Regulation and Efficiency in UK Public Utilities

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by

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1.1. Introduction

The divestiture of formerly nationalised public utilities during the 1980s and 1990s in the UK and elsewhere was accompanied by the vertical unbundling of their natural monopoly elements, i.e. the physical distribution networks, from upstream activities such as electricity generation and gas supply and downstream activities such as retail in order to facilitate competition in the latter. The expectation was that opening up these upstream activities to private firms would foster competition, which would in turn lead to improvements in efficiency, lower prices and increased consumer welfare. There are, on the other hand, possibilities for considerable rents to be made; these could be in the form of profits, but given the regulation that the firms face and the degree of informational asymmetry between utility managers and other stakeholders, such as regulators, shareholders, and customers, they may also take the form of slack within the firm, and the maximisation of managerial utility.

We analyse the effect of RPI-X regulation on the efficiency of the UK's water and sewage and electricity distribution industries using stochastic frontier analysis. We extend the literature in several ways; first, in the case of the water and sewage industry, we look at efficiency not only on the cost side, but also on the revenue side. Second, following the findings of Restrepo-Tobón and Kumbhakar (2014) on the shortcomings of the direct estimation of the alternative profit frontier, we show that the profit maximisation problem of a monopolist with fixed scale characteristics separates into separate cost minimisation and revenue maximisation problems, then derive an alternative specification for the revenue frontier with a firmer basis in theory. Third, we include the publicly-owned Northern Ireland Water and Scottish Water, and the three former Scottish Water Authorities that preceded the latter, in our water cost and revenue analyses, and likewise include Northern Ireland Electricity in one of our cost analyses, providing an original insight into the performance of these utilities relative to their English and Welsh and Great British counterparts, respectively. In addition, we use more recent samples than those found in the literature, providing new evidence relating to the latest price control periods in both industries.

We derive two new formulae for calculating the marginal effects of environmental variables on efficiency, and apply these to analyse the impact of annual price caps and time trends on revenue and cost efficiency, giving an insight into the static and dynamic impacts of RPI-X regulation, while also examining the impact of board composition variables and public ownership.

This thesis is organised into seven chapters. In the remainder of Chapter 1, we give a short history of the UK water and electricity industries. In Chapter 2, we introduce basic efficiency-related concepts, before moving on to discuss issues of market power and firm performance in utility firms, and the theory relating to utility regulation.

In Chapter 3, we review the literature on frontier analysis, introducing some of the main data envelopment analysis (DEA) and stochastic frontier analysis (SFA) methods in particular. The relative advantages and disadvantages of each method are considered, and the features of the method used in the subsequent empirical chapters are discussed.

Chapter 4 reviews the empirical literature on the performance of water and electricity utilities in the UK and internationally, along with several papers on the impact of regulation on the performance in other utility industries. Chapter 5 and Chapter 6 apply SFA to analyse the efficiency of UK water and sewage and electricity distribution utilities, respectively. Efficiency predictions are discussed and compared, trends are discussed, and the marginal effects of our environmental variables on the various efficiency measures are derived and discussed at length.

Finally, Chapter 7 summarises the conclusions from our analyses and relates them back to the existing literature, and discusses implications for utility performance and policy. The limitations of this thesis, and suggestions for future research, are also discussed.

1.2. An Economic History of UK Water and Electricity Utilities

1.2.1. Introduction

In this section, we give an account of the development of the water and sewage and electricity industries in the UK. We begin by discussing developments in Great Britain; though in the case of water supply there is a somewhat separate discussion of the Scottish industry, which has been quite separate from that of England and Wales in many respects. We then move on to briefly discuss developments in Northern Ireland. We pay particular attention to any major restructures that have occurred, and also to the various forms of economic regulation that have existed at various times.

1.2.2. Electricity and Water Supply in Great Britain

Prior to the mid-19th century, water supply in the UK consisted largely of local wells and rivers, and in some cases communal standpipes. The process of industrialisation and urban expansion led to intolerable strain on these resources, as well as deteriorating health and hygiene, outbreaks of water-borne diseases such as typhoid and cholera, and the pollution of many rivers by factories built along their banks. In response to the need for purer, piped supplies, the modern water industry began to emerge from around the 1840s, mostly in the form of statutory companies covering a prescribed area, though with some of the larger boroughs forming their own municipal waterworks (Hassan 1998, pp.11-16).

Recognition of the natural monopoly character of the industry meant that the statutory companies were usually granted a monopoly in their supply areas, with supply areas rarely overlapping. Direct competition in the form of overlapping supply areas was limited to two towns in the 1840s (Millward 1989, p.196), with two companies in Liverpool initially competing by laying mains in the same streets. Discovering that this was unprofitable, however, the two companies came together to divide up the city between them (Hope 1903, pp.186-187), and companies in general sought to avoid the threat of competition that came with outward expansion by restricting themselves to supplying only wealthy enclaves (Hassan 1998, p.17, Foreman-Peck and Millward 1994, pp.35-39).

Because of the lack of competition in the industry, the statutory companies faced a rudimentary system of regulation, set out in a code of practice and intended to curb the abuse of market power and improve provision. Dividend payouts were restricted, with any excess profits being invested in government stock, and companies were obliged to make a supply available to all houses on streets where their mains were laid, and also to provide fire plugs (i.e. fire hydrants) on their mains (Hassan 1998, p.17); Millward (1989, pp.201-204) describes these regulations as 'arm’s length' and 'largely a failure'.

Due to the increasing awareness of the link between hygiene and health from the mid-19th century, municipal water supply became the preferred arrangement, and the Public Health Act (1848) enabled towns to borrow money to finance the building of sewers and reservoirs. A second Public Health Act (1875) made the building of sewers compulsory and required local authorities to ensure adequate water supplies in their areas, if necessary by compulsory acquisition of private water companies, although several such acquisitions were refused by parliament (Millward 1989). There followed a significant shift toward municipal control, with the percentage of towns served by municipal suppliers increasing from 40.8% in 1861 to 80.2% in 1881, which brought about large increases in supply per head and an end to cholera outbreaks (Hassan 1998, pp.24,536,539). Throughout the latter half of the century, advances continued in water treatment, the development of sewage treatment methods, and the scale and ambition of supply projects, with Liverpool, Manchester and Glasgow, for example, all building new gravitation works and aqueducts far beyond their city boundaries (Hassan 1998, p.21).

Around this time, the electricity supply industry began to grow following the passage of the Electric Lighting Act (1882), which allowed private companies and local authorities to provide a supply of electricity, which was mainly at that time for the purposes of electric street lighting. As with the water supply industry, these early electricity suppliers were subject to economic regulation. Specifically, they were subject to a system of maximum price legislation—see Hammond et al. (2002), reviewed in section 4.2.1, for a description of this regime—administered by the Board of Trade. The early years of the electricity supply industry were characterised by extreme fragmentation, with integrated generation, distribution, and supply firms typically serving a few surrounding streets, and with no standardisation of voltages or frequencies.

Likewise, the water supply industry remained highly fragmented, however, it had the exceptions of a few large municipal suppliers, such as the (London) Metropolitan Water Board, Manchester, Liverpool, and the Derwent Valley Water Board, and a few of the larger private suppliers such as the South Staffordshire Water Company (Hassan 1998, p.60). Overall, however, even by 1944, though over half the total volume of water in England and Wales was delivered by the largest 26 suppliers, and another quarter by the next 97 largest, the remainder was delivered by over 900 small undertakings (Labour Party Research Department 1951). Problems with the fragmented and uncoordinated structure of the industry were highlighted by droughts in 1887, 1911, 1921, 1933 and 1934 and the industry's often makeshift and expensive responses to them (Hassan 1998, pp.56-59); there was even discussion of a national water grid, backed by the Institute of Mechanical Engineers and inspired by the success of the electricity industry's new national grid. Though the idea of a national grid still occasionally resurfaces in times of drought, it is usually dismissed on technical and cost grounds and generates little enthusiasm within the industry. Instead, efforts have focused on consolidation and coordination at a regional level, and Joint Water Boards (JWBs) and Regional Advisory Committees (RACs) covering large areas were formed.

A similar development took place in the electricity supply industry, when Joint Electricity Authorities (JEAs) were formed as a result of the Electricity (Supply) Act (1919), which also formed the Electricity Commission, a group of regional commissioners that took over the Board of Trade’s role as regulator. The need for greater standardisation and interconnection, and the move to more efficient and larger-scale generation that would enable, was however not acted upon until the passage of the Electricity (Supply) Act (1926), which created the National Grid and the Central Electricity Board (CEB), the body which owned and operated it, and which had control of generation and distribution assets, although these remained under the ownership of the private and municipal utilities.

Hannah (1979, p.121) explains that most of the construction of the National Grid took place between 1929 and 1932, and that unlike today's National Grid it was really more of a set of regional grids, with some connecting lines for use in emergencies or to facilitate maintenance. Nevertheless, it represented a significant step forward. The CEB selected 140 generation stations to supply the new National Grid (Hannah 1979, p.113), and these were operated so that the lowest-cost stations worked three shifts, i.e. continuously, providing the base load, the highest cost stations operated only to supply the peak load, i.e. at times of peak demand, and the intermediate stations operated for two shifts, shutting down at times of low demand, in order to minimise generation costs. Hannah (1979) documents some of the substantial improvements that resulted from the establishment of this system, from significant reductions in excess capacity, and large costs savings.

By 1932 there were 33 JWBs in the water industry, rising to 55 by 1953, the largest of which was the Durham County Water Board, which covered over twenty local authorities, while RACs failed to catch on to the same extent (Hassan 1998, pp.56-69). The success of these bodies (particularly the RACs which, as their name suggests, were purely advisory) in promoting cooperation within their regions was limited, however, by the difficulty of getting local authorities to agree with one another. The story was the same in the sewage sector; the first full-scale plant using the *activated sludge* process (which very significantly reduced treatment times) opened in 1916 in Worcester, and by

1944 there were around 1,600 separate authorities responsible for sewage treatment, little effort was made at sewage treatment and disposal on a larger scale: indeed sometimes separate sewage treatment works faced each other across rivers marking the boundary between one local authority and the next (Hassan 1998, pp.63-65).

The continuing need for consolidation of the water industry led to the passage of the Water Act (1945), which gave the Ministry of Health responsibility for promoting water resource development, and the power to force mergers between suppliers where necessary; this did not, however, lead to significant restructuring in practice: the number of undertakings in England and Wales reduced only slightly in subsequent years from 1,194 in 1944 to 1,055 in 1956 (Hassan 1998, pp.72,90). Due to the continuing need for consolidation, efforts were made by the government and senior figures in the British Waterworks Association from 1956 onwards to encourage suppliers to merge voluntarily (Kinnersley 1988, p.79). Hassan (1998, pp.92-95) argues that, while there was some success in consolidating the industry, with the number of English and Welsh suppliers falling to around 200 in 1970, piecemeal mergers between existing suppliers, based as they were upon arbitrary political boundaries between local authorities, were unlikely to achieve a rational river-catchment based organisation of water and sewage services.

Attempts at integrating river management functions began with the Land Drainage Act (1930), which created, in England and Wales, Catchment Boards each responsible for flood prevention and land drainage in one or more river basins, and Drainage Boards covering smaller lowland areas. After the later River Boards Act (1948), these were superseded by 32 River Boards, which also took over the responsibilities of the former Fisheries Boards and the County Councils' responsibility for pollution prevention. These River Boards were later replaced by River Authorities in 1965, following the Water

Resources Act (1963), which were given power over abstractions. The River Boards and later River Authorities were given the power to set standards for effluent quality and to prosecute transgressors, but the inclusion in these bodies of local councillors who also ran sewage treatment works led to what Hassan (1998, pp.108-110) describes as a 'feeble' pollution prevention system with 'derisory' penalties, and authorities in many cases 'turning a blind eye' to violations.

From 1939 to 1941 in the electricity industry, planned plant construction was reduced given the shortage of labour and other resources caused by the Second World War; the industry was especially affected by the diversion of the construction and electrical engineering industries towards munitions and other military priorities (1979, p.295). The inevitable result of this was a lack of capacity, meaning that electrification of industry and of rural areas was neglected (Hannah 1979, pp.298-299). The effect of this was that when the war ended, the industry’s installed capacity was not sufficient to meet demand; given the conditions of full employment in the post-war period, the labour shortage in the industry therefore continued. Coal supplies were also significantly below pre-war levels, and the combination of these factors meant that blackouts—very unusual before the war—continued for some time after the end of the war.

The electricity supply industry was nationalised in 1948, after the passage of the Electricity Act (1947), bringing 200 private companies and 369 local authority electricity suppliers into a new organisation, the British Electricity Authority (BEA) (Hannah 1982, p.7). Within the BEA, a Central Authority was responsible for the power stations and the National Grid, i.e. generation and transmission, while 14 Area Electricity Boards (AEBs) took on responsibility for distribution. The Electricity Commission continued for some time, but finally dissolved in 1953. Generation was later devolved to 14 Generation Divisions, covering the same areas as the AEBs.

It is notable that unlike the electricity and gas industries, which had faced similar issues of fragmentation and lack of coordination during their development, the water industry was not nationalised by the post-war Labour government. Nationalisation of the industry had been party policy since 1934, but never appeared to be a particularly high priority, though proposals were made in 1948 (Hassan 1998, pp.59-60,74) that would almost certainly have been passed in some form had the government not lost power in the 1951 general election (Hassan 1995, p.208). Instead, the industry was eventually restructured and brought under public ownership—with the exception of a number of Statutory Water Companies, some of which exist to this day as water only companies (WOCs)—under a Conservative government by the Water Act (1973). The act reorganised the entire water and sewage sector in England and Wales, combining the 29 River Authorities, the 1,393 Sanitary Authorities, and most of the 157 water suppliers into 10 Regional Water Authorities (RWAs), with just 28 private firms remaining and supplying water only. However most of the sewage business, while notionally the responsibility of the new RWAs, remained contracted out to local authorities, so that there remained considerable duplication of professional and planning functions until 1983 when the RWAs finally gained the right to end these arrangements and bring sewerage under direct control (Hassan 1998). Meanwhile in Scotland, responsibilities for water supply and sewage treatment and disposal similar to those of the English and Welsh RWAs were given to the 9 Regional Councils and the Islands Councils created by the Local Government (Scotland) Act (1973).

The Electricity Supply industry in Great Britain and the Water Supply industry in England and Wales thereafter retained the same organisation until the privatisations of the 1980s and 1990s. Both industries were privatised in 1989, by the Electricity Act (1989) and the Water Act (1989), respectively. All of the regulatory and river management functions were split off from the RWAs and given to a new body, the National Rivers Authority (NRA), and the RWAs were then sold as private Water and Sewage Companies (WaSCs). The remaining statutory water companies were also converted into ordinary water only companies (WOCs), with their dividend restrictions lifted. The AEBs were privatised as public electricity suppliers (PESs) with responsibility for distribution and supply. The generation assets of the CEGB were divided between two private companies, National Power and PowerGen, owning around 50% and 30% respectively of the former CEGB's generating capacity, while nuclear generation, which accounted for the remaining 20%, was combined into a new company, Nuclear Electric, which was retained under public ownership until 1996. The distribution and supply functions of the PESs were later separated by the Utilities Act (2000), creating a number of ex-PES supply companies in a newly competitive supply market, and 14 distribution network operators (DNOs) with the same service areas as the PESs and AEBs before them.

With the privatisation of the UK electricity supply industry, there was a vertical separation aimed at separating the functions which could be subject to competition, such as generation and supply, from functions such as transmission and distribution, where this is less feasible. Under the current structure of the industry, most electricity is generated by large power stations connected to the transmission network.

The transmission network in Great Britain is known as the National Grid, and is operated by National Grid plc—which also operates the analogous National Transmission System for gas—in England and Wales, and by Scottish Hydro Electric Transmission plc and Scottish Power Transmission Ltd in the north and south of Scotland, respectively. Undersea connectors link the National Grid to the separate transmission systems of Northern Ireland, which is operated by the integrated transmission and distribution company Northern Ireland Electricity Ltd, and the Isle of Man, and also to the transmission networks of the Republic of Ireland, France, and the Netherlands. These interconnectors are used both to import and to export electricity, and in 2013 net imports contributed 3.9% of supply (DECC 2014, p.113).

The National Grid comprises high voltage transmission lines which delivers electricity from generators to grid supply points (GSPs), which is then distributed by one of fourteen regional distribution network operators (DNOs) to customers in their supply area, although some exceptionally large customers are connected directly to GSPs and thus to the National Grid. Additionally, in recent years there has been a growth in distributed generation, which comprises small generators connected directly to a distribution network rather than to the National Grid.

Following the Utilities Act (2000) the distribution and supply activities of the then public electricity suppliers (PESs) were forcibly separated, creating the DNOs and a number of ex-PES supply companies, and consequently neither the transmission nor the distribution companies are involved in actually selling electricity to customers; instead, they derive their income from transmission use of system (TNUoS) and distribution use of system (DUoS) charges paid by the supply companies, who buy electricity at wholesale prices from the generation companies. Supply companies are now often integrated, both with generation and with gas supply.

At privatisation, independent regulatory agencies were created for several industries, e.g. the Office of Gas Supply (Ofgas) and the Office of Electricity Regulation (OFFER)—now merged into the Office of Gas and Electricity Markets (Ofgem)—the Water Services Regulation Authority (Ofwat), and the Office of Telecommunications (Oftel)—since replaced by the Office of Communications (Ofcom)—in order to regulate prices and encourage efficient practice. The regulatory regime introduced for these utilities is known as RPI-X, a form of price capping regulation developed by Littlechild (1983), and designed in order to avoid some of the shortcomings of traditional cost-plus or rate of return (RoR) regulation. Under RPI-X regulation, prices are allowed to move with inflation, minus some X factor which reflects the regulator's judgement of potential productivity gains, and is reset every five years. RPI-X incentivises efficiency gains by allowing utilities to retain the rewards of any outperformance of this productivity target. The X factor is based on estimated productivity growth among other firms in the industry—where there are any—using benchmarking techniques, and thus exposes the utilities to a form of yardstick competition (Shleifer 1985); see Sawkins (1995) for a discussion of the implementation of yardstick competition in the English and Welsh water industry. A variation on this, RPI-X+K, was adopted by Ofwat for regulation of water and sewage, in which K is an additional allowance reflecting capital investment requirements.

In the water supply industry, a Director General of Water Services was appointed to regulate the industry, supported by a number of staff referred to as the Office of Water Services (Ofwat); this was replaced by a Water Services Regulation Authority, still known as Ofwat, in 2006, with the then Director General becoming chairman of the new organisation. Ofwat is responsible for regulating both the large WaSCs and the smaller WOCs. Similarly, an Office of Electricity Regulation (OFFER) was created, headed by a Director General of Electricity Supply, to regulate the electricity supply industry; this was later merged in 1999 with the Office of Gas Supply (Ofgas) to form a single regulatory authority for energy supply, called the Office of Gas and Electricity Markets (Ofgem).

The impact of privatisation and regulation on the performance of the water and sewage and electricity distribution industries is analysed in a number of studies, which are reviewed in detail in Chapter 4. Domah and Pollitt (2001) discuss trends in the electricity supply industry in the first few years, explaining that price caps set by the Department of Energy for the first five years were considered too generous to the PESs, but that X factors set by OFFER in 1994 required cuts in distribution charges averaging 14% in real terms over the following five year period. The profits of the PESs increased substantially, especially in the early years as a result of the loose price caps imposed, contributing to the imposition of a one-off windfall tax on the profits of the privatised utilities in 1997. At the same time, Domah and Pollitt (2001) find an increase of 15% in real unit costs immediately following privatisation, remaining high until 1994-95, implying that the lax initial price caps led to a failure to minimise costs; the more demanding price caps imposed in 1994 seem to have been effective at improving cost performance. Mergers and acquisitions involving PESs were allowed from 1995 after ‘golden share’ arrangements came to an end. Changes in the ownership of the PESs and their successors the DNOs are detailed in Chapter 4. A social cost-benefit analysis by Domah and Pollitt (2001) suggests that privatisation had net benefits, but that benefits only surpassed costs around 2000, and that they mainly accrued to government and the industry, with consumers bearing significant costs in the early years.

A later study by Jamasb and Pollitt (2007) evaluates the impact of regulation on the electricity distribution; as in Domah and Pollitt (2001), the first price control period is judged to have significantly underestimated the potential for productivity improvements in the industry, and to have led to increased prices, costs, and profits. The second and third price control periods—1995-96 to 1999-00 and 2000-01 to 2004-05—implemented by OFFER and Ofgem, on the other hand, are shown to have brought about significant reductions in real distribution charges, with some indications that they may have improved productivity.

In the English and Welsh water supply industry a similar pattern has been noted by some—e.g. Saal and Parker (2000)—whereby generous initial price caps at the time of privatisation lead to stagnant total factor productivity (TFP), after which the significant tightening of price controls during Ofwat's first price control brought about significant reductions in prices and improvements in productivity. This is discussed in more detail in Chapter 4.

It is worth noting at this point that our discussion of the development of the water and sewage industry has focused on England and Wales. In Scotland, in the same year that the Water Act (1973) created the RWAs, the Local Government (Scotland) Act (1973) was passed, and water supply and sewage in Scotland became the responsibility of the nine regional and three island councils created by the act. Prior to the act, water supply in Scotland was in fact already relatively consolidated relative to England and Wales, having been in the hands of thirteen regional water boards created by the Water (Scotland) Act (1967); responsibility for sewage, on the other hand, remained in the hands of 234 separate local authorities (Sawkins and Dickie 1999). The main effect of the 1973 act was therefore to consolidate sewage activities and unite them with water supply, their having been organised separately beforehand. Unlike in England and Wales, the industry was not subject to privatisation and remains to this day under public ownership. Sawkins (1994) provides an overview of the functioning of the Scottish water industry in the early nineties, and examines various trends in the industry over the period 1989-90 to 1992-93, and compares these to trends in England and Wales. The author finds that water and sewage charges in Scotland were considerably lower than in England and Wales, and that they followed similar trends. Scotland also starts from a lower base in terms of capital investment—indicating a preference for a lower price, lower investment regime relative to England and Wales—and in addition the gap widens significantly during the period. Water and sewage remained in the hands of the twelve regional and island councils until further consolidation with the passage of the Local Government etc (Scotland) Act (1994), which transferred water and sewage functions away from the local councils and into three large water authorities: the North of Scotland Water Authority, the East of Scotland Water Authority, and the West of Scotland Water Authority, with effect from 1996. Regulation of the industry also passed from the local authorities to the Scottish Office and to the Scottish Water and Sewage Customers Council (SWSCC), which was charged with scrutinising and approving the authorities' charges, a process that was arbitrated by Secretary of State for Scotland. Sawkins and Dickie (1999) state that the three new authorities were able to exploit significant economies of scale, and give examples of some of the considerable cost reductions that were achieved by the authorities.

Despite improvements in regulation and the organisation of the industry in Scotland, Sawkins and Dickie (1999) identify several shortcomings, such as a high level of uncertainty resulting from the short termism of the regulatory regime—the SWSCC reviewed charges year by year, in contrast to the five year price controls in place in England and Wales—and the division of regulatory functions between the SWSCC and the Secretary of State for Scotland. This situation was remedied when, following the passage of Water Industry Act (1999), the SWSCC was dissolved and a new integrated and independent regulator, the Water Industry Commissioner for Scotland (WICS), was created with the power to set price caps; this was the first time that the authorities had been issued with individual price caps (Sawkins and Dickie 1999). The price capping approach used was similar in effect to the RPI-X method used by Ofwat in regulating the English and Welsh WaSCs and WOCs, and this was eventually explicitly adopted. In addition, the regulator began to collect operational and cost data using Ofwat's template in order to enable comparisons and benchmarking between the three authorities; the regulation and organisation of the water supply industry in Scotland was therefore increasingly coming to resemble that of England and Wales.

In 2003, the structure of the industry was changed yet again when the three water authorities were merged into a single public corporation called Scottish Water. The public corporation model came with greater independence from politics; despite the removal of water and sewage responsibilities from local authority control, local politicians had continued to have a large role in the three water authorities, and had dominated the authority's boards; this was no longer the case with Scottish Water. The new company continued to be regulated by WICS under an RPI-X regime. One of the main priorities at the time of the three authorities was to significantly increase investment, which as alluded to above had for years fallen short of requirements, and as a consequence WICS's price caps for their final two years of operation allowed for very substantial increases in real prices. For the first few years following Scottish Water's creation, WICS likewise allowed for real price increases; however, these were much more modest, and in 2005-06 the regulator for the first time imposed cuts to real prices. From the regulatory data and reports published by WICS since, there is some indication that productivity improvements have resulted in recent years.

1.2.3. Electricity and Water Supply in Northern Ireland

The development of the water and sewage industry in Northern Ireland was in many ways similar to that in Scotland. It was similarly fragmented, with water and sewage services mainly in the hands of local authorities, though a slightly different system was in place in Belfast, in which water supply was the responsibility of Belfast Water Commissioners created by Belfast Water Act (1840). As in England, Wales, and Scotland, the industry was consolidated in 1973 by the Water and Sewage Services (Northern Ireland) Order (1973), which transferred responsibility for water and sewage services to a new Water Executive within the Department of the Environment (Northern Ireland), a devolved Northern Irish government department.

A key difference, however, lies in the fact that, unlike the industries in England, Wales and Scotland, which have always been partially or wholly self-financing, domestic water and sewage services in Northern Ireland have for decades been supplied free of charge, and funded through taxation. This situation has persisted to the present day, despite the introduction of separate water and sewage charges being raised on several occasions in recent years, plans most notably being included in the Water and Sewerage Services (Northern Ireland) Order (2006); these plans later had to be abandoned, however, in the face of widespread opposition from the public. To the present day, only non-domestic customers pay any bills for their water and sewage, and even then a 'domestic allowance' is made for non-domestic customers who pay business rates on their property.

In the last twenty years, however, there have nonetheless been reforms altering the structure of the industry to be more like that of a private company. Responsibility for the industry was initially delegated to a Water Executive, which in 1996 was transferred to the Department for Regional Development (Northern Ireland), another devolved government department, being rebranded in the process as the Northern Ireland Water Service, and acquiring a more distinct identity of its own. A further restructuring saw the creation of Northern Ireland Water, a public corporation taking over the responsibilities of the Northern Ireland Water Service, in 2007. At the same time, an independent regulator, the Northern Ireland Authority for Utility Regulation (NIAUR), was established to regulate Northern Ireland's water, electricity, and gas utilities, again according to the RPI-X model of regulation. In the case of Northern Ireland Water, this means capping the charges made to non-domestic customers and the level of subsidy received for supplying domestic customers. The issues facing Northern Ireland Water are similar to those faced by Scottish Water: a need to make up for historic underinvestment, and a performance gap relative to the English and Welsh WaSCs and WOCS; NIAUR estimated that Northern Ireland Water would need to reduce its operating costs by around 49% to achieve similar levels of efficiency (Northern Ireland Audit Office 2010, p.62). A relatively large increase in allowed revenues was set in 2008-09, the first year of price capping.

Electricity supply in Northern Ireland was undertaken by the Northern Ireland Electricity Service from 1973, which was established as an integrated utility under public ownership, responsible for generation, transmission, distribution, and supply. This was transformed into a public corporation in 1991 as Northern Ireland Electricity; the company's generating arm was then split off and sold to the private sector the following year in 1992, and in 1993 the remainder of the company was privatised as an integrated transmission, distribution, and supply utility. The transmission network, though owned by the company, is operated by System Operator Northern Ireland, originally an internal division of the company, before being sold to Eirgrid, the transmission system operator in the Republic of Ireland, in 2009. This sale followed the establishment of the Single Electricity Market, a joint wholesale electricity market covering both Northern Ireland and the Republic of Ireland, on which all wholesale electricity is bought and sold. Along with Northern Ireland Water and the Northern Irish gas utilities, the company has been regulated by NIAUR according to the RPI-X method since 2007.

1.2.4. Summary

We have discussed the development of the electricity and water supply industries in the UK. Between these industries, and across national boundaries, many similarities are apparent: both industries emerged in something like their recognisable modern forms in the mid to late 19th century, with a fragmented structure dominated by small statutory companies or local authority suppliers with monopolies within their supply areas. Early forms of economic regulation were usually incorporated into the founding legislation of the utilities, and included simple measures such as dividend restrictions.

The industries were increasingly consolidated over the course of the 20th century, ultimately ending up with rationalised and coordinated structures under public ownership. Following a wave of privatisations in the late 1980s and early 1990s, which only the Scottish and Northern Irish water industries avoided, the industries became subject to a standard form of RPI-X price capping regulation, under various independent regulatory agencies, aimed at encouraging improvements in productivity.

2. Regulation and Firm Performance

2.1. Introduction

In the introduction to this thesis, we discussed the rationale for regulation of the natural monopoly elements of utility industries in the absence of competition, and the focus of this study on analysing the effects of regulation and other factors on efficiency in two such industries, water and sewage supply and electricity distribution, in the UK. In this chapter we discuss the underlying theory behind these analyses in some detail, beginning with basic definitions of efficiency concepts and the standard theory of the firm. We then move on to discuss the firm's utility maximisation problem in the context of monopoly, issues around market power in utility industries, and some of the theory concerning the various forms of economic regulation.

Finally, we introduce the theoretical framework upon which the subsequent empirical chapters are based. Specifically, we describe the profit maximisation problem of a monopolist, and derive new monopoly profit and revenue frontiers, which have a firmer grounding in theory than the 'alternative' profit and revenue frontier specifications often employed in the literature. We show that, in the context of fixed outputs, the monopolists' profit maximisation problem splits into separate problems of revenue maximisation and cost minimisation. The empirical component of this thesis therefore analyses the overall performance of the regulated water and sewage and electricity distribution industries via the estimation of the alternative monopoly revenue function shown in (34) and (35).

2.2. Firm Level Efficiency Concepts

In this section, we define several concepts of efficiency found in the economics literature and used to analyse performance at firm level and explain how these relate to one another. In general, efficiency refers to the extent to which desirable outputs are maximised for given inputs relative to some theoretical maximum. In economics, there are several efficiency concepts which relate to the performance of the firm, which are described below.

Given that firms are often assumed to be profit maximisers, an overall measure of firm performance is *profit efficiency*. Profit efficiency is the ratio of actual profit to the maximum profit the firm could potentially earn. It can be broken down into two components: *revenue efficiency*, i.e. the ratio of the firm's revenue to its potential maximum revenue, and *cost efficiency*, the ratio of the firm's actual cost to its potential minimum cost. Note however that the maximum revenue and minimum cost that we refer to are for a given—profit maximising—level of output chosen by the firm; we do not imply that the firm is cost minimising or revenue maximising, which are different and conflicting objectives.

The benchmark against which we measure revenue efficiency, i.e. the firm's theoretical profit maximising revenue, depends upon the nature of the market in which the firm operates, and the corresponding revenue function faced by the firm; if the firm operates in a perfectly competitive environment, it prices are exogenously determined and these simply influence the profit maximising combination of outputs to produce, however if the firm has market power, it must jointly determine its output and price levels to achieve the maximum possible profit, meaning that for a given level of output, there can be allocative inefficiency on the revenue side if the firm sets prices above or below their profit maximising levels; this is discussed further.

Cost efficiency can again be broken down further into two components: *technical efficiency* and *allocative efficiency*; the latter is the degree to which the firm employs inputs, e.g. labour and capital, in cost minimising proportions given relative input prices, while the former is the ratio between actual output and the firm's maximum achievable output given its inputs, or between actual inputs used and the minimum inputs required to produce a given level of output. According to the definition of Koopmans (1951, p.60), a firm is technically efficient if

' ... an increase in any output requires a reduction in at least one other output or an increase in at least one input, and if a reduction in any input requires an increase in at least one other input or a reduction in at least one output. Thus a technically efficient producer could produce the same outputs with less of at least one input, or could use the same inputs to produce more of at least one output'.

On the other hand, Debreu (1951) and Farrell (1957) suggest that technical efficiency should be measured as

'… one minus the maximum equiproportionate reduction in all inputs that still allows the production of given outputs, a value of one indicates technical efficiency and a score less than unity indicates the severity of technical inefficiency' (Lovell 1993, p.10)

These definitions of technical efficiency are similar, but not identical, with Debreu-Farrell efficiency a necessary, but not sufficient, condition for Koopmans efficiency. In particular, this is because Debreu-Farrell efficiency neglects the possibility of non-radial input ‘slacks’ that can arise in particular using linear programming techniques; see Lovell (1993).

2.3. Market Power in Utilities

Competition in utility industries, or some aspects of those industries, is usually considered infeasible in public utilities due to their supposed natural monopoly status. Baumol (1977) defines the criterion for natural monopoly as being global subadditivity of the cost function, i.e. that for any given vectors of outputs, it is more expensive for them to be produced separately than for them to be produced by a monopolist. This is especially plausible in utility industries, which are likely subject to increasing returns to network density—i.e. falling unit costs as the number of customers in a given service area increases, due to decreasing marginal infrastructure requirements—and increasing output density—i.e. falling unit costs as existing infrastructure is used more intensively—which would be lost if utilities competed directly for the same customers.

In natural monopoly scenarios, competition is therefore unfeasible, meaning that the utility can potentially earn considerable economic profit at the expense of consumers by exercising its market power. As noted in the previous chapter, this has partly been remedied by policymakers via vertical separation of those activities in which competition is potentially feasible—e.g. electricity generation—from those activities such as transmission and distribution where it is not; however, the problem of natural monopoly still endures in the latter activities, and for these discussion has tended to centre around regulation as a means of curbing market power.

2.4. Market Power and Efficiency

In the standard framework, differences in efficiency and productivity between utilities do not arise, since firms are assumed to maximise profits efficiently. In order to explain inefficiency, we therefore need an alternative theory of the firm.

The vital ingredient in any alternative theory of the firm is market power, since firms are constrained to earn normal profits as a minimum. Without some degree of market power, this constraint forces the firm to efficiently maximise profits. In the absence of competition, however, the firm no longer faces the profit-maximising imperative, and may pursue alternative goals; in the words of Hicks (1935, p.8), monopolistic firms

' ... are likely to exploit their advantage much more by not bothering to get very near the position of maximum profit, than by straining themselves to get very close to it. The best of all monopoly profits is a quiet life'.

This quiet life hypothesis (QLH) was one of the earliest moves toward a conception of a more generally utility-maximising firm and away from profit maximisation, which had long been—and in many contexts still is—taken for granted as the sole objective of the firm, as acknowledged by de Scitovszky (1943, p.60)

'Many of us have been in the habit of regarding this assumption [profit maximisation] *as similar in every respect to the assumption that the individual maximises his satisfaction'.*

Indeed Leibenstein (1966, 1975, 1977, 1978a, 1978b, 1978c, 1987), one of the first to advance an explanation of inefficiency did so in terms of selective rationality and non-maximising behaviour. According to the X-inefficiency hypothesis, inefficiency therefore serves no utilitarian purpose, within or without the firm; foregone profits are simply waste, a non-allocative welfare loss (Comanor and Leibenstein 1969). The X-inefficiency hypothesis is distinct in this regard, since a common strand to all other inefficiency hypotheses is that they all stem from some utility-enhancing motive. A powerful objection put forward against the idea of X-inefficiency is therefore that what is being measured as such is in fact a transfer; that the firm is simply realising its economic rent in some form other than profit, e.g. increased leisure time (Parish and Ng 1972, Stigler 1976, Pasour 1982). Leibenstein's X-inefficiency and Hicks' QLH can therefore be contrasted, in that while they both imply a reduction in the firm’s effort to profit maximise, X-inefficiency implies non-maximising behaviour and deadweight welfare loss, while the QLH simply implies that variables other than profit enter into the firm’s objective function.

Other proposed explanations fit squarely within the standard utility-maximising approach, such as the maximisation of growth (Marris, 1963) or revenue subject to a profit constraint. The expense preference hypothesis of Williamson (1963) states that there are certain expenses that managers have a preference for, and thus when there is scope for discretionary behaviour, spending on these will be motivated in part at the discretion of managers. It is suggested that increasing employee numbers is one activity that contributes to managerial utility in much the same way as promotion; by increasing status, power and prestige, as well as providing a rationale for increased salaries and other benefits. To an extent, there is also clearly an incentive for managers to capture some of the firm’s rents in the form pecuniary awards such as inflated managerial salaries and bonuses, but the author argues that regulatory constraints, tax structures and the fact that such spending is relatively easy for stakeholders with conflicting interests to detect can be part of the motivation for spending within the firm.

What these hypotheses have in common is that the ability for the utility manager to engage in discretionary behaviour stems from their ability to withhold information from other stakeholders. For example, expense preference behaviour as suggested by Williamson (1963) cannot be directly observed by regulators or shareholders, and nor can managers' effort level. This imbalance of knowledge between manager on the one hand, and shareholder or regulator on the other is known as informational asymmetry, or in the latter case as the principal-agent problem. Informational asymmetry is one of the main challenges of incentive regulation, which aims to make the manager reveal as much information as possible. Various approaches to incentive regulation in the context of asymmetric information are discussed in the next section.

2.5. Incentive Regulation

We have so far argued that utilities having natural monopoly characteristics will have potential market power, and that due to informational asymmetries between the firm and the regulator—and between different groups within the firm—there is an incentive for utility managers to engage in discretionary behaviour in order to pursue objectives other than profit maximisation, resulting in inefficiency.

Furthermore, in some cases regulatory regimes imposed on utilities, with the purpose of limiting their market power, can introduce perverse incentives, and result in inefficient practice. Some traditional forms of regulation offer particularly poor incentives for efficiency, and in particular cost efficiency. In recent years, regulators have therefore tended to move toward regulatory regimes with higher-powered incentives, known as incentive regulation.

From a social welfare perspective, an ideal form of regulation would maximise social welfare, subject to the constraint that the utility firm must earn a normal rate of profit; in this case, the regulator must set the mark-up to be inversely proportional to the price elasticity of demand for each of the firm's outputs, as found by Ramsey (1927) in the context of taxation, and applied by Boiteux (1960, 1971) in the context of public utility pricing. This rule is therefore known as Ramsey-Boiteux pricing. Its implementation, however, requires the regulator to have extensive knowledge about the regulated firm's costs, prices, and output demands, to the point where they can calculate reliable marginal costs and price elasticities of demand for each of the firm's outputs. In practice, however, the regulator is unlikely to have such extensive and reliable information, in part owing to the problem of information asymmetry already identified.

We therefore focus our discussion in this section on more practical regulatory rules of the kind that are commonly applied by regulators in the face of information asymmetry.

Waddams Price and Weyman-Jones (1996) show that many different price regulation regimes can be understood within a framework suggested by Laffont and Tirole (1993), in which

$$\sum_i p_{it} q_{*i} = \beta c_* + (1-\beta) c_t \tag{1}$$

Where p_{it} is the price charged by the utility for the output i in period t and c_t is actual cost of production in that period, q_{*i} is a fixed quantity weight for output i, set by the regulator, and c_* is the regulator's estimate of the utility's costs. Note that the utility is free to adjust the individual prices, as long as the weighted average price does not exceed the cost allowance on the right-hand side, offering some degree of flexibility in achieving allocative efficiency within the framework of the regulatory regime, though in practice regulators are likely to place some restrictions on price discrimination as well.

The parameter β is between zero and one, and reflects the incentive power of the regulatory regime; for example, when $\beta = 0$, we have a cost-plus regime with no incentive power. In this case, the regulator allows the utility to cover its actual costs, but does not permit supernormal profits to be earned; since in this case there is no link between profitability and managerial effort, the managers therefore have an incentive to put in low effort, capturing the potential rents themselves in the form of leisure and discretionary spending. Such regimes may therefore be associated with cost inefficiency.

An additional issue with traditional cost plus regulation lies in the way it is implemented in practice, i.e. the regulator allows the utility to cover its observed operating costs, and then adds on an additional allowance for capital costs that enables the firm to earn a ‘fair’ rate of return, defined by the regulator, on their capital. This is known as rate of return (RoR) regulation. Averch and Johnson (1962) demonstrate that under RoR regulation if, as seems likely, the regulator sets a RoR which is higher than the cost of capital and yet still binding—i.e. lower than the monopoly rate—then the opportunity cost of capital from the utility’s point of view is effectively lowered, leading the utility to substitute capital goods for labour and other factors. This Averch-Johnson effect, as it is known, therefore induces the firm to employ inputs in a way that is, from a societal point of view, allocatively inefficient, and raises the firm’s costs above their efficient level.

Referring back to (1) the regulator would like to set β to one—which corresponds to a high-powered fixed-priced regime—and therefore force the firm to minimise its costs. The regulator’s problem, therefore, is to generate an estimate of the utility’s efficient cost, c_*, as accurately as possible. This is made difficult by informational asymmetry: the regulator cannot directly observe the utility’s efficient cost, nor can it directly observe the level of effort and discretionary spending by the utility. It is therefore in the utility manager’s interest to mislead the regulator about the true level of efficient cost; if we assume that the regulator’s intention is to implement a high-powered $\beta = 1$ regime, then an overestimate of efficient costs, c_*, is equivalent in practical terms to setting a lower-powered incentive. A key requirement of any successful form of incentive regulation is therefore to minimise information asymmetry, for example by increasing the amount and quality of information that the regulator possesses.

One method of incentive regulation that provides high-powered incentives for cost efficiency and reduces the information asymmetry between regulator and utility is RPI-X, a form of price capping in which, referring back to (1), the utility sets

$$c_* = \left(1 + \frac{\Delta p}{p} - X\right) c_{t-1} \tag{2}$$

In which c_{t-1} is the utility's costs in period $t-1$, p is price level in the wider economy, as capture by the retail price index—or some similar measure of inflation—and X is the regulator's estimate of potential productivity growth. The incentive for cost efficiency comes from the fact that, if the firm manages to outperform the regulator's implicit productivity growth target, it may keep the difference in the form of supernormal profit. The regulator's problem in this case is therefore to generate as accurately as possible an estimate of X, requiring the gathering of significant amounts of information from the utility, and some way of analysing it. This form of regulation was devised by Littlechild (1983) as a way of regulating British Telecom, and later other privatised UK utility companies, while avoiding the problems associated with traditional RoR regulation.

As practised in the UK and elsewhere, X factors are determined by benchmarking the performance of the various firms within a regulated industry against one another. Some of the main methods involved in such benchmarking exercises are described in detail in Chapter 3, the effect of which are to reduce the information asymmetry faced by the regulator. In addition, in utilising information on the costs of comparator firms in determining price caps, RPI-X exposes the regulated firm to a form of yardstick competition, which as described by Schleifer (1985) sets prices on the basis of the costs of an identical firm, thereby simulating the effects of competition in cases where direct competition is not practical; although such identical firms are not likely to exist, the benchmarking techniques used allow the regulator to control for observable heterogeneity between firms, and therefore make comparisons between each of the firms they regulate.

Some theoretical guidance on the practical problems of implementing RPI-X regulation is provided by the literature. Armstrong et al. (1995) consider the optimal regulatory lag, i.e. the length of time between price reviews at which prices and X factors are reset. The authors note that, even though RPI-X style price capping permits the firms to retain any supernormal profits earned by outperformance of the X factor, the firm will still recognise that earning large profits in the present may lead the regulator to set tighter price caps at the next price review, in order to eliminate expected future profits, which are partly based on current realised revenues and costs. This effect will tend to dampen the firm's incentive to operate efficiently and, the authors note, will be greater the more regularly regulation is updated. On the other hand, as the authors point out, a long regulatory lag allows large supernormal profits to persist over a long time period, and the choice of regulatory lag is therefore a trade-off between maintaining the incentive power of regulation and reducing the ability of the firm to extract supernormal rents. The relative importance of these considerations depends on two factors in particular: the ability of the firm to influence its costs over time—which, in some cases, may be limited—and the price elasticity of demand for the firm's outputs, which determines the deadweight loss from the exploitation of the firm's market power.

Regarding the problem of setting appropriate X factors for regulated firms, Bernstein and Sappington (1999) consider several different cases. If all of the firms' activities are subject to price capping, the regulated industry's prices do not affect the rate of inflation in the economy as a whole, and no significant structural change is anticipated, the authors show that X factors should be set to reflect the extent to which TFP growth for the regulated firm exceeds—or falls short of—the rate of TFP growth in the economy as a whole, and also the extent to which inflation in the input prices faced by the firm falls short of—or exceeds—the rate of inflation in the wider economy. The optimal X factor for a target of zero profit, X_0, is therefore

$$X_i = \frac{\Delta\theta_i}{\theta_i} - \frac{\Delta\bar{\theta}}{\bar{\theta}} + \frac{\Delta\overline{w}}{\overline{w}} - \frac{\Delta w_i}{w_i} \tag{3}$$

Where θ_i and w_i are the TFP and input price levels of regulated firm or industry i, and $\bar{\theta}$ and $\overline{w}$ are the average TFP and input price levels in the wider economy.

The authors then consider the cases in which the regulated industry's prices do in fact have an impact on the economy-wide inflation rate, and in which not all of the firm's outputs are regulated. In the latter case, where we assume that only a proportion of the firm's outputs are subject to price capping regulation, and there are joint products and shared factors of production confounding the regulator's ability to measure separate input price and TFP growth rates for regulated and unregulated outputs, the authors show that (3) must be modified so that, in the case of zero profit

$$X_i = \frac{\Delta\theta_i}{\theta_i} - \frac{\Delta\bar{\theta}}{\bar{\theta}} + \frac{\Delta\overline{w}}{\overline{w}} - \frac{\Delta w_i}{w_i} + \left(\frac{1-\alpha}{\alpha}\right)\left(\frac{\Delta p_u}{p_u} - \frac{\Delta w_i}{w_i} + \frac{\Delta\theta_i}{\theta_i}\right) \tag{4}$$

Where α is the firm's regulated revenue as a proportion of total revenue, and p_u is the price of the firm's unregulated outputs.

The former case is plausible, not only because regulated utility industries tend to be relatively large, but also because some of their outputs are often important inputs into production processes in the wider economy, e.g. electricity, gas, water, and changes in their prices will consequently have knock-on impacts on prices in other industries, which should be taken into account when setting price caps. In this situation, the authors show that (3) should be modified to

$$X_i = \left(\frac{c_n}{\bar{c}+\bar{\pi}}\right)\frac{\Delta w_n}{w_n} + \left(\frac{c_i}{c_i+\pi_i}\right)\left(\frac{\Delta\theta_i}{\theta_i} - \frac{\Delta w_i}{w_i}\right) - \left(\frac{\bar{c}}{\bar{c}+\bar{\pi}}\right)\left(\frac{\Delta\bar{q}}{\bar{q}} - \frac{c_n}{\bar{c}}\frac{\Delta x_n}{x_n}\right)$$
$$+ \left(\frac{\pi_n}{c_n+\pi_n}\right)\left(\frac{\Delta\pi_n}{\pi_n} - \frac{\Delta q_n}{q_n}\right) + \left(\frac{\bar{\pi}}{\bar{c}+\bar{\pi}}\right)\left(\frac{\Delta\bar{q}}{\bar{q}} - \frac{\Delta\pi}{\bar{\pi}}\right) \quad (5)$$

Where c_i, c_n, and $\bar{c}$ are total costs relating to the regulated firm or industry, to the rest of the economy excluding the regulated firm or industry, and to the economy as a whole, respectively; likewise, π_i, π_n, and $\bar{\pi}$ are profits within the whole economy, the regulated firm or industry, and the rest of the economy, x_n and q_n are inputs and outputs in the rest of the economy, w_n is input prices in the rest of the economy, and $\bar{q}$ is output in the economy as a whole.

Finally, Bernstein and Sappington (1999) consider the impact of structural changes in the regulated industry, such as a shift from RoR to RPI-X regulation or an increase in competition; the authors argue that, in the absence of major structural changes, the regulator can reliably assume that potential future TFP growth rates are equal to historic TFP growth rates; however, if there have been recent structural changes, these may not reflect the true potential for TFP growth in the future under the new regulatory regime. The authors also discuss the complicating factors around competition, and how this can increase potential TFP growth on the one hand by creating greater incentives for efficiency. On the other hand, the authors argue that competition can lower TFP by reducing the firm's ability to exploit scale economies—note that the same point could also be made about economies of density—meaning that the overall impact is ambiguous, and derive an optimal X factor in terms of these factors, which we do not reproduce here owing to its complexity.

Burns and Weyman-Jones (2013) revisit the issue of optimal X factors in RPI-X regulation, and point out that the X factor should tend towards zero in the long run, as regulated firms catch up to the frontier, unless there are underlying reasons why either TFP growth or factor price inflation are expected to outstrip TFP growth and inflation in the wider economy; the authors recognise that increasing returns to scale among regulated firms as opposed to constant returns to scale in the competitive sectors of the economy is one reason why long-run TFP growth potential for regulated firms may be greater than that of the rest of the economy, thereby justifying a long-run positive X factor—again, the same argument could be made regarding increasing returns to density in utility industries—but argue that this will be small. The authors argue, however, that the regulator would be unlikely to adopt long-run X factors at or near zero, given that it would allow the regulated firm to accrue significant rents, which could lead to populist demands—according to the definition of Winston and Crandall (1994), demands for redistributive measures that maximise consumer welfare, while nonetheless having the indirect effect of raising costs, and therefore prices—for greater confiscation of profits.

In light of this dilemma, the authors outline two alternative responses on the part of the regulator; first, the regulator could set long run X factors at zero or near zero as is optimal, but weaken the incentive power of the regulatory regime, e.g. by moving further towards a cost-plus type of regime so that profits are not revealed to be too high, or by introducing an element of profit sharing. The weakening of incentives would in turn lead to increasing cost efficiency and reduced levels of service, leading potentially to a cycle in which the regulator switches between high and low powered incentive regimes as and when reducing profits or improving efficiency becomes customers' main priority. Alternatively, the regulator could opt to continue with positive X factors in order to capture the rents of the regulated firm and mitigate demands, dampening the incentive for cost efficiency, and risking degradation of service, loss-making, and eventually firms' exit from regulated industries, given that rewards in the non-regulated sectors of the economy would be greater than those in the regulated industry.

From the discussion of Armstrong et al. (1995) around optimal regulatory lag, and the discussion of Burns and Weyman-Jones (2013) on optimal long-term X factors, we can see that the regulator faces a trade-off between capturing the firm's rents on the one hand through a low powered regime, and incentivising cost efficiency through a high powered regime on the other. Burns et al. (1994) describe two explicitly 'intermediate' forms of regulation: the profits sliding scale, in which the firm's profits are shared with its customers according to a proportion set by the regulator, which is a function of the price charged, and the RoR sliding scale, which modifies standard RoR regulation so that the maximum allowed RoR increases as the firm lowers its prices below a maximum level; a strategy similar to these is when a regulator offers firms a finite 'menu' of regulatory contracts, some high powered, and thus attractive to low cost firms, and some low powered, and thus relatively attractive to high cost firms. Such forms of regulation reduce the information asymmetry between regulator and firm (Joskow 2014), since the firms' choices reveal information about their costs.

To summarise, in this section we have discussed various forms of incentive regulation, paying particular attention to the RPI-X method of price capping regulation—given its particular relevance to this thesis, being the method used by UK regulators across many industries—and its incentive properties. We have also discussed various practical issues such as optimal regulatory lag, the setting of optimal X factors, and the trade-off between incentivising efficient behaviour and capturing the firms' rents. Overall, we conclude that RPI-X is a high-powered form of incentive regulation with the potential to bring about substantial improvements in the performance of utility firms, especially in the early years of regulation.

2.6. A Monopoly Profit Benchmark

The standard profit maximisation problem takes output prices and factor prices as given, with the firm choosing output quantities and input quantities subject to its transformation function.

$$\max_{q,x} \sum_i p_i q_i - \sum_j w_j x_j \tag{6}$$

$$s.t.\ f(q,x,z) = 1$$

Solving gives the Standard Profit Function (SPF)

$$\pi = \pi(p,w,z) \tag{7}$$

in which $p, w,$ and z are vectors of output and factor prices and hedonic variables, respectively. In the standard revenue maximisation problem, output prices and factor prices are again taken to be exogenous, as are input quantities (and therefore costs). The firm's problem is then to choose output quantities so that revenue is maximised

$$\max_{q} \sum_i p_i q_i \tag{8}$$

$$s.t.\ f(q,x,z) = 1$$

the solution to which gives the Standard Revenue Function (SRF), i.e. revenue as a function of output prices, input quantities, and hedonic variables.

$$r = r(p, x, z) \tag{9}$$

The SPF and SRF are unsuitable however, when the firms in question have some degree of market power, since output prices are then endogenous. The Alternative Profit Function (APF) approach introduced by Humphrey and Pulley (1997) in studying the banking industry treats output quantities as given, with firms choosing output prices and inputs in order to maximise profit given outputs, factor prices and hedonic variables:

$$\max_{p,x} \sum_i p_i q_i - \sum_j w_j x_j \tag{10}$$

$$s.t.\ \ g(p, q, w) = 1, f(q, x, z) = 1$$

where output prices are constrained by a price possibility function $g(p, q, w)$ where p is a vector of output prices. This function reflects the firm's view of its market power and customers' reserve prices; factor prices are included on the grounds that higher input prices in a market may signal higher living costs and thus ability to pay. In the resulting APF, profits are a function of output quantities, factor prices and hedonic variables:

$$\pi = \pi(q, w, z) \tag{11}$$

likewise, Berger, Humphrey and Pulley (1996) derive a related Alternative Revenue Function (ARF) from the problem

$$\max_{p,x} \sum_i p_i q_i \tag{12}$$

$$s.t.\ p(q, w) = 1$$

which gives revenue also in terms of output quantities and factor prices. Many studies using the APF approach have assumed linear homogeneity, whether for convenience or because of convention, or because they believed it was required. Restrepo-Tobón and Kumbhakar (2014) formally derive the APF and study its homogeneity properties. Their conclusions are important: they find that the alternative profit maximisation problem splits into two separate problems: the alternative revenue maximisation problem, and the standard cost minimisation problem in which the firm minimises costs by choosing its input quantities given exogenous factor prices and its transformation function:

$$\min_{x_i} \sum_i w_i x_i \tag{13}$$

$$s.t.\ f(q, x, z) = 1$$

which solves for the Standard Cost Function (SCF) in terms of outputs, factor prices and hedonic variables

$$c = c(q, w, z) \tag{14}$$

which should be non-negative and non-decreasing in outputs and input prices, and homogenous of degree one with respect to factor prices, so that a proportional change in input prices, ceteris paribus, should change costs by the same proportion.

Whether or not the APF is linearly homogenous in input prices, given that the SCF must be, therefore depends on the ARF. Restrepo-Tobón and Kumbhakar (2014) point out that the assumption of linear homogeneity of the ARF is implausible unless there is complete cost pass-through and, according to the Panzar and Rosse (1987) framework, perfect competition, which clearly contradicts the assumption of imperfect competition underlying the APF approach. They further demonstrate that profit efficiency cannot be estimated directly from an alternative profit frontier function of the form

$$\pi = \pi(q, w, z)u_\pi \tag{15}$$

as is standard in the literature, where $u_\pi \in [0,1]$ is profit efficiency. Profit efficiency is the ratio of actually observed profit to the frontier function $\pi(q, w, z)$, which is a function of revenue efficiency $u_r \in [0,1]$ and cost inefficiency $u_c \in [1, \infty)$; the closeness to the revenue frontier $r(q, w)$ and distance from the cost frontier $c(q, w, z)$, respectively. This is because when estimating an econometric frontier, we assume that u_π is a random variable distributed independently of the $q, w,$ and z variables, whereas in fact substituting into (15) for u_π, we have

$$\pi = \pi(q, w, z)\frac{r(q, w)u_r - c(q, w, z)u_c}{\pi(q, w, z)} \tag{16}$$

i.e. u_π is a function of $q, w,$ and z. Also, as noted by Berger and Mester (1997), when negative profits are observed the ratio takes on negative values which are difficult to interpret; but more serious problems occur when potential profit is negative or zero. If potential profit is negative, which is after all perfectly feasible, the ratio can be greater than one, and if potential profit is zero then it is undefined. Berger et al. (1993) and Coelli et al. (2002) simply take the difference between potential and actual profit, which is always positive and easier to interpret. However, as with the profit efficiency ratio, this measure reflects not only efficiency but also the absolute levels of potential costs and revenues. For example, two firms with identical revenue and cost efficiency scores can have very different profit efficiency ratios and absolute efficiency losses.

For the reasons given above, profit and profit efficiency should therefore be analysed indirectly via the ARF and SCF. This brings the additional advantages that we are given a breakdown of profit efficiency into its revenue and cost components, and that we can model these cost and revenue components, which may have different drivers, and conflicting relationships with certain variables which would be obscured by modelling profit efficiency directly. There is also the practical advantage of avoiding the problem of dealing with zero and negative profits, discussed by Bos and Koetter (2011).

Restrepo-Tobón and Kumbhakar (2014) demonstrate the serious implications of these problems for existing studies using the data and model employed by Koetter et al. (2012), whose findings of a positive relationship between market power and cost efficiency and a negative relationship between market power and profit efficiency are reversed when the assumption of linear homogeneity of the APF is dropped and profit efficiency estimated indirectly via revenue and cost efficiency as discussed above.

Looking again at (10), we see that the choice of variables to include in the price constraint is fairly ad-hoc. In an environment of imperfect competition, the fundamental constraints on prices are exogenous determinants of demand, e.g. income, and prices of substitutes and complements; a fact that has surprisingly been overlooked in studies taking the APF approach, so that APF and ARF specifications usually include only output quantities, input prices and a vector of hedonic variables considered important to the model. In fact, even in mentioning the more extreme monopoly case, in which demand is taken to be known and prices and quantities of outputs are jointly determined, Humphrey and Pulley (1997, p.80) neglect non-price exogenous demand determinants, stating that the solution to the monopolist's problem gives profit as a function of factor prices only, which is 'too sparse' a specification. This is clearly true only if demand is taken to be a function of price alone; we demonstrate this by considering two problems: the first, of a profit-maximising monopolist that sets a single price for each distinct output produced, the second of a profit maximising monopolist practising first-degree price-discrimination.

Substituting in $p(q, y, h)$, the monopolist's inverse demand functions, for p allows us to express the first maximisation problem simply:

$$\max_{q,x} \sum_i p_i(q_i, y_i) q_i - \sum_j w_j x_j \qquad (17)$$

$$s.t.\ f(q, x, z) = 1$$

where y is a vector of non-price demand determinants. The associated Lagrangian is

$$\max_{q,x} \mathcal{L} = \sum_i p_i(q_i, y_i) q_i - \sum_j w_j x_j \; + \lambda[f(q,x,z) - 1] \tag{18}$$

and the first-order conditions for maximisation are

$$\frac{\partial \mathcal{L}}{\partial q_i} = \frac{\partial p_i(q_i, y_i)}{\partial q_i} q_i + p_i(q_i, y_i) + \lambda \frac{\partial f(q,x,z)}{\partial q_i} = 0, \qquad \forall \; i \tag{19}$$

$$\frac{\partial \mathcal{L}}{\partial x_j} = -w_j + \lambda \frac{\partial f(q,x,z)}{\partial x_j} = 0, \qquad \forall \; i,j \tag{20}$$

$$\frac{\partial \mathcal{L}}{\partial \lambda} = f(q,x,z) - 1 = 0 \tag{21}$$

This solves for profit as a function of input prices, non-price demand determinants, and hedonic factors.

$$\pi = \pi(y,w,z) \tag{22}$$

Under first-degree price-discrimination we have not one price per output but many, thus we calculate revenue by summing the prices of all units of output. Since we assume a continuous demand function and therefore infinitesimal units of output, this is an infinite sum, i.e. a definite integral; it is again simplest at this point to substitute in the inverse demand function, which defines the reserve price of each unit of output. This gives revenue in the i^{th} product market as

$$r_i = \int_0^{q_i} p_i(t, y_i)dt \ = \int p_i(q_i, y_i)dq_i \tag{23}$$

which is simply the indefinite integral of the inverse demand function evaluated at q_i. We can therefore state the first-degree price-discriminating monopolist's profit maximisation problem

$$\max_{q,x} \sum_i \int p_i(q_i, y_i)dq_i - \sum_j w_j x_j \tag{24}$$

$$s.t.\ \ f(q, x, z) = 1$$

and its associated Lagrangian

$$\max_{q,x} \mathcal{L} = \sum_i \int p_i(q_i, y_i)dq_i - \sum_j w_j x_j \ + \lambda[f(q, x, z) - 1] \tag{25}$$

for which the first-order conditions for maximisation are

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$$\frac{\partial \mathcal{L}}{\partial q_i} = p_i(q_i, y_i) + \lambda \frac{\partial f(q, x, z)}{\partial q_i} = 0, \qquad \forall\ \ i \tag{26}$$

$$\frac{\partial \mathcal{L}}{\partial x_j} = -w_j + \lambda \frac{\partial f(q, x, z)}{\partial x_j} = 0, \qquad \forall\ \ i, j \tag{27}$$

$$\frac{\partial \mathcal{L}}{\partial \lambda} = f(q, x, z) - 1 = 0 \tag{28}$$

Note that while (27) and (28) are identical to (20) and (21) and this problem also solves for profits as a function of factor prices and non-price demand determinants, (19) and (26) differ, so the profit function is not the same as in (22).

$$\pi = \varpi(y, w, z) \tag{29}$$

Monopoly profit maximisation problems in general therefore generate profits as a function of non-price demand determinants, factor prices, and hedonic variables; we may refer to this as the Monopoly Profit Function (MPF) in contrast to the SPF and APF.

Given that the industries we are studying consist of localised monopoly firms, an argument could be made for estimating an MPF; however they are also regulated not only on prices, but also on outputs: water and sewage companies may not disconnect domestic and mixed-purpose properties for non-payment of bills and are subject to regulation on various quality indicators concerning customer service, the quality of drinking water and bathing waters, and other areas. Likewise, electricity and gas distribution networks are subject to regulation of output and service quality measures, and train operating companies are highly restrained with respect to train provision, service quality and safety.

We therefore regard the APF framework of imperfect competition and fixed outputs as being the most appropriate for the present study. This is, however, subject to some important changes in the variables included in the price possibility frontier, which as shown in (10) typically includes output quantities, factor prices and hedonic variables. The appeal of this assumption is that it yields an ARF containing exactly the same variables as the SCF, excepting revenue-specific and cost-specific hedonic variables, simplifying data requirements. The tendency of the resulting ARF to perform well empirically is probably attributable to the tendency for revenue, even in imperfectly competitive markets, to be a reasonable proxy for costs: Lannier and Porcher (2014) even go so far as to make this argument to justify using revenues explicitly for this purpose in their study of the cost efficiency of French water utilities, given the lack of comparable data on costs.

Following from the above discussion, we include a vector of non-price demand determinants, since we would expect firms to have a good working knowledge of the factors affecting demand and their approximate effect on reserve prices—even if the demand function is not *known* as is assumed in the MPF approach—and to be able to observe these factors with relative accuracy. Output quantities, being exogenous, will of course be retained, as will hedonic variables. We see no compelling argument, however, for the inclusion of factor prices in the price possibility frontier, and therefore these are dropped. The resulting profit maximisation problem is therefore

$$\max_{p,x} \sum_i p_i q_i - \sum_j w_j x_j \tag{30}$$

$$s.t.\ \ g(p,q,y) = 1, f(q,x,z) = 1$$

which, assuming output quantities to be fixed as in the usual APF problem, splits into separate revenue maximisation and cost minimisation problems. The cost minimisation is as seen in (13), and yields an SCF as in (14). On the revenue side, however, we have the problem

$$\max_{p,x} \sum_i p_i q_i \tag{31}$$

$$s.t.\ \ g(p,q,y) = 1$$

which is distinct from the revenue maximisation problem in (12) because it yields revenue as a function of output quantities and non-price demand factors.

$$r = r(q,y) \tag{32}$$

This problem can therefore be seen as a hybrid of the APF and MPF, retaining the practical and theoretical advantages of the former approach whilst having a much less ad hoc revenue specification. Another useful feature of this approach is that in the monopoly case, the average of the estimated revenue function, or in the first-order profit-maximising monopoly case its partial derivative with respect to outputs, can be interpreted as the inverse industry demand function. Clearly, this is interesting in itself as a method that sidesteps the usual problems associated with demand estimation in general, and the problem of nonlinear pricing and the presence of diverse and complex tariff designs in the particular context of the industries we study here.

To summarise, for a monopolist with fixed output facing an inverse demand function $g(p, q, y)$, a production technology described by $f(q, x, z) = 1$, and a set of factor prices, overall performance can be assessed by analysing profit efficiency, which is given by

$$u_\pi = \frac{r(q, y)u_r - c(q, w, z)u_c}{\pi(q, y, w, z)} \tag{33}$$

Where $\pi(q, y, w, z) = r(q, y) - c(q, w, z)$ is the frontier level of profit, q is a vector of outputs, w is a vector of input prices, y is a vector of non-price demand determinants, and z is a vector of hedonic factors affecting costs. However, for a number of reasons—see Restrepo-Tobón and Kumbhakar (2014) and the discussion around (16), it is preferable to analyse revenue efficiency and cost inefficiency separately via the equations

$$r = r(q, y)u_r \tag{34}$$

And

$$c = c(q, w, z)u_c \tag{35}$$

Where u_r is revenue efficiency, the ratio of the actual to potential maximum revenue, and u_c is cost inefficiency, the ratio of actual to potential minimum cost. As explained in this section, this is a more appropriate approach than the estimation of standard revenue or profit functions, given the monopoly nature of the regulated firms analysed in this thesis. This is therefore the theoretical framework adopted in subsequent empirical chapters, in which we estimate revenue and cost frontiers in order to analyse the effects of regulatory and other factors on revenue and cost efficiency, and trends in revenue and cost inefficiency over time.

To recap, two particular assumptions underlie the derivation of (34) and (35). First, we assume that the firm is a monopolist, so that rather than an exogenously given price, the firm faces an inverse demand function. Given that the firms analysed in this thesis have monopolies over their service areas, we argue that this assumption is justified in that monopoly revenue and profit represent benchmarks the firms could theoretically attain in the absence of inefficiency. Note however that the notion of a frontier function means that departure from this ideal is implied. In this framework, departures from monopoly revenue, e.g. due to regulatory constraints or competition, are captured as revenue inefficiency, just as departures from cost minimisation are captured as cost inefficiency when estimating (38).

Second, we assume that the firm's output is exogenous. This assumption is standard in the literature on the alternative revenue and profit functions. We note that violation of this assumption is potentially more serious, since if it is relaxed, we arrive that the MPF shown in (29). However, we argue that the assumption of exogenous outputs is appropriate in the context of the water and sewage companies and electricity distribution networks since they have prescribed geographical supply areas outside of which they are unable to expand, and since they cannot refuse to connect customers within their supply areas. Nor are they allowed, in the water and sewage industry, to disconnect customers for non-payment of bills. For these reasons, we may see key outputs as being beyond the direct control of the firm.

Returning to (33), we can see that the welfare implications of a change in u_π are ambiguous, given that it can be brought about by changes in u_r or u_c or by shifts in the revenue or cost frontiers, or by some combination of these. This provides yet another rational for analysing u_r and u_c separately. Even so, there may still be some ambiguity with respect to the welfare implications of changes in u_r and u_c. Given that, in this framework, u_r is the ratio of actual revenue to potential monopoly revenue, a decrease in u_r implies a reduction in market power, and a transfer from the firm to the consumer. Unless the utility is able to practice first-degree price discrimination, this will also entail a reduction in deadweight loss. A reduction in revenue efficiency in this context will therefore be seen as undesirable from the firm's point of view, but an improvement from a social welfare perspective.

A change in u_c is less straightforward from a welfare perspective. Recalling the discussion in section 2.4, if we follow Leibenstein in viewing cost inefficiency as non-allocative welfare loss, a reduction in u_c implies an increase in social welfare. However if, following Stigler, we view cost inefficiency as resulting from transfers within the firm, improvements in cost efficiency simply reflect a redistribution from principal to agent.

2.7. Summary

In this chapter, we have introduced the theoretical framework upon which the subsequent empirical chapters are based. Specifically, we describe the profit maximisation problem of a monopolist, and derive new monopoly profit and revenue frontiers, which have a firmer grounding in theory than the 'alternative' profit and revenue frontier specifications often employed in the literature. We show that, in the context of fixed outputs, the monopolists' profit maximisation problem splits into separate problems of revenue maximisation and cost minimisation. The empirical component of this thesis therefore analyses the overall performance of the regulated water and sewage and electricity distribution industries via the estimation of the alternative monopoly revenue function shown in (34) and (35). The assumptions underlying this approach, and the consequences if these are violated, are discussed, along with the welfare implications of changes in profit efficiency and its components.

This chapter has also covered much of the theory relating to the performance of utilities under regulation. We began with some basic definitions of firm-level efficiency concepts, before discussing the problems that can arise in utility industries characterised by natural monopoly, from abuse of market power to failure to profit maximise, and the rationale for some form of regulation to alleviate these problems. We then discussed some of the theoretical literature relating to economic regulation, such as various forms of incentive regulation and their effect on firm efficiency. We paid particular attention to RPI-X regulation as practised in UK utility regulation, given its relevance for our study, looking at issues of regulatory lag and optimal X factors, and comparing its incentives to those of other forms of regulation. We conclude that RPI-X is a high-powered form of incentive regulation that encourages improvements in productivity and resulting reductions in cost.

A recurring theme in this chapter is the problem of information asymmetry. In implementing any form of incentive regulation, the regulator must have some information on firms' costs. In order to minimise informational asymmetry on the firms' costs and future potential for efficiency gains, many regulators utilise some form of benchmarking analysis which compares the performance of a regulated firm to its peers, thereby also exposing the firms to a form of yardstick competition (Shleifer 1985). Chapter 3 reviews some of the main methods used in analyses of efficiency and productivity, and describes the method employed in our empirical analyses.

3. Frontier Analysis Methods

3.1. Introduction

This chapter discusses the literature on econometric methods for modelling inefficiency, looking in detail at the features of the commonly used methods, and how these have developed over the years. We evaluate the advantages and disadvantages of some of the specifications appropriate to our study, and set out the methods used in our empirical chapters. We also discuss the formulae used to obtain point estimates of inefficiency and to generate estimated marginal effects from the models.

Conventional production economics usually features firms that maximise profits efficiently, subject to the production technology they face and the input and output prices that prevail. Under this assumption, the parameters of production, revenue, cost, and profit functions may be estimated by ordinary least squares (OLS). As discussed in the preceding chapters, however, this assumption may in many cases be inappropriate, and firms may fail to achieve full efficiency in practice. In this case, the assumptions of OLS are no longer appropriate, given the presence of one-sided disturbances relating to inefficiency effects in the residual. This motivates the use of alternative econometric and mathematical programming approaches, which are described in this chapter.

As described in Chapter 2, early definitions of economic efficiency concepts came from Koopmans (1951), who provided a definition of technical efficiency, and Debreu (1951) who first suggested an index for the measurement of technical efficiency, which he called 'the coefficient of resource utilisation'. The first attempt at the measurement of efficiency empirically came from Farrell (1957), who applied linear programming techniques to estimate state-level technical efficiency—though strictly speaking, since Farrell used revenue instead of output, he was actually estimating revenue efficiency—in US agriculture, and also proposed a basic method of decomposing cost inefficiency into its technical and allocative components.

Farrell's method was developed further and also inspired some interesting applications; for example Farrell and Fieldhouse (1962) and Seitz (1970, 1971) develop these methods further and apply them to data on British farms and steam electricity generating plants in the US respectively, but his paper's main importance lies in the influence it had on the two broad strands of literature that followed it: data envelopment analysis and stochastic frontier analysis.

3.2. Data Envelopment Analysis

3.2.1. Background

Data envelopment analysis (DEA) is a frontier method of efficiency measurement pioneered by Charnes et al. (1978). DEA in its most basic form, i.e. the method outlined in the original paper, is a non-parametric, linear programming method, similar in this respect to the method of Farrell (1957). DEA calculates an efficiency score for a given firm or decision making unit (DMU), by solving for the DMU under study—denoted DMU_0—the following problem

$$\min \theta \tag{36}$$

$$s.t.\ \sum_i \lambda_i X_i \leq \theta X_0$$

$$\sum_i \lambda_i Y_i \geq Y_0$$

where X_0 is a vector of inputs used by DMU_0 to produce the vector Y_0 of outputs, X_i and Y_i are the same for DMU_i, λ_i is the weight given to DMU_i in its effort to dominate DMU_0, and θ is the efficiency of DMU_0; note that DMU_0 itself should be included in the constraint, and that θ cannot exceed one. This formulation is known as the envelopment form; another formulation, known as the multiplier form, frames the problem as maximising the efficiency of DMU_0, which is a ratio of weighted outputs to weighted inputs, subject to the constraint that for every DMU this ratio is less than or equal to one; both of these formulations lead to equivalent results.

The method above essentially fits a piecewise-linear frontier to the data, with each point on the frontier representing either one of the most efficient DMUs in the sample or a 'virtual' DMU which is a composite of two or more of these against which the efficiency of each DMU can be calculated, with a θ of less than one indicating that some linear combination of other DMUs in the sample could produce the same output vector using no more of any input and less of at least one input than DMU_0. An early application of this model was that of Charnes et al. (1981) to public education programmes in the US.

The basic DEA model assumes constant returns to scale; an early adaptation in the literature was the introduction of a variable returns to scale DEA model by Banker et al. (1984); a review by Seiford (1996) discusses some of the other key developments in the early literature. These include the introduction of multiplicative models which fit a piecewise *log*-linear frontier to the data (Charnes et al. 1982, 1983), the establishment of a link between DEA and production theory via the analysis of Pareto efficient production functions through new DEA methods by Charnes et al. (1985), and the ability to incorporate non-discretionary—i.e. exogenously fixed—inputs and outputs and categorical variables (Banker and Morey 1986). Aside from technical efficiency, which is not the focus of our study, DEA can be adapted to analyse cost efficiency, revenue efficiency, profit efficiency and other efficiency concepts.

3.2.2. Modelling Inefficiency

Given our interest in analysing the determinants of inefficiency, of particular interest in the DEA literature are studies which seek to model inefficiency in terms of a set of explanatory variables. Probably the most common way of doing this is in the DEA literature is to first calculate efficiency—technical, cost, or other—for each observation using conventional DEA models, and then in a second stage to perform regression analysis of these efficiency scores against a set of variables thought to influence efficiency. The method used in the second stage varies from study to study; OLS is an option used in several applications, e.g. studies of independent banks by Aly et al. (1990), of public schools in Conneticut by Ray (1991), of Floridian hospitals by Chirikos and Sears (1994), of bank relationship managers by Stanton (2002), of Taiwanese hospitals by Chang et al. (2004), of public accounting firms by Chang et al. (2008), of Korean banks by Sufian and Habibullah (2009), of US insurance firms by Cummins et al. (2010), of Turkish secondary education at regional level by Davutyan et al. (2010), and others. This is despite the fact that DEA efficiency scores are limited to the interval $(0,1]$, and therefore a drawback of OLS in this instance is that it can lead to predicted values that are outside this interval. For this reason, most studies opt for a form of censored regression, commonly a two-limit tobit model —with one limit at zero and the other at one—in order to avoid this problem, e.g. a DEA study of Swedish day care centre by Bjurek et al. (1992), Oum and Yu (1994) in an industry level study of the efficiency of European railways, a study of the efficiency of 36 individual physicians from a single teaching hospital by Chilingerian (1995), Fethey et al. (2000) in an application to 17 European airlines from 1991-1995, an application to New York school districts by Ruggiero and Vitaliano (1999), Latruffe et al. (2004) in a DEA panel study of the technical efficiency of Polish farms, Bravo-Ureta et al. (2007) in a meta-regression analysis of scores from 167 DEA studies of farm-level technical efficiency, a study of the efficiency of Australian hospital food services by Assaf and Matawie (2009), and a study of haemodialysis facilities by Kontodimopoulos et al. (2011) among others.

However, Hoff (2007) points out that the two-limit tobit model is a misspecification given that the 'pile-up' of DEA efficiency scores occurs at only one of the two censoring points—i.e. at one, where the efficient firms in the sample lie, in contrast to zero, where no firm in the sample can possibly lie—and using Danish fishery data finds that OLS performs at least as well as the two-limit tobit method, as well as two other more well-specified non-linear methods. Similarly, McDonald (2009) argues that the two-limit tobit is a misspecification since DEA efficiency scores do not come from a censoring data generating process in any case and are instead simply fractional data, and that while that method is inappropriate, OLS is a consistent estimator and performs nearly as well as more complex methods. Simar and Wilson (2011), however, criticise the use of OLS and various other regression techniques in two-stage DEA as failing to provide valid inference, since the second stage regression uses only the DEA *estimates* of DMU efficiencies rather than the true values of these efficiencies, and failing to account for the highly complex serial correlations between inefficiency estimates—which arises from the fact that changing the observations that lie on the efficient frontier will in turn affect the estimated efficiencies in observations below the frontier, since they are measured relative to the frontier—and also criticises many applications in the literature as having chosen their second stage method on an ad hoc basis without reference to a well-defined statistical model. As an alternative to the two-stage DEA methods discussed above, exogenous variables may be included in a one-stage DEA analysis which allows for the inclusion of non-discretionary variables, such as in the Banker and Morey (1986) model, although this has the rather major limitations that the efficient observations are the same as those obtained in which all inputs are controllable by the DMU, and that the researcher must know in advance whether the effect of these environmental variables on efficiency is positive or negative when formulating the model (Cordero et al. 2009).

3.2.3. Advantages and Disadvantages

An advantage of DEA against the various parametric methods available is that there is no need to make any assumption on a functional form for the frontier before carrying out the analysis. It is, however, possible with parametric methods to select functional forms with a large degree of flexibility, which reduces the edge of DEA methods in this regard. DEA is also able to handle production frontiers with multiple outputs, though as we are concerned with the estimation of cost and revenue frontiers—which can only have one dependent variable—this is not of direct relevance to our study. One rather interesting advantage of DEA in cost studies is the ability to decompose estimated cost inefficiency into its technical and allocative components, which is problematic in parametric cost frontier studies, as discussed further on.

The main drawback of most DEA methods, however, is that they are mostly non-stochastic. This means that they do not distinguish between inefficiency effects and random variation due to, for example, measurement error, and that standard deviations for hypothesis testing cannot be obtained; there is also no way of testing for preferred specification in conventional DEA. It should be mentioned, however, that statistical inference and sensitivity analysis of results obtained in DEA is possible by the use of bootstrapping methods, and that a family of stochastic DEA models have been developed in order to cope with the presence of noise in the sample (Simar and Wilson 1998, 2000, Simar 2007, Simar and Zelenyuk 2011), but that the usefulness of these stochastic DEA models is limited to cases where the amount of noise present is small. In addition, DEA fits the frontier so that it contains the most efficient firms in the sample whereas in reality even the most efficient firms may be some way from the frontier; thus as Cook et al. (2014) state, with DEA we fit a 'best practice' frontier rather which may be quite different from the 'true' frontier:

... whatever form the production frontier takes, it is beyond the best practice frontier ... if one adds an additional DMU to an existing set, that DMU will either be inefficient or efficient. In the former case, the best practice frontier does not shift, and nothing new is learned about the production frontier. In the latter situation, the frontier may shift closer to the actual (but unknown) production frontier. (Cooke et al. 2014, p.3)

which is a major disadvantage if we are interested in obtaining a good approximation of the true frontier and the true magnitude of inefficiency in the sample and for specific observations. Having a large number of inputs and outputs relative to the size of the sample will also tend to lead to the model judging a large proportion of observations to be on the frontier, and thus fully efficient, unless some restrictions are placed on the weightings in the model, and this effect is exacerbated in the variable returns to scale case.

We now turn to discuss Stochastic Frontier Analysis (SFA), another approach to frontier modelling and efficiency estimation. Since there are many advantages and disadvantages to both DEA and SFA based approaches, i.e. in the jargon of DEA one does not dominate the other, the key consideration in choosing between these methods should be the specific requirements and objectives of the application at hand, i.e. each advantage and disadvantage should be weighted appropriately in evaluating the two. In our case the key features we want in our specification include the ability to make statistical inferences, the ability to incorporate exogenous environmental variables as factors influencing inefficiency and assess their impact on inefficiency at the margin, the ability to estimate a reasonable approximation of the true frontier—rather than the best practice frontier—and generate estimates of inefficiency relative to this frontier. We consider that in some of these regards there are still limitations to DEA based methods, and that while DEA models exist that incorporate many of the desirable features, there are options within the SFA literature that are more appropriate to our current needs, as can be seen in the following discussion.

3.3. Stochastic Frontier Analysis

3.3.1. Background

SFA is an approach to frontier estimation that involves the specification of a linear, parametric frontier model with a composite disturbance term, $\varepsilon = v + su$. The first component, $v \sim N(0, \sigma_v^2)$, is a normally distributed error term with zero mean and constant variance intended to capture random noise and measurement error, while the second component, u, is a random variable drawn from a one-sided distribution which is intended to capture inefficiency effects. This inefficiency term must be one sided, since in the context of a production or revenue frontier inefficiency will always result in a decrease in the dependent variable—i.e. output or revenue—and in the context of a cost frontier, inefficiency will always result in an increase in the dependent variable, costs; a firm cannot be more than 100% efficient. The only difference between a production or revenue specification and a cost frontier specification is thus a sign change; the parameter s, which takes on a value of -1 in the production or revenue case and a value of 1 in the cost case, simply enables us to discuss SFA models in general without having to write out all the related formulae twice.

Some early forerunners of SFA can be found in a general class of models, again inspired by the original work of Farrell (1957) on measuring technical efficiency, which are parametric like SFA, but also non-stochastic like basic DEA models, and thus often referred to in retrospect as deterministic frontier analysis (DFA) models. Among these early DFA models is that of Aigner and Chu (1968) who propose the problem

$$\min \sum_i [y_i - f(x_i, \beta)] \tag{37}$$

$$s.t.\ y_i \leq f(x_i, \beta)$$

or alternatively

$$\min \sum_i [y_i - f(x_i, \beta)]^2 \tag{38}$$

$$s.t.\ y_i \leq f(x_i, \beta)$$

where y_i is the output of firm i and $f(x_i, \beta)$ is the firm's production function in terms of its vector of inputs x_i and a vector of unknown parameters to be estimated, β. If we assume that $f(x_i, \beta)$ is linear in β—as is the case in most empirical production frontiers—this means that (37) is a linear programming problem and (38) is a quadratic programming problem. Schmidt (1976) gives these techniques a statistical basis by deriving the log-likelihood functions of two deterministic production frontiers: one in which the disturbances are assumed to follow an exponential distribution, and another in which they are assumed to follow a half-normal distribution, and then showing that these likelihood functions, respectively, are maximised by solving the problems (37) and (38) proposed by Aigner and Chu (1968), although Schmidt (1976) points out that the properties of these estimators are uncertain as the regularity conditions for maximum likelihood (ML) estimation are violated in both cases. Note that although these authors refer exclusively to the production frontier case, analogous DFA cost frontiers could be derived by changing the constraints in (37) and (38) to $y_i \geq f(x_i, \beta)$. Thus Schmidt (1976) introduced the idea that random variables drawn from a one-sided distribution could be used to capture inefficiency effects in a frontier function; DFA can thus be seen as merely a special case of SFA model in which the random noise term is absent and for this reason, as well as the other identified drawbacks of DFA, we do not consider these methods further.

3.3.2. Cross-Section Specifications

The basic SFA model, which introduced the stochastic element to parametric frontier models, was introduced almost simultaneously in two separate papers by Aigner et al.

(1977) and Meeusen and van Den Broeck (1977), and specified a cross-section stochastic frontier function with a composite disturbance term

$$y_i = f(x_i, \beta) + v_i + su_i \tag{39}$$

where y_i is the output—or revenue, or cost, etc.—and $f(x_i, \beta)$ is the production—or revenue, or cost—frontier function of firm i, v_i is the random noise term, and $u_i \sim |N(0, \sigma^2)|$ is a one-sided disturbance capturing inefficiency, which in the Aigner et al. (1977) case is drawn from a half-normal distribution. The model assumes that v_i and u_i are distributed independently of one another and of the regressors in the frontier, which means that the joint density function of the composite disturbance is simply the product of the density functions of v_i and u_i, which gives

$$f(v_i, u_i) = \frac{1}{\pi\sigma_v\sigma_u} \exp\left(-\frac{v_i^2}{2\sigma_v^2} - \frac{u_i^2}{2\sigma_u^2}\right) \tag{40}$$

and from here, bearing in mind that $\varepsilon = v + su$ the density function of the composite error is derived by integrating u_i out of (40), which gives

$$f(\varepsilon_i) = \frac{2}{\sqrt{2\pi}\sigma}\left[1 - \Phi\left(-s\frac{\varepsilon_i\lambda}{\sigma}\right)\right] \exp\left(-\frac{\varepsilon_i^2}{2\sigma^2}\right) \tag{41}$$

in which $\sigma^2 = \sigma_v^2 + \sigma_u^2$, thus σ is the square root of this, Φ is the standard normal cumulative distribution function, and $\lambda = \sigma_u/\sigma_v$. This latter term is often referred to as the 'signal-to-noise' ratio, since it gives an indication of magnitude of the one-sided inefficiency term to that of the symmetric noise term, making this a useful reparameterisation which is commonly adopted in the literature. An alternative parameterisation is that introduced by Battese and Corra (1977) in which $\gamma = \sigma_u^2/\sigma^2$—and $\sigma^2 = \sigma_v^2 + \sigma_u^2$ as before—which is less common but arguably more useful in terms of estimation and interpretation since it has a finite range, falling necessarily between zero. When $\gamma = 0$, the model collapses to an OLS function without inefficiency, and $\gamma = 1$ indicates a deterministic frontier without noise; we adopt the Battese and Corra (1977) notation from this point onwards. The log-likelihood function in the normal-half normal case with a cross-section of I firms is therefore

$$\ln \mathcal{L} = -\frac{I}{2}(\ln \sigma^2 + \ln 2\pi) - \frac{1}{2\sigma^2}\sum_i \varepsilon_i^2 + \sum_i \ln \Phi\left(s\frac{\varepsilon_i}{\sigma}\sqrt{\frac{\gamma}{1-\gamma}}\right) \tag{42}$$

which may be maximised by ML methods in order to obtain estimates of σ, γ, and the parameters of the frontier; methods of obtaining point estimates of inefficiency from this and similar models are discussed further on. Since the introduction of this basic SFA model, the literature has expanded to include many different specifications, which are discussed below.

Some early adaptations of the basic SFA model introduced specifications with alternative distributional assumptions about the inefficiency term and thus the composite error. Aside from the normal-half normal case, other viable one-sided distributional assumptions are the normal-exponential, which was used by Meeusen and van Den Broeck (1977) and also suggested in Aigner et al. (1968), the normal-truncated normal as proposed by Stevenson (1980), and the normal-gamma model as proposed by both Stevenson (1980) and Greene (1980a, 1980b). All of these distributional assumptions are reasonable, although it should be noted that the half normal distribution is simply a special case of the truncated normal distribution in which the point of truncation is at the mean, which in turn means that the normal-half normal model is simply a restricted case of the more general normal-truncated normal model. For reference further below, we note that the density function of a truncated normal one-sided disturbance $u_i \sim N^+(\mu, \sigma_u)$ in the Stevenson (1980) cross-function SFA model is

$$f(u_i) = \frac{1}{\sqrt{2\pi}\sigma_u \Phi(\mu/\sigma_u)} \exp\left(-\frac{(u_i - \mu)^2}{2\sigma_u^2}\right) \tag{43}$$

where the mean, μ, is a parameter to be estimated. Following the same method outlined above, the log-likelihood is derived

$$\ln \mathcal{L} = -\frac{I}{2}(\ln \sigma^2 + \ln 2\pi) - \frac{1}{2\sigma^2}\sum_i (\varepsilon_i - s\mu)^2 \tag{44}$$

$$+ \sum_i \ln \Phi \left[\frac{s}{\sigma}\left(\varepsilon_i \sqrt{\frac{\gamma}{1-\gamma}} + \mu \sqrt{\frac{1-\gamma}{\gamma}}\right)\right] - I \ln \Phi \left(-\frac{s\mu}{\sqrt{\gamma\sigma^2}}\right)$$

Similarly, since the exponential distribution is a special case of the gamma distribution in which the shape parameter $a = 1$, the normal-exponential model is a restricted version of the normal-gamma model in the same way. Further generalisations have been introduced, such as the normal-doubly truncated normal model proposed by Almanidis et al. (2014), which places an upper bound on inefficiency, and also allows for ‘wrong’ skewness (Almanidis and Sickles 2012), i.e. positively (negatively) skewed residuals in a production (cost) frontier model; this model involves a three parameter inefficiency distribution: a shape parameter, a scale parameter, and a truncation point.

These more general models therefore offer greater flexibility at the expense of increasing the number of parameters to be estimated. However, alternative efficiency distributions have recently been proposed that overcome this trade-off: a model with a Rayleigh inefficiency distribution was proposed by Hajargasht (2015), which has a relatively flexible one-parameter efficiency distribution which allows for a non-zero mode; likewise, a normal-Weibull model developed by Tsionas (2007) has a two parameter inefficiency distribution which can accommodate wrong skew.

While the early normal-half normal, normal-truncated normal, and exponential models were formulated and operationalised by the aforementioned authors, the normal-gamma model is less straightforward due to the complexity of the log-likelihood function. Early attempts were made by Beckers and Hammond (1987) and Greene (1990), the latter of which does include an application to US electricity data used earlier by Christensen and Greene (1976). Eventually Greene (2003) found a solution to these problems via maximum simulated likelihood estimation; this has since become the accepted method of estimation for the normal-gamma stochastic frontier model.

The choice of efficiency distribution clearly affects the estimates of inefficiency and the model as a whole, since the shape of the truncated normal and gamma distributions are quite different, but there is no clear a priori justification for choosing one distribution over the other—in principle, we would rather not impose any particular distribution at all—so the choice is usually driven by the various other characteristics of the models and their suitability to the application at hand.

Kumbhakar and Lovell (2000) address the question of the sensitivity of estimated efficiencies to changes in distributional assumptions about the one-sided disturbance and note the study by Greene (1990), which aside from that paper's early normal-gamma model, estimates the normal-half normal, normal-truncated normal, and normal-exponential models using the same data, finding very similar sample mean efficiencies in each case; the authors calculate rank correlations between the reported efficiency estimates from that study which range from 0.7467 to 0.9803, and suggest that the choice of distributional assumption may not have a particularly dramatic effect. Likewise, Cummins and Zi (1998), who use data on US life insurance firms to compare a range of frontier methods, including not only different SFA models under each of the distributional assumptions discussed but also 'distribution free' models—discussed below—and non-parametric DEA and free disposal hull (FDH) methods, find that while there are large differences between the mean efficiencies produced by the different classes of models—SFA methods on one hand and DEA and FDH methods on the other—there are smaller, though still significant, differences in the mean efficiencies between different specifications within the same class of models; i.e. the SFA models produce somewhat more similar mean efficiencies—with the exception of the distribution free models in which mean efficiencies are notably lower—as do the DEA and FDH models.

While the different distributional assumptions made under SFA do seem to have a significant effect on mean of the estimated efficiencies, their ranks are however strongly correlated, with the rank correlations of the efficiencies estimated by the various SFA models ranging from 0.96 to 0.99. A more recent study by Greene (2008), which uses the same electricity data as in his earlier studies but adopts a more flexible translog functional form, finds that mean inefficiencies are nearly identical regardless of distribution, ranging from 0.9240 to 0.9368, and that the efficiency rankings from the various models are also very strongly correlated, with rank correlations ranging from 0.9554 to 0.9999. Finally, Yane and Berg (2013) study the sensitivity of efficiency rankings to distributional assumptions using data on Japanese water utilities; the authors estimate not only homoskedastic SFA models such as those we have already discussed, but also doubly heteroskedastic SFA models, which are addressed further below, to see if this affects the models' sensitivity. They conclude that efficiency rankings are quite consistent regardless of distributional assumption in the case of the homoskedastic models, and also in the case of the doubly heteroskedastic models, except when they are extended to include a conditional mean model, another feature which is discussed further below. All of this suggests that while distributional assumptions will affect estimates obtained in SFA, results are usually quite consistent regardless of the choice made. We therefore place a greater emphasis on the various other important features when choosing our model.

3.3.3. Panel Data Specifications

The SFA models so far discussed are all appropriate to cross-section data. As in econometrics generally however, there are real advantages to using panel data, in which multiple cross-sections in time are pooled into a single model, in SFA. All of the usual benefits of panel data, in terms of more information and a higher number of degrees of freedom in the sample, apply; in addition to this, however, there are a number of benefits particular to SFA that come from the use of panel data models. One class of models enables the modelling of inefficiency along with the frontier function in a single step, and given the direct relevance of this capability to our study, these are discussed in greater detail below; in this section we restrict our attention to panel data models without this feature.

Panel data SFA models in general can be grouped into two broad categories: those in which inefficiency is assumed to be time-invariant, i.e. the efficiency of a given firm is assumed to remain constant over the sample period, and those in which the efficiency of each firm is allowed to vary over time, which we refer to as time-varying; there are of course many different specifications in each category, each with their own unique features, and as usual the appropriateness of particular specifications will depend on the focus of the application and the features of the data, but in general we may say that the assumption of time-invariant inefficiency is a restrictive one and harder to justify the longer the sample period, and therefore models that allow time-varying inefficiency are generally preferable.

3.3.3.1. Time-Invariant Inefficiency Models

Kumbhakar and Lovell (2000, pp.95-102) note how generic panel data methods may be adapted to study frontier models. For example, a simple fixed-effects regression may be estimated via OLS, either by means of including dummy variables or by applying a 'within' transformation to the data, in which all variables are transformed to deviations from their mean value for each firm; these methods both give equivalent results. In the case of the dummy variable method, if a binary dummy is added for each firm—and the intercept dropped in order to avoid the 'dummy variable trap' of perfect multicollinearity—differences in the parameter estimates relating to the various firms may be attributed to varying levels of efficiency; note that since these parameters are time-invariant, so are the estimated levels of efficiency. Where the dummy variable parameter estimate for firm i is denoted $\hat{\delta}_i$, the one-sided disturbance for firm j is given by

$$\hat{u}_j = \max_i \hat{\delta}_i - \hat{\delta}_j \tag{45}$$

in the case of a production or revenue frontier, or by

$$\hat{u}_j = \hat{\delta}_j - \min_i \hat{\delta}_i \tag{46}$$

in the case of a cost frontier. Note that this implies that at least—and almost certainly only—one firm lies on the frontier, i.e. is fully efficient. It is notable that this method does not require the assumption that the one-sided disturbance is uncorrelated with the other variables in the frontier. It is difficult to justify, however, the assumption that the differences in the fixed effects are due purely to inefficiency, since in principle they could be picking up any number of firm-specific effects not already captured by the model. Moreover, this means that the model cannot accommodate any other time-invariant variables.

It is also possible to adapt a simple random-effects model to estimate a frontier, in which case the random effects are interpreted as inefficiency effects. This method is somewhat similar to the standard SFA approach in that the inefficiency term is a random variable that is assumed to be uncorrelated with the noise term and the regressors in the frontier—note that this means that the model can include time-invariant variables, in contrast to the fixed-effects approach—but dissimilar in that no prior distributional assumption is made about the random effect a_i, which means that they can take on both positive and negative values. Instead, the random-effects model may be estimated using Generalised Least Squares (GLS) methods as normal, and is again adjusted to a frontier after estimation, in which the one-sided disturbance is calculated thus for the case of a production or revenue frontier

$$\hat{u}_j = \max_i \hat{a}_i - \hat{a}_j \tag{47}$$

or in the case of a cost frontier by

$$\hat{u}_j = \hat{a}_j - \min_i \hat{a}_i \qquad (48)$$

where $\hat{a}_i$ is the estimated random effect corresponding to firm i. Note that, as in the fixed effects model, the random effect could in principle be picking up not only inefficiency but any other time-invariant effects associated with firm i that are not accounted for in the model.

The first panel data method developed explicitly for SFA, in which the usual distributional assumptions are made about the one-sided error—was that proposed by Pitt and Lee (1981), in which the assumption made about the one-sided disturbance was the same as that in the Aigner et al. (1977) specification, i.e.

$$f(u_i) = \frac{2}{\sqrt{2\pi}\sigma_u} \exp\left(-\frac{u_i^2}{2\sigma_u^2}\right) \qquad (49)$$

so that it is drawn from a half normal distribution, and—note the lack of a t subscript—time-invariant. Using the same method described for the Aigner et al. (1977) cross-section specification in order to derive the log-likelihood function—a full derivation is shown in the appendices to Pitt and Lee (1981)—which may again be maximised via ML methods.

The above model is simply a normal-half normal SFA model adapted to handle panel data under the assumption that inefficiency is time-invariant, and as with the cross-section models, the model's distributional assumptions may be changed. Thus Battese and Coelli (1988) generalise the Pitt and Lee (1981) specification so that the one-sided disturbance follows a truncated normal distribution, which thus makes the model a panel data extension of the Stevenson (1980) normal-truncated normal model with time-invariant inefficiency.

A somewhat unusual approach to SFA is the 'distribution free' method proposed by Berger (1993), who avoids making any a priori assumption on the distribution of the one-sided error, instead exploiting the panel nature of his dataset in assuming that for any given firm—his paper uses OLS on cost data on US banks from 1980 to 1989—errors due to noise will average out over time, while the inefficiency component persists. Looking at the resulting efficiency estimates, Berger (1993) suggests that some of the common distributional assumptions adopted in SFA may not be appropriate—for his data, at least—though this method does have the disadvantages of picking up non-inefficiency effects as inefficiency and also in assuming that inefficiency is time-invariant—which is in fact especially hard to justify with a panel covering nine years—in common with the other models discussed in this section.

3.3.3.2. Time-Varying Efficiency Models

Given that we ideally would like to avoid making the particularly restrictive assumption that inefficiency remains fixed over time, we proceed now to discuss some of the options for SFA modelling in which inefficiency is allowed to change over time. There are, again, many different methods by which this may be achieved; Kumbhakar and Lovell (2000, pp.108-110) again note that fixed-effects and random-effects models may be adapted to this purpose. Cornwell et al. (1990) propose a model in which the single firm-specific effects—as seen in the time-invariant case—are replaced with intercepts which are firm-specific, but also a quadratic function of time

$$\delta_{it} = \theta_{i1} + \theta_{i2}t + \theta_{i3}t^2 \qquad (50)$$

which results in $3I$ such parameters where I is the number of firms in the sample. This may then be estimated by OLS or by GLS depending on the assumptions made about these effects—i.e. fixed-effects or random-effects, respectively—and the model is then converted into a frontier by the same method outlined in the previous section, in which there is always at least one observation on the frontier. The advantage of this model is that it allows the estimation of firm-specific inefficiencies which change over time in a way specific to each firm, though it has the obvious drawbacks of requiring a large number of parameters to be estimated, and of being rather ad-hoc in its specification.

The majority of time-varying inefficiency SFA models are extensions of the cross-section and time-invariant ML methods, in which various distributional assumptions are made about the one-sided disturbance. The basic model is simply (39) in a panel setting, thus

$$y_{it} = f(x_{it}, \beta) + v_{it} + su_{it} \qquad (51)$$

and the variations concern how to model u_{it}. One class of models specify u_{it} as the product of a disturbance u_{it}^* and some function of time $h(t)$, known as the scaling function—the scaling function can also be formulated as a function of inefficiency-affecting environmental variables, but this is covered in the section below—so that

$$u_{it} = h(t)u_{it}^* \qquad (52)$$

where u_{it}^* is subject to one of the usual distributional assumptions. One possibility is to assume that u_{it}^* is time-invariant, i.e. that $u_{it}^* = u_i$, and in this case the time-variance of the inefficiency term comes entirely from the scaling function; two such models are proposed by Kumbhakar (1990), who specifies a half normal u_i with the scaling function

$$h(t) = \frac{1}{(1 + \exp(bt + ct^2))} \tag{53}$$

where b and c are parameters to be estimated, and Battese and Coelli (1992), who alternatively specify a truncated normal u_i with the scaling function

$$h(t) = \exp[-\eta(t - T)] \tag{54}$$

which requires just one unknown parameter, η, to be estimated. Both functions have the crucial properties that they have values between zero and one, and do not therefore affect the sign of the disturbance u_{it} or allow it to take values outside of its intended range regardless of the estimated values of their parameters, and that they can be either increasing or decreasing in t—or indeed time-invariant—depending on the values of their parameters—which means that there are no a priori restrictions on the *direction* of change in the estimated inefficiencies; in addition (53) can be either monotonically increasing, monotonically decreasing, concave, or convex depending on the sign and magnitude of the b and c parameters. The specification of both scaling functions is, however, largely ad-hoc; furthermore, the models make the strongly restrictive assumption that the efficiency levels of all firms—though they may differ in their magnitudes—follow the same path over time. In reality, we may well expect the efficiency of different firms to change over time in different ways, whether converging or diverging. Nor would we necessarily expect the path of efficiency over time to conform to any particular function. In the following section, we discuss a class of SFA models which enable time-varying inefficiency which is dependent upon a set of environmental variables, which overcomes this problem and crucially allows us to examine the drivers of inefficiency.

3.3.4. Modelling Inefficiency

Given the ability to obtain estimates of firm-level inefficiencies, the question of how these might be modelled in terms of a set of exogenous explanatory variables is of course quite a natural one, and one that has attracted a lot of interest in the literature in terms of both theoretical studies and empirical applications. In the context of DEA, we previously discussed the various methods of doing so and the advantages and disadvantages of each, particularly around the problems associated with various two-step procedures—in which efficiency estimates derived in a first model are then regressed against a set of variables in a second model—in terms of the restriction of efficiency to between zero and one and the difficulty of reconciling the two models theoretically; to a large extent the issues that arise in the SFA literature on the subject are analogous.

3.3.4.1. Two-Step Methods

Many applications of SFA to analysing the determinants of firm-level efficiencies adopt a two-step approach, in which SFA is used to estimate a frontier from which to derive measures of efficiency in the first step, and in a second step regress the predicted efficiency scores on a vector of environmental variables. As with the analogous DEA literature, one issue is that because measures of productive or revenue efficiency must take on values between zero and one, the predictions of the second stage regression should ideally also stay within this range. On these grounds linear modelling methods such as OLS should not be employed, although this is observed in many cases; early examples of this include Pitt and Lee (1981) who, in applying their model to data on the Indonesian weaving industry, go on to regress their estimated efficiencies on firm age, size, and ownership variables; and Kalirajan (1981) modelling farmer-specific variability—efficiency—in rice paddy yields. More recent examples include Bonin et al. (2005) in a study using data on US banks, which regresses estimated cost and profit efficiencies on a set of ownership dummies, and also a series of studies examining the relationship between market power and profit and cost efficiency in banking which also use two-step methods: of these Koetter et al. (2012) and Restrepo-Tobón and Kumbhakar (2014) use instrumental variables regression methods, while Maudos and de Guevara (2007) uses a non-linear specification in the second step. The problems of any two-step approach in an SFA setting are however widely recognised, the main objection being that the assumption that the one-sided disturbances are identically distributed is made in the first stage and then violated in the second stage in which they are regressed against a vector of exogenous variables. Another issue is that the process assumes that the variables in the second stage regression are uncorrelated with the variables in the frontier, and that if this is not the case, the estimates of the frontier parameters obtained in the first stage will be biased due to the omission of the second stage regressors from the model; Wang and Schmidt (2002, p.130) employ a Monte Carlo experiment in order to determine the severity of the bias resulting from two-step methods. The authors report that

We find serious bias at all stages of this procedure. The size of the bias is very substantial and should argue strongly against two-step procedures ... It is widely appreciated that the severity of the bias depends on the magnitude of the correlation between [the frontier variables and the second-stage regressors]. *However, we also explain why, if the dependence of inefficiency on* [the second-stage regressor] *is ignored, the estimated firm-level efficiencies are spuriously under-dispersed. As a result the second-step regression understates the effect of* [the second-stage regressors] *on efficiency levels. Importantly, this is true whether or not* [the frontier variables and the second-stage regressors] *are correlated.*

Finally, there are clear issues with performing any kind of regression in which the dependent variable consists of estimates rather than the true, unknown, values. Given the many problems associated with the two-step approach, we now restrict our attention to a class of models which overcomes these problems by combining together the frontier and inefficiency models in various ways, and then estimating them in a single step.

3.3.4.2. One-Step Methods

Kumbhakar et al. (1991) introduce a cross-section model in which

$$u_i \sim N^+(\mu_i, \sigma_u^2) \tag{55}$$

$$v_i \sim N(0, \sigma_v^2)$$

$$\mu_i = \sum_l z_{li} \delta_l$$

that is, the one-sided disturbance is assumed to follow a truncated normal distribution in which the mean of the pre-truncation distribution $\mu = \sum_l z_{li}\delta_l$ is modelled as a linear function of a vector of environmental variables, z; the impact of the z variables therefore comes through their impact on μ. Meanwhile, the random noise component v_i is again assumed to follow a normal distribution with constant variance as usual. An alternative model is proposed by Reifschneider and Stevenson (1991), in which

$$u_i = g(z_{1i}, \dots, z_{Li}) + \omega_i \tag{56}$$

where ω_i is a one-sided disturbance following one of the usual distributions and $g(z_{1i}, \dots, z_{Li})$ is a rather complex function of the L environmental variables with a form that is strictly non-negative. In another paper, Huang and Liu (1994) suggest a specification almost identical to that of Kumbhakar et al. (1991) above, the sole difference being that instead of truncating a u_i with mean $\mu = \sum_l z_{li}\delta_l$ at zero, they truncate a u_i with mean $\mu = 0$ at the point $-\sum_l z_{li}\delta_l$ (Kumbhakar and Lovell 2000, p.269). Finally, Battese and Coelli (1995) introduce the model in a panel data context, where

$$u_{it} \sim N^{+}(\mu_{it}, \sigma_u^2) \tag{57}$$

$$v_i \sim N(0, \sigma_v^2)$$

$$\mu_{it} = \sum_l z_{lit}\delta_l$$

which is sometimes referred to as the 'conditional mean' model, and has become the canonical specification for modelling inefficiency effects in this way—i.e. through the mean of the pre-truncation distribution of u_{it}—and widely used in applied studies. Note that where δ_0 is the intercept in the inefficiency model and there are $\delta_1, \dots, \delta_L$ other parameters relating to each of the L environmental variables, the model collapses to the Stevenson (1980) normal-truncated normal model when $\delta_1 + \ \dots + \delta_L = 0$ and to the original Aigner et al. (1977) normal-half normal model when $\delta_0 + \ \dots + \delta_L = 0$. The log-likelihood of the model is a generalisation of that shown in (44), so that

$$\ln \mathcal{L} = -\frac{I}{2}(\ln \sigma^2 + \ln 2\pi) - \frac{1}{2\sigma^2}\sum_i \left(\varepsilon_i - s\sum_l \delta_l z_{lit}\right)^2 \tag{58}$$

$$+\sum_i \sum_t \ln \Phi \left[\frac{s}{\sigma}\left(\varepsilon_i \sqrt{\frac{\gamma}{1-\gamma}} + \sum_l \delta_l z_{lit} \sqrt{\frac{1-\gamma}{\gamma}}\right)\right]$$

$$-\sum_i \sum_t I \ln \Phi \left(-\frac{s \sum_l \delta_l z_{lit}}{\sqrt{\gamma \sigma^2}}\right)$$

a full derivation of which—with different notation—can be found in an earlier working paper version (Battese and Coelli 1993).

Aside from modelling the mean of the pre-truncation distribution of u_{it} as a function of the z environmental variables, there are several other ways in which these variables can enter the model. For example, a number of authors have suggested that the variance or standard deviation of the one-sided distribution—i.e. σ_u^2 or σ_u—be specified as a function of z variables, so that

$$\sigma_{uit}(z_{lit}, \theta_l) \rightarrow u_{it} \sim N^+(\mu, \sigma_{uit}(z_{it}, \theta)^2) \tag{59}$$

or,

$$\sigma_{uit}^2(z_{lit}, \theta_l) \rightarrow u_{it} \sim N^+\left(\mu, \sigma_{uit}^2(z_{it}, \theta)\right) \tag{60}$$

where θ and z_{it} are $(L+1) \times 1$ vectors of parameters and observations on the z variables. For example, Reifschneider and Stevenson (1991) specify—in a cross section setting—$\sigma_{ui} = \sigma_{u0} + h(z_{li})$ where $h(z_{li})$ is simply any function of a vector of environmental variables that is restricted to the range $(0, \infty)$, while Caudill et al. (1995) are more specific, specifying $\sigma_{uit} = \exp(\sum_l z_{lit}\, \theta_l)$. Hadri (1999) proposes a further extension by modelling the variance of the two-sided noise term in the same manner, so that $\sigma_{vit} = \exp(\sum_l z_{lit}\, \rho_l)$. The primary purpose of modelling the variances in this way was to account for the existence of heteroskedasticity in the disturbance terms, which is particularly desirable in the case of SFA as heteroskedasticity can affect not only parameter estimates but also estimates of inefficiency derived from the model (Caudill and Ford 1993). Thus Hadri (1999) refers to his model as doubly heteroskedastic owing to the treatment of the two variance terms in the model. Given that it is also a way of allowing a less restrictive way of modelling the effect of environmental variables on inefficiency, a logical next step is to combine the features of these models with those of the conditional mean model discussed above.

Wang (2002) presents a model which combines the Battese and Coelli (1995) conditional mean model with the Caudill et al. (1995) assumption on σ_{uit}, with the result

$$u_{it} \sim N^+(\mu_{it}, \sigma_{uit}^2) \tag{61}$$

$$v_{it} \sim N(0, \sigma_v^2)$$

$$\mu_{it} = \sum_l z_{lit}\delta_l$$

$$\sigma_{uit} = \exp\left(\sum_l z_{lit}\,\theta_l\right)$$

which has the interesting property that the marginal effects of the environmental variables—which are discussed in a following section—may be not only non-linear as in the Battese and Coelli (1995) model, but also non-monotonic. A further generalisation is possible, in which we also allow for heteroskedasticity in the two-sided disturbance:

$$u_{it} \sim N^+(\mu_{it}, \sigma_{uit}^2) \qquad (62)$$

$$v_{it} \sim N(0, \sigma_{vit}^2)$$

$$\mu_{it} = \sum_l z_{li}\delta_l$$

$$\sigma_{uit} = \exp\left(\sum_l z_{lit}\,\theta_l\right)$$

$$\sigma_{vit} = \exp\left(\sum_l z_{lit}\,\rho_l\right)$$

This model is employed by Hadri et al. (2003) and also appears in Kumbhakar and Sun (2013).

We have so far identified three ways in which environmental variables may enter a panel data SFA model: through the pre-truncation mean, or through the variance of the one-sided disturbance, or through the variance of the two-sided disturbance. A fourth way, which was alluded to briefly in the previous section, is through a scaling function. Following Wang and Schmidt (2002)—see also Alvarez et al. (2006) for further discussion—the term u_{it} could be specified as the product of a one-sided disturbance u_{it}^* and a scaling function $h(z_{0it}, \dots, z_{Lit}, \psi_0, \dots, \psi_L) \geq 0$. Wang and Schmidt specify

$$u_{it} = \exp\left(\sum_l z_{lit}\,\psi_l\right) u_{it}^* \tag{63}$$

which, as long as the distribution of u_{it}^* is not dependent on environmental variables, has the property that

$$\psi_l = \frac{\partial \ln u_{it}}{\partial z_{lit}} \tag{64}$$

regardless of the distribution of u_{it}^*, which makes for a much simpler—if arguably less interesting—interpretation of the inefficiency model coefficients. It would of course be possible in principle to add such a scaling function to the specification described in (62), which results in a model in which

$$u_{it} = \exp\left(\sum_l z_{lit}\,\psi_l\right) u_{it}^* \tag{65}$$

$$u_{it}^* \sim N^+(\mu, \sigma_{uit}^2)$$

$$v_{it} \sim N(0, \sigma_{vit}^2)$$

$$\mu_{it} = \sum_l z_{lit} \delta_l$$

$$\sigma_{uit} = \exp\left(\sum_l z_{lit}\, \theta_l\right)$$

$$\sigma_{vit} = \exp\left(\sum_l z_{lit}\, \rho_l\right)$$

Which, to the best of our knowledge, has not yet been implemented in the literature. This model encompasses the conditional mean specification of Battese and Coelli (1995), the doubly heteroskedastic model of Hadri (1999), and the scaling function model of Wang and Schmidt (2002).

For our study, we adopt the conditional mean model of Battese and Coelli (1995), which allows the estimation of a frontier and an inefficiency model in a single step, thereby avoiding the well-known problems associated with two-step methods. Although as discussed, extensions of the Battese and Coelli (1995) model exist in which heteroskedasticity may be introduced into one or both of the one-sided and two-sided disturbances such as the specifications of Wang (2002) and Hadri et al. (2003), in the context of the relatively limited sample sizes we utilise, there is a need to restrict ourselves to more parsimonious models—while bearing in mind that our chosen specification is in fact a relatively flexible one—in order to preserve degrees of freedom. It is interesting to note that despite the extended Wang (2002) specification having around for over a decade, a look at related search results and recent citations of both studies gives the impression that the original Battese and Coelli (1995) model remains the workhorse of the one-step inefficiency modelling literature. Recent applications include Pasiouras et al. (2009) in a study of the impact of regulation on cost and profit efficiency in banking, a study of the impact of non-traditional activities on banking efficiency by Lozano-Vivas and Pasiouras (2010), a study by Fiordelisi et al. (2011) into the relationship between efficiency and risks in European banking, Gaganis and Pasiouras (2013) in a study of the impact of financial supervision on banks' efficiency, a study into efficiency change in Chinese power plants following restructuring of the sector by Ma and Zhao (2015), a study into the relationship between migration and farm efficiency in Kosovo by Sauer et al. (2015), a study into the impact of agglomeration economies and fiscal transfers on the productivity of Japanese industries by Otsuka and Goto (2015), a study into the efficiency of gas distribution utilities in Brazil—and the factors that affect it—by Tovar et al. (2015), and many others.

3.3.5. Point Estimates

Naturally, in frontier analysis generally we are interested in obtaining observation-specific estimates of the one-sided disturbance term, u_{it}. In SFA, the total composite error is easily estimated, as is the mean of u, but the problem of obtaining point estimates went unsolved until Jondrow et al. (1982) proposed using the mean of u_{it} conditional on ε_{it} and derived formulae for the normal-truncated normal and normal-exponential cases; since we assume the former, the relevant formula is

$$E(u_{it}|\varepsilon_{it}) = \tilde{\mu}_{\mathrm{it}} + \sigma_* \frac{\phi(\tilde{\mu}_{\mathrm{it}}/\sigma_*)}{\Phi(\tilde{\mu}_{\mathrm{it}}/\sigma_*)} \tag{66}$$

where $\tilde{\mu}_{\mathrm{it}} = (\sigma_v^2 \mu_{\mathrm{it}} + s\sigma_u^2 \varepsilon_{it})/\sigma^2$ (the s being – 1 in production or revenue frontier specifications and 1 in cost frontier specifications) and $\sigma_* = \sqrt{\sigma_u^2 \sigma_v^2 / \sigma^2}$ and $\phi(\tilde{\mu}_{\mathrm{it}}/\sigma_*)$ and $\Phi(\tilde{\mu}_{\mathrm{it}}/\sigma_*)$ denote the standard normal probability density and cumulative density functions evaluated at $\tilde{\mu}_{\mathrm{it}}/\sigma_*$, respectively. When the dependent variable is logged, efficiency and inefficiency are given by

$$Eff_{it} = \exp(-u_{it}) \tag{67}$$

$$Ineff_{it} = \exp(u_{it}) \tag{68}$$

so we can therefore obtain point estimates of efficiency from

$$Eff_{it} = \exp[-E(u_{it}|\varepsilon_{it})] \tag{69}$$

$$Ineff_{it} = \exp[E(u_{it}|\varepsilon_{it})] \tag{70}$$

where $E(u_{it}|\varepsilon_{it})$ is as shown in (66). An alternative approach is to use the formula

$$E(\exp[su_{it}]\,|\varepsilon_{it}) = \left\{\exp\left[\frac{1}{2}\sigma_*^2 + s\tilde{\mu}_{it}\right]\right\}\left\{\frac{\Phi\left[\left(\tilde{\mu}_{it}/\sigma_*\right) + s\sigma_*\right]}{\Phi\left(\tilde{\mu}_{it}/\sigma_*\right)}\right\} \tag{71}$$

derived in Battese and Coelli (1988). This is preferable to the Jondrow et al. (1982) formula, of which it is a Taylor series expansion (Kumbhakar and Lovell 2000, pp. 77-78), though the differences between the two are usually negligible. These formulae are standard in the literature, and (71) is used to generate our point estimates in the following empirical chapters.

An alternative to the conditional mean is the conditional mode, which is the maximum of the conditional distribution of u_{it}, and is therefore a maximum likelihood predictor of inefficiency; Jondrow et al. (1982) proposed the conditional mode for the normal-half normal case. Its derivation is very simple and intuitive: since the conditional distribution in the normal-truncated normal or normal-half normal cases is simply that of the truncation at zero of a normally distributed variable with mean $\tilde{\mu}_{it}$ and variance σ_* (Battese and Coelli, 1988), the mode will be $\tilde{\mu}_{it}$ where $su_{it} \geq 0$ and zero otherwise. Therefore, we have

$$M(u_{it}|\varepsilon_{it}) = \begin{cases} \tilde{\mu}_{it}, & s\varepsilon_{it} \geq 0 \\ 0, & s\varepsilon_{it} < 0 \end{cases} \tag{72}$$

This predictor is rarely used, and we do not report it in our empirical chapters. We do, however, employ a formula for marginal effects based on this predictor, which is discussed in the section below.

3.3.6. Marginal Effects

Since we model u_{it} as a function of a set of Z variables, we naturally wish to examine the marginal effects of these variables on efficiency or inefficiency. However, since u_{it} is a random variable, we are restricted to analysing the marginal effects on efficiency *predictions*. Therefore, a fundamental issue is that there are alternative potential efficiency predictors, and calculated marginal effects will differ depending upon the predictor used.

Several different approaches have been suggested in the literature for estimating marginal effects. Clearly, as noted by Kumbhakar and Sun (2013), the simplest approach is to interpret the δ coefficients from the inefficiency model as marginal effects on u_{it}. This has some justification, since for $\mu_{it} > 0$, μ_{it} is the unconditional mode of the inefficiency distribution, which could potentially be used as an efficiency predictor given that—in the Battese and Coelli (1995) case—it is observation specific. The attraction of this approach is that it yields a constant marginal effect, and that inference may be based on the estimated δ parameters alone.

Wang (2002) derives a formula for the marginal effects of Z variables on $E(u_{it})$, the unconditional mean of u_{it}. For the Battese and Coelli (1995) case, the formula is shown to be

$$\frac{\partial E(u_{it})}{\partial z_{lit}} = \delta_l \left\{ 1 - \mu_{it}/\sigma_u \frac{\phi(\mu_{it}/\sigma_u)}{\Phi(\mu_{it}/\sigma_u)} - \left[\frac{\phi(\mu_{it}/\sigma_u)}{\Phi(\mu_{it}/\sigma_u)} \right]^2 \right\} \quad (73)$$

where δ_l is the estimated coefficient corresponding to the l_{th} Z variable. However, noting the inconsistency in using the Jondrow et al. (1982) formula in (66), which is based on the conditional mean, for point estimates, and using the Wang (2002) formula, which is based on the unconditional mean, to compute marginal effects, Kumbhakar and Sun (2013) derive a formula based on the conditional mean. For the Battese and Coelli (1995) case, the formula is shown to be

$$\frac{\partial E(u_{it}|\varepsilon_{it})}{\partial z_{lit}} = \delta_l (1-\gamma) \left\{ 1 - \tilde{\mu}_{it}/\sigma_* \frac{\phi(\tilde{\mu}_{it}/\sigma_*)}{\Phi(\tilde{\mu}_{it}/\sigma_*)} - \left[\frac{\phi(\tilde{\mu}_{it}/\sigma_*)}{\Phi(\tilde{\mu}_{it}/\sigma_*)} \right]^2 \right\} \quad (74)$$

the main difference between (73) and (74) being the inclusion of the $\sigma_v^2/\sigma^2 = 1 - \gamma$ term. Note that in both cases, the marginal effect of K_l is simply δ_l multiplied by a positive adjustment function, so that while we may nor interpret δ coefficients as marginal effects, they do reflect their sign. In their empirical application, Kumbhakar and Sun (2013) find that (73) tends to overestimate marginal effects; for this reason, and for the sake of consistency, the preferred formula for marginal effects is (74), though both are employed for comparison. Once the formulae have been estimated, it is straightforward to calculate the marginal effects of the Z variables on efficiency or inefficiency, since from (73) and (74), we can see that

$$\frac{\partial Eff_{it}}{\partial u_{it}} = -\exp(-u_{it}) \quad (75)$$

$$\frac{\partial Ineff_{it}}{\partial u_{it}} = \exp(u_{it}) \tag{76}$$

and therefore the marginal effects of z_{lit} on efficiency and inefficiency are, from the Wang (2002) formula

$$\frac{\partial Eff_{it}}{\partial z_{lit}} = \frac{\partial Eff_{it}}{\partial E(u_{it})}\frac{\partial E(u_{it})}{\partial z_{lit}} = -\exp(-u_{it})\frac{\partial E(u_{it})}{\partial z_{lit}} \tag{77}$$

$$\frac{\partial Ineff_{it}}{\partial z_{lit}} = \frac{\partial Ineff_{it}}{\partial E(u_{it})}\frac{\partial E(u_{it})}{\partial z_{lit}} = \exp(u_{it})\frac{\partial E(u_{it})}{\partial z_{lit}} \tag{78}$$

and from the Kumbhakar and Sun (2013) formula

$$\frac{\partial Eff_{it}}{\partial z_{lit}} = \frac{\partial Eff_{it}}{\partial E(u_{it}|\varepsilon_{it})}\frac{\partial E(u_{it}|\varepsilon_{it})}{\partial z_{lit}} = -\exp(-u_{it})\frac{\partial E(u_{it}|\varepsilon_{it})}{\partial z_{lit}} \tag{79}$$

$$\frac{\partial Ineff_{it}}{\partial z_{lit}} = \frac{\partial Ineff_{it}}{\partial E(u_{it}|\varepsilon_{it})}\frac{\partial E(u_{it}|\varepsilon_{it})}{\partial z_{lit}} = \exp(u_{it})\frac{\partial E(u_{it}|\varepsilon_{it})}{\partial z_{lit}} \tag{80}$$

which are both reported for the sake of comparison. Since in both cases Z_{lit} enters the adjustment function through μ_{it}, marginal effects can be non-constant. An alternative approach would be to use a formula derived from the Battese and Coelli (1988) estimator shown in (71), which as previously discussed is a preferable predictor of inefficiency. This has not apparently been derived previously, and therefore a derivation for the full Kumbhakar and Sun (2013) model is given in the appendix; in the Battese and Coelli (1995) case, this reduces to

$$\frac{\partial E[\exp(su_{it})|\varepsilon_{it}]}{\partial z_{lit}} = \tag{81}$$

$$\delta_l(1-\gamma)\left\{s+\frac{1}{\sigma_*}\left[\frac{\phi\left(\frac{\tilde{\mu}_{it}}{\sigma_*}+s\sigma_*\right)}{\Phi\left(\frac{\tilde{\mu}_{it}}{\sigma_*}+s\sigma_*\right)}-\frac{\phi\left(\frac{\tilde{\mu}_{it}}{\sigma_*}\right)}{\Phi\left(\frac{\tilde{\mu}_{it}}{\sigma_*}\right)}\right]\right\}$$

$$\times \exp\left[\frac{1}{2}\sigma_*^2+s\tilde{\mu}_{it}\right]\left\{\frac{\Phi\left[\left(\frac{\tilde{\mu}_{it}}{\sigma_*}\right)+s\sigma_*\right]}{\Phi\left(\frac{\tilde{\mu}_{it}}{\sigma_*}\right)}\right\}$$

Another previously unexplored approach is to derive a formula for marginal effects based on the conditional mode predictor; again, a derivation for the full Kumbhakar and Sun (2013) model is given in appendix 1, but in the Battese and Coelli (1995) case this simplifies to

$$\frac{\partial M(u_{it}|\varepsilon_{it})}{\partial z_{lit}} = \begin{cases} \delta_l(1-\gamma), & s\tilde{\mu}_{it} \geq 0 \\ 0, & s\tilde{\mu}_{it} < 0 \end{cases} \tag{82}$$

And translating this into inefficiency space, we have

$$\frac{\partial \exp[sM(u_{it}|\varepsilon_{it})]}{\partial z_{lit}} = \begin{cases} \delta_l(1-\gamma)s\exp(s\tilde{\mu}_{it}), & s\tilde{\mu}_{it} \geq 0 \\ 0, & s\tilde{\mu}_{it} < 0 \end{cases} \quad (83)$$

3.3.6.1. Statistical Significance of Marginal Effects

An additional issue in analysing marginal effects is that hypothesis testing is difficult to impossible, depending on the assumptions made. The choice of efficiency predictor is again crucial here: note that if we are basing our predictions on the distribution of u_{it}, then our predictors, i.e. the unconditional mean $E(u_{it})$ or unconditional mode $M(u_{it})$, are unknown parameters, for which standard errors and confidence intervals may be derived, e.g. using the delta method.

If, however, we are basing our predictions on the distribution of $u_{it}|\varepsilon_{it}$, then—given that we are conditioning on a random variable, ε_{it}—predictors such as $E(u_{it}|\varepsilon_{it})$ and $M(u_{it}|\varepsilon_{it})$ are random variables, as are the marginal effects $\partial E(u_{it}|\varepsilon_{it})/\partial z_{lit}$, $\partial E[\exp(su_{it})|\varepsilon_{it}]/\partial z_{lit}$, and $\partial E[sM(u_{it}|\varepsilon_{it})]/\partial z_{lit}$. The bootstrapping approach proposed by Kumbhakar and Sun (2013) to derive confidence intervals for $\partial E(u_{it}|\varepsilon_{it})/\partial z_{lit}$ is therefore inappropriate, since it treats ε_{it} as a known quantity; note also that the authors' marginal effects are not translated into efficiency space. An alternative approach may be to construct prediction intervals, rather than confidence intervals. However, this presents two difficulties: first, the distributions of the marginal effects are unknown, and to derive these distributions and then minimum with prediction intervals based upon them would be complex in the extreme. Furthermore, it is uncertain what this approach would add, because it is not possible to base hypothesis tests on prediction intervals.

To summarise, the issues around the statistical significance of marginal effects in Battese and Coelli (1995) type models are:

i. Hypothesis testing is only possible if the predictor underlying the marginal effects formula is based on the unconditional distribution of u_{it}. However, such predictors clearly do not perform as well as those based on the distribution of $u_{it}|\varepsilon_{it}$, and as Kumbhakar and Sun (2013) argue, marginal effects should be based on the preferred efficiency predictor.
ii. The distributions of marginal effects based on the conditional predictors are unknown, making the derivation of minimum width prediction intervals—which do not enable hypothesis testing in any case—particularly difficult.
iii. More fundamentally, we are only able to calculate marginal effects on efficiency predictions, not on efficiency itself, and the confidence intervals or prediction intervals derived depend upon the efficiency predictor used.

Given these complications, the approach usually taken in the applied literature is to simply state that, if the estimated δ_l parameter is statistically significant, then z_l has a significant impact on efficiency or inefficiency, and to note the direction of the relationship. Since, as discussed in section 3.3.6, δ_l is the marginal effect of z_l on $M(u_{it})$, this does have some justification. For expediency's sake, this is the approach taken in this thesis.

3.4. Other Methods and Their Use by Regulators

Aside from the DEA and SFA methods that we discuss and compare above there are a few other methods which, while not seriously considered for our study, deserve a mention in large part because of their use by economic regulators such as Ofwat and Ofgem as part of their benchmarking exercises, which is of clear interest given the industries under study here.

Benchmarking analyses by regulators generally rely on very simple methods. In many cases, OLS is used to estimate a cost function, with the estimated errors interpreted wholly as variations in efficiency; the resulting regression line may then be shifted so that the most efficient firm—or firms—lie on the regression line, in order to give the appearance of a frontier. For example, in a cost benchmarking exercise we would first perform OLS, and then look for the negative estimated error with the greatest magnitude; this magnitude would then be subtracted from the estimated intercept, resulting in a parallel shift in the estimated cost function; this method is known as corrected ordinary least squares (COLS). Clearly, not much is gained by this procedure relative to OLS—except for the fact that the result is a frontier of sorts—while the shortcomings are very obvious: the method is deterministic in that it does not allow for the presence of noise or other disturbances, which are treated as variations in efficiency—this makes COLS particularly sensitive to outliers in the direction of the shift, which could lead to the other observations being judged far too harshly—while lacking any of the redeeming features of the various deterministic non-parametric methods available. Moreover, in leaving all of the frontier parameters but the intercept unchanged the COLS frontier has the same scale and substitution properties as the function estimated by OLS. This is in contrast to SFA in which the most efficient firms have a greater impact on the scale and substitution properties of the estimated frontier, which is sensible, given the strong probability that the more efficient firms are nearer to the frontier precisely because they are better at exploiting scale and substitution effects in the frontier technology (Lovell 1993, p.22). Therefore COLS in effect rules out this possibility and makes the peculiar assumption that the structure of technology is identical between all firms, regardless of their level of efficiency.

Even more surprising than the simplicity of the methods used in regulators' benchmarking exercises are the data used, particularly as the regulators themselves have a large say in determining the sort of data that ought to be collected, and at what frequency. A report by Stern (2013) for the Office of Rail and Road (ORR)—formerly the Office of Rail Regulation—provides a good overview of the development of regulator's uses of econometric benchmarking techniques from privatisation onwards, stating that a 'first generation ' of econometric benchmarking models

'*... was developed during the 1990s based on cross-section modelling across the* [water and electricity distribution] *companies for a single time-period, with a new set of cross-section estimates at each successive price review. Ofgem and Ofwat were the UK pioneers for the first generation cross-section econometric benchmarking models.* (Stern 2013, p.3)'

Such simple cross-section models clearly bring a number of limitations, not only in terms of foregoing the general advantages of panel data over cross-section data and the inability to identify trends in firm performance from a single model, but also because in the context of regulated utilities in the UK, using cross-section data leads to very small sample sizes, especially considering that the Northern Irish utilities and Scottish Water have their own regulator and are usually therefore excluded from these analyses: there are currently only ten WaSCs and nine WOCs—excluding the very small concerns such as Albion Water—in England and Wales, and fourteen electricity DNOs and 20 TOCs in Great Britain, and on top of this certain companies are sometimes excluded because they are judged to be atypical in some way. Stern (2013) suggests that the regulated companies quickly learned to game the benchmarking process, and that the small number of observations helped them in this regard: companies are generally able to respond to the regulator's findings, and frequently choose to do so with their own results, which generally give a more favourable picture of the firm's performance. The use of such small sample sizes will tend to lead to results that are relatively highly sensitive to small changes in the sample or method used, creating lots of scope for the regulated companies to engage in the cherry picking of methods, samples, and specifications in order to show their company in the best possible light, and indeed there are many examples of companies doing just this, sometimes in-house, and sometimes by commissioning economics consultancies—which are also frequently commissioned by the regulators to carry out various kinds of work, including this kind of benchmarking analysis—to find more favourable results. Of course, in many cases the companies' concerns will be fully or partially justified, but there is also undoubtedly an element of rent seeking involved as well. (Stern 2013, p.4) describes this phenomenon:

'Wars of the models' developed in which regulators and companies, each with their own consultants, traded econometric equations and estimates. Given the very limited number of cross-section data points, there was little or no chance of a clear-cut decision.

The use of panel data methods could itself bring about significant improvements to regulatory benchmarking analyses in terms of increasing degrees of freedom and improving the efficiency of parameter estimates, making results more robust and hence less vulnerable to this line of attack. Stern (2013, p.5) notes an encouraging shift in this direction, with a 'second generation' of benchmarking models from the 2000s onwards making use of panel data, as well as more sophisticated and appropriate modelling methods including DEA and SFA methods. There have also been a number of attempts to benchmark firms internationally—typically involving data from other European countries—which is a good way of increasing sample sizes—indeed vital in cases where the regulator otherwise has no comparator, e.g. Network Rail, Scottish Water, and Northern Irish utilities—and allowing regulators to look at the wider picture of how utilities in different operating environments and under alternative regulatory regimes, etc. Regulators' work in this direction has thus far been limited, however, and is usually limited to making comparisons of fairly crude measures such as average costs, investment, and quality performance. Differences in the ways that industries are structured internationally, and the lack of directly comparable data continue to form a barrier to progress toward proper international benchmarking studies making full use of panel data and appropriate frontier methods.

As with the selection of models, the choice of both dependent and independent variables in regulatory benchmarking has also tended to be rather ad-hoc. Rather than the behavioural cost functions derived from production theory, regulators have until relatively recently tended to focus on the benchmarking of specific categories of expenditure—e.g. operating expenditure (opex), capital maintenance, or total capital expenditure (capex)—separately. In many instances, even more specific categories of expenditure are benchmarked, e.g. energy costs, and even tree-cutting costs in the case of electricity distribution. Beginning with Ofgem, however, regulators have more recently moved to modelling of total expenditure (totex), i.e. the sum of all opex and capex, which is a step closer to an economic cost function, although capex may deviate from the opportunity cost of capital according to the nature of the investment cycle.

Trends in the use of benchmarking methods by UK regulators are discussed by Thanassoulis (2000a, 2000b), Dassler et al. (2006), and Pollitt (2005). Thanassoulis (2000a, 2000b) discusses the use of DEA alongside COLS by Ofwat in order to assess the efficiency of English and Welsh WaSCs and WOCs for the 1994 price review, PR94, describing the process by which input and output variables to be included in the model were determined; the efficiency score for a firm was determined to be the higher of the two scores generated—clearly a conservative approach—and these scores are described as having had an impact on the price caps subsequently set by Ofwat, which though not ‘direct’, was nevertheless potentially substantial. Similarly, Pollitt (2005) assesses the use of benchmarking techniques by OFFER, and later Ofgem, to inform their price caps in their 1999 and 2004 price reviews for electricity transmission and distribution—known as distribution price controls two and three (DPCR2 and DPCR3) and transmission price controls two and three (TPCR2 and TPCR3), respectively—and describes how, for DPCR2 and DPCR3, simple COLS regressions of operating costs against a ‘composite’ output were used, both times employing only a single years’ data and therefore only 14 observations, on the PESs and DNOs, respectively. Furthermore, the costs benchmarked in the COLS regression were only a fraction of regulated revenue. According to the author, Ofgem has tended to use more than one methodology to benchmark controllable costs and then—as with Ofwat—to attribute to each DNO the highest of the resulting efficiency scores. These were then used in a rather straightforward way, being multiplied by those costs to calculate an associated revenue allowance.

Regarding transmission, the small number of transmission network operators (TNOs) regulated by Ofgem made a similar benchmarking exercise infeasible, as did the heterogeneity among them: TNOs in Great Britain include the National Grid, which is the TNO in England and Wales, and the much smaller transmission businesses of Scottish Power and Scottish Hydro Electric, which are the TNOs for southern and northern Scotland, respectively. Pollitt (2005) instead states that international benchmarking using simple comparisons of unit costs and cost trends was applied to costs consisting of only 26% of allowed revenue. The author concludes that Ofgem's approach to benchmarking during the two price reviews could have been strengthened by the use of panel data, which would have increased the robustness of parameter estimates and also allowed the decomposition of TFP change into technical change and efficiency change. The possible advantages of international benchmarking in increasing sample sizes, and the lower efficiency scores that would likely result, are also mentioned. The author criticises the arbitrary nature of Ofgem's cost benchmarking analyses, particularly for failing to incorporate input price measures, and for failing to allow for trade-offs between opex and capex.

Dassler et al. (2006) gives an overview of the use of benchmarking by regulators across several industries: telecommunications, electricity, gas, and water and sewage. They conclude that while benchmarking techniques have played a role in the setting of price caps, this role has in some cases been rather limited, being used alongside other tools such as engineering analyses, and that this has especially been the case in industries where there is a lack of comparator firms, such as in electricity transmission.

3.5. Summary

In this chapter, we have examined the development of the theoretical literature on frontier methods and efficiency estimation in detail. We have evaluated a range of alternative approaches ranging from DEA methods to SFA methods, and developed an explicit rationale for our choice of model for the following empirical chapters; specifically, we opt for the SFA specification of Battese and Coelli (1995) which allows us to incorporate a vector of environmental variables thought to affect inefficiency in a one-step model which avoids the shortcomings of two-step estimation procedures and allows the estimation of the marginal effects of these variables which may be non-linear. The specification is also highly flexible, given that, with the inclusion of environmental variables, allows for observation-specific inefficiency distributions, enables hypothesis testing regarding the environmental variables, and nests simpler specifications such as the normal-truncated normal and normal-half normal models. We also discussed the formulae used for obtaining point estimates of inefficiency and estimated marginal effects. Finally, we discussed some of the more basic frontier methods such as COLS which have been employed by regulators in the past, and the evolution of regulators' approach to econometric benchmarking.

The following empirical chapters will focus on applying SFA to the water and sewage and electricity distribution industries respectively, consisting of a general background to each and an explanation of the specific data and specifications used, presentation and discussion of the estimates of the parameters of the model, point inefficiencies, marginal effects, etc. and some discussion of their interpretation.

4. Literature Reviews: Cost and Production Studies of Utility Industries

4.1. Introduction

In the preceding chapters, we have discussed how issues of market power and regulation can affect the efficiency of utility industries, and some of the methods used to analyse firm-level efficiency. In this chapter, we review the existing empirical literature on efficiency and productivity in the electricity and water industries. We focus on four important issues in the literature. First, given the subject of this thesis, we review previous studies on the relationship between regulation and performance in the water and electricity supply industries. Second, we discuss the effect of ownership on performance. This is of interest given the inclusion of data on the publicly owned Scottish and Northern Irish water companies, and because it is a topic that has attracted a great deal of attention in the literature. Third, we discuss previous findings on the cost structures of the industries in terms of returns to scale and density. Finally, we briefly address the issue of quasi-fixed inputs and their implications for cost modelling.

4.2. Regulation and Efficiency

In this section, we review the evidence from previous empirical studies on the impact of various forms of regulation on performance in the water and sewage industry and electricity supply industries. We also review some relevant studies of other industries, such as gas supply, which are similar due to natural monopoly character or the forms of regulation they are subject to. Given the subject of this thesis and the data used in the empirical portion of it, we pay particular attention to previous studies of the industry in the UK, and analyses of the effectiveness of various forms of regulation.

Most of these studies analyse either cost efficiency, technical efficiency, or total factor productivity (TFP) using a variety of different methodologies, though a few do also analyse performance on the revenue side in terms of total price performance (TPP) indices. Some of the studies analyse the impact of regulation by comparing the performance of firms under different forms of regulation, however, since examples of firms within a given industry and country being subject to different regulatory regimes are rare, a larger number focus on trends in performance over time and how these are affected by regulation.

4.2.1. UK

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There have been a relatively large number of studies looking at the performance of water and sewage companies in England and Wales following privatisation, and how this has been affected by regulation. As discussed in chapter 1, since privatisation English and Welsh water and sewage companies have been subject to RPI+K regulation—a variant of RPI-X in which there is an additional allowance for capital investment requirements, so that real price increases may be permitted—by Ofwat; under this form of regulation, price reviews are undertaken every five years to set price caps. The stringency of these price caps has varied quite significantly in different price review periods, and several studies relate trends in performance to these regulatory changes.

The pre-privatisation period was characterised by stringent targets for cost reductions by the ten Regional Water Authorities (RWAs). Lynk (1993), using data from from 1979-80 to 1987-88, estimates a stochastic cost frontier for the RWAs, and finds substantial improvements in productivity prior to privatisation, attributing this to the cost reduction targets imposed. In contrast, Saal and Parker (2000) note that the price caps in the initial post-privatisation period were relatively lax and analyse the total factor productivity (TFP) growth among the RWAs and their successors, the water and sewage companies (WaSCs), from 1984-85 to 1998-99 by estimating a translog cost function. The authors reject the hypothesis that privatisation in 1989 led to a statistically significant increase in TFP growth, but fail to reject the hypothesis that such an increase did occur following PR94, Ofwat's first price review, in which the regulator tightened the price caps from their initial levels.

Several other studies also find improvements in performance following PR94: Bottasso and Conti (2003), estimating a stochastic cost frontier using data on the water supply activities of the WaSCs and WOCs from 1994-95 to 2000-01, find that cost efficiency increased over the sample period and that differences in cost efficiency between firms also diminished. Saal and Reid (2004), who estimate a translog variable cost function for the English and Welsh WaSCs using data from 1992-93 to 2002-03, likewise find that the first few years following the 1994-95 price review coincided with a statistically significant increase in productivity growth.

On the basis of these studies, it seems that gains in efficiency and productivity were stronger in the pre-privatisation and post-PR94 periods, when there were stronger incentives to minimise costs, than in the immediate post-privatisation period in between, when regulation was lax. On the other hand, the findings of Saal and Parker (2001) are mixed. Decomposing WaSC profit changes into TFP changes—calculated via a Tornqvist TFP index—and changes in total price performance (TPP)—the growth of input prices relative to the growth of output prices—from 1984-85 to 1998-99, the authors find that TFP growth did not improve in the post-privatisation period, but also that there was a reduction in TFP growth following PR94. Improvements in labour productivity observed after privatisation are however found to be concentrated in the period following PR94. Increases in TPP are found in the period between privatisation and PR94, after which TPP declined, reflecting the tightening of price caps. A later study by Saal et al. (2007), which estimates TFP growth from 1984-85 to 1999-00 using a stochastic distance function technique, likewise finds no increase in TFP growth following privatisation and a reduction following PR94.

Two other studies do pick up improved performance following PR94 among the WaSCs, but find that the water only companies (WOCs) did not follow the same trend. Stone & Webster (2004b) analyses trends in productivity from 1992-93 to 2002-03 from estimated variable cost models, and find that there was a positive step change in productivity increasing following PR94 explained mainly by improvements in labour and capital productivity and quality improvements in sewage activities. On the other hand, productivity growth among the WOCs is found to have declined over the period. Similarly, Saal and Parker (2006) estimate a stochastic distance function concerning English and Welsh WOCs' and WaSCs' water supply activities from 1992-93 to 2002-03. Average technical efficiency among WaSCs is shown to follow a similar trend: declining initially, then improving from 1995-96 onwards following PR94, while the trend in WOC efficiency is rather different, improving up to 1996-97 and remaining relatively stable thereafter.

Overall, there does seem to be evidence of improvements in performance following the tightening of price caps at PR94. Several later studies have included subsequent price reviews in their analyses, and offer insights into the effects of later regulatory changes in the industry. Price caps were tightened further in PR99, Ofwat’s second price control, to the point that significant price *reductions* were imposed for the first time, in contrast to PR94 which merely reduced allowed price *increases*. Erbetta and Cave (2007), applying the two-step DEA method of Fried et al. (1999) to data on the WaSCs from 1992-93 to 2004-05, find that the estimated impact of PR94 on input-specific inefficiencies—relating to labour, other operating expenditure, and capital—is in the expected direction, implying efficiency gains, but is not statistically significant. The impact of PR99 on the other hand is found to be much greater in magnitude and statistically significant, leading the authors to conclude that the further tightening of price caps at PR99 led to significant reductions in inefficiency in contrast to the relatively lax PR94.

Portela et al. (2011) measure productivity change among both WaSCs and WOCs in England and Wales from 1993-94 to 2006-07, a period covering four regulatory cycles: the two years prior to PR94, PR94 itself, PR99, and PR04. The authors estimate Malmquist and 'meta-Malmquist' TFP indices via DEA, and find that TFP increases throughout the sample period, with efficiency improvements following PR94 and PR99, until the final two years, in which TFP is found to decline. These final two years coincide with the onset of PR04, in which price caps were loosened significantly, so that average annual price increases permitted were larger than in any other price review, including even the pre-PR94 period.

Further evidence that performance deteriorated following the loosening of price caps in PR04 is provided by Molinos-Senante et al. (2014), who use DEA to calculate Luenberger TFP indices—a generalisation of the Malmquist index introduced by Chambers et al. (1998) which can account for output expansion and input contraction simultaneously—for the water supply activities of the WaSCs and WOCs from 2000-01 to 2007-08, therefore covering the PR99 and PR04 price reviews. The authors find reductions in TFP in each year, which with respect to the PR99 period contrasts with other findings in the literature, but consistent with the findings of Portela et al. (2011), they find that the decline in TFP was considerably greater following PR04.

Two papers by Maziotis et al. (2014, 2015) extend approach of Saal and Parker (2001) to decomposing profitability changes into TFP and TPP changes to a longer period, covering 1990-91 to 2007-08. The authors find negative profitability changes over the period were driven mainly by negative price effects, which can be attributed to price capping. An upward trend in TPP in the pre-PR94 period, is interrupted following PR94 and reversed following PR99, following a downward trend in each year except 2002 and 2006—the latter of which, again, is the beginning of PR04 which significantly loosened price caps—while TFP is found to increase steadily increased over the period.

Note that the studies discussed have exclusively focused on the English and Welsh WaSCs and WOCs, with none including the Scottish and Northern Irish water companies despite the availability of comparable data published by their regulators, WICS and NIAUR respectively. The only such study of the Scottish water industry—that we are aware of—is that of Sawkins and Accam (1994), who use DEA to assess the technical efficiency of the water supply operations of the nine regional and three islands councils—which provided water and sewage services before the creation of the three water authorities in 1996—from 1984-85 to 1992-93. The weakness of DEA in discriminating sufficiently between observations in small samples is evident in this case: of the 108 observations in the sample, a large proportion are found to lie on the frontier. The authors find relatively little movement in efficiency over time, which may be explained in terms of the organisation of the industry at the time and the lack of independent regulation in Scotland. We are not aware of any such study of the industry in Northern Ireland.

To summarise, there seem to be a few recurring findings from the literature on the performance of the English and Welsh WaSCs and WOCs: first, there seems to be little evidence that privatisation alone was responsible for any significant improvement in performance, and this seems to be linked to the relatively lax price caps imposed prior to PR94. Second, improvements in efficiency or productivity over the post-privatisation period as a whole seems to have been linked to regulatory changes. In particular, several studies indicate that performance improved following the tightening of price caps following the PR94 and PR99 price reviews, and that TFP may have declined following the subsequent loosening of price caps following PR04. As expected, improvements in efficiency and productivity therefore seem to be dependent on the stringency of price caps imposed.

A similar story emerges with regards to the electricity distribution industry in Great Britain. Similar to the water and sewage industry, electricity distribution network operators (DNOs) are subject to RPI-X regulation, where X is the required real revenue reduction. Again, initial revenue caps set by the government following privatisation were relatively lax, allowing real increases, and there is evidence that performance worsened or stagnated until the imposition of tighter revenue caps following OFFER's first distribution price control review, DPCR2, in 1994. Domah and Pollitt (2001) note that real unit costs rose by 15% immediately following privatisation and remained high, falling dramatically after 1994-95, i.e. immediately following DPCR2. The authors suggest that there was a clear relationship between this trend in costs and changes to the regulatory environment. Operating profits are shown to have increased in the immediate post-privatisation period, DPCR1, despite the increase in costs. Likewise, Jamasb and Pollitt (2007) judge the immediate post-privatisation revenue control, DPCR1, to have been too lax, and show that the DPCR2 and DPCR3 reviews by OFFER and its successor Ofgem brought about significant reductions in real distribution charges and may have improved productivity.

Further evidence for this is provided by Hattori et al. (2005), who use both DEA and SFA distance function approaches to calculate Malmquist TFP indices for the twelve English and Welsh Area Electricity Boards (AEBs) and their successors, the privatised Public Electricity Suppliers (PESs) from 1985-86 to 1997-98. Note that this analysis concerns only the distribution activities of the AEB-PESs that were later inherited by the DNOs. The DEA based TFP index suggests annual TFP growth of -6.1% in the pre-privatisation period, 1.2% during the DPCR1 control period, and 10% in the three years following DPCR2. Meanwhile, the SFA based TFP index implies that TFP fell by well over 10% in 1990-91, but increased by and even larger amount in 1995-96. Both approaches suggest that TFP growth improved following the tightening of revenue caps at DPCR2.

A later study by Giannakis et al. (2005) analyses the performance of the fourteen Great British PESs from 1991-92 to 1998-99, covering the immediate post-privatisation period and the first two price reviews, DPCR1 and DPCR2. The authors also use these DEA specifications to calculate Malmquist TFP indices. Average quadrennial TFP growth is found to be between 12.2% and 13.84%—in annual terms between approximately 2.9% and 3.3%—suggesting TFP growth over the period as a whole, but unfortunately the paper does not describe the changes in TFP growth or its components over time, and thus the changes in TFP growth from the post-privatisation period in response to the two price reviews and other events cannot be determined.

Jamasb et al. (2012) estimate a cost function using data on twelve of the fourteen DNOs in Great Britain from 1995-96 to 2002-03. The study's focus is on estimating the marginal costs of service quality improvements and comparing these to willingness to pay figures: the authors conclude that the incentive rates set by Ofgem for quality improvements were not sufficiently strong, leading the marginal social benefit of further service improvements to exceed the marginal social cost. The estimated coefficient on the time trend suggests that there were gains in TFP over the period, which covers DPCR2 and the first three years of DPCR3, when revenue caps were tightened further.

To reiterate our previous statement, the existing literature on the water and sewage and electricity distribution industries in the UK suggests that while privatisation in itself does not appear to have spurred significant increases in efficiency or productivity growth, and indeed may have caused a deterioration due to the generous price and revenue caps set by the government in the initial post-privatisation period, subsequent tightening of price and revenue caps by Ofwat and OFFER—of Ofgem—was followed by increases in efficiency and productivity growth.

We have so far focused on studies which have analysed trends in efficiency and productivity in the industries over time, and related these to regulatory changes. Another, and perhaps more powerful approach, is to compare the performance of firms within a given industry under different regulatory regimes. In the case of the UK water and sewage and electricity distribution industries, this is difficult, since in both cases every firm is subject to the same form of regulation. However, the use of international benchmarking is one potentially valuable way to analyse the effectiveness of different regulatory regimes.

For example, Dijkgraaf and de Jong (1998) compare the efficiency of the English and Welsh WaSCs and WOCs to that of their Dutch counterparts from 1991 to 1995. The Dutch water utilities differ from the WOCs in two important respects: first, they are all publicly owned. Second, a system of benchmarking regulation was not introduced until 1997—after the sample period—before which a form of cost-plus regulation was in force. Unable to estimate a common frontier due to data compatibility issues, the authors compare the efficiencies of the two groups relative to their own frontiers: COLS is used to estimate cost frontier for the Dutch water utilities, and the resulting efficiency scores are compared to those from an early Ofwat benchmarking exercise. Welfare losses calculated using implied mark-ups are also compared. The authors find that Dutch water utilities are significantly less efficient than the English and Welsh companies, but that overall welfare losses in England and Wales are higher given the higher profits of the latter. In addition, the previously discussed study by Hattori et al. (2005), which found that PES TFP growth increased following DPCR2, also included data on nine Japanese electric utilities in order to facilitate cross-country comparisons. The authors found that mean efficiency and TFP growth were higher in the UK than in Japan, where the firms were subject to rate of return (RoR) regulation, throughout the 1985-86 to 1997-98 period. The latter two studies imply that revenue and price capping regulation as applied to the UK water and sewage and electricity distribution industries yields superior performance in terms of efficiency and TFP compared to low-powered cost plus or RoR forms of regulation.

Another approach to analysing the effects of regulation is to analyse the performance of firms under the alternative forms of regulation that have existed in the UK historically. Two studies by Foreman-Peck and Waterson (1985) and Hammond (1992) estimate cost functions for steam generation plants during the interwar period. During this period, the National Grid was supplied by a variety of generation plants selected by the Central Electricity Board (CEB) to supply either the base load or at times of peak demand, with plants selected to supply the base load subject to CEB regulation and control. Foreman-

Peck and Waterson (1985), using a cross-section of 171 plants from 1937 finds that while privately owned plants are more cost efficient than those that are municipally-owned, among selected plants—i.e. those that are subject to CEB regulation—ownership has no statistically significant effect, and that privatisation in itself may not bring about any improvement in efficiency. Hammond (1992), using an enlarged dataset, likewise finds that plants under CEB regulation and control were more efficient than those that were not.

4.2.2. Non-UK

Several studies examine the relationship between regulation and performance in the water and electricity supply industries outside the UK. Since the introduction of RPI-X regulation in the UK, similar methods of regulation have been adopted in a number of other countries, and the impact of these changes in regulation have been the subject of several studies.

Edvardsen et al. (2006) suggest that a shift from RoR regulation to RPI-X revenue capping of electricity distribution utilities in Norway in 1997 has yielded impressive growth in TFP. The authors construct DEA-based Malmquist TFP indices from 1996 to 2003, and find that the average annual TFP growth over the period was 1.1%, with TFP growth fastest in the first few years of RPI-X regulation and levelling off around 2000. The authors state that this may be the effect of firms waiting for the next regulatory period—lasting from 2002 to 2006—since TFP growth resumed between 2002 and 2003.

Arocena and Waddams Price (2002) suggest that the introduction of revenue capping on the TFP of coal-fired generating plants in Spain resulted in catch-up between the most efficient and least efficient plants. Incentive regulation was introduced to the industry in

1988, replacing a previous system in which allowed revenues were allowed to increase in line with inflation; essentially RPI-X without any X factor. The authors calculate DEA-based Malmquist TFP indices using data on a mixture of publicly-owned and privately-owned plants from 1984 to 1997, finding that while privately-owned plants were initially less efficient than publicly-owned plants, they caught up following the introduction of revenue capping regulation, having higher TFP growth rates in the early years of revenue capping, and more similar growth rates in later years.

Another country in which RPI-X style regulation has been introduced is Australia. Evidence on the effectiveness of price regulation in the Australian water industry is mixed. Analysing the technical efficiency and TFP of eighteen rural water utilities in Australia from 1995-96 to 2002-03, Coelli and Walding (2006) find an overall decline in TFP over the period, despite the introduction of a system of independent price regulation based on the RPI-X model and reforms under which they have been required to generate sufficient revenues to cover their costs and earn a commercial rate of return on their capital. The authors explain that these tend to be owned by state governments or local councils, and have historically been cross-subsidised, with prices generally set below the cost of production. On the other hand, Abbott et al. (2012), who construct DEA-based Malmquist TFP indices to analyse changes in productivity among water and wastewater utilities in six Australian cities from 1995-96 to 2007-08, note that two of the best performers, Sydney and Melbourne, are both subject to independent price regulation intended to incentivise efficiency and innovation.

On the other hand, a study by Rungsuriyawiboon and Coelli (2006) suggests that substitution of various forms of incentive regulation—such as price capping—for traditional RoR regulation of US electricity supply utilities did not lead to efficient or productivity gains. Using data on 61 US electric utilities from 1986 to 1998, the authors apply three different approaches: a Tornqvist TFP index, a stochastic cost frontier, and a stochastic input distance function, and find that those subject to incentive regulation actually had lower rates of TFP growth and levels of technical efficiency. Furthermore, the authors find that adopters of incentive regulation seem to have deteriorated following adoption. In contrast to most similar studies, therefore, incentive regulation seems not to have been effective in improving efficiency and productivity.

Other studies compare the efficiency and productivity of utilities under differing forms of regulation. Aubert and Reynaud (2005) analyse the cost efficiency of water utilities subjected to a variety of regulatory regimes administered by the Public Service Commission of Wisconsin. Specifically, the utilities are ordinarily subject to a form of price capping regulation. However, a utility may request a price increase, which triggers a change in its regulatory regime to either a RoR regime in which the regulator undertakes a full audit of the utility in making its decision, or a simpler process which results in a hybrid regime combining features of RoR with an upper bound on prices, i.e. a price cap. Using a panel of 211 utilities from 1998 to 2001, the authors estimate a stochastic cost frontier, finding that the regulatory regime has a significant effect on cost inefficiency, with the most efficient firms being those under RoR regulation, the least efficient firms being those under hybrid RoR and price cap regulation, and those under price capping being intermediate. Though the finding that hybrid regulation is associated with lower efficiency than price capping is as expected due to its lesser incentives for efficiency, the finding that RoR regulated firms are more efficient than those under price capping is at first sight surprising. The authors explain this finding in two ways: firstly because of the requirement to provide the regulator with a large amount of information as part of the regulator's auditing process under RoR regulation—alleviating the regulator's asymmetric information problem—and secondly because of the Averch-Johnson effect that utilities under RoR regulation will tend to overcapitalise; as the authors model variable costs, any resulting decrease in variable costs from overcapitalisation is picked up, while the resulting increase in capital costs is not, making utilities under RoR regulation appear more, rather than less, efficient. In support of the latter explanation, the authors find that RoR regulated do indeed tend to overcapitalise to a greater extent.

Another study by Knittel (2002) use SFA to analyse the effects of three different types of incentive programme—heat rate and plant availability programmes, programmes limiting pass-through of fuel price increases, and revenue decoupling programmes—on the technical efficiency of US coal and gas generation plants. Using data from 1981 to 1996, the authors estimate production frontiers via SFA and find that heat rate and plant availability programmes, along with certain types of fuel cost pass-through programmes, are associated with an increased technical efficiency, whereas decoupling programmes, along with price capping and RoR regulation are found to be insignificant.

Additionally, two studies look at the impact of introducing competition on performance. Barros and Peypoch (2007) estimate a stochastic cost frontier using data on 25 hydroelectric plants belonging to Energias de Portugal over the eleven years from 1994 to 2004. The authors find no statistically significant effect of the establishment of a new regulatory agency, ERSE, in 1999, but find a significant reduction in costs following the onset of competition in 1996, concluding that competition has increased hydroelectric plant efficiency, while regulation has not. Fabrizio et al. (2007) analyse the impact of restructuring in the US electricity industry data on coal, gas, and combined cycle gas turbine generating plants over the 1981 to 1999. The authors estimate input demand functions for labour, energy, and nonfuel expenses, and find that opening up of competition in retail leads to significant reductions in input usage among privately-owned plants. These reductions are found to be larger than those of publicly and cooperatively-owned plants. The authors also suggest the threat of restructuring or competition may bring about efficiency gains.

To summarise this section, conclusions regarding the effect of various forms of regulation on the performance of water and electricity supply utilities internationally seem more mixed than those regarding the UK alone. For example, studies using US data seem to suggest that incentive regulation has not yielded improved performance relative to more traditional forms of regulation, whereas RPI-X regulation of electric utilities in Norway and Spain does seem to have brought about significant TFP gains. We note that the UK literature implies that efficiency and productivity performance depends not only on the regulatory regime, but also on the stringency with which it is applied, and that the mixed findings in this section may be explained in terms of differences in the way that regulation has been applied.

4.2.3. Other Industries

In addition to water and electricity supply, a number of other industries have been subject to similar forms of regulation in the UK and elsewhere. In this section, we consider evidence on the relationship between regulation and efficiency from previous studies of similar industries.

Bishop and Thompson (1992) construct Tornqvist TFP indices for several firms pre and post privatisation across a range of industries: British Airways, the British Airports Authority, British Coal, British Gas, British Rail, British Steel, British Telecom, the Post Office, and electricity suppliers, from 1970 to 1990. This period includes various regulatory reforms and also the first years of privatisation in some of the industries, e.g. British Telecom in 1984, British Gas in 1986, British Airways and the British Airports

Authority in 1987, British Steel in 1988, while just missing the privatisation of electricity supply in 1990 and 1991. The authors find that in most cases there was a noticeable increase in TFP growth and labour productivity growth rates in the 1980s relative to those of the 1970s, and suggest that the former result is driven partly by substitution of other factors for labour. Discussing trends in the various industries examined and the likely sources of observed TFP growth, the authors state that scale effects were probably part of the reason for TFP growth, albeit a small one, while changes in rates of technical change were likely immaterial; the authors therefore conclude that the main source of TFP growth over the period was efficiency improvements as a result of changes in regulation and ownership.

Similarly, an analysis of the twelve British Gas from 1977-78 to 1991 by Waddams Price and Weyman-Jones (1996) finds that TFP growth was significantly higher in the post-privatisation period—i.e. after 1985-86—than in the pre-privatisation period, and that almost all of the TFP growth over the entire sample period was driven by technical progress, with very little change in efficiency. The authors construct DEA-based Malmquist TFP indices for twelve British Gas distribution regions, and find evidence of structural breaks in TFP growth in 1983-84 and 1984-85 as well as 1985-86, coinciding with the announcement of the intention to privatise utilities generally, the announcement of the privatisation of gas specifically, and privatisation itself, respectively. Overall, the authors conclude that increases in TFP growth occurred in anticipation of privatisation, and then again following privatisation the move to incentive regulation led to an increase in TFP growth.

An analysis of historical forms of regulation in the UK gas supply industry is undertaken by Hammond et al. (2002), who compare the efficiency of UK gas utilities under three different systems of regulation—maximum price, sliding scale, and basic price—in the interwar period. As described by the authors, maximum price regulations were accompanied by dividend restrictions, and while companies were able to obtain increases in prices when costs increased, local authorities able to secure their reduction when costs fell. Sliding scale regulation established a 'standard price' alongside a maximum dividend; for every penny charged above (below) the standard price, the maximum dividend rate was reduced (increased) by 0.25%. Finally, the basic price system established a standard price and a basic, rather than maximum, dividend rate. If the company lowered its average price below the standard rate, then for each unit sold it was allowed to distribute a fixed share of the difference as additional dividends or employee bonuses or some mixture of both.

The authors argue that maximum prices were being largely non-binding during the sample period, and the associated dividend restrictions offered little incentive to minimise costs, while the sliding scale system allowed shareholders to capture the benefits of price and cost reductions. However, the authors argue that the basic price system had the strongest incentives of the three, since it regulated the average—rather than the maximum—price charged by the firm. Applying DEA to a 1937 cross-section of 121 gas utilities, the authors find, in line their expectations, that mean technical efficiency is highest among utilities subject to basic price regulation, followed by those under the sliding scale rule, then maximum price regulation.

Another analysis of alternative forms of regulation is that of Dalen and Gómez-Lobo (2003), who examine the impact of different regulatory contracts on the cost efficiency of Norwegian bus operators. The authors estimate a stochastic cost frontier using an unbalanced panel of data on 142 bus operators over the period 1987 to 1997. During the sample period, three different types of regulatory contract were in use: in the first, companies annually negotiate lump sum payments from county authorities given their costs of operation and is therefore argued to offer little incentive for cost efficiency. In the second, ‘standard cost’ is calculated as a linear function of certain characteristics such as route length, thus giving more incentive to lower cost relative to the standard cost benchmark. Third, a subsidy capping approach was introduced in some areas from 1994 onwards, in which a percentage reduction in subsidies over a five-year period is negotiated between counties and companies, resulting in a regime similar in spirit to RPI-X price capping arrangements. The authors find that the standard cost and subsidy capping approaches are associated with greater efficiency than the traditional negotiated lump sum subsidy approach, and also that, in the standard cost case, efficiency increases the longer the contract is in place. No similar dynamic effect is found for subsidy capping, though the authors point out that this may be due to the short length of time between the introduction of these contracts and the end of the sample. The authors therefore conclude that contracts with higher-powered incentives do in fact seem to have been effective at increasing cost efficiency of Norwegian bus operators.

4.3. Ownership and Efficiency

In the empirical literature on efficiency and productivity, a large number of studies are concerned with the relationship between ownership and efficiency, e.g. whether privately owned or publicly owned firms are more efficient. This question is particularly important in the context of utility industries such as water and electricity supply, where public, private, and other ownership models have been found, and ownership has varied over time and between countries. Although ownership effects are not the primary focus of this thesis, our empirical analysis of the water and sewage industry in chapter 5 includes data on the publicly owned Scottish and Northern Irish water companies. This section reviews the existing empirical literature on ownership and efficiency and productivity in the particular cases of the water and electricity supply industries.

4.3.1. Water and Sewage

The literature on the relationship between ownership and efficiency in the water industry is reviewed by Walter et al. (2009), who find that conclusions are mixed, with some studies indicating that publicly owned utilities are less efficient than privately owned utilities, others that they are more efficient, and yet others that there is no significant difference in efficiency. One strand of literature reviewed is that on trends in efficiency and productivity growth following the privatisation of the water industry in England and Wales, which we discussed in the previous section. To briefly recap, these studies generally find that there was no significant effect from privatisation alone, but that increased efficiency and TFP growth followed the tightening of price caps in subsequent price controls.

Aside from these, there is a large literature comparing directly the performance of water utilities under private, public, and other forms of ownership, made possible by the coexistence, in many countries, of utilities under various forms of ownership, and also by international comparisons. Several papers using US data address the issue of ownership in this way. Two papers by Bhattacharyya et al. (1994, 1995) use data on a 1992 cross-section of American water utilities. The first paper, using a shadow cost function approach, finds that publicly-owned utilities are more efficient than privately-owned utilities, in terms of both technical and allocative efficiency. Likewise, the second paper, which uses SFA, likewise finds that publicly owned utilities are more cost inefficient than their privately owned counterparts. Furthermore, Destandau and Garcia (2014) use 1996 data on US water utilities to estimate a variable cost function with a system of factor share equations, and find that privately-owned utilities have significantly higher marginal costs.

On the other hand, Mosheim (2006) uses data on US water utilities in 1996 to estimate a shadow cost function, and finds that there is no statistically significant ownership effect when more flexible specifications are used. Likewise, Teeples and Glyer (1987), who estimate cost functions with factor share equations using 1980 data on Californian water utilities, find no statistically significant ownership effect when more general specifications are used. Further, Feigenbaum and Teeples (1983) estimate cost functions using cross-sectional data on publicly-owned and privately-owned US waterworks in 1970, and conclude that there is no significant difference in the cost structures of the two groups of firms.

In France, Lannier and Porcher (2014), using a three-step DEA approach, find that publicly-owned utilities are more technically efficient than their privately-owned counterparts, and Chong et al. (2006), using data on a 2001 cross-section of all 5000 local authorities, find that public management tends to result in lower prices than public-private partnership. Another analysis of price differences between privately and publicly owned water utilities in France is that by Carpentier et al. (2006) using data from a 1998 survey of water prices at local authority level, who also find higher prices found among privately-owned utilities. However, the authors also find that these are mostly explained by the operating conditions of private firms, i.e. privately-owned firms operate in more difficult environments, since municipalities have a greater tendency to delegate water provision to the private sector where the operating environment is less favourable.

Zschille and Walter (2012) analyse the technical efficiency of German water utilities using a three-step DEA method, and estimate cost efficiency using SFA. The authors' DEA results suggest that privately owned water utilities are less technically efficient than those under public or mixed ownership, while the authors find no significant difference in cost efficiency using SFA. A study of municipal water services in Spain is undertaken by García-Sánchez (2006), who use a three-step DEA method. The authors find no significant difference between the technical efficiencies of publicly owned ad privately owned utilities.

Several papers concern the relationship between ownership and efficiency in water utilities in developing countries. Two papers by Estache and Rossi (2002a, 2002b) examine the efficiency of water utilities in Asia and Africa, respectively. In particular, the studies look at the impact of public versus private ownership—and in the second paper, indices relating to governance quality and corruption—on cost inefficiency. The first paper uses data on a 1995 cross-section of 50 firms from 19 different Asian countries. The authors find no evidence for a statistically significant difference in inefficiency between publicly owned and privately owned utilities. The second paper uses data from an unbalanced panel of 21 African water utilities from sixteen different countries from 1995 to 1997 to estimate a production frontier via GLS. Corruption and governance are found to negatively impact efficiency, and a positive and statistically significant relationship between private ownership and technical efficiency is found. Another study looking at the impact of ownership on water utility costs in Africa is that of Kirkpatrick et al. (2006), which uses data on 110 water utilities for the year 2000 to estimate cost efficiency via DEA and SFA. The DEA results indicate greater efficiency among privately owned utilities, whereas the SFA results show no significant difference between privately owned and publicly owned utilities.

Finally, two studies by Picazo-Tadeo et al. (2009a, 2009b) analyse the efficiency of Andalusian water utilities. The first uses a three-step DEA approach, and finds that with regards to the use of certain individual inputs, particularly labour, privately owned utilities are more efficient, but that the difference in overall technical efficiency is not statistically significant. The second paper takes a similar approach, and reaches a similar conclusion. Note that this complements the findings of Erbetta and Cave (2007) with respect to water privatisation in England and Wales.

4.3.2. Electricity Supply

As in the water industry, the relationship between performance and ownership in electricity supply has attracted a great deal of attention in the empirical literature. An example of this is the book-length investigation of the relationship between ownership and performance in electricity supply by Pollitt (1995), which across many different datasets and methodologies finds little evidence of ownership effects in either generation or in transmission and distribution. In one application, the author uses DEA and OLS to estimate technical efficiency scores and a cost function, respectively, using data on nine of the UK PESs and 145 US electricity distribution utilities in 1990, finding no significant ownership effect with regard to technical or cost efficiency.

In another application, Pollitt (1995) analyses the performance of electric utilities in generation and in transmission and distribution by applying the shadow cost function approach and the linear programming method of Färe et al. (1985) to estimate the cost efficiency of an international cross-section of 95 thermal electricity generating utilities in 1985-86. Results from the linear programming approach suggest that privately-owned utilities outperform municipally-owned utilities in terms of allocative efficiency, but only a negligible difference in technical efficiency, and no significant difference in overall efficiency. Likewise, using the shadow cost function method, the author finds no significant difference in the cost efficiency of privately-owned and municipally-owned utilities.

Yet another application by Pollitt (1995) applies four methods—DEA, linear programming, COLS, and SFA—to an international cross-section of 768 plants in 1989. Overall, the author concludes that there seems to be no statistically significant effect of ownership on technical efficiency. A later study by Pollitt (1996) applies DEA to assess plant level technical efficiency in nuclear power generation using international data from 1988-89 on 78 plants. Comparing single-factor productivities, the author finds that privately-owned and publicly-owned plants are very similar in terms of capital and energy productivity, but that the labour productivity of publicly-owned plants is notably lower. However, little difference is found in ex-ante technical efficiency or allocative efficiency, or therefore in efficiency overall.

On the basis of Pollitt's analyses of international data, there does not seem to be any clear relationship between ownership and the performance of electric utilities. A slightly clearer picture emerges when we consider studies pertaining to particular countries, however.

A relatively large strand of literature examines the relationship between ownership and performance among US electric utilities, and with several using data on utilities within the Tennessee Valley Authority in particular. These studies are of particular interest due to the diversity of the modes of ownership analysed. For example, aside from public and private ownership, several studies cover utilities under municipal or cooperative ownership.

A common finding in this literature is that public, municipal, and private ownership are generally associated with lower prices and profits than private ownership. Hollas and Stansell (1988) use data on US generation utilities from 1977 to 1980 to examine the differences in profit efficiency between privately-owned, cooperatively-owned, and publicly owned utilities. The authors estimate a translog profit function, together with a set of input demand functions, and therefore conclude that privately-owned utilities are the closest to profit maximising, followed by cooperatively-owned utilities, and then publicly-owned utilities. Similarly, Hollas et al. (1994) use data on utilities in the Tennessee Valley Authority area for the 1987 financial year to estimate a system of demand, price, and cost equations. The impact of ownership on costs is not reported, but municipal ownership is found to be associated with lower prices and a greater tendency to engage in a form of price discrimination that favours domestic and commercial customers at the expense of industrial customers.

A perhaps more surprising conclusion from this literature is that privately owned electric utilities are generally found to have higher costs, other things being equal, than publicly or municipally owned utilities. Meyer (1975) estimates cost models for various electricity supply chain activities—generation, plant maintenance, transmission, and distribution—using data on integrated US electricity utilities from 1967 to 1969, finding significantly lower production and maintenance costs among publicly owned utilities, but no significant difference in transmission and distribution costs. In addition, the authors find that publicly-owned utilities charged significantly lower prices on average for all classes of customers.

Neuberg (1977) estimates cost functions using data on US utilities in 1972, and finds that municipally-owned utilities have lower costs than privately-owned utilities. Similarly, Pescatrice and Trapani (1980), using data on US generation utilities from

1965 to 1970 find that publicly-owned utilities have significantly lower costs, other things being equal.

Two studies by Atkinson and Halvorsen (1984, 1986) use the Christensen and Greene (1976) dataset on US generation utilities in order to estimate shadow cost functions with factor share equations. The results of both studies suggest that there is no systematic difference in allocative efficiency levels according to ownership. Using the same dataset, Färe et al. (1985) apply the linear programming method of Farrell (1957) to estimate the overall cost efficiency of the generation utilities in the sample, finding greater technical efficiency among publicly owned utilities, but no significant difference in allocative efficiency.

Running counter to the aforementioned studies, Berry (1994) extends the analysis of Hollas and Stansell (1988) by including distribution utilities, and finds that cooperatively-owned utilities have higher costs than privately owned utilities.

Two studies of Tennessee Valley Authority distribution utilities compare performance under cooperative ownership and municipal ownership. Clagget (1994) estimates a modified translog cost function with factor share equations, finding that cooperative ownership is associated with lower costs compared to municipal ownership, and Clagget and Ferrier (1998), using data from 1984 to 1989 covering 157 of the 160 distributors in the area during that period, applies the linear programming method of Farrell (1957) to derive estimates of technical, allocative, and scale efficiency, finding that cooperatively-owned distributors are more technically efficient, but less allocatively efficient than their municipally-owned counterparts, and that there is no apparent ownership effect on overall cost efficiency.

In addition to the US literature, several studies have compared performance under the various forms of ownership found in the Swedish electricity distribution industry, e.g. privately-owned companies, municipally-owned companies, municipal utilities, and economic associations, the latter being a form of cooperative. Two studies by Hjalmarsson and Veiderpass (1992a, 1992b), analysing technical efficiency and TFP growth from 1970 to1986. In the first study, the authors find higher efficiency scores on average for municipally-owned companies and municipal utilities than for economic associations and privately-owned companies, though since the former tend to be much larger than the latter, no significant difference is found when scale effects are controlled for. The second study finds no significant difference in DEA-based Malmquist TFP between the four aforementioned forms of ownership, though municipal utilities appear to be generally the most technically efficient. Kumbhakar and Hjalmarsson (1998) cover a similar period, from 1970 to 1990, using three different methods: an input requirement function, a stochastic input requirement frontier, and DEA. In contrast to the findings of Hjalmarsson and Veiderpass (1992a, 1992b), the authors conclude that privately-owned firms were more efficient over the period.

The general impression from the US and Swedish studies, then, is that municipal ownership and public ownership are lower cost and more efficient than private ownership, whereas findings on cooperative ownership are mixed. Meanwhile, privately-owned utilities seem to be more profitable and charge higher prices.

A study by Diewert and Nakamura (1999) implies that the relationship between ownership and efficiency may differ depending on a country's level of development. The authors apply the Farrell (1957) linear programming method to analyse plant-level efficiency in diesel generation using data on 77 plants from 28 developed and developing countries. The authors find that the average efficiency of privately-owned plants is higher than that of publicly-owned plants in Tanzania and the Caribbean, but that the reverse is true in the UK.

4.4. Economies of Scale and Density

Although scale and density properties are not the focus of this thesis, they are an important consideration in modelling of costs or production. Large literatures exist estimating returns to scale and density in the water and sewage and electricity distribution industries, among others, and these are of natural interest given their implications for optimal firm size and industry structure. In a regulatory context, the extent to which the firm is subject to economies or diseconomies of scale or density also has implications for potential TFP growth and therefore optimal price or revenue caps, as discussed in section 2.5. In this section, we review existing findings regarding economies of scale and density, first in the water and sewage industry, and then in the electricity distribution industry.

4.4.1. Water and Sewage

The literature on economies of scale and density in the water industry is reviewed Carvalho et al. (2012). The authors perform a metaregression study of scale and scope economy estimates from 35 published costs studies of the water industries of various countries. This is essentially a systematic method of reviewing the relevant literature review and summarising findings, in which estimates of scale economies are regressed on several variables capturing characteristics of the firms studied, the studies, and the methods used. Among these variables, only three—country GDP per capita, number of estimation methods used, and crucially the average size of the firms under study—are found to be statistically significant. The sign on the latter variable is negative, suggesting that the larger the utilities in the sample, the lower the average estimate of scale economies. Similarly, in another review of the literature, Walter et al. (2009) conclude that economies of scale exist only in fragmented water industries.

This finding seems to complement the overall impression from the literature, in which average economies of scale tend to be greater the smaller the firms in the sample, and also reported variation in economies of scale within studies, as discussed below. With regards to density, Carvalho et al. (2012) find that the picture is more straightforward: most studies indicate significant economies of density, i.e. that unit costs fall as network density or usage per customer increases. We also find that this is the case in studies where a measure of density is included. For the avoidance of repetition, we remark on findings with respect to density only when they are at odds with the wider literature.

In line with the findings of Carvalho et al (2012), we tend to find in the literature that the English and Welsh WaSCs are subject to constant or decreasing returns to scale, while studies including the smaller WOCs tend to suggest increasing returns to scale for these firms. An analysis of economies of scale and scope in the English and Welsh industry by Stone & Webster (2004), which estimates a variety of different models, suggests increasing returns to scale among the smaller WOCs and decreasing returns to scale among the large WaSCs.

Taking into account the firms included in each study, results from the literature on costs and production in the English and Welsh water industry generally reinforce this picture. For example, the WOC cost function estimated by Lynk (1993) implies increasing returns to scale amongst the small statutory water companies—which later became the WOCs—in the pre-privatisation period.

Furthermore, analyses considering only the WaSCs tend to find constant or decreasing returns to scale: Saal and Parker (2000), estimating a translog cost function, find decreasing returns to scale among English and Welsh WaSCs from 1985-1999. Estimating a stochastic distance function, Saal and Parker (2007) likewise find decreasing returns to scale. Saal and Parker (2001) use various parametric and non-parametric methods to estimate changes in TFP among the WaSCs over the 1985-1999 period, and their results suggest constant returns to scale. Saal and Reid (2004) estimate a variable cost function for the WaSCs using data from 1993 to 2003, and likewise their findings suggest approximately constant returns to scale. The authors' estimates of economies of density in the latter study are interesting, since they imply economies of density in sewage treatment, but diseconomies of density in water supply, in contrast to most studies.

One exception is a study by Ashton (2000), who estimates a translog cost function and finds substantial economies of scale using data on the WaSCs from 1987-1997. This finding seems to be the exception, as most studies suggest the WaSCs are characterised by constant or decreasing returns to scale. This unusual finding may however be explained by the author's use of a fixed effects specification: given that we generally observe scale variables for utility firms to be relatively invariant over time, scale effects are likely being picked up in part by the fixed effects. Bottasso and Conti (2003), who estimate a translog cost function for water activities—excluding sewage activities—using data on both the WaSCs and the WOCs, find increasing returns to scale at the sample means.

Outside of the UK, the literature also generally reinforces the idea of increasing returns to scale for smaller utilities and constant or decreasing returns to scale for larger utilities. First, a number of studies analysing data on small water utilities find increasing returns to scale. Two studies by Battacharyya et al (1994, 1995) find increasing returns to scale among US water companies. Kim and Lee (2004) analyse economies of scale in the fragmented water industry around the Seoul Metropolitan Region, finding evidence of increasing returns to scale. Fillipini et al (2008) find increasing returns to scale for small firms in their analysis of the Slovenian water industry, in which companies tend to be very small, with the mean number of customers at just 7,402. Teeples and Glyer (1987) also find economies of scale—at least at the sample mean—in their analysis of 119 Southern Californian water firms, and although no specific information is provided on the average size of these firms, they are bound to be far smaller than the English and Welsh WaSCs given their number. In a study of the costs of French municipal water suppliers, which are generally than UK water companies, Garcia and Thomas (2001) find substantial increasing returns to scale. Unusually, they also fail to reject a unit elasticity with respect to network density.

Second, several other studies also find that increasing returns to scale are exhausted beyond a certain size, and in some cases that decreasing returns set in. Hayes (1987) estimates a cost function using data on US water utilities, and finds increasing returns to scale for small firms, but not for large firms in the US. This finding is echoed by Torres and Morrison Paul (2006), also on the basis of a cost function for US water utilities. Likewise Aubert and Reynaud (2005), estimating a cost function for Wisconsin water companies over the 1998 to 2001 period, finding increasing returns to scale for the smallest firms, while failing to reject constant returns to scale among medium to large firms, and Feigenbaum and Teeples (1983), analysing the costs of US waterworks, find that there are initially increasing returns to scale, but that these are exhausted for higher levels of output.

A set of studies on cost in the Italian water industry also paints a very similar picture. The Italian water industry is particularly interesting in this regard, since it is highly fragmented and contains a wide range of firm sizes. Fabbri and Fraquelli (2000) find increasing returns to scale at for smaller Italian water utilities being exhausted by the sample average, with decreasing returns to scale setting in largest firms in the sample. Because their sample contains most of the larger water companies in Italy but only a small proportion of the smaller companies, the authors conclude that most Italian water companies fall within a range in which large economies of scale are present. Fraquelli and Giandrone (2003) also find large economies of scale for smaller firms in Italy, while Fraquelli and Moiso (2005) find economies of scale generally, though again larger for smaller companies. Using data on a small number of mainly larger Italian water utilities, Antonioli and Filippini (2001) estimate a variable cost function and find decreasing returns to scale.

To summarise, there is strong evidence from the existing literature, as noted previously by Carvalho et al. (2012) and Walter et al. (2009) that small water utilities are subject to increasing returns to scale, while larger water utilities are subject to constant or even decreasing returns to scale.

4.4.2. Electricity Supply

As with the water and sewage industry, a large literature exists estimating returns to scale and density in the electricity supply industry, though to our knowledge no extensive review of this literature currently exists. We begin by reviewing the existing literature on returns to scale and density in the UK electricity distribution industry, before moving on to consider evidence from other countries.

Compared to the extensive literature on the UK water and sewage industry, studies on electricity distribution costs in the UK are relatively sparse. Burns and Weyman-Jones (1996), using data on the distribution and supply activities of the English and Welsh PESs from 1980-81 to 1992-93, estimate a variety of cost models using OLS and SFA methods, and find evidence of significant economies of both scale and density, as do Frontier Economics (2013) using more recent data on the DNOs in Great Britain. Likewise, in their study comparing the efficiency of distribution utilities in Great Britain and Japan, Hattori et al. (2005) find evidence of increasing returns to scale in both countries. In contrast, Jamasb et al. (2012) find decreasing returns to scale but increasing returns to density at the sample means.

Outside of the UK, several studies indicate increasing returns to scale. Using data on US electricity distribution utilities in 1972, Neuberg (1977) finds that economies of scale are present over most of the observed output range, as do Kumbhakar and Hjalmarsson (1998) using data on the Swedish electricity distribution industry, and Kleit and Terrell (2001), analysing data on US generation plants in 1996. Hayashi et al. (1997), estimating a translog cost function using data on US electric utilities between 1983 and 1987, find evidence of economies of scale in generation for all sizes of firms.

Two studies using data on Swiss utilities, by Filippini (1996) and Filippini and Wild (2001) likewise find increasing returns to scale for all firms. The latter study also finds increasing returns to customer density and increasing returns to output density. Scully (1999) estimates a translog cost function using data on New Zealand electric utilities, finding evidence of scale economies at all levels of output within the sample, and Huang et al. (2010) apply SFA to data on the 24 distribution districts of Taipower—Taiwan's state-owned electric utility—over the 1997-2002, finding that the districts are operating considerably below their optimal scales. A study of the German electricity distribution industry by von Hirschhausen et al. (2006) also finds evidence for slightly increasing returns to scale.

Other studies findings are more nuanced, with Coelli et al. (2013) finding increasing returns to scale among low density networks, but decreasing returns to scale for high density networks. Salvanes and Tjøtta (1994) estimate a translog variable cost function using data on Norwegian electricity distribution utilities. The authors find increasing returns to density and modest increasing returns to scale for small firms, but fail to reject increasing constant returns to scale at the sample average. Similarly, Christensen and Greene (1976) find significant increasing returns to scale at low levels of output and constant returns to scale at higher levels of output among US generation utilities, and Rungsuriyawiboon and Coelli (2006) find constant returns to scale at the sample mean using data on US electricity supply utilities from 1986 to 1998. Fraquelli et al. (2005) find decreasing returns to scale in generation, but constant returns to scale in distribution using data on Italian municipal electric utilities.

The literature on electricity supply therefore generally indicates either increasing returns to scale at all output levels, or that returns to scale are initially increasing but exhausted beyond a certain point.

4.5. Quasi-Fixed Inputs and Variable Costs

In section 2.6, we show the firm’s standard cost minimisation problem. This assumes that the firm is able to minimise costs with respect to all inputs, and yields costs as a function of output and input prices. In reality, there may be certain quasi-fixed inputs which the firm is unable to adjust in the short term. Factor costs associated with such quasi-fixed inputs are then quasi-fixed costs, and the firm’s problem in the short run is to minimise variable costs, disregarding quasi-fixed costs and taking quantities of quasi-fixed inputs as given. In this way, a variable cost model may be derived in which variable costs—i.e. the sum of costs relating to non-quasi fixed inputs—are a function of output, the factor prices for non-fixed inputs, and the volumes of the quasi fixed factors.

This approach was suggested by Caves et al. (1981) and applied to estimate a variable cost function using data on US and Canadian railways, in which they argued capital was a quasi-fixed input, and has since been applied in a large number of studies in which one or more inputs—usually capital—is thought to be quasi-fixed. Oum et al. (1991) discuss the estimation of returns to scale via such models. A variant of this approach, suggested by Oum and Zhang (1991), is to allow for the possibility that the capital price is a function of capital utilisation, and while capital is quasi-fixed, the firm can choose its capital utilisation rate. A proportion of the costs relating to quasi-fixed capital are then variable. The authors show that this approach yields a kinked variable cost function with no continuous partial derivative with respect to capital stock, so that no smooth, flexible functional form can serve as a satisfactory second order approximation. To solve this issue, the authors suggest that capital stock in the variable cost model be replaced by a measure of the service flow from capital. This, however, requires a reliable measure of the rate of utilisation of the capital stock. Given these issues, the Oum and Zhang (1991) approach has not been widely applied.

In the literature modelling water utility costs, variable cost functions have been estimated by Bhattacharyya et al. (1995), Garcia and Thomas (2001), Antonioli and Filippini (2001), Saal and Reid (2004), Stone & Webster (2004b), Aubert and Reynaud (2005), and Destandau and Garcia (2014) among others. Saal and Reid (2004) suggest that this approach is appropriate in the context of the water industry, with its quasi-fixed capital stock, and use regulatory accounting data on fixed assets as a measure of capital.

On the other hand, Saal and Parker (2000) argued that, in the English and Welsh water and sewage industry, an increase in capital growth and evidence of substitution of capital for other inputs indicates that a total cost approach is appropriate, and most of the cost studies discussed in the preceding sections estimate total, rather than variable, cost functions. In our empirical chapter on the water industry, we estimate both total cost and variable cost models so that we may see the sensitivity of our results to the approach used.

Returning to the derivation of our revenue frontier (34) and cost frontier (35), consider that altering the monopolist's profit maximisation problem shown in such that one of the inputs are does not affect the revenue maximisation problem, meaning that we simply substitute a variable cost frontier for (35).

4.6. Summary

This chapter has reviewed a large number of studies on cost and production in the water and sewage industry, the electricity generation, transmission, and distribution industries, and other regulated industries. This section summarises previous findings and discusses their implications for our empirical analyses in the next two chapters.

Summarizing the existing evidence on the relationship between regulation and performance in the UK water and sewage and electricity distribution industries, we can say that:

i. There is little to suggest that efficiency or TFP growth significantly improved as a direct result of privatisation in either industry. The immediate post-privatisation periods were characterised by loose price and revenue caps set by government, which allowed significant profits to be made but created little incentive to increase productivity.
ii. The tightening of price and revenue caps by Ofwat and OFFER respectively in PR94 and DPCR2, and further tightening in PR99 and DPCR3, both seem to have spurred significant gains in efficiency and TFP.
iii. In the water and sewage industry, TFP seems to have declined following a substantial loosening of price caps in PR04.
iv. Firms in both industries seem to have performed better than their counterparts in other countries that are subject to more low-powered RoR regulatory regimes.

Together, these points suggest that incentive regulation can be effective in inducing improvements in performance in terms of efficiency and productivity growth, but that this effectiveness is dependent on the stringency of the regulatory constraints imposed.

With respect to the effect of ownership on efficiency and productivity in the water and sewage and electricity supply industries, findings in the literature are mixed, though a number of US studies seem to indicate that municipally or publicly owned electric utilities are more efficient than those that are privately owned.

In terms of economies of scale, the literature on the water and sewage industry strongly suggests that returns to scale are increasing for small firms, but constant or decreasing for larger firms. In electricity distribution and supply, many studies indicate increasing returns generally, including in the UK where the DNOs are rather large. These findings indicate the importance of allowing for variable returns to scale in water and sewage and electricity distribution, and therefore provide a motivation for using a flexible translog functional form in cost and production modelling when seeking to analyse efficiency. A further important observation from the literature is that density-related costs appear to be important, with the majority of studies that account for network density—in both the water and sewage supply and electricity distribution industries—finding that there are economies of network or output density; this is reasonable, since in network industries, the main effect of increasing network density is to reduce the amount of infrastucture, and hence infrastructure-related costs, per customer. It is therefore important to include network density measures to capture this effect.

5. Regulation and the Efficiency of UK Water and Sewage Companies

5.1. Introduction

In this chapter, we analyse the efficiency of firms in the water and sewage industry in the UK, adopting the theoretical framework and empirical specification outlined in previous chapters. Specifically, we analyse the revenue and cost efficiency by estimating revenue and cost frontiers as described by (34) and (35), using the Battese and Coelli (1995) stochastic frontier specification in which inefficiency is a function of a vector of environmental variables. We begin by identifying relevant peculiarities in the water and sewage case, describing the data, the sample, and model specifications. Following this, we present parameter estimates, post-estimation predictions of cost inefficiencies and revenue efficiencies, and the marginal effects of our environmental variables on inefficiency.

5.2. Models

In this chapter we use data on the water and sewage companies (WaSCs) and water only companies (WOCs) in England and Wales, along with data on the publically-owned Scottish and Northern Irish water companies and the former Scottish water authorities, to estimate four stochastic frontier models: a total cost model, a variable cost model, a water revenue model, and a sewage revenue model. We use these models to analyse the overall efficiency of firms in the industry and how this has been affected by regulation and other factors. In particular, we focus on the trends in revenue and cost efficiency measures and the estimated marginal effects of regulatory and other environmental variables on them.

As discussed in chapter 3, we use the Battese and Coelli (1995) stochastic frontier model, in which inefficiency is modelled as a function of a set of covariates. The following sections outline the model specifications for each of our four models.

5.2.1. Cost Models

As explained in chapter 2, the difference between total cost and variable cost functions are that, in the latter, capital is treated as a fixed factor. The dependent variable therefore becomes variable costs—that is, total costs minus capital costs—and on the right hand side, the capital price is replaced by a measure of the physical quantity of capital as an independent variable.

We estimate both total and variable cost frontiers, since on the one hand it may be argued that the assumption of total cost minimisation is inappropriate in the case of the water and sewage industry because the firm's influence over its capital stock is constrained by the need to meet regulatory and legal requirements on environmental standards, water quality and service levels. On the other hand, the findings of Saal and Parker (2001) imply a significant degree of substitution of capital for other inputs, especially labour, in the English and Welsh water-and-sewage companies (WaSCs) since privatisation. By estimating both total and variable cost frontiers, we may examine the robustness of our conclusions to the specification used.

We specify a flexible translog functional form for the cost models. The advantage of the translog form over the Cobb-Douglas is its flexibility; it allows for non-constant returns to scale and elasticities of substitution, and for non-neutral technical change. The main disadvantage is multicollinearity, especially between variables and their squared terms and cross products, which can lead to implausible parameter estimates and inflated standard errors. For this reason, many studies exploit the fact that Shephard's lemma can be used to derive input cost-share equations (Diewert 1971, 1974), which gives a system of simultaneous equations consisting of the cost function and W-1 cost-share equations—where W is the number of inputs, one being omitted in order to avoid singularity of the covariance matrix—increasing degrees of freedom and enabling more accurate parameter estimates. However, in the context of frontier estimation, we encounter what is known as the Greene problem: that the overall cost inefficiency effect in the cost frontier and the disturbances in the cost-share equations are complicated functions of allocative efficiency (Greene 1980b); notwithstanding several approaches suggested for this problem—notably (Kumbhakar and Tsionas 2005)—most studies of cost efficiency simply opt for simpler functional forms such as the Cobb-Douglas. As previously mentioned, we employ both translog and Cobb-Douglas forms, since although multicollinearity may lead to implausible parameter estimates in the frontier itself, estimates of the residual and its decomposition into noise and inefficiency effects—our primary concern—should not be adversely affected; indeed, they should improve along with the fit of the model.

We estimate the following translog stochastic total cost frontier model:

$$\ln C_{i,t} = \ln\alpha + \theta t + \sum_{q=1}^{2}\beta_q \ln Q_{qit} + \sum_{w=1}^{4}\gamma_w \ln W_{wit} \tag{84}$$

$$+\sum_{h=1}^{4}\beta_h \ln H_{hit} + \vartheta t^2 + \sum_{q=1}^{2}\varphi_q t \ln Q_{qit} + \sum_{w=1}^{4}\phi_w t \ln W_{wit}$$

$$+\frac{1}{2}\sum_{q=1}^{2}\sum_{y=1}^{2}\zeta_{qy}\ln Q_{qit}\ln Q_{yit} + \frac{1}{2}\sum_{w}^{4}\sum_{p}^{4}\eta_{wp}\ln W_{wit}\ln W_{pit}$$

$$+\sum_{q=1}^{2}\sum_{w=1}^{4}\lambda_{qw}\ln Q_{qit}\ln W_{wit} + v_{it} + u_{it}$$

And the following translog stochastic variable cost frontier model:

$$\ln VC_{i,t} = \ln\alpha + \theta t + \sum_{q=1}^{2}\beta_q \ln Q_{qit} + \sum_{w=1}^{3}\gamma_w \ln W_{wit} + \chi \ln K_{i,t} \tag{85}$$

$$+\sum_{h=1}^{4}\beta_h \ln H_{hit} + \vartheta t^2 + \sum_{q=1}^{2}\varphi_q t \ln Q_{qit} + \sum_{w=1}^{3}\phi_w t \ln W_{wit} + \kappa t \ln K_{i,t}$$

$$+\frac{1}{2}\sum_{q=1}^{2}\sum_{y=1}^{2}\zeta_{qy}\ln Q_{qit}\ln Q_{yit} + \frac{1}{2}\sum_{w=1}^{3}\sum_{p=1}^{3}\eta_{wp}\ln W_{wit}\ln W_{pit}$$

$$+\mu\left(\ln K_{i,t}\right)^2 + \sum_{q=1}^{2}\sum_{w=1}^{3}\lambda_{qw}\ln Q_{qit}\ln W_{wit} + \sum_{q=1}^{2}\varpi_q \ln Q_{q,i,t}\ln K_{i,t}$$

$$+\sum_{w=1}^{3}\pi_w \ln W_{w,i,t}\ln K_{i,t} + v_{it} + u_{it}$$

Where in both cases:

$$v_{it} \sim N(0, \sigma_v^2) \tag{86}$$

$$u_{it} \sim N^+(\mu_{it}, \sigma_u^2)$$

$$\mu_{it} = \delta_0 + \sum_{z=1}^{6} \delta_z Z$$

In the expressions above, i, t, q, w and z are indices for specific firms, years, outputs, input prices, and hedonic variables, respectively.

We now briefly summarise the variables included in the cost models; detailed information about definition and construction of variables is given in section 5.3, and summary statistics are given in section 5.3.3. Both total and variable cost models include two output variables, Q_1 and Q_2, which refer to the number of properties connected for water and billed for sewage, respectively.

There are four input prices: W_1, W_2, W_3, and W_4. Respectively, these are labour costs per employee, an industrial price index for electricity, the retail price index, and a measure of the opportunity cost of capital. All of these are included in the total cost model, whereas the capital price W_4 is replaced by K, a measure of the capital stock, in the variable cost model. The coefficient on K is usually expected to have a negative sign, given that capital costs are excluded from the variable cost model, and an increase (decrease) in capital employed should reduce (increase) the use of non-capital inputs, ceteris paribus. However, in the empirical literature, a positive estimated sign is relatively common. Two possible explanations for this have been advanced: firstly, that it indicates a very high degree of overcapitalisation, to the extent that both fixed capital costs and variables costs are increasing in capital stock, as proposed by Cowing and Holtman (1983), and secondly, that it is caused by a high degree of multicollinearity between capital stock and output, meaning that the result does not have a clear interpretation, as proposed by Guyomard and Vermersch (1989).

We also include four 'hedonic' variables in the cost frontiers: H_1 is the proportion of water properties that are metered, H_2 is the density of the company's network measured by the number of water properties connected per km of water mains, H_3 is a measure of water quality, and H_4 is the proportion of water properties above a reference pressure level. The former two capture important characteristics of the firm's network, while the latter two capture quality of service.

The inefficiency model, shown in (86), includes six 'environmental' variables. First, Z_1 is the replacement value of the firm's fixed assets, included as a proxy for size. There is a large literature on the relationship between firm size and efficiency, and though this is not of primary interest in this thesis, we include Z_1 as a control. To capture the impact of regulation on efficiency, we include two variables. First, Z_2 is the number of years the firm has been subject to a form of price capping regulation, intended to capture the long term effect of incentive regulation. Following the discussion in chapter 2, and previous findings reviewed in chapter 4, we would expect cost efficiency to improve over time under incentive regulation. Second, Z_3 is the K factor, or the allowed percentage increase in prices, for the firm in a given year, intended to capture the short term effect on efficiency of a change in the price cap. Note that this is not to be confused with K, the capital stock. We expect an inverse relationship between efficiency and Z_3, since a smaller (larger) K factor creates more (less) incentive to improve efficiency.

In addition, we include a dummy for public ownership, Z_4, in the inefficiency model. As discussed in chapter 4, there is a large literature on the impact of ownership on efficiency, and our sample includes several publicly owned firms, specifically Scottish Water, Northern Ireland Water, and the three former Scottish water authorities. The expected impact of ownership on efficiency is unclear, since as Renzetti and Dupont (2004) point out, while we may expect publicly owned firms to be less efficient on the basis of public choice theory, differences in property rights, or a more pronounced principal-agent problem, empirical findings on the impact of ownership on performance in the water industry are mixed.

Finally, we include two variables capturing the effect of board structure on efficiency. We are primarily concerned with the impact of information asymmetry between regulator and firm; however, another potential explanation of inefficiency is the principal-agent problem created by the divorce of ownership and control. Owners, in turn, may seek to minimise this information in a number of ways: e.g. through performance-related pay, or by increasing the intensity of monitoring. Data on performance-related pay arrangements was unfortunately unavailable, but using a combination of the firms' regulatory and statutory accounts, we were able to construct two measures of the structure of the board—i.e. the board of directors—which we regard as reflecting the ability of management to withhold information from the firm's owners.

The first of these is the proportion of board members that are non-executives, Z_5. A non-executive director is a member of the board of directors who is not otherwise an employee of the company, as opposed to an executive director who is part of the executive management team. Non-executive directors are usually appointed for their independence as well as their expertise, and their responsibilities include the monitoring of management's performance and the accuracy of financial information. The presence of non-executives on the board may therefore serve as a check on the ability of executive management to capture rents in the form of shirking and discretionary spending, and align decision making with the interests of the firm's owners.

We therefore take the proportion of non-executives on the board as a measure of the independence of the board, and on this basis would expect a higher proportion to be associated with greater revenue and cost efficiency. Alternatively, stewardship theory posits that insiders such as executives may perform better than outsiders with regard to profit maximisation due to a greater and more intimate understanding of the firm and the environment in which it operates; see e.g. Donaldson (1990), Donaldson and Davis (1991), and Donaldson and Preston (1995), and if this is the case, we would expect a negative relationship with revenue and cost efficiency.

Our second measure of board structure is Z_6, the average number of years that a director has sat on the board. We include this as a measure of the degree of entrenchment of the firm's leadership, which may serve as an indicator of the ability of the firm's managers to resist attempts to resist efforts by the firm's owners to exert control or increase monitoring. We may therefore expect a negative relationship between this variable and firms' revenue and cost efficiency. Again however, an alternative possibility is that the measure picks up the experience of the board, which may lead to an increase in efficiency due to a learning-by-doing effect. We take the date of a directors' first appointment to the company's board—regardless of any break in their employment—as the start of their time on the board.

Before we estimate the cost models shown in (84) and (85), two changes must be made. First, both functions must be homogenous of degree one with respect to input prices. This condition is satisfied if

$$\sum_w \gamma_w = 1, \sum_w \phi_w = 0, \sum_w \eta_{w,p} = 0, \sum_w \lambda_{q,w} = 0, \sum_w \pi_w = 0 \qquad (87)$$

which can be imposed by normalising costs and input prices by one input price (Jorgenson 1986). We therefore normalise our cost and input price variables by W_3, the Retail Price Index. The variable W_3 itself therefore drops out of the model, along with its interactions. Another requirement is that the Hessian of the cost function must be symmetric with respect to input prices, that is $\eta_{w,p} = \eta_{p,w}$, which is of course imposed by the estimation in any case.

Second, the inclusion of the WOCS means that there are observations in which $Q_2 = 0$. This is problematic, given the translog functional form used, since the logarithm of zero is undefined. There are several approaches to dealing with zero values when estimating multi-output cost functions. One is to simply exclude firms with zero values of particular outputs, and model them separately. Most existing studies of the industry in England and Wales include only the WaSCs (Saal, Parker 2000, Ashton 2000); Bottasso and Conti (2003) include both WaSCs and WOCs, but model only water costs.

Another approach is to use an alternative functional form. Alternative flexible functional forms, such as the quadratic form, the generalised Leontief form proposed by Diewert (1971), or the hybrid Diewert form proposed by Hall (1973), allow for zero values for outputs. However, Caves et al. (1982) note that they have their own serious drawbacks: the hybrid Diewert form imposes constant returns to scale, while the quadratic form does not allow for the imposition of linear homogeneity in input prices. Several proposals involve the use of the Box-Cox transformation (Box and Cox 1964), which replaces x_{it} with x_{it}^*, where $x_{it}^* = \left(x_{it}^{\theta} - 1\right)/\theta$.

The advantages of this approach are that it is allows greater flexibility in functional form, and that the Box-Cox transformation includes the natural logarithmic transformation as a limiting case, since $\left(x_{it}^{\theta} - 1\right)/\theta \to \ln x_{it}$ as $\theta \to 0$. Berndt and Khaled (1979) propose a generalised Box-Cox functional form which nests generalised Leontief and quadratic forms proposed by Diewert (1971), and contains the translog as a limiting case. More commonly used are variants of the simpler Box-Tidwell functional form (Box and Tidwell 1962), in which the Box-Cox transformation is applied to the dependent variables and the dependent variable is transformed by the natural logarithm, which likewise contains the translog form as a limiting case.

The Box-Tidwell form has its own disadvantages, however. Shin and Ying (1994) discuss three variants of the Box-Tidwell form, and the issues that arise in each case in the context of cost function estimation. In the standard Box-Tidwell case described above, the authors show that it is not possible—except in the limiting translog case—to impose linear homogeneity in input prices, and that applications by Evans and Heckman (1983), Waverman (1989), and Röller (1990) claim to do so by normalising costs and input prices by one input price—as described above—which is not valid. In the case in which the Box-Cox transformation is also applied to the dependent variable, the authors show that linear homogeneity may be imposed, but that the restrictions needed to do so sacrifice the flexibility of the form. The authors therefore recommend that a hybrid functional form, in which the logarithmic transformation is applied to cost and input price variables—allowing linear homogeneity to be imposed—and the Box-Cox transformation is applied to other independent variables such as outputs. This is identical to the form earlier suggested by Caves et al. (1980), which they named the generalised translog.

Although this hybrid Box-Tidwell-translog form is a viable solution to the problem of zero values of outputs, it is unattractive for two practical reasons. First, unless the parameter θ is fixed at some arbitrary value, the model is nonlinear in its parameters. Estimation of θ together with the rest of the model parameters would require amendments to existing packages used for SFA, although given that least squares yields unbiased estimates of the frontier parameters, some two-step approach wherein the level at which to fix θ is first estimated using non-linear least squares could be justified. Second, the estimated coefficients on Box-Cox transformed variables are difficult to interpret, though they clearly are not elasticities.

An expedient often used in the applied literature is to simply replace zero values with some arbitrarily small number greater than zero. However this method has been known to produce erratic results and serious biases (Pulley and Humphrey 1993, Weninger 2003). A simple remedy proposed by Battese (1997) is, where the value of a given output is zero, to set the value to one—and hence its natural logarithm to zero—and include a dummy indicating the observations for which that output is zero. The author shows that the parameters of the model can then be estimated in an unbiased way. This approach, in contrast to the use of Box-Tidwell and related forms, allows the interpretation of the estimated cost function parameters as elasticities, but is not particularly parsimonious given that dummy variables must be added for each output with zero values. An alternative approach is to apply the inverse hyperbolic sine transformation to those variables containing zero values. That is, x is replaced by x^* where $x^* = \ln\left(x + \sqrt{x^2 + 1}\right)$. Except for very small values of x_{it}, this is approximately equal to $\ln 2x_{it}$, so that if evaluated at any reasonably large value of x_{it}, e.g. the sample mean, the derivative of the cost function with respect to this variable can be reasonably interpreted as an elasticity. To the best of our knowledge, this approach has not been adopted in the literature on cost and production function estimation, but has often been applied in the modelling of wealth—see for example Burbidge et al. (1988), Carroll et al. (2003), Pence (2006), Friedline et al. (2015), and Grabka et al. (2015)—in which log-linear or semilog functional forms are likewise attractive but the wealth variable can take on negative or zero values. Using this transformation is also more parsimonious than either the Battese (1997) or Box-Tidwell type approaches, since it does not require the estimation of any additional parameters. We therefore take this approach, including in our model ihs Q_2 in place of $\ln Q_2$, where ihs $Q_2 = \ln\left(Q_2 + \sqrt{Q_2^2 + 1}\right)$. After imposing linear homogeneity of degree one in input prices, and substituting ihs Q_2 for $\ln Q_2$, the total cost frontier we estimate is:

$$\ln\left(\frac{C_{i,t}}{W_{3it}}\right) = \ln\alpha + \theta t + \beta_1 \ln Q_{1it} + \beta_2 \,\text{ihs}\, Q_{2it} + \gamma_1 \ln\left(\frac{W_{1it}}{W_{3it}}\right) \tag{88}$$

$$+\gamma_2 \ln\left(\frac{W_{2it}}{W_{3it}}\right) + \gamma_4 \ln\left(\frac{W_{4it}}{W_{3it}}\right) + \vartheta t^2 + \zeta_{11}(\ln Q_{1it})^2 + \zeta_{22}(\text{ihs}\, Q_{2it})^2$$

$$+\eta_{11}\left[\ln\left(\frac{W_{1it}}{W_{3it}}\right)\right]^2 + \eta_{22}\left[\ln\left(\frac{W_{2it}}{W_{3it}}\right)\right]^2 + \eta_{44}\left[\ln\left(\frac{W_{4it}}{W_{3it}}\right)\right]^2 + \varphi_1 t \ln Q_{1it}$$

$$+\varphi_2 t \,\text{ihs}\, Q_{2it} + \phi_1 t \ln\left(\frac{W_{1it}}{W_{3it}}\right) + \phi_2 t \ln\left(\frac{W_{2it}}{W_{3it}}\right) + \phi_4 t \ln\left(\frac{W_{4it}}{W_{3it}}\right)$$

$$+\zeta_{11} \ln Q_{1it} \,\text{ihs}\, Q_{2it} + \lambda_{11} \ln Q_{1it} \ln\left(\frac{W_{1it}}{W_{3it}}\right) + \lambda_{12} \ln Q_{1it} \ln\left(\frac{W_{2it}}{W_{3it}}\right)$$

$$+\lambda_{14} \ln Q_{1it} \ln\left(\frac{W_{4it}}{W_{3it}}\right) + \lambda_{21} \,\text{ihs}\, Q_{2it} \ln\left(\frac{W_{1it}}{W_{3it}}\right) + \lambda_{22} \,\text{ihs}\, Q_{2it} \ln\left(\frac{W_{2it}}{W_{3it}}\right)$$

$$+\lambda_{24} \,\text{ihs}\, Q_{2it} \ln\left(\frac{W_{4it}}{W_{3it}}\right) + \eta_{12} \ln\left(\frac{W_{1it}}{W_{3it}}\right) \ln\left(\frac{W_{2it}}{W_{3it}}\right) + \eta_{14} \ln\left(\frac{W_{1it}}{W_{3it}}\right) \ln\left(\frac{W_{4it}}{W_{3it}}\right)$$

$$+\eta_{24} \ln\left(\frac{W_{2it}}{W_{3it}}\right) \ln\left(\frac{W_{4it}}{W_{3it}}\right) + \beta_3 \ln H_{1it} + \beta_4 \ln H_{2it} + \beta_5 \ln H_{3it} + \beta_6 \ln H_{4it}$$

$$+v_{it} + u_{it}$$

Where

$$v_{it} \sim N(0, \sigma_v^2) \tag{89}$$

$$u_{it} \sim N^+(\mu_{it}, \sigma_u^2)$$

$$\mu_{it} = \delta_0 + \sum_{z=1}^{6} \delta_z Z$$

And the variable cost frontier model we estimate is:

$$\ln\left(\frac{VC_{i,t}}{W_{3it}}\right) = \ln\alpha + \theta t + \beta_1 \ln Q_{1it} + \beta_2 \operatorname{ihs} Q_{2it} + \gamma_1 \ln\left(\frac{W_{1it}}{W_{3it}}\right) \tag{90}$$

$$+\gamma_2 \ln\left(\frac{W_{2it}}{W_{3it}}\right) + \chi \ln K_{it} + \vartheta t^2 + \zeta_{11}(\ln Q_{1it})^2 + \zeta_{22}(\operatorname{ihs} Q_{2it})^2$$

$$+\eta_{11}\left[\ln\left(\frac{W_{1it}}{W_{3it}}\right)\right]^2 + \eta_{22}\left[\ln\left(\frac{W_{2it}}{W_{3it}}\right)\right]^2 + \mu\left(\ln K_{i,t}\right)^2 + \varphi_1 t \ln Q_{1it}$$

$$+\varphi_2 t \operatorname{ihs} Q_{2it} + \phi_1 t \ln\left(\frac{W_{1it}}{W_{3it}}\right) + \phi_2 t \ln\left(\frac{W_{2it}}{W_{3it}}\right) + \kappa t \ln K_{i,t}$$

$$+\zeta_{11} \ln Q_{1it} \operatorname{ihs} Q_{2it} + \lambda_{11} \ln Q_{1it} \ln\left(\frac{W_{1it}}{W_{3it}}\right) + \lambda_{12} \ln Q_{1it} \ln\left(\frac{W_{2it}}{W_{3it}}\right)$$

$$+\lambda_{21} \operatorname{ihs} Q_{2it} \ln\left(\frac{W_{1it}}{W_{3it}}\right) + \lambda_{22} \operatorname{ihs} Q_{2it} \ln\left(\frac{W_{2it}}{W_{3it}}\right) + \eta_{12} \ln\left(\frac{W_{1it}}{W_{3it}}\right) \ln\left(\frac{W_{2it}}{W_{3it}}\right)$$

$$+\pi_1 \ln\left(\frac{W_{1it}}{W_{3it}}\right) \ln K_{i,t} + \pi_2 \ln\left(\frac{W_{2it}}{W_{3it}}\right) \ln K_{i,t} + \varpi_1 \ln Q_{1it} \ln K_{i,t}$$

$$+\varpi_2 \operatorname{ihs} Q_{2it} \ln K_{i,t} + \beta_3 \ln H_{1it} + \beta_4 \ln H_{2it} + \beta_5 \ln H_{3it} + \beta_6 \ln H_{4it}$$

$$+v_{it} + u_{it}$$

Where

$$v_{it} \sim N(0, \sigma_v^2) \tag{91}$$

$$u_{it} \sim N^+(\mu_{it}, \sigma_u^2)$$

$$\mu_{it} = \delta_0 + \sum_{z=1}^{6} \delta_z Z$$

As is common practice in the literature, each variable—except the time trend t—is mean-centred. For variables in the frontier, this means that variables are divided by their sample means, before taking logarithms, in order to aid interpretation of the estimated parameters: due to the inclusion of interaction terms, this mean centring allows us to interpret the estimated parameters on the first-order terms as elasticities at the sample means. In the case of the variables in the inefficiency model, sample means are subtracted from each variable, though due to the absence of second order terms in the inefficiency model, only the intercept δ_0 is affected by this.

The following section outlines the revenue models estimated in this chapter.

5.2.2. Revenue Models

As discussed in chapter 2, the appropriate revenue frontier specification in the context of fixed-output monopolies consists of outputs, exogenous demand determinants and hedonic factors, with the firm's problem being to maximise revenue given its inverse demand functions, as shown in (84). The WaSCs in England and Wales, along with the Scottish and Northern Irish water and sewage companies, produce two distinct sets of outputs: one related to water supply, and the other relating to sewage disposal. We therefore estimate two revenue functions: one for water revenue, and the other for sewage revenue.

As is standard in the empirical literature on stochastic revenue frontier estimation, we use a simple Cobb-Douglas functional form, which given the firm's revenue maximisation problem, results if we assume a Cobb-Douglas demand function. This underlying assumption of a Cobb-Douglas demand function is common in the literature on water demand; a commonly adopted alternative is the linear functional form, but this has been criticised for the implication that the change in quantity demanded resulting from a change in price is the same at every price level (Arbuès et al. 2003, Worthington and Hoffman 2008). A Cobb-Douglas functional form also has the advantage that the estimated parameters may be interpreted as elasticities; note that in the case of our monopoly revenue functions, the parameter can be interpreted as minus the ratio of the elasticity of demand with respect to that variable to the price elasticity of demand. Given a reliable estimate of the price elasticity of demand, we may therefore derive implied elasticities of demand with respect to, for example, income.

Variables representing fixed outputs included in the water and sewage revenue frontiers are Q_1 and Q_2—the number of properties connected for water and billed for sewage—respectively. These are as defined in the previous section.

For the relevant demand variables, we look to the literature on demand. Since an early study by Gottlieb (1963), there has been a large empirical literature on demand for water, either at the level of individual households or properties, or aggregated across areas. Surveys of this literature are provided by Arbués et al. (2003), and more recently by Worthington and Hoffman (2008); much of the discussion is on methodology and the crucial issue of how to define price variables where multi-part tariffs are used, which we are not concerned with here. From these surveys, however, we can identify the independent variables most commonly used in modelling demand: aside from price, income is included in most—if not all—studies, and other variables include household size and variables concerning household structure, climate variables—including rainfall and temperature—and property characteristics.

Climate variables vary by study. Rainfall may be included, along with temperature, sunshine, and any others that can be regarded as influencing demand for water. Some studies include rainfall or precipitation, either alone or along with other variables such as mean or maximum temperature (Moncur 1987, Thomas and Syme 1988, Nieswiadomy 1992, Stevens et al. 1992, Nieswiadomy and Cobb 1993, Barkatullah

1996, Renwick and Archibald 1998, Renwick et al. 1998, Pint 1999, Timmins 2002, Martínez-Espiñeira and i 2004, Gaudin 2006, Martínez-Espiñeira 2007, Babel et al. 2007, Grafton and Kompas 2007, Davis 2008, Grafton and Ward 2008, Kenney et al. 2008, Dharmaratna and Harris 2012, Polycarpou and Zachariadis 2013, Price et al. 2014, Yoo et al. 2014), or only summer rainfall (Williams and Suh 1986, Garcia and Reynaud 2004) on the basis that water requirements, for example for lawn maintenance, are zero at lower temperatures regardless of rainfall; Foster and Beattie (Foster and Beattie 1979, 1981),who use US city-level data, divide the US into two regions in which cool-season and warm-season grasses are generally found: these types of grasses are dormant—and water use essentially zero—until the temperature reaches 4.4ºC-7.2ºC and 15.6ºC, respectively, thus the authors construct a measure including rainfall only in those months where the temperature exceeds 7.2ºC in the first region and 15.6ºC in the second. Others take this a step further and construct some measure of requirement based on the evapotranspiration of grasses minus rainfall or similar (Nieswiadomy and Molina 1989, Hewitt and Hanemann 1995, Agthe and Billings 1980, 1987, Billings and Agthe 1980, Agthe et al. 1986, Gaudin et al. 2001, Olmstead et al. 2007, Olmstead 2009, Nataraj and Hanemann 2011, Mansur and Olmstead 2012). Yet another alternative is to capture the occurrence, rather than the intensity of, e.g. rain through the number of days during a period that rainfall exceeds some threshold, as in (Schleich and Hillenbrand 2009, Klaiber et al. 2014).

In our water revenue model, we therefore include three 'demand' variables: for income we use gross domestic household income (GDHI), Y_1. Our other two variables are Y_2, the number of days with rainfall over 1mm, and Y_3, average temperature. We also include a number of hedonic variables that may influence demand, or the ability of the firm to extract revenue from customers. In the water revenue model, these are the same variables included in the cost models: H_1, the proportion of water properties metered, H_2, is the number of water properties connected per km of water mains, H_3, water quality, and H_4, the proportion of water properties above a reference pressure level. The density variable, H_2, is in this case included as a proxy for urbanisation and the characteristics of average households, etc. in a supply area. For example, households in more urban areas will tend to have smaller gardens and therefore lower water demand.

On the revenue side, there is unfortunately a paucity of empirical evidence. We adopt a relatively sparse specification for the revenue frontier model, consisting only of the number of properties billed for sewage, Q_2, gross domestic household income, Y_1, our density measure, H_2, and one additional variable: H_5, the proportion of sewage properties metered.

We estimate the following stochastic water revenue frontier model:

$$\ln WR_{it} = \alpha + \theta t + \beta_1 \ln Q_{1it} + \beta_2 \ln Y_{1it} + \beta_3 \ln Y_{2it}$$
$$+\beta_4 \ln Y_{3it} + \beta_5 \ln H_{1it} + \beta_6 \ln H_{2it} + \beta_7 \ln H_{3it} + \beta_8 \ln H_{4it}$$
$$+v_{it} - u_{it} \quad (92)$$

Where

$$v_{it} \sim N(0, \sigma_v^2) \quad (93)$$
$$u_{it} \sim N^+(\mu_{it}, \sigma_u^2)$$
$$\mu_{it} = \delta_0 + \delta_1 Z_1 + \delta_2 Z_2 + \delta_4 Z_4 + \delta_5 Z_5 + \delta_6 Z_6 + \delta_7 Z_7$$

And the following stochastic sewage revenue frontier model:

$$\ln SR_{it} = \alpha + \theta t + \beta_1 \ln Q_{2it} + \beta_2 \ln Y_{1it} + \beta_3 \ln H_{2it} + \beta_4 \ln H_{5it} + v_{it} - u_{it} \tag{94}$$

Where

$$v_{it} \sim N(0, \sigma_v^2) \tag{95}$$

$$u_{it} \sim N^+(\mu_{it}, \sigma_u^2)$$

$$\mu_{it} = \delta_0 + \delta_1 Z_1 + \delta_2 Z_2 + \delta_4 Z_4 + \delta_5 Z_5 + \delta_6 Z_6$$

In the inefficiency model, we include a set of variables similar to that included in the cost models. We include Z_1, our proxy for firm size, Z_2, the number of years that the firm has been subject to price capping regulation, Z_4, a dummy for public ownership, Z_5, the proportion of the board that are non-executives, and Z_6, the directors' average years on the board. In the water revenue model, which includes data on WOCs, we also include Z_7, a dummy indicating firms that also supply sewage services, on the basis that they may have greater scope for price discrimination via the bundling of water and sewage services.

Section 5.3 contain more detailed information on variable definitions, data sources, and variable construction and data compatibility issues, and provides summary statistics for each variable included in the four models described in this section.

5.3. Data

In this section, we discuss in detail the definitions of the variables included in the models outlined in section 5.2, along with data sources and the compatibility of data taken from different sources. A key source of data on the WaSCs and WOCs in England and Wales are the June Returns, which Ofwat required the companies to publish annually until 2010-11. These contain a wide variety of financial and non-financial data on the English and Welsh companies, and were taken from current and archived versions of Ofwat’s website. For the years 2011-12 and 2012-13, June Returns were not published, but the companies voluntarily released some of the key variables in the ‘Industry Facts and Figures’ published by Water UK, a membership organisation representing water and sewage companies in the UK.

Analogous documents are published by the Scottish and Northern Irish water regulators. The Water Industry Commission for Scotland (WICS) publishes an Annual Return for Scottish Water, while the Northern Ireland Authority for Utility Regulation (NIAUR) publishes an Annual Information Return for Northern Ireland Water. These both follow broadly the same format as the June Returns, contain much of the same data, and generally using the same definitions, particularly relating to key financial and output measures. Annual Returns for Scottish Water back to 2002-03 were obtained from the WICS website, while the earlier Annual Returns for the three former Scottish Water Authorities were obtained by request from WICS. Annual Information Returns for Northern Ireland Water are available from 2007-08, when the company was created, and were taken from the NIAUR website.

Other key data sources are the companies’ regulatory and statutory accounts. Regulatory accounts are submitted by the English and Welsh WaSCs and WOCs to Ofwat, and contain key financial data. Much the same information is contained in the companies’ statutory accounts filed at Companies House. Regulatory accounts were obtained from the companies’ websites, or by request—either from the companies themselves or via

Ofwat, WICs or NIAUR—for earlier years. Statutory accounts were likewise obtained from the companies' websites, or from Companies House for earlier years.

TABLE 1: DEFINITIONS AND SOURCES FOR WATER AND SEWAGE DATA

Variable	Definition	Sources			
		England and Wales	Scotland		Northern Ireland
			Scottish Water	Water Authorities	
WR	Revenue from water supply activities.	JR table 23	AR table M7	AR table F10	AIR table 23
SR	Revenue from sewage services.	JR table 23	AR table M7	AR table F10	AIR table 23
VC	Variable costs. We take operating expenditure (opex) as our measure of variable costs. These include all non-capital costs, including employment, power, materials, services, and agency costs relating to both water and sewage activities.	JR tables 21 and 22	AR table M18	AR table F1	AIR tables 21 and 22
C	Total costs. Defined as variable costs plus capital costs. Capital costs include depreciation costs and estimated financing costs of capital. See below for details.	-	-	-	-
Q_1	Total number of household and non-household properties connected for water.	JR table 2	AR table A1	AR table A1	AIR table 2
Q_2	Total number of household and non-household properties billed for sewage.	JR table 13	AR table A1	AR table A3	AIR table 13
W_1	Labour price. Total employment costs per employee.	RAs and SAs	RAs and SAs	RAs and SAs	RAs and SAs
W_2	Capital price. See below for details on construction.	-	-	-	-
W_3	Energy price. Industrial Energy Price Index (IEPI) for electricity, including effects of Climate Change Levy. National index with no regional breakdown.	DECC	DECC	DECC	DECC
W_4	Price for other inputs. Retail Price Index (RPI). National index.	ONS	ONS	ONS	ONS

Variable	Definition	Sources			
		England and Wales	Scotland		Northern Ireland
			Scottish Water	Water Authorities	
K	Physical capital stock. Based on reported Modern Equivalent Asset Value (MEAV), except for Scottish Water in 2004-05 and 2005-06, for which an analogous Equivalent Asset Replacement Cost (EARC) measure is used. Deflated by the Construction Output Price Index (COPI) for all new construction. Important alterations made to recalculate historic values for comparability with recent values: for details, and for comment on compatibility of MEAV and EARC, see below.	JR table 25	AR tables M18BW and M18BWW (from 2006-07) AR tables F1.1, G1, and G3 (to 2005-06)	AR table H1	AIR table 25
H_1	Percentage of water properties metered. Constructed by dividing total number of household and non-household properties billed for metered water by Q_1.	JR tables 2 and 7	AR table A1	AR table A1	AIR tables 2 and 7
H_2	Properties connected for water per km of water mains. Constructed by dividing Q_1 by the total length of water mains at the end of the year.	JR tables 2 and 11	AR table E6	AR table E6	AIR tables 2 and 11
H_3	Water quality. An index constructed by averaging the percentages of zones without failures for turbidity, iron, and manganese. See below for further explanation.	DWI reports	DWQR reports	DWQR reports	DWI(NI) Reports
H_4	Percentage of water properties above a reference level of pressure. Constructed using data on the total number of properties below the reference level and Q_1	JR table 2	AR table E6	AR table 6	AIR table 2
H_5	Percentage of sewage properties metered. Constructed by dividing total number of household and non-household properties billed for metered sewage by Q_2.	JR table 13	AR table E1	AR table E3	AIR table 13

Variable	Definition	Sources			
		England and Wales	Scotland		Northern Ireland
			Scottish Water	Water Authorities	
Y_1	Gross Domestic Household Income (GDHI) per capita. Constructed from ONS data by NUTS 3 region. Where a firm's supply area covers more than one NUTS 3 region, a population-weighted average is constructed.	ONS	ONS	ONS	ONS
Y_2	Days with rainfall over 1mm. Constructed using monthly data from the Met Office's UKCP09 5km gridded data set. The 5km squares are assigned to the English and Welsh WaSCs using a map provided by the Environment Agency, and to the WOCs, Northern Ireland Water, the former Scottish Water authorities, and Scottish water by overlaying maps of supply areas onto that of the 5km grid.	UKCP09	UKCP09	UKCP09	UKCP09
Y_3	Mean temperature. Constructed using monthly data from the Met Office's UKCP09 5km gridded data set. The 5km squares are assigned to the English and Welsh WaSCs using a map provided by the Environment Agency, and to the WOCs, Northern Ireland Water, the former Scottish Water authorities, and Scottish water by overlaying maps of supply areas onto that of the 5km grid.	UKCP09	UKCP09	UKCP09	UKCP09
Z_2	Years of regulation. The number of years that the firm has been subject to RPI+K style regulation. The first year or regulation was taken to be 1990-91 in England and Wales, 1999-00 in Scotland, and 2007-08 in Northern Ireland.	-	-	-	-

Variable	Definition	Sources			
		England and Wales	Scotland		Northern Ireland
			Scottish Water	Water Authorities	
Z_3	K factor. The maximum (minimum) price increase (decrease) allowed in the year, as set by the regulator. Taken from final determinations documents.	Ofwat	WICS	WICS	NIAUR
Z_5	Percentage of the board that are non-executives. Constructed from regulatory and statutory accounting data on board members at the end of the financial year.	RAs and SAs	RAs and SAs	RAs and SAs	RAs and SAs
Z_6	Directors' average years on the board. Constructed as the average number of years since first appointment to the board, regardless of any absences.	RAs and SAs	RAs and SAs	RAs and SAs	RAs and SAs

5.3.1. Capital Stock, Capital Price, and Capital Costs

Two different measures of capital stock are collected by Ofwat: the Regulatory Capital Value (RCV) representing the economic value of the firm's assets, and the replacement cost of the company's fixed assets represented by the Modern Equivalent Asset Value (MEAV). The Water Industry Commission for Scotland (WICS) and the Northern Ireland Authority for Utility Regulation (NIAUR)—Ofwat's counterparts in Scotland and Northern Ireland—have also produced RCVs and MEA values for Scottish Water and Northern Ireland Water going back to the 2006-07 and 2007-08 financial years, respectively.

Prior to 2006-07 the capital base of Scottish Water and the former Scottish water authorities was calculated as the Equivalent Asset Replacement Cost (EARC) of fixed assets, a method conceptually identical to the MEAV, and in practice yielding such similar results that when initially asked to produce MEAV for the Annual Returns to WICS, having not completed a MEA valuation, the company continued to report EARC values for the 2004-05 and 2005-06 returns, considering the difference between the EARC and MEA values to be within normal accuracy bands used in reporting.

As Saal and Parker (2000) acknowledge, the replacement costs of fixed assets may exceed their economic value, and many of the industry's assets, e.g. underground infrastructure, may have no opportunity cost because they lack alternative uses. This certainly seems to be the case, since reported MEAVs are several times greater than reported RCVs. We therefore take MEAV as the appropriate measure of the quantity of capital inputs used in production, K.

MEAVs are reported in the companies' regulatory accounts and table 25 of the June Returns, and in between periodic Asset Management Plan (AMP) revaluations are adjusted for changes in the Retail Price Index (RPI) and the net impact of additions, disposals and current cost depreciation (CCD). There are two issues with using the MEA values as reported; firstly, the Asset Management Plan (AMP) revaluations, which result in large and arbitrary jumps in the series, and secondly, the use of an inappropriate price index, the RPI, to adjust nominal MEAVs. The process followed in order to resolve these problems is similar to that described in Saal and Parker (2001) and Stone & Webster (2004a): the series is recalculated using Ofwat's preferred price index for the purchase cost of fixed assets in the industry, the Construction Output Price Index (COPI) for all new construction published by the Department for Business, Innovation and Skills (BIS), and all but the most recent (and therefore the most accurate and up-to-date) MEAV revaluations and reclassification adjustments are removed. Where mergers occurred, we calculate the closing MEA of the pre-merger firms thus:

$$FNMEAV_t = s_t.INMEAV_{t+1} \tag{96}$$

where $FNMEA_t$ is the recalculated final net MEAV of the pre-merger firm, $INMEAV_{t+1}$ is the recalculated initial net MEAV of the merged firm, and s_t is the proportion of the sum of the final net MEAV of the pre-merger firms attributable to the firm as originally reported.

Another issue, unique to this sample, is the transfer of private sewers, lateral drains, and pumping stations to the WaSCs following the Water Industry (Schemes for the Adoption of Private Sewers) Regulations (2011), the values of which were entered as additions to the MEAVs of sewage collection infrastructure assets in 2011-12. This caused a considerable jump in the reported MEAVs, therefore in order to obtain values consistent with previous years, we remove this by subtracting their value. Where this was not explicitly stated, it was estimated by subtracting the mean of the 2010-11 and 2012-13 values of additions to sewage collection infrastructure assets from those of 2011-12.

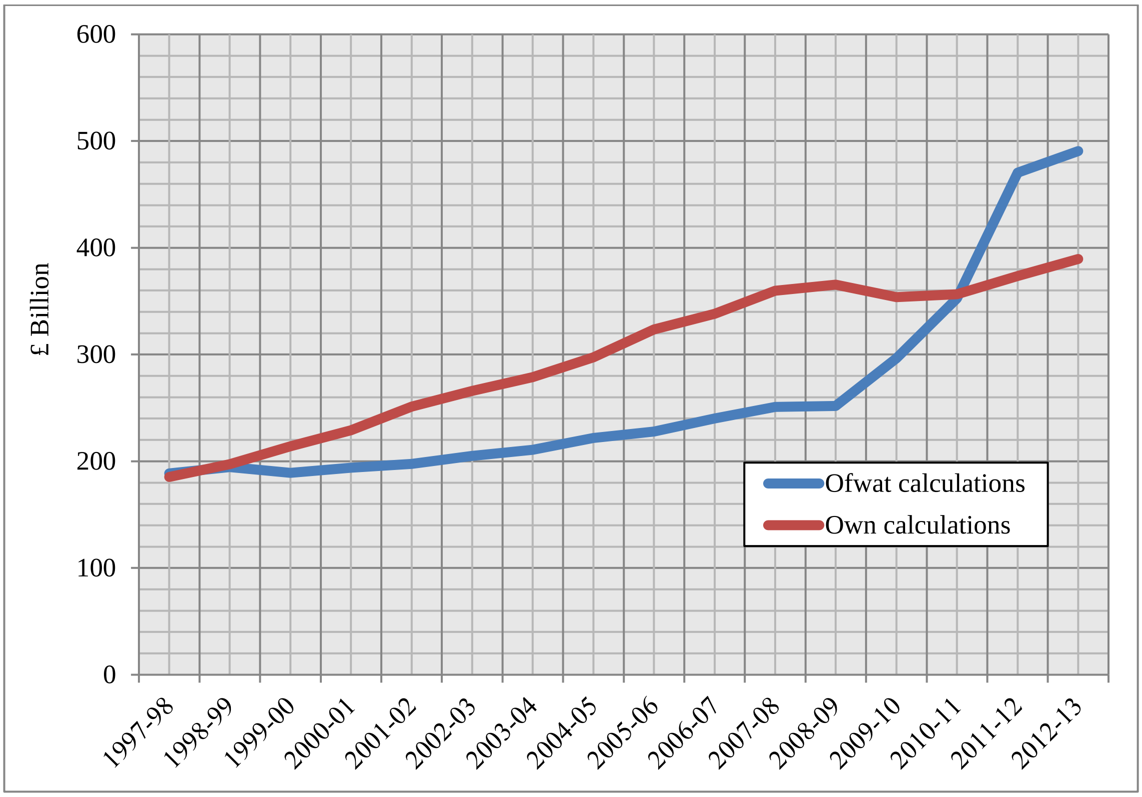

FIGURE 5.3.1: INDUSTRY NET MEA VALUE OF FIXED ASSETS, ENGLAND AND WALES

Figure 5.3.1 compares the adjusted nominal MEAVs described above to the unadjusted values reported in the regulatory accounts. The adjusted series shows a steady growth in MEAVs, excepting a slowing down and a fall during the Great Recession, reflecting a fall in the COPI. Large upward AMP revaluations were made in 2009-10 and 2010-11, meaning that the reported MEAVs in previous years had undervalued fixed assets considerably, as can be seen in the large difference between the adjusted and unadjusted series up to that point. The noticeable jumps in the unadjusted series in recent years reflect the WaSCs' adoption of private sewers and recent AMP revaluations as described above. Removing these brings the data more in line with expectations, with steady growth in nominal MEAVs excepting a slight decline and subsequent slowing of growth around the Great Recession, largely reflecting changes in the COPI. These nominal values are then deflated using the COPI in order to obtain a physical measure of fixed assets.

As our capital price, for use in the total cost model, we construct a measure of the user cost of capital similar to that used by Saal and Parker (2000, 2001) and Stone & Webster (2004a) is calculated as

$$W_4 = \delta + \tau \qquad (97)$$

where δ is capital charges, i.e. the depreciation rate where depreciation is the sum of current cost depreciation (CCD) and the infrastructure renewals charge (IRC). For the English and Welsh WaSCs and WOCS, data on CCD and IRCs are taken from tables 29 and 33 of the June Returns, respectively. For Scottish Water, these data are taken from table M4 of the Annual Returns, while for the former Scottish water authorities, they are taken from table F1 of the old Annual Returns. For Northern Ireland Water, the data are taken from tables 29 and 33 of the Annual Information Returns. The second component, τ, is the pre-tax weighted-average cost of capital (WACC). Saal and Parker (2000, 2001) calculate τ as an inflation-adjusted nominal rate of return sufficient to ensure a 6% post tax real rate of return. Stone & Webster (2004a) calculate τ as

$$\tau = r_f + r_p - t \qquad (98)$$

where r_f is the nominal 10-year UK gilt rate—a proxy for the risk-free rate—r_p is an implied weighted-average risk premium on the firm's equity and debt, computed by subtracting Ofwat's estimate of the risk-free rate from its estimate of post-tax WACC for the relevant price control then dividing this by one minus the corporation tax rate in order to express it as a pre-tax value, and t is the debt interest tax shield, calculated by multiplying gross interest by the corporation tax rate as a percentage of the capital base. Saal and Parker (2000) and Stone & Webster (2004a) use the MEAV as their measure of the capital base in this calculation. However, while MEAV is an appropriate measure of the *quantity* of capital for inclusion in the variable cost specification, it may not be an appropriate base against which to calculate capital *prices*, since as discussed above, the replacement cost of the firms' capital exceeds their economic values. We therefore use RCVs as our measure of the capital base in this calculation.

Finally, we construct our measure of capital costs by multiplying the capital price W_4 by the RCVs. Capital costs therefore include depreciation and financing costs of capital. These are added to VC in order to obtain our measure of C, total costs. Comparing the resulting total cost values to total revenues indicates that they have been calculated in a sensible way. By contrast, the use of MEAV instead of RCV in these calculations yields estimates of total cost that are far in excess of total revenues.

5.3.2. Water Quality

Water quality data are taken from the annual reports of: the Drinking Water Inspectorate (DWI) (1998-2014) for England and Wales; the Drinking Water Quality Regulator (DWQR) (1999-2014) for Scotland; the Drinking Water Inspectorate of Northern Ireland (DWI(NI)) (1999-2014) for Northern Ireland. The current measure of overall quality constructed by these regulators is Mean Zonal Compliance (MZC), which for each of the 39 quality parameters, calculates the mean percentage of tests in compliance with Parameter Control Values across the supply zones within a given area, and then takes the mean of all these parameter-specific MZCs.

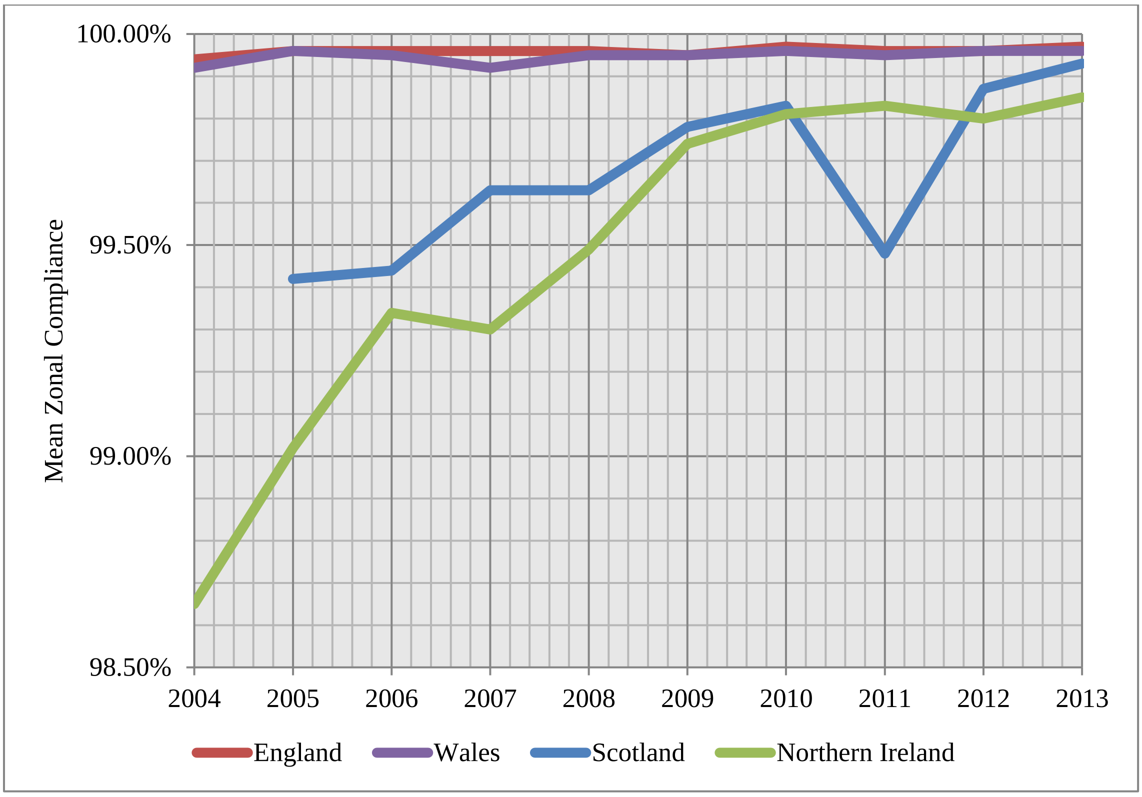

FIGURE 5.3.2: WATER QUALITY (MEAN ZONAL COMPLIANCE) IN THE UK BY COUNTRY

Figure 5.3.2 shows the trends in MZC in England, Wales and Northern Ireland. English and Welsh firms have had, for most of the sample period, noticeably higher MZC scores than their Scottish and Northern Irish counterparts. The difference, however, narrows over the period, which coincides with the transfer of the former Northern Ireland Water Service to the Department for Regional Development (DRD) in 1999 and its transformation into Northern Ireland Water—a government-owned company—and the creation of Scottish Water in 2002, and subsequent increases in investment in both regions.

This measure was not constructed, however, until well into the sample, particularly in Scotland; an earlier measure, the Operational Performance Index (OPI), takes the mean of the MZCs for just three key parameters: turbidity, iron and manganese, though again, these data are not available for all years. However, using these parameters, we construct an alternative measure: the mean percentage of zones without failures for each; a similar measure was employed by Stone & Webster (2004a).

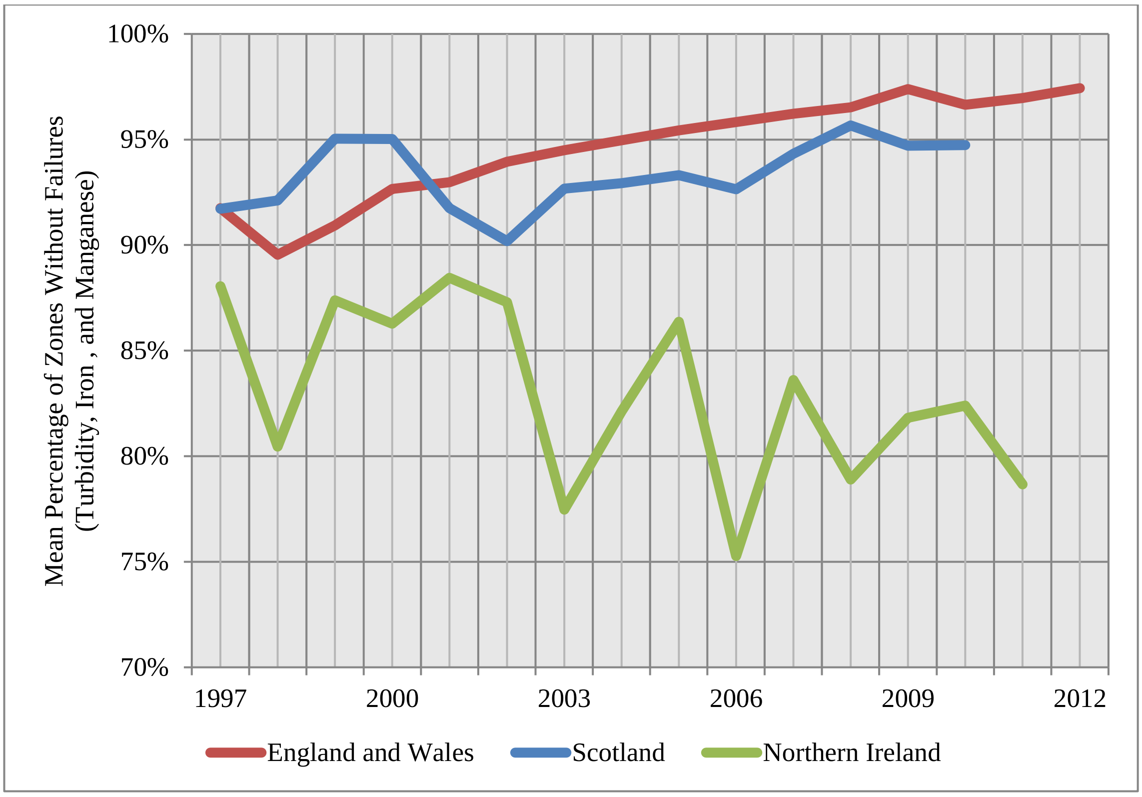

FIGURE 5.3.3: MEAN PERCENTAGE OF ZONES WITHOUT FAILURES (TURBIDITY, IRON, AND MANGANESE) BY COUNTRY

Figure 5.3.3 above shows our quality measure by country over the sample period. As can be seen, this measure shows considerably more variation than the MZC; this is because of the smaller number of parameters and the absence of dozens of parameters for which failures are rarely observed. Again, we see English and Welsh firms generally scoring higher, and a general improvement for Scotland over the period, but in this case the contrast with Northern Ireland is even starker, and shows no improvement. Another feature is a much clearer upward trend in English and Welsh water quality over the period.

5.3.3. Observations Included

Given the availability of the data described in this section, we are able to assemble a dataset on costs covering the English and Welsh WaSCs and WOCs over the years 1997-98 to 2012-13. Data on the former Scottish water authorities and Scottish Water are included in the variable cost model from 1999-00 to 2011-12, though owing to the lack of data on RCVs, the Scottish water authorities are excluded from the total cost model, and Scottish Water is included only from 2007-08. Northern Ireland Water is included in both the variable and total cost models from 2007-08 onwards. The water and sewage revenue models include the same firms as the variable cost model, but excludes the years 2011-12 and 2012-13 owing to a lack of climate data.

We refer to each firm using the three letter codes adopted by Ofwat. Table 2 lists the three letter codes and full names of each firm, whether or not they are responsible for sewage services, and briefly describes the relationships between firms that have merged during the sample period. A fuller description of each firm, including mergers and changes in ownership before and during the sample period, is given in appendix 2.
At the start of the sample period, responsibility for sewage in the UK was divided between the 10 English and Welsh WaSCs, the three former Scottish water authorities, and what was then the Northern Ireland Water Service. By the end of the sample period, the Scottish Water Authorities had been merged into Scottish Water, and the Northern Ireland Water Service had been transformed into the publicly-owned company Northern

Ireland Water. In England, the sewage service areas of the WaSCs are essentially unchanged since 1973. Figure 5.3.4 shows the sewage collection areas of each.

TABLE 2: WATER AND SEWAGE FIRMS

Code	Name	Sewage	Note
AFF	Affinity Water	No	Merger of VSE, VWE, and VWC
ANG	Anglian Water	Yes	Merged with HPL to form ANH
ANH	Anglian Water	Yes	Merger of ANG and HPL
BWH/SMB	Sembcorp Bournemouth Water	No	Formerly Bournemouth Water
BRL	Bristol Water	No	
CAM	Cambridge Water	No	
DVW	Dee Valley Water	No	
EoS	East of Scotland Water Authority	Yes	Merged with NoS and WoS to form SCW
ESK	Essex and Suffolk Water	No	Merged with NNE to form NES
FLK/VSE	Veolia Water Southeast	No	Formerly Folkestone and Dover Water
HPL	Hartlepool Water	No	Merged with ANG to form ANH
MKT	Mid Kent Water	No	Merged with MSE to form SEW
NoS	North of Scotland Water Authority	Yes	Merged with EoS and WoS to form SCW
NSY	North Surrey Water	No	Merged with TVW to form TVN
NIW	Northern Ireland Water	Yes	
NNE	Northumbrian Water	Yes	Merged with ESK to form NES
NES	Northumbrian Water	Yes	Merger of NNE and ESK
PRT	Portsmouth Water	No	
SCW	Scottish Water	Yes	Merger of EoS, NoS, and WoS
SVT	Severn Trent Water	Yes	
MSE	South East Water	No	Merged with MKT to form SEW
SEW	South East Water	No	Merger of MSE and MKT
SST	South Staffordshire Water	No	
SWT	South West Water	Yes	
SRN	Southern Water	Yes	
SES	Sutton and East Surrey Water	No	
THD/VWE	Tendring Hundred Water	No	
TMS	Thames Water	Yes	
TVW	Three Valleys Water	No	Merged with NSY to form TVN
TVN/VWC	Three Valleys Water	No	Merger if TVW and NSY
NWT	United Utilities	Yes	Formerly North West Water
WSH	Welsh Water	Yes	
WSX	Wessex Water	Yes	
WoS	West of Scotland Water Authority	Yes	Merged with EoS and NoS to form SCW
YRK	York Waterworks	No	Merged with YKS to form YKY
YKS	Yorkshire Water	Yes	Merged with YRK to form YKY
YKY	Yorkshire Water	Yes	Merger of YKS and YRK

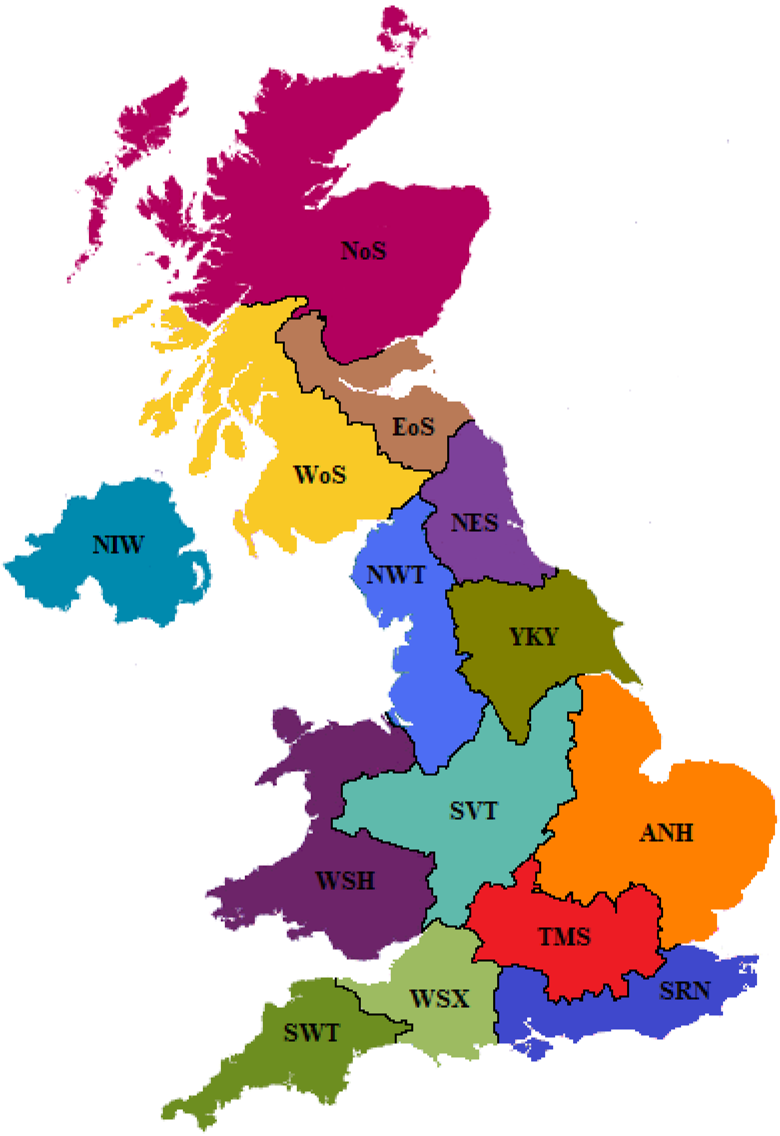

FIGURE 5.3.4: MAP OF THE SEWAGE COLLECTION AREAS OF THE WATER AND SEWAGE COMPANIES IN THE UNITED KINGDOM (INCLUDING THE FORMER SCOTTISH WATER AUTHORITIES, NOW MERGED AS SCOTTISH WATER)

Water supply, on the other hand, is more fragmented. This is due to the presence of WOCs in England and Wales, mostly in the South of England. There has been a gradual consolidation among the WOCs since the birth of the industry—see chapter 1—and continuing through the sample period. In several cases, there have been mergers between WOCs, e.g. the merger of MSE and MKT to form SEW, or the merger of VWC, VWE, and VSE to form AFF.

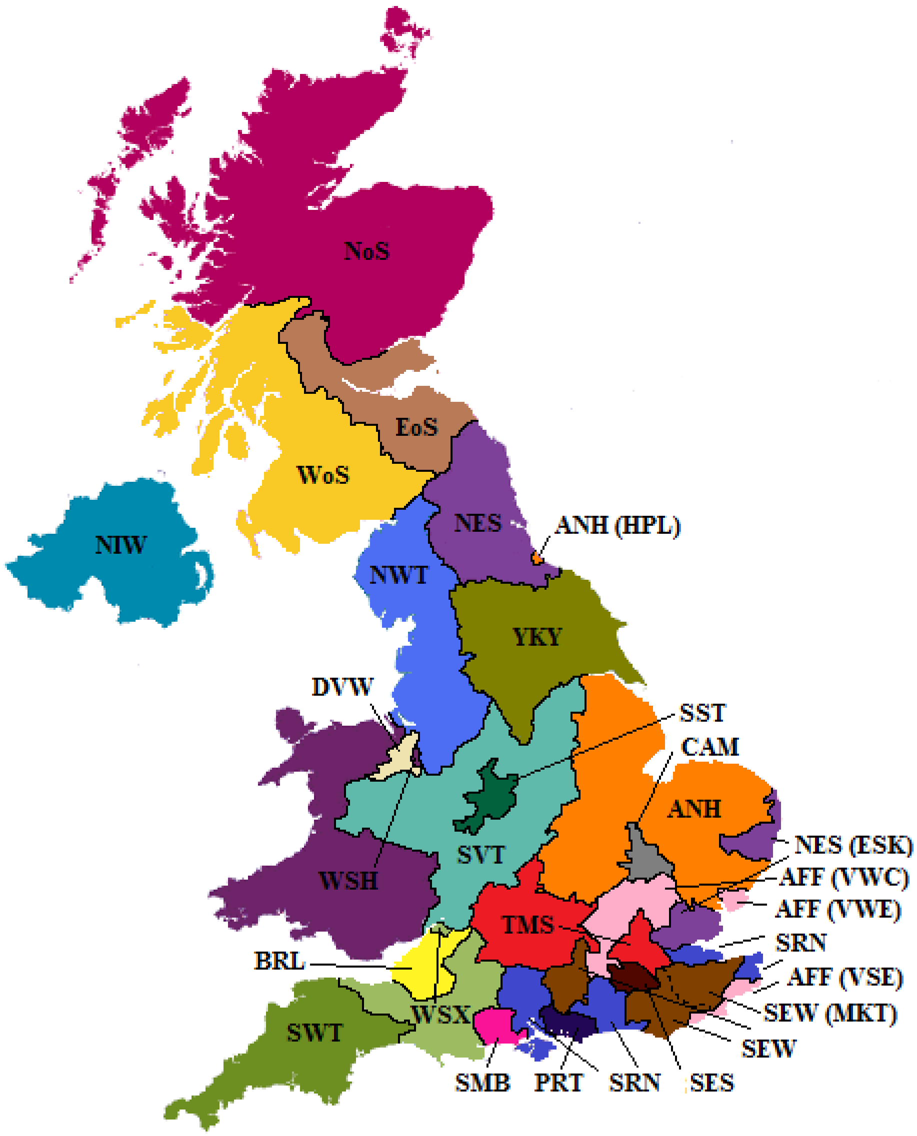

FIGURE 5.3.5: MAP OF THE WATER SUPPLY AREAS OF THE WATER AND SEWAGE AND WATER ONLY COMPANIES IN THE UNITED KINGDOM (INCLUDING THE FORMER SCOTTISH WATER AUTHORITIES, NOW MERGED AS SCOTTISH WATER)

In three cases, WOCs have been acquired by WaSCs. YKS acquired the sole WOC in its sewage collection area, YRK, to form YKY. Interestingly, in the other two cases, WaSCs acquired WOCs far outside of their sewage collections: NNE and ANG acquired WOCs—ESK and HPL—in each other's sewage collection areas, becoming NES and ANH, respectively. Figure 5.3.5 shows a map of water supply areas in the UK.

Where mergers or takeovers occur, the combined firm enters the sample as a continuation of the largest pre-merger firm, while the smaller firms disappear from the sample. This is clearly justified, as in most cases mergers involved two firms, one small and the other much larger. In England and Wales, all mergers were either between WOCs, or between a WaSC and a WOC, i.e. there were no mergers of the large WaSCs. In Scotland, however, the former Scottish Water Authorities were of roughly equal size, and thus as an exception to the rule, Scottish Water enters the sample as an entirely new firm. Owing to a lack of data, the predecessors of Northern Ireland Water are not included in the sample, and the company enters the sample as a new firm in 2007-08. Table 3 describes the years in which each firm is included in each model, and lists the firm number each firm is given.

TABLE 3: INCLUSION OF WATER AND SEWAGE FIRMS

Firm	No.	Revenue	Total Cost	Variable Cost
AFF	1	-	2013	2013
ANG	2	1998-2000	1998-2000	1998-2000
ANH	2	2001-2011	2001-2013	2001-2013
BWH/SMB	3	1998-2011	1998-2013	1998-2013
BRL	4	1998-2011	1998-2013	1998-2013
CAM	5	1998-2011	1998-2013	1998-2013
DVW	6	1998-2011	1998-2013	1998-2013
EoS	7	2000-2002	-	2000-2002
ESK	8	1998-2000	1998-2000	1998-2000
FLK/VSE	9	1998-2011	1998-2012	1998-2012
HPL	10	1998-2000	1998-2000	1998-2000
MKT	11	1998-2008	1998-2008	1998-2008
NoS	12	2000-2002	-	2000-2002
NSY	13	1998-2000	1998-2000	1998-2000
NIW	14	2008-2011	2008-2013	2008-2013
NNE	15	1998-2000	1998-2000	1998-2000
NES	15	2001-2011	2001-2013	2001-2013
PRT	16	1998-2011	1998-2013	1998-2013
SCW	17	2003-2011	2007-2012	2003-2012
SVT	18	1998-2011	1998-2013	1998-2013
MSE	19	1998-2008	1998-2008	1998-2008
SEW	19	2009-2011	2009-2013	2009-2013
SST	20	1998-2011	1998-2013	1998-2013
SWT	21	1998-2011	1998-2013	1998-2013
SRN	22	1998-2011	1998-2013	1998-2013
SES	23	1998-2011	1998-2013	1998-2013
THD/VWE	1	1998-2011	1998-2012	1998-2012
TMS	24	1998-2010	1998-2010, 2012-2013	1998-2010, 2012-2013
TVW	25	1998-2000	1998-2000	1998-2000
TVN/VWC	25	2001-2011	2001-2012	2001-2012
NWT	26	1998-2011	1998-2013	1998-2013
WSH	27	1998-2011	1998-2013	1998-2013
WSX	28	1998-2011	1998-2013	1998-2013
WoS	29	1998-2000	1998-2000	2000-2002
YRK	30	1998-2000	1998-2000	1998-2000
YKS	31	1998-2000	1998-2000	1998-2000
YKY	31	2001-2011	2001-2013	2001-2013
Total observations		338	368	381

5.3.4. Summary Statistics

Table 4 below shows summary statistics for the data described in this section. For each variable, means and standard deviations are shown for the sample period and various subperiods, and means are further broken down by location and firm type: England and Wales—divided into WaSCs and WOCs—Scotland, and Northern Ireland. This gives a picture of the time trends in the data, and how they vary from one firm type to another.

Where a variable is included in multiple models, the summary statistics are constructed using all observations from the model containing the largest number of observations. For example, Q_1 is included in the water revenue model and both cost models. As seen in table 2, of these the variable cost model contains the most observations, so the summary statistics shown are based on these. Similarly, Y_1 is included in the water and sewage revenue models, the former of which contains the most observations, and thus Y_1 is summarised over all observations included in the water revenue model. On the other hand, the dependent variables C, VC, WR, and SR are included only in their respective models, and are summarised over the observations included in these.

TABLE 4: SUMMARY STATISTICS FOR WATER AND SEWAGE DATA

Variable	Period	Mean					St. dev.
		WaSCs	WOCs	Scotland	N. Ireland	All	All
$\ln C$ Total cost	1997-98 2000-01	571.057	42.231	-	-	253.762	316.779
	2001-02 2004-05	649.217	49.060	-	-	321.858	363.895
	2005-06 2008-09	818.462	62.336	843.559	367.694	423.199	453.608
	2009-10 2012-13	888.785	77.465	1,004.334	420.603	484.222	484.688
	All years	730.893	56.203	923.946	402.966	367.515	416.220
$\ln VC$ Variable cost	1997-98 2000-01	226.716	23.262	134.269	-	106.321	123.296
	2001-02 2004-05	251.199	24.785	269.054	-	136.723	144.382
	2005-06 2008-09	310.318	29.896	376.418	197.108	169.008	177.630
	2009-10 2012-13	348.413	37.652	465.741	181.505	196.508	194.206
	All years	283.757	28.284	280.149	186.706	149.954	163.528
$\ln WR$ Water revenue	1997-98 2000-01	254.955	237.607	121.955	-	128.385	131.327
	2001-02 2004-05	279.187	48.14	293.735	-	162.134	158.216
	2005-06 2008-09	371.717	61.839	452.846	156.706	213.977	208.396
	2009-10 2010-11	398.268	72.97	474.277	167.682	232.364	218.913
	All years	315.118	53.68	291.893	162.194	175.165	178.838
$\ln SR$ Sewage revenue	1997-98 2000-01	341.078	-	110.404	-	310.990	174.168
	2001-02 2004-05	348.887	-	319.476	-	345.051	159.757
	2005-06 2008-09	452.661	-	549.217	154.020	448.073	196.701
	2009-10 2012-13	519.262	-	582.855	185.799	494.413	224.382
	All years	414.819	-	343.406	175.206	399.631	202.982

Variable	Period	Mean / Standard deviation					St. dev.
		WaSCs	WOCs	Scotland	N. Ireland	All	All
Q_1 Properties connected for water	1997-98 2000-01	1,847.763	319.577	766.474	-	921.547	996.073
	2001-02 2004-05	1,963.765	353.954	1,622.095	-	1,119.925	1,090.076
	2005-06 2008-09	2,007.255	370.316	2,502.743	802.000	1,175.377	1,115.485
	2009-10 2012-13	1,984.229	423.749	2,574.481	808.375	1,206.129	1,094.584
	All years	1,950.542	362.268	1,687.675	806.250	1,098.179	1,074.010
Q_2 Properties billed for sewage	1997-98 2000-01	2,126.547	-	735.068	-	844.078	1,291.213
	2001-02 2004-05	2,196.881	-	1,505.550	-	1,030.942	1,393.675
	2005-06 2008-09	2,251.160	-	2,323.276	625.879	1,081.627	1,434.435
	2009-10 2012-13	2,220.954	-	2,377.098	611.195	1,093.106	1,404.377
	All years	2,198.747	-	1,572.005	616.090	1,005.684	1,377.088
W_1 Labour costs per employee	1997-98 2000-01	26.018	23.888	26.324	-	24.830	3.161
	2001-02 2004-05	30.682	28.662	30.512	-	29.640	3.743
	2005-06 2008-09	36.806	35.126	35.110	41.035	35.975	3.665
	2009-10 2012-13	39.973	38.927	39.949	41.546	39.544	4.001
	All years	33.328	30.939	31.648	41.376	32.136	6.772
W_2 Opportunity cost of capital	1997-98 2000-01	12.761	15.780	-	-	14.572	4.111
	2001-02 2004-05	12.657	15.338	-	-	14.120	2.061
	2005-06 2008-09	12.312	15.131	10.306	17.569	13.801	2.324
	2009-10 2012-13	11.106	13.975	9.220	15.655	12.618	2.691
	All years	12.216	15.133	9.763	16.293	13.804	3.024

Variable	Period	Mean / Standard deviation					St. dev.
		WaSCs	WOCs	Scotland	N. Ireland	All	All
W_3 Industrial electricity price index	1997-98 2000-01	48.656	48.917	47.373	-	48.731	2.234
	2001-02 2004-05	44.989	44.989	45.209	-	45.003	2.038
	2005-06 2008-09	85.833	85.312	85.833	96.244	85.794	15.383
	2009-10 2012-13	105.035	104.671	103.326	104.895	104.797	3.596
	All years	70.915	68.530	63.621	102.011	69.808	26.169
W_4 Retail Price Index (January 1987=100)	1997-98 2000-01	165.058	164.641	168.833	-	165.036	4.458
	2001-02 2004-05	180.504	180.504	178.294	-	180.363	5.424
	2005-06 2008-09	204.200	203.975	204.200	211.687	204.247	8.219
	2009-10 2012-13	231.182	230.416	226.528	231.065	230.653	10.956
	All years	195.010	191.914	188.376	224.606	193.544	25.945
K Modern Equivalent Asset Value	1997-98 2000-01	26,465.800	1,080.151	9,466.296	-	11,134.329	16,975.077
	2001-02 2004-05	28,261.613	1,293.572	21,658.895	-	14,069.248	18,574.648
	2005-06 2008-09	29,745.743	1,409.300	34,150.371	5,783.072	15,099.295	19,405.849
	2009-10 2012-13	30,204.375	1,684.524	34,241.823	6,705.446	15,662.135	19,249.392
	All years	28,659.729	1,339.531	22,425.163	6,397.988	13,872.049	18,527.776
H_1 Percentage of water properties metered	1997-98 2000-01	20.541	19.080	3.026	-	18.723	10.071
	2001-02 2004-05	28.970	30.750	3.569	-	28.258	13.675
	2005-06 2008-09	37.007	40.090	3.159	9.453	36.517	16.106
	2009-10 2012-13	46.534	48.447	3.367	8.512	44.247	19.032
	All years	33.180	33.197	3.280	8.825	31.314	17.647

Variable	Period	Mean / Standard deviation					St. dev.
		WaSCs	WOCs	Scotland	N. Ireland	All	All
H_2 Properties connected for water per km of water mains	1997-98 2000-01	66.889	73.900	51.842	-	70.005	16.377
	2001-02 2004-05	68.223	73.044	53.579	-	69.750	16.677
	2005-06 2008-09	69.191	73.682	53.097	30.602	69.939	17.431
	2009-10 2012-13	67.814	76.278	54.185	30.482	69.692	17.896
	All years	68.031	74.146	53.025	30.522	69.854	17.002
H_3 Water quality index	1997-98 2000-01	99.847	99.669	99.184	-	99.709	0.557
	2001-02 2004-05	99.946	99.922	99.529	-	99.907	0.172
	2005-06 2008-09	99.974	99.983	99.702	98.996	99.946	0.162
	2009-10 2012-13	99.984	99.988	99.922	99.773	99.974	0.048
	All years	99.937	99.874	99.519	99.514	99.877	0.334
H_4 Percentage of water properties above reference pressure	1997-98 2000-01	89.700	94.929	91.463	-	92.760	7.079
	2001-02 2004-05	93.160	96.213	93.464	-	94.739	4.402
	2005-06 2008-09	95.122	97.782	92.890	79.438	96.033	4.001
	2009-10 2012-13	96.703	98.091	94.900	80.441	96.565	4.261
	All years	93.652	96.597	92.938	80.107	94.926	5.372
H_5 Percentage of sewage properties metered	1997-98 2000-01	18.463	-	2.338	-	16.360	9.891
	2001-02 2004-05	27.067	-	2.664	-	23.884	13.234
	2005-06 2008-09	36.602	-	2.502	7.636	32.377	16.805
	2009-10 2012-13	45.630	-	2.757	3.684	39.186	20.674
	All years	31.854	-	2.541	5.002	27.952	17.784

Variable	Period	Mean / Standard deviation					St. dev.
		WaSCs	WOCs	Scotland	N. Ireland	All	All
Y_1 Gross Domestic Household Income per capita	1997-98 2000-01	10,289.488	10,277.176	10,195.095	-	10,955.421	1,734.927
	2001-02 2004-05	12,322.306	13,678.993	11,518.167	-	12,963.754	1,805.033
	2005-06 2008-09	14,034.554	15,464.825	13,657.749	12,811.000	14,714.860	2,105.449
	2009-10 2010-11	15,089.107	16,795.066	15,131.998	13,142.500	15,838.522	2,164.871
	All years	12,608.252	13,793.528	11,954.142	12,976.750	13,198.471	2,611.934
Y_2 Days with rainfall over 1mm	1997-98 2000-01	151.787	155.945	183.659	-	142.489	25.685
	2001-02 2004-05	135.779	121.057	188.013	-	131.595	21.546
	2005-06 2008-09	137.256	121.094	190.150	175.915	132.195	22.971
	2009-10 2010-11	137.437	119.476	185.190	169.822	132.218	26.225
	All years	141.037	124.638	186.723	172.868	135.259	24.321
Y_3 Mean temperature	1997-98 2000-01	9.905	9.636	7.843	-	10.199	0.914
	2001-02 2004-05	10.127	10.772	8.263	-	10.338	0.784
	2005-06 2008-09	10.109	10.756	8.109	9.325	10.333	0.974
	2009-10 2010-11	9.37	10.063	7.306	8.535	9.58	0.833
	All years	9.955	10.632	7.983	8.93	10.192	0.917
Z_2 Years of regulation	1997-98 2000-01	9.500	9.400	1.500	-	8.991	2.136
	2001-02 2004-05	13.500	13.500	4.000	-	12.894	2.592
	2005-06 2008-09	17.500	17.404	8.500	1.500	16.720	3.122
	2009-10 2012-13	21.513	21.429	12.000	4.500	20.375	4.044
	All years	15.465	14.873	5.421	3.500	14.470	5.226

Variable	Period	Mean / Standard deviation					St. dev.
		WaSCs	WOCs	Scotland	N. Ireland	All	All
Z_3 K factor	1997-98 2000-01	-1.892	-1.975	11.467	-	-1.183	6.998
	2001-02 2004-05	0.787	-0.197	10.283	-	0.891	3.546
	2005-06 2008-09	5.117	3.523	-3.175	5.450	3.962	4.618
	2009-10 2012-13	0.971	0.493	-1.667	-0.300	0.595	1.958
	All years	1.247	0.296	5.937	1.617	0.995	5.115
Z_5 Percentage of the board that are non-executives	1997-98 2000-01	30.850	49.533	91.667	-	44.868	28.282
	2001-02 2004-05	42.450	55.375	75.333	-	51.149	25.414
	2005-06 2008-09	49.400	64.234	62.000	53.500	57.527	20.372
	2009-10 2012-13	61.897	62.667	62.000	51.250	61.784	14.850
	All years	46.050	57.264	75.579	52.000	53.415	23.918
Z_6 Directors' average years on the board	1997-98 2000-01	4.321	4.497	2.470	-	4.316	1.466
	2001-02 2004-05	4.701	5.716	3.298	-	5.129	1.731
	2005-06 2008-09	4.401	6.802	5.277	2.388	5.609	2.360
	2009-10 2012-13	5.081	6.492	5.464	3.193	5.681	2.109
	All years	4.623	5.769	3.795	2.925	5.148	2.001

5.4. Results

In this section, we present results from each of the of the models discussed in section 5.2. Estimation of each model is undertaken using the user-written *sfcross* and *sfpanel* packages (Belotti et al. 2013) for Stata and Frontier 4.1c (Coelli 1996); results presented are taken from the former.

Parameter estimates are shown and discussed in section 5.4.1. Likelihood ratio tests are shown in section 5.4.2 and preferred specifications are identified on the basis of these. Our main results, concerning efficiency trends and the effects of our environmental variables on efficiency, are then discussed in section 5.4.3. Section 5.5 summarises.

5.4.1. Parameter Estimates

Tables 5 and 6 show the estimated parameters of the total cost and variable cost frontier models, respectively. Results are shown for the full translog specifications given in (84) and (85) and also for restricted Cobb-Douglas forms for comparison. The estimated water revenue and sewage revenue frontiers are shown in tables 7 and 8, respectively.

In each case, parameter estimates are shown along with standard errors in parentheses and stars indicating significance. Further results are shown in appendix 3. Likewise, and as in previous studies, our density measure H_2 is associated with reduced costs, although this is insignificant in the variable cost model.

TABLE 5: WATER AND SEWAGE TOTAL COST MODEL ESTIMATES

Parameter (Variable)	Estimate (Standard Error)			
	Translog		Cobb-Douglas	
α	0.130 (0.060)	**	0.057 (0.055)	
θ (t)	-0.011 (0.012)		-0.010 (0.005)	**
β_1 ($\ln Q_1$)	0.611 (0.042)	***	0.954 (0.015)	***
β_2 ($\ln Q_2$)	0.211 (0.034)	***	0.145 (0.006)	***
γ_1 ($\ln W_1$)	0.179 (0.216)		0.293 (0.087)	***
γ_2 ($\ln W_2$)	0.137 (0.084)		0.028 (0.047)	
γ_3 ($\ln W_3$)	0.441 (0.226)	*	0.165 (0.049)	***
ϑ (t^2)	0.001 (0.001)		-	-
$\zeta_{1,1}$ ($\ln Q_1^2$)	0.051 (0.012)	***	-	-
$\zeta_{2,2}$ ($\ln Q_1^2$)	0.019 (0.005)	***	-	-
$\eta_{1,1}$ ($\ln W_1^2$)	0.389 (0.238)		-	-
$\eta_{2,2}$ ($\ln W_2^2$)	0.101 (0.092)		-	-
$\eta_{3,3}$ ($\ln W_3^2$)	0.379 (0.160)	**	-	-
φ_1 ($t \ln Q_1$)	-0.005 (0.003)		-	-
φ_2 ($t \ln Q_2$)	0.005 (0.001)	***	-	-
ϕ_1 ($t \ln W_1$)	-0.018 (0.024)		-	-
ϕ_2 ($t \ln W_2$)	-0.003 (0.013)		-	-
ϕ_3 ($t \ln W_3$)	-0.023 (0.026)		-	-
$\zeta_{1,2}$ ($\ln Q_1 \ln Q_2$)	-0.078 (0.006)	***	-	-
$\lambda_{1,1}$ ($\ln Q_1 \ln W_1$)	0.331 (0.116)	***	-	-
$\lambda_{1,2}$ ($\ln Q_1 \ln W_2$)	-0.008 (0.037)		-	-
$\lambda_{1,3}$ ($\ln Q_1 \ln W_3$)	0.017 (0.053)		-	-
$\lambda_{2,1}$ ($\ln Q_2 \ln W_1$)	-0.072 (0.032)	**	-	-
$\lambda_{2,2}$ ($\ln Q_2 \ln W_2$)	0.030 (0.012)	**	-	-
$\lambda_{2,3}$ ($\ln Q_2 \ln W_3$)	0.004 (0.017)		-	-
$\eta_{1,2}$ ($\ln W_1 \ln W_2$)	0.501 (0.291)	*	-	-
$\eta_{1,3}$ ($\ln W_1 \ln W_3$)	-0.181 (0.264)		-	-
$\eta_{2,3}$ ($\ln W_2 \ln W_3$)	0.574 (0.235)	**	-	-
β_3 ($\ln H_1$)	0.141 (0.013)	***	0.106 (0.019)	***
β_4 ($\ln H_2$)	-0.287 (0.037)	***	-0.271 (0.045)	***
β_5 ($\ln H_3$)	-0.262 (0.135)	*	-1.152 (0.382)	***
β_6 ($\ln H_4$)	-1.537 (0.509)	***	-0.024 (0.166)	
δ_0	-0.023 (0.011)	**	0.218 (0.046)	***
δ_1 (Z_1)	0.006 (0.000)	***	-0.013 (0.003)	***
δ_2 (Z_2)	-0.012 (0.000)	***	-0.006 (0.005)	
δ_3 (Z_3)	0.005 (0.001)	***	0.007 (0.003)	***
δ_4 (Z_4)	-0.008 (0.015)		-1.056 (1.031)	
δ_5 (Z_5)	-	-	0.001 (0.001)	
δ_6 (Z_6)	-	-	-0.008 (0.007)	
σ^2	0.011 (0.001)		0.029 (0.003)	
γ	0.050 (0.004)		0.646 (0.105)	
lnLikelihood	307.452		165.163	
Mean inefficiency	1.048		1.332	

Significance level: * 10% ** 5% ***1%

TABLE 6: WATER AND SEWAGE VARIABLE COST MODEL ESTIMATES

Parameter (Variable)	Estimate (Standard Error)			
	Translog		Cobb-Douglas	
α	-0.034 (0.097)		0.012 (0.039)	
θ (t)	-0.008 (0.017)		-0.008 (0.004)	**
β_1 ($\ln Q_1$)	0.901 (0.079)	***	0.660 (0.025)	***
β_2 ($\ln Q_2$)	0.096 (0.046)	**	0.048 (0.005)	***
γ_1 ($\ln W_1$)	0.350 (0.243)		0.151 (0.063)	**
γ_2 ($\ln W_2$)	0.167 (0.242)		0.173 (0.036)	***
γ_3 ($\ln K$)	-0.095 (0.086)		0.293 (0.024)	***
ϑ (t^2)	0.001 (0.001)		-	-
$\zeta_{1,1}$ ($\ln Q_1^2$)	0.084 (0.067)		-	-
$\zeta_{2,2}$ ($\ln Q_1^2$)	-3.39E-04 (0.008)		-	-
$\eta_{1,1}$ ($\ln W_1^2$)	0.070 (0.295)		-	-
$\eta_{2,2}$ ($\ln W_2^2$)	0.249 (0.193)		-	-
$\eta_{3,3}$ ($\ln K^2$)	-0.123 (0.089)		-	-
φ_1 ($t \ln Q_1$)	-0.027 (0.007)	***	-	-
φ_2 ($t \ln Q_2$)	-5.89E-05 (0.001)		-	-
ϕ_1 ($t \ln W_1$)	-0.030 (0.023)		-	-
ϕ_2 ($t \ln W_2$)	-0.003 (0.026)		-	-
ϕ_3 ($t \ln K$)	0.023 (0.007)	***	-	-
$\zeta_{1,2}$ ($\ln Q_1 \ln Q_2$)	-0.055 (0.034)		-	-
$\lambda_{1,1}$ ($\ln Q_1 \ln W_1$)	0.072 (0.257)		-	-
$\lambda_{1,2}$ ($\ln Q_1 \ln W_2$)	0.120 (0.117)		-	-
$\lambda_{1,3}$ ($\ln Q_1 \ln K$)	0.062 (0.154)		-	-
$\lambda_{2,1}$ ($\ln Q_2 \ln W_1$)	-0.118 (0.052)	**	-	-
$\lambda_{2,2}$ ($\ln Q_2 \ln W_2$)	0.015 (0.025)		-	-
$\lambda_{2,3}$ ($\ln Q_2 \ln K$)	0.051 (0.035)		-	-
$\eta_{1,2}$ ($\ln W_1 \ln W_2$)	0.098 (0.348)		-	-
$\eta_{1,3}$ ($\ln W_1 \ln K$)	0.180 (0.249)		-	-
$\eta_{2,3}$ ($\ln W_2 \ln K$)	-0.119 (0.116)		-	-
β_3 ($\ln H_1$)	0.120 (0.020)	***	0.137 (0.018)	***
β_4 ($\ln H_2$)	-0.037 (0.05)		-0.029 (0.035)	
β_5 ($\ln H_3$)	-3.903 (2.369)	*	-1.102 (2.299)	
β_6 ($\ln H_4$)	-0.176 (0.135)		0.100 (0.124)	
δ_0	0.063 (0.043)		0.133 (0.043)	***
δ_1 (Z_1)	0.004 (0.001)	**	-0.008 (0.001)	***
δ_2 (Z_2)	-0.028 (0.007)	***	-0.022 (0.005)	***
δ_3 (Z_3)	0.005 (0.002)	***	0.004 (0.002)	**
δ_4 (Z_4)	0.176 (0.089)	**	0.331 (0.068)	***
δ_5 (Z_5)	4.81E-04 (0.001)		-9.60E-04 (0.000)	**
δ_6 (Z_6)	-0.008 (0.006)		-0.004 (0.005)	
σ^2	0.014 (0.002)		0.016 (0.002)	
γ	0.666 (0.097)		0.696 (0.090)	
lnLikelihood	352.620		306.381	
Mean Inefficiency	1.172		1.257	

Significance level: * 10% ** 5% ***1%

Our total cost and variable cost models yield plausible parameter estimates, as shown in tables 6 and 7. As previously discussed, since our variables are mean-centred, the first order parameters from the translog model are interpreted as elasticities at the sample means.

Estimated returns to scale at the sample means, defined as the inverse of the sum of the first order output elasticities, are 1.217 in the translog total cost model, and 1.003 in the translog variable cost model. Respectively, these suggest substantial increasing returns to scale and constant returns to scale at the sample means, though it should be noted that the sample means are not the same across the two models owing to the inclusion of additional observations on Scottish Water and the former Scottish water authorities in the variable cost model.

Input price elasticities are also plausible. As explained in section 5.2.1, costs and input prices are normalised by W_4, the retail price index, in order to impose linear homogeneity of degree one in input prices as required. However, no restriction is made to ensure that the estimated elasticities for each input price is positive. Nevertheless, in both the total cost and variable cost models, the estimated elasticities at the sample means are positive in each case.

The proportion of water properties that are metred, H_1, is found to increase costs as expected, with estimated elasticities of 0.141 and 0.120 in the total and variable cost models respectively. Likewise, our water quality variable, H_3, is found to be negatively related with cost. Our density and pressure variables, H_2 and H_4, are on the other hand only found to be significant in the total cost model; density is found to reduce costs, as expected, while water pressure is has a negative estimated elasticity. It is noteworthy that both water quality and water pressure are negatively associated with costs. This contrasts with the expectation that in most cases increasing quality will be costly, suggesting a positive relationship. However, in the context of the regulation faced by UK water and sewage firms, the finding of a negative relationship may be explained by the fact that lapses in quality—i.e. incidents in which water is contaminated, or water pressure is affected—are likely to be require costly remedial spending.

Finally, the first order coefficients on our time trend variable are estimated at -0.011 in the total cost model and -0.008 in the variable cost model, and estimated second order coefficients are around 0.001 in both cases. Since we do not take the logarithm of the time trend variable, the relationship between the time trend and costs is semi-logarithmic, with the first order coefficient being the annual percentage change in costs holding everything else constant, which is interpreted as the rate of technical change. Since we also do not mean-centre the time trend, the first order coefficients is the annual rate of technical change at the beginning of the period. Given the negative first order coefficients and positive second order coefficients, our models imply technical progress initially, but at a declining rate.

Results regarding the environmental variables in the inefficiency model, their estimated coefficients, and their marginal effects on inefficiency are discussed in section 5.4.3.2.

TABLE 7: WATER REVENUE MODEL ESTIMATES

Parameter (Variable)	Estimate (Standard Error)	
	Translog	
α	-0.043 (0.035)	
θ (t)	0.021 (0.004)	***
β_1 ($\ln Q_1$)	0.936 (0.012)	***
β_2 ($\ln Y_1$)	0.268 (0.07)	***
β_3 ($\ln Y_2$)	0.114 (0.061)	*
β_4 ($\ln Y_3$)	-0.179 (0.125)	
β_5 ($\ln H_1$)	0.042 (0.016)	**
β_6 ($\ln H_2$)	-0.261 (0.041)	***
β_7 ($\ln H_3$)	-0.045 (0.152)	
β_8 ($\ln H_4$)	-0.82 (2.724)	
δ_0	-0.018 (0.121)	
δ_1 (Z_1)	-0.019 (0.007)	***
δ_2 (Z_2)	0.013 (0.005)	**
δ_3 (Z_4)	0.017 (0.074)	
δ_4 (Z_5)	0.046 (0.155)	
δ_5 (Z_6)	-6.06E-04 (0.001)	
δ_6 (Z_7)	-0.007 (0.008)	
σ^2	0.029 (0.006)	
γ	0.742 (0.07)	
lnLikelihood	208.585	
Mean Efficiency	0.855	

Significance level: * 10% ** 5% ***1%

TABLE 8: SEWAGE REVENUE MODEL ESTIMATES

Parameter (Variable)	Estimate (Standard Error)	
	Translog	
α	-0.663 (0.072)	***
θ (t)	0.054 (0.005)	***
β_1 ($\ln Q_1$)	0.676 (0.033)	***
β_2 ($\ln Y_1$)	-0.455 (0.126)	***
β_3 ($\ln H_2$)	0.034 (0.059)	
β_4 ($\ln H_5$)	0.204 (0.031)	***
δ_0	0.176 (0.067)	***
δ_1 (Z_1)	0.004 (0.001)	***
δ_2 (Z_2)	-0.023 (0.007)	***
δ_3 (Z_4)	0.03 (0.083)	
δ_4 (Z_5)	-0.002 (0.001)	
δ_5 (Z_6)	-0.021 (0.01)	**
σ^2	0.873 (0.091)	
γ	0.022 (0.004)	
lnLikelihood	129.196	
Mean Efficiency	0.804	

Significance level: * 10% ** 5% ***1%

Water revenue and sewage revenue are both, as expected, found to be increasing in the number of water and sewage properties respectively. In the water case, the elasticity of revenue with respect to properties is 0.936, while in the sewage case the elasticity is 0.676. An increasing trend over time is also found in both cases, with estimated 2.1% and 5.4% per year increases in water revenue and sewage revenue respectively, after controlling for scale, income, climate variables, and hedonic variables.

As expected, water revenue is found to increase with average income as measured by Y_1, gross domestic household income per capita. On the other hand, the estimated effect elasticity of sewage revenue with respect to income is negative. Since the relationship between income and revenue depends upon the relationship between income and demand, this implies that sewage services are an inferior good. Water revenue is also found to increase with the number of rainy days in the year, although no statistically significant temperature effect is found.

Water revenue is found to increase with H_1, the proportion of water properties metred, and likewise sewage revenue is found to increase with H_5, the proportion of sewage properties metred. This is as expected, since metring allows the companies to measure customers' usage. Also as expected, water revenue is found to decrease with network density, H_2, since customers in denser areas are likely to have smaller gardens, or no garden. Sewage revenue, on the other hand, is found to increase with network density.

Again, our main results around our environmental variables and their effects on efficiency are discussed in section 5.4.3.2.

5.4.2. Likelihood Ratio Tests

In this section, we assess the appropriateness of our models, and identify preferred specifications, on the basis of likelihood ratio tests. Likelihood ratio tests are commonly used in SFA for the purpose of hypothesis testing. For example, as discussed in chapter 3, many more complex models nest simpler models, for example with more restrictive distributional assumptions.

The first null hypothesis that we test, in the context of the total cost and variable cost models, is that the second-order terms in the translog models are jointly equal to zero, in which case the simpler Cobb-Douglas model is the null model. This is a standard problem, in which the likelihood ratio statistic follows a chi-squared distribution with degrees of freedom equal to the number of parameter restrictions.

Some common hypothesis tests in the SFA involve non-standard problems. For example, testing for the presence of inefficiency is of particular interest. In the standard normal-half normal model, the relevant null hypothesis is therefore $H_0: \sigma_u = 0$—or, under the alternative parameterisation adopted here $H_0: \gamma = 0$. Under this null hypothesis, the errors are normally distributed with no one-sided component, and OLS is the maximum likelihood estimator. The standard result that the likelihood ratio statistic follows a χ_1^2 distribution does not apply in this case, since σ_u—or γ—is at the boundary of the parameter space under the null hypothesis. In such cases, the likelihood ratio follows a mixture of chi-squared distributions, e.g. a 50:50 mixture of χ_1^2 and χ_0^2 distributions, denoted $\chi_{1:0}^2$, in the normal-half normal case (Coelli 1995).

However, in the case of the Battese and Coelli (1995) model, the null hypothesis that there is no inefficiency requires that all of the coefficients on the environmental variables, in addition to the intercept δ_0 and the γ parameter, are equal to zero, in which case the likelihood ratio follows an approximately chi-squared distribution with degrees of freedom equal to the number of parameter restrictions (Battese and Coelli 1995). This is our second test.

Third, we test the null hypothesis that the coefficients on the environmental variables in the inefficiency model are jointly equal to zero, i.e. that inefficiency is present, but is not a function of the environmental variables. The null model in this case is the simple normal-truncated normal model proposed by Stevenson (1980). Again, this is a standard problem, in which the likelihood ratio follows a chi-squared distribution with degrees of freedom equal to the number of parameter restrictions.

TABLE 9: LIKELIHOOD RATIO TESTS

Null Hypothesis	Likelihood ratio			
	Total Cost	Variable Cost	Water Revenue	Sewage Revenue
$\mathrm{H}_0: \vartheta = \zeta_{1,1} = \zeta_{2,2} = \eta_{1,1} = \eta_{2,2} = \eta_{3,3} = \varphi_1 = \varphi_2 = \phi_1 = \phi_2 = \phi_3 = \zeta_{1,2} = \lambda_{1,1} = \lambda_{1,2} = \cdots = \lambda_{2,3} = \eta_{1,2} = \eta_{1,3} = \eta_{2,3} = 0$ Cobb-Douglas functional form.	284.578 ***	92.479 ***	-	-
$\mathrm{H}_0: \gamma = \delta_0 = \delta_1 = \cdots = \delta_6 = 0$ No inefficiency, null model estimated via OLS.†	54.450 ***	126.633 ***	55.908 ***	47.424 ***
$\mathrm{H}_0: \delta_1 = \delta_2 = \cdots = \delta_6 = 0$ Inefficiency is present, but is not a function of environmental variables. Inefficiency distribution is truncated normal.	54.450 ***	103.873 ***	55.034 ***	47.424 ***
Significance level: * 10% ** 5% ***1% † Log-likelihood for null model assumes normal errors.				

Table 9 above shows the likelihood ratio values in each case, along with stars indicating significance levels. As can be seen, for both cost models, we strongly reject the null hypothesis that the functional form is Cobb-Douglas. We therefore prefer the more flexible translog specifications in each case, and the subsequent tests assume the translog functional form for the cost frontiers.

For all four models we are able to strongly reject the null hypothesis of no inefficiency. Likewise, we are also able to strongly reject the null hypothesis that inefficiency is not a function of our environmental variables across all four models. Our preferred models are therefore those shown in tables 5 to 8, and for our cost models the translog specifications in particular. All of the discussion of results that follows is based on these preferred models.

Two things should be noted at this point: first, variables Z_5 and Z_6 are excluded from our preferred total cost specification, since these were not found to be statistically significant and no improvement in the log-likelihood could be found when these variables were included. Note that these variables are also found to be insignificant in the Cobb-Douglas total cost specification.

Second, the values of the likelihood ratio under the second and third null hypotheses are the same for the total cost and sewage revenue models: this is due to the fact that the skewness of the OLS residuals is in the ‘wrong’ direction in these cases, resulting in an estimated γ near zero. As discussed above, extreme values of γ are not as concerning in the Battese and Coelli (1995) specification, in which evidence for inefficiency is based not on skewness alone, but also on the significance of the environmental variables.

5.4.3. Main Results

In this section, we present and discuss our main results based on the preferred models identified in section 5.4.2. We focus on the trends and distribution of efficiency scores, discussed in section 5.4.3.1, and the effects of our environmental variables on efficiency, discussed in 5.4.3.2.

5.4.3.1. Efficiency Trends

As discussed in chapter 3, efficiency predictions are obtained, following Jondrow et al. (1982) and Battese and Coelli (1988), using the conditional mean $E[\exp(su_{it})|\varepsilon_{it}]$, the formula for which is shown by (71) for the Battese and Coelli (1995) case.

Trends in average efficiency scores are shown in figures 5.4.1 to 5.4.6. Figure 5.4.5 shows trends in total cost inefficiency, figure 5.4.6 shows trends in variable cost inefficiency, figure 5.4.4 shows trends in water revenue efficiency, and figure 5.4.3 shows trends in sewage revenue efficiency. This information is summarised in figures 5.4.1 and 5.4.2, which combine trendlines for overall revenue efficiency with the trendlines for total cost and variable cost inefficiency, respectively.

Overall revenue efficiency is calculated by weighting water and sewage revenue efficiency scores by the revenue shares of water and sewage activities. Since sewage revenue efficiency scores are only available up to 2010-11, overall revenue efficiency is shown only up to this year. Figure 5.4.4 shows trends in sewage revenue efficiency up to 2012-13. Our conclusions based on these efficiency trends are discussed below.

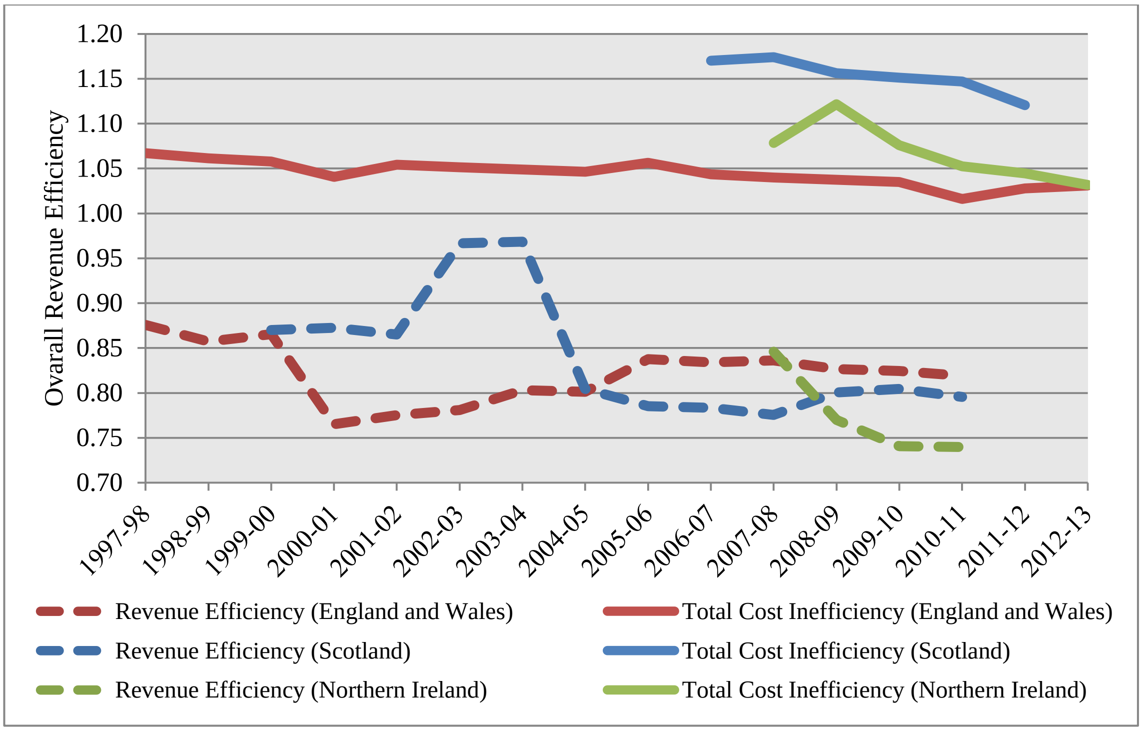

FIGURE 5.4.1: TRENDS IN REVENUE EFFICIENCY AND TOTAL COST INEFFICIENCY

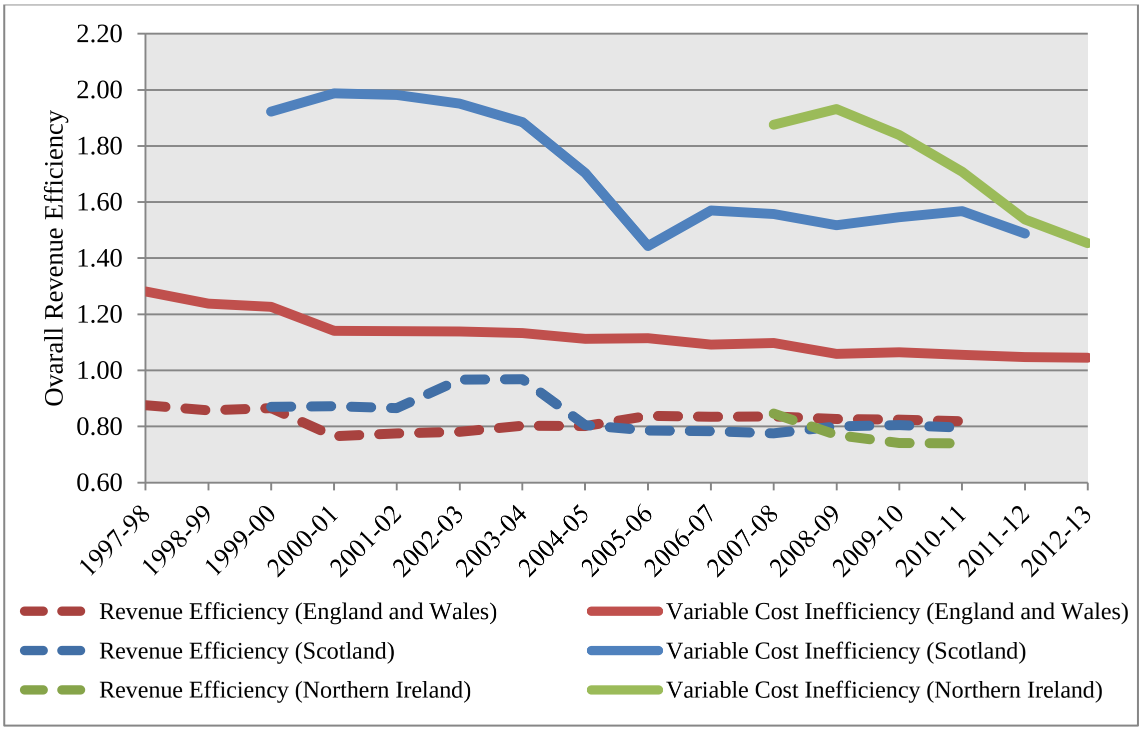

FIGURE 5.4.2: TRENDS IN REVENUE EFFICIENCY AND VARIABLE COST INEFFICIENCY

First, average predicted total cost inefficiency, variable cost inefficiency, and overall revenue efficiency have all decreased over the sample period and across all three country groupings, as can be seen in figures 5.4.1 and 5.4.2. We therefore conclude that RPI+K price capping regulation therefore appears to have been effective over this period, first in terms of incentivising improvements in cost efficiency, and second in terms of reducing revenues away from their potential monopoly levels. In terms of welfare, the reduction in overall revenue efficiency implies a transfer from the WaSCs and WOCs to consumers and a reduction in deadweight loss, and the reductions in cost inefficiencies can be interpreted as transfers within the firm, from agent to principal.

Second, average predicted total cost inefficiencies and variable cost inefficiencies are significantly higher in Scotland and Northern Ireland than in England and Wales. These differences in cost efficiency, however, have decreased over the sample period, with the Scottish and Northern Irish companies catching up to their English and Welsh counterparts. We therefore conclude that the onset of RPI+K style price capping regulation, which as discussed in chapter 1 was introduced in Scotland and Northern Ireland more recently than in England and Wales—1999-00 and 2007-08 respectively, compared to 1990-91 in England and Wales—has been effective in reducing the gap in cost efficiency among the Scottish and Northern Irish companies relative to their English and Welsh counterparts.

Third, the variable cost model predicts very similar initial inefficiencies in Scotland and Northern Ireland, i.e. at the onset of RPI+K regulation, and also predicts very similar inefficiencies at the end of the sample period. Furthermore, the trends in predicted variable cost inefficiency are also similar between Scotland and Northern Ireland, increasing slightly in the second year of price capping before falling rapidly in the following five or six years. All of this suggests that the introduction of RPI+K regulation has had a very similar impact in Scotland and Northern Ireland.

Note that in the Scottish case, the reduction in variable cost inefficiency seems to have slowed down or stopped around 2005-06, so that most of the cost efficiency gains made by the company were made in the first six years following the onset of RPI+K regulation. This is despite the fact that, at the end of the sample period, a significant gap remains between Scottish Water and its English and Welsh counterparts, which are approaching the frontier towards the end of the sample period, in terms of predicted variable cost efficiency. The picture from total cost model is slightly different, and suggests that Northern Ireland Water started with a much closer to the English and Welsh companies than did Scottish Water, and converged to English and Welsh cost efficiency levels by the end of the sample period; Scottish Water nevertheless appears to have been converging rapidly to the cost efficiency levels of the English and Welsh firm, which again appear to be approaching the frontier towards the end of the sample period. We therefore conclude that the cost efficiency gains resulting from RPI+K regulation are concentrated in the early years and diminish as time goes on and firms approach the frontier.

The trends in overall revenue efficiency have been more modest, and it is less clear that there is any systematic difference between England and Wales on the one hand, and Scotland and Northern Ireland on the other. Average predicted overall revenue efficiency in England and Wales declined from 0.876 in 1997-98 to 0.819 in 2010-11, in Scotland from 0.870 in 1999-00 to 0.796 in 2010-11, and in Northern Ireland from 0.846 in 2007-08 to 0.740 in 2010-11. Aside from these declines in overall revenue efficiency, however, are the separate trends in water and sewage revenue efficiencies. Tables 5.4.3 and 5.4.4 show the trends in average predicted water revenue efficiency and sewage revenue efficiency, respectively. Average predicted water revenue efficiency in England and Wales has declined from 0.909 in 1997-98 to 0.839 in 2010-11, similar to the steady decline in overall revenue efficiency over the period. However, in Scotland and Northern Ireland, water revenue efficiency initially increases following the onset of price capping regulation, before declining subsequently.

Sewage revenue efficiency, on the other hand, appears to have increased substantially over the sample period in England and Wales, from 0.668 in 1997-98 to 0.909 in 2012-13. In Scotland and Northern Ireland however, predicted sewage revenue efficiency fell for the first two and three years of price capping respectively, from 0.759 to 0.637 in Scotland and from 0.880 to 0.645 in Northern Ireland. In Scotland, sewage revenue efficiency then began to increase, reaching 0.824 by 2011-12; likewise, in Northern Ireland, there has been a slight increase since 2009-10. Notably, while overall revenue efficiency is declining, water and sewage revenue efficiencies seem to be moving in opposite directions, with declining water revenue efficiency partially offset by increasing sewage revenue efficiency; this may be an indication of cross-subsidisation between water and sewage activities, and changes in the extent of this over the period.

To summarise, the conclusions reached in this section are that:

i. RPI+K regulation has been effective, first in terms of incentivising improvements in cost efficiency, and second in terms of reducing revenues away from their potential monopoly levels.
ii. RPI+K regulation has been effective in reducing the gap in cost efficiency among the Scottish and Northern Irish companies relative to their English and Welsh counterparts.

iii. Cost efficiency gains resulting from RPI+K regulation are concentrated in the early years and diminish as time goes on and firms approach the frontier.

In terms of welfare, we note that the reduction of revenues away from their potential monopoly levels captured by the observed downward trends in overall revenue efficiencies implies both transfers from the companies to customers, and reductions in deadweight losses. On the cost side, the observed reductions in cost inefficiency can be interpreted as transfers within the firm, i.e. from principals to agents.

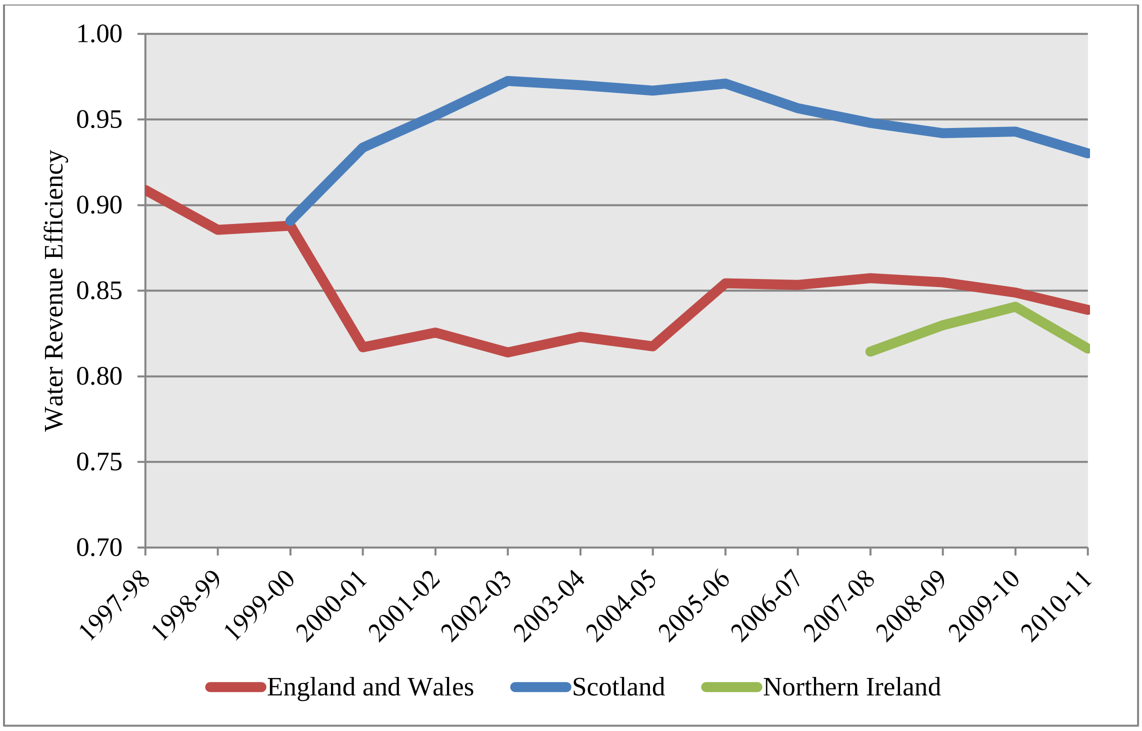

FIGURE 5.4.3: TRENDS IN MEAN WATER REVENUE EFFICIENCY

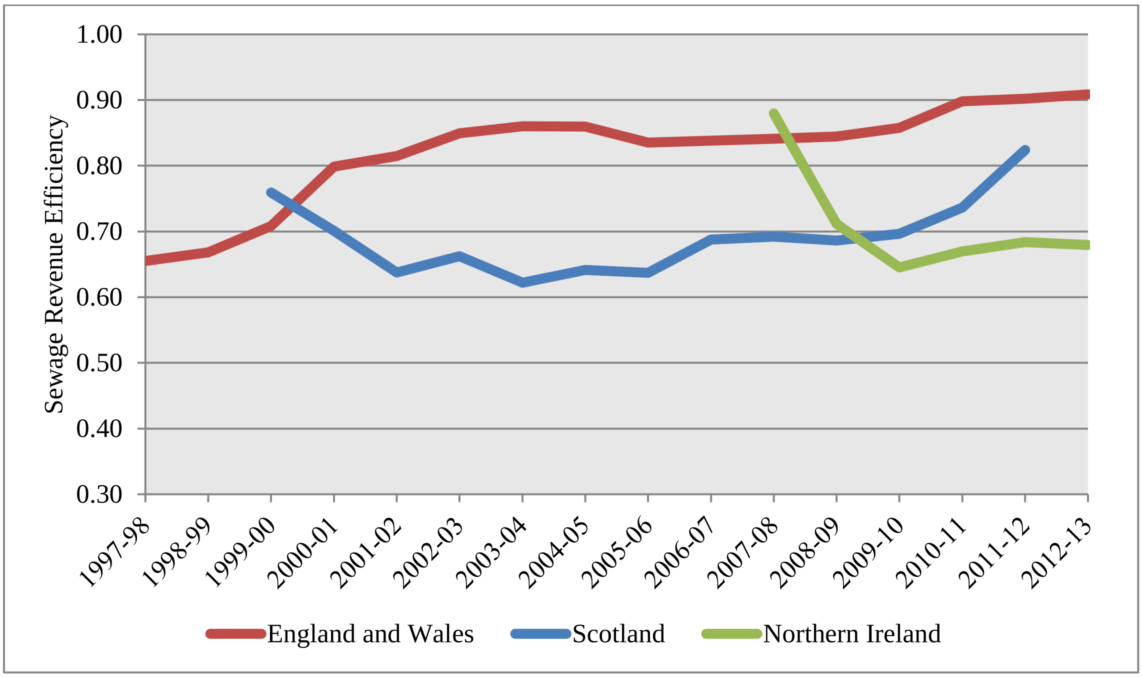

FIGURE 5.4.4: TRENDS IN MEAN SEWAGE REVENUE EFFICIENCY

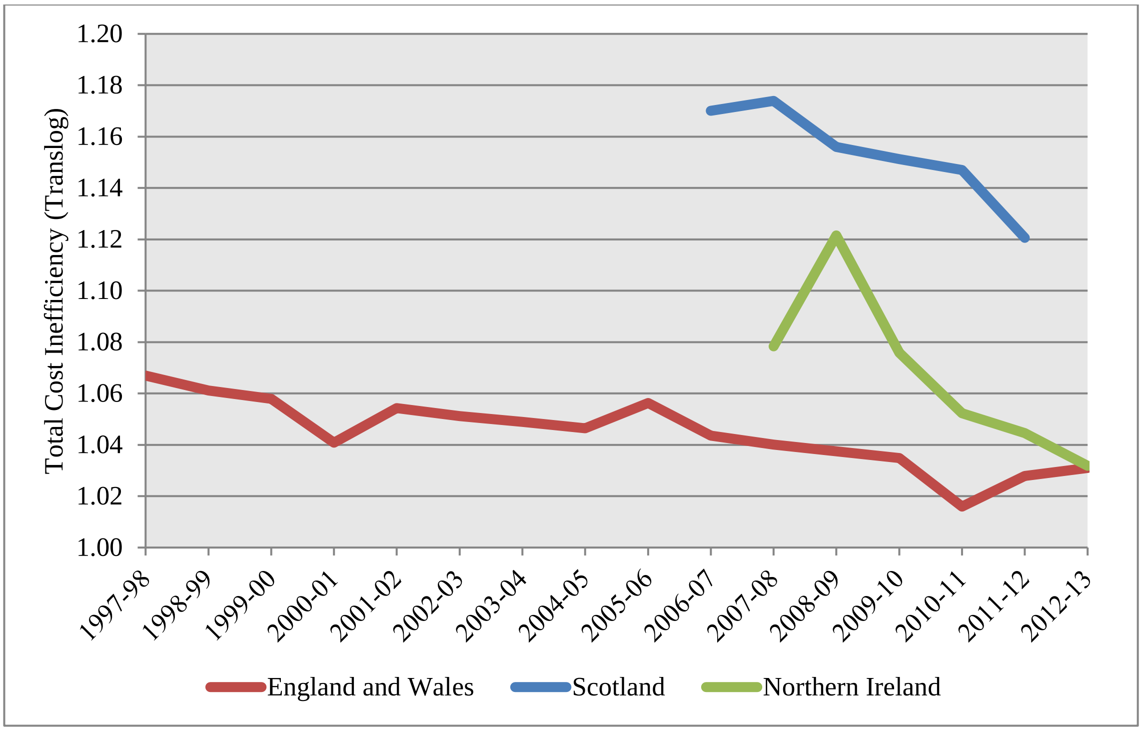

FIGURE 5.4.5: TRENDS IN MEAN TOTAL COST INEFFICIENCY

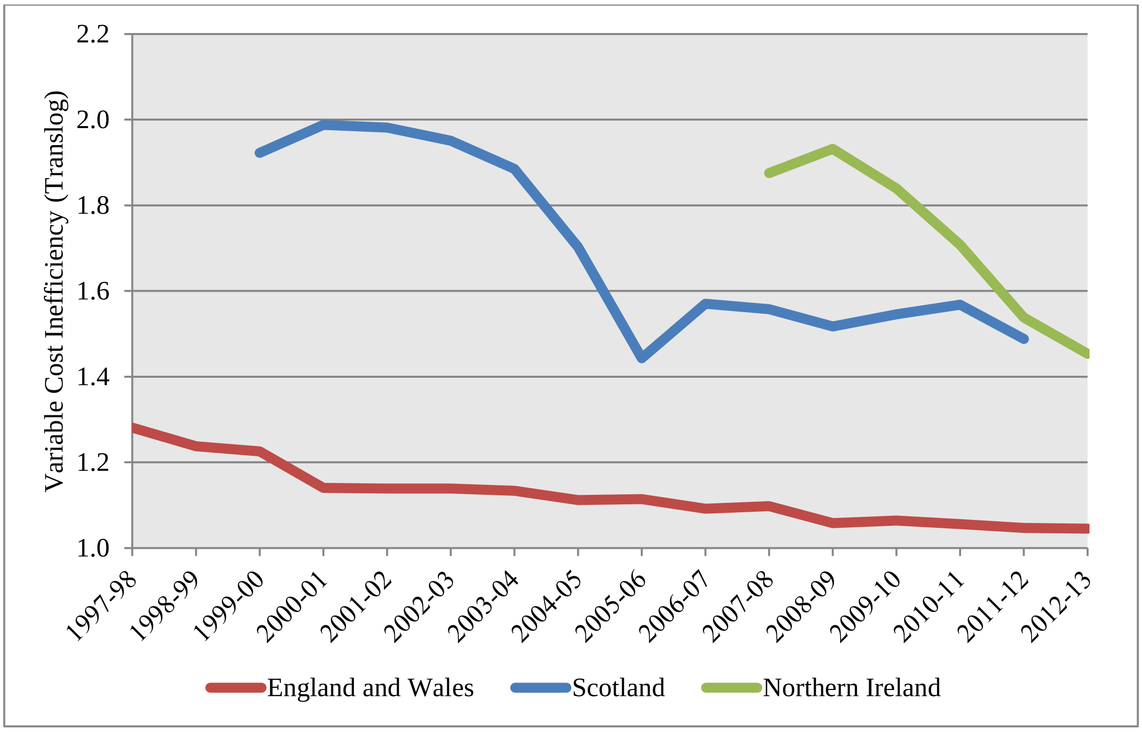

FIGURE 5.4.6: TRENDS IN MEAN VARIABLE COST INEFFICIENCY

5.4.3.2. Marginal Effects

In this section, we discuss the impact of our environmental variables on inefficiency in each of the four preferred models. This provides additional context to the changes in efficiency predictions discussed in the section 5.4.3.1 and helps us to understand the impact of regulation and other factors on revenue and cost efficiency.

As discussed in sections 3.3.6, quantifying the impact of environmental variables on efficiency or inefficiency from Battese and Coelli (1995) models is not straightforward. There are several different formulae for marginal effects, each based on different efficiency predictors. To briefly recap:

i. Wang (2002) takes derivative of the unconditional mean, $\partial E(u_{it})/\partial z_{lit}$, while Kumbhakar and Sun (2013) take the derivative of the Jondrow et al. (1982) conditional mean predictor, $\partial E(u_{it}|\varepsilon_{it})/\partial z_{lit}$. These formulae are shown, for the Battese and Coelli (1995) case, in (73) and (74) respectively, and transformed as shown in (78) and (80) so that we may interpret them as marginal effects on cost inefficiency and revenue efficiency.

ii. Two additional formulae are derived in this thesis: the first is the derivative of the Battese and Coelli (1988) conditional mean predictor, $\partial E[\exp(su_{it})|\varepsilon_{it}]/\partial z_{lit}$, and the second is the derivative of the conditional mode predictor, $\partial \exp[sM(u_{it}|\varepsilon_{it})]/\partial z_{lit}$.

Since predictors based on the distribution of $u_{it}|\varepsilon_{it}$ are preferred, the conditional mean and conditional mode based marginal effects formulae are preferred to the Wang (2002) formula, which is based on the unconditional mean predictor. All four formulae are used to calculate marginal effects. However, given the difficulties with respect to hypothesis testing based on these marginal effects, as discussed in section 3.3.6.1, we restrict discussion of statistical significance to that of the δ parameters in the inefficiency models.

The following charts plot the estimated marginal effects of each Z variable on cost inefficiency—in both the total and variable cost cases—and water and sewage revenue efficiency, over the observed or feasible range of that variable, whilst holding the value of the other exogenous variables at their sample means, or zero in the case of dummy variables.

5.4.3.2.1. Firm Size

Figures 5.4.7 through to 5.4.18 show the estimated marginal effects of firm size—in terms of billions of pounds of assets—on cost inefficiency and revenue efficiencies according to our preferred cost and revenue models. Firm size is positively associated with u_{it}, and therefore with cost inefficiency, in both the total cost and variable cost models, as can be seen in tables 5 and 6.

Figures 5.4.7 and 5.4.8 show that the estimated marginal effects of firm size on cost inefficiency in both the total cost and variable cost models are positive, i.e. that inefficiency increases with the size of the firm. In both cases, the marginal effect also increases with firm size. There are two noticeable differences, however. First, the magnitude of the effects are quite different, being greater in the total cost model than in the variable cost model, with the former suggesting marginal effects of up to 0.0086 per billion pounds for the largest firm compared to between 0.0047 or 0.0016 in the latter.

Second, the two cost models differ with respect to the shapes of the marginal effects functions and the sensitivity of marginal effects to the formula used. In the total cost model, $\partial \exp[sM(u_{it}|\varepsilon_{it})]/\partial z_{lit}$ increases approximately linearly with size from 0.0055, while $\partial E[\exp(su_{it})|\varepsilon_{it}]/\partial z_{lit}$, $\partial \exp[sE(u_{it}|\varepsilon_{it})]/\partial z_{lit}$, and $\partial \exp[sE(u_{it})]/\partial z_{lit}$ are approximately zero for the smallest firms, before increasing sharply between £10 billion and £20 billion until they converge to $\partial \exp[sM(u_{it}|\varepsilon_{it})]/\partial z_{lit}$. In the variable cost model, marginal effects start at 0.0016 according to $\partial \exp[sE(u_{it})]/\partial z_{lit}$, 0.0013 according to $\partial \exp[sM(u_{it}|\varepsilon_{it})]/\partial z_{lit}$, and 0.0009 according to $\partial E[\exp(su_{it})|\varepsilon_{it}]/\partial z_{lit}$ and $\partial \exp[sE(u_{it}|\varepsilon_{it})]/\partial z_{lit}$; while the latter functions converge by around £30 billion, $\partial \exp[sE(u_{it})]/\partial z_{lit}$ diverges from these.

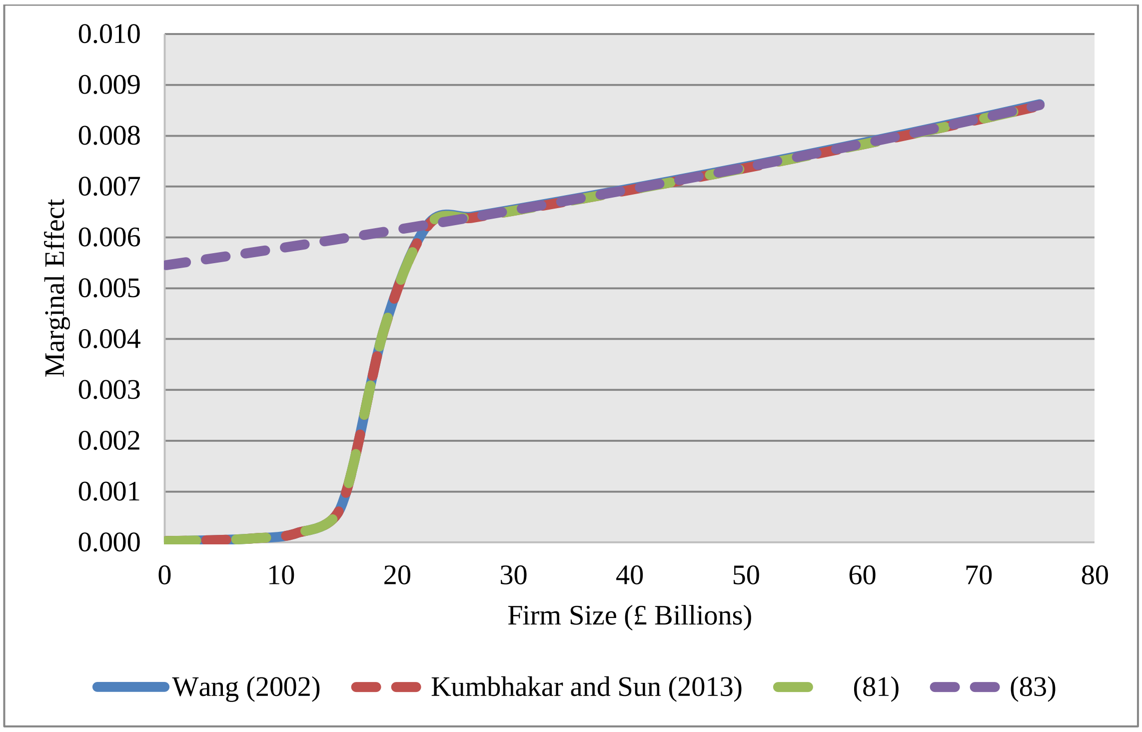

FIGURE 5.4.7: MARGINAL EFFECT OF FIRM SIZE OF TOTAL COST INEFFICIENCY

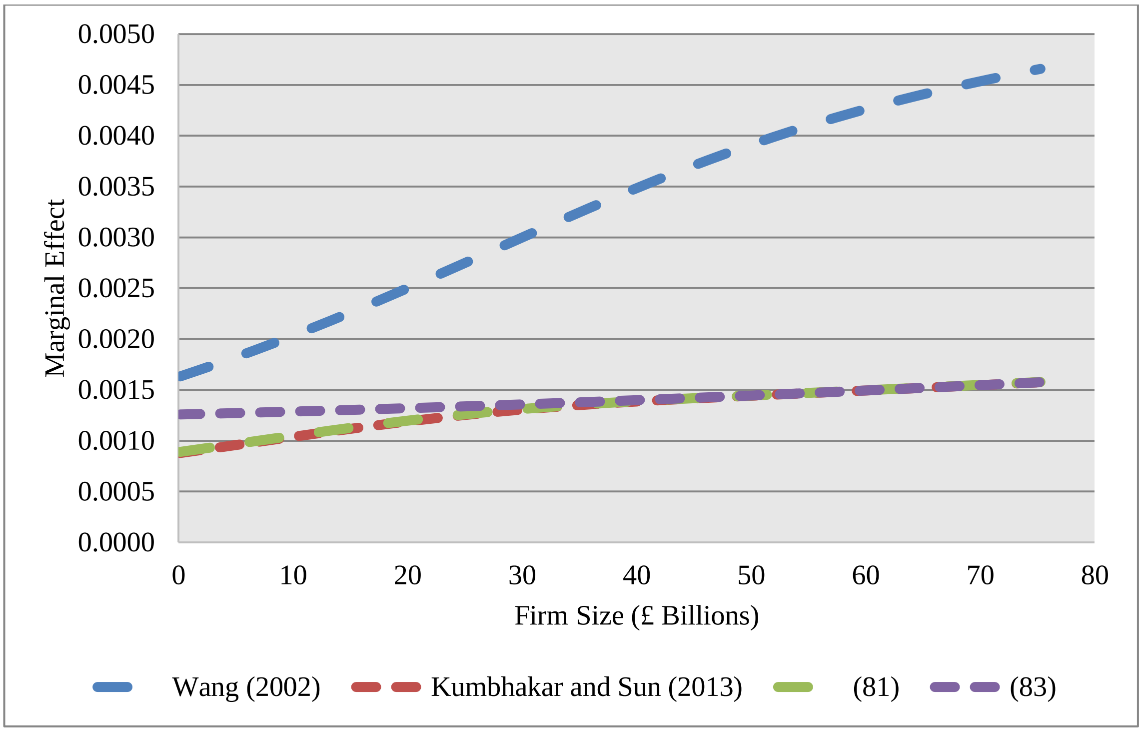

FIGURE 5.4.8: MARGINAL EFFECT OF FIRM SIZE ON VARIABLE COST INEFFICIENCY

On the revenue side, the direction of the marginal effects varies between the water revenue and sewage revenue models. As can be seen in tables 7 and 8, the δ_1 parameter is positive and significant in the water revenue model, and negative and significant in the sewage revenue model. Respectively, this means that water revenue efficiency decreases and sewage revenue efficiency increases with firm size.

Figures 5.4.9 and 5.4.10 show the calculated marginal effects of firm size on water and sewage revenue efficiency. In the water revenue model, $\partial E[\exp(su_{it})|\varepsilon_{it}]/\partial z_{lit}$, $\partial \exp[sE(u_{it}|\varepsilon_{it})]/\partial z_{lit}$, and $\partial \exp[sM(u_{it}|\varepsilon_{it})]/\partial z_{lit}$ start at 0.0038, but while the former two decline steadily to zero for the largest firms, the latter increases with firm size to 0.0065. The change in the unconditional mean, $\partial \exp[sE(u_{it})]/\partial z_{lit}$, is greater, starting at 0.017 but declining to zero as firm size increases. The difference in the shapes of the functions based on the conditional and unconditional means on the one hand and that based on the conditional mode is due to the way that the means of the distributions of u_{it} and $u_{it}|\varepsilon_{it}$, which are both truncated at zero, increase more slowly than their modes as the mode is shifted right by increases in firm size.

In the sewage revenue model, $\partial E[\exp(su_{it})|\varepsilon_{it}]/\partial z_{lit}$ and $\partial \exp[sE(u_{it}|\varepsilon_{it})]/\partial z_{lit}$ increase in magnitude from -0.0002 to -0.0004 as firm size increases, while $\partial \exp[sE(u_{it}|\varepsilon_{it})]/\partial z_{lit}$ increases from -0.0004 to -0.0014. On the other hand, $\partial \exp[sM(u_{it}|\varepsilon_{it})]/\partial z_{lit}$ decreases—albeit slightly—in magnitude as firm size increases. Again, the difference the slopes of the marginal effects can be explained by the way that the mean and mode of the distribution of $u_{it}|\varepsilon_{it}$ converge as the mode increases.

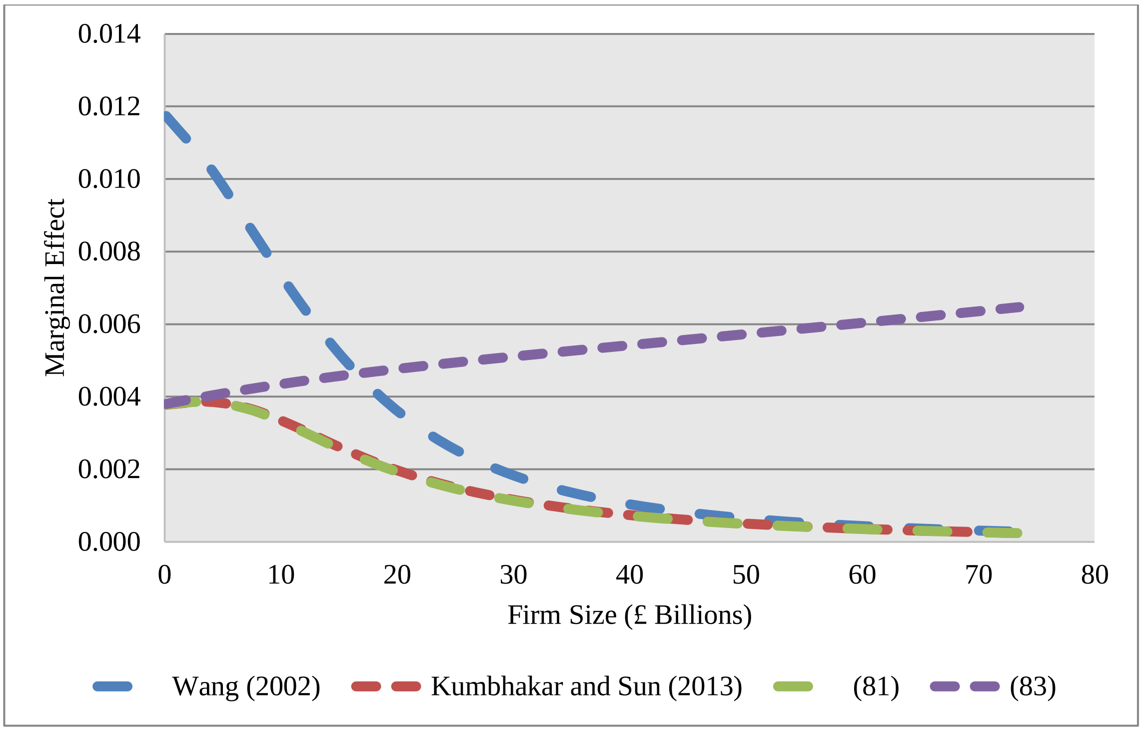

FIGURE 5.4.9: MARGINAL EFFECT OF FIRM SIZE ON WATER REVENUE EFFICIENCY

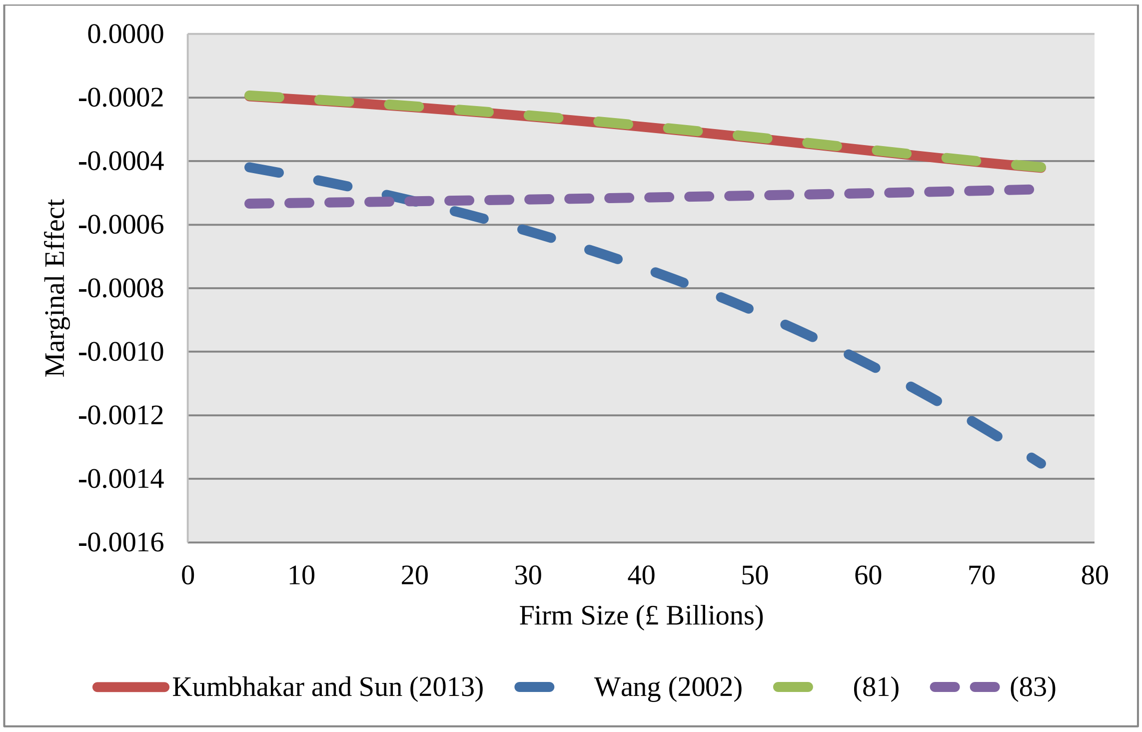

FIGURE 5.4.10: MARGINAL EFFECT OF FIRM SIZE ON SEWAGE REVENUE EFFICIENCY

5.4.3.2.2. Years of Regulation

The estimated marginal effect of years of regulation on cost and revenue efficiencies according to our preferred models are shown in figures 5.4.11 to 5.4.14. As shown in tables 5 and 6, μ_{it} is negatively and significantly related to the year of regulation in both the total cost model and the variable cost model, implying that cost inefficiency decreases with year of regulation. The relationship between year of regulation and revenue efficiency, on the other hand, varies between the water revenue and sewage revenue models: table 7 shows a positive and significant relationship between μ_{it} and year of regulation—implying that water revenue efficiency is lower the longer the firm has been subject to RPI+K regulation--whereas table 8 shows a positive and significant relationship between, implying that sewage revenue efficiency increases with year of regulation.

As can be seen in figure 5.4.11, the marginal effect of years of regulation on cost inefficiency in the total cost model starts at 0.0137 according to all four formulae. However, while $\partial \exp[sM(u_{it}|\varepsilon_{it})]/\partial z_{lit}$ increases approximately linearly to -0.0106, $\partial E[\exp(su_{it})|\varepsilon_{it}]/\partial z_{lit}$, $\partial \exp[sE(u_{it}|\varepsilon_{it})]/\partial z_{lit}$, and $\partial \exp[sE(u_{it})]/\partial z_{lit}$ decline sharply in magnitude between eleven and fifteen years to approximately zero. In the variable cost model, $\partial E[\exp(su_{it})|\varepsilon_{it}]/\partial z_{lit}$, $\partial \exp[sE(u_{it}|\varepsilon_{it})]/\partial z_{lit}$, and $\partial \exp[sM(u_{it}|\varepsilon_{it})]/\partial z_{lit}$ start at -0.0113, but while $\partial \exp[sM(u_{it}|\varepsilon_{it})]/\partial z_{lit}$ decreases approximately linearly in magnitude to -0.0093 at 23 years, $\partial E[\exp(su_{it})|\varepsilon_{it}]/\partial z_{lit}$ and $\partial \exp[sE(u_{it}|\varepsilon_{it})]/\partial z_{lit}$ decrease more rapidly to -0.0034; $\partial \exp[sE(u_{it})]/\partial z_{lit}$ also decreases to this level, but from a starting point of -0.0339.

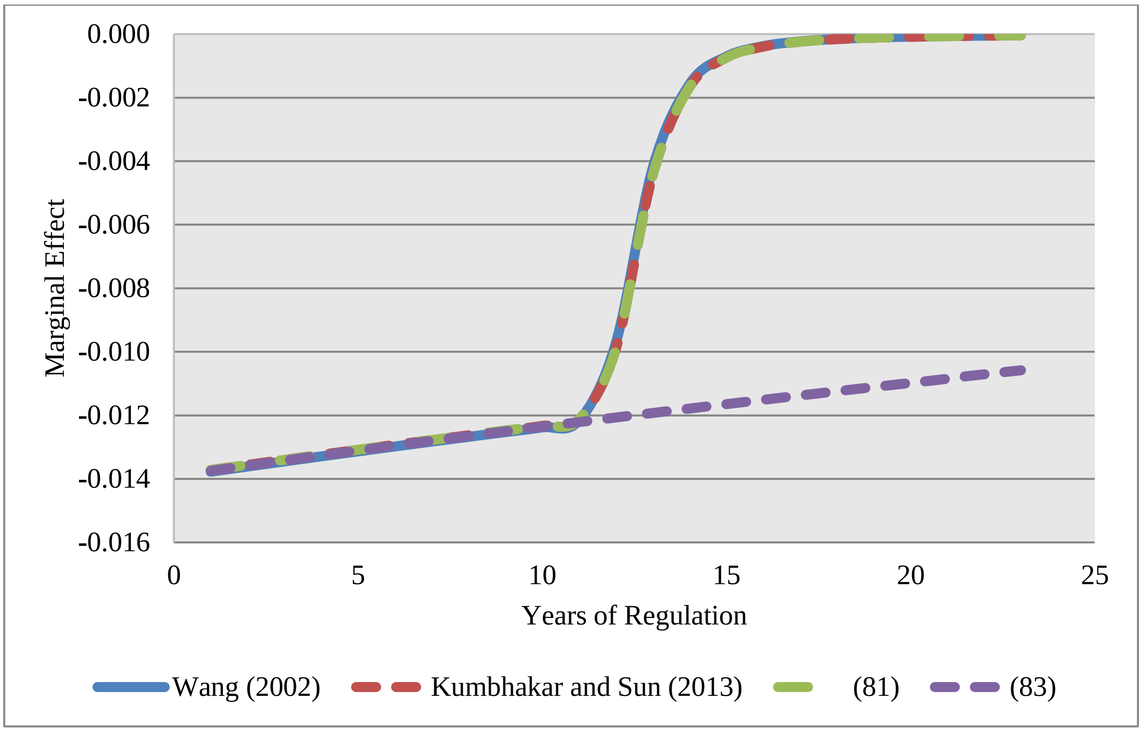

FIGURE 5.4.11: MARGINAL EFFECT OF YEARS OF REGULATION ON TOTAL COST INEFFICIENCY

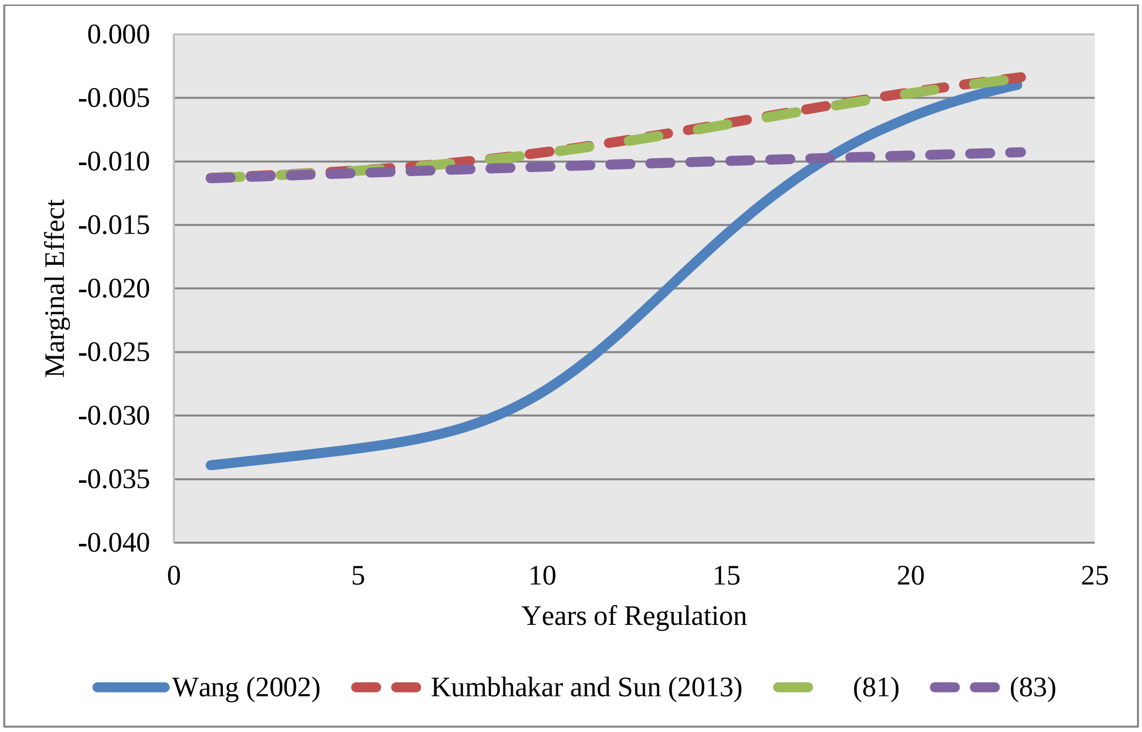

FIGURE 5.4.12: MARGINAL EFFECT OF YEARS OF REGULATION ON VARIABLE COST INEFFICIENCY

On the revenue side, table 7 shows that μ_{it} is positively and significantly related to year of regulation, while table 8 shows that μ_{it} is negatively related to year of regulation. Respectively, this implies that water revenue efficiency has increased and sewage revenue efficiency has decreased with year of regulation.

Figure 5.4.13 shows the calculated marginal effects of year of regulation on water revenue efficiency according to all four formulae. The marginal effect increases in magnitude with year of regulation, from -0.0012 to -0.0024 according to $\partial E[\exp(su_{it})|\varepsilon_{it}]/\partial z_{lit}$ and $\partial \exp[sE(u_{it}|\varepsilon_{it})]/\partial z_{lit}$, and from -0.0021 to -0.0055 according to $\partial \exp[sE(u_{it})]/\partial z_{lit}$. On the other hand, $\partial \exp[sM(u_{it}|\varepsilon_{it})]/\partial z_{lit}$ decreases slightly in magnitude as year of regulation increases, from -0.0033 to -0.0029.

The marginal effects of year of regulation on sewage revenue efficiency are shown by figure 5.4.14. Again, the magnitudes of the marginal effects change with year of regulation, but the direction of the relationship varies depending on the formula: the marginal effect increases according to $\partial \exp[sM(u_{it}|\varepsilon_{it})]/\partial z_{lit}$ from 0.0026 to 0.0028. However according to the other formulae, marginal effects decline, from a starting point of 0.0024 according to $\partial E[\exp(su_{it})|\varepsilon_{it}]/\partial z_{lit}$ and $\partial \exp[sE(u_{it}|\varepsilon_{it})]/\partial z_{lit}$ and 0.0110 according to $\partial \exp[sE(u_{it})]/\partial z_{lit}$, to 0.0018.

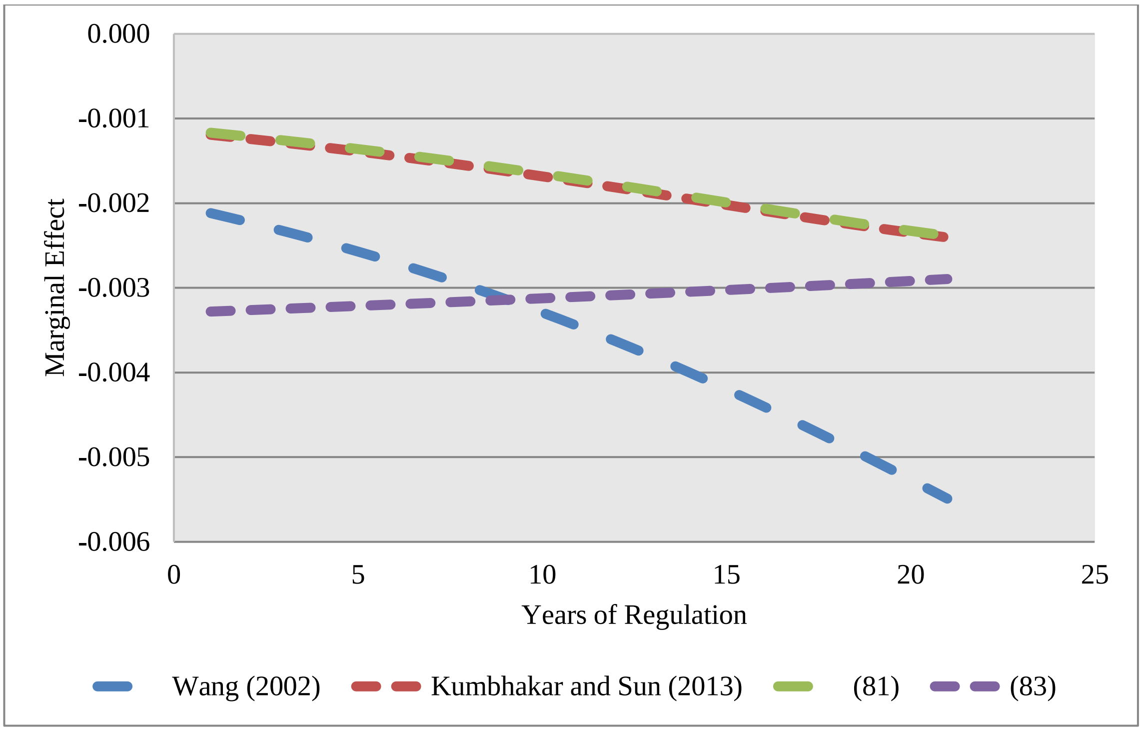

FIGURE 5.4.13: MARGINAL EFFECT OF YEARS OF REGULATION ON WATER REVENUE EFFICIENCY

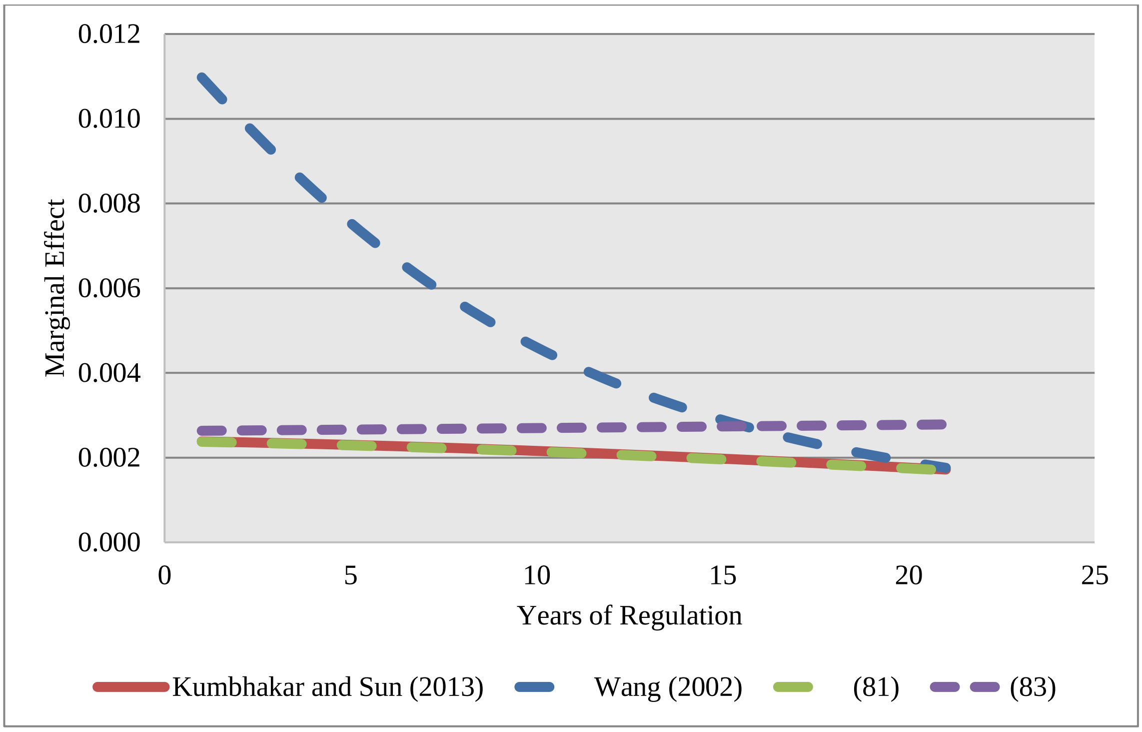

FIGURE 5.4.14: MARGINAL EFFECT OF YEARS OF REGULATION ON SEWAGE REVENUE EFFICIENCY

5.4.3.2.3. K Factor

On the cost side, tables 5 and 6 both show that μ_{it} increases with the K factor in our preferred total cost and variable cost models. This implies that cost inefficiency increases with the allowed price increase, as expected: the tighter the price cap in a given year, the greater the pressure to maximise cost efficiency. Furthermore, as discussed below, in each case the marginal effect increases with the level of the K factor, which is intuitive since the tighter the price cap, the closer to the cost frontier a firm must operate.

The calculated marginal effects of the K factor on cost inefficiency in the total cost model are shown in figure 5.4.15. As stated above, the marginal effect increases with the K factor according to all four formulae. However, while the effect increase only slightly according to $\partial \exp[sM(u_{it}|\varepsilon_{it})]/\partial z_{lit}$ and$\partial \exp[sE(u_{it})]/\partial z_{lit}$, from 0.0041 and 0.0046 respectively to 0.0048, $\partial E[\exp(su_{it})|\varepsilon_{it}]/\partial z_{lit}$ and $\partial \exp[sE(u_{it}|\varepsilon_{it})]/\partial z_{lit}$ increase from near zero to 0.0048, with most of the increase concentrated between K factors of zero and ten.

In the variable cost model, as shown in figure 5.4.16, marginal effects likewise increase with the K factor according to all four formulae: $\partial E[\exp(su_{it})|\varepsilon_{it}]/\partial z_{lit}$ and $\partial \exp[sE(u_{it}|\varepsilon_{it})]/\partial z_{lit}$ increase steadily from 0.0010 to 0.0023, and $\partial \exp[sM(u_{it}|\varepsilon_{it})]/\partial z_{lit}$ is similar, increasing from 0.0019 to 0.0023. Marginal effects according to $\partial \exp[sE(u_{it})]/\partial z_{lit}$ follow a similar trend, but are of a greater magnitude, increasing from 0.0057 to 0.0068.

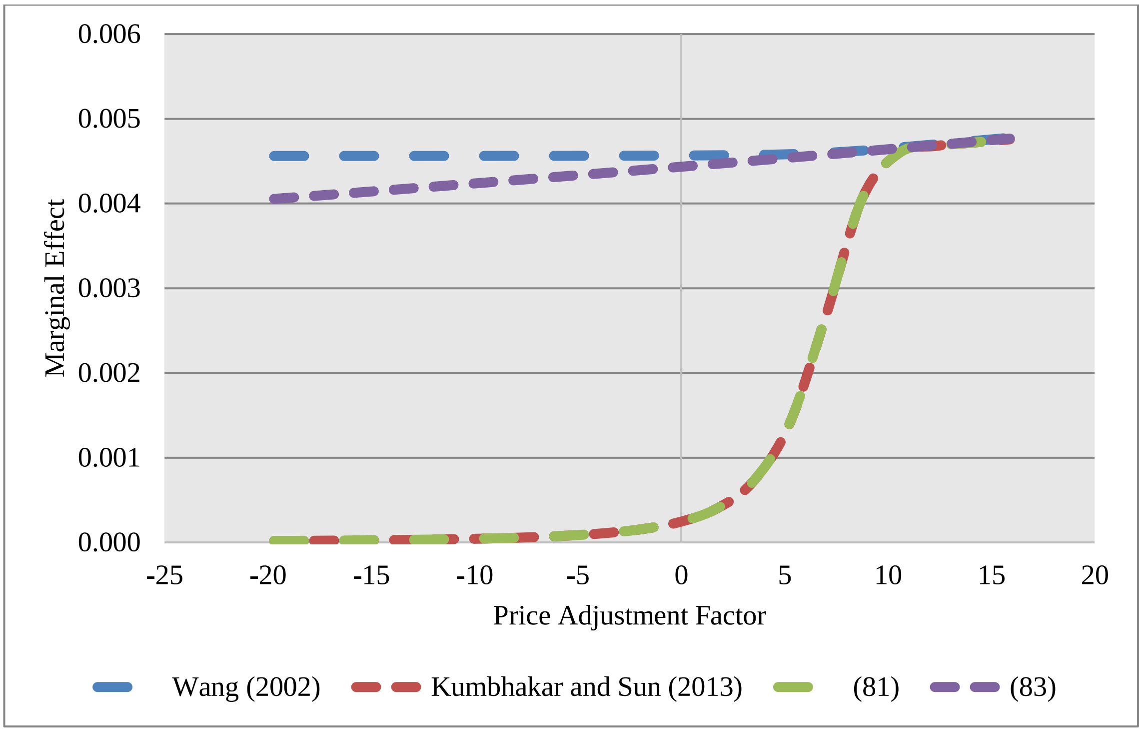

FIGURE 5.4.15: MARGINAL EFFECT OF PRICE ADJUSTMENT FACTOR ON TOTAL COST INEFFICIENCY

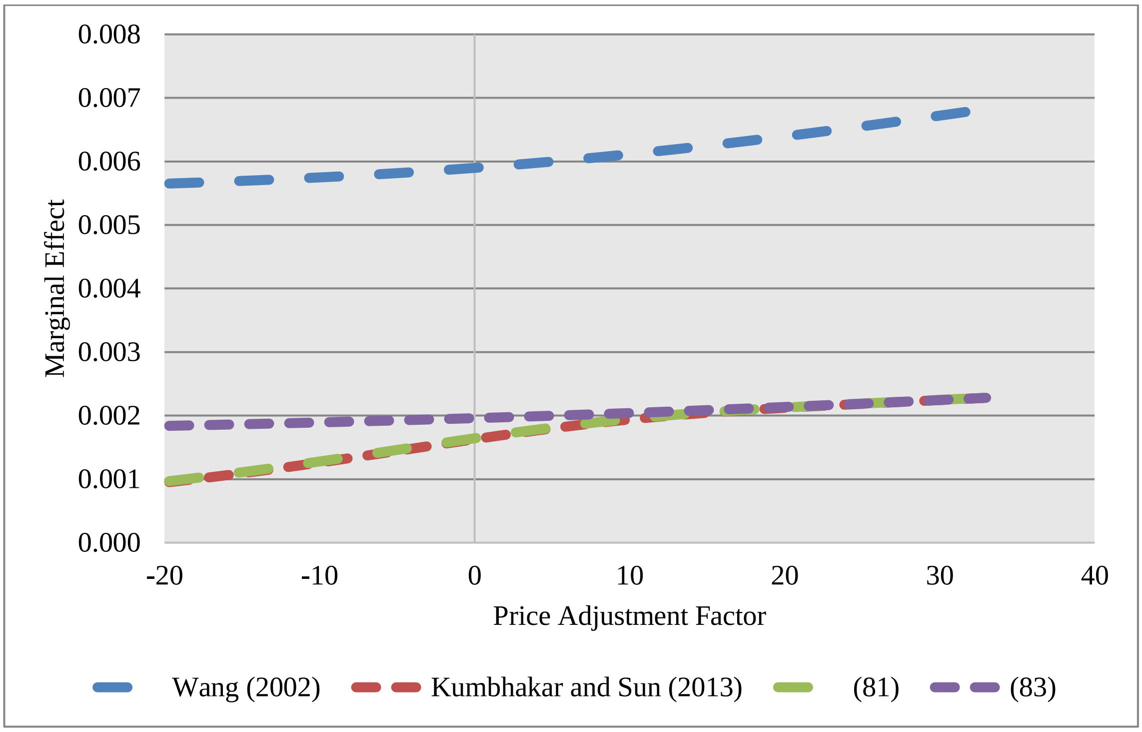

FIGURE 5.4.16: MARGINAL EFFECT OF PRICE ADJUSTMENT FACTOR ON VARIABLE COST INEFFICIENCY

5.4.3.2.4. Board Composition

In our preferred variable cost model, our board composition variable—i.e. the proportion of board members who are non-executives—is found to be negatively related to μ_{it}, as shown in table 6, suggesting that cost inefficiency decreases as the proportion of board members who are non-executives increases. On the other hand, this variable is excluded from our preferred total cost model along with directors' average years on the board, as discussed in section 5.4.2. This variable is found to be insignificant in both our water revenue and sewage revenue models, as shown in tables 7 and 8, and therefore we do not present marginal effects calculations for these models.

The marginal effects of our board composition variable are shown in figure 5.4.17. According to all four formulae, marginal effects are positive and increasing with the proportion of board members who are non-executives. Again, however, the magnitudes of the marginal effects differ: $\partial E[\exp(su_{it})|\varepsilon_{it}]/\partial z_{lit}$ and $\partial \exp[sE(u_{it}|\varepsilon_{it})]/\partial z_{lit}$ increase approximately linearly from 0.0137 to 0.0162, and $\partial \exp[sM(u_{it}|\varepsilon_{it})]/\partial z_{lit}$ is similar, increasing only slightly from 0.0175 to 0.0180. In contrast, $\partial \exp[sE(u_{it})]/\partial z_{lit}$ increases from 0.0259 to 0.0541, with most of the change occurring between 0% to 30% non-executive board membership.

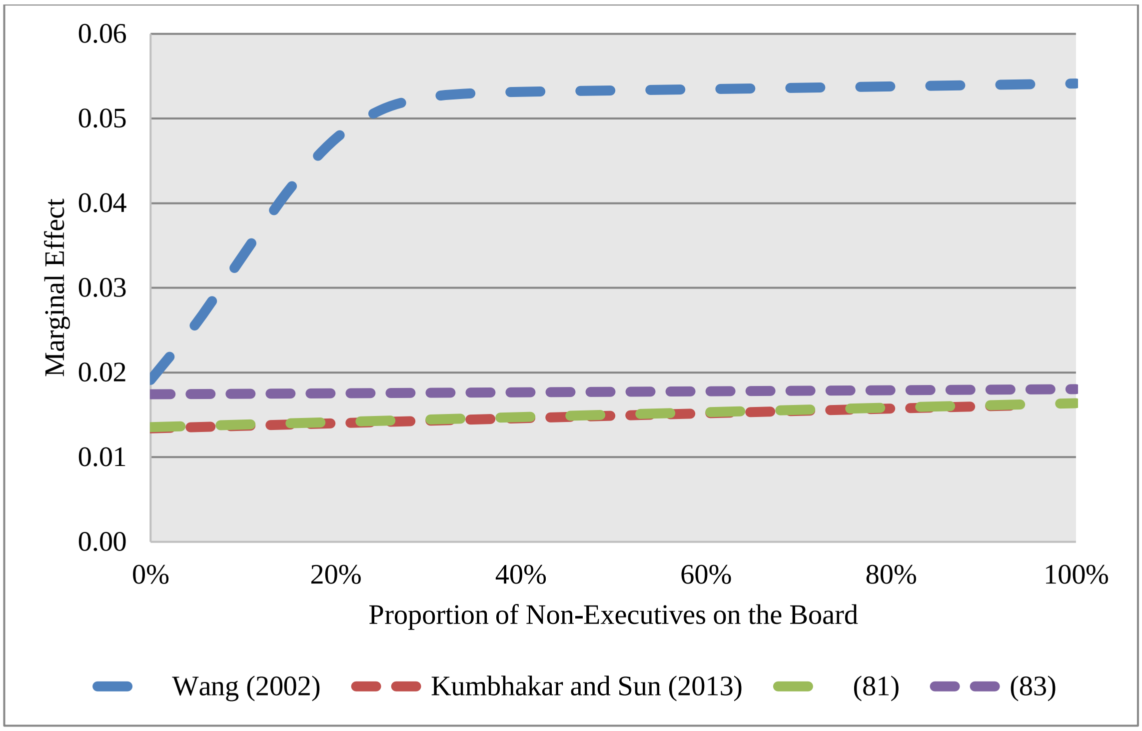

FIGURE 5.4.17: MARGINAL EFFECT OF BOARD COMPOSITION ON VARIABLE COST INEFFICIENCY

5.4.3.2.5. Directors' Average Years on the Board

As shown in table 6, directors' average years on the board is found to be insignificant in our preferred variable cost model. This is also the case in our preferred water revenue model as shown in table 7. Noting also that this variable is excluded from our preferred total cost model, this variable is only found to be significant in our sewage revenue model, in which a negative relationship with μ_{it} is estimated, implying that sewage revenue efficiency decreases as director's average years on the board increases.

Figure 5.4.18 shows the calculated marginal effects of this variable on sewage revenue efficiency. Marginal effects are positive and decreasing according to $\partial E[\exp(su_{it})|\varepsilon_{it}]/\partial z_{lit}$ and $\partial \exp[sE(u_{it}|\varepsilon_{it})]/\partial z_{lit}$, from 0.0016 to 0.0008, while marginal effects are increasing according to $\partial \exp[sM(u_{it}|\varepsilon_{it})]/\partial z_{lit}$ and $\partial \exp[sE(u_{it})]/\partial z_{lit}$: in the former case rising steadily from 0.0025 to 0.0027, and in the latter case increasing from 0.0071 to 0.0201, with almost all of the increase occuring between zero and one years.

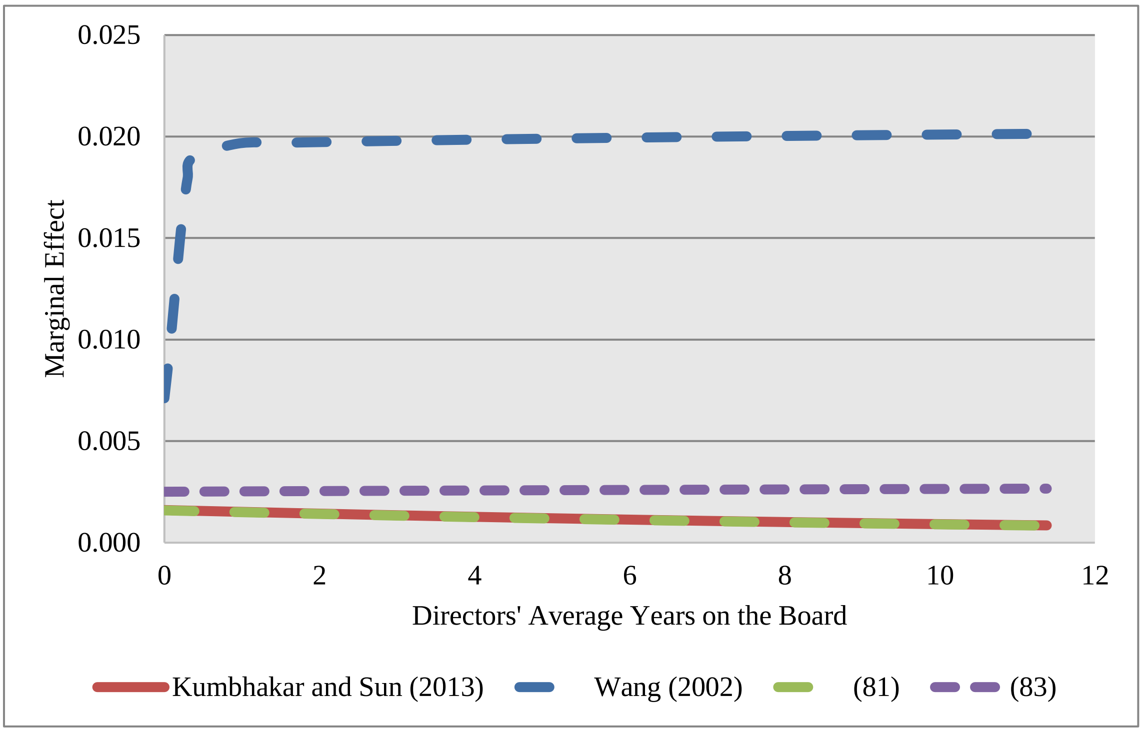

FIGURE 5.4.18: MARGINAL EFFECT OF DIRECTORS' AVERAGE YEARS ON THE BOARD ON SEWAGE REVENUE EFFICIENCY

5.4.3.2.6. Discussion

This section summarises the marginal effects results presented in the previous sections. First, however, note these discussion of two environmental variables has been excluded: our ownership dummy, Z_4, which is included in all four cost and revenue models, and a dummy denoting WaSCs, Z_7, included only in the water revenue to control for possible revenue efficiency gains from joint billing. Since these are dummy variables, it is not sensible to discuss marginal effects. Furthermore, due to the way in which these dummies enter the inefficiency models, their impacts on efficiency predictions are dependent on every other variable and thus difficult to quantify in general terms. Note, however, that Z_7 is found to be insignificant in the water revenue model, suggesting no advantage for WaSCs from joint billing, and Z_4 is found to be insignificant except in the variable cost model: in this case, it is possible to construct counterfactual efficiency predictions for publicly-owned firms by setting the public ownership dummy to zero. We found that doing so decreased cost inefficiency predictions by between 0.08 and 0.12 in each case.

From the figures and discussion in previous sections, we can see that the various marginal effects formulae differ, in some cases to a great extent, with regard to the magnitudes of the marginal effects they yield and the direction and extent of the changes in these marginal effects for changes in the corresponding environmental variable. There are various reasons for this: first, derivatives of conditional and unconditional predictors will differ due to the fact that they are based on different distributions: that of u_i and that of $u_i|\varepsilon_i$ respectively. As shown by Wang and Schmidt (2009), the distribution of $E(u_{it}|\varepsilon_{it})$ is not the same as that of u_i, the former being a shrinkage of the latter toward its mean; the degree of shrinkage increases with the noise variance σ_v^2, or terms of the parameterisation adopted here, as γ becomes small. This means that when there is a low ratio of signal to noise, the distribution of $u_i|\varepsilon_i$ approaches that of u_i, and hence $E(u_{it}|\varepsilon_{it})$ approaches $E(u_{it}|\varepsilon_{it})$. We can see this in the way that $\partial \exp[sE(u_{it})]/\partial z_{lit}$ is practically the same as $\partial E[\exp(su_{it})|\varepsilon_{it}]/\partial z_{lit}$ and $\partial \exp[sE(u_{it}|\varepsilon_{it})]/\partial z_{lit}$ in the total cost model, where γ is low, in contrast to the considerable differences between these formulae in the variable cost model.

Second, the derivative of the conditional mode predictor, $\partial \exp[sM(u_{it}|\varepsilon_{it})]/\partial z_{lit}$ differs in various degrees from the aforementioned conditional mean formulae. Given that $u_i|\varepsilon_i$ follows a truncated normal distribution (Jondrow et al. 1982), the mean and mode of $u_i|\varepsilon_i$ converge as μ_i becomes large, and diverge for smaller values of μ_i. The change in the conditional mean for an increase in μ_i will therefore be lower than that of the conditional mode until the two converge.

As discussed in section 3.3.6.1 however, although the exact magnitudes of the marginal effects of environmental variables on efficiency or inefficiency differs according to the predictor used, we may nevertheless identify the direction and the significance of the relationship by reference to δ_l parameter—interpreted as the marginal effect of z_l on the unconditional mode predictor—which is the usual approach in the applied literature. In addition, it seems sensible to comment on the slope of the marginal effects functions where the various formulae are in agreement. Based on the discussion in this section, we therefore conclude that:

i. Cost inefficiency is found to decrease with year of regulation according to our preferred total cost and variable cost models. The marginal effects formulae suggest that this effect diminishes as the years of regulation progress and the scope for further improvements is diminished.
ii. Cost inefficiency is also found to increase with the allowed K factor, suggesting as expected that the tighter the price cap that is imposed, the greater the incentive for cost efficiency, and conversely that when loose price caps are imposed, there is less pressure to minimise costs. Again, the marginal effects appear to increase with the K factor, implying that this effect diminishes (increases) as the price cap is tightened (loosened) further.
iii. Water revenue efficiency is found to decrease with year of regulation, suggesting that RPI+K regulation has progressively lowered water revenue away from its potential monopoly level. Sewage revenue efficiency on the other hand is found to have increased with year of regulation.

iv. Cost inefficiency increases with firm size, and at an increasing rate, according to our preferred total cost and variable cost models. On the revenue side, however, the relationship is more mixed: water revenue efficiency appears to increase with firm size, sewage revenue appears to decrease with firm size. Overall, firm size is found to be significant in explaining efficiency in each of the four models, and appears to be an important control variable.

v. Board composition, in terms of the proportion of the board who are non-executives, was found to be insignificant as a driver of efficiency except in the variable cost model, where it was found to have a positive relationship with cost inefficiency. Note that this finding may be explained in terms of stewardship theory—see e.g. Donaldson (1990), Donaldson and Davis (1991), and Donaldson and Preston (1995)—as discussed in section 5.2.1.

vi. Similarly, directors' average years on the board is found to be insignificant except in the sewage revenue model, in which case it was found to be positively associated with sewage revenue efficiency. This finding may again be explained in terms of stewardship theory.

5.5. Summary

In this chapter, we have analysed the efficiency of water and sewage firms in the UK. Following the theoretical framework set out in chapter 2, we estimated cost frontiers and monopoly revenue frontiers, and calculated efficiency predictions based on these in order to analyse performance in terms of both revenue efficiency and cost inefficiency. Specifically, stochastic frontier analysis (SFA) was used to estimate four frontier models: a total cost model, a variable cost model, a water revenue model, and a sewage revenue model.

The focus of our analysis was on the impact of economic regulation, specifically RPI+K price capping as practiced in the UK water and sewage industry, on firm performance measured in terms of revenue efficiency and cost efficiency. This was evaluated by analysing the trends in average revenue efficiency and cost inefficiency over the sample period, and by analysing the impact of regulatory and other environmental variables on firm-level revenue and cost efficiencies. In contrast to previous studies, we included data on the publicly-owned Scottish and Northern Irish water and sewage firms, allowing us to compare the performance of these firms to that of their English and Welsh counterparts, and to analyse the impact of the more recent introduction of price capping in Scotland and Northern Ireland.

Our main finding is that RPI+K price capping regulation appears to have reduced both cost inefficiency and overall revenue efficiency. This is evidenced both by trends in efficiency over time, and analysis of the impact of regulatory and environmental variables on cost and revenue inefficiencies. Average cost inefficiencies for England and Wales, Scotland, and Northern Ireland are all found to have fallen over the sample period according to both our total cost and variable cost models, and this is complemented by the finding—again in both cost models—that year of regulation, i.e. the number of years that RPI+K has been in place, is negatively related to cost inefficiency. Given that we benchmark against a monopoly revenue frontier, the reduction in overall revenue efficiency involves reducing revenues away from their potential monopoly levels. In terms of social welfare, this implies transfers from the water and sewage companies to consumers and reductions in deadweight loss over the sample period.

Likewise, average overall revenue efficiencies for England and Wales, Scotland, and Northern Ireland are all found to have decreased over the period, and this is complemented by the finding that year of regulation is negatively associated with water revenue efficiency. However, on the other hand sewage revenue efficiency is found to be positively associated with year of regulation, and while average water revenue declines, average sewage revenue is found to increase. This may indicate changes in cross-subsidies between water and sewage.

In addition to the evidence that regulation reduces cost inefficiency over time, there are also indications that these gains are particularly large at the onset of regulation. This can be seen in the relatively rapid cost efficiency gains made by the Scottish and Northern Irish firms, which initially have far higher predicted cost inefficiency than their English and Welsh counterparts, but catch up to a considerable extent by the end of the sample period. The estimated marginal effects of year of regulation on cost efficiency also suggest a greater impact in the early years of regulation. Cost efficiency gains then diminish as time goes on and firms approach the frontier.

We also estimate a positive relationship between annual K factors, i.e. maximum allowed price increases, and cost inefficiency in both cost models. As expected, this suggests that tighter price caps lead to lower cost inefficiency, and looser price caps lead to greater cost inefficiency. As with years of regulation, the calculated marginal effects imply that this effect increases with the K factor, so that as price caps are tightened and firms approach the frontier, the scope for further efficiency gains diminishes.

We find that firm size is positively related to cost inefficiency and water revenue efficiency, but negatively related to sewage revenue efficiency. Variable cost inefficiency is found to increase with the proportion of non-executives on the board, and sewage revenue efficiency is found to increase with the directors' average years on the board, lending support to stewardship theory.

6. Regulation and the Efficiency of UK Electricity Distribution Companies

6.1. Introduction

Following our look at the performance of the UK water and sewage industry in the previous chapter, we now move on to look at the electricity distribution industry. Like the water and sewage industry, electricity distribution in the UK is dominated by a small number of large regional monopolists which are subject to RPI-X price capping regulation. Because this industry is structured and regulated along similar lines, we apply the same theoretical framework and similar econometric methods in our analysis, and we are interested in any similarities or dissimilarities in the findings of our analyses of the two industries. We begin by describing the data, the sample, and the models estimated. Parameter estimates and efficiency predictions are presented and discussed, along with calculated marginal effects from the inefficiency model.

6.2. Model

In this chapter we use data on the distribution network operators (DNOs) in the UK to estimate a stochastic cost frontier model. In contrast to the previous chapter, we do not estimate a revenue frontier for the DNOs owing to the way that electricity distribution revenue is regulated: the DNOs are subject to revenue capping, rather than a price capping as is the case in the water and sewage industry. DNOs therefore have little discretion in terms of revenue. We estimate a stochastic total cost frontier model in order to analyse the impact of regulation and other factors on cost efficiency in the industry, again focusing on trends in efficiency and the marginal effects of regulatory and other environmental variables on cost inefficiency.

As in the previous chapter, and as discussed in chapter 3, we use the Battese and Coelli (1995) stochastic frontier specification, in which inefficiency is modelled as a function of a vector of environmental variables. This section discusses the specification used in detail.

As in the previous chapter, we estimate a total cost frontier, using a measure of total costs as the dependent variable, and including a capital price as one of the independent variables. In contrast to the previous chapter, we do not estimate a variable cost frontier; this is owing to the lack of comparable data on capital volumes as is available for the water and sewage industry.

Compared to the relatively large empirical literature on costs in the UK water and sewage industry, there have been only a handful of previous cost studies on the UK electricity distribution industry, and these have used differing measures of cost: Burns and Weyman-Jones (1996) use operating costs as reported in the companies' regulatory accounts, which is the sum of operating expenditure (opex) and depreciation. On the other hand, Jamasb and Pollitt (2003), Giannakis et al. (2005), Yu et al. (2009), Jamasb et al. (2012), and Frontier Economics (2013) use total expenditure (totex), which is the sum of opex and capital expenditure (capex).

The latter approach substitutes a measure of capex for capital costs; this has the advantage of simplicity, and is often the approach taken by regulators: data on opex, capex, and totex used for benchmarking are available from the DPCR5 Performance Report published by Ofgem (2015). Furthermore, it may be argued that capital expenditure is more directly under the control of the firm. However, a fundamental issue is that capex may be very lumpy, and changes from one year to the next may be more reflective of the firm's investment cycle than any change in underlying steady-state capital costs. Arbitrary fixes—such as smoothing out capex by constructing a moving average or similar—aside, the preferred approach is therefore to use a consumption-based measure of capital costs such as that used in the previous chapter. Accounting data on operating costs, such as those used by Burns and Weyman-Jones (1996) contain an element of capital consumption, but exclude opportunity costs of capital. For our measure of total cost, we therefore take regulatory accounting data on operating costs, and add a measure of opportunity costs of capital constructed by multiplying an estimate of the post-tax WACC by a measure of the capital base. The result is a measure of total costs analogous to that used in the previous chapter. A detailed description of the construction of capital costs is provided in section 6.3.1.

We also estimate a model using totex as the dependent variable. Totex data, in contrast to cost data, are only available for more recent years. This model differs from the total cost model in three respects: first, it covers a shorter sample period. Second, it includes electricity distributed per customer—for which data are not available for the full sample period covered by the total cost model—as an additional output variable. Third, an alternative capital price is used. In light of the issues around the use of totex as a proxy for total costs, discussed above, the totex model is not presented or discussed at length in this chapter, and serves only to illustrate the robustness of our findings to the modelling approach used. Outputs from the totex model are presented in appendix 4.

Again, following the reasoning in the previous chapter, we use a translog functional form for the cost frontier, allowing for flexibility with regards to returns to scale, substitution, and technical change, and we also estimate a simpler and more restrictive Cobb-Douglas function—in which second-order terms are restricted to be zero—for comparison. We estimate the following translog stochastic total cost frontier model:

$$\ln C_{it} = \alpha + \theta t + \beta_1 \ln Q_{1it} + \sum_{w=1}^{2} \gamma_w \ln W_{wit} + \beta_2 \ln H_{1it}$$

$$+\vartheta t^2 + \varphi t \ln Q_{1it} + \sum_{w=1}^{2} \phi_w t \ln W_{wit} + \frac{1}{2}\zeta(\ln Q_{1it})^2$$

$$+\frac{1}{2}\sum_{w=1}^{2}\sum_{p=1}^{2} \eta_{wp} \ln W_{wit} \ln W_{pit} + \sum_{w=1}^{2} \lambda_w \ln Q_{1it} \ln W_{wit} + v_{it} + u_{it} \tag{99}$$

Where

$$v_{it} \sim N(0, \sigma_v^2) \tag{100}$$

$$u_{it} \sim N^+(\mu_{it}, \sigma_u^2)$$

$$\mu_{it} = \delta_0 + \sum_{z=1}^{4} \delta_z Z$$

In which i, t, q, w and z are indices for specific firms, years, outputs, input prices, and hedonic variables, respectively. In the remainder of this section, we briefly discuss the variables included in the model. More details are provided in section 6.3 on data sources and, where applicable, data construction. Summary statistics are shown in section 6.3.6.

Our output variable, Q_{1it}, is the number of customers. We also include two price variables: a labour price, W_1, and a capital price, W_2. One option for our labour price variable is to use reported labour costs and employee numbers from the companies' regulatory and statutory accounts, as in chapter 5. However, in many cases DNOs have contracted out most or all of their labour, making this an inappropriate measure. Instead, we follow Frontier Economics (Frontier Economics 2013) in using Annual Survey of Hours and Earnings (ASHE) (ONS 2004a, 2004b, 2005a, 2005b, 2006-2013, 2014a, 2014b, 2015, DETINI 2000-2014) data on mean gross hourly wages by NUTS 1 region for the relevant industry. Our capital price variable, W_2, is a measure of the opportunity cost of capital plus depreciation analogous to that used in the previous chapter. Further details of the construction of both factor price variables are given in section 6.3.

We also include a measure of network density, H_1, measured in terms of customers per km2. Network density is an important driver of costs in electricity transmission and distribution, since a more sparsely (densely) populated area will require a larger (smaller) network length per customer. Density will also affect the voltage structure of the network, since a more sparsely (densely) populated area will require a relatively greater (lesser) proportion of low voltage lines servicing relatively isolated properties and small communities; this is important since transmission and distribution is more energy efficient at higher voltages. For these reasons, we would expect to see an inverse relationship between density and costs. Frontier Economics (2013) discuss and employ several potential measures of network density, such as customers per hectare, customers per network length, meters per hectare, and total electricity demand per hectare. We include customers per hectare as our measure of network density. Data on distribution area by hectares is taken from Frontier Economics (2013) for all Great British DNOs. For NIE's distribution area, we refer to the Competition Commission's final determinations (Competition Commision 1997) for NIE for RP2, which states that NIE's area is 14,122 km^2 (or 1,412,200 hectares).

In contrast to the previous chapter, we do not include quality variables in the cost frontier. Previous studies, such as those of Farsi et al. (2006) and Jamasb et al. (2012), have accounted for differences in quality by incorporating the two quality measures collected by Ofgem, customer interruptions (CI) and customer minutes lost (CML), into the model as independent variables. However, given potential endogeneity issues concerning the relationship between cost and quality, Frontier Economics (2013) take an alternative approach in which quality is monetised, and the result is used to adjust the cost data used. We take the latter approach: the construction of the cost adjustments is explained in section 6.3.4.

We include four environmental variables in the inefficiency model. As in the previous chapter, the impact of regulation on cost inefficiency is captured by two variables. The fist, Z_1, is a simple time trend; this is similar to the years of regulation variable used in the previous chapter. Again, this variable is intended to capture the long run effect of price capping regulation on cost efficiency. Second, Z_2 is the X factor, i.e. the minimum percentage reduction—or maximum allowed increase—in prices set by Ofgem. Similar to the way that the K factor was included in the previous chapter, this is meant to capture the short run effects of a change in the price cap on cost inefficiency.

Again, we also include two variables relating to the structure of the board: first is Z_3, the proportion of board members who are non-executives, and the second is Z_4, the directors' average years on the board. Both of these are defined and constructed identically in this chapter as in the last, and as explained in the previous chapter, according to the hypothesis that a more independent board reduces agency costs, we expect a negative sign on Z_3 and a positive sign on Z_4, while a positive sign on Z_3 and a negative sign on Z_4 could be explained in terms of stewardship theory.

The inclusion of a firm size variable in the inefficiency model, as in the previous chapter, was explored, but it was found that the inclusion of such a variable led to implausible estimates of returns to scale. In addition, no public ownership dummy is included in the inefficiency model owing to the fact that all of the UK DNOs are privately owned throughout the sample period.

As explained in section 5.2.1, we impose homogeneity of degree one with respect to input prices by imposing the restrictions

$$\sum_{w} \gamma_w = 1, \sum_{w} \phi_w = 0, \sum_{w} \eta_{w,p} = 0, \sum_{w} \lambda_w = 0 \qquad (101)$$

This is achieved by normalising our cost and labour price variables by our capital price variable. The total cost frontier we estimate therefore becomes:

$$\ln\left(\frac{C_{i,t}}{W_{2it}}\right) = \ln\alpha + \theta t + \beta_1 \ln Q_{1it} + \gamma_1 \ln\left(\frac{W_{1it}}{W_{2it}}\right) + \vartheta t^2 + \zeta(\ln Q_{1it})^2 \tag{102}$$

$$+\eta_{11}\left[\ln\left(\frac{W_{1it}}{W_{2it}}\right)\right]^2 + \varphi_1 t \ln Q_{1it} + \phi_1 t \ln\left(\frac{W_{1it}}{W_{2it}}\right) + \lambda_1 \ln Q_{1it} \ln\left(\frac{W_{1it}}{W_{2it}}\right)$$

$$+\beta_2 \ln H_{1it} + v_{it} + u_{it}$$

Where

$$v_{it} \sim N(0, \sigma_v^2) \tag{103}$$

$$u_{it} \sim N^+(\mu_{it}, \sigma_u^2)$$

$$\mu_{it} = \delta_0 + \sum_{z=1}^{4} \delta_z Z$$

As in the previous chapter, every variable in the model, with the exception of the time trend t, is mean-centred so that the first-order coefficients may be interpreted as elasticities at the sample means.

The following section contains detailed information on data sources, variables definitions, and the comparability of data taken from different sources. Summary statistics are also included for each of the variables included in the model.

6.3. Data

In this section, we discuss data sources and provide more detail on variable definitions and construction. Although there is no equivalent of the June Returns formerly published by Ofwat for the water and sewage industry, various reports that have been published intermittently by Ofgem are a particularly important source of data, particularly the Electricity Distribution Annual Report (EDAR) for 2010-11 (Ofgem 2012b) and the DPCR5 Performance Report (2015), the latter covering the period of the 5th Distribution Price Control Review (DPCR5), i.e. 2010-11 to 2014-15, and the former including certain data as far back as 2001-02. These contain important financial, output, and quality data.

As discussed in chapter 1, in contrast to the water and sewage industry, there is no separate Scottish energy regulator, so the reports published by Ofgem include data on all 14 of the Great British DNOs under the regulator's jurisdiction. In Northern Ireland, however, economic regulation of the energy industry, as well as the water and sewage industry, is the responsibility of the Northern Ireland Authority for Utility Regulation (NIAUR). Since we were unable to find reports comparable to the EDARs and the DCPR5 performance report, certain data on Northern Ireland were be obtained via Freedom of Information (FOI) requests to NIAUR, who also gave helpful guidance on the data and their comparability with those on the Great British DNOs.

The DNOs' regulatory accounts (RAs) and statutory accounts (SAs) are also important sources of data. Regulatory accounts were variously obtained from the DNOs' websites or requested from the companies. Statutory accounts were obtained from the DNOs' websites or from Companies House.

Table 10 defines each variable and lists the main source of data for each. More detailed descriptions follow where necessary.

TABLE 10: DEFINITIONS AND SOURCES FOR WATER AND SEWAGE DATA

Variable	Definition	Sources	
		Great Britain	Northern Ireland
C	Total costs. Operating costs (operating expenditure plus depreciation) from RAs plus opportunity cost of capital and quality adjustment, both explained below.	RAs and SAs (operating costs), capital costs explained below	RAs and SAs
$C - A$	Total costs, excluding quality adjustments.	RAs and SAs (operating costs), capital costs explained below	RAs and SAs
T	Total expenditure. Operating and capital expenditures plus quality adjustment.	EDAR 2010-11 and DPCR5 Performance Report	Not available
$T - A$	Total expenditure, defined above, excluding quality adjustment.	EDAR 2010-11 and DPCR5 Performance Report	Not available
A	Quality adjustment. Monetised value of service reliability, explained below.	Various Ofgem reports	FOI request
Q_1	Total number of customers	EDAR 2010-11 and DPCR5 Performance Report	FOI request
Q_2	Energy delivered per customer (kWh/customer).	EDAR 2010-11 and DPCR5 Performance Report	Not available
W_1	Labour price. Mean gross hourly wage for full time workers by NUTS 1 region. Data relate to SIC2003 industry 40 to 2007, and SIC2007 industry 35 from 2008.	ASHE Table 5.5a	NI ASHE
W_2	Capital price for total cost model. See below for details on construction.	-	-
W_3	Capital price for totex model. Producer price index (PPI) for Inputs for Electricity Production and Distribution, excluding Climate Change Levy.	ONS PPIs	ONS PPIs
H_1	Customer density. Customers per km^2 of network area. Sources given related to network area data, while the numerator is Q_1.	Frontier Economics (2013)	Competition Commission (1997)

Variable	Definition	Sources	
		Great Britain	Northern Ireland
Z_1	Years of regulation. The number of years that the firm has been subject to RPI-X style regulation, starting from 1986-87 in Great Britain and 1988-89 in Northern Ireland.	-	-
Z_2	X factor. The maximum (minimum) price increase (decrease) allowed in the year, as set by the regulator. Taken from final determinations documents.	Ofgem	NIAUR
Z_3	Percentage of the board that are non-executives. Constructed from regulatory and statutory accounting data on board members at the end of the financial year.	RAs and SAs	RAs and SAs
Z_4	Directors' average years on the board. Constructed as the average number of years since first appointment to the board, regardless of any absences.	RAs and SAs	RAs and SAs

6.3.1. Capital Prices and Costs

As in the previous chapter, we define total costs as the sum of opex—i.e. all non-capital costs—and capital costs. Rather than taking data on opex and depreciation from different sources, however, we take operating costs—the sum of the two—from the DNOs' regulatory accounts. We have regulatory accounting data—and other supporting data—from 2001-02 to 2013-14. These data cover not only the 14 Great British DNOs regulated by Ofwat, but also NIE, which has not been included in cost studies of UK electricity distribution previously.

Remaining capital costs, i.e. opportunity costs of capital, are then added to operating costs to arrive at total costs. Opportunity costs of capital, in turn, are calculated by multiplying the WACC by the DNOs' capital base. The WACC, τ, is calculated in the same way as in the previous chapter, i.e.

$$\tau = r_f + r_p - t \qquad (104)$$

Where r_f is the nominal 10-year UK gilt rate—a proxy for the risk-free rate—and r_p is a weighted-average risk premium calculated by subtracting the regulator's view of the risk-free rate from their estimate of WACC in the relevant price control. In this case, we are able to use Ofgem's own estimate for pre-tax WACC, meaning that no further adjustment is needed. For the DNOs in Great Britain, data on WACCs are taken from the Final Proposals for DPCR3, DPCR4, and DPCR5 (Ofgem 1999, 2004a, 2009a) while the WACC for Northern Ireland Electricity (NIE) is similarly taken from NIAUR's final determinations for the RP3, RP4, and RP5 price controls (NIAUR 2002, 2006, 2012). The final component, t, is the debt interest tax shield, which is gross interest payable—taken from the DNOs' regulatory and statutory accounts—multiplied by the corporation tax rate and divided by the firm's capital base.

For the firm's capital base, used to calculate t and multiplied by the WACC to obtain opportunity cost of capital, we use the Regulatory Asset Value (RAV) calculated by Ofgem for the Great British DNOs, and the equivalent Regulatory Asset Base (RAB) calculated by NIAUR for Northern Ireland Electricity. Both the RAVs and RABs are measures of the economic value of a firm's assets, and as such are analogous to the RCVs calculated by Ofwat for the water and sewage industry. Data on RAVs are taken from the EDAR 2010-11 and the DPCR5 and RIIO-ED1 financial models (2012b, Ofgem 2009a, 2013, 2014b), while data on NIE's RAB were obtained via FOI request.

Our capital price, W_4 is given by

$$W_4 = \delta + \tau \tag{105}$$

Where τ is the WACC as described above, and δ is depreciation—taken from the regulatory accounts—divided by the RAV, or the RAB in the case of NIE. In our totex model, we use an alternative capital price, W_3, which is the Producer Price Index for Inputs for Electricity Production and Distribution produced by ONS.

Note that NIE's RAB and WACC data are both affected by the larger scope of NIE's activities, given that NIE is responsible for transmission as well as distribution; in their Final Proposals document for RP4, NIAUR attribute 18% of NIE's RAB to transmission and 82% to distribution, and report separate WACCs for each which are then weighted by RAB into a single 'blended' rate; the distribution WACC was set explicitly to match that of the Great British DNOs, and while we cannot decompose the WACC in

NIAUR's other price controls—for which only single overall WACCs were reported—we take this to be reasonable grounds to assume that NIE's risk premium for distribution is in line with that of the Great British DNOs.

A similar issue arises with respect to the operating cost data taken from the regulatory accounts: NIE and the two Scottish DNOs differ from the English and Welsh DNOs in that they also run the transmission networks in their areas. Whereas transmission costs are excluded from the totex benchmarking data published by Ofgem, the regulatory accounts of these DNOs include both transmission and distribution costs. It is therefore important to control for the resulting difference in costs.

One option is to distinguish between transmission and distribution costs in some way. In Scotland, there is an accounting separation between the distribution networks—operated by SP Distribution plc (SPD) and Scottish Hydro Electric Distribution plc (SSEH)—and transmission networks—operated by SP Transmission plc and Scottish Hydro Electric Transmission plc—which simplifies matters. On the other hand, NIE's reporting of transmission and distribution costs has varied over the sample period: the transmission network is *operated* by System Operator Northern Ireland (SONI), which was an internal division within NIE included as a separate accounting category until SONI was sold to EirGrid plc—the transmission system operator in the Republic of Ireland—in 2009, but *owned* by NIE whose associated transmission costs were reported under a transmission and distribution category; separate transmission and distribution data are only available from 2006-07 onwards. However, NIE's regulatory accounts explain that the separation of all income, expenditure, assets, and liabilities between transmission and distribution is done on a rather straightforward basis, i.e. by allocating 18% and 82% respectively, in line with the allocation used in tariff setting. It is therefore possible to construct data on distribution costs and revenues for previous years on this basis.

A potential problem with simply separating distribution from transmission costs lies in the fact that the demarcation between transmission and distribution also differs, with 132kV lines forming part of the distribution network in England and Wales, but part of the transmission network in Scotland and in Northern Ireland, which also encompasses 110kV assets. In their benchmarking study of NIE's opex for NIAUR, CEPA (2011) instead adjust NIE's submitted opex in order to remove the estimated 7.5% that relates to the 275kV transmission network; this leaves only the opex relating to NIE's distribution network and the lower-voltage parts of the transmission network that would be defined as distribution assets in England and Wales (the authors mistakenly state that this adjustment brings NIE into line with the Great British DNOs, not accounting for the attribution of 132kV assets to transmission in Scotland, for which no similar adjustment is made). Such an adjustment is not possible in our case, since we have no indicator of the share of the 275kV network in NIE's costs as reported in their regulatory accounts or to capital costs, and similarly no basis on which to make a similar adjustment for the Scottish DNOs. Furthermore, Frontier Economics (2013) conclude that there is no evidence that voltage structure in general is a significant driver of DNO costs, or that any accounting needs to be made for the absence of 132kV assets in the Scottish DNOs in particular in their totex models, arguing that any residual effect voltage structure may have is likely to be captured by their density variables. We therefore simply use the regulatory accounting data pertaining to the distribution networks in Scotland and Northern Ireland as they are defined, with no further adjustment.

Another more minor issue regarding the comparability of the regulatory accounting cost data is that they includes some excluded activities—i.e. those not subject to regulation—the most significant of which is connections. Connections activities in Great British have been open to competition since 1995. In spite of this, the penetration of Independent Connections Providers (ICPs) has generally been very limited, with the vast majority of new connections being carried out by the DNOs or affiliated firms, to the extent that in June 2014 Ofgem opened a recently-concluded review of competition in connections (Ofgem 2014a), which concluded that competition for new connections was not developing fast enough. Nevertheless, there is a degree of variation in connections activities across DNOs: the EDAR 2010-11 (Ofgem 2012b) provides industry-level data on connections to DNO networks provided by DNOs, their affiliate companies, and ICPs from 2005-06 to 2010-11, which is shown in Figure 6.3.1 below.

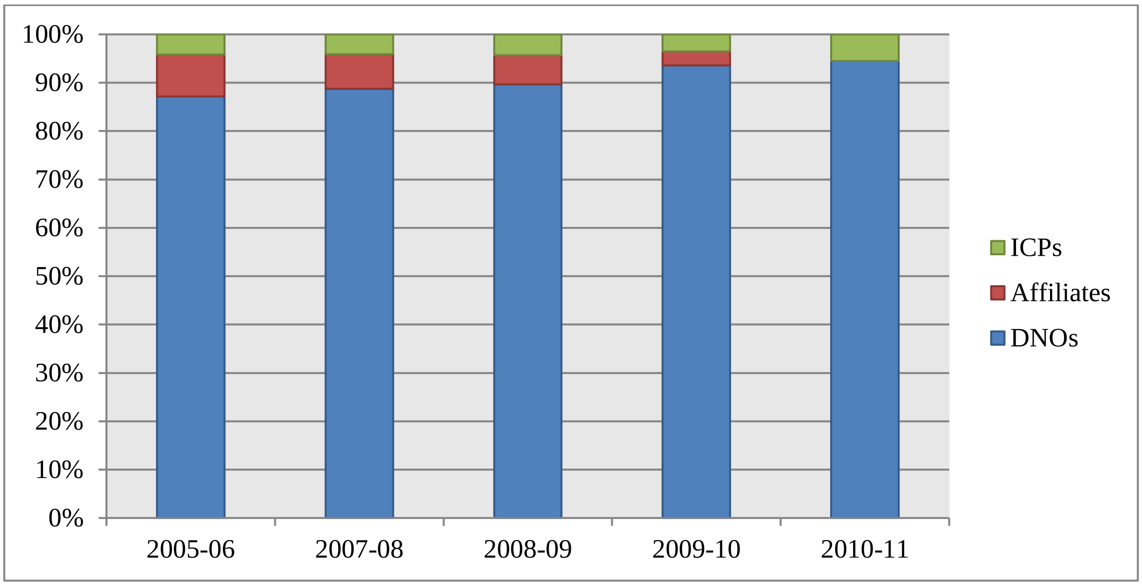

FIGURE 6.3.1: CONNECTIONS MARKET SHARE OF DNOS, AFFILIATES, AND ICPS (GREAT BRITAIN ONLY)

We can see that there has been a slight increase in the market share of the DNOs at the expense of their affiliated companies, but that the change is not dramatic. DNO-specific figures for 2007-08 to 2010-11 are taken from the EDAR 2010-11, and figures for 2005-06 and 2006-07 are taken from the CIRs for those years—note that the latter are extracted from charts, the underlying data being unavailable, and are thus approximate—and these are shown in figure 6.3.2 below, which shows that changes in the market have been driven mostly by a few firms. It should be noted that this shows only connections to the DNO's network, i.e. those parts of the network operated by the DNOs, and exclude the impact of the penetration of independent distribution network operators (IDNOs) within their Distribution Supply Areas (DSAs). While this is appropriate for our purposes, the picture changes when IDNO networks are taken into account; Ofgem's CIRs (Ofgem 2004b, 2005-2011, 2012a) show the share of IDNOs—which perform connections in their own networks—increasing over time along with that of ICPs, which have made far greater inroads into IDNO than DNO networks.

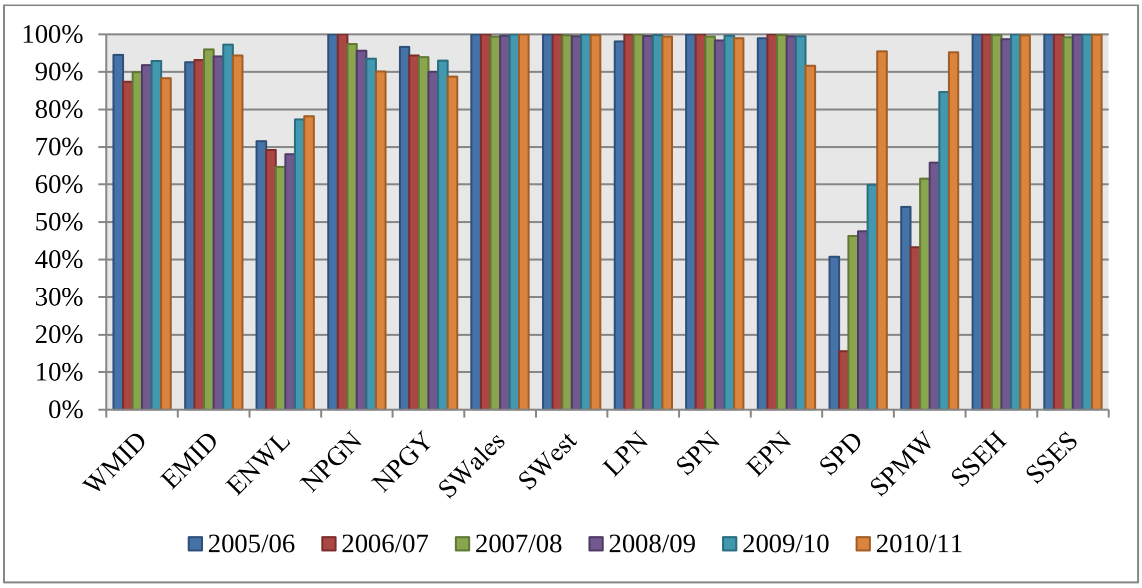

FIGURE 6.3.2: MARKET SHARE OF DNOS IN CONNECTIONS TO OWN NETWORKS, GREAT BRITAIN ONLY

A special case is S+S Limited, which was a company in the SSE group which performed connections to the networks of SSEH and SSES, as well as a relatively insignificant number of out-of-area connections; while the company might more properly have been regarded as an affiliate of those networks, it is clear that connections carried out by S+S have been attributed to the DNOs themselves. SSEH and SSES assumed direct control over the assets and operations of S+S in their respective areas from the beginning of the 2010-11 financial year, and thus a breakdown of various items between continuing operations and the acquired S+S is given in that year's regulatory accounts. Given the lack of any specific data on connections by S+S to the SSEH and SSES networks, we instead attribute the various costs (and revenues) reported in the statutory accounts of S+S—up to its acquisition—to SSEH and SSES according to their shares of those costs reported in 2010-11; no breakdown of depreciation was given, however, so S+S depreciation is allocated according to the share of S+S tangible fixed assets inherited by each company.

6.3.2. Output

Customer numbers for NIE were provided by NIAUR via FOI request. These, however, correspond not to financial years as with the rest of our data, but instead to the years to the 31st of August 2003-2009 and the years to the 30th of November 2010-2014. Looking at figure 6.3.3 below, we can see that customer numbers have followed a very clear trend over time; a quadratic time trend, estimated via OLS, produces a very good fit, accounting for 99.6% of the variation in customer numbers. We therefore use this estimated time trend to interpolate customer numbers for the financial years 2003-04 to 2013-14, and to extrapolate values for 2001-02 and 2002-03, as shown in figure 6.3.3.

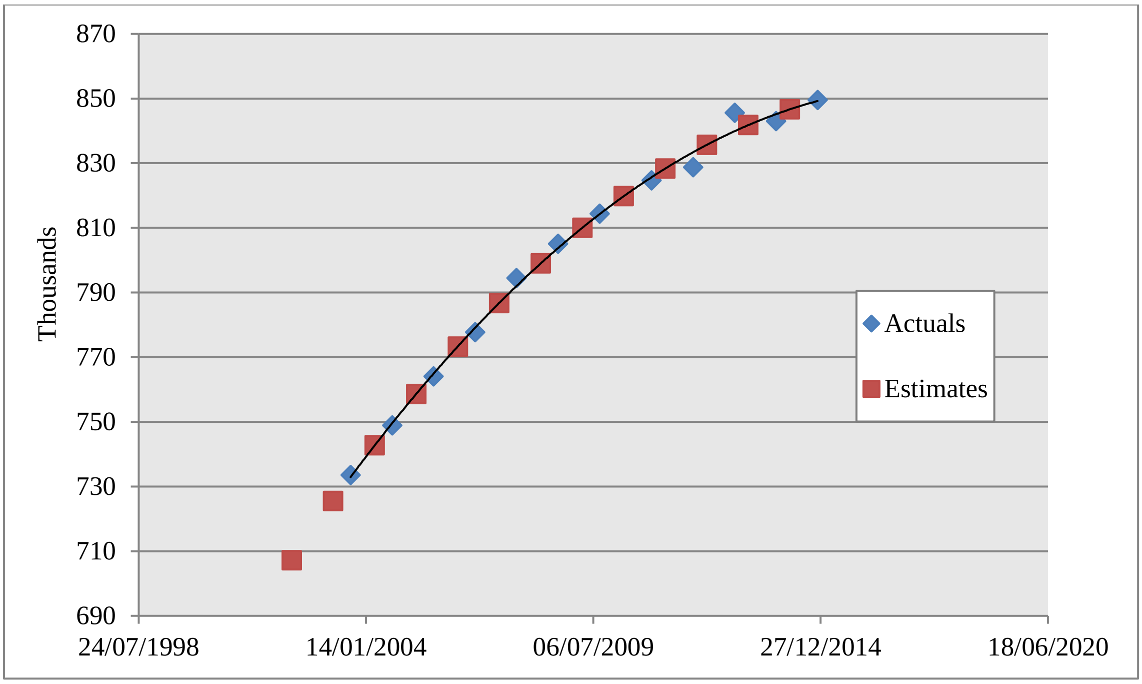

FIGURE 6.3.3: NORTHERN IRELAND ELECTRICITY CUSTOMER NUMBERS

As an alternative to energy delivered per customer, the inclusion of data on peak demand was explored. Peak demand data may be calculated by summing demands at each GSP supplying a given DNO at the National Grid system peak as contained in the National Grid's past Seven Year Statements (SYS) (National Grid 2006-2011). Note that this is a proxy, since peak demand on a given DNO's distribution network need not necessarily coincide with the National Grid peak, though a quick comparison of these data and actual values reported in the regulatory accounts of SPD and SPMW confirm that it is a reasonable one. A set of alternative totex models including peak demand in place of energy delivered and using a more restricted sample is not reported here, but give very similar results to those of Frontier Economics and to our final totex models.

6.3.3. Labour Prices

One option for our labour price variable is to use reported labour costs and employee numbers from the companies' regulatory and statutory accounts, as in Chapter 5.

However, in many cases DNOs have contracted out most or all of their labour, making this an inappropriate measure. Instead, we follow Frontier Economics (2013) in using Annual Survey of Hours and Earnings (ASHE) (ONS 2004a, 2004b, 2005a, 2005b, 2006-2013, 2014a, 2014b, 2015, DETINI 2000-2014) data on mean gross hourly wages by NUTS 1 region for the SIC2003 industry 40—electricity, gas, steam and hot water supply—until 2007, and for the SIC2007 industry 35—electricity, gas, steam and air conditioning supply—from 2008 onwards, with the same regional mapping. We use data for full-time employees only, since these are more complete in earlier years. In a very small number of cases, missing data were interpolated using percentage change figures in the following years' reports, or—in the case of Northern Ireland—as the mean of the preceding and following years' values. Since these data relate to calendar years, we construct a mean which gives a weighting of 0.75 to the first calendar year and 0.25 to the second calendar year in the financial year.

6.3.4. Quality Adjustment

The quality adjustment made to costs follows the same approach taken by Frontier Economics (2013), which is to calculate a monetised value for customer minutes lost (CML) and customer interruptions (CI), the two measures of reliability collected by Ofgem. The regulator’s Interruption Incentive Scheme (IIS) sets annual targets for both measures, and the differences between the actual and target values—plus or minus a deadband allowing for normal fluctuations—are multiplied by incentive rates set by Ofgem to calculate penalties (rewards) for underperformance (overperformance). The IIS was first introduced for 2002-03—two years in to DPCR3—giving us data for each year in our larger sample except 2001-02. Data on IIS-weighted CIs and CMLs are taken from EDAR 2010-11 and the DPCR5 Performance Report, while incentive rates are taken from the Final Proposals document for the IIS scheme (Ofgem 2001), and the DPCR4, and DPCR5 Final Proposals documents (Ofgem 2004a, p.19, 2009a, p.88). For 2001-02, we use CI and CML without storms in place of IIS-weighted figures, and use 2002-03 incentive rates adjusted to 2001-02 prices.

In Northern Ireland, CI and CML are also used as measures of service quality; targets have been set for CML and CI in recent years, and NIAUR first proposed incentive rates for the current price control, RP5—covering 01/01/2013 to 30/09/2017—in its Final Determination (2012), which was rejected by NIE and referred to the Competition Commission. Under the subsequent Final Determination by the Competition Commission (2014), NIE sets its own targets for CI and CML and there is currently no incentive scheme, though since NIE agreed to such a scheme in principle—while objecting to the targets proposed for RP5—it is likely that one will be introduced at the next price control. Data on CI and CML for NIE were obtained from NIAUR via FOI request.

Figure 6.3.4 shows the values of monetised service quality to be added to total costs for each observation.

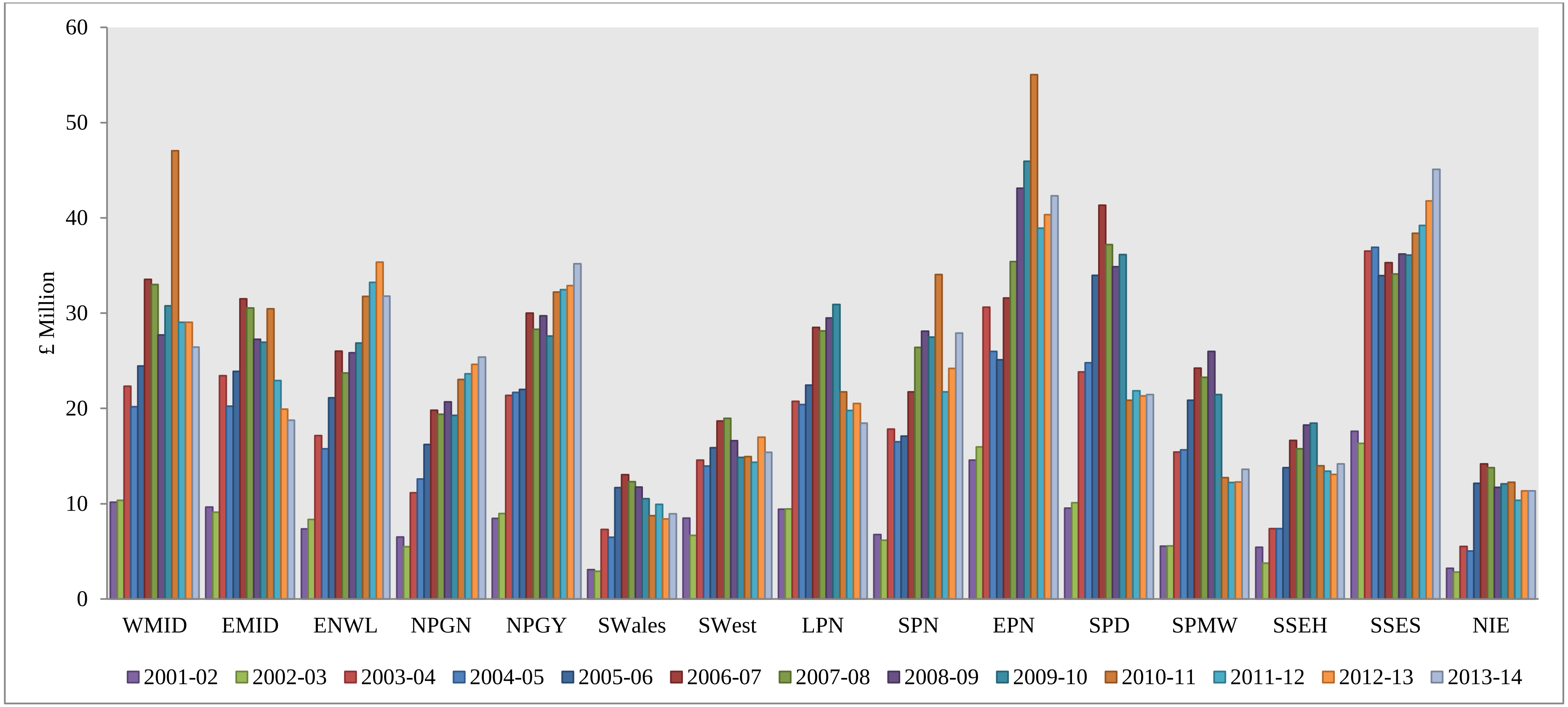

FIGURE 6.3.4: MONETISED VALUES OF CIS AND CMLS (ZERO BENCHMARK)

6.3.5. Observations Included

Given the availability of the data described in previous section, we are able to construct a dataset including all DNOs in the UK and covering the period 2001-02 to 2013-14. There are currently 14 DNOs in Great Britain—whose distribution areas correspond exactly to the former PESs and the pre-privatisation Area Electricity Boards (AEBs) before them—and an integrated transmission and distribution company in Northern Ireland, bringing the total number of firms to 15. Due to a lack of mergers and takeovers between DNOs, we a balanced panel consisting of the 15 UK DNOs from 2001-02 to 2013-14, yielding 195 observations. Table 11 below lists each of the 15 DNOs, showing abbreviations, full names, and parent companies. Note that some DNOs share parent companies. Detailed information on each DNO is given in Appendix 2.

TABLE 11: ELECTRICITY DISTRIBUTION NETWORK OPERATORS

Code	Name	Parent
EMID	Western Power Distribution (East Midlands)	Western Power Distribution
ENWL	Electricity North West	None, formerly United Utilities
EPN	Easter Power Networks	UK Power Networks
LPN	London Power Networks	UK Power Networks
NIE	Northern Ireland Electricity	Electricity Supply Board (Republic of Ireland)
NPGN	Northern Powergrid (Northeast)	Northern Powergrid Holdings Company
NPGY	Northern Powergrid (Yorkshire)	Northern Powergrid Holdings Company
SPD	SP Distribution	Scottish Power Energy Networks Holdings
SPMW	SP Manweb	Scottish Power Energy Networks Holdings
SPN	South Eastern Power Networks	UK Power Networks
SSEH	Scottish Hydro Electric Power Distribution	SSE
SSES	Southern Electric Power Distribution	SSE
SWALES	Western Power Distribution (South Wales)	Western Power Distribution
SWEST	Western Power Distribution (South West)	Western Power Distribution
WMID	Western Power Distribution (West Midlands)	Western Power Distribution

Figure 6.3.5 shows a map of the 14 DNOs in Great Britain, colour coded according to parent company. Northern Ireland is not shown, but is served entirely by NIE.

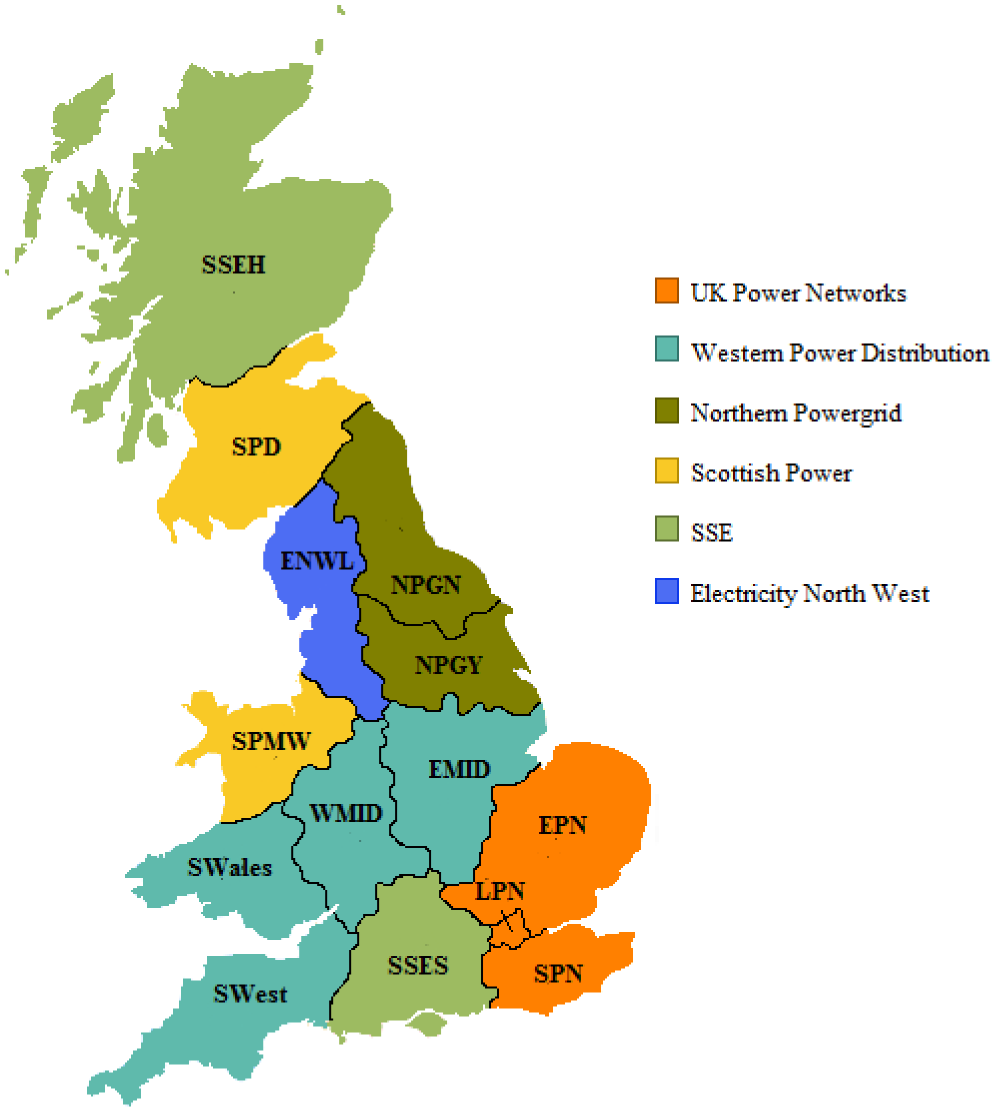

FIGURE 6.3.5: MAP OF ELECTRICITY DISTRIBUTION NETWORK OPERATORS IN GREAT BRITAIN

6.3.6. Summary Statistics

Table 12 below contains summary statistics for each of the variables included in the total cost model, along with those included in the totex model. As in the previous chapter, means and standard deviations are shown for the sample period and four subperiods so that trends over time can be examined. Means are further broken down by country.

TABLE 12: SUMMARY STATISTICS

Variable	Period	Mean					St. dev.
		England	Wales	Scotland	N. Ireland	All	All
C Total cost plus quality adjustment	2001-02 2004-05	225.912	155.386	231.763	157.931	212.757	59.858
	2005-06 2007-08	241.003	172.599	242.307	151.639	226.099	66.204
	2008-09 2010-11	276.605	172.823	254.486	186.913	253.839	76.753
	2011-12 2013-14	276.533	190.488	272.553	208.784	260.013	77.282
	All years	252.775	171.483	248.853	174.902	236.221	71.915
T Total expenditure plus quality adjustment	2005-06 2007-08	189.392	135.718	140.103	-	174.683	50.635
	2008-09 2010-11	237.926	148.59	152.582	-	212.971	73.896
	2011-12 2014-15	276.582	198.453	177.512	-	251.268	75.081
	All years	238.828	164.674	158.81	-	216.804	74.943
$C-A$ Total cost, excluding quality adjustment	2001-02 2004-05	210.517	147.648	220.238	153.790	199.649	54.539
	2005-06 2007-08	215.116	155.049	215.857	138.273	202.083	59.959
	2008-09 2010-11	246.598	157.623	230.736	174.893	227.840	68.189
	2011-12 2013-14	248.279	179.604	255.003	197.769	236.652	69.332
	All years	228.619	159.033	229.672	165.228	215.255	64.213
$T-A$ Total expenditure, excluding quality adjustment	2005-06 2007-08	163.506	118.168	113.653	-	149.907	44.729
	2008-09 2010-11	207.919	133.39	128.832	-	185.974	65.333
	2011-12 2014-15	249.422	187.703	160.25	-	227.866	68.933
	All years	211.196	150.549	136.845	-	191.911	69.238

Variable	Period	Mean / Standard deviation					St. dev.
		England	Wales	Scotland	N. Ireland	All	All
A Quality adjustment (see section 6.3.4)	2001-02 2004-05	15.395	7.738	11.525	4.140	13.108	8.101
	2005-06 2007-08	25.887	17.550	26.450	13.367	24.016	7.885
	2008-09 2010-11	30.007	15.200	23.750	12.020	25.999	10.664
	2011-12 2013-14	28.253	10.883	17.550	11.015	23.361	10.286
	All years	24.155	12.450	19.181	9.674	20.966	10.598
Q_1 Number of customers	2001-02 2004-05	2,270.253	1,263.193	1,314.732	733.540	1,906.128	735.304
	2005-06 2007-08	2,329.564	1,280.133	1,349.031	786.374	1,956.023	749.658
	2008-09 2010-11	2,365.841	1,288.991	1,363.543	819.394	1,985.525	759.428
	2011-12 2013-14	2,394.451	1,299.381	1,372.503	841.380	2,008.644	767.425
	All years	2,334.660	1,281.407	1,347.243	790.431	1,959.622	746.909
Q_2 Energy delivered per customer (kWh per customer)	2005-06 2007-08	11,318.540	11,691.619	11,433.313	-	11,388.233	844.699
	2008-09 2010-11	10,612.805	11,062.414	10,893.653	-	10,717.156	956.364
	2011-12 2014-15	10,144.572	10,749.354	10,715.366	-	10,312.511	920.759
	All years	10,637.233	11,125.951	10,984.236	-	10,756.621	1,008.056
H_1 Customer Density (Customers per km^2)	2001-02 2004-05	461.245	106.037	50.924	51.943	331.888	742.932
	2005-06 2007-08	466.922	107.460	52.086	55.684	336.266	746.879
	2008-09 2010-11	472.845	108.174	52.392	58.023	340.507	755.341
	2011-12 2013-14	480.976	109.020	52.593	59.579	346.171	770.965
	All years	469.785	107.547	51.916	55.972	338.183	747.407

Variable	Period	Mean / Standard deviation					St. dev.
		England	Wales	Scotland	N. Ireland	All	All
W_1 Regional gross wage for all workers in SIC 40/35 (2003/2007) £/hr	2001-02 2004-05	15.276	14.079	14.182	15.497	14.986	1.580
	2005-06 2007-08	17.245	16.055	15.133	18.234	16.871	2.029
	2008-09 2010-11	18.826	17.340	16.750	18.398	18.323	2.025
	2011-12 2013-14	20.186	17.430	18.190	20.568	19.578	2.720
	All years	17.683	16.061	15.919	17.968	17.250	2.728
W_2 Opportunity cost of capital (% return on RAV)	2001-02 2004-05	7.757	8.140	7.911	8.800	7.898	0.833
	2005-06 2007-08	7.519	7.583	7.550	8.534	7.599	0.483
	2008-09 2010-11	6.481	6.488	6.682	7.387	6.569	1.022
	2011-12 2013-14	4.226	4.127	4.433	5.102	4.299	0.457
	All years	6.593	6.705	6.741	7.559	6.692	1.588
W_3 Producer Price Index for electricity inputs	2005-06 2007-08	69.187	69.186	69.186	-	69.186	4.834
	2008-09 2010-11	98.223	98.223	98.222	-	98.223	3.977
	2011-12 2014-15	121.797	121.797	121.796	-	121.797	5.983
	All years	98.942	98.941	98.941	-	98.942	22.446
Z_1 Years of regulation	2001-02 2004-05	17.500	17.500	17.500	15.500	17.367	1.235
	2005-06 2007-08	21.000	21.000	21.000	19.000	20.867	0.968
	2008-09 2010-11	24.000	24.000	24.000	22.000	23.867	0.968
	2011-12 2013-14	27.000	27.000	27.000	25.000	26.867	0.968
	All years	22.000	22.000	22.000	20.000	21.867	3.784

Variable	Period	Mean / Standard deviation					St. dev.
		England	Wales	Scotland	N. Ireland	All	All
Z_2 X factor	2001-02 2004-05	-7.811	-7.506	-4.144	-3.884	-7.020	1.815
	2005-06 2007-08	0.094	-0.990	0.512	-1.284	-0.087	1.472
	2008-09 2010-11	2.213	2.223	0.341	1.767	1.935	3.486
	2011-12 2013-14	6.450	8.650	0.000	2.847	5.643	3.440
	All years	-0.382	-0.029	-1.078	-0.426	-0.431	5.499
Z_3 Percentage of the board that are non-executives	2001-02 2004-05	9.525	12.488	0.000	66.700	12.462	21.640
	2005-06 2007-08	6.230	8.333	0.000	55.567	8.969	16.538
	2008-09 2010-11	19.560	12.500	0.000	64.467	19.004	28.917
	2011-12 2013-14	49.337	27.217	8.333	60.000	41.631	32.658
	All years	20.268	14.931	1.923	62.069	19.897	28.117
Z_4 Directors' average years on the board	2001-02 2004-05	2.294	2.305	1.683	8.954	2.658	2.042
	2005-06 2007-08	4.676	3.186	2.855	6.303	4.343	2.172
	2008-09 2010-11	4.576	5.654	3.939	4.400	4.623	2.502
	2011-12 2013-14	4.267	7.354	4.902	2.012	4.613	3.143
	All years	3.826	4.446	3.217	5.689	3.951	2.600

6.4. Results

In this section, we present and discuss the results from our stochastic cost frontier model. As with our water and sewage models, the model is estimated using the *sfcross* and *sfpanel* packages (Belotti et al. 2013) for Stata and Frontier 4.1c (Coelli 1996), and results presented are taken from the former.

In section 6.4.1, we discuss parameter estimates. In section 6.4.2, likelihood tests are presented, and the preferred specification is identified. Our main results, relating to the trend in cost inefficiency over time and the effects of our environmental variables on cost inefficiency, are presented in sections 6.4.3.1 and 6.4.3.2. Section 6.5 summarises.

6.4.1. Parameter Estimates

Table 13 shows the estimated parameters of our total cost model. Results from the full translog model described in section 6.2 are shown, along with those from a restricted Cobb-Douglas model for comparison. Standard errors for each parameter estimate are included in parentheses, and stars indicating significance are shown. Restricted versions of each model are shown in appendix 3. Results from our alterative totex model are not shown here, but are displayed in appendix 4.

At the bottom of the table, again, are the sigma squared and gamma parameters, along with the model's log-likelihood. At the very bottom is the mean cost inefficiency prediction from the model.

TABLE 13: ELECTRICITY DISTRIBUTION TOTAL COST MODEL ESTIMATES

Parameter (Variable)	Estimate (Standard Error)			
	Translog		Cobb-Douglas	
α	-0.517 (0.137)	***	-0.245 (0.08)	***
θ (t)	8.28E-05 (0.029)		-0.005 (0.011)	
β_1 ($\ln Q_1$)	0.636 (0.234)	***	0.484 (0.037)	***
γ_1 ($\ln W_1$)	-0.009 (0.324)		0.711 (0.072)	***
ϑ (t^2)	-2.57E-04 (0.002)			
ζ ($\ln Q_1^2$)	0.401 (0.055)	***		
η_{11} ($\ln W_1^2$)	-0.094 (0.227)			
φ_1 ($t \ln Q_1$)	-0.003 (0.03)			
ϕ_1 ($t \ln W_1$)	0.065 (0.044)			
λ_1 ($\ln Q_1 \ln W_1$)	-0.017 (0.281)			
β_3 ($\ln H_1$)	-0.042 (0.015)	***	-0.099 (0.015)	***
δ_0	0.362 (0.084)	***	0.198 (0.029)	***
δ_1 (Z_1)	0.050 (0.015)	***	0.039 (0.012)	***
δ_2 (Z_2)	0.008 (0.004)	*	0.003 (0.004)	
δ_3 (Z_3)	-0.003 (0.001)	***	-0.002 (0.001)	***
δ_4 (Z_4)	-0.041 (0.006)	***	-0.05 (0.006)	***
σ^2	0.022 (0.003)		0.026 (0.003)	
γ	0.910 (0.269)		4.33E-06 (0)	
lnLikelihood	112.319		79.699	
Mean u	1.501		1.264	

Significance level: * 10% ** 5% ***1%

The estimated total cost models shown above give plausible parameter estimates. As mentioned in section 6.2, since our variables are mean-centred, the first order coefficients are interpreted as elasticities at the sample means.

Estimated returns to scale at the sample means, given in this case by $1/\beta_1$, imply substantially increasing returns to scale in both cases: 1.573 in the translog model, and 2.066 in the Cobb-Douglas model. This implies that the DNOs are on average operating below their optimal scales, and is consistent with the general impression from the literature—reviewed in section 4.4.2—that electricity distribution is subject to increasing returns to scale in the UK and elsewhere.

The wage elasticity is 0.711 in the Cobb-Douglas model, and is therefore within the required range of zero to one. On the other hand, in the translog model, the sample mean wage elasticity is negative and insignificant. However, we found that this is misleading since no observation is near the sample means for all variables: looking at observation-by-observation wage elasticities, we find in each case that they are between zero and one as required. Figure 6.4.1 below shows the distribution of observation-specific wage elasticities.

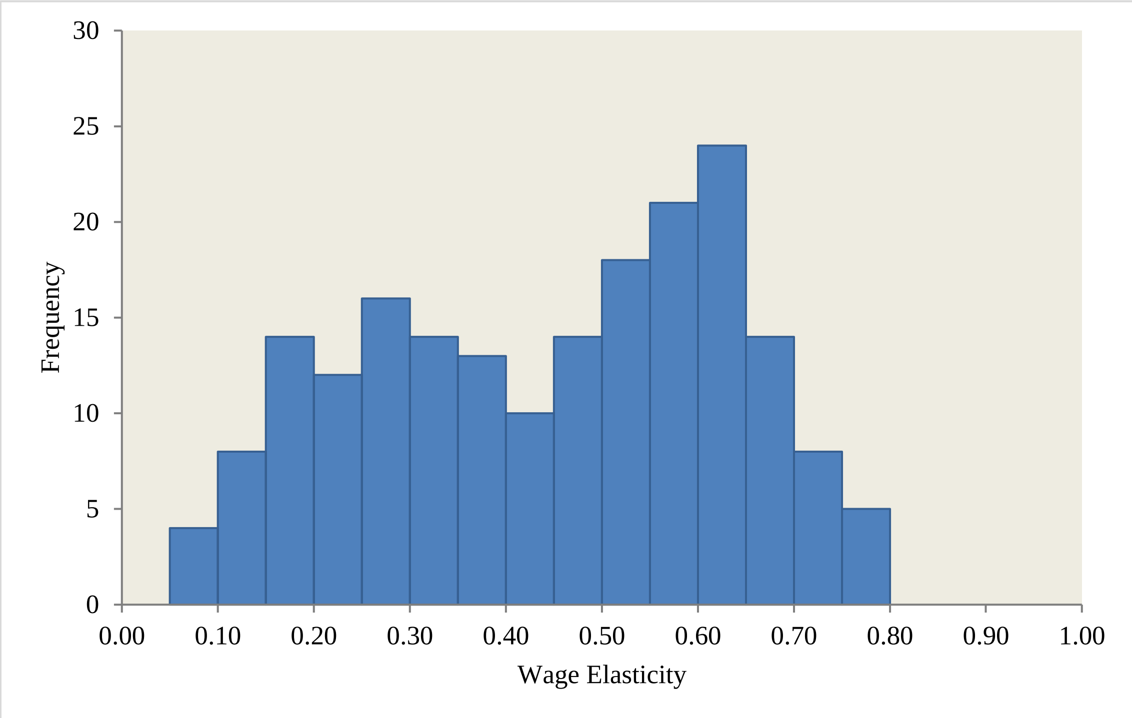

FIGURE 6.4.1: HISTOGRAM OF OBSERVATION-SPECIFIC WAGE ELASTICITIES

Both the Cobb-Douglas and translog models give an insignificant estimate with respect to the first-order time trend, implying no significant technical change over time. Both models yield negative and significant elasticities with respect to the density variable, H_1. This implies that costs decrease as the density of the network—measured in terms of customers per km^2—increases. This is in line with expectations, since as discussed in section 6.2, an increase in the density of the network both reduces the average network length per customer and favourably changes the optimal voltage structure of the network to include a higher proportion of more energy efficient high voltage lines. This finding is also in line with our findings of an inverse relationship between density and cost in the water and sewage industry.

Note that our translog and Cobb-Douglas totex models, shown in table 21 in appendix 4, give similar results to those from our total cost models. As in the previous chapter, discussion of results regarding the effect of our environmental variables on cost inefficiency is reserved for section 6.4.3.2.

6.4.2. Likelihood Ratio Tests

In this section, we identify our preferred model on the basis of a series of likelihood ratio tests. As discussed in chapter 5, this is a common approach to testing more complex models against simpler nested models in SFA.

The null hypotheses we consider are the same as those from the previous chapter: first, that the second-order terms in the translog model are jointly equal to zero, or in other words that the Cobb-Douglas model is preferred. As explained in the previous chapter, this is a standard problem for which the likelihood ratio follows a chi-squared distribution with degrees of freedom equal to the number of restrictions: in this case, six.

Second, we test for the presence of inefficiency by testing the restriction that the coefficients relating to the environmental variables, along with the δ_0 and the γ parameters, are jointly equal to zero. As explained in the previous chapter, the likelihood ratio follows an approximately chi-squared distribution with degrees of freedom equal to the number of parameter restrictions (Battese and Coelli 1995).

Third, we test the null hypothesis that inefficiency is present, but is not explained by our environmental variables. This involves restricting the parameters on the environmental variables to be zero, but no restriction is placed on γ or δ_0 in this case: the null model is therefore normal-truncated normal model proposed by Stevenson (1980). This is again a standard problem in which the likelihood ratio follows a chi squared distribution with degrees of freedom equal to the number of restrictions; in this case four.

TABLE 14: LIKELIHOOD RATIO TESTS

Null Hypothesis	Likelihood ratio
	Total Cost
$H_0: \vartheta = \zeta = \eta_{1,1} = \varphi_1 = \phi_1 = \lambda_1 = 0$ Cobb-Douglas functional form.	65.241 ***
$H_0: \gamma = \delta_0 = \delta_1 = \cdots = \delta_4 = 0$ No inefficiency, null model estimated via OLS.†	66.989 ***
$H_0: \delta_1 = \delta_2 = \cdots = \delta_4 = 0$ Inefficiency is present, but is not a function of environmental variables. Inefficiency distribution is truncated normal.	66.989 ***
Significance level: * 10% ** 5% ***1 † Log-likelihood for null model assumes normal errors.	

Table 14 above shows the likelihood ratio values for each of the three tests described above. Stars indicate significance. The first test indicates that we can strongly reject the null hypothesis that the Cobb-Douglas functional form is preferred model. We therefore take the translog model as our preferred specification.

Likewise, we also strongly reject the second and third null hypotheses. We therefore conclude that cost inefficiency is present, and that our environmental variables are significant drivers of cost inefficiency.

6.4.3. Main Results

In this section we present and discuss out main results. These relate to the trend in mean cost inefficiency over the sample period, which is discussed in section 6.4.3.1, and the marginal effects of our environmental variables on cost inefficiency, which is discussed in section 6.4.3.2.

6.4.3.1. Efficiency Trend

As discussed in chapter 3, we obtain point predictions of cost inefficiency using the Battese and Coelli (1988) conditional mean formula, $E[\exp(su_{it})|\varepsilon_{it}]$, which is shown for the Battese and Coelli (1995) case by (71). The trends in the mean total cost inefficiency ratios are shown is shown in figure 6.4.2.

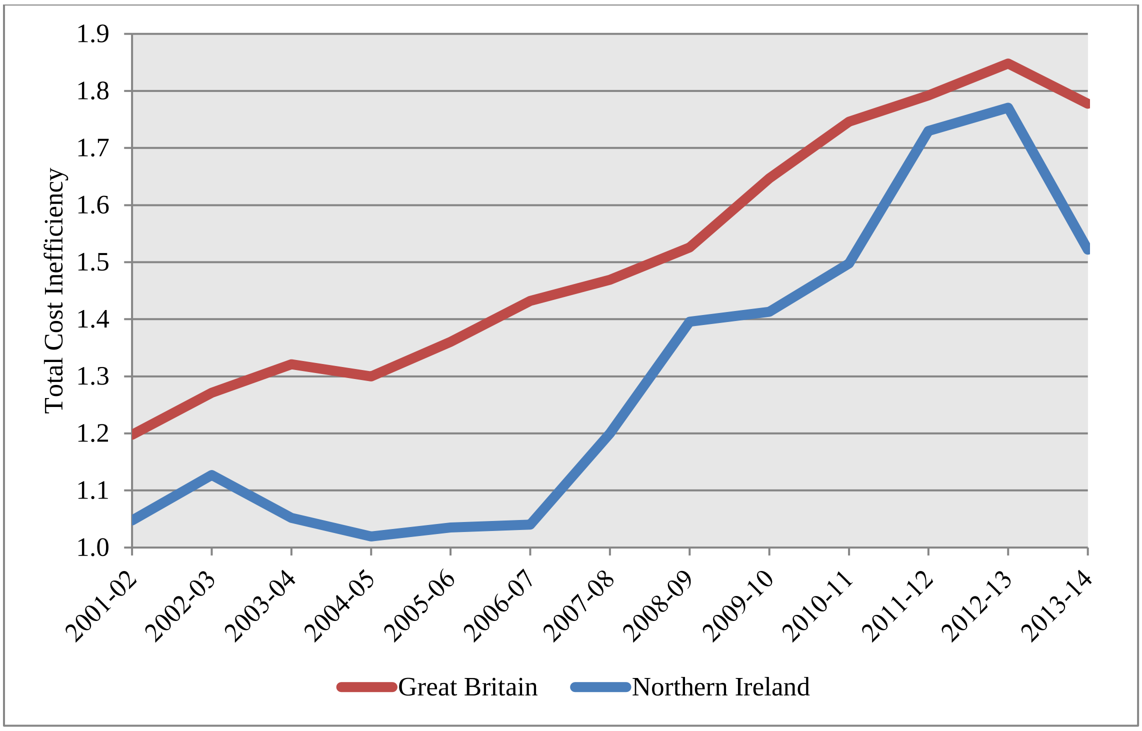

FIGURE 6.4.2: TREND IN MEAN TOTAL COST INEFFICIENCY RATIOS

Separate trends are shown for Great Britain and Northern Ireland, given that they have different regulators, and we may therefore expect to see differences in cost inefficiency reflecting differences in the effectiveness of regulation. However, as can be seen, the cost inefficiency of NIE is quite similar to the average in Great Britain, not only in terms of magnitude, but also in terms of the trend in cost inefficiency over the sample period. In contrast to our findings in the previous chapter relating to the water and sewage industry, we find that NIE is if anything slightly more cost efficient than the average DNO in Great Britain; this is despite the fact that NIE's regulator, NIAUR, arguably suffers from greater information asymmetry due to a lack of comparator firms.

The similarity between NIE's cost inefficiency and the Great British average lends further weight to our finding in the previous chapter that price capping regulation causes the efficiency levels of firms to converge. In the previous chapter, we found large initial differences in the cost inefficiency of the Scottish and Northern Irish water companies relative to their English and Welsh counterpart, but with considerably catch-up with the onset of regulation. In this case, the similarity in cost inefficiency between countries is as expected, since regulation of DNOs was introduced at similar times, long before the start of our sample period.

Looking at direction of the trends in cost inefficiencies, however, we see that there appears to have been a considerable increase in cost inefficiency over the sample period in both Great Britain and Northern Ireland. At first glance, this is contrary to our expectations and our findings in the previous chapter, since it suggests that cost inefficiency in the industry has increased despite the DNOs being subject to RPI-X regulation. However, this may be explained in terms of the loose revenue caps that have been set over the sample: table 12 shows that, while negative X factors were set in the early years of the sample period—i.e. the DNOs were required to reduce real revenues, creating pressure to minimise costs—increases in real revenue were have been allowed in later years, and these allowed increases are particularly large towards the end of the sample period. This is in spite of the fact that positive X factors were not originally envisioned under RPI-X—in contrast to the RPI+K variant applied to the water industry, which explicitly allows for real price increases—and are hard to explain except in terms of technical regress or input prices rising faster than inflation. From this, we therefore conclude that, in contrast to the water industry, cost inefficiency has increased over the sample period as a result of the progressive loosening of revenue caps over the sample period.

To summarise, we reach two conclusions based on the observed trends in cost inefficiency:

i. NIE and the Great British DNOs have similar levels of cost inefficiency, and their trends over time are likewise similar. This is as expected, given that they have been subject to the same form of regulation from approximately the same time, and is in contrast with the large gap in the cost inefficiency of the Scottish and Northern Irish water companies relative to their English and Welsh counterparts—and the catch-up observed over the sample period—found in the previous chapter.

ii. Cost inefficiency has increased significantly over the sample period in both Great Britain and Northern Ireland. This suggests that RPI-X regulation has not been effective in reducing cost inefficiency over the period, again in contrast to the improving cost efficiency found in the water and sewage industry, and can be explained in terms of the way that revenue caps have been loosened to the point that significant real revenue increases were allowed towards the end of the period.

6.4.3.2. Marginal Effects

In this section, we discuss the impact of the environmental variables included in the inefficiency model on cost inefficiency in our total cost model. This will help to understand the changes in cost inefficiency observed in the previous section.

As in the previous chapter, and as discussed in section 3.3.6, there are several different ways of calculating the marginal effects of environmental variables on cost efficiency, based on the various different efficiency predictors, and this complicates discussion of the effects of the variables.

As discussed in section 5.4.3.2, we calculate four alternative formulae for marginal effects: $\partial E(u_{it})/\partial z_{lit}$, as proposed by Wang (2002), $\partial E(u_{it}|\varepsilon_{it})/\partial z_{lit}$ as proposed by

Kumbhakar and Sun (2013), and two formulae derived in this thesis: $\partial E[\exp(su_{it})|\varepsilon_{it}]/\partial z_{lit}$ and $\partial \exp[sM(u_{it}|\varepsilon_{it})]/\partial z_{lit}$, which are based in the conditional mean and conditional mode predictors of efficiency, respectively.

Again, since our efficiency predictions are based on the distribution of $u_{it}|\varepsilon_{it}$, our preferred marginal effects formulae are the conditional mean and mode. As in the previous chapter, given the difficulties associated with hypothesis testing based on these marginal effects formulae, discussion of the significance of our environmental variables in the inefficiency model is based on the significance of the corresponding δ_l parmeters, which give the change in the unconditional mode of the inefficiency distribution for a change in z_l.

The marginal effects shown in figures 6.4.3 to 6.4.6 below are calculated over the observed ranges of the corresponding variables, and with the values of the other environmental variables held at their means.

6.4.3.2.1. Years of Regulation

Estimated marginal effects of years of regulation on total cost inefficiency are shown in figure 6.4.3. As can be seen in table 13, μ_{it} is positively and significantly related to year of regulation in our total cost model, implying that cost inefficiency has increased over time.

Accordingly, figure 6.4.3 shows positive marginal effects according to all four formulae. According to $\partial \exp[sE(u_{it})]/\partial z_{lit}$, the marginal effect is increasing over time, from 0.0569 at year 15 to 0.0964 at year 28. On the other hand, the remaining three formulae suggest lower magnitudes and a less dramatic increase with year of regulation, staying at around 0.010.

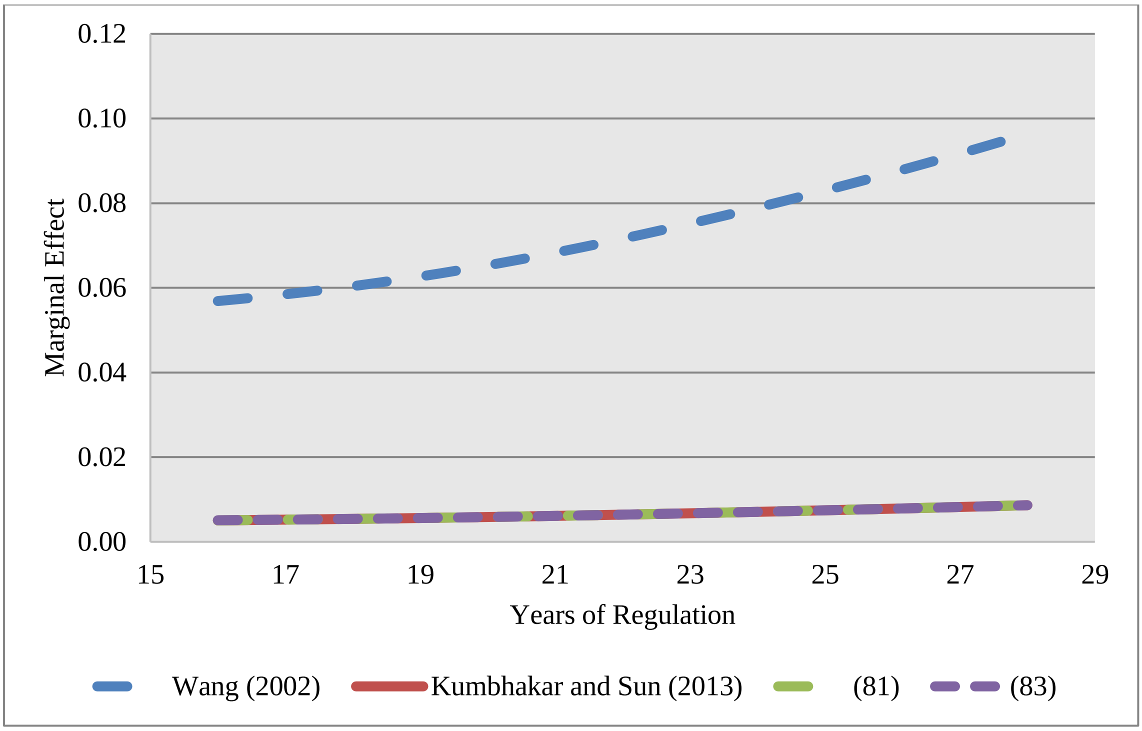

FIGURE 6.4.3: MARGINAL EFFECT OF YEARS OF REGULATION ON TOTAL COST INEFFICIENCY

6.4.3.2.2. X Factor

The estimated marginal effects of the price adjustment factor on total cost inefficiency are shown in figure 6.4.4. As can be seen in table 13, the estimated coefficient on Z_2, the X factor, is positive and significant in our preferred model, meaning that μ_{it} and therefore cost inefficiency increases with the X factor. Again, this is in line with our finding in the previous chapter, and implies that cost inefficiency increases with the X factor. Tighter revenue caps are therefore associated with greater cost efficiency, and looser caps associated with greater cost inefficiency.

Furthermore, as in the previous chapter, the marginal effect is found to increase with the adjustment factor, which reflects the diminishing capacity for efficiency gains as firms approach the frontier.

According to $\partial \exp[sE(u_{it})]/\partial z_{lit}$, the marginal effect increases from 0.0106 for an X factor of -8.4—i.e. a required reduction in real revenue of 8.4%, the tightest revenue cap observed during the sample period—to 0.0120 for an X factor of 8.5, i.e. an allowed increase in real revenue of 8.5%, the loosest revenue cap observed. On the other hand, the marginal effects formulae based on the conditional mean and mode again suggest lower magnitudes, with marginal effects staying around 0.001 in each case.

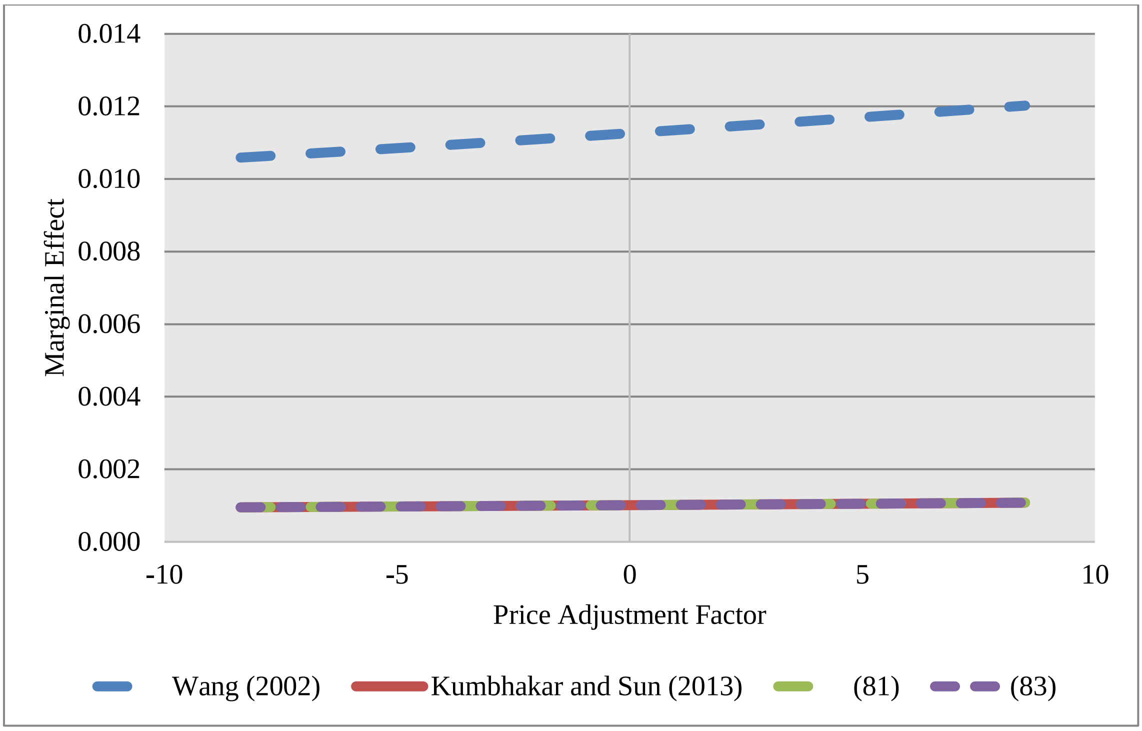

FIGURE 6.4.4: MARGINAL EFFECT OF PRICE ADJUSTMENT FACTOR ON TOTAL COST INEFFICIENCY

6.4.3.2.3. Board Composition

As shown in table 13, the estimated coefficient on Z_3, the proportion of non-executives on the board, is negative and statistically significant. We therefore conclude that cost inefficiency decreases as the proportion of non-executives increases. This lends support to the idea of agency costs from divorce of ownership and control being reduced as the proportion of non-executives increases. Note that this finding is in contrast to the finding of a positive relationship between board composition and cost inefficiency in the variable cost mode in the previous chapter. In each case, the marginal effect is shown to diminish as the proportion of non-executives increases, which is intuitively sensible and in line with the fact that the capacity for efficiency improvement diminishes as firms approach the frontier.

Again, the magnitudes of the marginal effects of this variable differ according to the formula used, with $\partial \exp[sE(u_{it})]/\partial z_{lit}$ increasing from -0.426 when there are no non-executives to -0.196 when the board is entirely composed of non-executives, whereas the conditional mean and mode marginal effects start at around -0.0390 and decrease in magnitude only slightly to -0.0305.

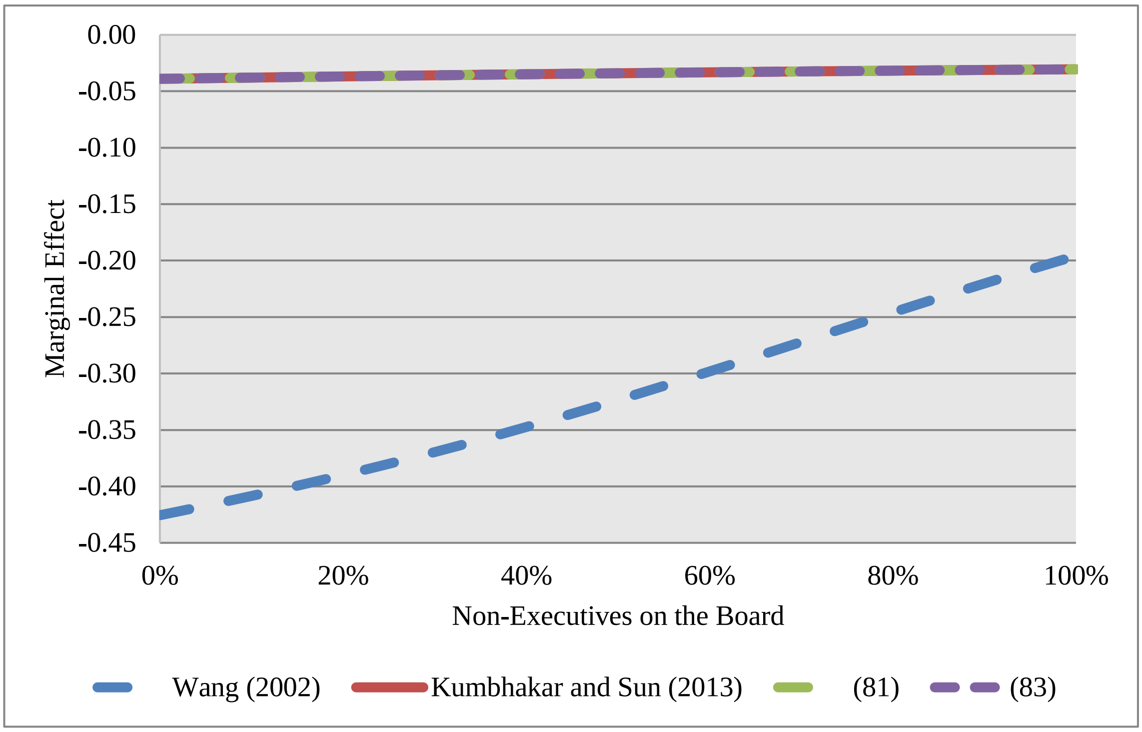

FIGURE 6.4.5: MARGINAL EFFECT OF BOARD COMPOSITION ON TOTAL COST INEFFICIENCY

6.4.3.3. Director's Average Years on the Board

Table 13 shows that the estimated coefficient on Z_4, director's average years on the board, is negative and significant in our preferred total cost model. From this, we conclude that cost inefficiency decreases as the average number of years served by board members increases. This is consistent with our finding from our preferred variable cost model in the previous chapter, and again we argue that this can be explained in terms of a learning-by-doing process on the part of the directors.

Again, we find a considerable difference in the magnitude of the marginal effects suggested by $\partial \exp[sE(u_{it})]/\partial z_{lit}$ and those suggested by the derivatives of the conditional mean and conditional mode predictors. The marginal effects are approximately constant in each case, being around -0.068 in the former case and -0.010 in the latter.

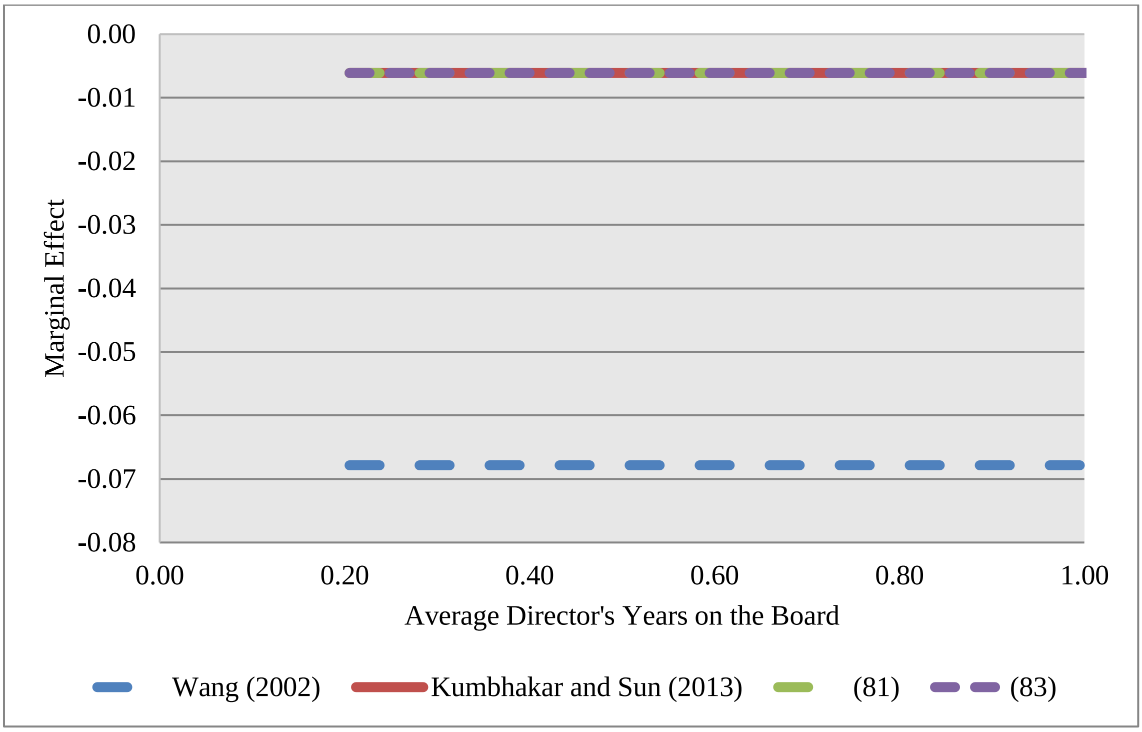

FIGURE 6.4.6: MARGINAL EFFECT OF DIRECTORS' AVERAGE YEARS ON THE BOARD ON TOTAL COST INEFFICIENCY

6.4.3.3.1. Discussion

In this section, we summarise the marginal effects results presented in the preceding sections. As in the previous chapter, and as seen in Kumbhakar and Sun (2013), we find that the magnitude of the calculated marginal effects differ considerably according to the formula used. Generally, we find that $\partial \exp[sM(u_{it}|\varepsilon_{it})]/\partial z_{lit}$, $\partial \exp[sE(u_{it}|\varepsilon_{it})]/\partial z_{lit}$, and $\partial E[\exp(su_{it})|\varepsilon_{it}]/\partial z_{lit}$ yield similar estimates of marginal effects, while $\partial \exp[sE(u_{it})]/\partial z_{lit}$yields estimated marginal effects that are greater in magnitude. A wider explanation of the reasons for the differences between these formulae is provided in section 5.4.3.2.6; in this case, the large difference in magnitude between $\partial \exp[sM(u_{it}|\varepsilon_{it})]/\partial z_{lit}$ and the other formulae is due to the relatively large estimated γ parameter in our preferred total cost model.

As discussed previously, despite these differences in the magnitudes and the difficulty of hypothesis testing around marginal effect—see section 3.3.6.1—the estimated δ_l parameters can be interpreted as the marginal effect of z_l on the unconditional mode of the inefficiency distribution, and the usual approach is therefore to base discussion of the significance of environmental variables in the inefficiency model on these parameters. In addition, it is useful to comment on the directions of the slopes of the marginal cost formulae. Given this approach, we find that:

i. Cost inefficiency has increased with year of regulation in our preferred total cost model. The slopes of the marginal effects formulae imply that the marginal effect is greater as year of regulation increases.
ii. Cost inefficiency increases with the X factor. This is consistent with our finding in the previous chapter that water and sewage companies' cost inefficiency increases with the K factor imposed. In both cases, this implies that the tighter

the price cap imposed, the greater the incentive to minimise costs, while loose price caps lead to greater inefficiency.

iii. Cost inefficiency decreases as the proportion of non-executives on the board increases. This supports the idea that a more independent board lowers agency costs, and is in contrast to the result from the variable cost model in the previous chapter.

iv. Cost inefficiency decreases as directors' average years on the board increases. This is in line with the finding that sewage revenue efficiency increases with this variable, and again may be explained by stewardship theory.

6.5. Summary

In this chapter, we have analysed the cost efficiency of the electricity distribution industry in the UK. In contrast to the water and sewage industry, in which the firms are subject to price capping, in electricity distribution firms are subject to a revenue cap, making the estimation of a revenue frontier inappropriate. We therefore restrict attention to efficiency on the cost side, using stochastic frontier analysis (SFA) to estimate a total cost frontier model. Cost inefficiency predictions based on our preferred model are calculated.

We focus on the impact of RPI-X revenue capping regulation on cost inefficiency in the UK electricity distribution industry. This is assessed in two ways: first, by analysing trends in mean cost inefficiencies over the sample period, and second by analysing the effect of regulatory and other environmental variables on cost inefficiency. In contrast to previous studies which use data on only the Great British DNOs, we include data on Northern Ireland Electricity, which is regulated by NIAUR, allowing us to compare the efficiency us to compare its cost efficiency to that of its counterparts in Great Britain.

Our main finding is that RPI-X revenue capping regulation imposed on the DNOs has not been effective at reducing cost inefficiency. This is reflected in an increase in cost inefficiency—in both Great Britain and Northern Ireland— over the sample period and an estimated positive relationship between year of regulation and cost inefficiency. Second, we find a positive relationship between X factors set by the regulator and cost inefficiency, so that when tighter revenue caps are imposed, cost inefficiency decreases, while when price caps are loosened, cost inefficiency increases.

Given that price caps are seen to have been loosened both in Great Britain and in Northern Ireland, so that toward the end of the sample significant increases in real revenues were allowed, the former finding may be explained in terms of the latter.

We find that cost inefficiency decreases when the proportion of non-executives on the board increases, and also decreases when the directors' average number of years on the board increases. The former finding can be interpreted as supporting the idea that having a more independent board reduces agency costs, while the latter can be explained in terms of stewardship theory and a learning-by-doing effect.

7.Conclusions

In this thesis, we have analysed the effect of RPI-X style regulation on the efficiency of electricity distribution and water and sewage supply utilities in the UK. Our theoretical contribution is to outline an alternative monopoly profit and revenue frontier approach which measures firm performance against a monopoly benchmark. We derive separate revenue and cost frontiers for a profit-maximising monopolist with fixed outputs, given the analogous result that the firm's profit maximisation problem under the Alternative Profit Function approach separates into separate revenue maximising and cost minimisation problems (Restrepo-Tobón and Kumbhakar 2014).

Adopting this theoretical framework, we have analysed the performance of UK water and sewage companies by estimating revenue and cost frontiers using stochastic frontier analysis. We have also analysed the cost efficiency of UK electricity distribution network operators. Our focus in these analyses was on the impact of RPI-X style regulation on efficiency, and the trends in revenue and cost efficiency over the sample periods analysed.

With respect to the water and sewage industry, our main finding is that there were reductions in average cost inefficiency and average overall revenue efficiency over the sample period. The welfare implications of this are as follows: on the revenue side, given our theoretical framework, reductions in revenue efficiency involve reducing revenue away from its potential monopoly level. This implies reduced market power, and therefore transfers from the water and sewage companies to customers and reductions in deadweight losses. On the cost side, the observed reductions in cost inefficiency can be discussed in terms of transfers within the firm from agents to principals. In the electricity distribution industry, on the other hand, we find a substantial increase in cost inefficiency. In welfare terms, where there is pass-through of the resulting increases in costs, this implies transfers from customers to the firm, and within the firm from principal to agent.

In terms of policy implications, these results suggest that RPI+K price capping regulation in the water and sewage industry has been successful in curbing market power and incentivising improvements in cost efficiency over the period, while the analogous RPI-X revenue capping regulation applied to the electricity distribution has failed to prevent large increases in cost inefficiency.

Our modelling of inefficiencies in terms of regulatory and other environmental variables helps to explain why this is the case: in each of our cost models, in both the water and sewage industry and the electricity distribution industry, we find a positive relationship between cost inefficiency and the price cap or revenue cap imposed. Tighter price or revenue caps are associated with greater cost efficiency, and looser price caps are associated with greater cost inefficiency. This result is robust to across alternative specifications—i.e. total cost versus variable cost approaches in the water and sewage case, and total cost versus total expenditure approaches in the case of electricity distribution—and is in line with previous studies of the industries which suggest a link between efficiency or productivity and the stringency of regulation.

This relationship helps to explain the very different outcomes from RPI-X style regulation in the two industries, since over the sample period revenue caps in the electricity distribution industry were progressively loosened to the point that large increases in real revenue were allowed, while price caps in the water and sewage industry remained relatively tight. This suggests that the regulation in electricity distribution has been too lax over the period, and that a tightening of revenue caps by Ofgem could yield substantial efficiency gains.

In addition to the evidence that regulation reduces cost inefficiency over time, there are also indications that these gains are particularly large at the onset of regulation. This study has been the first—to our knowledge—to analyse the efficiency of the publicly-owned Scottish and Northern Irish water and sewage companies, which enter the sample in both cases with the introduction of price capping regulation of the sort applied in England and Wales. We find that these companies are initially much less cost efficient than their English and Welsh counterparts, but that they catch up to a considerable extent, making large improvements over the sample.

The initial gap in cost efficiency between the Scottish and Northern Irish water and sewage companies and those in England and Wales could be explained in a number of ways, such as in terms of the prior lack of regulation, or by an ownership effect: an ownership dummy is found to be significant after controlling for year of regulation, but the two factors are ultimately hard to disentangle. Nevertheless, whatever the reason for the initial gap, it seems clear that price-capping has been effective in inducing the Scottish and Northern Irish water and sewage companies to catch up to the frontier.

This implies that various forms of incentive regulation could be effective in promoting cost savings in certain public services, even in the absence of a profit incentive. For example, the UK Department for Transport (DfT) recently began operating an ‘incentive fund’ for local authorites’ highways maintenance in which the funding awarded to an authority depends upon their performance, which is measured via a self-assessment score. This works in much the same way as incentive regulation, as an authority is encouraged to demonstrate improvements in efficiency in order to obtain more funding. The findings of this study suggest that this initiative may prove effective in promoting efficiency, and could be a model for introducing performance incentives in other public services such as education and health.

We identify no clear trend in water or sewage revenue efficiency over the period, although revenue efficiency does appear lower in Scotland and Northern Ireland than in England and Wales, perhaps reflecting a greater preference for lower prices among publicly-owned companies.

One possible explanation of the apparent difference in the effectiveness of price capping regulation between the water and sewage and electricity distribution industries is that Ofgem is at a disadvantage in terms of its ability to reduce the information asymmetry between itself and the firms it regulates due to the smaller number of firms in the industry—14 DNOs in Great Britain compared to currently 10 WaSCs and 8 WOCs in England and Wales, this being a reduction from the earlier years of our sample—reducing the number of comparator firms and hence the ability of the regulator to estimate efficiency and predict the scope for TFP growth accurately.

This may also be a contributory factor to the observed lower efficiency of water and sewage firms in Scotland and Northern Ireland, which both have separate regulators and only a single regulated company, making benchmarking impossible. Regulators must therefore consider the impact of mergers on their ability to benchmark effectively; possibly of greater significance, however, are the potential gains from international benchmarking. WICS and NIAUR in particular could benefit from greater cooperation in benchmarking with the other UK regulators, Ofwat and Ofgem, which could hasten convergence in efficiency between WICS and NIAUR regulated firms and those in the rest of the UK. This applies not only to water and electricity distribution, but also to gas distribution, in which Ofgem regulates eight firms and NIAUR regulates three. International benchmarking is used by ORR in evaluating the performance of the UK's rail infrastructure manager, Network Rail.

Concerning the effect of board structure on efficiency, our analyses of electricity distribution suggest that cost efficiency improves with directors' average years on the board, suggesting a learning-by-doing effect, as do some of our water and sewage cost models and our water revenue model, though these latter results are not statistically significant. Likewise, the proportion of non-executives on the board seems to be associated with increasing cost efficiency in the electricity distribution cost models, suggesting that non-executives improve efficiency by reducing agency costs, though results from the water and sewage industry are less clear, again with mixed and generally insignificant findings.

Departing from the main focus of this thesis, our findings on the cost structure of the water and sewage supply and electricity distribution industries appear comparable to those of previous studies: in water and sewage, we find evidence of moderate increasing or constant returns to scale at the mean of our sample, which included both WOCs and WaSCs which are usually suggested to have increasing and either constant or decreasing returns to scale, respectively. Among DNOs, we find increasing returns to scale at the sample mean. Also in common with previous studies, we find increasing returns to network density in both industries, and increasing returns to output density in electricity distribution. Note that these findings of economies of density or economies of scale suggest that the regulated firms we study have greater potential long run TFP growth than the economy as a whole, thereby justifying positive X factors—real price reductions—in the long run (Burns and Weyman-Jones 2013).

On the methodological side, we make a contribution to the literature on one-step estimation of frontiers and inefficiency models, deriving two new formulae for marginal effects from these models, and apply these to analyse the impact of regulatory and other environmental variables on cost and revenue efficiency.

There are a number of possible ways in which the analysis in this thesis could be built upon. First, although our datasets are large and cover a long time period relative to some other studies of these industries, the incorporation of more data relating to earlier or later years, particularly those immediately following privatisation, would increase the robustness of our estimates and allow us to build up a fuller picture of trends in efficiency and the effectiveness of RPI-X regulation. Second, the data used all relate to companies under a *single* form of regulation. The incorporation of international data including companies under different forms of regulation, e.g. franchising or RoR regulation, would enable a direct comparison of the effectiveness of different regulatory regimes.

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9. Appendix 1

9.1. Derivation of Formulae for Marginal Effects

In this appendix, we derive two new formulae for the marginal effects of environmental variables on efficiency predictions in SFA; specifically, for the Kumbhakar and Sun (2013) model in which the pre-truncation mean and standard deviation of the truncated-normal inefficiency term u, as well as the standard deviation of the noise term v are a function of a set of environmental variables, z. The vectors of environmental variables that enter each function need not be identical; although our formulae assume that they are, it is straightforward to amend them for the case where the vectors differ. It is also straightforward to modify the formulae for nested models such as those of Wang (2002) and Battese and Coelli (1995), as we do.

We derive two formulae: one is based on the conditional mean predictor of Battese and Coelli (1988), which is preferred to the Kumbhakar and Sun (2013) formula based on the Jondrow et al. (1982) conditional mean predictor, as discussed in Chapter 3—though as we see in Chapter 5 and Chapter 6, there is little difference between them in our examples—and the second is based on the conditional mode formula, which is less frequently used in SFA despite, as Jondrow et al. (1982) point out, having an interpretation as a maximum likelihood estimator of efficiency.

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9.1.1. Based on the Conditional Mean

The Battese and Coelli (1988) conditional mean efficiency predictor for the Kumbhakar and Sun (2013) model is

$$E(\exp[su_{it}]\,|\varepsilon_{it}) = \left\{\exp\left[\frac{1}{2}\sigma_{*it}^2 + s\tilde{\mu}_{it}\right]\right\}\left\{\frac{\Phi[(\tilde{\mu}_{it}/\sigma_{*it}) + s\sigma_{*it}]}{\Phi(\tilde{\mu}_{it}/\sigma_{*it})}\right\} \tag{106}$$

Where

$$\sigma_{*it} = \sqrt{\sigma_{vit}^2\sigma_{uit}^2/\sigma_{it}^2}$$

$$\tilde{\mu}_{it} = \left(\sigma_{vit}^2\mu_{it} + s\sigma_{uit}^2\varepsilon_{it}\right)/\sigma_{it}^2$$

$$\sigma_{it} = \sqrt{\sigma_{vit}^2 + \sigma_{uit}^2} \tag{107}$$

$$\mu_{it} = \delta' z_{it}$$

$$\sigma_{uit} = \gamma' z_{it}$$

$$\sigma_{vit} = \rho' z_{it}$$

Below, we break down the derivative of (106) into successively more manageable derivatives

$$\frac{\partial E(\exp[su_{it}]\,|\varepsilon_{it})}{\partial z_{lit}} = \frac{\partial \exp\left[\frac{1}{2}\sigma_{*it}^2 + s\tilde{\mu}_{it}\right]}{\partial z_{lit}} \left\{ \frac{\Phi\left[\left(\frac{\tilde{\mu}_{it}}{\sigma_{*it}}\right) + s\sigma_{*it}\right]}{\Phi\left(\frac{\tilde{\mu}_{it}}{\sigma_{*it}}\right)} \right\} + \frac{\partial \left\{ \frac{\Phi\left[\left(\frac{\tilde{\mu}_{it}}{\sigma_{*it}}\right) + s\sigma_{*it}\right]}{\Phi\left(\frac{\tilde{\mu}_{it}}{\sigma_{*it}}\right)} \right\}}{\partial z_{lit}} \exp\left[\frac{1}{2}\sigma_{*it}^2 + s\tilde{\mu}_{it}\right] \tag{108}$$

$$\frac{\partial \exp\left[\frac{1}{2}\sigma_{*it}^2 + s\tilde{\mu}_{it}\right]}{\partial z_{lit}} = \exp\left[\frac{1}{2}\sigma_{*it}^2 + s\tilde{\mu}_{it}\right] \frac{\partial \left[\frac{1}{2}\sigma_{*it}^2 + s\tilde{\mu}_{it}\right]}{\partial z_{lit}} = \exp\left[\frac{1}{2}\sigma_{*it}^2 + s\tilde{\mu}_{it}\right]\left[\frac{1}{2}\frac{\partial \sigma_{*it}^2}{\partial z_{lit}} + \frac{\partial s\tilde{\mu}_{it}}{\partial z_{lit}}\right] \tag{109}$$

$$\frac{\partial \left\{ \frac{\Phi\left[\left(\frac{\tilde{\mu}_{it}}{\sigma_{*it}}\right) + s\sigma_{*it}\right]}{\Phi\left(\frac{\tilde{\mu}_{it}}{\sigma_{*it}}\right)} \right\}}{\partial z_{lit}} = \frac{\frac{\partial \Phi\left[\left(\frac{\tilde{\mu}_{it}}{\sigma_{*it}}\right) + s\sigma_{*it}\right]}{\partial z_{lit}} \Phi\left(\frac{\tilde{\mu}_{it}}{\sigma_{*it}}\right) - \frac{\partial \Phi\left(\frac{\tilde{\mu}_{it}}{\sigma_{*it}}\right)}{\partial z_{lit}} \Phi\left[\left(\frac{\tilde{\mu}_{it}}{\sigma_{*it}}\right) + s\sigma_{*it}\right]}{\left[\Phi\left(\frac{\tilde{\mu}_{it}}{\sigma_{*it}}\right)\right]^2} \tag{110}$$

$$\frac{\partial \Phi\left[\left(\frac{\tilde{\mu}_{it}}{\sigma_{*it}}\right) + s\sigma_{*it}\right]}{\partial z_{lit}} = \phi\left[\left(\frac{\tilde{\mu}_{it}}{\sigma_{*it}}\right) + s\sigma_{*it}\right] \frac{\partial \left[\left(\frac{\tilde{\mu}_{it}}{\sigma_{*it}}\right) + s\sigma_{*it}\right]}{\partial z_{lit}} = \phi\left[\left(\frac{\tilde{\mu}_{it}}{\sigma_{*it}}\right) + s\sigma_{*it}\right]\left[\frac{\partial \left(\frac{\tilde{\mu}_{it}}{\sigma_{*it}}\right)}{\partial z_{lit}} + s\frac{\partial \sigma_{*it}}{\partial z_{lit}}\right] \tag{111}$$

$$\frac{\partial \Phi\left(\frac{\tilde{\mu}_{it}}{\sigma_{*it}}\right)}{\partial z_{lit}} = \phi\left(\frac{\tilde{\mu}_{it}}{\sigma_{*it}}\right) \frac{\partial \left(\frac{\tilde{\mu}_{it}}{\sigma_{*it}}\right)}{\partial z_{lit}} \tag{112}$$

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$$\frac{\partial \tilde{\mu}_{it}}{\partial z_{lit}} = \frac{\frac{\partial\left(\sigma_{vit}^2 \mu_{it} + s\sigma_{uit}^2 \varepsilon_{it}\right)}{\partial z_{lit}} \sigma_{it}^2 - \frac{\partial \sigma_{it}^2}{\partial z_{lit}} \left(\sigma_{vit}^2 \mu_{it} + s\sigma_{uit}^2 \varepsilon_{it}\right)}{\sigma_{it}^4} \tag{113}$$

$$\frac{\partial \sigma_{*it}}{\partial z_{lit}} = \frac{\frac{\partial \sigma_{vit}\sigma_{uit}}{\partial z_{lit}} \sigma_{it} - \frac{\partial \sigma_{it}}{\partial z_{lit}} \sigma_{vit}\sigma_{uit}}{\sigma_{it}^2} \tag{114}$$

$$\frac{\partial\left(\sigma_{vit}^2 \mu_{it} + s\sigma_{uit}^2 \varepsilon_{it}\right)}{\partial z_{lit}} = \frac{\partial \sigma_{vit}^2 \mu_{it}}{\partial z_{lit}} + \frac{\partial s\sigma_{uit}^2 \varepsilon_{it}}{\partial z_{lit}} \tag{115}$$

$$\frac{\partial \sigma_{it}^2}{\partial z_{lit}} = 2\sigma_{it} \frac{\partial \sigma_{it}}{\partial z_{lit}} \tag{116}$$

$$\frac{\partial \sigma_{vit}\sigma_{uit}}{\partial z_{lit}} = \frac{\partial \sigma_{vit}}{\partial z_{lit}} \sigma_{uit} + \frac{\partial \sigma_{uit}}{\partial z_{lit}} \sigma_{vit} \tag{117}$$

$$\frac{\partial \sigma_{vit}^2 \mu_{it}}{\partial z_{lit}} = 2\sigma_{vit} \frac{\partial \sigma_{vit}}{\partial z_{lit}} \mu_{it} + \frac{\partial \mu_{it}}{\partial z_{lit}} \sigma_{vit}^2 \tag{118}$$

$$\frac{\partial \sigma_{it}}{\partial z_{lit}} = \frac{\frac{\partial\left(\sigma_{vit}^2 + \sigma_{uit}^2\right)}{\partial z_{lit}}}{2\sqrt{\sigma_{vit}^2 + \sigma_{uit}^2}} = \frac{2\sigma_{vit} \frac{\partial \sigma_{vit}}{\partial z_{lit}} + 2\sigma_{vit} \frac{\partial \sigma_{vit}}{\partial z_{lit}}}{2\sqrt{\sigma_{vit}^2 + \sigma_{uit}^2}} \tag{119}$$

$$\frac{\partial s\sigma_{uit}^2 \varepsilon_{it}}{\partial z_{lit}} = 2s\varepsilon_{it}\sigma_{vit} \frac{\partial \sigma_{vit}}{\partial z_{lit}} \tag{120}$$

$$\frac{\partial \mu_{it}}{\partial z_{lit}} = \delta_l \tag{121}$$

$$\frac{\partial \sigma_{vit}}{\partial z_{lit}} = \rho_l \sigma_{vit} \tag{122}$$

$$\frac{\partial \sigma_{uit}}{\partial z_{lit}} = \gamma_l \sigma_{uit} \tag{123}$$

Substituting backwards, and with much rearranging, we arrive at

$$\begin{aligned}\frac{\partial E(\exp[su_{it}]\,|\varepsilon_{it})}{\partial z_{lit}} = &+\delta_l\left\{\frac{\sigma_{vit}^2}{\sigma_{it}^2}\left[s+\frac{1}{\sigma_{*it}}(C_1-C_2)\right]\right\}\exp\left[\frac{1}{2}\sigma_{*it}^2+s\tilde{\mu}_{it}\right]\left\{\frac{\Phi\left[\left(\frac{\tilde{\mu}_{it}}{\sigma_{*it}}\right)+s\sigma_{*it}\right]}{\Phi\left(\frac{\tilde{\mu}_{it}}{\sigma_{*it}}\right)}\right\}\\
&+\gamma_l\left\{\sigma_{*it}^2+\frac{\sigma_{uit}^2}{\sigma_{it}^2}[\sigma_{*it}^2-2s(\tilde{\mu}_{it}+s\varepsilon_{it})]+(C_1-C_2)\frac{1}{\sigma_{*it}}\left[2\frac{\sigma_{uit}^2}{\sigma_{it}^2}(s\varepsilon_{it}-\tilde{\mu}_{it})-\frac{\sigma_{vit}^2}{\sigma_{it}^2}\tilde{\mu}_{it}\right]-sC_1\frac{\sigma_{vit}^2}{\sigma_{it}^2}\sigma_{*it}\right\}\exp\left[\frac{1}{2}\sigma_{*it}^2+s\tilde{\mu}_{it}\right]\left\{\frac{\Phi\left[\left(\frac{\tilde{\mu}_{it}}{\sigma_{*it}}\right)+s\sigma_{*it}\right]}{\Phi\left(\frac{\tilde{\mu}_{it}}{\sigma_{*it}}\right)}\right\}\\
&+\rho_l\left\{\sigma_{*it}^2+\frac{\sigma_{vit}^2}{\sigma_{it}^2}[\sigma_{*it}^2-2s(\tilde{\mu}_{it}+s\varepsilon_{it})]+(C_1-C_2)\frac{1}{\sigma_{*it}}\left[2\frac{\sigma_{vit}^2}{\sigma_{it}^2}(\mu_{it}-\tilde{\mu}_{it})-\frac{\sigma_{uit}^2}{\sigma_{it}^2}\tilde{\mu}_{it}\right]-sC_1\frac{\sigma_{uit}^2}{\sigma_{it}^2}\sigma_{*it}\right\}\exp\left[\frac{1}{2}\sigma_{*it}^2+s\tilde{\mu}_{it}\right]\left\{\frac{\Phi\left[\left(\frac{\tilde{\mu}_{it}}{\sigma_{*it}}\right)+s\sigma_{*it}\right]}{\Phi\left(\frac{\tilde{\mu}_{it}}{\sigma_{*it}}\right)}\right\}\end{aligned} \tag{124}$$

Where

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$$\frac{\phi\left[\left(\frac{\tilde{\mu}_{it}}{\sigma_{*it}}\right)+s\sigma_{*it}\right]}{\Phi\left[\left(\frac{\tilde{\mu}_{it}}{\sigma_{*it}}\right)+s\sigma_{*it}\right]}=C_1,\frac{\phi\left(\frac{\tilde{\mu}_{it}}{\sigma_{*it}}\right)}{\Phi\left(\frac{\tilde{\mu}_{it}}{\sigma_{*it}}\right)}=C_2 \qquad (125)$$

In the Battese and Coelli (1995) model, where $\gamma_l = \rho_l = 0$ for all l, (124) becomes (74).

9.1.2. Based on the Conditional Mode

The conditional mode estimator of efficiency in the Kumbhakar and Sun (2013) model is

$$\mathrm{M}(su_{it}|\varepsilon_{it}) = \begin{cases} \exp(s\tilde{\mu}_{it}), & s\tilde{\mu}_{it} \geq 0 \\ 1, & s\tilde{\mu}_{it} < 0 \end{cases} \tag{126}$$

And the marginal effect of z_{lit} on this predictor is

$$\frac{\partial \exp(s\,\mathrm{M}[u_{it}]\,|\varepsilon_{it})}{\partial z_{lit}} = \begin{cases} s\dfrac{\partial \tilde{\mu}_{it}}{\partial z_{lit}} \exp(s\tilde{\mu}_{it}), & s\tilde{\mu}_{it} \geq 0 \\ 0, & s\tilde{\mu}_{it} < 0 \end{cases} \tag{127}$$

The derivative $\partial\tilde{\mu}_{it}/\partial z_{lit}$ can be determined from the previous section, from (113) down, as

$$\frac{\partial \tilde{\mu}_{it}}{\partial z_{lit}} = \frac{1}{\sigma_{it}^2}[2\rho_l\sigma_{vit}^2(\mu_{it} + \tilde{\mu}_{it}) + \delta_l\sigma_{vit}^2 + 2\gamma_l\sigma_{uit}^2(s\varepsilon_{it} + \tilde{\mu}_{it})] \tag{128}$$

And substituting this into (127), we have our marginal effect formula

$$\frac{\partial \exp(s\,\mathrm{M}[u_{it}]\,|\varepsilon_{it})}{\partial z_{lit}} = \begin{cases} \dfrac{s}{\sigma_{it}^2}[2\rho_l\sigma_{vit}^2(\mu_{it} + \tilde{\mu}_{it}) + \delta_l\sigma_{vit}^2 + 2\gamma_l\sigma_{uit}^2(s\varepsilon_{it} + \tilde{\mu}_{it})]\exp(s\tilde{\mu}_{it}), & s\tilde{\mu}_{it} \geq 0 \\ 0, & s\tilde{\mu}_{it} < 0 \end{cases} \tag{129}$$

Which, in the Battese and Coelli (1995) model, reduces to (83).

10. Appendix 2

10.1. Description of Water and Sewage Firms

AFF: Affinity Water Limited, a WOC formed in 2012 by the merger of VSE, VWE, and VWC after their sale from Veolia to Rift Acquisitions, which was formed by Morgan Stanley and M&G Investments. Veolia retains a 10% stake in the company.

ANG: Anglian Water Services Limited, a WaSC. Originally the Anglian Water Authority (AWA) from 1974, it was privatised in 1989. It took over HPL in 1997, forming ANH.

ANH: Anglian Water Services Limited (Including Hartlepool Water), a WaSC formed by the takeover of HPL by ANG. Its parent company was acquired in 2008 by the Osprey Consortium, consisting of the Canadian Pension Plan Investment Board, Colonial First State—part of the Commonwealth Bank of Australia—Industry Funds Management, and 3i Group.

BWH/SMB: Sembcorp Bournemouth Water, a WOC formerly known as Bournemouth and West Hampshire Water, which was formed by the merger of Bournemouth and District Water (BRN) and The West Hampshire Water Company (WHW) in 1994. It was acquired by Sembcorp, a Singaporean engineering company, in 2010.

BRL: Bristol Water plc, a WOC. It was acquired by Grupo Agbar—a Spanish water company—in 2006, which then sold a 70% stake in the company to Capstone Infrastructure in 2011. Since 2012, its owners have been Capstone Infrastructure (50%), Grupo Agbar (30%), and Itochu Corporation (20%), a Japanese trading company.

CAM: Cambridge Water, a WOC. It became a Public Limited Company in 1996 and was bought by Chung Kong Infrastructure Holdings, a Hong Kong infrastructure company, in 2004. In 2011 it was then sold on to HSBC and then to SST. It became a part of SST in 2013, after the end of our sample period.

DVW: Dee Valley Water, a WOC. Created by the purchase of Chester Waterworks (CHR) by Wrexham Water (WRX)—formerly known as the Wrexham and East Denbighshire Water Company. Its parent is a listed company.

EoS: East of Scotland Water Authority, formed in 1996 taking over the water and sewage responsibilities of the Lothian, Borders, Fife, and Central Regional Councils, and the responsibilities of the Central Scotland Water Development Board (CSWDB), as well as Kinross in Tayside. The authority was subject to regulation by the Water Industry Commissioner for Scotland, the forerunner of WICS, and was merged with NoS and WoS to form SCW in 2002.

ESK: Essex and Suffolk Water plc, a WOC. It was created in 1994 by the merger of the Essex Water Company (ESX) and the Suffolk Water Company (SFK), which had both been acquired by Lyonnaise des Eaux, a French water company, in 1988. It was merged into NNE in 2000, creating NES.

FLK/VSE: Veolia Water Southeast Limited, a WOC formerly known as Folkestone & Dover Water Services. Veolia Water—then named General Utilities—became the majority shareholder in 1989, and in 2009 the company's name was changed when that parent decided to use the Veolia brand across its various businesses. It was sold in 2012 to Rift Acquisitions—consisting of Morgan Stanley and M&G Investments—along with Veolia's other water supply businesses—VWC and VWE—which were merged to form AFF, in which Veolia retains a 10% stake.

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HPL: Hartlepool Water plc, a WOC. It was taken over by ANG in 1997 to form ANH.

MKT: Mid Kent Water Limited, a WOC. It was taken over by MSE in 2007, creating SEW.

NoS: North of Scotland Water Authority, formed in 1996 taking over the water and sewage responsibilities of the Highland, Grampian, and Tayside—excluding Kinross—Regional Councils, and the Island Councils of Orkney, Shetland and the Western Isles. The authority was subject to regulation by the Water Industry Commissioner for Scotland, the forerunner of WICS, and was merged with EoS and WoS to form SCW in 2002.

NSY: North Surrey Water Limited, a WOC. It was owned by Veolia Water—then named General Utilities—and was merged with TVW in 2000, creating TVN.

NIW: Northern Ireland Water Limited, a publicly-owned WaSC. Originally the Water Executive within the Department of the Environment (Northern Ireland) from 1974, it became the Northern Ireland Water Service—an executive agency—in 1996, and was transferred to the Department for Regional Development in 1999, finally becoming a publicly-owned company in 2006. It is regulated by NIAUR.

NNE: Northumbrian Water Limited, a WaSC. A 1996 merger of Northumbrian Water (NBN)—originally the Northumbrian Water Authority (NWA) from 1974—and North East Water (NEW). NEW was itself the product of a 1992 merger between the Newcastle and Gateshead Water Company (NCL) and the Sunderland and South Shields Water Company (SUN), which had both been acquired by Lyonnaise des Eaux in 1988. Lyonnaise des Eaux acquired NBN in 1995 and therefore owned both NBN and NEW, as well as ESK. The former two were merged in 1996 to create NNE, which was then merged with the latter in 2000 to form NES.

NES: Northumbrian Water (Including Essex and Suffolk Water), a WaSC formed from the 2000 merger of NNE and ESK. Its owner, Lyonnaise des Eaux, had been acquired by Suez, a French multinational utility corporation, in 1997, and in 2003 sold 75% of the Northumbrian Water Group to a consortium of private investors. The group was then listed in 2003 until 2011, when it was acquired by Cheung Kong Infrastructure Holdings.

SCW: Scottish Water Limited, a publicly-owned WaSC formed by the merger of EoS, NoS, and WoS in 2002. It is regulated by WICS.

SVT: Severn Trent Water Limited, a WaSC. Originally the Severn Trent Water Authority (STWA) from 1974, it was privatised in 1989. It absorbed the East Worcestershire Waterworks Company (EWR) in 1993.

MSE: South East Water, a WOC formed by the 1999 merger of Mid Southern Water (MSN) and South East Water (SEW), the latter of which was created by a 1991 merger between three firms: the West Kent Water Company (WKT), the Eastbourne Water Company (EBN), and the Mid Sussex Water Company (MSX). MSE was acquired by the Macquarie group in 2003, who then sold the company to Hastings Diversified Utilities Fund and the Utilities Trust of Australia, both managed by the Australian bank Westpac. These funds already owned MKT, and the two companies were merged in 2007 to form SEW.

SEW: South East Water (Including Mid Kent Water), a WOC formed by the 2007 merger between MSE and MKT. SEW was owned by Hastings Diversified Utilities

Fund and the Utilities Trust of Australia until Caisse de Dèpôt et Placement du Québec—a Canadian pension fund—acquired a 50% share in 2011, with the rest retained by the Utilities Trust of Australia.

SST: South Staffordshire Water plc, a WOC. It was acquired by Arcapita—a Bahraini bank—in 2004, then by the Alinda Infrastructure Fund in 2007, and finally by KKR & Co—an American private equity firm—in 2013. It acquired CAM in 2011.

SWT: South West Water Limited, a WaSC. Originally the South West Water Authority from 1974, it was privatised in 1989.

SRN: Southern Water Services Limited, a WaSC. Originally the Southern Water Authority from 1974, it was privatised in 1989 and taken over by ScottishPower in 1996. It was then sold to a holding company with the Royal Bank of Scotland as majority shareholder in 2002. It was then sold again in 2007 to Greensands Investments, a consortium owned by JP Morgan (32%), Challenger Infrastructure Fund (27%)—an Australian company, UBS (18%), a group of seven Australasian superannuation funds advised by Access Capital (18%), Hermes (4%), and Peaceweald (1%).

SES: Sutton and East Surrey Water plc, a WOC formed by the 1996 merger of Sutton District Water (SUT) and East Surrey Water (ESY). The company was acquired by Terra Firma—a UK private equity firm—in 2005, and then sold on to the Japanese Sumitomo Corporation in 2013, with Osaka Gas becoming joint owners later that same year.

THD/VWE: Veolia Water East Limited, a WOC formerly known as Tendring Hundred Water Services Limited. It was acquired by Veolia Water—then General Utilities—in 1989, and renamed using the Veolia brand in 2009.It was then sold in 2012 to Rift

Acquisitions along with VSE and VWC, with which it was merged in 2012 to form AFF.

TMS: Thames Water Utilities Limited, a WaSC. Originally the Thames Water Authority from1974, it was privatised in 1989 and taken over by the German energy utility RWE in 2001. RWE sold the company to Kemble Water Holdings, a consortium including the Macquarie Group, an Australian investment banking group.

TVW: Three Valleys Water plc, a WOC formed by the 1994 merger of three companies: the Colne Valley Water Company (CVW), Rickmansworth Water Company (RIC), and Lee Valley Water Company (LVW), all acquired by Veolia in the late 1980s. It then merged with NSY to form TVN in 2000.

TVN/VWC: Veolia Water Central Limited, a WOC formerly known as Three Valleys Water, formed by the 2000 merger of TVW and NSY. It was later renamed Veolia Water Central in 2009, and in 2012 sold to Rift Acquisitions along with VSE and VWE, with which it was merged in 2012 to form AFF.

NWT: United Utilities Water plc, a WaSC. Originally the North West Water Authority (NWWA), it was privatised in 1989 as North West Water, and changed its name to United Utilities Water after merging with the electricity distribution network Norweb—the former North Western Electricity Board—which it later sold on in 2007.

WSH: Dŵr Cymru Cyfyngedig—which translates to Welsh Water Limited—is a WaSC. Originally formed as the Welsh National Water Development Authority in 1974 (WNWDA), it was renamed the Welsh Water Authority (WWA) in 1984 following a reorganisation, and was privatised in 1989. Its parent was renamed as Hyder after a takeover of South Wales Electricity—formerly the South Wales Electricity Board

(SWALEB)—in 1996. Following financial difficulties, Hyder was purchased by Western Power Distribution, which split up the water and electricity businesses and sold Dŵr Cymru to Glas Cymru, a company set up to run Dŵr Cymru as a non-profit enterprise, in 2000.

WSX: Wessex Water Services Limited, a WaSC. Originally the Wessex Water Authority (WWA), it was privatised in 1989 and purchased by Enron in 1998. After the collapse of Enron, the company was sold in 2002 to the YTL corporation, a Malaysian infrastructure company.

WoS: West of Scotland Water Authority, formed in 1996 taking over the water and sewage responsibilities of the Dumfries and Galloway, and Strathclyde Regional Councils. The authority was subject to regulation by the Water Industry Commissioner for Scotland, the forerunner of WICS, and was merged with EoS and NoS to form SCW in 2002.

YRK: The York Waterworks Limited, a small WOC serving the city of York. It was taken over by YKS in 1999.

YKS: Yorkshire Water Services Limited, a WaSC. Originally the Yorkshire Water Authority (YWA) from 1974, then privatised in 1989. Its parent company changed its name to Kelda Group in 1999. It took over YRK in 1999 to form YKY.

YKY: Yorkshire Water Services Limited (Including York Waterworks), a WaSC, formed by the takeover of YRK by YKS in 1999. Its parent company Kelda Group was de-listed in 2008 after being acquired by Saltaire Water, a global infrastructure consortium including Citigroup and HSBC.

10.2. Description of Electricity Distribution Network Operators

WMID: Western Power Distribution (West Midlands) plc. Originally the Midlands Electricity Board (MEB) from 1947, vested as Midlands Electricity plc in 1990, and taken over by Avon Energy Partners in 1996 and renamed GPU Power Networks (UK) Limited in 2000. Renamed again as Aquila Networks plc in 2002 following purchase by Aquila, which was itself sold to E.ON in 2004, who also owned Central Networks East plc, with which it was jointly operated and again renamed as Central Networks West plc. The Central Networks division of E.ON were then sold to PPL Corporation in 2011 and operated as Western Power Distribution, with the company renamed Western Power Distribution (West Midlands) plc.

EMID: Western Power Distribution (East Midlands) plc. Originally the East Midlands Electricity Board (EMEB) from 1947, vested as East Midlands Electricity Distribution in 1990 and taken over by Dominion Resources in 1996. Sold to Powergen, which was later rebranded as E.ON in 1998, it was renamed Central Networks East in 2004 and operated as part of E.ON's Central Networks division, which was again sold on to PPL Corporation in 2011 and renamed Western Power Distribution, with the company itself given its current name.

ENWL: Electricity North West Limited. Originally the North Western Electricity Board (NORWEB) from 1947 and vested as Norweb in 1990, being eventually taken over by North West Water in 1995 and renamed as Norweb Distribution, forming United Utilities. North West Water and Norweb Distribution were then renamed United Utilities Water and United Utilities Electricity in 2000 and 2001, respectively. The electricity company was then sold to North West Electricity Networks (Jersey), a joint venture between Colonial First State—part of the Commonwealth Bank of Australia—and the US investment bank JPMorgan Chase, and given its current name.

NPGN: Northern Powergrid (Northeast) Limited. Originally the North Eastern Electricity Board (NEEB) from 1947, vested as Northern Electric in 1990. It was taken over by CE Electric in 1996, which in turn was sold to MidAmerican Energy (now Berkshire Hathaway Energy) in 1998. It was renamed as Northern Powergrid (Northeast) in 2001.

NPGY: Northern Powergrid (Yorkshire) plc. Originally the Yorkshire Electricity Board (YEB) from 1947, vested as the Yorkshire Electricity Group in 1990. In 1997 it was taken over by American Electric Power—which completed a merger with the Central and South West Corporation in 2000-and the Public Service Company of Colorado. The company then purchased by Innogy in 2001 and renamed twice, to Yorkshire Electricity Distribution, and then to Yorkshire Electricity Distribution. It was then given to MidAmerican Energy in a swap for that company's electricity and gas supply and metering businesses. Since then, it has been run jointly with NPGN, and was renamed to Northern Powergrid (Yorkshire) in 2011.

SWales: Western Power Distribution (South Wales) plc. Originally the South Wales Electricity Board (SWALEB) from 1947, and vested as South Wales Electricity in 1990. In 1995, it was taken over by Welsh Water, forming a part of Hyder. Hyder failed, however, and the electricity distribution business was eventually sold to PPL Corporation, which then operated the company as part of their Western Power Distribution division, under its current name.

SWest: Western Power Distribution (South West) plc. Originally the South Western Electricity Board (SWEB), it was vested as South Western Electricity in 1990 and was taken over in 1995 by Southern Electric International which sold a 25% stake in the business to the PPL Corporation the following year. PPL then increased their stake to 51% in 1998, and the company has since been incorporated to PPL's Western Power Distribution division under its current name.

LPN: London Power Networks plc (2010-present). Originally the London Electricity Board (LEB) from 1947, vested as London Electricity in 1990 and bought by Entergy in 1997. The company was then sold to EDF in 1998, and renamed London Power Networks, before being renamed again to EDF Energy Networks (LPN) in 2003. The company's name was then reverted back to its current name after being sold to UK Power Networks in 2010.

SPN: South Eastern Power Networks plc. Originally the South Eastern Electricity Board (SEEB) from 1947, it was vested in 1990 as SEEBOARD, which was taken over in 1996 by the Central and South Western Corporation, which merged with American Electric Power in 2000. The company was then sold to EDF and renamed EDF Energy Networks (SPN), then sold to UK Power Networks in 2010 and given its current name.

EPN: Eastern Power Networks plc. Originally the Eastern Electricity board from 1947, it was vested as Eastern Electricity in 1990 and taken over by Hanson in 1995. It was renamed Eastern Group in 1996, before being unbundled from Hanson and floated in 1997. It was then taken over in 1999 by TXU Europe, which soon after failed, and was sold to EDF in 2002. Its name changed several times, from Eastern Electricity in 2002, to EPN Distribution, to EDF Energy Networks (EPN). It was then acquired by UK Power Networks in 2010 and given its current name.

SPD: SP Distribution plc. Originally the South of Scotland Electricity Board (SSEB) from 1947, and vested in 1990 as ScottishPower, an integrated generation, distribution, and supply business. The distribution business was named ScottishPower Distribution, and was given its current name in 2002.

SPMW: SP Manweb plc. Originally the Merseyside and North Wales Electricity Board (MANWEB) from 1947, it was vested as Manweb in 1990, taken over by ScottishPower in 1995, and renamed SP Manweb plc in 2001.

SSEH: Scottish Hydro Electric Power Distribution plc. Originally the North of Scotland Hydro-Electric Board (NSHEB) from 1947, it was vested as Scottish Hydro-Electric in 1990 and in 1998 merged with Southern Electric to form Scottish and Southern Energy (now SSE).

SSES: Southern Electric Power Distribution plc. Formerly the Southern Electricity Board from 1947, and vested as Southern Electric in 1990. It merged with Scottish Hydro-Electric in 1998 to form Scottish and Southern Energy (now SSE).

NIE: Northern Ireland Electricity Limited. Originally the Northern Ireland Electricity Service from 1973, vested as Northern Ireland Electricity in 1991. In 1998, the company became part of Viridian Group.

11. Appendix 3

11.1. Further Parameter Estimates

11.1.1. Water and Sewage

TABLE 15: FURTHER COBB-DOUGLAS WATER AND SEWAGE VARIABLE COST MODEL ESTIMATES

Parameter (Variable)	Estimate (Standard Error)			
α	-0.004 (0.041)		0.166 (0.027)	***
θ (t)	-0.008 (0.004)	**	-0.012 (0.003)	***
β_1 (ln Q_1)	0.677 (0.024)	***	0.725 (0.029)	
β_2 (ln Q_2)	0.05 (0.005)	***	0.055 (0.006)	***
γ_1 (ln W_1)	0.165 (0.064)	***	0.261 (0.074)	***
γ_2 (ln W_2)	0.176 (0.036)	***	0.164 (0.042)	***
γ_3 (ln K_3)	0.28 (0.024)	***	0.204 (0.027)	
β_3 (ln H_1)	0.126 (0.018)	***	-0.005 (0.011)	
β_4 (ln H_2)	-0.043 (0.037)		-0.286 (0.035)	***
β_5 (ln H_3)	-1.213 (2.328)		-6.015 (2.392)	**
β_6 (ln H_4)	0.083 (0.125)		0.063 (0.143)	
δ_0	0.151 (0.053)	***	-	-
δ_1 (Z_1)	-0.007 (0.001)	***	-	-
δ_2 (Z_2)	-0.023 (0.006)	***	-	-
δ_3 (Z_3)	0.003 (0.002)	**	-	-
δ_4 (Z_4)	0.266 (0.065)	***	-	-
δ_5 (Z_5)	-	-	-	-
δ_6 (Z_6)	-	-	-	-
σ^2	0.016 (0.002)		0.018	
γ	0.701 (0.087)		-	
lnLikelihood	303.215		229.196	

Significance level: * 10% ** 5% ***1%

Appendix 3

TABLE 16: FURTHER TRANSLOG WATER AND SEWAGE VARIABLE COST MODEL ESTIMATES

Parameter (Variable)	Estimate (Standard Error)			
α	-0.045 (0.104)		0.129 (0.073)	*
θ (t)	-0.006 (0.018)		-0.019 (0.014)	
β_1 (Q_1)	0.872 (0.08)	***	0.923 (0.09)	***
β_2 (Q_2)	0.115 (0.045)	***	0.18 (0.048)	***
γ_1 (W_1)	0.328 (0.244)		0.658 (0.29)	**
γ_2 (W_2)	0.176 (0.248)		0.09 (0.271)	
χ (K)	-0.07 (0.09)		-0.121 (0.084)	
ϑ (t^2)	5.75E-04 (0.001)		0.001 (0.001)	
$\zeta_{1,1}$ (Q_1^2)	0.104 (0.063)	*	0.034 (0.076)	
$\zeta_{2,2}$ (Q_2^2)	0.004 (0.008)		0.014 (0.008)	*
$\eta_{1,1}$ (W_1^2)	0.029 (0.3)		-0.046 (0.373)	
$\eta_{2,2}$ (W_2^2)	0.24 (0.194)		0.183 (0.232)	
μ (K^2)	-0.073 (0.085)		-0.113 (0.093)	
φ_1 (tQ_1)	-0.025 (0.007)	***	-0.029 (0.009)	***
φ_2 (tQ_2)	-1.75E-04 (0.001)		0.001 (0.002)	
ϕ_1 (tW_1)	-0.028 (0.024)		-0.039 (0.03)	
ϕ_2 (tW_2)	-0.004 (0.026)		6.29E-04 (0.029)	
κ (tK)	0.022 (0.007)	***	0.018 (0.008)	**
$\zeta_{1,2}$ (Q_1Q_2)	-0.037 (0.031)		-0.073 (0.036)	**
$\lambda_{1,1}$ (Q_1W_1)	0.029 (0.257)		0.043 (0.315)	
$\lambda_{1,2}$ (Q_1W_2)	0.113 (0.117)		0.228 (0.144)	
ϖ_1 (Q_1K)	-0.013 (0.142)		0.137 (0.164)	
$\lambda_{2,1}$ (Q_2W_1)	-0.122 (0.052)	**	-0.074 (0.066)	
$\lambda_{2,2}$ (Q_2W_2)	0.016 (0.025)		-0.002 (0.03)	
ϖ_2 (Q_2K)	0.031 (0.034)		0.034 (0.038)	
$\eta_{1,2}$ (W_1W_2)	0.097 (0.356)		0.163 (0.445)	
π_1 (W_1K)	0.217 (0.25)		0.146 (0.309)	
π_2 (W_2K)	-0.12 (0.116)		-0.148 (0.142)	
β_3 ($\ln H_1$)	0.124 (0.019)	***	-0.014 (0.011)	
β_4 ($\ln H_2$)	-0.019 (0.045)		-0.212 (0.041)	***
β_5 ($\ln H_3$)	-4.094 (2.403)	*	-10.356 (2.436)	***
β_6 ($\ln H_4$)	-0.186 (0.138)		0.003 (0.144)	
δ_0	0.057 (0.057)		-	-
δ_1 (Z_1)	0.002 (0.002)		-	-
δ_2 (Z_2)	-0.03 (0.007)	***	-	-
δ_3 (Z_3)	0.006 (0.002)	***	-	-
δ_4 (Z_4)	0.201 (0.086)	**	-	-
δ_5 (Z_5)	-	-	-	-
δ_6 (Z_6)	-	-	-	-
σ^2	0.014 (0.002)		0.014	
γ	0.671 (0.1)		-	-
lnLikelihood	351.415		289.304	

Significance level: * 10% ** 5% ***1%

TABLE 17: FURTHER WATER REVENUE MODEL ESTIMATES

Parameter (Variable)	Estimate (Standard Error)			
α	-0.034 (0.035)		-0.11 (0.03)	***
θ (t)	0.019 (0.004)	***	0.012 (0.004)	***
β_1 ($\ln Q_1$)	0.932 (0.013)	***	0.994 (0.008)	***
β_2 ($\ln Y_1$)	0.283 (0.069)	***	0.271 (0.07)	***
β_3 ($\ln Y_2$)	0.123 (0.059)	**	0.112 (0.066)	*
β_4 ($\ln Y_3$)	-0.207 (0.122)	*	-0.418 (0.131)	***
β_5 ($\ln H_1$)	0.047 (0.016)	***	0.067 (0.015)	***
β_6 ($\ln H_2$)	-0.255 (0.041)	***	-0.284 (0.04)	***
β_7 ($\ln H_3$)	-0.034 (0.152)		-0.048 (0.157)	
β_8 ($\ln H_4$)	-0.779 (2.741)		-0.992 (2.443)	
δ_0	-0.024 (0.129)		-	-
δ_1 (Z_1)	-0.02 (0.008)	***	-	-
δ_2 (Z_2)	0.01 (0.005)	**	-	-
δ_3 (Z_4)	0.031 (0.075)		-	-
δ_4 (Z_5)	-0.012 (0.152)		-	-
δ_5 (Z_6)	-	-	-	-
δ_6 (Z_7)	-	-	-	-
σ^2	0.029 (0.006)		0.021	
γ	0.733 (0.071)		-	-
lnLikelihood	207.826		180.630	

Significance level: * 10% ** 5% ***1%

TABLE 18: FURTHER SEWAGE REVENUE MODEL ESTIMATES

Parameter (Variable)	Estimate (Standard Error)			
α	-0.298 (0.055)	***	-0.357 (0.042)	***
θ (t)	0.062 (0.008)	***	0.045 (0.005)	***
β_1 ($\ln Q_1$)	0.681 (0.036)	***	0.8 (0.025)	***
β_2 ($\ln Y_1$)	-0.678 (0.116)	***	-0.46 (0.117)	***
β_3 ($\ln H_5$)	0.128 (0.069)	*	-0.092 (0.058)	
β_4 ($\ln H_2$)	0.221 (0.027)	***	0.112 (0.016)	***
δ_0	0.205 (0.045)	***	-	-
δ_1 (Z_1)	-0.002 (0.001)	***	-	-
δ_2 (Z_2)	0.021 (0.008)	***	-	-
δ_3 (Z_4)	-0.045 (0.078)		-	-
δ_4 (Z_5)	-	-	-	-
δ_5 (Z_6)	-	-	-	-
σ^2	0.016 (0.002)		0.019	
γ	2.32E-04 (0.003)		-	-
lnLikelihood	117.806		105.484	

Significance level: * 10% ** 5% ***1%

Appendix 3

TABLE 19: FURTHER COBB-DOUGLAS ELECTRICITY DISTRIBUTION TOTAL COST MODEL ESTIMATES

Parameter (Variable)	Estimate (Standard Error)			
α	-0.246 (0.079)	***	-0.205 (0.052)	***
θ (t)	-0.005 (0.011)		0.019 (0.008)	**
β_1 ($\ln Q_1$)	0.483 (0.037)	***	0.597 (0.041)	***
γ_1 ($\ln W_1$)	0.712 (0.072)	***	0.670 (0.079)	***
β_3 ($\ln H_1$)	-0.099 (0.015)	***	-0.113 (0.017)	***
δ_0	0.197 (0.032)	***	-	-
δ_1 (Z_1)	0.042 (0.01)	***	-	-
δ_2 (Z_2)	-0.002 (0.001)	***	-	-
δ_3 (Z_3)	-0.050 (0.006)	***	-	-
δ_4 (Z_4)	-	-	-	-
σ^2	0.026 (0.003)		0.036	
γ	2.53E-05 (0.001)		-	-
lnLikelihood	79.509		48.941	

Significance level: * 10% ** 5% ***1%

TABLE 20: FURTHER TRANSLOG ELECTRICITY DISTRIBUTION TOTAL COST MODEL ESTIMATES

Parameter (Variable)	Estimate (Standard Error)			
α	-0.417 (0.111)	***	-0.37 (0.123)	***
θ (t)	-2.31E-04 (0.034)		0.021 (0.038)	
β_1 ($\ln Q_1$)	0.806 (0.116)	***	0.906 (0.13)	***
γ_1 ($\ln W_1$)	0.261 (0.32)		-0.049 (0.361)	
ϑ (t^2)	0.003 (0.003)		0.001 (0.003)	
$\zeta_{1,1}$ ($\ln Q_1^2$)	0.349 (0.062)	***	0.427 (0.066)	***
$\eta_{1,1}$ ($\ln W_1^2$)	-0.007 (0.229)		-0.183 (0.259)	
φ_1 ($t \ln Q_1$)	-0.021 (0.016)		-0.022 (0.018)	
ϕ_1 ($t \ln W_1$)	0.032 (0.045)		0.064 (0.051)	
$\lambda_{1,1}$ ($\ln Q_1 \ln W_1$)	0.277 (0.17)		0.158 (0.191)	
β_3 ($\ln H_1$)	-0.059 (0.015)	***	-0.059 (0.017)	***
δ_0	-0.218 (0.079)	***	-	-
δ_1 (Z_1)			-	-
δ_2 (Z_2)			-	-
δ_3 (Z_3)	-0.019 (0.004)	***	-	-
δ_4 (Z_4)	-0.016 (0.01)		-	-
σ^2	0.021 (0.002)		0.028	
γ	5.34E-06 (0.003)		-	-
lnLikelihood	99.0187		78.824	

Significance level: * 10% ** 5% ***1%

12. Appendix 4

12.1. Electricity Distribution Totex Model

TABLE 21: ELECTRICITY DISTRIBUTION TOTEX MODEL ESTIMATES

Parameter (Variable)	Estimate (Standard Error)			
	Translog		Cobb-Douglas	
α	-0.086 (0.106)		0.063 (0.047)	
θ (t)	-0.06 (0.028)	**	-0.03 (0.008)	***
β_1 ($\ln Q_1$)	0.733 (0.104)	***	0.849 (0.038)	***
β_2 ($\ln Q_2$)	-0.078 (0.468)		0.308 (0.153)	**
γ_1 ($\ln W_1$)	0.779 (0.248)	***	0.304 (0.081)	***
ϑ (t^2)	0.005 (0.002)	***	-0.082 (0.015)	***
$\zeta_{1,1}$ ($\ln Q_1^2$)	0.189 (0.149)		-	-
$\zeta_{2,2}$ ($\ln Q_2^2$)	-2.508 (2.431)		-	-
$\eta_{1,1}$ ($\ln W_1^2$)	-0.67 (0.302)	**	-	-
φ_1 ($t \ln Q_1$)	0.003 (0.017)		-	-
φ_2 ($t \ln Q_2$)	-0.035 (0.082)		-	-
ϕ_1 ($t \ln W_1$)	-0.054 (0.04)		-	-
$\zeta_{1,2}$ ($\ln Q_1 \ln Q_2$)	0.331 (0.771)		-	-
$\lambda_{1,1}$ ($\ln Q_1 \ln W_1$)	-0.023 (0.234)		-	-
$\lambda_{2,1}$ ($\ln Q_2 \ln W_1$)	1.382 (0.956)		-	-
β_3 ($\ln H_1$)	-0.025 (0.036)		-	-
δ_0	0.295 (0.084)	***	-1.186 (0.245)	***
δ_1 (Z_1)	0.022 (0.015)		0.166 (0.029)	***
δ_2 (Z_2)	0.008 (0.005)	*	0.041 (0.01)	***
δ_3 (Z_3)	-0.004 (0.001)	***	-0.004 (0.001)	***
δ_4 (Z_4)	-0.046 (0.013)	***	-0.042 (0.011)	***
σ^2	0.019 (0.005)		0.013 (0.002)	
γ	0.856 (0.102)		5.54E-05 (0.002)	
lnLikelihood	110.444		104.273	
Mean u	1.206			

Significance level: * 10% ** 5% ***1%

Appendix 4

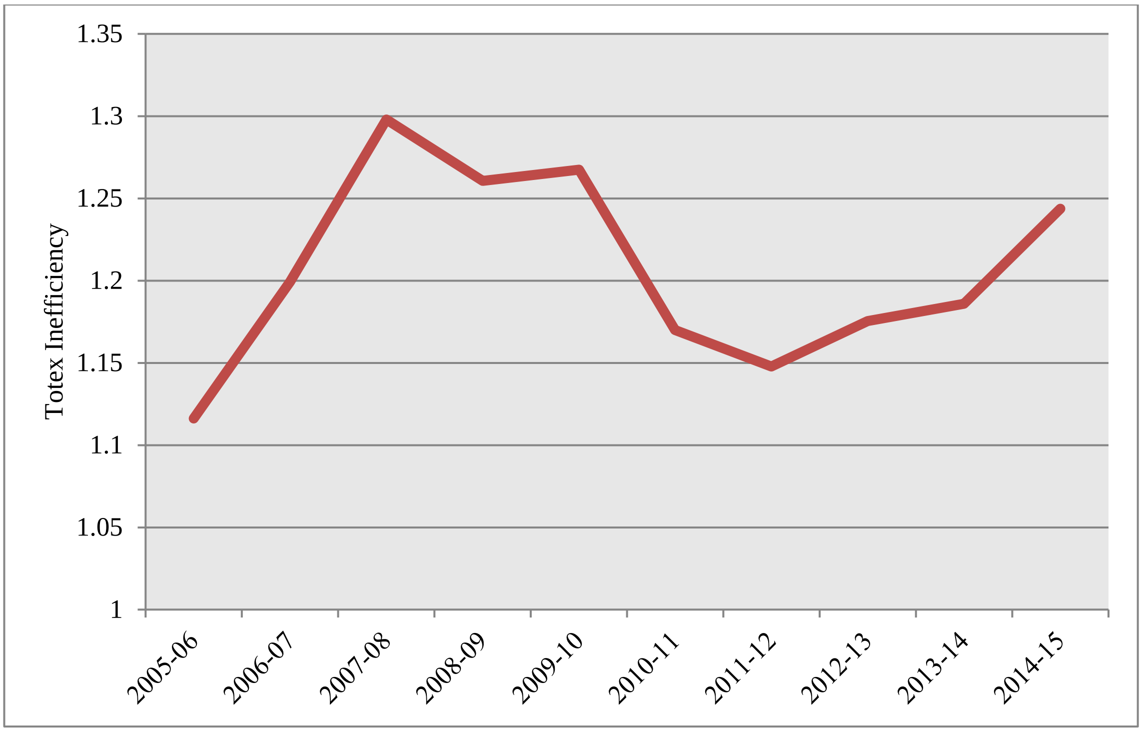

FIGURE 12.1.1: TREND IN MEAN TOTEX INEFFICIENCY RATIO

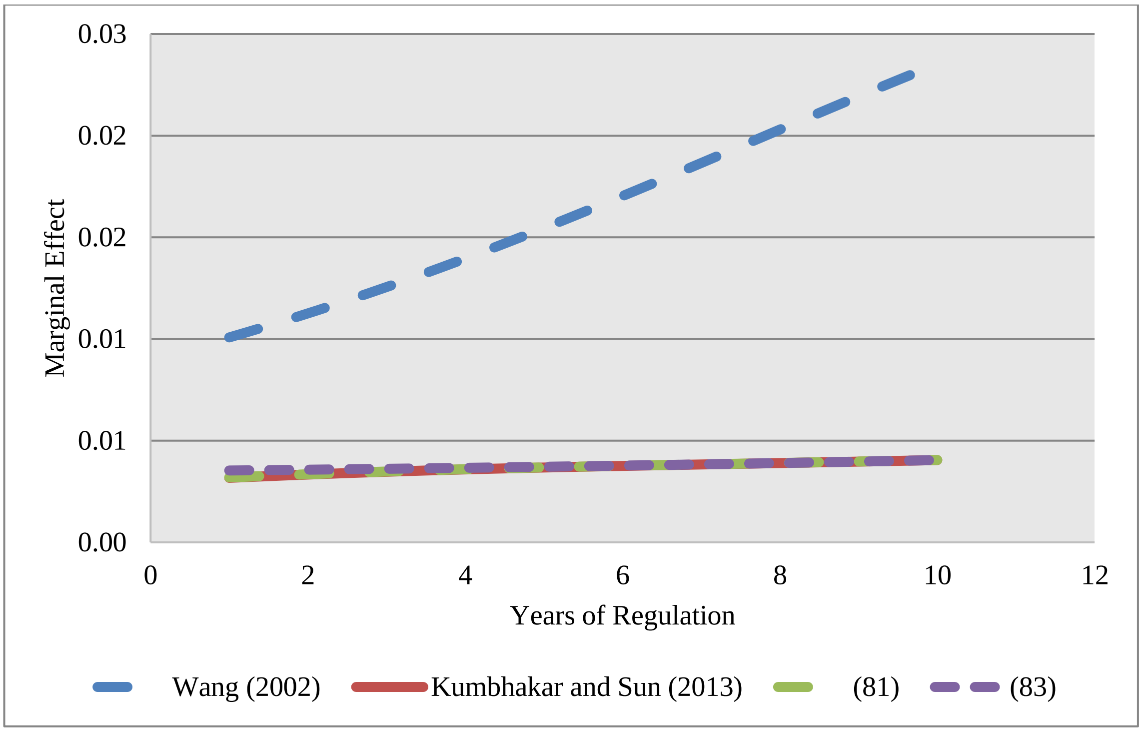

FIGURE 12.1.2: MARGINAL EFFECT OF YEARS OF REGULATION ON TOTEX INEFFICIENCY

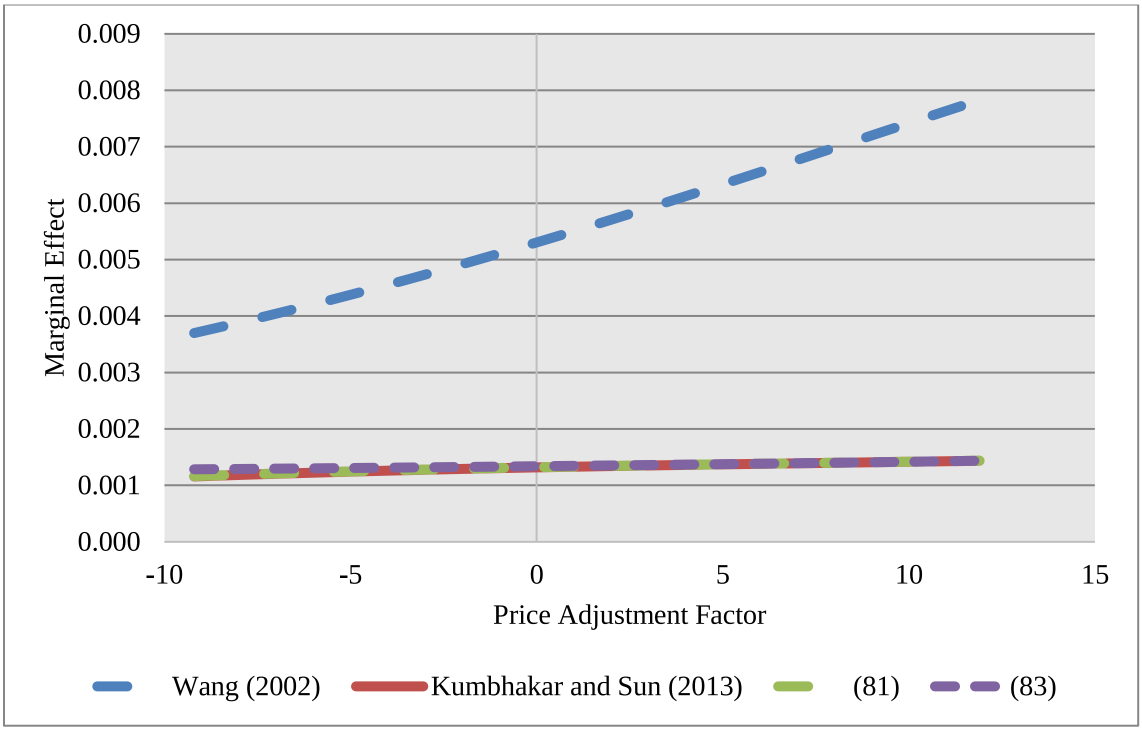

FIGURE 12.1.3: MARGINAL EFFECT OF PRICE ADJUSTMENT FACTOR ON TOTEX INEFFICIENCY

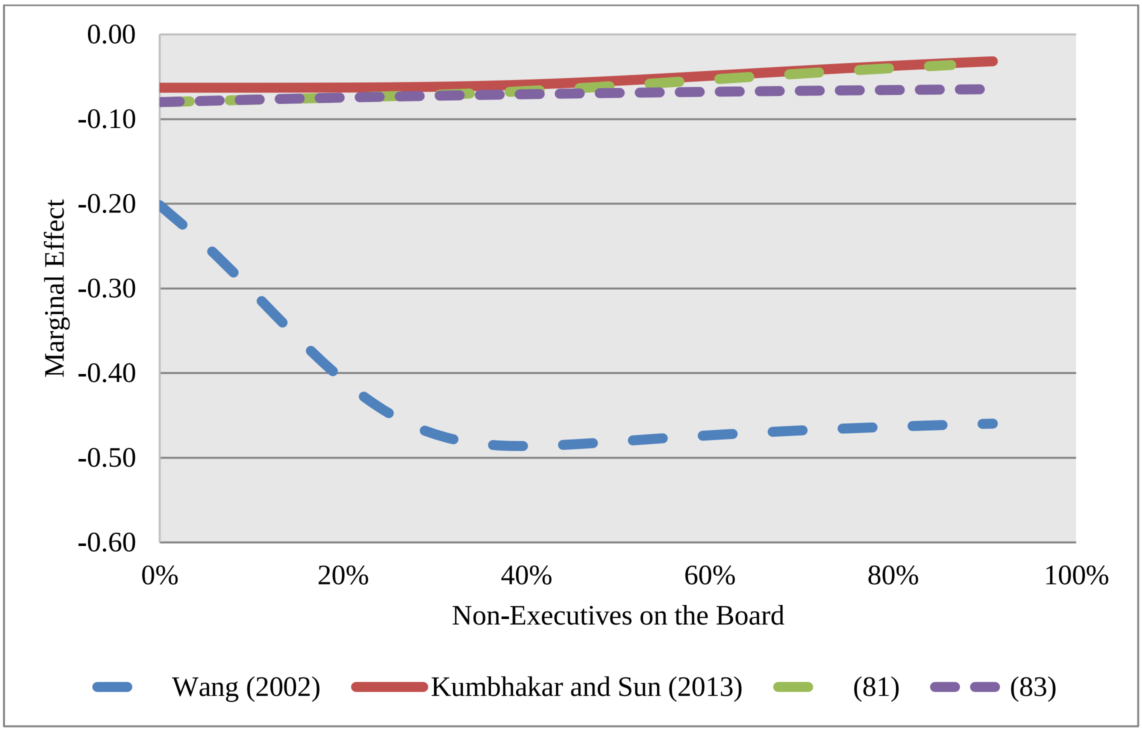

FIGURE 12.1.4: MARGINAL EFFECT OF BOARD COMPOSITION ON TOTEX INEFFICIENCY

Appendix 4

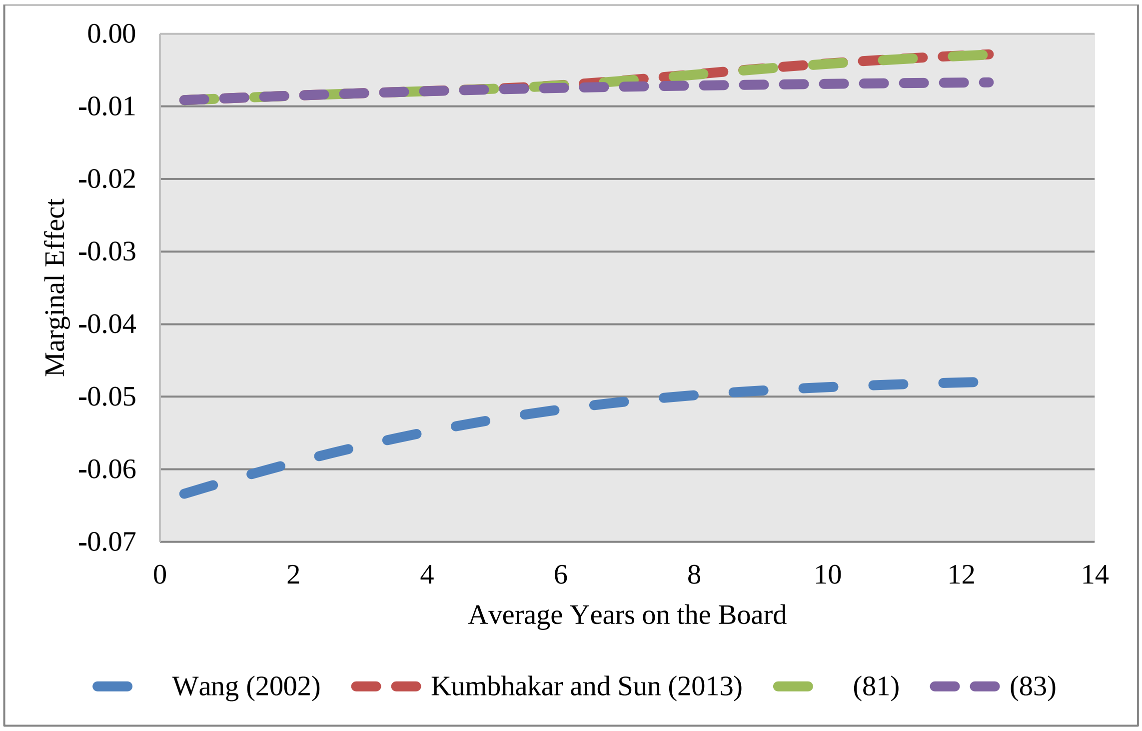

FIGURE 12.1.5: MARGINAL EFFECT OF DIRECTORS' AVERAGE YEARS ON THE BOARD ON TOTEX INEFFICIENCY

TABLE 22: FURTHER COBB-DOUGLAS ELECTRICITY DISTRIBUTION TOTEX MODEL ESTIMATES

Parameter (Variable)	Estimate (Standard Error)			
α	0.088 (0.054)		-0.115 (0.044)	**
θ (t)	-0.037 (0.009)	***	0.009 (0.006)	
β_1 ($\ln Q_1$)	0.871 (0.039)	***	0.854 (0.044)	***
β_2 ($\ln Q_2$)	0.484 (0.155)	***	0.505 (0.176)	***
γ_1 ($\ln W_1$)	0.213 (0.088)	**	0.499 (0.085)	***
β_3 ($\ln H_1$)	-0.091 (0.016)	***	-0.102 (0.017)	***
δ_0	-1.012 (0.069)	***	-	-
δ_1 (Z_1)	0.124 (0.014)	***	-	-
δ_2 (Z_2)	0.019 (0.005)	***	-	-
δ_3 (Z_3)	-	-	-	-
δ_4 (Z_4)	-	-	-	-
σ^2	0.015 (0.002)		0.020	-
γ	8.90E-07 (0)		-	-
lnLikelihood	93.819		76.674	

Significance level: * 10% ** 5% ***1%

TABLE 23: FURTHER TRANSLOG ELECTRICITY DISTRIBUTION TOTEX MODEL ESTIMATES

Parameter (Variable)	Estimate (Standard Error)			
α	-0.098 (0.099)		-0.05 (0.109)	
θ (t)	0.013 (0.033)		-0.01 (0.034)	
β_1 ($\ln Q_1$)	0.888 (0.114)	***	0.866 (0.117)	***
β_2 ($\ln Q_2$)	0.551 (0.571)		0.636 (0.606)	
γ_1 ($\ln W_1$)	0.891 (0.318)	***	0.976 (0.293)	***
ϑ (t^2)	-0.001 (0.003)		0.002 (0.003)	
$\zeta_{1,1}$ ($\ln Q_1^2$)	-0.229 (0.16)		-0.26 (0.175)	
$\zeta_{2,2}$ ($\ln Q_2^2$)	-0.331 (2.778)		-1.045 (3.056)	
$\eta_{1,1}$ ($\ln W_1^2$)	-0.705 (0.439)		-0.925 (0.43)	**
φ_1 ($t \ln Q_1$)	-0.015 (0.019)		-0.016 (0.019)	
φ_2 ($t \ln Q_2$)	-0.013 (0.094)		-0.023 (0.097)	
ϕ_1 ($t \ln W_1$)	-0.073 (0.059)		-0.086 (0.048)	*
$\zeta_{1,2}$ ($\ln Q_1 \ln Q_2$)	-2.107 (0.843)	**	-2.03 (0.925)	**
$\lambda_{1,1}$ ($\ln Q_1 \ln W_1$)	0.144 (0.263)		0.147 (0.279)	
$\lambda_{2,1}$ ($\ln Q_2 \ln W_1$)	0.594 (1.164)		0.686 (1.23)	
β_3 ($\ln H_1$)	-0.097 (0.037)	***	-0.094 (0.041)	**
δ_0	-29.599 (40.495)		-	-
δ_1 (Z_1)	2.72 (3.701)		-	-
δ_2 (Z_2)	0.24 (0.463)		-	-
δ_3 (Z_3)			-	-
δ_4 (Z_4)			-	-
σ^2	0.176 (0.324)		0.018	
γ	0.924 (0.144)		-	-
lnLikelihood	96.939		90.910	

Significance level: * 10% ** 5% ***1%