Stochastic Frontier Analysis (SFA)⁷⁹

The empirical analysis first presents the results derived from the conventional DEA non-parametric approach. The original DEA model assumes the constant returns to scale (CRS)

⁷⁹ Both the conventional DEA TE scores and the homogenous bootstrap DEA TE scores are obtained in R using the FEAR software package of Paul Wilson (2008). The double bootstrap DEA estimations are performed in R using the rDEA package using the algorithm 2 of Simar and Wilson (2011). The SFA input distance function estimations are performed in Stata 14.

technology which infers that care units operate at optimal scale. However, this technique is here extended to incorporate variable returns to scale (VRS) to allow for the estimation of a pure TE and scores devoid of scale inefficiency. The CRS and VRS DEA results are also used to derive the scale efficiency (SE) scores alongside the TE results for the INHs. While conventional DEA is the prevailing method for estimating TE in the NH arena, a notable weakness of this approach is that it assumes that all distance between an individual observation and the efficient frontier reflects inefficiency. This method does not allow for measurement error or noise in the data due to omitted variables or random shocks and implies that the TE scores do not have a random distribution. To control for this weakness in the non-parametric approach, the present research applies two DEA bootstrapping techniques that simulate the random distribution of the TE scores. Accordingly, the bias-corrected TE scores and their corresponding confidence intervals (CIs) are derived.

The first bootstrapping technique is the HB DEA which is used to examine the robustness of our estimated conventional DEA IO TE scores by correcting for any bias in these scores. The HB DEA method, however, does not account for the efficiency determinants in the estimation of the TE scores. In light of this, the present thesis employs the two-stage DB DEA as the second bootstrap technique of this study. In this semi-parametric method, the bias-corrected TE scores incorporate the effects of the determining variables as further elucidated in Chapter Six. While the DB DEA technique adjusts the bias-corrected estimates by the values of the efficiency determining variables, the data is still subject to noise which can only be accounted for within the parametric SFA model. As such, the final estimation technique employed in this study is the parametric SFA IDF model which assumes that any deviation from the frontier is composed of two parts: one representing noise; and the other inefficiency.

Section 5.2 presents the IO TE scores of INHs by applying the conventional DEA model and Section 5.3 outlines the HB DEA bias-corrected TE results. Section 5.4 provides the TE results for the DB DEA method. Section 5.5 compares the results of the different techniques with the conventional DEA TE scores to determine whether the original TE scores underestimate or overestimate the true TE scores of INHs. Section 5.6 discusses the results of the parametric SFA approach and Section 5.7 offers concluding remarks.

5.2 Conventional DEA Model Results

The conventional DEA is employed to estimate the IO TE of INHs. By applying both CRS and VRS DEA models, the present study can also ascertain whether the NHs are scale efficient. The section commences with the discussion on the optimal model choice in terms of the inputs used in the DEA specification leading to a discussion on the estimated TE and SE scores for all homes. Attention then turns to the subsamples of public and private NHs, private NHs with chain and non-chain status, and finally, urban and rural units.

Optimal model choice

Before moving to the detailed analysis of the TE and SE scores by applying the different estimation techniques, the study firstly applies the conventional DEA to identify the optimal empirical model choice. The obtained average TE scores for all three model specifications, outlined in Chapter Four, are outlined in Appendix 5A-5-1 and confirm that the three models vary depending on the measurement of labour input. Whereas DEA *Model 1* excludes the non-medical staff from the labour input, DEA *Model 2* excludes the medical staff, and DEA *Model 3* includes all labour inputs (both medical and non-medical staff). The TE scores vary between 0 and 1, where a TE score of 1 indicates that the care unit is fully (100%) efficient and a score smaller than 1 indicates that the unit could decrease its levels of inputs producing the same level of output in order to be fully technically efficient.

The VRS estimates in Appendix 5A-5-1 present the mean TE scores for all NHs for *Models 1, 2, 3* are 0.65, 0.62 and 0.66, respectively. This indicates that they are technically inefficient and need to decrease input levels between 34 and 38% to achieve full efficiency. The TE scores are lower, however, using the non-medical staff only (*Model 2*), relative to *Models 1* and *3* where medical staff is taken into account. This suggests that medical staff is the most important labour input for INHs, while employing less medical staff leads to inefficient outcomes. Following these results, and to ensure an holistic measurement of the TEs of Irish care homes, the results of *Model 3* are presented as the main findings here and in Chapter Six. Thus, the DEA *Model 3* will be used for all estimation techniques discussed in the empirical part of the thesis.

The research also compares the findings of the original model when the high-max dependency (HMD) rate is included as the fourth input in Appendix 5A-5-1 with alternative findings in Appendix 5A-5-2 which presents the prior three model specifications but exclude the HMD rate as the fourth input in the DEA linear programming. For example, the preferred model, namely *Model 3*, illustrates the VRS TE scores are lower for all, private and public homes (=0.69; 0.64; 0.62) than in Appendix 5A-5-1 when the HMD rate is accounted for in the DEA model (=0.78; 0.69; 0.66). The same finding applies to the CRS TE scores. Thus, comparison of the results clearly shows that both VRS and CRS TE scores are higher when the HMD rate is included as it accounts for the case-mix in the NH sector. From this follows that the optimal empirical model includes four inputs: capital, both labour inputs (medical and non-medical staff), and the HMD rate as an additional input. Accordingly, this research will continue reporting the results of this main model specification for all estimation techniques presented in this thesis.⁸⁰

⁸⁰ The alternative results excluding the HMD rate as an input (for all specifications presented in Chapters 5 and 6) are available on request.

All Homes

Table 5-1 summarizes the results of the estimated TE and SE scores for all NHs and the different subsamples of this study. The CRS DEA model implicitly assumes that NHs are scale-efficient, whereas the VRS DEA model estimates a ‘pure’ efficiency estimate which is devoid of scale inefficiencies. The average CRS TE score is equal to 0.58 for all NHs; implying these homes could reduce their inputs usage by up to 42% for the same level of patient days. In contrast, the VRS estimates (0.664) are higher than the CRS scores. Where scale inefficiencies are present, the CRS TE scores will underestimate the ‘true’ VRS DEA TE scores. The SE is obtained as the ratio of CRS TE scores to the VRS TE scores. Table 5-1 also reports a mean SE score of Irish care units as 0.861, implying that the SE score is less than 1 and such facilities are not scale efficient. Moreover, as the SE is on average higher than the TE, the productivity of the NHs is driven to a greater extent by SE than as a result of TE.

The results confirm that the efficiency performance of Irish care facilities is poor compared to previous research as summarized in Table 2-1. For example, Bjorkgren *et al.* (2001) and Laine *et al.* (2005a) found the mean TE estimates of around 0.85 and 0.72, respectively, for the long-term residential care units in Finland. As the output variable used in these studies was also adjusted by the case-mix, their results provide a useful benchmark to assess the productive efficiency performance of INHs. Similarly, Borge and Hardaldsvik (2009) reported a mean input-oriented DEA TE estimate of 0.84 for Norwegian NHs, where their output variable was measured using the total number of residents. This finding corresponds to an earlier Norwegian study by Kalseth (2003). Nyman and Bricker (1989) obtained an average TE estimate of 0.89 for Wisconsin NHs in the USA, whereas DeLellis and Ozcan (2013) found a mean TE score of 0.87 relating to a random sample of US NHs. Interestingly, Kleinsorge and Karney (1992) found 22 Kansas NHs to be fully efficient, meaning these homes had an average TE score

of 1. The average SE scores of INHs broadly align to those derived by Chattopadhyay and Ray (1996) who found mean levels of SE of 0.96 for non-profit homes in Connecticut.

Public and Private NHs

Table 5-1 presents the TE scores for the subsamples of public and private NHs. The CRS TE scores demonstrate that private facilities are less technically efficient (0.617) than public homes (0.618). Table 5-2 shows that this difference is statistically significant, as based on the mean-comparison (one tailed) t-test and the Mann Whitney test, although the numeric difference between the scores is miniscule. Likewise, the VRS TE scores, which show a 'pure' TE, indicate that private homes are less efficient than public homes but there is no statistical difference in the average means of these subsamples. The inconclusive differences in the mean scores of private and public homes highlights the necessity to investigate the 'ownership' variable as an efficiency determinant in the multivariate regression analysis which is conducted in Chapter Six.

The average VRS TE scores of public and private facilities are at 0.78 and 0.70, respectively, and they are also lower for private homes compared to other efficiency studies of the NH sector. For example, Chattopadhyay and Heffley (1994) obtained average TE estimates of 0.71 and 0.92 for non-profit and for-profit facilities in Connecticut, respectively. Similarly, Ozcan *et al.* (1998) derived mean productive efficiency scores of 0.80 for non-profit homes, and 0.84 in for-profit units in skilled nursing facilities in the USA. Equally, Anderson *et al.* (1999) found for-profit homes to have an average efficiency scores of 0.90 and non-profit homes to have a mean TE score of 0.73.

The average SEs of public and private NH homes are also presented in Table 5-1. The average SE score is equal to 0.78 for public NHs and 0.873 for private facilities. Table 5-2 confirms that the difference in the SE scores between private and public units is statistically significant. Furthermore, as the SE score is greater on average than the TE estimates of public and private

NH units, it is evident that the overall productivity of the facility emanates from the SE as opposed to the TE.

While no statistical difference in the mean VRS TE scores between public and private units was found, there are important differences in the distribution of these scores between the two groups of NHs. Table 5-3 presents the percentage distribution of VRS TE and SE scores when the NHs are split into public and private units. A total of 42% of private units display TE scores which are below 0.60, indicating that they could reduce their inputs usage by up to 40% for the same level of total patient days. In comparison, 16% of public facilities have TE scores lower than 0.60. Moreover, 21% of public homes are fully technically efficient, and 15% of private facilities are found to have a TE score equal to 1. Conversely, 13% of public homes and 14% of private facilities are scale efficient.

This study also compares the TE scores obtained for the non-increasing returns to scale (NIRS) and VRS DEA models in order to determine whether NHs which are scale inefficient produce at increasing or decreasing returns to scale. Table 5-4 demonstrates that 77% of all homes exhibit increasing returns to scale (IRS) and should therefore increase their operations (all inputs) to become scale efficient. Similarly, 14% of all homes are operating at the decreasing returns to scale (DRS) and should reduce their scale of operation in order to achieve optimal scale. Just 9% of all homes are operating at optimal scale (CRS) and scale efficient. A similar pattern for returns to scale can be observed for both public and private NHs and other respective subsamples in Table 5-4.

Private Chain and Non-Chain NHs

The private NHs sample is also split into private chain and private non-chain homes. Private chain NHs in Ireland are a part of a group: in other words, an owner can own more than one nursing home. NHs which are run as a part of the chain enjoy many advantages, including

sharing of resources and bulk-purchasing, which can yield economies of scale and cost savings. On the other hand, decision-making in the chain NHs can be slower than in the non-chain facilities as the latter homes are independent singular institutions. Table 5-1 demonstrates that private chain facilities (0.848) are more efficient than private non-chain homes (0.753), while Table 5-2 highlights that the difference is statistically significant. Moreover, the CRS and VRS technical efficiencies of private chain homes (0.716; 0.848) and private non-chain homes (0.677; 0.753) are significantly higher than the TE scores obtained for the overall private sample (0.617; 0.698). Additionally, the frequency distribution of the TE scores of private chain and private non-chain homes shown in Table 5-3 illustrates that 38% of private chain and 25% of non-chain homes are technically efficient. Similarly, the frequency distribution of SE scores in Table 5-3 indicates that 22% of private chain homes and 23% of private non-chain homes are operating at CRS.

Since these results slightly differ from those obtained for the overall sample of all private homes, they emphasize the advantage of evaluating the subsamples over the full sample in the DEA model. In short, the two groups of NHs may have different production technologies and these differences cannot be captured by applying the pooled DEA model.

Urban and Rural NHs

Table 5-1 shows that urban homes are more technically efficient than rural homes regardless of whether the CRS or VRS DEA model is used. The difference in the CRS TE scores between rural and urban NHs is statistically significant based on the mean comparison (one tailed) t-test and the Mann Whitney test. In contrast, the difference in the VRS TE estimates between these homes is not statistically significant. Furthermore, the frequency distribution of TE and SE scores for both urban and rural homes shows a 'broadly' similar pattern to that presented for public and private NHs. Table 5-4 demonstrates that 52% of urban homes and 80% of rural homes are operating at IRS meaning these facilities must increase their scale of operation in

order to achieve optimal scale. Conversely, 30% of urban homes and 6% of rural homes must decrease their scale of operation in order to reach their optimal scale.

Table 5-1: Conventional DEA Model Result

	No. NHs	Conv. DEA Mean	Std. Dev	Min	Max
CRS TE Scores					
All Homes	110	0.577	0.218	0.088	1
Public	38	0.618	0.217	0.100	1
Private	72	0.617	0.228	0.142	1
Private Chain	32	0.716	0.217	0.225	1
Private Non-Chain	40	0.677	0.241	0.183	1
Urban	44	0.656	0.222	0.258	1
Rural	66	0.576	0.219	0.092	1
VRS TE Scores					
All Homes	110	0.664	0.196	0.345	1
Public	38	0.781	0.184	0.368	1
Private	72	0.698	0.194	0.355	1
Private Chain	32	0.848	0.161	0.540	1
Private Non-Chain	40	0.753	0.187	0.397	1
Urban	44	0.747	0.204	0.389	1
Rural	66	0.706	0.174	0.359	1
Scale Efficiency					
All Homes	110	0.861	0.173	0.204	1
Public	38	0.780	0.175	0.199	1
Private	72	0.873	0.170	0.318	1
Private Chain	32	0.833	0.161	0.417	1
Private Non-Chain	40	0.886	0.184	0.375	1
Urban	44	0.874	0.149	0.337	1
Rural	66	0.804	0.201	0.211	1

Table 5-2: Mean Comparison Tests for Conventional DEA Results

	Public-Private		Private Chain-Non-Chain		Urban-Rural	
	Criterion value (z/t) (p value)	Decision with respect H ₀	Criterion value (z/t) (p value)	Decision with respect H ₀	Criterion value (z/t) (p value)	Decision with respect H ₀
CRS TE						
t-test H ₀ : TE – TE = 0	-2.134** (0.035)	Reject	2.308** (0.023)	Reject	-2.145 (0.034)	Reject
Mann-Whitney test	-2.138** (0.032)	Reject	2.528** (0.011)	Reject	-1.910 (0.056)	Reject
VRS TE						
t-test H ₀ : TE – TE = 0	-0.903 (0.368)	Accept	3.25*** (0.001)	Reject	-1.622 (0.107)	Accept
Mann-Whitney test	-0.881 (0.378)	Accept	3.02*** (0.002)	Reject	-1.344 (0.178)	Accept
Scale Efficiency (SE)						
t-test H ₀ : SE – SE = 0	-2.310** (0.022)	Reject	-1.174 (0.244)	Accept	-1.643 (0.103)	Accept
Mann-Whitney test	-2.81*** (0.004)	Reject	-1.250 (0.211)	Accept	-1.233 (0.217)	Accept

***significant difference at the 1% level, ** significant difference at the 5% level, and * significant difference at the 10% level.

Table 5-3: Frequency Distribution of Efficiency (VRS DEA) of the Different Samples

Range	All Homes		Public		Private		Private Chain		Private Non-Chain		Urban		Rural	
	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%
Technical Efficiency														
1.00	15	14	8	21	11	15	12	38	10	25	11	25	9	14
0.90-0.99	4	4	6	16	3	4	4	13	2	5	4	9	1	2
0.80-0.89	7	6	3	8	6	8	4	13	3	7	3	7	8	12
0.70-0.79	13	12	9	24	10	14	2	6	6	15	7	16	12	18
0.60-0.69	23	21	6	16	12	17	9	28	12	30	6	14	18	27
Below 0.60	48	44	6	16	30	42	1	3	7	18	13	30	18	27
Total	110	100	38	100	72	100	32	100	40	100	44	100	66	100
Scale Efficiency														
1.00	10	9	5	13	10	14	7	22	9	23	8	18	9	14
0.90-0.99	58	53	4	11	47	65	8	25	20	50	18	41	21	32
0.80-0.89	15	14	12	32	6	8	1	3	4	10	6	14	9	14
0.70-0.79	8	7	6	16	3	4	8	25	0	0	6	14	3	5
0.60-0.69	8	7	4	11	2	3	6	19	3	7	4	9	14	21
Below 0.60	11	10	7	18	4	6	2	6	4	10	2	5	10	15
Total	110	100	38	100	72	100	32	100	40	100	44	100	66	100

Table 5-4 :The Nature of Returns to Scale Obtained from NIRS DEA Model

	All Home		Public		Private		Private Chain		Private Non-Chain		Urban		Rural	
	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%
Constant returns to scale (CRS)	10	9	5	13	10	14	7	22	9	23	8	18	9	14
Increasing Returns to Scale (IRS)	85	77	28	74	55	76	21	66	27	68	23	52	53	80
Decreasing Returns to Scale (DRS)	15	14	5	13	7	10	4	13	4	10	13	30	4	6
Total	110	100	38	100	72	100	32	100	40	100	44	100	66	100

5.3 Homogenous Bootstrap DEA Model Results

The homogenous bootstrap (HB) DEA technique is employed to validate the conventional non-parametric DEA scores. This study applies the bootstrapping in DEA proposed by Simar and Wilson (1998; 2000) as delineated in Chapter Four. The procedure entails repeated sampling from the obtained conventional DEA TE scores to construct an empirical sampling distribution for the bootstrapped DEA scores of the NHs. The bias in the DEA efficiencies can then be estimated and 95% CIs can be built using this empirical distribution.⁸¹ This section therefore commences with the estimation of the HB DEA results for all NHs, and then proceeds to the analysis of the results obtained for the subsamples of public and private homes, private chain and non-chain facilities, and urban and rural care facilities.

All Homes

Table 5-5 presents the mean HB DEA TE scores. Their corresponding CIs are also included and denoted as lower bounds (LBs) and upper bounds (UBs). The conventional DEA TE scores are also included for the purposes of comparison with the bootstrap DEA results. In relation to

⁸¹ The method developed by Simar and Wilson (2000) is relatively robust to the chosen bandwidth of the confidence intervals.

the overall sample, any bias is reflected in the difference between the mean conventional TE scores and the mean HB DEA TE estimates. The table illustrates that the conventional mean DEA CRS TE score for all INHs (0.577) exceeds the mean HB DEA TE score (0.466), indicating a positive bias. As such, the biased-corrected average TE scores for all NHs and their subsamples are much lower than the average conventional TE scores, implying that the NHs are considerably more inefficient than shown in the conventional DEA results. Furthermore, the bias is significant at the 5% level for both the VRS and CRS TE estimates for the overall sample in Table 5-5, as the average conventional DEA VRS and CRS TE scores are outside the bootstrapped upper bounds (UBs). The bias is statistically significant for all subsamples for the VRS technology in Table 5-5 as opposed to CRS technology where the bias is significant for the full sample of all NHs only.

With regard to SE, the CRS TE estimates obtained in the HB DEA method are very close to the VRS TE scores. Accordingly, the mean bias-corrected SE scores are 1 for all homes or very close to unity for the subsamples, indicating that the INHs are operating at CRS frontier and are scale efficient. This starkly contrasts with the earlier results wherein the VRS TE scores were greater than the CRS TE scores, and where scale inefficiencies were apparent for all NHs (e.g. conventional SE scores of all NHs were 0.86 on average). Accordingly, Table 5-7 presents the distribution of the TE and SE scores obtained in the HB DEA model, and all NHs have SE levels between 0.90 and 1, indicating very low scale inefficiency, with 75% of all homes producing at optimal scale.

Public and Private NHs

The average conventional VRS TE scores of public and private homes exceed the HB VRS DEA scores, inferring a positive bias in Table 5-5. Additionally, the bias is significant in these subsamples as the average conventional VRS TE scores exceed the upper bounds of the bootstrapped CIs. This suggests that the conventional VRS TE scores of public and private

homes over-estimate the ‘true’ or bias-corrected TE scores. Focusing on the VRS HB DEA scores, Table 5-5 demonstrates that private homes are more technically efficient (0.492) than public facilities (0.436), while Table 5-6 confirms the difference to be statistically significant.

Additionally, the HB DEA results in Table 5-5 demonstrate that both public and private NHs are operating close to the CRS technology. The mean HB DEA SE estimate for public homes is 0.99. This score is higher than the average conventional SE result (0.780) for public homes; reflecting a negative bias in the conventional DEA SE scores. Furthermore, this bias is significant as the average conventional SE scores are outside the lower bounds of the CIs. In relation to private facilities, the average HB DEA SE estimate is 0.999, and it is greater than its mean traditional SE score (0.873). Table 5-7 shows the frequency distribution of the HB SE scores and reveals that 71% of public homes and 72% of private units have SE estimates in the range of 0.90-0.99.

Figure 5-1 compares the kernel density functions of the original conventional DEA TE scores and the HB DEA TE scores for public and private homes, and for both CRS and VRS technologies. Thus, the kernel density functions are broadly similar for the CRS DEA methods (i.e. conventional CRS DEA versus HB CRS DEA). Moreover, a number of differences in the distribution of the CRS and VRS TE scores are evident for conventional DEA for public homes in panel (a). The CRS and VRS distributions of conventional TE scores are different and the variance of the CRS DEA model in panel (b) is wider than in the VRS model for public homes. Conversely, for private NHs, the distributions of both CRS and VRS scores of both the conventional DEA and the HB technique are very similar.

Private Chain and Non-Chain NHs

Table 5-5 presents the HB DEA TE scores of private chain homes and non-chain homes. In terms of ‘pure’ VRS efficiency estimates, private chain homes are more technically efficient

(0.617) than non-chain homes (0.571). The Mann-Whitney test shown in Table 5-6 confirms this difference to be statistically significant. Additionally, the HB DEA results in Table 5-5 reveal that private chain and non-chain homes are more inefficient than the conventional estimates indicate. The conventional DEA TE scores for these subsamples (0.848; 0.753) are outside the bootstrapped 95% CIs, and hence they are significantly different from the HB DEA TE estimates. This result infers that conventional DEA TE scores overestimate the true efficiency of private chain and non-chain homes which appears to be much lower in the bias-corrected HB DEA model. Given that Table 5-5 shows the HB CRS and VRS TE scores to be very similar on average, the mean HB SE scores of private chain and non-chain facilities are close to 1 as found for other NHs groups.

Urban and Rural NHs

Table 5-5 presents the average bias-corrected TE scores and their CIs, as well as the mean conventional TE estimates of urban and rural NHs. The conventional TE scores of urban (0.747) and rural homes (0.706) exceed the HB DEA TE scores (urban = 0.477; rural = 0.475), indicating a positive bias. Moreover, the fact that the conventional TE scores are outside the UBs, infers an over-estimation of the true efficiencies of urban and rural homes. In short, these facilities are more inefficient than originally estimated by the conventional DEA model. Furthermore, the results of Table 5-5 demonstrate that rural and urban homes have an average HB SE score equivalent to 1, while Table 5-7 shows the frequency distribution of HB DEA SE scores, where 82% of urban and 77% of rural homes are scale efficient.

Table 5-5: HB DEA Model Results

	No. NHs	Conv. DEA	HB DEA	LB	UB
CRS TE Scores					
All Homes	110	0.577*	0.466	0.378	0.575
Public	38	0.618	0.432	0.269	0.641
Private	72	0.617	0.492	0.397	0.618
Private Chain	32	0.716	0.618	0.531	0.748
Private Non-Chain	40	0.677	0.572	0.474	0.729
Urban	44	0.656	0.477	0.343	0.665
Rural	66	0.576	0.473	0.380	0.605
VRS TE Scores					
All Homes	110	0.664*	0.464	0.376	0.575
Public	38	0.781*	0.436	0.277	0.642
Private	72	0.698*	0.492	0.397	0.620
Private Chain	32	0.848*	0.617	0.529	0.756
Private Non-Chain	40	0.753*	0.571	0.473	0.734
Urban	44	0.747*	0.477	0.341	0.669
Rural	66	0.706*	0.475	0.385	0.609
Scale Efficiency					
All Homes	110	0.861*	0.997	0.995	1.000
Public	38	0.780*	0.994	0.993	0.999
Private	72	0.873*	0.999	1.003	1.004
Private Chain	32	0.833*	0.999	0.985	1.006
Private Non-Chain	40	0.886*	1.003	0.996	1.008
Urban	44	0.874*	1.005	0.976	0.999
Rural	66	0.804*	1.002	1.000	1.008

* denotes conventional DEA efficiency estimate is outside the bootstrapped 95% confidence interval, i.e. it is significantly different from the bias-corrected efficiency score.

Table 5-6: Mean Comparison Tests for Homogenous Bootstrap (HB) DEA Results

	Public-Private		Private Chain-Non-Chain		Urban-Rural	
	Criterion value (z/t) (p value)	Decision with respect H ₀	Criterion value (z/t) (p value)	Decision with respect H ₀	Criterion value (z/t) (p value)	Decision with respect H ₀
CRS TE						
t-test	-2.064**	Reject	1.509	Accept	-1.118	Accept
H ₀ : TE – TE = 0	(0.041)		(0.135)		(0.265)	
Mann-Whitney test	-1.993*	Reject	1.745*	Reject	-0.988	Accept
	(0.046)		(0.081)		(0.322)	
VRS TE						
t-test	-2.033**	Reject	1.492	Accept	-1.111	Accept
H ₀ : TE – TE = 0	(0.044)		(0.140)		(0.268)	
Mann-Whitney test	-1.974*	Reject	1.677*	Reject	-1.007	Accept
	(0.048)		(0.093)		(0.314)	
Scale Efficiency (SE)						
t-test	-0.550	Accept	0.580	Accept	-0.133	Accept
H ₀ : SE – SE = 0	(0.583)		(0.563)		(0.894)	
Mann-Whitney test	0.541	Accept	0.079	Accept	0.921	Accept
	(0.588)		(0.936)		(0.356)	

***significant difference at the 1% level, ** significant difference at the 5% level, and * significant difference at the 10% level.

Table 5-7: Frequency Distribution of Homogenous Bootstrap Efficiency (VRS DEA)

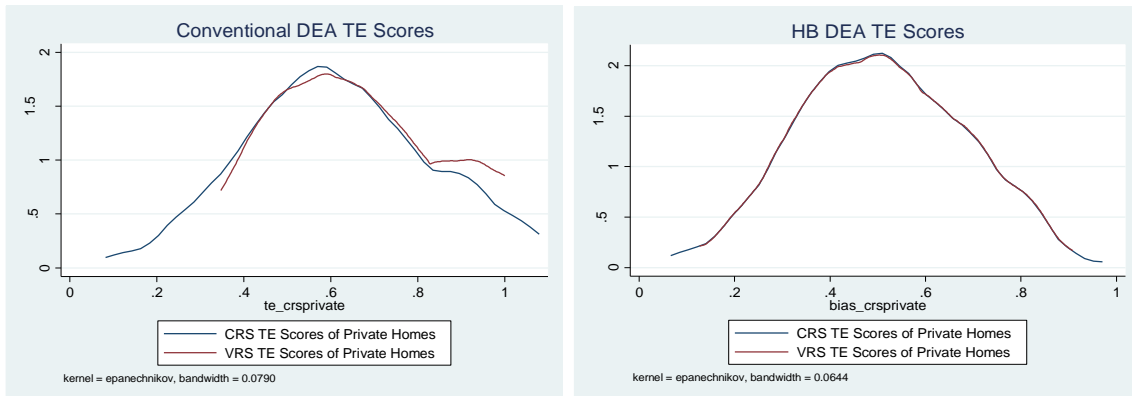
Range	All Homes		Public		Private		Private Chain		Private Non-Chain		Urban		Rural	
	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%
TE														
1.00	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0.90-0.99	0	0	0	0	1	1	2	6	1	3	0	0	0	0
0.80-0.89	3	3	0	0	1	1	5	16	4	7	0	0	3	5
0.70-0.79	8	7	0	0	11	15	1	3	3	7	5	11	5	8
0.60-0.69	9	8	4	11	10	14	9	28	12	30	2	5	8	12
Below 0.60	90	82	34	89	49	68	15	47	20	50	37	84	50	76
Total	110	100	38	100	72	100	32	100	40	100	44	100	66	100
Scale Efficiency														
1.00	82	75	11	29	20	28	9	28	35	87	36	82	51	77
0.90-0.99	28	25	27	71	50	72	23	72	5	13	8	18	15	23
0.80-0.89	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0.70-0.79	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0.60-0.69	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Below 0.60	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Total	110	100	38	100	72	100	32	100	40	100	44	100	66	100

Figure 5-1: Kernel Density Functions of Conventional DEA and HB DEA TE Scores

Panel (a): Public NHs



Panel (b): Private NHs



5.4 Double Bootstrap DEA Model Results

This section presents the DB DEA bias-corrected estimates of the overall sample in addition to the relevant subsamples. While the HB DEA technique estimates the bias corrected TE scores of the NHs, the DB DEA procedure in line of Simar and Wilson (2007; 2011) results in unbiased estimates of the parameters of the posited determining variables and bias-corrected bootstrap TE scores which are adjusted by the values of the efficiency determining variables.⁸² This section therefore delineates and compares the DB DEA scores with the scores derived from earlier methods.

⁸² The impact of those variables is further discussed in Chapter Six.

All Homes

Table 5-8 presents the DB DEA bias-corrected TE scores and the corresponding lower and upper CI bounds for all NHs. The conventional DEA TE estimates are also included in this table for the purposes of direct comparison. In relation to all NHs, the conventional VRS TE estimates are outside the CIs for the DB DEA scores, indicating that the conventional DEA scores overestimate the efficiency for all homes and that INHs are more inefficient than originally suggested by the conventional TE results. Additionally, the average conventional VRS TE score of all homes (0.664) is greater than the DB DEA bias-corrected TE estimate (0.581), which again implies a positive bias.

The results for the SE are similar to those obtained for the conventional DEA method. The average DB DEA VRS scores are higher than the mean DB DEA CRS estimates, which implies that scale inefficiencies are apparent across all NHs. However, the average DB DEA SE estimates (0.890) are higher than the mean conventional DEA SE scores for all homes (0.861) which infers a downward bias in the conventional SE scores. This result is as expected as the DB DEA model adjusts the bootstrapped CRS and VRS TE scores for the effects of size and other determinants to derive the bias-corrected TE scores.

Public and Private NHs

Given that the average conventional CRS TE scores for public and private homes are within the DB DEA lower and upper bounds as shown in Table 5-8, there is no significant difference between the traditional TE estimates and the DB DEA TE scores. Additionally, Table 5-8 demonstrates that private facilities are more technically efficient than public units since the CRS DB DEA estimates of private units (0.576) are greater than public care homes (0.572). Table 5-9 confirms this difference to be statistically significant. Moreover, the average conventional VRS TE scores of private facilities exceed the DB DEA CI bounds, inferring the true efficiencies of these facilities have been overestimated by the conventional DEA model.

Additionally, the traditional VRS TE scores of private units (0.698) are greater than the corresponding DB DEA estimates (0.622) which indicates a positive bias. Furthermore, the DB VRS results show that public homes (0.728) are more efficient than private facilities (0.622), although Table 5-9 shows this difference is insignificant.

In relation to the DB SE results, it is apparent that public and private units are more scale efficient than the average conventional SE scores suggested in Table 5-1. In fact, downward bias is apparent, since the average conventional DEA SE scores for public and private homes (0.780; 0.873) are less than the DB DEA SE scores (0.789; 0.914). Interestingly, the illustration of the frequency distribution of the DB DEA SE scores in Table 5-10 reveals that 84% of public homes and 96% of private homes have SE scores greater than 60%. In contrast, the frequency distribution of the conventional SE scores for these homes illustrates that 82% of public units and 94% of private units have SE estimates greater than 0.60.

Figure 5-2 illustrates the kernel density functions of conventional and DB DEA for public and private NHs and for CRS and VRS technologies. The graphs demonstrate that the statistical distributions of public and private homes do not significantly differ between the different estimation techniques. However, the distributions of the VRS TE scores versus CRS TE estimates of public homes show considerable divergence, in contrast to the private homes for both conventional and DB DEA results.

Private Chain and Non-Chain NHs

Table 5-8 also presents the DB DEA TE scores of private chain and non-chain homes alongside their CIs. For comparison purposes, the average conventional TE scores are also presented. Interestingly, the average conventional VRS TE estimates of private chains are greater than the DB DEA scores, inferring a positive bias. Moreover, this bias is significant as the average conventional DEA TE scores exceed the UBs of the DB DEA results. This means that the

conventional DEA scores over-estimated the true-efficiency of private chain homes. Moreover, the average DB DEA VRS TE score of chain units (0.695) indicates it is more technically efficient than the private non-chain facilities (0.656), while Table 5-9 reveals the difference in these mean TE scores between the subsamples to be statistically significant.

In relation to the DB SE of private chain and non-chain homes, the average conventional SE scores are less than the mean DB SE estimates, inferring a negative bias. These results emphasize that the subsamples of INHs are more scale efficient than originally suggested by the average conventional SE scores. In fact, the mean DB SE result of private chain and non-chain homes are close to 1 (0.999; 0.907), meaning that these facilities are approaching their most productive scale size (MPSS).

Urban and Rural NHs

The DB DEA scores in Table 5-8 highlight that urban homes (CRS model = 0.587; VRS model = 0.671) are more technically efficient than rural facilities (CRS model = 0.522; VRS model = 0.642). Table 5-9 shows a significant difference in the CRS estimates. However, in contrast, there is no significant difference in the VRS scores of urban and rural homes. Additionally, Table 5-8 shows no significant difference between the mean conventional SE scores and the DB SE estimates for both urban and rural homes. Interestingly, Table 5-10 indicates that 73% of urban homes and 59% of rural facilities have SE scores between 0.80-1. Similarly, 73% of urban homes and 60% of rural homes were operating within this range when assessing the frequency distribution of the conventional SE scores.

Table 5-8: Double Bootstrap DEA Results

	No. NHs	Conv. DEA	DB DEA	LB	UB
CRS TE Scores					
All Homes	110	0.577*	0.520	0.486	0.562
Public	38	0.618	0.572	0.542	0.620
Private	72	0.617	0.576	0.546	0.620
Private Chain	32	0.716*	0.695	0.682	0.714
Private Non-Chain	40	0.677*	0.598	0.554	0.656
Urban	44	0.656*	0.587	0.550	0.642
Rural	66	0.576	0.522	0.486	0.580
VRS TE Scores					
All Homes	110	0.664*	0.581	0.535	0.641
Public	38	0.781	0.728	0.692	0.786
Private	72	0.698*	0.622	0.578	0.686
Private Chain	32	0.848*	0.695	0.683	0.712
Private Non-Chain	40	0.753*	0.656	0.603	0.723
Urban	44	0.747	0.671	0.622	0.747
Rural	66	0.706*	0.642	0.608	0.694
Scale Efficiency					
All Homes	110	0.861*	0.890	0.873	0.905
Public	38	0.780*	0.789	0.785	0.794
Private	72	0.873*	0.914	0.892	0.933
Private Chain	32	0.833*	0.999	0.997	1.000
Private Non-Chain	40	0.886*	0.907	0.905	0.914
Urban	44	0.874	0.871	0.856	0.883
Rural	66	0.804	0.809	0.801	0.832

* denotes conventional DEA efficiency estimate is outside the bootstrapped 95% confidence interval, i.e. it is significantly different from the bias-corrected efficiency score.

Table 5-9: Mean Comparison Tests for Double Bootstrap (DB) DEA Results

	Public-Private		Private Chain-Non-Chain		Urban-Rural	
	Criterion value (z/t) (p value)	Decision with respect H ₀	Criterion value (z/t) (p value)	Decision with respect H ₀	Criterion value (z/t) (p value)	Decision with respect H ₀
CRS TE						
t-test	-1.920*	Reject	2.250**	Reject	-2.074**	Reject
H₀: TE – TE = 0	(0.057)		(0.027)		(0.040)	
Mann-Whitney test	-2.056**	Reject	2.538**	Reject	-1.965*	Reject
	(0.039)		(0.011)		(0.049)	
VRS TE						
t-test	-0.783	Accept	3.14***	Reject	-0.807	Accept
H₀: TE – TE = 0	(0.434)		(0.002)		(0.421)	
Mann-Whitney test	-0.723	Accept	2.99***	Reject	-0.775	Accept
	(0.469)		(0.002)		(0.438)	
Scale Efficiency (SE)						
t-test	-1.848*	Reject	-0.907	Accept	-2.353**	Reject
H₀: SE – SE = 0	(0.067)		(0.367)		(0.020)	
Mann-Whitney test	-1.622	Accept	-1.133	Accept	-1.940*	Reject
	(0.104)		(0.257)		(0.052)	

*** significant difference at the 1% level, ** significant difference at the 5% level, and * significant difference at the 10% level.

Table 5-10: Frequency Distribution of DB DEA Efficiency (VRS DEA)

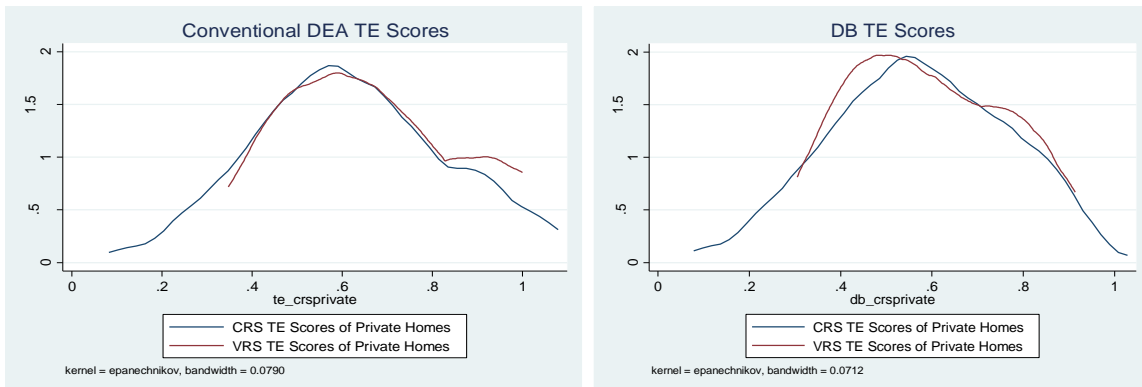
Range	All Homes		Public		Private		Private Chain		Private Non-Chain		Urban		Rural	
	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%
TE														
1.00	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0.90-0.99	4	4	8	21	1	1	8	25	4	10	6	14	6	9
0.80-0.89	10	9	6	16	11	15	3	9	5	13	5	11	5	8
0.70-0.79	13	12	10	26	9	13	2	6	7	18	10	23	12	18
0.60-0.69	19	17	4	11	12	17	10	31	8	20	6	14	12	18
Below 0.60	64	58	10	26	39	54	9	28	16	40	17	39	31	47
Total	110	100	38	100	72	100	32	100	40	100	44	100	66	100
Scale Efficiency														
1.00	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0.90-0.99	68	62	9	24	60	83	32	100	27	68	24	55	25	38
0.80-0.89	19	17	15	39	3	4	0	0	5	13	8	18	14	21
0.70-0.79	5	5	3	8	4	6	0	0	2	5	7	16	5	8
0.60-0.69	6	5	5	13	2	3	0	0	2	5	3	7	10	15
Below 0.60	12	11	6	16	3	4	0	0	4	10	2	5	12	18
Total	110	100	38	100	72	100	32	100	40	100	44	100	66	100

Figure 5-2 Kernel Density Functions for Conventional DEA and DB DEA

Panel (a): Public NHs



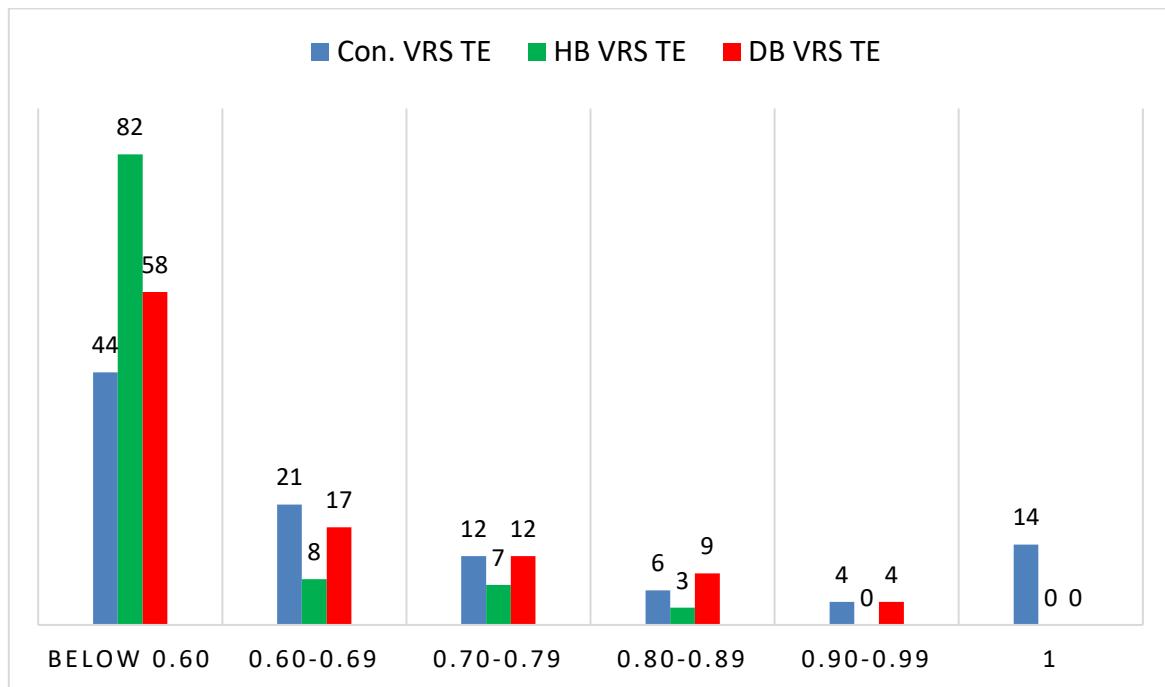
Panel (b): Private NHs



5.5 Comparison of the Three DEA Methods

The results of this chapter clearly indicate that the conventional DEA method overestimates the ‘true’ TEs of INHs relative to HB or DB DEA methods. In fact, the LTC facilities in Ireland are more inefficient than the conventional DEA model indicated. This means INHs must reduce their inputs to a greater extent in order to become fully technically efficient. The Figure 5-3 comparison of the distribution of the VRS TE scores for the overall sample, and for conventional, HB and DB DEA demonstrates that a greater proportion of care facilities fall ‘below 0.60’ when evaluating the estimates of HB and DB DEA relative to conventional DEA. On the other hand, 14% of all NHs have a technical efficiency score of 1 when assessing original or conventional DEA scores relative to the HB or DB DEA results. Moreover, the DB DEA scores are higher than the HB DEA scores on average.

Figure 5-3 Distribution of VRS TE Scores in % for Three DEA Methods Across All Homes



The Table 5-11 presentation of the Spearman’s correlations of the TE scores between the different methods confirms the strong correspondence between conventional DEA and DB DEA. High correlation between these scores ($=0.983$ for all homes) implies that the rankings of the TEs for the individual NH units will not change, even though the average conventional TE scores are higher than the average DB DEA estimates. The correlation between DB DEA and conventional DEA scores is higher and much closer to 1 than the correlation between DB DEA and HB DEA scores ($=0.880$ for all homes). Furthermore, the kernel density functions in Appendix 5A-5-3 show that the distribution of the CRS and VRS TE scores across the different methods are broadly similar.

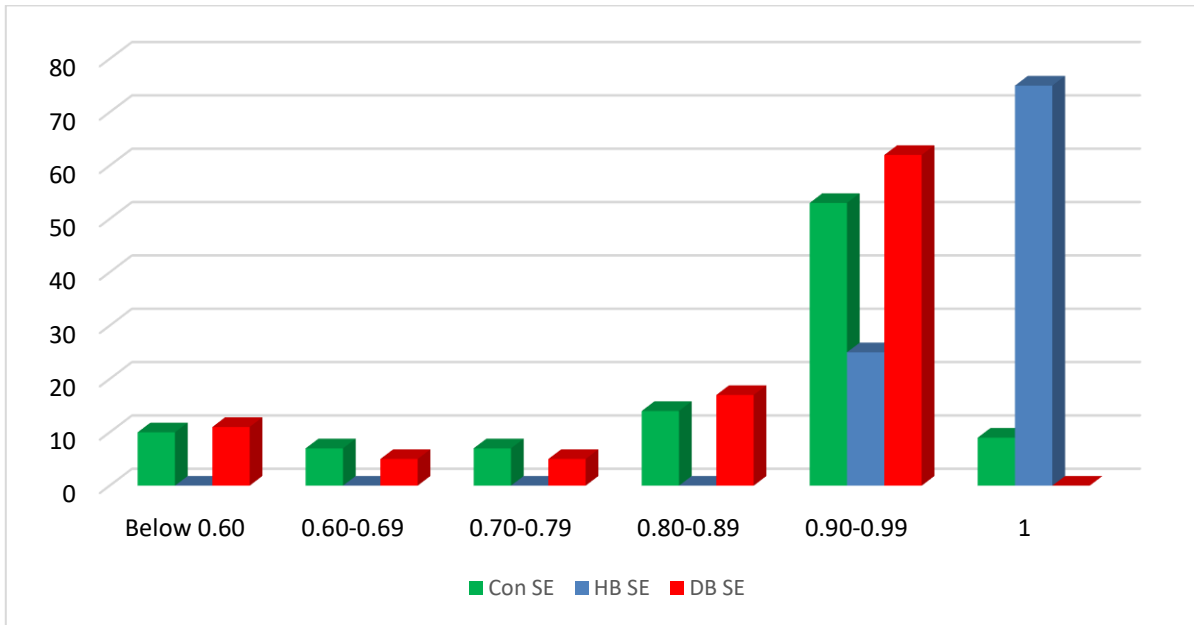
Table 5-11: Correlation Matrix of CRS and VRS TE Scores of the Different DEA Methods

CRS TE Scores												
	All Homes			Public			Private			Chain		
	Conv	HB	DB	Conv	HB	DB	Conv	HB	DB	Conv	HB	DB
Conv	1			1			1			1		
HB	0.814	1		0.717	1		0.780	1		0.883	1	
DB	0.983	0.880	1	0.991	0.722	1	0.996	0.812	1	0.992	0.901	1
	NonChain			Urban			Rural					
Conv	1			1								
HB	0.840	1		0.698	1							
DB	0.974	0.88	1	0.980	0.754							

VRS TE Scores												
	All Homes			Public			Private			Chain		
	Conv	HB	DB	Conv	HB	DB	Conv	HB	DB	Conv	HB	DB
Conv	1			1			1			1		
HB	0.630	1		0.616	1		0.631	1		0.714	1	
DB	0.964	0.647	1	0.977	0.608	1	0.975	0.663	1	0.815	0.898	1
	NonChain			Urban			Rural					
Conv	1			1			1					
HB	0.659	1		0.554	1		0.565	1				
DB	0.954	0.60	1	0.975	0.558		0.967	0.529	1			

In relation to the SE scores, Figure 5-4 compares the SE results of the conventional, HB and DB DEA methods. The diagram demonstrates that a greater proportion of homes are scale efficient when evaluating the DB DEA SE results compared to the conventional DEA SE scores. On the other hand, the HB DEA method delivers the highest average SE scores compared to the other two techniques, indicating that 75% of all NHs are scale efficient, while the kernel density functions presented earlier for HB DEA in Figures 5-1 and Appendix 5A-5-3, confirm the findings that the VRS TE scores are very close the CRS TE estimates.

Figure 5-4 Distribution of SE Scores in % for Three DEA Methods Across All Homes



5.6 Stochastic Frontier Analysis

A significant advantage of the DB DEA method is that it estimates bias-corrected bootstrap TE scores which have been adjusted by the values of the efficiency determining variables. However, the DB DEA still does not control for random error (or noise) which reflects all events outside the producer's control and may affect the production process resulting in non-robust estimates of TE. Therefore, as delineated in Chapter Four, the stochastic frontier analysis (SFA) is the final method employed in this thesis since it yields unbiased estimates of both TE and its determinants by controlling for both the noise and the inefficiency.

SFA estimates of TE often depend on model specification and distributional assumptions of the inefficiency term. This study estimates an IO TE and uses the same model specification as for the previous DEA methods. Hence, four inputs (capital, medical and non-medical staff, and the HMD rate) and one output (total patient days) are used to describe the relevant production technology. To estimate the IO TE, an input distance function (IDF) in the SFA parametric framework is selected. While the simplest and the most common functional form used in many

SFA applications is the Cobb-Douglas function, this form imposes certain restrictions on the production structure, such as non-varying returns to scale and unitary elasticity of substitution. Therefore, to account for the non-standard features of production technology associated with NHs, a flexible functional form is preferred and the translog (logarithmic transcendental) function devised by Christensen *et al.* (1973) is applied using the SFA model, as previously outlined in Chapter Four.

In order to estimate the parameters of the translog IDF, additional distributional assumptions are made concerning the error terms, the noise (v_i) and the inefficiency (u_i), prior to using the maximum likelihood (ML) method. In the SFA model, v_i is normally distributed with 0 mean and constant variance. However, no economic criteria are available to guide the choice of distribution to apply to the inefficiency component (Schmidt and Sickles, 1984). Standard computer software allows four options: a half-normal, truncated normal, exponential and gamma (Greene, 2002). In light of this, all four choices are considered in estimating the TE in this research. Unfortunately, since the maximum likelihood functions did not converge for the specified SFA model and using the current data on NHs in this research, no empirical results for TE scores of INHs are yielded. However, Chapter Six presents the SFA IDF results estimating both TE scores and the determinants of efficiency, albeit applying a different output measure which is the average length of stay.

The subsequent TE scores are not comparable with those obtained using the various DEA techniques in this chapter. The reasons why SFA IDF cannot be estimated using the current data samples are as follows:

- Jacob *et al.* (2006) suggested that SFA was vulnerable to small sample sizes. Similarly, Banker *et al.* (1993) observed that SFA estimates were likely to be more imprecise the

smaller the sample size. The present dataset comprises only 110 observations which could be considered too small for parametric estimations.

- More importantly, the present cross-sectional dataset does not allow for estimation of panel data SFA. Applying panel data SFA would allow to control not only for noise and inefficiency, but would also control any biases caused by unobserved heterogeneity of NHs. However, at present, it is unlikely that the dataset can be extended to panel data due the time and financial constraints involved in data gathering as the primary dataset of this study took 15 months to collate.
- Additionally, given the limited number of observations in this research, the SFA may be susceptible to the influence of outliers. To test for ‘this challenge’, one observation at a time was eliminated from the dataset, and the maximum likelihood method was applied to estimate the TE scores of all care facilities. Regardless of these efforts, no empirical results could be obtained. Furthermore, strong correlations between inputs, for example, medical staff and capital (correlation value = 0.8264) and inputs and output, such as, capital and total patient days (correlation value = 0.8077) indicate that multicollinearity is likely in this dataset.
- Moreover, to ensure the correct model specification is formulated for this research, application of the ‘skewness statistic’ indicated a left-skewed error distribution (-1.226); a result which supports the current SFA specification. Furthermore, the skewness test on the OLS residuals reject the null hypothesis of no skewness (p -value of 0.000) is less than 0.01), inferring additional support for the model of this work.
- While this work commenced with a half-normal distribution of the inefficiency component of the error term, the precise specification of the distribution of the inefficiency component is difficult (sometimes even impossible) to ascertain. Indeed, Cullinane *et al.* (2006)

claimed such specification as likely to introduce another potential source of error. Cullinane *et al.* (2006) further elaborated that the continuity presumed in SFA may lead to approximation errors.

- It is proposed that the SFA does not converge due of an information problem in this research. As previously acknowledged, the current sample size is relatively small. In consequence, this present research is unable to isolate the individual impact of the regressors on the dependent variable due to multicollinearity.

5.7 Conclusions

This chapter estimated input-oriented TEs and also derived SEs of INHs, using methods ranging from non-parametric to parametric techniques for all homes and their subsamples. While the SFA IDF model did not converge, the empirical estimates of the other approaches found that across all care homes considerable technical inefficiencies are evident.

Based on the conventional VRS DEA model, the estimated average TE score is 0.664 for all nursing facilities, with only 15% of all private and 21% of all public units being fully technically efficient. This result indicates that NHs in Ireland should reduce their level of inputs by an average of 34% in order to produce efficiently. Moreover, the VRS TE scores confirm that public homes are more technically efficient than private homes, although this difference is statistically insignificant. The ‘pure’ TE estimates also show that private chain homes have on average a higher TE score (0.848) compared to private non-chain homes (0.753). This finding aligns with the fact that private chain homes can reduce costs by sharing of labour resources and specializations. Finally, the last subsample demonstrates that 25% of urban NHs have a TE score of 1 compared to 14% of rural homes.

The bootstrap DEA results suggest that the conventional DEA TE scores of Irish care facilities are overestimated. The bias-corrected mean VRS TE scores for all NHs when employing the

homogenous and double bootstrap DEA, are equivalent to 0.464 and 0.581, respectively. The HB DEA result is 31% lower than the score obtained using the conventional DEA method, whereas the DB DEA result is 13% lower than the traditional DEA score. These results imply that INHs are even more inefficient than the conventional DEA findings would suggest. This finding is relevant for both public and private NHs, and for other sub-samples (i.e. private chain, private non-chain, urban and rural homes). None of the public or private facilities are fully technically efficient when assessing the HB or DB DEA TE results relative to the conventional TE results, when 21% of public and 15% of private homes were fully technically efficient. Moreover, both HB and DB DEA results indicate that the private NHs are more technically efficient than public units. This finding confirms the necessity for further investigation of ownership variable as efficiency determinant in Chapter Six.

In terms of SE in the conventional DEA model, the CRS TE scores are lower on average than the scores obtained using VRS technology; indicating that scale inefficiencies exist in the NH sector in Ireland. The estimated average SE score of 0.86 for all NHs is higher than the mean VRS TE score. Moreover, according to the conventional NIRS DEA frontier, 77% of facilities produce on the increasing returns to scale part of the production frontier, indicating the existence of economies of scale. This implies that INHs are not operating in the economically feasible region and could decrease their average costs and move to the point of minimum marginal costs by extending their scale of production. Additionally, only 9% of all NHs are fully productive (both technically and scale efficient) and operating at optimal scale. In respect of public and private homes, only 13% of the former have reached their most productive scale size and 14% of profit-oriented homes have SEs equal to 1. When this research evaluates the SE of private chain and non-chain homes, it finds that 22% of the former and 23% of the latter are operating at minimum average cost.

With regard to the obtained SE in HB DEA, the average CRS and VRS TE scores are similar, inferring that the majority of NHs are scale efficient and they are operating at their most productive scale size. However, when the application of the DB DEA integrates the effects of explanatory variables in estimating the true efficiencies, this study notes that INHs and their subsamples are more scale efficient than the conventional DEA results reveal, but less scale efficient than the HB DEA results imply.

In what follows, Chapter Six evaluates the determinants of efficiency by identifying the factors that affect the TE of the INHs which is another important step to provide further insights into potential TE improvements of these facilities.

5A Appendices

Appendix 5A-5-1 Conventional DEA scores obtained by using different measurement of labour inputs and by including HMD rate as an input.

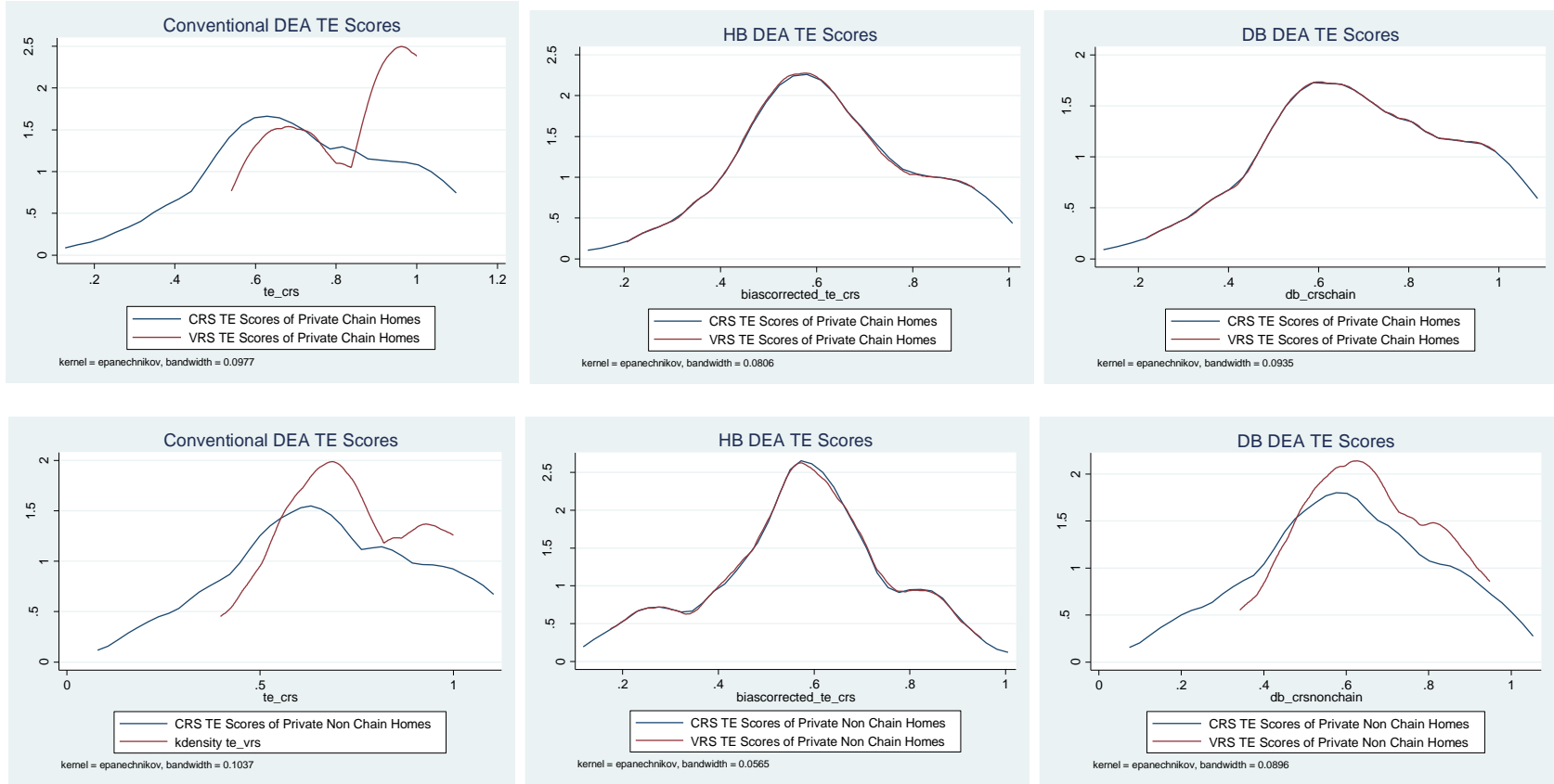
	Model 1 <i>Medical staff</i>			Model 2 <i>Non- medical staff</i>			Model 3 <i>Both labour inputs</i>		
	No. Obs.	Mean	St. Dev.	No. Obs.	Mean	St. Dev.	No. Obs.	Mean	St. Dev.
CRS TE									
Public	38	0.603	0.214	38	0.505	0.192	38	0.617	0.217
Private	72	0.604	0.227	72	0.606	0.222	72	0.617	0.228
All homes	110	0.566	0.216	110	0.544	0.209	110	0.577	0.218
VRS TE									
Public	38	0.771	0.186	38	0.640	0.217	38	0.781	0.184
Private	72	0.683	0.189	72	0.691	0.191	72	0.698	0.194
All homes	110	0.650	0.190	110	0.618	0.205	110	0.664	0.196
Scale efficiency (SE)									
Public	38	0.775	0.178	38	0.798	0.184	38	0.780	0.175
Private	72	0.870	0.173	72	0.867	0.171	72	0.873	0.170
All homes	110	0.859	0.174	110	0.877	0.167	110	0.861	0.173

Appendix 5A-5-2 Conventional DEA scores obtained by using different measurement of labour inputs and by excluding HMD rate as an input.

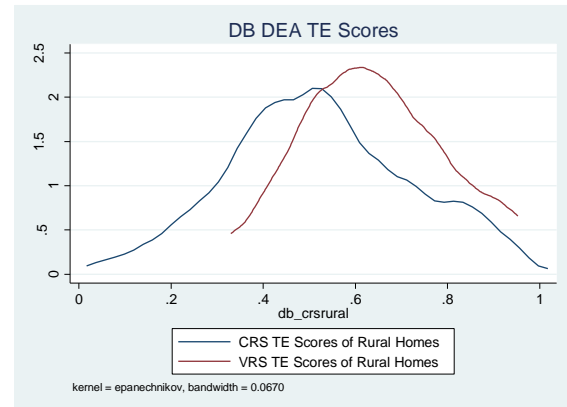
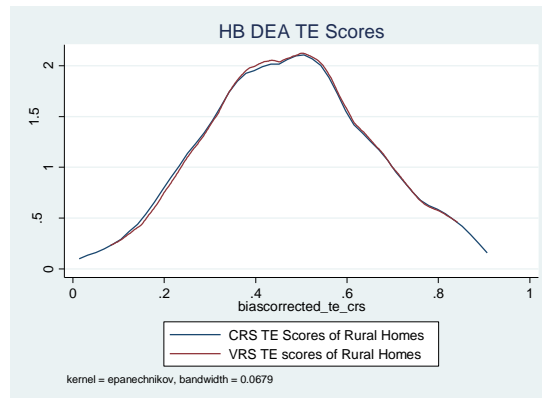
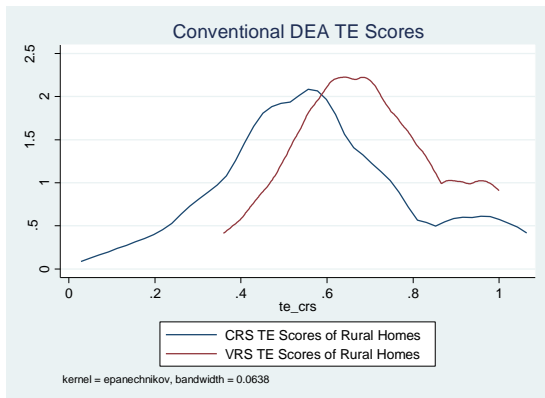
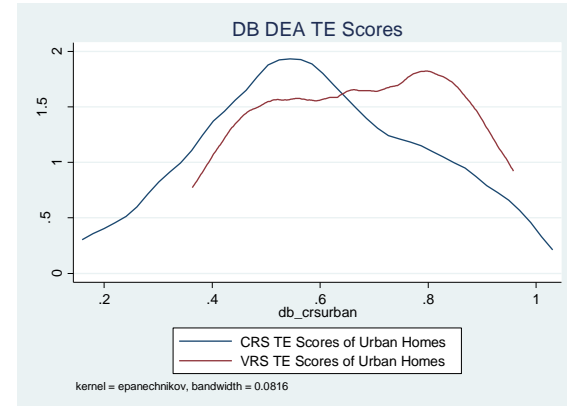
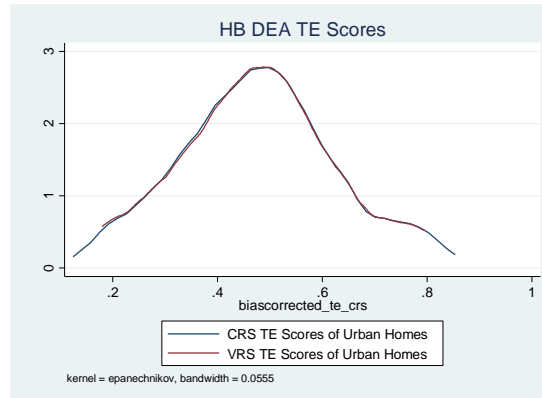
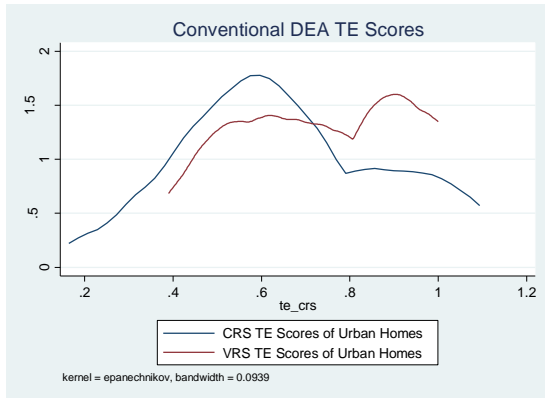
	Model 1 <i>Medical staff</i>			Model 2 <i>Non- medical staff</i>			Model 3 <i>Both labour inputs</i>		
	No. Obs.	Mean	St. Dev.	No. Obs.	Mean	St. Dev.	No. Obs.	Mean	St. Dev.
CRS TE									
Public	39	0.577	0.211	38	0.491	0.187	38	0.583	0.217
Private	73	0.589	0.226	72	0.580	0.218	72	0.588	0.225
All homes	112	0.550	0.212	110	0.524	0.201	110	0.549	0.212
VRS TE									
Public	39	0.677	0.193	38	0.613	0.214	38	0.690	0.200
Private	73	0.633	0.198	72	0.630	0.194	72	0.639	0.198
All homes	112	0.616	0.196	110	0.593	0.194	110	0.624	0.197
Scale efficiency (SE)									
Public	39	0.841	0.149	38	0.811	0.184	38	0.835	0.155
Private	73	0.914	0.167	72	0.907	0.170	72	0.905	0.172
All homes	112	0.883	0.174	110	0.878	0.167	110	0.873	0.179

Appendix 5A-5-3 Kernel Density Functions of Conventional DEA, Homogenous Bootstrap and Double Bootstrap DEA TE Scores.

Panel (a): Private Chain and Non-Chain Homes



Panel (b): Urban and Rural NHs



Chapter Six: Determinants of Technical Efficiency

6.1 Introduction

The purpose of this chapter is to empirically investigate the variables which determine the TE scores of INHs. Efficiency determinants are neither inputs nor outputs in the production process, but rather factors which might influence the production frontier, and hence might impact the TE of the NHs (Coelli *et al.* 2005). Based on the preferred DB DEA model results, Chapter Five demonstrated that obtained TE estimates of Irish care homes are low and range between 52% and 58% on average, and these estimates were based on the most preferred estimation method which is the DB DEA. This chapter extends the analysis by estimating the impact of efficiency determinants through application of both semi-parametric and parametric methods.

As outlined in Chapters One and Three, determining the relevant factors which affect inefficiency in the NH sector is critical given the rising costs of the health sector in Ireland, and in particular, the rising expenditures of NH care are linked to increases in Ireland's aging population. Moreover, finding the relevant factors affecting the productive efficiency of INHs could help policymakers to account for possible managerial slack in the INH sector. If NHs in Ireland could deploy their inputs more effectively by the given level of output (i.e. the total patient days), the increased TE could lead to improvements in CEs and concomitant reductions in public spending on future NH care.

This research applies a comprehensive set of potential determinants of efficiency which have been explored to various extent in prior NH literature. As outlined in Chapter Four, they are classified into the three main categories of: (1) ownership; (2) conventional (firm) characteristics; and (3) output characteristics. While the conventional factors are common to any firm in any sector, such

as size, location, and age, the last group of efficiency determinants obtains to the specific characteristics of the NHs: namely, the case-mix, chain status of the nursing home, and the numerous structural quality factors of the NHs. All methods used to estimate efficiency determinants in this chapter are summarized in Table 6-1 and include the two-stage OLS regression on conventional DEA and HB DEA TE scores, the two-stage Tobit regression on both conventional and HB DEA TE scores, the semi-parametric two-stage DB DEA, and the fully parametric SFA. Both DB DEA and SFA directly incorporate the potential TE determinants into the calculation of TE.

Additionally, this research divides the pooled sample of all NHs into public and private NHs, and further subdivides them into the private chain and private non-chain NHs. As noted in Chapter Five, it is likely that private and public NHs, the chain and non-chain private facilities, and the NHs located in urban and rural areas, have different technologies which could result in the same determinants influencing the TE scores of each group differently.

Section 6.2 of the chapter explicates why the DB DEA is chosen as the most preferred method to estimate TE determinants, while Section 6.3 discusses the findings derived from this model. Section 6.4 then presents the results of the alternative two-stage OLS and Tobit regression methods. The determinants with consistent results are identified, along with the variables which generate different results across these second-stage approaches. Section 6.5 provides estimates for the marginal effects for all the methods used and identifies the variables which exert the greatest impact on TE in terms of the magnitude of their effects. Section 6.6 focuses upon the estimation of the parametric SFA IDF when a different output measure (i.e. average length of stay) is applied. Section 6.7 summarizes the key findings with regard to: (1) method, and (2) efficiency determinants. Section 6.8 offers concluding remarks.

6.2 Choice of Method Used

As Table 6-1 demonstrates, this research employs various two-stage semi-parametric approaches, wherein non-parametric DEA efficiency scores from the first stage are regressed on a vector of efficiency determinants in a parametric analysis in the second stage. The first and most simple technique applied is the OLS regression on the conventional DEA scores. This firstly entails using the conventional DEA TE scores and regressing them on the set of environmental factors using the linear least squares regression. However, as the TE scores are limited between 0 and 1, Kooreman (1994) noted that applying OLS to a censored regressed model yields estimates which are asymptotically biased toward 0 (see e.g., Greene, 1981). Coelli *et al.* (2005) likewise recommended the use of Tobit regression as the OLS regression could predict TE scores greater than 1. In light of, this the two-stage Tobit regression is chosen as the first modification of the basic two-stage OLS and it is presented in Section 6.4.

Table 6-1: Models Applied to Estimate Efficiency Determinants

Model	Accounts for efficiency determinants	Accounts for noise when estimating TE scores	Accounts for sampling variability in the TE scores	Adjusts TE scores after correction for determining variables
Two-Stage Semi-Parametric Methods in combination with DEA				
OLS with conventional DEA scores	✓	No	No	No
OLS Regression with HB DEA scores	✓	No	✓	No
Tobit Regression with conventional DEA Scores	✓	No	No	No
Tobit Regression with HB DEA scores	✓	No	✓	No
Two-Stage DB DEA	✓	No	✓	✓
Parametric SFA Method				
SFA input distance function	✓	✓	✓	✓

Furthermore, the TE score is a point estimate without a probability distribution around it as required by the Tobit method or any other parametric regression technique used in the second

stage. As argued by Kumbakhar and Lovell (2000), Simar and Wilson (2011), and Badunenko *et al.* (2012), whatever the second-stage regression technique employed, conventional inference methods fail to give valid inference due to the fact that in the second-stage, true efficiency remains unobserved and must be replaced with the DEA TE scores that are not random, and are serially correlated by construction, and are also biased. Therefore, using the DEA point estimates in a second stage analysis may also generate biased and inconsistent estimates of the parameters of the efficiency determining variables. To address this issue, this study employs both OLS and Tobit regressions using the bias-corrected HB DEA TE scores as the dependent variable to identify the determinants of TE. HB DEA in contrast to the conventional TE scores, accounts for sampling variability of the dependent variable (Table 6-1). However, the final and the most preferred two-stage method used is the two-stage double bootstrap (DB) DEA developed by Simar and Wilson (2007; 2011). This semi-parametric approach not only produces equally robust and unbiased estimation of the TE scores, similarly to the HB DEA method, but it also re-estimates the TE scores to adjust for the values of the efficiency determining variables to give unbiased efficiency estimates. In this regard, this method is similar to parametric SFA approach where the inefficiency and its determinants are estimated simultaneously in the single step procedure. The DB DEA method has had relatively few applications in efficiency studies in the wider health-care efficiency literature. To the researcher's knowledge, only Borge and Haraldsvik (2009) and Ni Luasa *et al.* (2018) have previously applied this technique to interrogate the impact of key determinants of efficiency in the elderly care sector.

The drawback of all the semi-parametric two-stage methods which are summarised in Table 6-1, is that these models do not account for noise in contrast to fully parametric SFA techniques. In contrast, SFA includes both the inefficiency component and the random error or noise as the

possible deviations from the actual frontier. In this research, SFA could not be applied for the output variable ‘total patient days’ for the reasons specified in Chapter Five. Nonetheless, in order to investigate the robustness of the results using the fully parametric SFA, this study presents additional results for the output variable defined as ‘average length of stay’. These SFA results are discussed in Section 6-6.

In summary, as stated in Chapter Four and empirically tested in Chapter Five, since the SFA is not fully feasible to NH data which are used in this study, the two-stage DB DEA is chosen here as the main and most appropriate method to estimate TE determinants. This method controls for sampling variability of TE scores and hence produces bias-corrected coefficients of efficiency determinants. In addition, the bias-corrected TE scores are adjusted by the values of efficiency determining variables in the second stage. Therefore, this procedure more closely resembles the parametric SFA where both TE and efficiency factors are estimated at once.⁸³ Nevertheless, other two-stage OLS and Tobit regression approaches are also considered in this chapter in order to ensure the best practice and the robustness check of the results.⁸⁴

6.3 Semi-parametric DB DEA Results

Table 6-2 presents the estimates of the TE determinants using the most preferred semi-parametric VRS DB DEA method, while Table 6-3 presents the DB DEA results for CRS technology. The results are presented for the pooled sample of all NHs, and the respective subsamples of NH facilities. The estimated coefficients of TE determinants in both tables present their effects on the bias-corrected reciprocals of the DEA TE scores (i.e. $1/TE^*$). According to this, a negative sign of

⁸³ In the SFA framework, the variance or mean of the inefficiency is modelled in terms of efficiency determining variables (see section 6.6 in this chapter).

⁸⁴ Table 4-1 in chapter 4 presents numerous nursing home studies (e.g. Nyman *et al.* (1990); Chattopadhyay and Heffley (1994); Kooreman (1994) Borge and Haraldsvik (2009)) which utilize more than one two-stage methods as a robustness check regarding the efficiency determinants.

the coefficient of an efficiency determinant indicates a negative effect on the reciprocal of TE scores ($1/TE^*$), and hence a positive effect on TE^* . Conversely, a positive sign of the coefficient indicates a positive impact on $1/TE^*$ and hence a negative effect on the estimated TE^* .⁸⁵ Tables 6-2 and 6-3 also demonstrate the CIs of the obtained coefficients of the TE determinants which are the lower (LB) and upper bounds (UB).⁸⁶

It is noted that the presented VRS DB DEA results in Table 6-2 were estimated by assuming the variable returns to scale (VRS) technology. The VRS TE scores are devoid of scale inefficiencies and the main focus of this chapter is to examine the effect of these determinants on the ‘pure’ TEs which are devoid of scale inefficiencies. However, in Table 6-3, the results of the constant returns to scale (CRS) DB DEA are also presented in order to compare the findings with the VRS results. The CRS technology is often used in the two-stage analyses for two main reasons. Firstly, the CRS TE scores provide a measure of the overall efficiency of each NH unit in terms of aggregating pure TE and SE, while the VRS TE score measures the pure TE only.⁸⁷ Second, the CRS TE scores exhibit more variability compared to the VRS TE scores. In light of this, the TE determinants are fully discussed below using the findings presented for both VRS technology (Table 6-2) and CRS technology (Table 6-3), and for the full sample and subsequent subsamples of NHs, respectively.

⁸⁵ All double-bootstrap DEA estimations were performed in R-software using rDEA package where the bias-corrected TE scores (TE^*) were returned as the reciprocals of the DEA scores ($1/TE^*$), defined in terms of the input-distance function.

⁸⁶ Hence, the lower and upper bounds indicate the significance level of the estimated coefficients of TE determinants at 90%, 95% and 99% level respectively, confirming in each case 10%, 5% and 1% significance level of the individual coefficients.

⁸⁷ In chapter 5, the obtained VRS TE scores were higher than the constant return to scale (CRS) TE scores, indicating that the nursing homes are not producing at optimal scale. Where scale inefficiencies are present, the CRS TE scores will underestimate the ‘true’ VRS TE scores.

6.3.1 Ownership

This study contends the ownership variable to be the most important conventional determinant of TE for INHs. Inclusion of this TE determinant directly addresses the research question as to whether private NHs which receive a quasi-subsidy from the State are more technically efficient than the public facilities. In Chapter Five, the average TE scores were obtained separately for the subsamples of public and private NHs, respectively. Based on the summary statistics of the obtained VRS TE scores, the private NHs were on average more technically efficient than the public units, albeit the difference was statistically significant for the HB DEA model only. However, for the CRS technology, the TE scores of private NHs were higher on average than of public units, and this difference was statistically significant.⁸⁸ To properly examine the effect of ownership on TE in the NHs in the second stage analysis, this chapter includes a ‘for-profit’ indicator variable in the pooled sample of all NHs. The coefficient takes a value of 1 for the private NH facility and 0 is assigned to the public units. Both Tables 6-2 and 6-3 confirm this coefficient to be statistically significant at the 1% level and negative, indicating a positive effect on TE and demonstrate that private NHs in receipt of a quasi-subsidy by the State are more technically efficient than their public counterparts. This result is consistent with the US NH efficiency literature (Nyman and Bricker 1989; Nyman *et al.* 1990; Fazel and Nunnikhoven 1992; Chattopadhyay and Heffley 1994) who purport private homes’ exclusive rights to profits contrast to public counterparts whose rights to income are attenuated. In fact, most efficiency studies of European care homes do not examine the effect of ownership on TE since the vast majority of care

⁸⁸ On the other hand, in the VRS DB DEA model, public homes were more technically efficient than private facilities, although this difference was not statistically significant (see Table 5-8 and 5-9).

homes are state-owned. Thus, the results from this work extend the debate on the private versus public provision of care to the elderly.

Furthermore, as discussed in Chapter Three, private homes of this study report that at least 10% or more of their total beds capacity is contracted to the State en-bloc. Therefore, column 3 of both Tables 6-2 and 6-3 includes another ‘ownership’ variable which is the percentage share of *contract beds* received by private homes. The share of contract beds, however, does not affect TE scores of private NHs as it is not statistically significant for both VRS and CRS technology.

6.3.2 *Conventional characteristics*

Following the ownership status of the NHs, the most important firm characteristics which are examined in this research as potential efficiency determinants are: *size*, *location* and *age* of the NHs. Table 6-2 demonstrates that size has a significant and negative impact for all NHs and for most of the NH groups. It therefore follows that the NHs which have between 50-99 beds at their disposal (*size_2* category) are less technically efficient than the small NHs with less than 50 beds (*size_1* category). The same results apply to the large NHs which have 100+ beds (*size_3* category) and they hold for the samples of all NHs, private units, private non-chain facilities and rural entities presented in Table 6-2. While the consistent results for the size hold for the VRS model only (Table 6-2), this is not the case for CRS (Table 6-3).⁸⁹ This finding indicates a negative relationship between the size of the nursing home and the ‘pure’ TE obtained under the VRS technology, which separates the scale inefficiency from TE. As only 48% of the NHs in the present sample are small-sized units with less than 50 beds, the results imply that larger NHs should decrease their scale of operation to become more productive. This result aligns with that of Wang and Chou (2005),

⁸⁹ Focusing on the CRS model (Table 6-3) the results regarding *size_2* are mixed – the sign of this coefficient changes between public and private chain homes. In relation to *size_3*, it shows a positive relationship with TE.

Sexton *et al.* (1989), and Nyman *et al.* (1990), but contrasts to the findings of Ozcan *et al.* (1998) and Filippini (2001). The present findings also inform the extant literature that the INHs are scale inefficient as found in Chapter Five. Hence, INHs are not operating at the MPSS and many units must decrease their scale of operation in order to become more scale efficient and therefore, more productive by increasing the average product per unit of input.

The next variable of interest is the *location* indicator variable denoted as *urban* which takes the value of 1 for NHs located in urban regions, and 0 for units located in rural areas. The preliminary results indicated that this location variable was only significant and positive for private chain NHs for CRS technology only. Therefore, given that the sample size for private chain homes is very small with just 32 observations, the potential effect of this variable on TE cannot be firmly concluded. Consequently, this variable was excluded from the estimations as the potential efficiency determinant.⁹⁰ Overall, the insignificant effects of location on the NHs efficiency is in contrast to previous research. For example, Nyman and Bricker (1989) found that Wisconsin NHs located in urban areas had greater resource use leading to lower efficiencies. In relation to the NH literature, Nyman and Bricker (1989) found that efficiencies decrease in for-profit homes in urban areas. On the other hand, Fazel and Nunnikhovern (1992) asserted that location has no significant effect on efficiency.

The last conventional characteristic examined in this research is the *age* of the NHs. In this study, the age variable is important as it recognizes that public NHs are older than private nursing facilities, owing to the former being constructed in the ‘workhouse era’. Table 6-2 confirms that

⁹⁰ Furthermore, another location dummy variable was used which equalled 1 for Dublin area, and 0 otherwise. The latter variable was also never statistically significant in any of the samples of the nursing homes, and was eventually excluded from the estimations due to the high correlation with the ‘Urban’ dummy variable.

the age variable has a significant adverse effect on TE for the private chain homes only, while for the CRS technology (Table 6-3) it is significant and negative for all NHs, public NHs, private chain units, and NHs in rural areas. These results imply that the age has a negative or no effect on TE of INHs and indicates that as the age of the facility increases, the efficiency may decrease and costs increase due to depreciation of the facility assets and premises (Martin and Jerome 2016). These results correspond with the hypotheses outlined for this determinant in Chapter Four. As public NHs in Ireland are considerably older than private facilities, they are also less efficient. This suggests that public facilities have less up-to-date capital inputs which drive down their TEs. Additionally, it is likely that rural NHs are not upgraded as frequently as urban centres, due to lower demand for NH care services in less populated areas. As the result, the work environments in rural homes are less advanced which could drive down the TE's of these firms.

6.3.3 Output Characteristics

The results in Tables 6-2 and 6-3 also emphasize the effects of important output characteristics specific to the NH sector. In line with Chapters One and Four, these are the HMD rate, the chain status of the private NHs, and the various structural quality factors.

High-max dependency (HMD) rate

One of the most important output-characteristic variables for the NHs is the HMD rate which measures the case-mix in this study. The HMD rate is measured as the proportion of high-maximum dependency residents in a nursing home. It is reiterated that this is the first study which includes the high-max dependency rate as the proxy of case-mix directly in both the DEA model specification and as an efficiency determinant.

The HMD rate is statistically significant and positive for all homes and their subsamples in Tables 6-2 and 6-3; implying a strong and negative effect of the dependency index on the TE. This result

is consistent with the hypothesis proposed in Chapter Four, suggesting that higher dependency levels of elderly persons lead to lower TEs of the NHs as more resources are required to meet the care needs of the residents in a nursing home. This finding also aligns with previous studies which found that the more complicated the case-mix status or the higher dependency level of elderly people, the more inputs are likely to be required, leading to lower TEs (Nyman and Bricker 1989; Nyman *et al.* 1990; Fazel and Nunnikhoven 1992; Chattopadhyay and Heffley 1994).

Chain Status

As previously stated in Chapter Five, private chain homes are part of a group of NHs which espouse similar values and beliefs, goals, and objectives. Advantages of chain homes include the sharing of resources and bulk-purchasing power, which may lead to economic savings. In contrast, private non-chain houses are independent units who take decisions solely for the purpose of their home. Therefore, decision-making processes can be more rapid and less bureaucratic in these facilities.

This study uses the chain status as a relevant variable for private homes only, indicating that the nursing home is part of a group of NHs (inferring the owner of the facility owns more than one facility) in contrast to independent singular facilities (referred to as private non-chain homes). Chain ownership is therefore measured by a dummy variable, with a value of 1 assigned to private chain facilities and a value of 0 assigned to non-chain facilities. The results shown in Tables 6-2 and 6-3 demonstrate that private chain homes are less technically efficient than non-chain homes: results are highly consistent for both CRS and VRS technologies. This is unanticipated since Fazel and Nunnikhoven (1993) emphasized that chain NHs afford opportunities to share resources, minimize waste, and reduce excess capacity. On the other hand, the finding of this study might

imply that the decisional process in chain NHs is overly slow and cumbersome, leading to lower NHs efficiency compared to non-chain NHs in Ireland.

Structural Quality Factors

The discussion with regard to the quality in the NHs focuses here on the structural dimension of quality according to Donebian's (1988) framework discussed in Chapters Two and Four of this thesis. Quality is defined here using: (1) the proportion of single bedrooms; and (2) the labour management variables which might reflect structural quality in the NHs.

The first quality variable, the percentage of *single rooms*, had a significant and positive effect on TE scores for the public facilities for VRS technology only, which is in contrast to the result found by Laine *et al.* (2005b). This finding was not surprising in the context of this study, since public NHs have previously been found to be less technically efficient than private units, and only 9% of rooms are single-bedded. In fact, the dormitory style 'norm' of Irish public facilities could result in staff becoming accustomed to servicing these types of rooms only in contrast to the single rooms. Nevertheless, as the sample size of public homes used in this study consists of just 38 observations, it is difficult to draw inferences with certainty about the likely effect of this variable on TE. As such, this determinant was excluded from the final estimations and therefore, is not presented in Tables 6-2 and 6-3.

The *medical to non-medical staff (M-NM)* ratio is significant and negative for the VRS technology, and also for CRS technology of most of the groups, implying a positive impact on TEs.⁹¹ This result is reassuring since it implies that employing more full-time nurses (medical staff) relative to

⁹¹ This finding holds in Table 6-2 both for the pooled sample (Column 1) and all the sub-samples except for rural homes (Columns 2-5). As regards the CRS model in Table 6-3, the results are similar for the pooled sample, private homes, private chain and for urban nursing homes.

the health-care attendants (non-medical staff) might not only increase quality of care, but also positively affect TE scores of both public and private NHs. As discussed in Chapter Four, private facilities employ an average of nine nurses and 18 health-care attendants, while public NHs employed 15 nurses per home in contrast to 19 health-care attendants (Table 4-11). Therefore, increasing the number of nurses relatively to the HCA staff could improve both the caring process and the TE, especially of the private NH units: a finding which chimes with the research conclusions of Delellis and Ozcan (2013).

The *staffing level* is another indicator of structural quality which measures the number of nurses per 1000 patient days. The results for the staffing level coefficient are very robust for all the samples for both the VRS and CRS technologies (Tables 6-2 and 6-3), and the coefficient shows a significant and negative effect on TE. This finding is in line with expectations and the study of Laine *et al.* (2005a). Importantly, it suggests that while increasing the number of nurses per patient days might improve quality, but the quality would also then decrease TEs of all NH groups, which would be in contrast to Delellis and Ozcan (2013). It is noted that although the staffing level in public NHs is about 30% higher than in private units, the results with regard to this coefficient are very consistent across the two groups of the NHs. This finding further corresponds with the earlier result that public NHs are less technically efficient because they also employ more nurses per patient days.

The next structural quality variable of interest is the labour-capital ratio (*L-C ratio*) which is measured as the proportion of full-time nurses to the number of beds available in a nursing home unit. The coefficient of the L-C ratio, as already noted, is almost always negative and significant at the 1% significance level for the VRS model (Table 6-2), except for the sample of public NHs which includes just 32 observations. This finding indicates that a higher number of nurses per

number of beds in a nursing home might increase the TE scores. The same results hold for all NH groups, including the public homes for the CRS model (Table 6-3). This result explains that having more nurses relative to the number of beds permits the nurses to advance their knowledge and to engage in person-centred care. This, in turn, improves the overall caring process and TE of the nursing home. Moreover, employing more nurses per bed, as measured by the *L-C* ratio, increases TE in contrast to the staffing level. The latter finding implies that better utilization of medical staff per patient days is required in the INH sector.

Another indicator of structural quality is the *staff flexibility* in terms of the ratio of part-time nurses to full-time nurses. These results are also very reliable for all model specifications. For both CRS and VRS models shown in Tables 6-2 and 6-3, the coefficient of *staff flexibility* ratio is statistically significant at the 1% level and negative for all samples of NHs; indicating that higher proportion of part-time medical staff will increase TE of the NHs. NHs with greater staff flexibility are less likely to improve the quality of care of their patients. This finding is consistent with the earlier result obtained for the staffing level, implying that lower staff flexibility could be associated with higher quality. As such, higher quality can also decrease TE as has been confirmed by prior studies (Garavaglia *et al.* 2011; Laine *et al.* 2005a). Part-time personnel can be less familiar with daily routines of the resident resulting in lower quality, which, in turn, may increase TE as fewer full-time nurses are needed. Additionally, part-time nurses may not be as embedded in the culture of the organization, which may result in more productive medical staff, leading to higher TE levels.

The final structural quality variables which relate to labour management factors are the nurse and HCA turnover rates, respectively. The *nurse turnover* rate is defined as the percentage of nurses who left the organization in 2007. This variable is statistically significant at the 1% level and positive for all NHs, mostly for all private homes but not for public homes. This suggests that the

nurse turnover rates decrease the TE scores of private NHs. The findings are robust for both CRS and VRS model specifications shown in Tables 6-2 and 6-3 and in line with expectations. As delineated in Chapter Four, private NHs have much higher nurse turnover rates compared to the public homes (41.03% versus 11.44%). This finding is also consistent with the hypothesis that nurses who frequently leave the organization might take their expertise, knowledge, and understanding of the resident, with them. This can lead to an overall lowering of quality of care and declining TE of the nursing home. Moreover, high nurse turnover rates in the private NHs might be due to the difficulties attracting permanent medical staff in contrast to public homes since private units homes can offer less favourable terms and conditions than their public sector counterparts.

The *HCA turnover* coefficient, which measures the percentage share of health-care attendants who left the organization in 2007, has a negative sign, and hence a positive effect on VRS TE scores, for private chain homes only (Table 6-2). On the other hand, the findings of the CRS DB DEA model shown in Table 6-3 demonstrates that *HCA turnover* has a positive sign for all homes, public homes, and rural facilities, indicating that nurse turnover rate has a decreasing impact on TE scores. As such, the findings with regard to HCA turnover are not fully conclusive, although the CRS results imply rather a negative effect of this variable on TE scores for the most NHs in the sample.

Table 6-2: Double Bootstrap VRS DEA Estimates of the TE Determinants

	All homes	Public	Private	Private Chain	Private Non-Chain	Urban	Rural
Size_2 (50-99 beds)	0.553*** (0.336, 0.729)	0.512*** (0.224, 0.788)	0.380*** (0.146, 0.605)	0.086*** (0.029, 0.152)	0.306*** (0.056, 0.656)	0.425*** (0.147, 0.684)	0.436*** (0.301, 0.579)
Size_3 (≥100 beds)	0.263*** (0.001, 0.556)	-0.303 (-0.620, 0.018)	0.329*** (0.055, 0.582)	-0.123*** (-0.218, -0.017)	0.692*** (0.224, 1.149)	-0.158 (-0.541, 0.223)	0.584*** (0.343, 0.840)
Age of premises	0.001 (-0.003, 0.004)	-0.002 (-0.005, 0.002)	0.004 (-0.004, 0.010)	0.008*** (0.001, 0.016)	-0.001 (-0.006, 0.009)	-0.002 (-0.007, 0.003)	0.001 (-0.003, 0.002)
HMD rate	0.755*** (0.175, 1.463)	1.731*** (0.519, 3.169)	1.181*** (0.524, 1.939)	0.862*** (0.608, 1.059)	0.767** (0.148, 1.388)	1.572*** (0.844, 2.687)	1.048*** (0.567, 1.494)
Nurse turnover	0.007*** (0.002, 0.013)	0.012 (-0.008, 0.031)	0.008*** (0.002, 0.014)	0.001 (-0.001, 0.003)	0.009*** (0.004, 0.014)	0.009*** (0.001, 0.018)	0.006*** (0.003, 0.011)
HCA turnover	0.004 (-0.002, 0.010)	-0.013 (-0.030, 0.008)	0.004 (-0.002, 0.009)	-0.002*** (-0.004, -0.001)	0.004 (-0.001, 0.011)	0.003 (-0.006, 0.014)	-0.002 (-0.007, 0.003)
M-NM staff ratio	-0.399*** (-0.602, -0.212)	-0.564*** (-0.853, -0.231)	-0.560*** (-0.994, -0.226)	-0.735*** (-0.859, -0.594)	-0.730*** (-1.429, -0.336)	-0.620*** (-1.058, -0.278)	0.018 (-0.300, 0.270)
L-C ratio	-1.836*** (-2.955, -0.701)	2.287*** (0.125, 3.988)	-4.445*** (-6.915, -1.804)	-4.692*** (-5.147, -4.313)	-4.604*** (-7.653, -1.332)	-2.722*** (-5.309, -0.281)	0.085 (-0.807, 1.096)
Staffing levels	1.465*** (1.050, 1.822)	0.927*** (0.333, 1.5)	1.831*** (1.013, 2.557)	7.486*** (7.191, 7.741)	1.244** (0.498, 2.227)	2.998*** (1.673, 4.190)	0.898*** (0.561, 1.191)
Staff flexibility	-0.105*** (-0.163, -0.049)	-0.135*** (-0.344, -0.018)	-0.190*** (-0.346, -0.073)	-0.223*** (-0.298, -0.148)	-0.176*** (-0.323, -0.058)	-0.104*** (-0.266, -0.005)	-0.071*** (-0.114, -0.027)
Contract Beds	n/a	n/a	-0.001 (-0.006, 0.004)	-0.003*** (-0.005, -0.002)	0.001 (-0.009, 0.010)	n/a	n/a
For-profit dummy	-0.557*** (-0.895, -0.246)	n/a	n/a	n/a	n/a	-0.641*** (-1.143, -0.219)	-0.435*** (-0.654, -0.177)
Chain dummy	n/a	n/a	0.219*** (0.052, 0.372)	n/a	n/a	n/a	n/a
No. Observations:	110	38	72	32	40	44	66

Lower and upper bounds are presented in parentheses. A positive sign of coefficients of the efficiency determinants indicate a positive effect on the bias-corrected reciprocals of the TE scores and hence a negative effect on the TE scores (and vice versa). *** significant difference at the 1 % level, ** significant at the 5 % level and * significant difference at the 10 % level.

Table 6-3: Double Bootstrap CRS DEA Estimates of the TE Determinants

	All homes	Public	Private	Private Chain	Private Non-Chain	Urban	Rural
Size_2 (50-99 beds)	0.049 (-0.171, 0.294)	-0.371*** (-0.620, -0.131)	0.011 (-0.194, 0.244)	0.084*** (0.010, 0.176)	-0.055 (-0.325, 0.220)	-0.029 (-0.335, 0.219)	-0.276 (-0.751, 0.256)
Size_3 (≥100 beds)	-0.449*** (-0.897, -0.136)	-1.015*** (-1.469, -0.598)	-0.347* (-0.660, -0.049)	-0.123* (-0.218, -0.017)	-0.012 (-0.682, 0.434)	-0.810*** (-1.157, -0.474)	-0.692** (-1.288, -0.117)
Age of premises	0.004** (0.001, 0.008)	0.003*** (0.001, 0.007)	0.003 (-0.005, 0.010)	0.007** (0.001, 0.016)	0.001 (-0.011, 0.007)	-0.001 (-0.004, 0.004)	0.006** (0.001, 0.012)
HMD rate	1.138*** (0.265, 2.074)	0.446 (-0.494, 1.324)	1.407*** (0.870, 2.104)	0.865*** (0.557, 1.153)	0.890*** (0.057, 2.023)	1.842*** (0.940, 2.621)	2.265*** (0.802, 3.345)
Nurse turnover	0.007*** (0.001, 0.015)	-0.004 (-0.019, 0.010)	0.003 (-0.003, 0.008)	0.001* (0.001, 0.003)	0.005 (-0.002, 0.014)	0.012*** (0.005, 0.020)	0.011*** (0.001, 0.024)
HCA turnover	0.008*** (0.002, 0.017)	0.011* (0.001, 0.024)	0.006 (-0.001, 0.010)	-0.002** (-0.004, -0.001)	0.006 (-0.002, 0.015)	-0.001 (-0.011, 0.010)	0.009** (0.001, 0.026)
M-NM staff ratio	-0.211* (-0.389, -0.008)	-0.127 (-0.450, 0.112)	-0.417*** (-0.823, -0.063)	-0.738*** (-1.014, -0.571)	-0.158 (-0.461, 0.153)	-0.437*** (-0.699, -0.271)	0.015 (-0.529, 0.654)
L-C ratio	-11.801*** (-13.791, -10.082)	-7.511*** (-8.975, -6.285)	-11.640*** (-13.833, -9.567)	-4.683*** (-5.253, -4.151)	-13.351*** (-18.819, -9.176)	-9.887*** (-11.953, -7.414)	-12.180*** (-16.034, -9.119)
Staffing levels	9.095*** (8.259, 9.692)	7.934*** (7.482, 8.526)	9.564*** (8.567, 10.518)	7.482*** (7.104, 7.980)	7.267*** (6.065, 8.578)	8.567*** (7.518, 9.762)	8.636*** (7.568, 9.787)
Staff flexibility	-0.059*** (-0.115, -0.003)	-0.063*** (-0.133, -0.017)	-0.272*** (-0.514, -0.132)	-0.222*** (-0.324, -0.112)	-0.369 (-0.602, -0.158)	-0.085*** (-0.163, -0.023)	-0.138*** (-0.301, -0.056)
Contract Beds	n/a	n/a	-0.004 (-0.008, 0.001)	-0.003*** (-0.006, -0.001)	0.008*** (0.001, 0.018)	n/a	n/a
For-profit dummy	-0.379*** (-0.755, -0.016)	n/a	n/a	n/a	n/a	-0.691*** (-1.121, -0.369)	-0.310 (-0.990, 0.249)
Chain dummy	n/a	n/a	0.185** (0.052, 0.335)	n/a	n/a	n/a	n/a
No. Observations:	110	38	72	32	40	44	66

Lower and upper bounds are presented in parentheses. A positive sign of coefficients of the efficiency determinants indicate a positive effect on the bias-corrected reciprocals of the TE scores and hence a negative effect on the TE scores (and vice versa). *** significant difference at the 1 % level, ** significant at the 5 % level and * significant difference at the 10 % level.

6.4 OLS and Tobit Regression Results

This section presents the two-stage OLS and Tobit regressions results and compares them with the results obtained using the preferred DB DEA discussed in the previous Section 6.3. The regressions involve a two-step process. Firstly, the TE scores are estimated using: (1) the conventional DEA TE scores; and (2) the HB DEA TE scores, all of which were presented in Chapter Five. Secondly, the obtained conventional DEA and HB DEA TE scores are regressed on the same array of conventional and output-characteristic variables in the second stage, using the Tobit or OLS regressions.

The Tobit regression is preferable to the OLS method to analyze TE determinants due to the fact that TE scores are bound between 0 and 1. However, the model diagnostics from the OLS regression is also utilized here to examine the goodness of fit and the overall significance of the regression model. Moreover, as highlighted earlier, the conventional DEA TE scores do not have probabilistic distribution and do not account for sampling variability. While Table 6-4 presents the Tobit regression on both conventional and HB VRS DEA TE scores, Appendix 6A-6-2 outlines the same model results but for the CRS technology, and Appendix 6A-6-3 presents the two-stage OLS regression for the VRS technology.

6.4.1 Model diagnostics

The standard but important regression model diagnostic such as the goodness of fit, the overall significance of the model and the multicollinearity are discussed before considering the impact of potential efficiency determinants. Following the approach of Blank and Valdmanis (2010), these model diagnostic checks are conducted using the OLS regression on conventional DEA and HB DEA scores (Appendix 6A-6-3).⁹² This shows the R-squared for the full sample varies between 0.62 and 0.64, and indicates that between 62 to 64% of the variation in the TE scores

⁹² Whilst Table 6-4 presents the statistics for Tobit regressions using McFadden's pseudo R², it should be interpreted with caution as the pseudo R-squared often does not range from 0 to 1 (Freese and Long, 2006).

is explained by the TE determinants. The adjusted R-squared which ‘penalises’ the inclusion of more explanatory variables into the regression models ranges between 0.57 and 0.59 for all homes.⁹³ Thus, there is a relatively high goodness of fit of the presented regressions. Furthermore, the *F*-test of the null hypothesis that all coefficients of the variables are jointly equal to 0, was overwhelmingly rejected at the 1% level with the *p-value* for the *F*-test for the different samples being well below 0.001. Hence, the efficiency determining factors jointly explain TE scores for all the models used.

The correlation matrix of all variables elucidated in Appendix 6A-6-1 also indicates that multicollinearity is not a concern in this data sample, since none of TE determinants are highly correlated, except for the high correlation coefficient between *Urban*-location and *Dublin*-location variables that resulted in excluding both indicator variables fully from the regressions.⁹⁴

As expected for the Tobit regressions on conventional DEA TE scores, about 14% of all observations for the whole sample in Table 6-4 are right-censored. This is because certain homes are fully efficient with the TE scores equal to 1 (Section 5.2). The share of the censored observations is the highest for private-chain homes (38%) and is the lowest for the pooled sample (14%). With regard to the Tobit regression on HB DEA TE scores, Table 6-4 confirms there are no censored observations on TE scores.

These results are consistent with findings presented in Chapter Five as the obtained HB DEA TE scores are always below 1, and hence are uncensored. This also further implies that the estimated coefficients in the *Tobit* regression on HB DEA scores (Table 6-4) are the same as

⁹³ Notably, the subsamples in Appendix 6A-6-3 illustrate even higher R-squared and adjusted R-squared figures than the full sample of all nursing homes. This implies that splitting the full sample into groups of nursing homes increases the explanatory power of the regression model.

⁹⁴ The variance inflation factors (VIF), also obtained after the OLS regressions were much smaller than 10 for all TE determinants, and these results are available on request.

those obtained in the *OLS* regression on the same HB DEA scores (Appendix 6A-6-3 for details).

6.4.2 Comparison of results

The estimated coefficients of the two-stage Tobit regressions for VRS technology are presented in Table 6-4.⁹⁵ The estimated coefficients of TE determinants obtained from Tobit regressions are compared with the DB DEA results presented in the earlier section.⁹⁶ The Tobit regressions results are generally similar to the results obtained in the VRS DB DEA. However, it is also noted in the Tobit regression shown in Table 6-4, that some variables, such as *age* and *HCA turnover*, are not significant, or that they differ in their sign in contrast to the most preferred method which is DB DEA. The insignificant results apply in particular for Tobit regression on HB DEA scores.

Other important determinants presented in Table 6-4, such as the ownership, size and structural quality factors (i.e. staffing level and staff flexibility) have the same and significant effect as in the DB DEA specification. Most importantly, the *for-profit dummy* variable has the same positive and significant effect on TE. Hence, the Tobit regression results reaffirm that private NHs are more technically efficient than the public homes. In addition, and similarly to the DB DEA findings which were presented in the previous section, the percentage share of *contract beds* for the private NHs is never significant for the Tobit regression specifications.

With regard to the size of NHs, the Tobit regression results again clearly indicate that the middle-size NHs (50-99 beds) are less technically efficient than the small NHs (less than 50 beds). These findings are very similar to the results found for the VRS DB DEA model in

⁹⁵ It should be noted that the signs of the coefficients of efficiency determining variables in Table 6-4 show the exact effects on the estimated TE scores and not the reverse (opposite effect) on the TE scores as it was the case for the DB DEA models (Tables 6-2 and 6-3).

⁹⁶ Tobit regression is regarded as the more preferred method than the *OLS* regression. Also, in line with the previous discussion, both Tobit and *OLS* regressions on HB DEA TE scores give the same results due to uncensored TE scores obtained in HB DEA.

Section 6.3. The results for large NHs with 100+ beds (the *size_3* category) are, however, less clear-cut, indicating no difference in TE between the small and large NHs.

Resembling to the output-characteristic variables, the Tobit regression results in Table 6-4 indicate that the HMD rate has a negative effect on TE. However, the Tobit regressions on HB DEA TE scores show that the HMD rate positively affects the TE of all homes and rural homes only. The latter finding contradicts the findings of the DB DEA and it also runs counter to the present hypothesis which suggests that residents with higher care needs would require more nursing services, thereby reducing efficiency.

The chain status has a significant and negative effect on TE for private homes as in the DB DEA model for both CRS and VRS technologies. Therefore, these results coincide with the DB DEA results presented in the previous section, confirming that being a part of the chain will decrease TE scores of private NHs.

With regard to the structural quality factors, the *L-C ratio* in Table 6-4 changes the sign between public and private homes, indicating that no conclusions can be inferred for this determinant. However, as the CRS Tobit regression results in Appendix 6A-6-2 show, this variable has a positive and significant effect for all homes and most of the subsamples, similarly to DB DEA model, thereby confirming an overall positive effect of L-C ratio on TE in the NHs.

The *M-NM ratio* coefficient is significant and positive for all NHs and the subsamples (except for rural homes) in Tobit regressions on conventional DEA TE scores, confirming a positive effect of this determinant on TE as in the DB DEA model. However, the *M-NM ratio* is never significant in Table 6-4, and is negative only for rural NHs in the Tobit regression on HB DEA TE scores (for both VRS and CRS technologies).

The coefficient of the variable *staffing level* is significant and negative for all NHs and all subsamples, implying a negative effect on TE. These results apply to both VRS and CRS

technology and align with the DB DEA findings. *Staff flexibility* is significant and positive for all homes and subsamples for the Tobit regression on conventional DEA TE scores. Although this variable is not significant for the Tobit regression on HB DEA scores, these findings again echo DB BEA results.

The *nurse turnover* has a significant and negative effect on the VRS TE scores of all homes and most of the subsamples in Table 6-4. This result is similar to the VRS DB DEA model. In contrast, *HCA turnover* rate is never significant in Table 6-4 and has a negative and significant effect on TE for the Tobit regression on conventional CRS DEA scores only (Appendix 6A-6-2).⁹⁷

In summary, the results obtained in the Tobit regression largely resemble those obtained in the DB DEA, thereby consolidating the robustness of the empirical results. Surprisingly, these findings apply to a much greater extent to the results obtained in the Tobit regression on conventional DEA TE scores than on HB DEA TE scores, for both VRS and CRS technologies. Nevertheless, like the DB DEA, the Tobit regression results confirm that the ownership and size of the nursing home are important determinants of TE. The Tobit regressions also reinforce the findings with regard to several important indicators of structural quality such as staffing level and nurse turnover of the NHs. While the *nurse turnover* has a positive effect on the TE of the homes, *staffing level* clearly exerts a negative effect on TE of those units. Finally, the chain status of private units has, as before, a negative effect on TE of the private NHs. All these effects reinforce the findings obtained in the most preferred DB DEA specification.

⁹⁷ In contrast, this determinant affects negatively the TE scores of all homes, public homes, private chain facilities and rural homes in the DB DEA model.

Table 6-4; Tobit Regression Results for VRS DEA TE Scores

	Tobit regression on conventional VRS DEA TE scores							Tobit regression on HB VRS DEA TE scores						
	All homes	Public	Private	Private Chain	Private Non-Chain	Urban	Rural	All homes	Public	Private	Private Chain	Private Non-Chain	Urban	Rural
Size_2 (50-99 beds)	-0.110*** (0.031)	-0.101** (0.043)	-0.086** (0.036)	-0.205*** (0.038)	-0.047 (0.055)	-0.102 (0.055)	-0.124*** (0.028)	-0.078*** (0.022)	-0.074** (0.032)	-0.067** (0.027)	-0.189*** (0.029)	0.002 (0.040)	-0.073* (0.035)	-0.097*** (0.028)
Size_3 (≥100 beds)	0.064 (0.050)	0.180** (0.060)	0.044 (0.062)	n/a	0.003 (0.100)	0.225** (0.076)	-0.045 (0.057)	-0.053 (0.036)	-0.012 (0.045)	-0.068 (0.045)	-0.135 (0.066)	-0.067 (0.072)	0.042 (0.048)	-0.177*** (0.056)
Age of premises	-0.00003 (0.0005)	0.0003 (0.0004)	-0.001 (0.001)	0.0007 (0.004)	-0.0008 (0.001)	0.001 (0.0008)	-0.0005 (0.0004)	-0.0007 (0.0003)	-0.00009 (0.0003)	-0.001 (0.0008)	-0.005 (0.003)	0.00005 (0.001)	-0.0007 (0.0005)	-0.0007 (0.0004)
HMD rate	-0.377*** (0.102)	-0.608*** (0.158)	-0.532*** (0.115)	-0.473** (0.154)	-0.431** (0.179)	-0.755*** (0.178)	-0.423*** (0.088)	0.157** (0.070)	0.093 (0.106)	0.054 (0.081)	0.130 (0.113)	-0.143 (0.123)	-0.060 (0.099)	0.222** (0.086)
Nurse turnover	-0.002*** (0.0008)	-0.002 (0.003)	-0.002** (0.0009)	-0.0006 (0.001)	-0.002* (0.001)	-0.004** (0.001)	-0.003*** (0.0007)	-0.001*** (0.0006)	0.0009 (0.002)	-0.001** (0.0006)	-0.0007 (0.001)	-0.002** (0.0009)	-0.002 (0.001)	-0.002*** (0.0007)
HCA turnover	-0.0009 (0.001)	0.0005 (0.002)	-0.0008 (0.001)	0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)	0.0004 (0.0009)	-0.00006 (0.0007)	0.002 (0.002)	0.0002 (0.0007)	0.002 (0.0009)	0.0002 (0.001)	0.0001 (0.001)	0.0003 (0.0009)
M-NM staff ratio	0.204*** (0.040)	0.198*** (0.050)	0.307*** (0.085)	0.527*** (0.141)	0.291** (0.107)	0.279*** (0.059)	0.087 (0.049)	-0.051 (0.027)	-0.007 (0.034)	-0.066 (0.035)	0.039 (0.094)	-0.026 (0.042)	-0.042 (0.030)	-0.238*** (0.047)
L-C ratio	0.356 (0.217)	-0.653** (0.270)	1.063*** (0.343)	-0.407 (0.327)	1.361 (0.858)	0.747 (0.402)	0.136 (0.182)	1.170*** (0.145)	0.317 (0.174)	2.008*** (0.251)	1.344*** (0.259)	2.072*** (0.623)	1.438*** (0.245)	1.166*** (0.163)
Staffing levels	-0.467*** (0.091)	-0.345*** (0.091)	-0.615*** (0.151)	-0.668** (0.221)	-0.650** (0.228)	-1.299*** (0.243)	-0.286*** (0.069)	-0.681*** (0.066)	-0.460*** (0.071)	-1.033*** (0.113)	-1.217*** (0.182)	-1.181*** (0.170)	-1.20*** (0.155)	-0.520*** (0.070)
Staff flexibility	0.038*** (0.010)	0.020 (0.012)	0.085*** (0.023)	0.147** (0.054)	0.103** (0.035)	0.039 (0.021)	0.042*** (0.011)	-0.004 (0.004)	-0.001 (0.005)	0.0006 (0.010)	0.085 (0.043)	0.013 (0.014)	-0.018 (0.010)	0.010* (0.005)
Contract Beds			-0.0006 (0.0008)	0.0005 (0.0009)						0.00001 (0.0006)	0.001 (0.0008)	0.0005 (0.001)		
For-profit dummy	0.191*** (0.047)				0.0004 (0.001)	0.251** (0.083)	0.188*** (0.043)	0.121*** (0.033)					0.059 (0.047)	0.167*** (0.042)
Chain dummy			-0.083** (0.031)							-0.048* (0.023)				

Table 6-4: Tobit Regression Results (continued)

	Tobit regression on conventional VRS DEA TE scores							Tobit regression on HB VRS DEA TE scores						
	All homes	Public	Private	Private Chain	Private Non-Chain	Urban	Rural	All homes	Public	Private	Private Chain	Private Non-Chain	Urban	Rural
Total	110	38	72	32	40	44	66	110	38	72	32	40	44	66
Left-censored	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Right-censored	15	8	12	12	10	11	9	0	0	0	0	0	0	0
Uncensored	95	30	60	20	30	33	57	110	38	72	32	40	44	66
Log Likelihood	41.423	22.78	33.73	20.615	12.500	15.009	49.467	98.185	43.856	71.014	43.936	35.997	47.824	65.220
Pseudo R ²	4.897	5.062	4.379	3.169	2.275	2.128	-70.758	-1.302	-0.808	-2.043	-3.403	-2.0613	-1.080	-1.896
LR Chi ²	104.10 (0.000)	56.79 (0.0001)	87.43 (0.000)	60.24 (0.000)	44.60 (0.000)	56.62 (0.000)	97.56 (0.000)	111.10*** (0.000)	39.22*** (0.000)	95.36*** (0.000)	67.92*** (0.000)	48.48*** (0.000)	49.67*** (0.000)	85.41*** (0.000)

Standard errors in parentheses. *** significant at the 1% level, ** significant at the 5% level * significant at the 10% level.

6.5 Marginal Effects

The previous sections discussed the results of the TE determinants for all two-stage semi-parametric models with respect to the significance levels and signs of the estimated coefficients of TE determinants. This section presents the marginal effects (MEs) of the estimated determinants, which, in turn, account for a unit change in the dependent variable (i.e. the TE score) due to a one unit increase in one of the explanatory variables. As such, the MEs will not only indicate the directions, but also the magnitudes of the effects.

Table 6-5 presents the MEs of the two-stage methods for all homes, and public and private facilities, while the MEs of other NH groups are available on request. It is noted that the MEs from the OLS regressions (on both conventional and HB DEA TE scores) are the actual regression coefficients presented in previous sections of this chapter. The same interpretation applies to the MEs estimated using the DB DEA method which uses the truncated regression in the second stage. On the other hand, the Tobit regression is a non-linear model, and the MEs have to be derived.

While there a number of important differences between the two-stage methods as previously elucidated, the MEs are very similar with respect to the sign and significance levels as shown in Table 6-5. The same table highlights, however, that the main differences between the two-stage semi-parametric approaches relate to the magnitude of the MEs. Firstly, the MEs for the Tobit regression on the HB DEA TE scores are the same as the MEs obtained in the OLS regression on HB DEA TE scores. This is because all observations on the dependent variable (here HB DEA TE score) are uncensored.⁹⁸

Secondly, and as discussed earlier, the DB DEA procedure is the preferred approach as it yields unbiased estimates of TE similar to the HB DEA method. More importantly, however, it re-

⁹⁸ The MEs for the Tobit regression on the HB DEA TE scores are also the same as the actual Tobit regression coefficients obtained in Table 6-4.

estimates the bias-corrected TE scores to take account of the coefficients of the determining variables. Table 6-5 also indicates that larger number of MEs obtained in the DB DEA are statistically significant in contrast to other two-stage methods. The DB DEA method presents the largest magnitudes of the effects of the significant TE determinants in contrast to the other two-stage (OLS and Tobit) approaches. This confirms that similarly to the SFA, the DB DEA model which estimates both TE determinants and TE scores simultaneously is the most efficient method for the examined data.

The main differences in the MEs are also highlighted in Table 6-5. For example, for the DB DEA model and the full sample of all NHs, a 1% point increase in the *L-C* ratio (as it is measured in %) causes a 1.836% increase in the overall TE score which from the definition lies between 0-100%. This ME is by 37% larger than in the Tobit regression and 45% higher than in the OLS regression. Similar results apply to the *staffing level*, whereby for the full sample in the DB DEA model, a 1 unit increase in the number of full-time nurses per 1000 patient days leads to a decrease in TE score by 1.46%. This ME is again much larger than the same effect obtained under the other two-stage semi-parametric methods (Tobit and OLS regressions). The same finding applies to the size variables (*size_2* and *size_3*), and to the *for-profit* dummy variable, with MEs being much higher for DB DEA than for the other two-stage methods. Being the middle-sized nursing home (50-99 beds) or a very large nursing home (100+ beds) reduces the TE score by 0.55 and 0.26 percentage points, respectively. On the other hand, private ownership (indicated by the *for-profit* dummy in Table 6-5), increases the TE score by 0.55 percentage point.

Overall, it is reasonable to conclude that alternative two-stage regressions underestimate the magnitude of the efficiency determinants compared to DB DEA results. Furthermore, there are not only differences in the magnitude of MEs between the different two-stage methods but also between different TE determinants. For example, the *L-C* ratio and the *staffing level* have a

greater impact on TE than other structural quality indicators such as the *staff flexibility* and *nurse turnover*, since their MEs are relatively small compared to the MEs found for other determinants. As regards public homes, *L-C* ratio and *HMD* rate have the largest impact on TE in contrast to other determinants. For the full sample, the *HMD* rate indicates that rising the dependency rate by 1% will result in decreasing TE scores of all homes by 0.75%.

The important differences in ME also hold for the different subsamples of the NHs and it is noted that MEs are much higher for the sample of private NHs than for the public NHs. For example, increasing the *L-C* ratio by 1%, increases the TE scores for private NHs by over 4 percentage points, whereas it influences TE's of public homes by only 2%. Increasing the *staffing level* by one unit per 1000 patient days for private homes, decreases their TE scores by 1.83% while it decreases TE scores of public homes by 0.92%.

In summary, the MEs of efficiency determinants obtained from the DB DEA show the largest effects on TEs, in contrast to the alternative two-stage methods (OLS and Tobit). The findings confirm that the *HMD* rate and the structural quality are important factors in the NH sector, as they exert the largest effects on TE scores in the sector in terms of magnitude, and also affect the quality of care. Other important determinants are size and the ownership structure of the NHs, while other factors, such as for example, the *chain* status, have still significant but smaller effects in terms of magnitudes.

Table 6-5: Comparison of Marginal Effects of Efficiency Determinants for VRS Technology

	All Homes					Public Homes					Private Homes				
	OLS and Convent. DEA	OLS with Homo. Bootstrap	Tobit on Conv. DEA	Tobit on HB DEA	Two- Stage DB DEA ^(a)	OLS and Convent. DEA	OLS with Homo. Bootstrap	Tobit on Conv. DEA	Tobit on HB DEA	Two- Stage DB DEA ^(a)	OLS and Convent. DEA	OLS with Homo. Bootstrap	Tobit on Conv. DEA	Tobit on HB DEA	Two- Stage DB DEA ^(a)
Size_2 (50-99 beds)	-0.116***	-0.078***	-0.032***	-0.078***	-0.553***	-0.095**	-0.074**	-0.034**	-0.074**	-0.512***	-0.099**	-0.067**	-0.023**	-0.067**	-0.380***
Size_3(>=100 beds)	0.050	-0.053	0.019	-0.053	-0.263***	0.154**	-0.012	0.060***	-0.012	0.303	0.014	-0.068	0.012	-0.068	-0.329***
Age of Premises	0.00001	-0.0007	-0.00001	-0.0007	-0.001	0.0003	-0.00009	0.0001	-0.00009	0.002	-0.001	-0.001	-0.0005	-0.001	-0.004
HMD rate	-0.299***	0.157**	-0.112***	0.157**	-0.755***	-0.476***	0.093	-0.204***	0.093	-1.731***	-0.442***	0.054	-0.145***	0.054	-1.181***
Nurse turnover	-0.002***	-0.001***	-0.0008***	-0.001***	-0.007***	-0.001	0.0009	-0.0007	0.0009	-0.012	-0.002***	-0.001**	-0.0008***	-0.001**	-0.008***
HCA turnover	-0.0007	-0.00006	-0.0002	-0.00006	-0.004	0.001	0.002	0.0001	0.002	0.013	-0.0006	0.0002	-0.0002	0.0002	-0.004
M-NM staff ratio	0.168***	-0.015	0.061***	-0.051	0.399***	0.163***	-0.007	0.066***	-0.007	0.564***	0.197***	-0.066	0.083***	-0.066	0.560***
L-C ratio	0.292	1.170***	0.106	1.170***	1.836***	-0.609**	0.317	-0.219**	0.317	-2.287***	1.063***	2.008***	0.290***	2.008***	4.445***
Staffing levels	-0.448***	-0.681***	-0.139***	-0.681***	-1.465***	-0.339***	-0.460***	-0.115***	-0.460***	-0.927***	-0.592***	-1.033***	-0.167***	-1.033***	-1.831***
Staffing flexibility	0.024***	-0.004	0.011***	-0.004	0.105***	0.008	-0.001	0.006	-0.001	0.135***	0.040***	0.0006	0.023***	0.0006	0.190***
Contract Beds											-0.0004	0.00001	-0.0001	0.00001	0.001
For-profit dummy Chain	0.164***	0.121***	0.057***	0.121***	0.557***						-0.069**	-0.048*		-0.048*	-0.219***
No. Observations	110	110	110	110	110	38	38	38	38	38	72	72	72	72	72

Standard errors in parentheses. *** significant at the 1% level, ** significant at the 5% level * significant at the 10% level. (a) The signs of the estimated coefficients from the two-stage double bootstrap DEA model *have been reversed* in this table to enable comparison of marginal effects with the Tobit and OLS regressions. The results for other subsamples are available on request.

6.6 Parametric SFA Results

The main advantage of DB DEA method is that it estimates bias-corrected bootstrap TE scores which are also adjusted by the values of TE determinants. Nevertheless, the DB DEA does not control for random error (or noise) which reflect all events outside the producer's control and may affect the production process resulting in biased estimates of TE. For this reason, the present research applies also a fully parametric SFA as the final method considered in this research. The SFA assumes that any deviation from the frontier is composed of two parts: one representing inefficiency and another one statistical noise.

As previously delineated in Chapter Five, the SFA could not be applied to the full extent in this study due to the problems with convergence of the input-distance function (IDF) when the output is measured as the 'total patient days'.⁹⁹ Even though the SFA results are therefore not directly comparable with the semi-parametric two-stage results discussed earlier, this chapter nonetheless provides the SFA results for an alternative output variable which is the 'average length of stay', in order to establish the robustness of the findings regarding the effects of TE determinants. These additional robustness check results for the SFA IDF are presented in Appendix 6A-6-4. The results are presented for *all homes* and *private NHs* only. No empirical results for public, private non-chain, and private chain NHs are included, since the IDFs did not converge for these particular samples, while the results for urban and rural homes are available on request. The results imply that the significant determinants of all homes and private units are the *HMD* rate, the *L-C* ratio, and the *nurse turnover* and *staffing levels* for the sample of all NHs. The HMD rate has a strong significant and positive effect on inefficiency and hence a negative effect on TE, indicating that

⁹⁹ The reasons for non-convergence of both Translog and Cobb-Douglas IDFs were outlined in Chapter 5, and rationale for using the average length of stay as an alternative output measure was explained in Chapter 4.

the NHs with higher dependency levels of their patients are less technically efficient.¹⁰⁰ This finding coincides with the results of the two-stage methods discussed earlier and, in particular, with the DB DEA results. The nurse turnover also negatively affects TE scores of all homes in the SFA model which aligns with the results obtained in the semiparametric two-stage methods. However, the findings with regard to the variables such as *L-C ratio* and *staffing level* are in contrast to the robust findings obtained for the same group of homes in the two-stage semi-parametric methods.

The TE scores obtained using the average length of stay as an output variable in the IDF SFA model are on average higher than the TE scores obtained in all non-parametric (conventional DEA, HB and DB DEA) methods as discussed in Chapter Five. These SFA TE scores equate to 0.83 for the full sample and 0.85 for the private NHs. However, and as already established, the SFA results must be interpreted with caution due to: (i) the different output variable chosen, and (ii) problems with convergence for the full sample and other subsamples of NHs. Thus, while the SFA results obtained for the HMD rate are the same as those found for the other semi-parametric methods, the SFA results are not fully comparable with the more homogenous and robust results obtained using the two-stage DB DEA. As such, robust results and policy implications cannot be derived from the SFA results and the conclusions on key findings regarding the TE determinants are solely derived from the results from the respective two-stage methods. Nevertheless, this section reveals that applying an SFA IDF is an important model extension for future research, should better panel data on NHs in Ireland become available.

¹⁰⁰ The estimated coefficients of TE factors in Appendix 6A-6-4 show their direct effect on technical *inefficiency*, and hence an opposite effect on TE.

6.7 Summary of Key Findings

Following the earlier discussion of this chapter, the DB DEA (Section 6-3) is used as the benchmark method to estimate TE determinants, followed by OLS and Tobit regressions results (section 6-4). Table 6-6 summarizes the key findings with regard to the efficiency determinants estimated from all these models. It also compares the findings with the previous literature and provides an evidence that a broad set of determinants have an important influence on the TEs of INHs.

With regard to the ownership variable, private NHs are more technically efficient than the public units. This is consistent with the US efficiency literature, including that of Nyman and Bricker (1989), Nyman *et al.* (1990), Fazel and Nunnikhoven (1992). On the other hand, most European care homes do not evaluate the effect ownership has on TE since the majority of such units in Europe are state-owned. Thus, the findings of this study provide important insights as Ireland's NH industry is dominated by a mixed-ownership model. Moreover, the share of the private NHs beds which are contracted to the State have no significant impact on the TEs of these units. This is somewhat unexpected as all private NHs included in this study report that 10% or more of their total bed capacity is contracted in this way. Clearly, the higher the share of the state-contracted beds, the more dependent they are on public funds and the less efficient these homes might be. The insignificant coefficient of this variable indicates that further investigation into the ownership structure of INHs is needed. Table 6-6 also demonstrates that no previous study has examined the latter variable as an efficiency determinant in the NH literature.

This work also illustrates that the *size* of NHs will have a negative effect on TE. In particular, the DB DEA results clearly indicate that smaller NHs with less than 50 beds are more efficient than the middle-sized homes (50-99 beds) and the larger homes (100+ beds). As such, the results

indicate that the INHs could improve their productivity by decreasing their scale of operation (i.e. the number of beds) and increasing their specialization. This finding aligns with those of Sexton *et al.* (1989) and Nyman *et al.* (1990) who concluded that larger homes could be more difficult to manage effectively due of increased bureaucracy and slow decision-making.¹⁰¹

Furthermore, while *location* is excluded from the final analysis as it is not statistically significant in the majority of models and samples used, the conventional determinant of *age* of the premises exerts a significant and negative effect on the TE scores of all homes, public facilities, rural NHs, and in particular, *private-chain* homes. While private-chain homes are not as old as public NHs, they may not be ameliorated as frequently as necessary. This important finding adds to the literature on private-chain NHs, which despite the increasing ubiquity of this new organizational form, has been scarce to date.

The primary and the most important output characteristic which is specifically attributable to the health-care sector, is the HMD rate which is measured by the proportion of the ‘high-maximum’ dependency residents in the NHs. In this study, the HMD rate is a proxy for case-mix which is uniquely incorporated into the efficiency model in this research both as an input in the production and as a TE determinant. The results demonstrate that HMD rate has a strong and negative effect on the TE scores for all methods and subsamples of NHs.¹⁰² This result confirms the hypothesis that the higher dependency rate of the residents, the more resources used in those NHs lead to lower TEs. This finding also coincides with the efficiency studies of Nyman and Bricker (1989), Nyman *et al.* (1990), Fazel and Nunnikhoven (1992), and Chattopadhyay and Heffley (1994), who

¹⁰¹ This finding is in contrast to Ni Luasa *et al.* (2018), as the focus of that study was mainly on appropriate estimation of TE of Irish nursing homes, and not on the TE determinants. As the authors argue, their analysis of TE factors was preliminary as it did not involve a wide spectrum of methods and variables which were applied in this thesis.

¹⁰² This result is also found for the SFA IDF model when although a different output measure was used as the dependent variable.

concluded that the higher the dependency level of the resident, the more likely more inputs are needed to deliver NH services. These findings confirm the research hypotheses that the greater care needs of the LTC patients, the more likely more resources are required, leading to lower TE scores. As such, adjusting for this variable is crucial for this type of efficiency analysis in the LTC sector in Ireland.

The next output characteristics that negatively affects TE scores of private NHs is the *chain status*. Private-chain NHs are less technically efficient than the private non-chain homes. Having multiple NHs can create bureaucratic environments wherein decision making can be slower and more arduous. While the literature on the performance of multi-plants versus independent NH operators is rather limited, the result of this study contrast to Fazel and Nunnikhoven's (1993) findings that multi-plants carry significant economic advantages such as sharing the resources and the opportunity for large discounts on bulk purchases. In view of this, the empirical result of this work contributes to the performance of chain versus non-chain NHs.

Table 6-6: Key Findings for Efficiency Determinants¹⁰³

TE Determinant	Effect on TE	Studies with the same effect	Studies with different or insignificant effect
(1) Ownership			
Ownership (for-profit dummy variable)	Positive	<ul style="list-style-type: none"> • Ozcan et al. (1988), • Nyman et al. (1990), • Fizel and Nunnikhoven (1992); • Chattopadhyay and Heffley (1994) 	Crivelli et al. (2002), Ni Luasa et al. (2018)
Share of contract beds of private homes	Not significant	n.a.	n.a.
(2) Conventional characteristics			
Size of the NHs	Negative	Sexton et al. (1989), Nyman et al. (1990), Wang and Chou (2005)	Nyman & Bricker (1989), Chattopadhyay and Heffley (1994); Ni Luasa et al. (2018)
Age of premises	Negative	Martin and Jerome (2016)	n.a.
(3) Output characteristics			
<i>HMD rate (proxy for case mix)</i> ¹⁰⁴	Negative	Nyman and Bricker (1989), Fizel and Nunnikhoven (1992), Chattopadhyay and Heffley (1994)	Kooreman (1994) Ni Luasa et al. (2018)
<i>Chain status of private homes</i>	Negative	n.a.	Fizel and Nunnikhoven (1993)
<i>Structural quality factors</i> ¹⁰⁵			
M-NM (<i>Medical to non-medical staff</i>) ratio	Positive	n.a.	n.a.
L-C (<i>labour to capital</i>) ratio	Positive	n.a.	n.a.
Staffing level	Negative	Laine <i>et al.</i> (2005a)	n.a.
Staff Flexibility	Positive	n.a.	n.a.
HCA/Nurse turnover rates	Negative	n.a.	Nyman and Bricker (1989), Laine <i>et al.</i> (2005b)

¹⁰³ The variables *single bedrooms* and *urban* were excluded from the final analysis as they were not statistically significant for most of the samples used, or they changed the signs.

¹⁰⁴ As noted previously in Chapter Two, these authors utilized different indicators of case-mix relative to this study.

¹⁰⁵ Delellis and Ozcan (2013), Kooreman (1994), Zhang et al. (2008) utilized process-oriented measures of quality to evaluate the relationship between quality and efficiency. While Delellis and Ozcan (2013) found a positive relationship between quality and efficiency, the other two studies find a significantly negative effect between quality and efficiency.

Moreover, structural quality factors have consistent and significant impacts on TEs of NHs, in spite of certain differences in these results between the subsamples. The *medical staff to non-medical staff* ratio and the *labour to capital* ratio, both exert a positive impact on TEs of all NHs and their subsamples.¹⁰⁶ The findings with regard to these two structural quality factors support the work by Delellis and Ozcan (2013) and they indicate that higher quality will also enhance TE. Table 6-6 also demonstrates that *nurse turnover* and *HCA turnover* rates have negative impacts on TE scores of all homes and some of their groups, indicating that higher turnover rates will also imply lower quality. On other hand, *lower* nurse turnover rates will lead to *higher* TE, but they will also indicate *higher* quality, overall implying a positive relationship between quality and TE. On other hand, the *staff flexibility* ratio, as measured by part-time to full-time nurses, consistently illustrates a positive effect on TE. However, and as discussed earlier, only lower staff flexibility can lead to improved qualities and this will result in lower TEs. Similarly, the *staffing level* as the ratio of nurses per 1000 patient days, has a negative and significant effect on TE, while at the same time enhancing quality. It is also important in terms of the magnitude of the effect. Thus, in terms of staffing level and staff flexibility, there is a clear trade-off between quality and TE: a conclusion also reached in previous studies such as that of Kooreman (1994) and Zhang *et al.* (1998). Table 6-6 also illustrates that the efficiency-quality relationship has been only marginally addressed in the efficiency studies literature. To date very few studies have addressed the quality-efficiency relationship as noted by DiGiorgio *et al.* (2014). The findings of this chapter also call attention to how quality, and in particular, structural quality, should be measured, which as Garavaglia *et al.* (2011) noted, is a complex and contingent undertaking.

¹⁰⁶ It should also be noted that these quality indicators are also very important determinants in terms of the magnitude of their direct effects on TE in the Irish nursing homes sector (see section 6.5 in this chapter).

6.8 Conclusions

This chapter investigated the determinants of TE for all NHs and their subsamples by employing a wide spectrum of two-stage semi-parametric approaches. TE determinants were also estimated using a fully parametric SFA IDF, albeit using a different measure of output as the dependent variable.

While the two-stage OLS regressions provide insightful model diagnostics in relation to the TE model specification, the two-stage Tobit regression was found to be the preferred approach for evaluating TE determinants, since it can account for the fact that TE scores are limited between 0 and 1. Moreover, HB DEA TE scores which have random distribution due to bootstrapping were also used, along the conventional DEA TE scores in these two-stage regressions. Nevertheless, this chapter concluded that the DB DEA method is the most preferred semi-parametric method as it enables not only robust estimations of the parameters of TE determinants, but also re-estimates the bias-corrected TEs to take account of these efficiency determining variables in the first place. In this way, although this method does not account for noise, it is the most comparable method with the fully parametric SFA technique. The combination of the small sample size of NHs used in this research, cross-sectional nature of the dataset, and functional form restrictions, imposed by parametric framework, hindered a proper application of SFA. In summary then, the present research has proved the DB DEA method to be an important instrument to derive unbiased estimates of both TE and the determinants of TE in the NH sector, in particular in cases where the size and the nature of the data are restricted. It is also acknowledged that acquiring more data in the future of the INH sector would facilitate the application of a fully parametric SFA approach.

In relation to the estimated TE determinants, this research applied an holistic approach. To this end, it employed an extensive set of potential efficiency determining variables which, in many

cases, proved to be relevant factors affecting TE in the NH sector (Table 6-6).¹⁰⁷ The analysis presented in this chapter confirmed that conventional determinants and output characteristics such as the *ownership*, the *size* of the facilities, the *chain status* of private homes, and *HMD* rate, are the significant determinants affecting TE of INHs. This chapter also evaluated structural quality factors of the NHs, many of which relate to labour management factors such as *staff flexibility*, *staffing levels*, and *nurse turnover rates*. These determinants are important in terms of policy considerations as it is imperative to increase both the quality of care and efficiency of the sector. The results present a mixed relationship between TE and structural quality. Some measures of quality (e.g. *M-NM* ratio *C-L* ratio) indicate a positive association between quality and TE, while others expose a trade-off between quality and TE (e.g. *staffing levels* and *staff flexibility*). Yet other proxies, such as *nurse* and *HCA turnover rates*, imply low quality and have a negative effect on TE; in turn illustrating a positive association between quality and efficiency. All the aforementioned determinants are important policy considerations for this sector in the context of increasing pressure to ensure both quality of care and efficiency of the NHs.

¹⁰⁷ The findings were also discussed for different groups of nursing homes and some important differences in the impact of certain TE determinants depending on the nursing home group were highlighted. The magnitude of the marginal effects (ME) of the TE determinants between the two-stage methods applied in this research was also investigated, for the various sub-samples of the nursing homes.

6A Appendices

Appendix 6A-6-1 Correlation Matrix Of Potential Efficiency Determinants

	Ownership	Size1	Size2	Size3	Location	Urban	Age	HMD rate	Chain	Single	M-NM ratio	L-C ratio	Nurse Turnover	HCA Turnover	Staff Level	Staff Flex	% of Contract Beds
Ownership	1																
Size1	-0.141	1															
Size2	0.176	-0.802	1														
Size3	-0.052	-0.337	-0.291	1													
Location	0.191	0.163	-0.092	-0.116	1												
Urban	-0.070	-0.118	0	0.190	-0.823	1											
Age	-0.656	0.144	-0.259	0.178	-0.099	0.092	1										
HDM rate	-0.390	-0.224	0.031	0.31	0.093	-0.017	0.392	1									
Chain	0.465	-0.096	0.118	-0.031	-0.04	-0.032	-0.401	-0.225	1								
Single	0.826	-0.042	0.091	-0.075	0.105	-0.090	-0.654	-0.442	0.415	1							
M-NM ratio	-0.259	-0.156	0.054	0.165	-0.080	0.172	0.083	0.134	-0.119	-0.165	1						
L-C ratio	-0.368	-0.094	-0.015	0.175	-0.293	0.107	0.342	-0.014	-0.130	-0.233	0.521	1					
Nurse Turnover	0.608	-0.143	0.116	0.046	0.007	0.027	-0.492	-0.372	0.507	0.490	-0.072	-0.104	1				
HCA Turnover	0.536	-0.113	0.157	-0.065	-0.084	-0.018	-0.413	-0.428	0.376	0.436	-0.157	-0.099	0.676	1			
Staffing Level	-0.290	-0.172	0.111	0.100	-0.122	-0.042	0.240	0.095	-0.100	-0.293	0.290	0.555	-0.021	0.064	1		
Staff Flex	-0.307	0.301	-0.243	-0.099	0.154	-0.026	0.265	0.219	-0.217	-0.298	-0.223	-0.359	-0.339	-0.178	-0.235	1	
% Contract Beds	-0.922	0.120	-0.138	0.026	-0.181	0.061	0.581	0.360	-0.411	-0.759	0.259	0.331	-0.537	-0.480	0.319	0.270	1

Appendix 6A-6-2 Tobit Regression Results for CRS DEA Scores

	Tobit regression on conventional CRS DEA TE scores							Tobit regression on HB CRS DEA TE scores						
	All homes	Public	Private	Private Chain	Private Non-Chain	Urban	Rural	All homes	Public	Private	Private Chain	Private Non-Chain	Urban	Rural
Size_2 (50-99 beds)	-0.062* (0.030)	-0.025 (0.051)	-0.004 (0.033)	-0.102 (0.052)	0.066 (0.054)	-0.039 (0.043)	-0.069 (0.037)	-0.080*** (0.022)	-0.073** (0.033)	-0.068** (0.027)	-0.188*** (0.029)	0.002 (0.040)	-0.072* (0.034)	-0.096*** (0.028)
Size_3 (≥100 beds)	-0.004 (0.049)	0.124 (0.071)	0.026 (0.057)	-0.018 (0.118)	0.055 (0.096)	0.140** (0.058)	-0.087 (0.073)	-0.057 (0.036)	-0.015 (0.045)	-0.072 (0.045)	-0.132 (0.066)	-0.065 (0.073)	0.041 (0.047)	-0.176*** (0.056)
Age of premises	-0.0003 (0.0005)	-0.0005 (0.0005)	-0.0009 (0.001)	0.0003 (0.006)	-0.0001 (0.001)	0.0005 (0.006)	-0.0009 (0.0006)	-0.0007* (0.0003)	-0.0001 (0.0003)	-0.001 (0.0008)	-0.005 (0.003)	0.00005 (0.001)	-0.0006 (0.0005)	-0.0007 (0.0004)
HMD rate	-0.207** (0.099)	-0.206 (0.172)	-0.327*** (0.104)	-0.092 (0.205)	-0.427** (0.175)	-0.628*** (0.132)	-0.013 (0.113)	0.163** (0.070)	0.108 (0.108)	0.065 (0.082)	0.124 (0.113)	-0.148 (0.124)	-0.061 (0.098)	0.220** (0.085)
Nurse turnover	-0.002** (0.0008)	0.001 (0.003)	-0.001 (0.0008)	-0.002 (0.001)	-0.001 (0.001)	-0.003** (0.001)	-0.003*** (0.0009)	-0.001*** (0.0006)	0.001 (0.002)	-0.001** (0.0006)	-0.0007 (0.001)	-0.002** (0.0009)	-0.002 (0.001)	-0.002*** (0.0007)
HCA turnover	-0.002** (0.001)	-0.003 (0.003)	-0.001 (0.001)	0.002 (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.00007 (0.0007)	0.002 (0.002)	0.0002 (0.0007)	0.002** (0.0009)	0.0002 (0.001)	0.00007 (0.001)	0.0003 (0.0009)
M-NM staff ratio	0.161*** (0.039)	0.124** (0.053)	0.227*** (0.057)	0.351 (0.172)	0.243** (0.079)	0.210*** (0.042)	0.098 (0.063)	-0.049 (0.027)	-0.008 (0.034)	-0.066 (0.035)	0.040 (0.094)	-0.018 (0.042)	-0.038 (0.030)	-0.256*** (0.047)
L-C ratio	0.912*** (0.204)	0.542 (0.285)	1.827*** (0.314)	1.166** (0.465)	1.679 (0.838)	1.344*** (0.308)	1.260*** (0.233)	1.151*** (0.144)	0.323 (0.176)	2.023*** (0.252)	1.339*** (0.259)	2.062*** (0.626)	1.425*** (0.241)	1.182*** (0.162)
Staffing levels	-0.821*** (0.091)	-0.688*** (0.111)	-1.334*** (0.140)	-1.859*** (0.326)	-1.379*** (0.223)	-1.792*** (0.190)	-0.682*** (0.090)	-0.682*** (0.066)	-0.459*** (0.072)	-1.031*** (0.113)	-1.220*** (0.182)	-1.186*** (0.171)	-1.203*** (0.153)	-0.513*** (0.069)
Staff flexibility	0.020*** (0.006)	0.036** (0.012)	0.109*** (0.022)	0.110 (0.079)	0.127*** (0.035)	0.028 (0.015)	0.055*** (0.013)	-0.003 (0.004)	-0.002 (0.005)	0.0002 (0.010)	0.085 (0.043)	0.012 (0.014)	-0.016 (0.010)	0.011** (0.005)
Contract Beds			0.000008 (0.0007)	0.001 (0.001)	0.0008 (0.001)					-0.00001 (0.0006)	0.001 (0.0008)	0.0005 (0.001)		
For-profit dummy	0.232*** (0.046)					0.238*** (0.061)	0.275*** (0.056)	0.124*** (0.033)					0.067 (0.047)	0.165*** (0.042)
Chain dummy			-0.071** (0.029)							-0.048* (0.023)				

Appendix 6A-6-2 Continued.

	Tobit regression on conventional CRS DEA TE scores							Tobit regression on HB CRS DEA TE scores						
	All homes	Public	Private	Private Chain	Private Non-Chain	Urban	Rural	All homes	Public	Private	Private Chain	Private Non-Chain	Urban	Rural
Total	110	38	72	32	40	44	66	110	38	72	32	40	44	66
Left-censored	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Right-censored	10	5	9	7	9	8	6	0	0	0	0	0	0	0
Uncensored	100	33	63	25	31	36	60	110	38	72	32	40	44	66
Log Likelihood	47.540	19.325	42.700	14.571	14.663	26.418	39.045	98.675	43.378	70.764	43.908	35.808	48.460	65.474
Pseudo R ²	5.334	4.0189	3.959	2.515	1.922	3.173	6.833	-1.306	-0.778	-2.057	-3.400	-2.039	-1.086	-1.963
LR Chi ²	117.02 (0.000)	51.45 (0.000)	114.26 (0.000)	48.38 (0.000)	61.11 (0.000)	77.15 (0.000)	91.48 (0.000)	111.79*** (0.000)	37.99*** (0.000)	95.23*** (0.000)	67.86*** (0.000)	48.05** *	50.47** *	86.75*** (0.000)

Standard errors in parentheses. *** significant at the 1% level, ** significant at the 5% level * significant at the 10% level.

Appendix 6A-6-3 OLS Regression Results for VRS DEA Scores

	OLS regression on conventional VRS DEA TE scores							OLS regression on HB VRS DEA TE scores						
	All homes	Public	Private	Private Chain	Private Non-Chain	Urban	Rural	All homes	Public	Private	Private Chain	Private Non-Chain	Urban	Rural
Size_2 (50-99 beds)	-0.116*** (0.029)	-0.095** (0.043)	-0.099** (0.035)	-0.152*** (0.032)	-0.078 (0.054)	-0.121** (0.051)	-0.123*** (0.028)	-0.078*** (0.023)	-0.074** (0.038)	-0.067** (0.029)	- (0.036)	0.002 (0.048)	-0.073 (0.041)	-0.097*** (0.031)
Size_3 (≥100 beds)	0.050 (0.047)	0.154** (0.060)	0.014 (0.059)	0.137 (0.073)	-0.061 (0.096)	0.178** (0.070)	-0.055 (0.056)	-0.053 (0.038)	-0.012 (0.053)	-0.068 (0.050)	-0.135 (0.084)	-0.067 (0.086)	0.042 (0.056)	-0.177*** (0.062)
Age of premises	0.00001 (0.0004)	0.0003 (0.0004)	-0.001 (0.001)	0.004 (0.004)	-0.0001 (0.001)	0.0008 (0.0007)	-0.0003 (0.0004)	-0.0007 (0.0003)	-0.00009 (0.0004)	-0.001 (0.0009)	-0.005 (0.004)	0.00005 (0.001)	-0.0007 (0.0006)	-0.0007 (0.0005)
HMD rate	-0.299*** (0.091)	-0.476*** (0.142)	-0.442*** (0.106)	-0.285** (0.125)	-0.349** (0.164)	-0.560*** (0.146)	-0.406*** (0.086)	0.157** (0.074)	0.093 (0.126)	0.054 (0.090)	0.130 (0.143)	-0.143 (0.147)	-0.060 (0.117)	0.222** (0.095)
Nurse turnover	-0.002*** (0.0008)	-0.001 (0.002)	-0.002*** (0.0008)	0.00003 (0.001)	-0.002** (0.001)	-0.003 (0.001)	-0.002*** (0.0007)	-0.001*** (0.0006)	0.0009 (0.002)	-0.001** (0.0007)	-0.0007 (0.001)	-0.002** (0.001)	-0.002 (0.001)	-0.002*** (0.0007)
HCA turnover	-0.0007 (0.001)	0.001 (0.002)	-0.0006 (0.001)	0.001 (0.001)	-0.0005 (0.001)	-0.0008 (0.001)	0.0001 (0.0009)	-0.00006 (0.0008)	0.002 (0.002)	0.0002 (0.0008)	0.002 (0.001)	0.0002 (0.001)	0.0001 (0.001)	0.0003 (0.001)
M-NM staff ratio	0.168*** (0.035)	0.163*** (0.045)	0.197*** (0.046)	0.267** (0.104)	0.178*** (0.056)	0.207*** (0.044)	0.065 (0.047)	-0.015 (0.028)	-0.007 (0.040)	-0.066 (0.039)	0.039 (0.119)	-0.026 (0.050)	-0.042 (0.035)	-0.238*** (0.052)
L-C ratio	0.292 (0.188)	-0.609** (0.231)	1.063*** (0.329)	-0.106 (0.286)	1.149 (0.828)	0.803** (0.359)	0.001 (0.163)	1.170*** (0.154)	0.317 (0.206)	2.008*** (0.278)	1.344*** (0.328)	2.072** (0.745)	1.438*** (0.287)	1.166*** (0.180)
Staffing levels	-0.448*** (0.086)	-0.339*** (0.094)	-0.592*** (0.148)	-0.766*** (0.201)	-0.606** (0.227)	-1.162*** (0.228)	-0.280*** (0.070)	-0.681*** (0.070)	-0.460*** (0.084)	-1.033*** (0.125)	-1.217*** (0.230)	-1.181*** (0.204)	-1.207*** (0.182)	-0.520*** (0.077)
Staff flexibility	0.024*** (0.006)	0.008 (0.006)	0.040*** (0.013)	0.082 (0.047)	0.041* (0.019)	0.018 (0.015)	0.0215*** (0.005)	-0.004 (0.005)	-0.001 (0.006)	0.0006 (0.011)	0.085 (0.054)	0.013 (0.017)	-0.018 (0.012)	0.010* (0.005)
Contract Beds			-0.0004 (0.0008)	0.001 (0.0008)	0.0005 (0.001)					0.00001 (0.0007)	0.001 (0.001)	0.0005 (0.001)		
For-profit dummy	0.164*** (0.043)					0.177** (0.070)	0.156*** (0.042)	0.121*** (0.035)					0.059 (0.056)	0.167*** (0.047)
Chain dummy			-0.069** (0.030)							-0.048* (0.026)				
Total	110	38	72	32	40	44	66	110	38	72	32	40	44	66
F -Value	14.29	9.57	11.1	14.15	4.71	8.44	17.12	15.55	4.88	13.57	13.37	6.01	6.09	13
P-Value (F Statistic)	0.000	0.000	0.000	0.000	0.0004	0.000	0.000	0.000	0.0005	0.000	0.000	0.0001	0.0006	0.000
R ²	0.616	0.779	0.693	0.886	0.649	0.743	0.777	0.635	0.643	0.734	0.880	0.702	0.676	0.725
Adjusted R ²	0.572	0.698	0.630	0.823	0.511	0.655	0.731	0.594	0.511	0.68	0.814	0.585	0.565	0.67

The results from two-stage OLS regression under CRS technology are available on request only for clarity reasons, and they are very close to the OLS results presented in Appendix 6A-6-2. Standard errors in parentheses. *** significant at the 1% level, ** significant at the 5% level * significant at the 10% level.

Appendix 6A-6-4 Estimates of Input Distance Function and Determinants of TE¹⁰⁸

Dependent variable: Total patient days		IDF SFA model			
Input distance function (IDF) coefficients	All Homes	Private Homes	Estimated determinants of inefficiency (u _i) ^(a)	All Homes	Private Homes
Constant	5.361 (5.742)	12.739 (13.284)	For-profit Dummy	0.838 (0.982)	n/a
ln(lengthstay)	0.154 (1.238)	0.989 (2.854)	Share of Contract Beds	n/a	0.012 (0.019)
ln(nonmedstaff*)	1.066 (1.664)	-1.301 (2.624)	Chain Status	n/a	0.223 (0.721)
ln(capital*)	-2.883 (2.704)	-11.062*** (3.656)	Age of Premises	-0.005 (0.007)	0.004 (0.024)
ln(highmax*)	4.159*** (1.178)	5.226*** (1.540)	HMD rate	15.779*** (3.466)	15.609*** (4.205)
0.5ln(lengthstay) ²	0.162 (0.182)	-0.168 (0.322)	Nurse T/O	0.030* (0.017)	0.024 (0.019)
0.5 ln(nonmedstaff*) ²	-0.107 (0.160)	-0.284 (0.184)	HCA T/O	-0.009 (0.025)	-0.043 (0.036)
0.5ln(capital*) ²	1.756*** (0.433)	2.874*** (0.657)	M-NM ratio	-0.334 (0.792)	-1.354 (1.639)
0.5ln(highmax*) ²	0.845*** (0.162)	0.921*** (0.179)	L-C ratio	16.363*** (5.528)	18.351** (8.619)
ln(nonmedstaff*) x ln(capital*)	0.075 (0.267)	0.401 (0.447)	Staffing Level	-3.923* (2.096)	0.042 (5.556)
ln(nonmedstaff*) x ln(highmax*)	-0.080 (0.145)	-0.324 (0.209)	Staff Flexibility	-0.0009 (0.138)	0.489 (0.385)
ln(nonmedstaff*) x ln(lenghtstay)	-0.194 (0.188)	-0.024 (0.254)	Log Likelihood	5.119	16.930
ln(capital*) x ln(highmax*)	-1.019*** (0.234)	-1.371*** (0.296)	Observations	110	72
ln(capital*) x ln(lenghtstay)	-0.413 (0.283)	0.283 (0.400)	Estimated TE scores in one step		
ln(highmax*) x ln(lenghtstay)	0.089 (0.105)	0.094 (0.168)	Mean TE score	0.827	0.849
			Std. Deviation TE score	0.182	0.149
			Min. TE score	0.205	0.448
			Max TE score	0.998	0.998

*** significant at the 1% level, ** significant at the 5% level * significant at the 10% level. (a) The estimated coefficients of the TE factors show their direct effect on technical *inefficiency* which is the opposite effect on TE.

¹⁰⁸ The starred variables in the IDF are transformed as follows: *nonmedstaff**=*nonmedstaff/medstaff*, *capital**=*capital/medstaff*, *highmax**=*highmax/medstaff* and see chapter 4 for further details. Results are not presented for public, private chain and non-chain homes due to the non-convergence issues as discussed in Section 6-6. The results for rural and urban nursing homes are available on request.

Chapter Seven: Conclusions

7.1 Introduction

The final chapter of this thesis presents the conclusions of this research and contributions to scholarship in terms of the evaluation TE. The research contributions are based on four pillars: theoretical; empirical; methodological and policy. Theoretical impacts inform the novel holistic multivariate approach adopted in this study: for example, valuable insights emerge in relation to the identification of non-clinical factors that influence TE. Empirical contributions include the estimation of technical and scale efficiencies for INHs and the sub-samples, and the identification of the determinants of TE. The methodological contributions relate to: (1) the wide spectrum of methods employed in this study; (2) the efficacy of the semi-parametric two-stage double bootstrap DEA approach when the fully parametric SFA is not feasible; and (3) the unique primary dataset used in this research. A number of policy recommendations are proposed which would enable limited resources to be deployed more efficiently in the NH sector. Finally, limitations of the study and suggestions for future research are presented and discussed. Section 7.2 therefore provides a brief summary of each chapter, while Section 7.3 outlines the theoretical, empirical, methodological, and policy contributions. Section 7.4 the acknowledged the limitations of this investigation and suggests future avenues of research. Section 7.5 concludes the chapter with closing remarks.

7.2 Summary and Discussion

This section provides a short overview of each chapter and illustrates how each of the chapters is interconnected through the objectives associated with the following research questions outlined initially in Chapter One, Section 1.3:

1. *How to appropriately measure TE for the NH sector in Ireland?*
2. *What are the determinants of TE in INHs?*

3. *Are private NHs more technically efficient than public homes in Ireland?*

Chapter Two surveyed the literature on efficiency in the NH sector and found that TE is the predominant measure used. Previous studies, such as those by Chang and Cheng (2013) and DeLellis and Ozcan (2013) demonstrated that TEs are primarily estimated because it is not necessary to specify a behavioural assumption of cost minimization or revenue maximization. Moreover, managers focus on input-orientations of TE since they can better control inputs than outputs. Chapter Two also reviewed the determinants of TE. The US literature, such as that of Nyman *et al.* (1990), Fazel and Nunnikhoven (1992) and Ozcan *et al.* (1998) concurred that private care facilities attain higher TE scores than public NHs. In contrast, since many European NHs are publicly owned, the question of whether ownership status affects their efficiency is not widely considered. Indeed, no research on efficiency performance in the context of Ireland has been undertaken prior to this thesis. Yet, given that Ireland has a mixed public-private NH care system, questions of how ownership affects the TE of these homes, are key considerations.

Furthermore, some private NHs in Ireland are subsidized by the State in the form of fixed contracts to supply beds which cushions them from the market imperatives of minimizing costs and producing efficiently. Previous efficiency studies also applied other determinants which can influence efficiency, including case-mix, chain affiliations versus independent units, and the reimbursement policy of the care facility. Since Ni Luasa *et al.* (2018) is the only published study to evaluate the efficiency of INH services to date, the present thesis addresses this gap in the literature. The research area is important as resources are limited, and it is now imperative for stakeholders such as Government and policymakers, to have access to up-to-date determinations of whether private INHs are more efficient than public care homes in order to formulate effective policy decisions. This matter is amplified by forecasts of unprecedented demand for LTC as a rapidly expanding growing population continues to age.

The literature review also surveyed the efficiency measurement methods employed by the studies Nyman and Bricker (1989), Nyman *et al.* (1990), and Crivelli *et al.* (2002). These approaches range from conventional non-parametric DEA method to the fully parametric SFA. Nonetheless, it is noted that most previous efficiency studies used DEA because it does not impose a specific functional form on the production technology and uses the observed data to infer the shape of the frontier. In addition, this method facilitates analysis of the productivity of NH units which is composed of both TE and SE.

Chapter Three presented an overview of the locale for this study: namely, the INH sector. Public NHs were the historically dominant setting for long-term residential care in Ireland. However, between 1998 and 2011, the Irish Government afforded capital allowances to the NH care market as a means to stimulate private supply. By 2013, private and voluntary NHs provided 80% of the overall long-stay beds capacity. In spite of this, there has been little empirical evidence to support the proposition that private facilities are more productively efficient than State provision.

Chapter Four discussed the methods employed to estimate the TEs of INHs and to evaluate the determinants of TE. This study commenced by using conventional DEA to estimate the technical and scale efficiencies. Next, both the homogenous bootstrap (HB) and the two-stage double bootstrap (DB) DEA methods were applied to obtain CIs for the bias-corrected DEA TE scores. In addition, and in order to examine the impact of potential TE determinants, this thesis applied alternative semi-parametric two-stage methods, such as OLS and Tobit regressions and the DB DEA model. Crucially, the DB DEA approach integrated the effects of TE determinants as explanatory variables in estimating the true efficiencies. In this way, the DB DEA method afforded estimates of the parameters of the efficiency determinants as well as bias-corrected DEA scores after controlling for the effects of the efficiency factors. However, neither of the two-stage approaches accounted for statistical noise. Consequently,

this research also estimated the fully parametric SFA input-distance function which controls for statistical noise and enabled unbiased TE estimates and parameters of the determining variables to be obtained. As well as considering the wide spectrum of methods applied in this thesis, Chapter Four also delineated the unique and detailed primary dataset on which this investigation was based. This dataset was collected via face-to-face interviews with NH managers throughout the Republic of Ireland (ROI) during the period 2008 to 2009. Furthermore, the inputs and outputs of the efficiency model were outlined, along with the potential efficiency determining variables.

Chapter Five was the first of two empirical chapters in the thesis, and used the broad spectrum of methods described in Chapter Four to estimate the technical and scale efficiencies of INHs. The pooled sample was truncated into the following subsamples: public and private (and voluntary) units; private chain and non-chain homes; and urban and rural facilities. The empirical results suggested that the conventional DEA scores overestimate both the technical and scale efficiencies of INHs in comparison to the semi-parametric (HB and DB) DEA methods. This finding also applies to all of the subsamples analyzed in this research. INHs were found to be only 52 to 58 % technically efficient, on average, and based on the DB DEA approach, which is the preferred estimation method in this thesis. Thus, NHs in Ireland were found to be considerably inefficient and need to reduce their usage of resources by 42 to 48% in order to be technically efficient. In addition, INHs were also found to be only 89% scale efficient. The average scale efficiency (SE) is higher than for TE; inferring that the productivity of INHs will result to a greater extent from pure TE improvement rather than from SE.

Finally, it is deemed important that the SFA method failed to deliver valid results when output is measured as total patient days due to convergence issues. This may be due to the relatively small data sample and the cross-sectional nature of the data in this research.

Chapter Six evaluated the determinants of TE using two-stage semi-parametric and fully parametric methods. The results revealed that the ownership variable was positive and significant for the pooled sample across the two-stage semi-parametric approaches. This infers that private NHs which have 10% or more of their total beds capacity contracted by the State are more technically efficient than public homes. Furthermore, the marginal effects results show that private ownership increases the TE score by 0.55 of 1% compared to public provision. Nonetheless, it is acknowledged that an alternative measure of ownership, namely the percentage share of contract beds, is not statistically significant for private homes. The results also demonstrated a negative relationship between size and TE. INHs and the subsamples in this investigation were found to be scale inefficient, inferring that care facilities could improve their productivity by decreasing their scale of operations and increasing their specialization. Additionally, the HMD rate was found to have a negative effect on the TEs of all homes and the subsamples. The study confirmed that the higher the proportion of high to maximum dependency residents, the greater the resource requirements; leading to falling TEs. The empirical analysis also revealed that certain indicators of quality improve the quality of care, and at the same time, increase the overall TEs of INHs; while other measures improve quality, but negatively affect efficiency performance. Furthermore, increasing other quality proxies actually generates worse quality and TE outcomes. Finally, the chain status of private NHs was found to exert a negative effect on TE. Chapter Six also applied the SFA model to estimate potential TE determinants. However, it was not possible to evaluate the factors which explain TE using the SFA method, as the maximum likelihood function did not converge when output was measured as total patient days. Hence, average length of stay, which is a component of total patient day, was employed as an alternative output measure. Disappointingly, the results of this fully parametric approach were not found to be directly comparable with the two-

stage semi-parametric techniques employed in this study due to the use of different output variables.

7.3 Contributions

This study makes important contributions in the area of efficiency evaluation, and in relation to general NH performance, and the Irish case, in particular. The contributions from this work can be classified into four key areas: namely, (1) theoretical; (2) empirical; (3) methodological; and (4) policy and are discussed as follows:

7.3.1 Theoretical Contributions

This study developed a holistic multivariable modelling approach by integrating a comprehensive set of three types of potential determinants to estimate and explain TE. Furthermore, this research advances the literature on how organizational performance is measured and TE scores validated. Extending the efficiency model to incorporate the ‘case-mix’ variable both as an input and a determinant of efficiency is a novel and original conceptualization which significantly extends the discourse on the evaluation of efficiency in the extant literature. The holistic multivariate model integrates three types of potential determinants to explain efficiency: namely, (1) ownership; (2) NH characteristics; and (3) quality. Incorporating such an extended set of variables addresses a number of gaps identified in the literature by eliciting unique insights into: (a) the identification of non-clinical factors which affect (in)efficiency; (b) the potential relationship between quality and efficiency (which has been only marginally addressed in efficiency studies); and (c) whether private chain homes are more efficient than independently operated units: a topic that has attracted scant attention in the efficiency literature despite the growth of this organizational form.

7.3.2 *Empirical Contributions*

This thesis contributes to society's knowledge of efficiency performance by estimating TE and evaluating its determinants for all INHs in the dataset and for the subsamples. It is stressed that this study is the first such attempt to estimate the TEs of NHs and to assess whether care units are utilizing their limited resources in an optimal manner. This is of increasing concern as Ireland's aging population is booming, meaning that a vastly increased number of citizens will require LTC in the future.

This research presented two empirical chapters: Chapter Five estimated the technical and scale efficiencies of INHs, while Chapter Six assessed the determinants of TE. As such, this combination of empirical findings offers unique insights into the efficiency performance of INHs. In terms of estimating TE, the conventional DEA approach showed that INHs are considerably inefficient, with TE scores ranging between 66 and 85 % for all NHs and subsamples. These results indicated that the Irish NH units in this investigation need to reduce their inputs while holding output constant to become technically efficient. Comparing these findings to those from the previous NH efficiency studies summarized in Table 2-1, it is evident that Irish long-stay care homes are considerably less efficient than their counterparts in other countries. Furthermore, after correcting for bias using bootstrap techniques (HB DEA and two-stage DB DEA), INHs were found to be even more technically inefficient than was originally indicated by the conventional DEA method. Given the absence of previous economic research in Irish care homes, these robust and significant results make a clear contribution to the extant efficiency literature.

While the conventional DEA TE results indicated that public NHs are more technically efficient than private homes, the bootstrap approaches (HB DEA and two-stage DB DEA) found the opposite. Such contradictory findings underscore the importance of further enquiry into ownership as an efficiency determinant. Moreover, when comparing the estimates in this

research to the results from previous studies (Table 2-1), private NHs in Ireland were found to perform less favourably than their counterparts in the efficiency literature. As regards private chain and non-chain homes in Ireland, the findings proved robust across the different methods. On average, private chain facilities were found to be more technically efficient than private non-chain units, and the difference in the mean TE scores statistically significant. The empirical evidence also confirmed that urban INHs are more technically efficient than rural homes; although the difference was only found to be statistically significant for the CRS TE estimates using the conventional DEA and two-stage DB DEA methods. The policy implications of some of these results are further discussed in Section 7.3.4.

Based on the DB DEA method, INHs were found to be only 87 % scale efficient. Nevertheless, the average SE was higher than for TE, inferring that greater productivity in INHs will result in increasing ‘pure’ TE, rather than SE. This result is validated by other findings, wherein smaller NHs (1 to 49 beds) were found to be more technically efficient than larger homes. With the exception of Chattopadhyay and Ray (1996), who found that scale efficiencies close to 100% for NHs in Connecticut, SE is largely neglected in the NH efficiency literature. However, SE scores for INHs are approximately 10 % less than those reported for facilities in Connecticut.

To reiterate: this study is the first attempt to evaluate the determinants of TE for NHs using Irish data. Thus, the empirical findings in this study add to the debate regarding the factors that drive efficiency. The unique dataset on which this research is based demonstrated that private NHs which have at least 10% of their total bed capacity contracted to the State on a fixed contract basis, are more technically efficient than public NHs. This empirical finding is entirely consistent with the results in the long-stay care efficiency literature. However, for context, most of these previous studies primarily focus on US NHs, whereas in many European countries, care of the elderly is generally provided by public municipalities (Nyman and Bricker 1989;

Nyman *et al.* 1990; Fazel and Nunnikhoven 1992; Chattopadhyay and Heffley 1994; Ozcan *et al.* 1998). Significantly for policymakers, the findings of this study provides evidence that the private NH setting as the more efficient organizational structure is better placed to provide future LTC beds in Ireland.

The results also found that the size variable has a negative relationship with TE. This investigation concluded that medium-sized homes (50-99 beds) should reduce their scale of operations to smaller entities (1-49 beds) in order to improve their TEs. This negative effect between size and efficiency is corroborated by Sexton *et al.* (1989), but at variance with the wider literature (Nyman and Bricker 1989; Chattopadhyay and Heffley 1994; Filippini 1999). Moreover, the findings demonstrated that INHs are not operating at their TOPS; inferring these care facilities are not minimizing costs.

The high-max dependency (HMD) rate which measures the severity cases of patients and is a proxy for a case-mix, was found to negatively affect the TEs of INHs and the subsamples investigated. This result confirms that a greater proportion of NH residents with high or maximum dependency have need of a higher amount of NH care services, which, in turn, requires more medical and non-medical staff to meet care needs of these people, and leads to lower TEs. The findings in this research are consistent with Nyman and Bricker (1989) and Fazel and Nunnikhoven (1992) who surmised that the more complicated the case-mix status of the elderly people, the more likely technical efficiencies will fall, as additional inputs may be required.

The 'chain' determinant was found to negatively influence the TEs of private NHs. As such, being part of a chain exerted a negative effect on TE for private homes relative to non-chain units. While the NH literature is rather limited in this regard, the findings in this study are at variance with the previous study of Fazel and Nunnikhoven (1992) and Kleinsorge and Karney

(1992) who concurred that being part of chain improved the efficiency of the nursing home. Therefore, the findings of this investigation make an important contribution to the multi-plant versus independent operator efficacy debate.

The empirical analysis found that for some indicators of quality, TE was increased with improvements in quality. For example, increases in some labour management factors (i.e. the ratio of medical staff to non-medical staff, the ratio of labour to capital, staff flexibility) exerted a positive effect on both the quality of care and TE. However, other proxies of quality (e.g. staff levels) precipitated a trade-off between quality and TE (e.g. increasing staff levels will improve quality but decrease the overall TE of the nursing home). In addition, ancillary labour management measures, such as nurse turnover rates, were found to have a negative effect on both quality and TE. To date, the link between quality and efficiency has been rather sparsely addressed in the NH literature (Nyman and Bricker 1989; Kooreman 1994; Shimshack *et al.* 2009; Garavaglia *et al.* 2011) and most prior efficiency studies have applied clinical indicators to explain the quality-efficiency relationship. In contrast, many of the indicators of quality in this are novel as the dataset enabled focus on non-clinical elements of quality (e.g. ratio of full-time nurses to capital, the ratio of full-time equivalent nurses (FTE) per 1,000 adjusted inpatient-days) in assessing the quality-TE relationship. Nevertheless, a small cohort of previous studies incorporated some structural indicators of quality into their evaluation of efficiency and quality. For instance, Martin and Tiphaine (2016) concluded that the ratio of nursing auxiliary staff to total staff had a positive effect on CE; while in contrast, Laine *et al.* (2005a) surmised that raising the ratio of registered nurses to total staff enhanced quality, but reduced TE. Similarly, the empirical results here corroborated that increasing the ratio of medical staff to non-medical staff improved both quality and TE, whereas increased staffing levels resulted in better quality of care, but decreased TE. Thus, this study educed rich insights

into the quality-efficiency relationship which has been largely ignored in other efficiency studies of the NH sector.

7.3.3 Methodological Contributions

This research investigated how to appropriately measure the TEs of INHs. To this end, it integrated an extensive set of potential determinants to estimate and explain TE. To validate the robustness of the estimates, a full spectrum of methods was applied, ranging from non-parametric to fully parametric approaches. This study therefore makes a number of worthy methodological contributions to knowledge which are summarized as follows:

Conventional DEA is the dominant method used in the efficiency literature to estimate TE. The present study extended beyond this scope of this approach by employing the HB DEA and two-stage DB DEA techniques to validate the robustness of the non-parametric conventional DEA TE scores. Since bootstrapping DEA methods have only rarely been used in NH studies, the application of these techniques amplified the efficiency measurement literature in this setting. In order to evaluate the determinants of TE, this study used a number of alternative two-stage semi-parametric methods as follows:

- OLS with conventional and HB DEA TE scores
- Tobit regression with conventional and HB DEA TE scores
- Two-stage DB DEA

To the best of the researcher's knowledge, this is the first study to compare the determinants of TE across various semi-parametric methods in the same investigation. Furthermore, very few studies applied the two-stage DB DEA in the health sector. As such, this thesis advances the discourse on the measurement of efficiency in all settings, and in relation to NHs, in particular. Nonetheless, it is noted that the two-stage DB DEA method proved the preferred approach in this study as it afforded estimates of the parameters of the efficiency determinants,

as well as bias-corrected DEA TE scores after controlling for the effects of the efficiency factors. Moreover, as the fully parametric SFA could not be applied, most likely because of the relatively small dataset used in this research, the DB DEA technique was deemed the best in the class between the two-stage semi-parametric approaches when identifying the TE determinants.

Another important contribution of this study is the detailed primary dataset used. This unique dataset is the first to provide insights into the examination of the relationship between quality of elderly care and the NHs performance, using the labour management measures as the quality indicators, such as the *number of nurses per patient*, the *ratio of medical to non-medical staff*, the *labour to capital ratio*, and *staff flexibility*. It is clear that this novel dataset curates an in-depth understanding of INHs: an industry that has been largely neglected by economic research to date.

7.3.4 Policy Contributions

The combined insights accruing from the empirical findings of this research and the long-stay care efficiency performance literature have very important policy implications for INHs. First, the compelling results of this study reveal that INHs are technically inefficient; indicating that these homes are not making optimal use of their limited resources. It is therefore vital that Government and policymakers instantiate performance measurement to ensure scarce public resources are used efficiently. Moreover, nursing homes which are technically inefficient cannot be cost efficient. Therefore, it is crucial that an appropriate framework for measuring efficiency be formulated and implemented in INHs. This is particularly pressing given the expected rapid growth in the need for LTC, and the sharp rise in expenditure tied to demographic trends. Moreover, if the issue of inefficiency is not addressed, there could be severe implications for Irish society as deficits in the supply of long-term residential care is acknowledged to exacerbate delays in discharging people from acute hospital beds. This could

have the knock-on effect of even greater over-crowding in Accident and Emergency Departments and further delays in hospital discharges. This, in turn, would adversely impact the general ability of society to access acute hospital care in a timely manner. Thus, policymakers have a critical role in developing strategies which allocate public resources fairly and efficiently. Developing a culture of performance measurement could increase the productivity of NHs together with the identification of top performing care facilities to serve as a best practice tool for other NHs. This would motivate managers to monitor care delivery and assess how the performance of the home can be improved.

In addition, performance measurement offers practical benefits in meeting the very real challenges of rising long-term health-care expenditure due to an aging population.

Secondly, the empirical findings of this research found that private NHs with at least 10% of their bed capacity contracted to the State are more technically efficient than public NHs. This suggests that public provision of LTC could be re-targeted towards the private sector, which would result in a reduction of public spending on NH care provision and an improvement in value for money. Given the multitude of demands placed on the health-care system, taxpayers, and society require assurance that limited public resources are being utilized efficiently. This particular finding from the empirical analysis is timely, as the Irish NH industry is at a crossroads, and key planning decisions must now be taken for the future provision of LTC beds as the costs of LTC are expected to increase dramatically. The development of private nursing facilities has been curtailed as the capital allowances, which were introduced in 1998 to stimulate private supply, were abolished in 2011. Additionally, there has been little investment in new private sector capacity over the past decade, given the reversals of the Irish economy, the general strain on private balance sheets, and problems in the banking sector. Furthermore, due to the age of public NHs and a lack of significant capital investment in public facilities in the past, there is increased uncertainty on whether public homes can meet the HIQA standards

without considerable public investment. This, in turn, could adversely impact the State's ability to adhere to its own policy objective of providing 20% of all long-stay beds in the public sector, thereby resulting in an over-reliance on the private market. Moreover, while government policy advocates for support for older people to remain living in their own home for as long as possible, there will always be individuals whose care needs can only be met in a long-term residential care setting.

In Ireland, the cohort requiring the highest level of care, the number of people aged 85 and over, is the fastest growing group. Informal care (which is currently unregulated) is not always suitable to meet the care needs of this cohort. Given that private NHs are more technically efficient than public units, such facilities have a key role to play in meeting the accelerating forecasted demand. In consequence, careful consideration must be given to identifying how the State can stimulate new investment in private NHs.

Nonetheless, it is noted that private homes have a lower proportion of high-maximum dependency residents, whose care needs are greatest. As a result, these facilities consume fewer resources relative to public units, which generates better TE performance. While the current funding model is a positive from the point of view of NH residents, payments do not increase in line with the dependency levels of the resident. This creates an incentive for NHs to actively discourage acceptance of high-dependency residents. Furthermore, this study shows that private NHs employ fewer medical personnel compared to public homes, which could also adversely impact the quality of care being delivered. Thus, Government and stakeholders must engage constructively with the NH sector to address these issues, so that both private and public NHs can provide first-class care services to all of their elderly citizens, while at the same time ensuring a more equitable playing field in terms of productive efficiency.

Thirdly, the results of this research reveal that the INHs and the subsamples considered are scale inefficient; meaning that such homes are not operating at optimal scale. As such, these facilities should adjust their size to reach their optimal scale size. Moreover, the negative relationship between the size determinant and TE confirms that NHs at the larger end of the scale (less than 50 beds) should reduce the size of their operations to improve their TEs. Smaller homes (1-49 beds) should be incentivized as these units utilize their resources more efficiently compared to larger care homes, resulting in cost savings and benefits for taxpayers and society. Additionally, smaller NHs often epitomize the person-centred ethos of a home for older people and are generally located near the person's home community. These are deemed critical attributes in the care of the elderly.

The movement towards 'chain homes' is a relatively recent phenomena in private NHs in Ireland. Some economists argue that this 'new structure' within the NH industry delivers increased efficiencies relative to non-chain homes due to sharing of resources and specializing in a 'narrow product array'. On the other hand, it can be posited that decision-making is slower and arduous. The empirical evidence in this study found that NHs which are part of a 'chain' have lower TEs than non-chain homes; arguably indicating that the number of private non-chain homes should be expanded to meet the future needs of an increasingly elderly population.

The findings from this research offer further interesting insights into the quality-efficiency relationship which is only 'marginally addressed' in the literature. These provide important learnings for policymakers and other stakeholders in elderly care (NH management, advocates of the elderly, family members, regulators). A number of structural indicators of quality, such as the ratio of medical staff to non-medical staff, and the ratio of labour to capital, not only improve the quality of care, but also increase the overall TEs of the NHs. These proxies for quality provided a strategy for NHs to realise both TE and better quality outcomes: indeed, achieving both productive efficiency and a high-quality service is a fundamental challenge for

health-care practitioners and policymakers everywhere. The empirical evidence in this study found that having more qualified nurses involved in the caring process yields benefits for the service user and the overall efficiency performance of the nursing home. In light of this, the role of the nurse in the caring process is deemed critical and should not be substituted with non-clinical personnel. In fact, a clear and cohesive policy should be formulated to stipulate the appropriate proportion of nurses in relation to other inputs (health care attendants and NH beds) as this would promote both efficiency and enhanced quality of care.

The empirical results of this thesis also found that some other measures of quality (e.g. staff turnover) can exert a negative effect on both quality and TE. Approximately 30% of nurses leave their posts in INHs: a loss of experience which reduces the well of knowledge and the 'know-how' of the medical personnel caring for the residents. In light of this, the NH industry needs to adopt more effective workforce planning, recruitment and retention policies, so that care homes can attract sufficient appropriately trained and skilled people to meet the needs of its patients. Nurse recruitment is a critical issue as there is a shortage of qualified nurses world-wide. Moreover, as nearly every developed country is faced with prospect of a population that is getting older, and with this a greater incidence of conditions such as Alzheimer's and Dementia, there will be an increasing demand for gerontology nurses who specialize in elder care. Professional care-staff now expect life-long learning programmes, training programmes, career pathways, and work-life balance. As a service provider, the NH industry therefore has many challenges to grapple with in terms of staff recruitment, development, and retention. Thus, creating the right culture will attract the best personnel to the long-stay care industry and ultimately lead to improved efficiency and quality.

Finally, other measures of quality in this research demonstrated a trade-off with TE; implying that increasing quality may require additional labour and capital resources, whilst a tendency towards efficiency improvements and cost containment can lead to a poorer performance in

quality. For instance, while staff flexibility, as measured by ratio of part-time nurses to full-time nurses, increases the TE of the nursing home, it can lead to reduced quality. Hence, reducing the number of part-time medical staff will increase quality, but will not lead to more efficient outcomes. Given that quality of care can be measured using a variety of non-clinical indicators, it is now imperative that stakeholders in the NH industry come together to map out how the efficiency-quality relationship can be best evaluated.

7.4 Limitations of the Study and Suggestions for Future Research

Prior to this study, no economic research had been undertaken to evaluate the efficiency of INHs. This research utilizes a novel primary dataset which was collated in the period 2008-2009 via face-to-face interviews, to estimate the TEs of care facilities in the ROI and to identify the determinants of efficiency. As it is now more than 10 years since the data were collected, the dataset is arguably obsolete and the policy implications no longer relevant. On the contrary, however, the issues facing the Irish NH sector remain the same: if anything, these are now even more acute owing to spending cuts and under-investment during the period of austerity which followed the onset of the Global Financial Crisis. In fact, today Ireland faces even more pressing policy imperatives to provide for an increasingly elderly population and the additional resources needed to meet future demands for LTC beds.

Research in economics to date has largely neglected the NH setting in Ireland due to the paucity of published data. One of the many significant contributions of this thesis is the collation of a unique and detailed primary dataset. However, this is a very time-consuming undertaking, and the present dataset took almost two full years to compile. Given the considerable demands, involved, therefore, it is hardly surprising that the dataset is cross-sectional.

The empirical results from this research could well be considered a starting point for future investigations to build upon. Indeed, it would be important to add a time-series dimension with

a view to carrying out a panel data analysis. Such a dataset would allow for additional model extensions, such as the application of the SFA approach. This, in turn, would allow comparisons between the estimates afforded by semi-parametric and fully parametric techniques. Moreover, the use of longitudinal data could generate an enhanced holistic multivariate modelling approach and build additional knowledge in the evaluation of TE.

7.5 Final Conclusions

Applying a novel primary dataset and a wide spectrum of methods, ranging from non-parametric to two-stage semi-parametric approaches, this study concluded that INHs are technically inefficient. This implies that these homes must reduce their inputs for a given level of output in order to be efficient. This research also found that INHs are not operating at their optimal scale, although smaller homes employ their resources more efficiently, resulting in cost savings. In light of this, the present investigation suggests that larger scale homes which have 50 or more beds, should rationalize the scale of their processes to enhance their productive efficiencies.

An additional key finding from the empirical analysis demonstrated that private NHs are more technically efficient than public units. This offers important guidance to stakeholders, such as Government and other policymakers, on the optimum nursing home ownership model to meet the LTC bed capacity demands of Ireland's future. It also emerged that private NHs have a lower proportion of high-maximum dependency residents relative to public homes and employ fewer medical personnel on average.

This study also found that certain structural indicators of quality positively influence both quality and TE, while others foster trade-offs between quality and TE. These results significantly extend the understanding of the quality-efficiency relationship in the NH sector in Ireland. This is important as a key challenge for practitioners and policymakers is ensuring

high-quality care delivery, while simultaneously pursuing productive efficiency in the long-term care. While this investigation acknowledges certain limitations, such as a relatively small data sample and the cross-sectional nature of the data, the evaluation of TE in INHs in this thesis nonetheless affords rich insights into the organizational performance of LTC facilities, which strongly suggest that performance measurement should become part of the analytic armoury of all policymakers, NH operators, and other stakeholders involved in the NH industry.

References

- Aaronson, W.E., Zinn, J.S. & Rosko, M. D. (1994). Do for-profit and not-for-profit nursing homes behave differently? *The Gerontologist*, 34 (6), 775-786.
- Afriat, S.N. (1972). Efficiency estimation of production functions. *International Economic Review*, 13(3), 568-598.
- Aigner, D.J., & Chu, S.F. (1968). On estimating the industry production function. *American Economic Review*, 58(4), 826-839.
- Aigner, D., Lovell, C.A.K. and Schmidt, P. (1977). Formulation and estimation of stochastic frontier production function models. *Journal of Econometrics*, 6(1), 21-37.
- Alchian, A.A. & Demsetz, H. (1972). Production, information costs, and economic organization. *American Economic Review*, 62(5), 777-795.
- Anderson, R. L., Lewis, D. & Webb, J. R. (1999). The efficiency of nursing home chains and the implications of non-profit status. *Journal of Real Estate Portfolio Management*, 5(3), 235-245.
- Anderson, R.I., Weeks, H. Shelton, Hobbs, B.K. & Webb, J.R. (2003). Nursing home quality, chain affiliation, profit status and performance. *Journal of Real Estate Research*, 25(1), 43-60.
- Badunenko, O., Henderson, D. J. & Kumbhakar, S. C. (2012). When, where and how to perform efficiency estimation. *Journal of the Royal Statistical Society*, 175(4), 863-892.
- Banker, R. D., Charnes, A. & Cooper, W. W. (1984). Some models for estimating technical and scale inefficiencies in data envelopment analysis. *Management Science*, 30(9), 1078-1092.
- Banker, R.D., Gadh, V.M & Gorr, W.L. (1993). A Monte Carlo comparison of two production frontier estimation methods: corrected ordinary least squares and data envelopment analysis. *European Journal of Operational Research*, 67(3), 332-343.
- BDO (2014). Health's ageing crisis: time for action - a future strategy for Ireland's long-term residential care sector. BDO Report. http://www.nhi.ie/?p=publications_BDO_report. Accessed 18 Oct 2016.
- Bhatnagar, R., Chandra, P. & Goyal, S.K. (1993). Models for multi-plant coordination. *European Journal of Operational Research*, 67(3), 332-343.
- Blank, J. L.T. & Valdmanis, V.G. (2010). Environmental factors and productivity on Dutch hospitals: a semi-parametric approach. *Health-care Management Science*, 13(1), 27-34.
- Blegen, M.A., Goode, C.J. & Reed, L. (1998). Nurse staffing and patient outcomes. *Nursing Research*, 47(1): 43-50.
- Björkgren, M. A., Häkkinen, U. & Linna M. (2001). Measuring efficiency of long-term care units in Finland. *Health-care Management Science*, 4(3), 193-200.
- Boles, J.N. (1966). Efficiency squared—efficient computation of efficiency indexes. *Proceedings of the 39th Annual Meeting of the Western Farm Economics Association*, 137-142.

- Borge, L-E. & Haraldsvik, M. (2009). Efficiency potential and determinants of efficiency: an analysis of the care for the elderly sector in Norway. *International Tax and Public Finance*, 16(4), 468-486.
- Bostick, J., Rantz, M., Flesner, M. & Riggs, C. (2006). Systematic review of studies of staffing and quality in nursing homes. *Journal of American Medical Directors Association*, 7(6), 366–376.
- Brannon, D., Zinn, J.S., Mor, V., Davis, J.A. (2002). An exploration of job, organizational, and environmental factors associated with high and low nursing assistant turnover. *The Gerontologist*, 42(2), 159-68.
- Bryman, A. (1989). *Research Methods and Organization Studies*, London: Unwin Hyman.
- Cameron A.C. & Trivedi, P.K. (2010). *Microeconometrics using Stata*. Texas. Stata Press.
- Campbell, D. (2015). NICE criticizes flying home care visits as short as five minutes. *The Guardian*, 23rd September 2015.
- Canniffe, M. (1999). One answer to age-old problem. *The Irish Times*, 24th September 1999. <http://www.irishtimes.com/business/one-answer-to-age-old-problem-1.231138>. Accessed 19 October 2016.
- Care Alliance Ireland (2016). *Analysis of Home Care Supports funded by the HSE 2008-2016*. Briefing Paper 1 (June). Dublin.
- Castle, N.G. (2006). Measuring staff turnover in nursing homes. *Gerontologist*, 2006 46(2), 210–219.
- Castle N.G. & Engberg, J. (2005). Staff turnover and quality of care in nursing homes. *Medical Care*, 43(6), 616–626.
- Castle, N.G. & Ferguson, J.C. (2010). What is nursing home quality and how it is measured? *The Gerontologist*, 50(4), 426-442.
- Central Statistics Office (2013). Population and labour force projections 2016-2046. *Central Statistical Office*, Dublin.
- Centre for Ageing Research and Development (2012). Future demand for long-term care in Ireland, *Centre for Ageing Research and Development*, Dublin/Belfast.
- Chang, S. J. & Cheng, M. A. (2013). The impact of nursing quality on nursing home efficiency: evidence from Taiwan. *Review of Accounting and Finance*, 12(4), 369-386.
- Charnes, A., Cooper, E. & Rhodes, E. (1978). Measuring the efficiency of decision-making units. *European Journal of Operational Research*, 2(6): 429-444.
- Chattopadhyay, S. & Heffley, D. (1994). Are for-profit nursing homes more efficient? Data envelopment analysis with a case-mix constraint. *Eastern Economic Journal*, 20(2): 171-186.
- Chattopadhyay, S. & Ray, S.C. (1996). Technical scale and size efficiency in nursing home care: a non-parametric analysis of Connecticut homes. *Health Economics*, 5(4): 363-373.
- Christensen, L., Jorgensen, D. & Lau, L. (1973). Transcendental logarithmic production frontier. *Review of Economics and Statistics*, 55(1), 28-45.

- Coelli, T.J., Rao, D., O'Donnell, C.J. & Battese, G.E. (2005). *An Introduction to Efficiency and Productivity Analysis*, 2nd Ed., USA, Springer.
- Cohen-Mansfield, J. (1997). Turnover among nursing home staff. A review. *Nurse Management*, 28 (5): 59–62.
- Crivelli, L., Filippini, M. & Lunati, D. (2002). Regulation, ownership and efficiency in the Swiss nursing home industry. *International Journal of Health-care Finance and Economics*, 2(2), 79–97.
- Cullen, P. (2013). Nursing home sector in need of long-term care and attention. *The Irish Times*, 9th August.
- Cullen, P. (2016). Bridhaven nursing home: We lose staff to better-paid HSE jobs. *The Irish Times*, 5th October.
- Cullinane, K., Wang, T-F., Song, D-W. & Ji, P. (2006). The technical efficiency of container ports: Comparing data envelopment analysis and stochastic frontier analysis. *Transportation Research Part A: Policy and Practice*, 40(4), 354-374.
- Culliton, G. (2010). Cost of HIQA standards. *Irish Medical Times*, 21st October.
- Czypionka, T., Kraus, M., Mayer, S. & Rohrling, G. (2014). Efficiency, ownership, and financing of hospitals: The case of Austria. *Health-care Management Science*, 17(4), 331-347.
- Debreu, G. (1951). The coefficient of resource utilization. *Econometrica*, 19(3), 273-292.
- Delellis, N.O. & Ozcan, Y.A. (2013). Quality outcomes among efficient and inefficient nursing homes: A national study. *Health-care Management Review*, 38(2), 156-165.
- Department of Health (2008). *Long Term Care Report*. Dublin. The Stationery Office.
- Department of Health and Children (1998-2013). *Long Stay Activity Statistics 1998-2013*. Dublin. The Stationery Office. <https://health.gov.ie/publications-research/statistics/statistics-publications>. Accessed 10 October 2018.
- Department of Health and Children (2015a). *Review of the Nursing Homes Support Scheme, A Fair Deal*. Dublin. The Stationery Office. <https://health.gov.ie/wp-content/uploads/2015/07/Review-of-Nursing-Homes-Support-Scheme.pdf>. Accessed 10 October 2018.
- Department of Health and Children (2015b). *Potential Measures to Encourage Provision of Nursing Home and Community Nursing Unit Facilities*. DKM Economic Consultants. <https://health.gov.ie/wp-content/uploads/2015/12/2015-07-30-DoH-Nursing-Homes-Study-Final-Report.pdf>. Accessed 23rd October, 2018.
- Department of the Taoiseach (2006). *Towards 2016 Ten-Year Framework Social Partnership Agreement 2006-2015*. Dublin. The Stationery Office. <https://www.welfare.ie/en/downloads/Towards201626June06.pdf>. Accessed 5th January 2018.
- Dervaux, B., Leleu, H., Nogues, H. & Valdmanis, V. (2006). Assessing French nursing home efficiency: An indirect approach via budget-constrained DEA models. *Socio-Economic Planning Sciences*, 40, 70-91.

- DG ECFIN (2012). The 2012 Ageing Report: Economic and budgetary projections for the EU27 Member States 2010-2060. *Joint Report prepared by the European Commission (DG ECFIN) and the Economic Policy Committee (AWG)*, European Union.
- Dineen, D., Ni Luasa, S., & Zieba, M. (2019). *Determinants of Technical Efficiency in the Irish nursing homes – a semi-parametric double bootstrap DEA*. University of Limerick Working Paper.
- Donabedian, A. (1988). The quality of care. How can it be assessed? *Journal of the American Medical Association*, 260 (12), 1743 -1748.
- Donnelly, S., O'Brien, M., Begley, E. & Brennan, J. (2016). *I'd Prefer to Stay at Home but I don't have a Choice: Meeting Older People's Preference for Care: Policy, but what about Practice?* University College Dublin. <https://researchrepository.ucd.ie/handle/10197/7670>. Accessed 10th September 2018.
- DiGiorgio, L., Filippini, M. & Masiero, G. (2014). The relationship between costs and quality in non-profit nursing homes, Center for Economic and Political Research on Aging. *Idep Economic Papers 02*.
- DTZ Sherry Fitzgerald (2015). *Irish Nursing Home Market Report*. Dublin.
- Dulai, R. (2018). Technical efficiency of nursing homes: do five-star quality ratings matter? *Health-care Management Science*, 21(3), 393-400.
- Färe, R., Grosskopf, S. & Logan, J. (1983). The relative efficiency of Illinois electric utilities. *Resources and Energy*, 5, 349-367.
- Färe, R., Grosskopf, S. & Logan, J. (1985). The relative performance of publicly-owned and privately owned electric utilities. *Journal of Public Economics*, 26, 89-106.
- Färe, R., Grosskopf, S. & Roos, P. (1998). Malmquist Productivity Indexes: A Survey of Theory and Practice. In R. Färe, S. Grosskopf and R.R. Russell (eds.), *Index Numbers: Essays in Honour of Sten Malmquist*, Kluwer Academic Publishers, Boston.
- Fare, R. & Lovell, C.A. (1978). Measuring the technical efficiency of production. *Journal of Economic Theory*, 19(1), 150-162.
- Farsi, M., Filippini, M. & Lunati, D. (2008). Economies of scale and efficiency measurement in Switzerland's nursing homes. *Swiss Journal of Economics and Statistics*, 144(3): 359-378.
- Farrell, M. (1957). The measurement of productive efficiency. *Journal of the Royal Statistical Society*, 120A (3), 253-281.
- Filippini, M. (1999). Cost and scale efficiency in the nursing home sector: evidence from Switzerland. *Decanato Della Facolta Di Scienze Economiche Quaderno N. 99-02*.
- Filippini, M. (2001). Economies of Scale in the Swiss Nursing Home Industry. *Applied Economics Letters*, 8 (1), 43-46.
- Fizel, J. L. & Nunnikhoven, T. S. (1992). Technical efficiency of for-profit and non-profit nursing homes. *Managerial and Decision Economics*, 13(5), 429-439.

- Fizel, J. L. & Nunnikhoven, T. S. (1993). The efficiency of nursing home chains. *Applied Economics*, 25(1): 49-55.
- Frech III, H.E. (1985). The property rights theory of the firm: some evidence from the nursing home industry. *Zeitschrift Fur die Gesamte Staatswissenschaft*, 141(2), 146-166.
- Freese, J. & Long, S. (2006). *Regression Models for Categorical Dependent Variables Using Stata*, College Station, Stata Press.
- Fried, H.O., Knox Lovell, C.A. & Schmidt, S.S. (1993). *The Measurement of Productive Efficiency*, Oxford: Oxford University Press.
- Friedman, B. & Shortell, S. M. (1988). The financial performance of selected investor-owned and not-for-profit system hospitals before and after medicare prospective payment. *Health Services Research*, 23 (2), 237-267.
- Garavaglia, G., Lettieri, E., Agasisti, T. & Lopez, S. (2011). Efficiency and quality of care in nursing homes: an Italian case study. *Health-care Management Science*, 14(1), 22-35.
- Gill, I., Koettl, J. & Packard, T. (2013). Full employment: a distant dream for Europe. *IZA Journal of European Labor Studies*, 2(19), 1-34.
- Government of Ireland. (1968). *The Care of the Aged: Report of an Inter-Departmental Committee on the Care of the Aged, 1968*. Dublin: Government Publications.
- Greene, W.H. (1981). On the asymptotic bias of the ordinary least squares estimator of the Tobit model. *Econometrica*, 49(2), 505-513.
- Greene, W.H. (2002). *Limdep Version 8.0 Econometric Modelling Guide*. Plainview, N.Y. Econometric Software, Inc.
- Griffin, R., Montgomery, J., and Rister, E. (1987). Selecting functional forms in production analysis. *Western Journal of Agricultural Economics*, 12(2), 216-227.
- Grosskopf, S. & Valdmanis, V. (1987). Measuring hospital performance, a non-parametric approach. *Journal of Health Economics*, 89-107.
- Halbur, B.T. & Fears, N. (1986). Nursing personnel turnover rates turned over: potential positive effects on resident outcomes in nursing homes. *The Gerontologist*, 26(1), 70-76.
- Harrington, C., Zimmerman, D., Karon, S.L., Robinson, J. & Beutel, P. (2000). Nursing home staffing and its relationship to deficiencies. *The Journals of Gerontology Series B*, 55(5), S278-S278.
- Health Information Quality Authority (2016). *National Standards for Residential Care Settings for Older People in Ireland*. <https://www.hiqa.ie/system/files/National-Standards-for-Older-People.pdf>. Accessed 10 October 2018.
- Health Service Executive (2015). *Home Care Package Scheme*. HSE. <https://www.hse.ie/eng/services/list/4/olderpeople/>. Accessed 2 February 2017.
- Hofmarcher, M.M., Paterson, I. & Riedel, M. (2000). Measuring hospital efficiency in Austria – A DEA approach. *Health-care Management Science*, 5(1), 7-14.

- Hoffler, R. A. & Rungeling, B. (1994). US nursing homes: Are they cost efficient? *Economics Letter*, 44(3): 301–305.
- Hollingsworth, B. (2003). Non-parametric and parametric applications measuring efficiency in health-care. *Health-care Management Science*, 6(4), 203-218.
- Hollingsworth, B. (2008). The measurement of efficiency and productivity of health-care delivery. *Health Economics*, 17(10), 1107-1128.
- Horwath Bastow Charleton Limerick (2010). Annual Private Nursing Home Survey 2009/2010. *Nursing Homes Ireland*, Dublin. http://www.nhi.ie/index.php?p=annual_survey. Accessed 10th September 2015.
- Irish Nursing Homes Organization (1999). *Irish Nursing Homes Organization Sectoral Study of Long Term Care*, Irish Nursing Homes Organization, Dublin.
- Iparraquirre, J.L. & Ma, R. (2015). Efficiency in the provision of social care for older people. A three-stage data envelopment analysis using self-reported quality of life. *Socio-Economic Planning Sciences*, 49(1): 33-46.
- Jacobs, R., Smith, P.C. & Street, A. (2006). *Measuring Efficiency in Health-care Analytic Techniques and Health Policy*, Cambridge: Cambridge University Press.
- Jondrow, J., Lovell, C.A.K., Materov, I.S. & Schmidt, P. (1982). On estimation of technical inefficiency in the stochastic frontier production function model. *Journal of Econometrics*, 19, 233-238.
- Kalseth, J. (2003). Political determinants of efficiency variation in municipal service production: an analysis of long-term care in Norway, Norwegian University of Science and Technology.
- Kleinsorge, I.K. & Karney, D.F. (1992). Management of nursing homes using data envelopment analysis. *Socio-Economic Planning Sciences*, 26(1), 57-71.
- Kooreman, P. (1994). Nursing home care in the Netherlands: a nonparametric efficiency analysis. *Journal of Health Economics*, 13(3), 301-316.
- Koopmans, T.C. (1951). *Activity Analysis of Production and Allocation*. New York City, Wiley and Sons.
- Knox, K.J., Blankmeyer, E.C. & Stutzman, J.R. (2001). The efficiency of nursing home chains and the implications of nonprofit status: A comment. *Journal of Real Estate Portfolio Management*, 7, 177-182-86.
- Knox, K.J., Blankmeyer, E.C. & Stutzman, J.R. (2007). Technical efficiency in Texas nursing facilities: A stochastic production frontier approach. *Journal of Economics and Finance*, 31(1), 75-86.
- Kumbhakar, S.C. & Lovell, C. (2000). *Stochastic Frontier Analysis*. Cambridge: Cambridge University Press. ISBN 0-521-481848.
- Kumbhakar, S.C., Lien, G. & Hardaker, J.B. (2014). Technical efficiency in competing panel data models: a study of Norwegian grain farming, *Journal of Productivity*, 41(2), 321-337.
- Kumbhakar, S., Wang, H-Jen, Horncastle, A.P. (2015). *A practitioner's guide to stochastic frontier analysis using Stata*, New York, Cambridge University Press.

- Laine, J., Finne-Soveri, U., Björkgren, M., Linna, M. Noro A. & Häkkinen, U. (2005a). The association between quality of care and technical efficiency in long-term care. *International Journal for Quality in Health-care*, 17(3), 259-267.
- Laine, J., Linna, M., Hakkinen, U. & Noro, A. (2005b). Measuring the productive efficiency and clinical quality of institutional long-term care for the elderly. *Health Economics*, 14(3), 245-256.
- Laing & Buisson (2011). *Laing's Health-care Market Review*. Laing & Buisson. London.
- Lipszyc, B., Sail, E. & Xavier, A. (2012). Long-term care: need, use and expenditures in the EU-27, *Economic Commission Economic Papers* 469.
- Martin, C. & Jerome, T. (2016). Cost (In) Efficiency and Institutional Pressures in Nursing Home Chains. *European Accounting Review*, 25(4), 687-718.
- McEnery, B. (2007). *Nursing Home Cost of Care A Fair Price – Ireland*, Horwath Bastow Charleton Limerick.
- Meeusen, W. & Van Den Broeck, J. (1977). Efficiency estimation from Cobb-Douglas production functions with composed error. *International Economic Review*, 18(2), 435-444.
- Mercer Ltd (2002). Study to Examine the Future Financing of Long-Term Care in Ireland. *Department of Social & Family Affairs*. <http://www.welfare.ie/en/downloads/stetffolcii.pdf>. Accessed 4 June 2017.
- Ni Luasa, S., Dineen, D., & Zieba, M. (2018). Technical and scale efficiency in public and private Irish nursing homes – a bootstrap DEA approach. *Health-care Manag Science* **21**, 326–347. <https://doi.org/10.1007/s10729-016-9389-8>
- Nyman, J. A. & Bricker, D. L. (1989). Profit incentives and technical efficiency in the production of nursing home care. *The Review of Economics and Statistics*, 71(4), 586-594.
- Nyman, J. A., Bricker, D. L. & Link, D. (1990). Technical efficiency in nursing homes. *Medical Care*, 28(6), 541-551.
- Office of the Attorney General (2007), *Health Act 2007*, Dublin.
- Ozcan, Y.A., Wogen, S.E. & Mau, L.W. (1998). Efficiency Evaluation of Skilled Nursing Facilities. *Journal of Medical Systems*, 22(4), 211-224.
- O' Neill, C., Harrington, C., Kitchener, M. & Saliba, D. (2003). Quality of care in nursing homes: an analysis of relationships among profit, quality and ownership. *Medical Care*, 41(12), 1318-1330.
- O'Shea, E. (2002). *Review of the Nursing Home Subvention Scheme*, Dublin: The Stationery Office.
- Perelman, S. & Pestieau, P. (1988). Technical Performance in Public Enterprises A Comparative Study of Railways and Postal Services. *European Economic Review*, 32, 432-441.
- Pestiau, P. & Tulkens, H. (2006). Assessing and explaining the performance of public enterprises: some recent evidence from the productive efficiency viewpoint. In P. Chander, J., Dreze, C. Knox Lovell and J. Mintz (eds.), *Public Goods, Environmental Externalities and Fiscal Competition*, Springer, US, 343-372.

- Pierce, M., Fitzgerald, S. & Timonen, V. (2010). Summary and Comparison of Key Social Provisions for Older People in the Republic of Ireland and Northern Ireland. *Centre for Ageing and Research and Development*. Belfast.
- Register, C.A. & Bruning, E. R. (1987). Profit incentives and technical efficiency in the production of hospital care, *Southern Economic Journal*, 53(4), 899-914.
- Rodriguez-Alvarez, A., Fernandez-Blanco, V. & Lovell, C.A.K. (2004). Allocative Efficiency and its Cost: The Case of Spanish Public Hospitals, *International Journal of Production Economics*, 92(2), 99-111.
- Rosko, M.D., Chilingerian, J.A., Zinn, J. S. & Aaronson, W.E. (1995). The effects of ownership, operating environment, and strategic choices on nursing-home efficiency. *Medical Care*, 33(10), 1001-1021.
- Schmidt, P. & Sickles, R.C. (1984). Production frontiers and panel data, *Journal of Business and Economic Studies*, 2, 299-326.
- Sexton, T., Leiken, A., Sleeper, S. & Coburn, A. (1989). The impact of prospective reimbursement on nursing home efficiency. *Medical Care*, 27(2), 154-163.
- Shephard, R.W. (1970). *Theory of Cost and Production Function*, Princeton: Princeton University Press.
- Shimshak, D.G., Lenard, M.L. & Klimberg, R. K. (2009). Incorporating quality into data envelopment analysis of nursing home performance: a case study. *The International Journal of Management Science*, 37(3), 672-685.
- Simar, L. & Wilson, P. W. (1998). Sensitivity analysis of efficiency scores: How to bootstrap in nonparametric frontier models. *Management Science*, 44(1), 49-61.
- Simar, L. & Wilson, P. W. (2000). Statistical inference in nonparametric frontier models: The state of the art. *Journal of Productivity Analysis*, 13(1), 49-78.
- Simar, L. & Wilson, P. W. (2007). Estimation and inference in two-stage, semi-parametric models of productive efficiency. *Journal of Econometrics*, 136(1), 31-64.
- Simar, L. & Wilson, P. W. (2011). Two-stage DEA: caveat emptor. *Journal of Productivity Analysis*, 36(2), 205-218.
- Simm and Besstremyannaya (2015). *Robust Data Envelopment Analysis (DEA) for R*, Version 1.2-2.
- Spector, W. & Takada, H.A. (1991). Characteristics of nursing homes that affect resident outcomes. *Journal of Aging & Health*, 4(3): 427-454.
- Timonen, B., Doyle, M. & Prendergast, D. (2006). *No Place like Home. Domiciliary Care Services for Older People in Ireland*, The Liffey Press, Dublin.
- Tobin, J. (1958). Estimation of relationships for limited dependent variables. *Econometrica*, 26(1), 24-36.
- U.S. Health-care Financing Administration (2000). *Health-care Financing Administration Report*. Washington, DC: U.S. Government Printing Office.

- Vitaliano, D.F. & Toren, M. (1994). Cost and Efficiency in Nursing Homes: a Stochastic Frontier Approach. *Journal of Health Economics*, 13(3), 281-300.
- Wang, Y. H. & Chou, L. F. (2005). The efficiency of nursing homes in Taiwan: An empirical study using data envelopment analysis. *Management Review*, 12(1), 167-194.
- Wilson, G.W. & Jadlow, J.M. (1982). Competition, profit incentives, and technical efficiency in the provision of nuclear medicine services. *The Bell Journal of Economics*, 13(2), 472-482.
- Wilson, P. (2008). "FEAR: A software package for frontier efficiency analysis with R". *Socio-Economic Planning Sciences*, 42(4): 247-254.
- Working Party on Services for the Elderly (1988). *The Years Ahead... A Policy for The Elderly*, Dublin. The Stationery Office.
- World Health Organization (2000). *The World Health Report 2000 - Health Systems: Improving Performance*. World Health Organization. ISBN 924156198.
- Worthington, C. (2004). Frontier efficiency measurement in health-care: A review of empirical techniques and selected applications. *Medical Care Research and Review*, 61(2): 135-170.
- Wren, M. (2009). Long-Term Health and Social Care. In R. Layte (ed.), *Projecting the Impact of Demographic Change on the Demand for and Delivery of Health-care in Ireland*, Research Series No. 13, Dublin, Economic and Social Research Institute, 100-143. <https://www.esri.ie/pubs/RS013.pdf>. Accessed 10th July 2017.
- Wren, M.A., Normand, C., O'Reilly, D., Cruise, S.M., Connolly, S. & Murphy, C. (2012). *Towards the Development of a Predictive Model of Long-Term Care Demand for Northern Ireland and the Republic of Ireland*. Centre for Health Policy and Management, TCD. http://doras.dcu.ie/17967/1/Towards_the_Development_of_a_Predictive_Model_of_Long-Term_Care_Demand_For_Northern_Ireland_and_the_Republic_of_Ireland.pdf. Accessed 25th April, 2016.
- Wren, M.A., Keegan, C., Walsh, B., Bergin, A., Eighan, J., Brick, A., Connolly, S., Watson, D. & Banks, J. (2017). *Projections of Demand for Health-care in Ireland, 2015-2030*. Economic and Social Research Institute, Research Series Report, No.67.
- Zieba, M., Dineen, D., Ni Luasa, S. (2020). *The role of labour management factors in determining Irish nursing homes efficiency*. University of Limerick Working Paper.
- Zhang, N.J., Unruh, L., Wan, T.T.H. (2008). Has the Medicare prospective payment system led to increased nursing home efficiency? *Health Services Research*, 43(3), 1043-1061.
- Zinn, J.S. (1993). The influence of nurse wage differentials on nursing home staffing and resident care decisions, *Gerontologist*, 33(6), 721-729.

With Profit -----

Non-Profit -----

Home in (not necessary to ask)

HSE South -----

HSE West -----

HSE Dublin – North East -----

HSE Dublin – Mid Leinster -----

1 The first set of questions refer to the **Characteristics of the Home, the number of beds, the types of bedrooms, etc.**

1 Regarding ‘beds’, how many **‘long stay beds’** are in your home?

2 What % do long stay beds represent of overall capacity?

3 How many bedrooms does this home have?

4 Looking at the types of bedrooms in this nursing home, how many

Single En-Suite Room? -----

Singe Room? -----

Double/Twin Room? -----

Double/Twin En-Suite Rooms? -----

Multiple Rooms? -----

5 Moving on to rates, what is your average weekly rate for ‘room and board’? (Show CARD)

€700 - €750 †

€751 - €800 †

€801 - €850 †

€851 - €900 †

€901 - €950 †

€951 - €1000 †

€1001 - €1050 †

€1051 - €1100 †

>€1101 †

Don’t Know? †

Not Relevant? †

6 Focusing on contract beds (beds that are **fully funded by the HSE**), did your home have any contract beds with the HSE in 2007? Yes/No (Q7)

If Yes, In 2007 how many of your total beds were contracted to the HSE?

In 2007 what was the contract rate per bed you received from the HSE?

In 2007 what % did contract beds contribute to overall income?

7 In 2007 how many HSE inspections did your home have?

2 In this section we're going to look at the **second issue**, namely **staff**. I have broken staff into 2 components, namely, 'clinical' and 'non-clinical'. Clinical includes nurses and health-care assistants only. Non-Clinical includes all other staff.

To discuss the issue of **Staff**, we'll firstly examine Clinical Staff and then we'll move on to Non-Clinical Staff.

Staff - Clinical (includes Nurses and Health-care Assistants (sometimes referred to as Multi-Task Attendants))

In this section the 'first sets of questions' relate to the 'Nursing Staff' and following that I have some questions pertaining to Health-care Assistants.

Nurses

8 How many nurses work in this nursing home?

9 How many nurses are full time?

10 How many of the nursing staff are 'non-nationals'?

11 Focusing on today's 'day roster' (relevant time 8am – 1pm only), how many nurses are working during this period?

12 Focusing on tonight's 'night roster' (8pm – 8am), how many nurses will work during this period?

13 Looking at 'formal qualifications' do any of your nurses have a diploma in gerontology? Yes/No (Q14)

If Yes, are these members of staff paid more than staff that don't have a diploma in gerontology Yes/No

14 Does this nursing home offer its nurses an opportunity to engage in further education within company 'time'? Yes/No (Q15)

If Yes, does this home offer financial support to engage in further studies? Yes/No

15 Focusing on 'nurse turnover rates' what % was your 'nurse turnover rate' for 2007?

16 Could you identify main and secondary reasons as to why you think some of your nurses left the organization?

17 What is the average annual salary for a staff nurse employed full time in this home?

Health-care Assistants (HCAs)/Multitask Attendants (MTAs)

18 How many HCAs work in this nursing home?

19 How many HCAs are full time?

20 How many HCAs are 'non-nationals'?

21 Focusing on today's day roster (relevant period 8am – 1pm), how many HCAs are involved in patient care?

22 Focusing on tonight's night roster (relevant period 8pm-8am), how many HCAs are involved in patient care?

23 Regarding 'HCA turnover rates' what % was your 'HCA turnover rate' for 2007?

24 Could you identify main and secondary reasons as to why you think some of your HCA left the organization?

25 What is the average annual salary for a health-care assistant employed full time in this home?

Staff - Non-Clinical (All other staff members except Nurses and Health-care Assistants)

26 From the following list of ‘non-clinical personnel’, please state number of staff employed in this home and indicate whether they are Full Time (FT) or Part Time (PT)

	No. of Employees in each category	FT/PT
Domestic Staff(cleaning/laundry)		
Cook/Chef		
Kitchen Staff		
Administration Staff		
Maintenance		
Therapists		
Other -----		

27 How many ‘non-clinical staff’ are non-nationals?

28 Focusing on the ‘Manager’, can you please indicate from the following list what your average salary was for 2007? (SHOW CARD)

<=€50,000	1
€50,000 - €70,000	2
€70,001 - €90,000	3
€90,001 - €110,000	4
€110,001 - €130,000	5
€130,001 - €150,000	6
>=€150,001	7
Don't Know	9

29 In May of 2008 what was your monthly staff costs?

30 During 2007 did your organization provide training on any of the following ‘areas’?

Health & Safety	Y/N
Hygiene	Y/N
Nutrition	Y/N
Manual Handling	Y/N
Palliative Care	Y/N
Regulatory Environment	Y/N
Communication & Listening Skills	Y/N
Dealing with customer complaints	Y/N
Fire Drills	Y/N

Organizational roles & responsibilities Y/N
 Technological developments in the care of the elderly Y/N
 Care of the Elderly with Dementia Y/N
 Other

----- Y/N

31 In 2007 how many training days did your organization have for staff development?

32 In 2007 how much did your organization spend on staff training?

3 **The 3rd issue** I would like to discuss with you is your **therapeutic Services** that your organization provides.

The questions relate to the types of services that are on offer in this home.

33 Does this home offer therapeutic services to its residents? Y/N(Q35)

34 In the following table, please indicate 'Yes or No' as to what therapeutic services you currently provide 'on site'?

	Yes	No
Physiotherapy		
Occupational Therapy		
Chiropody		
Hairdressing		
Arts & Crafts		
Excursions to outside events, such as the theatre, social events in the community/Church		
Tuition classes in bridge/ chess/cards		
Opportunity to Garden		
Opportunity to invite external community/visitors in for lunch/dinner		
Other -----		

35 Are there any services that you feel you should be offering to your clients but at the moment you're not?

Yes/No(Q36)

If Yes, please state what these services should be

4 The **fourth issue** I would like to discuss with you is your **Residents**. I believe some homes may have more complex ‘cases’ than others. Thus I would like to get an understanding of the profile of people you ‘serve’.

36 How many residents live in this home? (on the day questionnaire is being completed)?

37 In 2007 what was your average occupancy?

38 How many of your current resident are of

Dependency Level	Low Dependency	Medium Dependency	High Dependency	Maximum Dependency
%age				

39 What is the average length of stay for a long-term resident in this nursing home?

40 How many of your residents are

Age Category	<65	65-75	76-85	>85

Concluding Questions

41 Is this home a Single home operator -----

Multi home operator ----- No. of homes operated -----

42 In 2007 what was the financial turnover for this home?

43 In 2007 how much was the food bill for this home?

44 In 2007 how much were the total costs for this nursing home?

45 In 2007 how much were the ‘non pay items’ in this home?

46 How *many years* has this nursing home been in *operation*?

Thank you for your time and cooperation