Developing infant technologies in mature industries: A case study on renewable energy

A thesis submitted for the degree of

Doctor of Philosophy

Division of Economics

Stirling Management School

By

Neil John Odam

December 2011

Declaration

In accordance with the Regulations for Higher Degrees by Research, I hereby declare that the whole thesis now submitted for the candidature of Doctor of Philosophy is a result of my own research and independent work except where reference is made to published literature. I also hereby certify that the work embodied in this thesis has not already been submitted in any substance for any degree and is not being concurrently submitted in candidature for any degree from any other institute of higher learning. I am responsible for any errors and omission present in the thesis.

Candidate: Neil Odam

Neil John Odam

Abstract

The purpose of this thesis is to investigate the development of new technologies in the energy industry and to explore how it is possible for these technologies to compete with incumbent technologies in a mature market. The pursuit of renewable energy has been at the forefront of national government and international institutional policy in recent years due to the desire to improve the security of energy supply and to reduce CO_2e emissions. This thesis aims to contribute to this policy debate, particularly by focussing on the issue of governmental support for infant energy technologies. In order to conduct this investigation, two main topics have been analysed.

Firstly, learning curves have been studied to establish whether support for new technologies can be justified by the potential cost reductions which arise from learning-by-doing. This research evolved into the investigation of econometric issues which affect learning curves. Patent counts are used to demonstrate an alternative output-based measurement of industry wide knowledge stock, which is used as a proxy for innovation. This alternative specification of knowledge stock corroborates recent findings in the literature, that learning curves which model cost using only cumulative capacity leads to the over-estimation of cost reductions from learning-by-doing and the failure to capture cost reductions resulting from innovation. This suggests that government support for infant technologies should form a dual strategy of incentivising the deployment of generators as well as encouraging innovation, instead of using feed-in tariffs or renewable obligations which narrowly focus on increasing deployment.

A great deal of progress has been made in identifying further econometric problems affecting learning curves in recent years. In the progress of this study, it was identified that cumulative capacity, the cost of wind power and knowledge stock are all non-stationary time series variables. The hypothesis that these variables are cointegrated was rejected by the Westerlund test, which implies that learning curves produce spurious results. This has major consequences for government policy as it suggests that learning curves should not be used to justify support for infant technologies.

Secondly, a choice experiment was conducted to determine Scottish households' willingness to pay for electricity generated from renewable sources compared to conventional sources such as coal, oil and gas. A labelled choice experiment was used to determine whether households have preferences between onshore wind power, offshore wind power and wave power. The results of a latent class model reveal that the majority of households (76.5%) are willing to pay an additional £89-£196 per year to obtain electricity from renewable resources instead of conventional sources. However, there is no statistically significant difference in the willingness to pay between the renewable technologies included in the choice experiment. The latent class model also illustrated that there is a sizeable minority (23.5%) who are opposed to renewable energy development. Older respondents and those less concerned about CO_2 emissions are significantly more likely to form part of this group at the 5% level of significance. The study also included a unique addition by identifying households which purchased a house in the previous seven years. Interacting the actual transaction prices of these houses in a multinomial logit model suggested that households may be concerned about renewable energy developments devaluing their properties or the additional expense required to power larger houses.

Due to the increasing difficulty of conducting choice experiments in the UK, a novel method of eliciting choice experiment responses from online advertising was tested and was found to be a cost-effective method of eliciting choice experiment responses. Overall, the research indicates that caution should be exercised when interpreting the results of a choice experiment which elicits responses using Internet advertising. It can be observed that the pseudo R^2 of the Internet-based sample is lower than the mail-based sample and that the mean respondent to the Internet-based choice experiment is willing to pay significantly more for renewable electricity than the mean respondent to the mail-based choice experiment at the 5% level of significance. Furthermore, the mean willingness to pay estimate in the Internet-based choice experiment appears to be unrealistically high. Further research investigating the elasticity of survey responses to the prize fund on offer would be valuable in identifying the most cost-effective strategy to obtain responses and to generate a more representative sample.

Acknowledgements

It is hard for me to believe that it has been just over five years since I left my fairly comfortable career in the City, working for KPMG. Moving from a profession with a fairly obvious career progression path and fairly rigid rules to academia was not without its challenges. It has been a long and sometimes arduous journey to the submission of my doctoral thesis but I believe, or maybe just hope, that fulfilling this ambition has been worth the sacrifices.

I would like to thank my supervisors, Professor Nicholas Hanley and Frans de Vries, for their support throughout my PhD studies, particularly for the autonomy they allowed me which has helped me to discover and understand my best skills and what subjects I would like to pursue next.

I am grateful to the Economic and Social Research Council for providing the funding, without which I would not have been able to justify pursuing this project. I would like to thank the University of Stirling for providing good facilities and for fostering a welcoming academic environment, particularly due to the approachability of all the teaching staff and the support and affability of the PhD and research students. I should note that without a chance meeting with Dugald Tinch, towards the end of my MSc studies, it is highly unlikely that I would have chosen to study the topic that I really desired and I would like to thank him for his guidance throughout my studies. I am also thankful to all the generous people who contributed to my focus groups, pilot study and choice experiment.

I cannot express how important those closest to me have been during the last five years: my parents who have supported every decision, even those that have repeatedly extended my studies, and who have always been there for me; my brother who deserves a medal for letting me practically steal his car and flat year after year, I promise I will return the favours one way or another; my friends and relatives who continue to provide me with strength despite my frequent unavailability, I look forward to catching up with so many people in the coming months; and finally to Linda, my girlfriend, fiancé and, recently, wife for putting up with my frugal and often unsociable career choice, without your constant encouragement, advice, loyalty and determination this study would not have been worthwhile or fulfilling.

Contents

Index of tables

Multi-Factor Learning in Renewable Energy Technology: Evidence from Patent Data

Electricity in Scotland: A choice experiment

A comparison of choice experiment elicitation methods

Index of figures

Multi-Factor Learning in Renewable Energy Technology: Evidence from Patent Data

Electricity in Scotland: A choice experiment

A comparison of choice experiment elicitation methods

Preface

1. Motivation for thesis

In 2007, I was granted funding by the Economic and Social Research Council to investigate the economic viability of marine power sources, particularly wave and tidal power; two infant technologies early in their development cycle. At the time, it appeared that these two technologies could potentially serve as an important part of the UK's electricity mix. These technologies could have helped the UK to achieve its carbon reduction targets, which was increased from a 60% reduction in CO_2e emissions from the 1990 baseline by 2050 to 80% by the Climate Change Act in 2008 (UK Parliament, 2008). They could also have contributed towards the UK's target to generate 10% of its electricity from renewable sources by 2010 (DTI, 2003); however it was unlikely that technologies in such an early stage of development would have been able to contribute substantially. More realistically, wave and tidal power could have helped to achieve the UK's target of generating 20% of electricity from renewable sources by 2020. As part of the EU's strategy (EU, 2009) to produce 20% of total energy consumption from renewable sources, the UK negotiated that 15% of its final energy consumption, calculated on a net calorific basis, would come from renewable sources. This negotiation removed any explicit target for renewable electricity generation by 2020; however, the lead scenario, as set out in the UK's renewable energy strategy (HM Government, 2009), to achieve the 15% target agreed with the EU supposes that approximately 30% of electricity will be generated from renewable sources by 2020.

Optimism for the rapid development of wave power technologies was justified by multiple reports which stated that the technology had the potential to generate a significant percentage of the UK's electricity and that the technology was on the cusp of commercialisation. For instance, Clément et al. (2002) reported that the total available wave resource in the UK is 120GW, or approximately 33%

higher than the UK's total plant capacity, which was approximately 90GW in 2011 (DECC, 2011a). They also noted that wave power technology had significantly advanced in recent years, which resulted in some wave power devices being at the end of their R&D phase of development, while others were beginning to be deployed in 2002. Furthermore, the Department for Trade and Industry (DTI, 2007a) stated that wave power could produce the same amount of electricity as wind power in the UK and that the development of the technology was only 10 years behind wind power.

At this time, tidal power did not have the same ambitious timetable for commercialisation. However, the recent deployment of prototype tidal stream devices provided the possibility of generating electricity from the tides which was predictable, a vital characteristic shared by few other renewable technologies, and less environmentally destructive than tidal range electricity generation, involving the damming of estuaries. Furthermore, the UK was imminently due to make a decision on whether to proceed with the construction of the Severn tidal barrage, which could have generated up to 5% of the UK's annual electricity demand (HM Government, 2009).

Combining the seemingly rapid technological progress of wave and tidal power with the release of the Stern Review (2007), which recommended that worldwide government incentives for new electricity generating technologies should increase to between $68 billion and $170 billion per annum to accelerate the adoption of new technologies, this provided the ideal opportunity to investigate whether wave and tidal power were suitable candidates for a portion of this financial support. One of the main goals of my research proposal was to investigate Clément et al's. (2002, p23) claim that, "the potential market for several wave power technologies is large, but initial political and financial support is needed for their breakthrough". I hoped to be able to compare wave and tidal power technological development to wind power development, particularly since Douglas and Saluja (1995, p2) contended that, "much of the recent wind energy progress throughout the world can be attributed to the fact that governments have started taking a proactive role in encouraging renewable energy by offering financial stimuli to renewable generators".

However, early in the project it became apparent that wave power commercialisation was not developing as expected. After repeated delays, the first wave farm was connected to a national grid in Aguçadoura, Portugal, in late 2008. Early on, the project suffered from technical problems which were exacerbated by the onset of the global financial crisis resulting in a key partner in the project facing severe financial difficulties (Pelamis, 2009). As a result, the expected expansion of wave power devices has almost entirely stalled worldwide. The tidal power industry, particular in the UK also faced similar challenges at this time. The enormous tidal energy potential in the Severn estuary has resulted in almost continuous proposals to harness the energy for the past several decades. After an extensive study into many different tidal power proposals, the UK government decided that it would not be possible to obtain sufficient private funding in the current financial climate and that it would create unprecedented environmental destruction (HM Government, 2010). It was their view that this meant that too much risk would be borne by the UK taxpayer and it was anticipated that tidal power options on the Severn estuary would not be considered again until 2015 at the earliest.

By the end of 2010, DECC (2011b) reported that only 2MW of wave power capacity and 2MW of tidal power capacity were deployed in the UK. This report also states that the central projection for wave and tidal electricity capacity is between 200MW and 300MW by 2020, which translates to approximately 0.3% of the UK's total electricity generating capacity in 2011 (DECC, 2011a). Between 2007 and 2010, the UK's percentage of electricity generated from renewable sources only increased from 4.9% (Eurostats, 2011) to 7.4% (DECC, 2011c), falling considerably short of the 10% target.

As part of my intended investigation into the economic viability of marine power, I intended to study the optimal amount of support which governments should give to new technologies to hasten their development. Section 2 outlines the multitude of well-established potential justifications for providing support to new technologies. More recently, a wide literature focussing on environmental valuation has been developed and applied to varied policy debates. Section 3 summarizes the pivotal literature in establishing households' stated preferences for attributes relating to energy.

In addition to the reasons outlined in Section 2, learning curves have been used extensively in the energy industry, much more so than any other industry, to justify support for new technologies due to the potential to foster cost reductions which arise from learning-by-doing. Initially, one of the main objectives of my research was to extend the extensive literature on learning curve analysis of solar and wind power to wave and tidal power, with the hope that the installed capacity of wave and tidal devices would be sufficient to form an early learning rate towards the end of my research. At the start of my research I studied learning curves to ensure I would be able to apply the concept to wave and tidal power if and when the data became available. This was a fortuitous time to study learning curves because the topic was going through a revolution at this time, starting with the creation of the two-factor learning curve (2FLC) by Kouvaritakis et al. (2000), further development of the 2FLC by Klaassen et al. (2005) and an examination of many of the econometric issues affecting learning curves by Söderholm and Sundqvist (2007). These developments in learning curve theory suggested that, even if sufficient data was available to develop a learning curve for wave and tidal power, there was a great deal of theoretical development likely to transpire which could alter the results of a simple learning curve analysis. It was at this point that I decided to re-direct my efforts towards developing learning curve theory, as well as extending my research to the development of infant technologies in mature industries, while maintaining a focus on renewable energy. This work is presented in the first paper of this thesis. It should be noted that a literature review on the development of learning curves has been included in the first paper. This literature review does not include a thorough review of one-factor learning curves because it is the theoretical development of learning curves which is addressed by this thesis. Lindman and Söderholm (2011) recently conducted a meta-analysis of learning curves which contains references to the majority of the one-factor learning curves.

The second paper in this thesis attempts to expand on the literature outlined in section 3 by establishing Scottish households' willingness to pay for electricity generated from renewable sources compared to conventional sources such as coal, oil and gas. This study uses the Scottish Government's ambitious renewable electricity targets (generating electricity from renewable sources equal to 100% of domestic demand by 2020) as context to present a labelled choice experiment to determine whether households have preferences between onshore wind power, offshore wind power and wave power. The third paper in this thesis focuses on overcoming the escalating methodological problem of conducting cost-effective choice experiments in the UK due to declining response rates to mail surveys. A novel method of eliciting choice experiment responses from online advertising was tested and compared to an identical mail-based choice experiment, which was used in the second paper in this thesis.

2. Market Failure

In order to justify government intervention in a market, it is essential to first establish whether market failure exists. In a similar study to this thesis, investigating the introduction of solar power to the energy industry, Yokell (1979) identifies several instances of market failure justifying intervention in the energy market. Solomon (1987) expands upon these reasons for market failure in a paper which investigates new technologies in the energy industry more broadly. These reasons are divided into first-best reasons (policies which could increase social welfare even in the presence of perfectly competitive markets) and second-best reasons (policies which would increase social welfare in the presence of imperfectly competitive markets).

First-best reasons for market intervention:

1) Encouraging the positive public good externality derived from innovation, which is likely to be sub-optimal partly due to the inability of the innovator to capture the full social returns. This occurs for two reasons. The first is that limitations of patent laws mean that innovators can expect to share the returns from their innovations with their competitors as patents are often awarded for minor technological developments. This can serve to dilute the value of the initial, perhaps larger, development. The second reason is that consumers' surplus results in consumers potentially capturing much of the benefits derived from innovation. Romer (1990, p30) argues that, "in the absence of feasible policies that can remove the divergence between the social and private returns to research, a second-best policy would be to subsidize the accumulation of total human capital";

2) Overcoming the sub-optimal innovation caused by investor risk aversion by pooling the risk over a far larger number of individuals, which should support a higher level of investment in new technologies than would occur if private firms and individuals were left to their own devices;

3) Overcoming the sub-optimal private purchases of new technology caused by risk aversion to the increased likelihood of product failure and improper installation, which is inherent in new technologies, by pooling this risk;

4) Overcoming capital market imperfections caused by the nature of commercial loan decisions which take into account cash flow and are generally restricted to a sub-optimal duration typical of loans, caused by myopic private banks. A perfect credit market functions by comparing the economic value of an investment rather than aforementioned banking criteria. Government subsidies can, therefore, help to bridge this gap between economic and commercial assessment allowing a purchaser to take advantage of potential life cycle savings offered by new technologies with high initial costs.

Second-best reasons for intervention include:

1) Cancelling out the effect caused by unjustifiable, distorting subsidies to conventional energy technologies;

2) Ensuring that conventional energy producers face their full economic costs by creating markets for emissions which cause negative externalities;

3) Reducing the risk to national security caused by an energy export embargo and to reduce the monopoly rents collected by foreign oil producers. It has also been argued that renewables contribute

to greater price stability in the electricity market, which has benefits for the whole economy (EEA, 2004).

Despite the above list of reasons legitimizing government intervention in the energy market being compiled in a different era, all of the reasons are just as applicable to the development of wave and tidal power today. However, the first example listed in the second-best reasons for intervention is somewhat contentious because it could be argued that Yokell (1979) is in effect advocating for a second market imperfection to be introduced, in an attempt to counteract a pre-existing market imperfection. The author does recognise that the most efficient method of tackling this market imperfection would be to remove the initial 'unjustifiable' subsidies to conventional energy technologies; however, he dismisses this possibility due to the strength of fossil fuel lobby groups. One of the greatest reasons for this strength is that regional governments have an incentive to reduce environmental standards in order to attract coveted skilled employment opportunities and tax windfalls which the oil industry generates; also known as the 'race to the bottom'. This was first described by Cumberland (1979) and subsequently demonstrated by Oates (1999) using game theoretic models of regional government policy which produce Nash equilibria with suboptimal public outputs.

The notable omission from this list is the added dimension of global warming, which had not been recognized as a significant problem by scientists at the time, although the second reason from the second-best list does cover this topic inadvertently. The Intergovernmental Panel on Climate Change recently released their Fourth Assessment Report which states that there is a very high likelihood that anthropogenic greenhouse gas (GHG) emissions are influencing the global climate (IPCC, 2007a) and that there is a clear trend towards levels of warming which will adversely affect a significant proportion of humans and ecosystems; particularly through the increased incidence and severity of droughts and floods (IPCC, 2007b). Consequently, climate change is currently the most palpable and severe failure in the energy market. The incomplete market for GHGs has resulted in an excessive and sub-optimal quantity of GHGs being emitted; principally carbon dioxide in the energy industry.

Recently, Nordhaus (2011, p8) has argued that the best method to deal with carbon emissions is to internalize the externality by ensuring that carbon emissions are priced appropriately and that this endeavour is "fundamentally important for stimulating innovation in technologies to mitigate global warming". A large volume of literature, surveyed by Elkins and Baker (2001), discusses how this price can be achieved through the use of a carbon tax or an emission trading scheme, such as the EU ETS. However, Nordhaus (2011) also notes that further support for technological innovation may be necessary where networking or large scale projects are barriers to optimal levels of innovative research. One method of achieving this is to strengthen intellectual property rights, with the caveat that the increased incentive to innovate should be balanced against the losses incurred from greater monopoly power which is granted by the strengthened property rights.

3. Energy Preference Valuation Studies

In this section I have sought to identify the literature most relevant to the second topic of this thesis: the use of choice experiments to establish householders' willingness to pay (WTP) for environmental goods associated with electricity generation. For a good overview of the development of choice experiments in both theory and practice, Louviere et al. (2000) and Hensher et al. (2005) are recommended. The following papers, all of which attempt to establish householders' preferences for wind power generation, are presented in chronological order so that it can be demonstrated how this line of research has developed.

Ek (2002) conducted one of the first comprehensive studies into preferences associated with the generation of electricity. The author used a choice experiment to determine Swedish households' WTP to improve the attributes associated with wind power. The study found that households' had statistically significant WTP to move wind turbines from mountainous regions to offshore locations and to construct smaller wind farms. Bergmann et al. (2006) followed this study with a choice experiment which was designed to determine Scottish households' WTP for environmental improvements associated with energy production. This study found that households had statistically significant WTP to minimise the landscape impact, to minimise the impact on wildlife and to minimise air pollution associated with energy production. These two studies were the main inspirations for the second paper in this thesis, which attempted to address a broad range of energy issues.

Recently, studies have tended to focus on more specific aspects of electricity generation, particularly on the visual impact of wind turbines. Ladenburg and Dubgaard (2007) initiated this trend by estimating the WTP for reducing the visual disamenities from future offshore wind farms using a choice experiment in Denmark. They found that households were WTP €46, €96 and €122 per year to move a large proposed offshore wind farm, situated 8km from the coast, to distances of 12, 18 and 50km from the coast. In an extension to this study, Ladenburg (2008) evaluated the attitudes of households towards offshore wind power development in Denmark and found a lack of evidence for the 'Not in my back yard' (NIMBY) effect. This result corroborated the findings of Ek (2005) in Sweden, but was contrary to a study by Firestone and Kempton (2009), who found strong opposition to an offshore wind development in the Cape Cod region of the U.S. The second paper in this thesis included location dummy variables to establish whether a NIMBY effect was evident amongst Scottish households.

A relatively recent development is the increasing application of latent class models in evaluating choice experiments. Meyerhoff et al. (2010) utilise this approach to investigate heterogeneity in the preferences of respondents to improve environmental attributes associated with onshore wind farms in 2 different areas of Germany. They split each of their 2 samples into 3 segments which they label advocates, opponents and moderates. The segments were divided fairly evenly by the modelling software. The advocate group was the largest segment (40%) in Westsachsen, while the opponent group was the largest segment (44%) in Nordhessen. The only attribute which was statistically significantly different across both regions was the minimum distance wind turbines would be placed from homes. In both regions the opponent group was WTP significantly more (up to €120 per household per year in Westsachsen) to increase the minimum distance wind turbines were placed from homes, compared to €0 in the Nordhessen advocate group at the 5% level of significance. The authors also use a conditional logit model to find that respondents were WTP statistically significant positive amounts to protect the Red Kite population and to increase the minimum distance wind turbines are placed from homes (€3.18 per household per month to increase minimum distance from

750m to 1,100m and €3.81 per household per month to increase minimum distance from 750m to 1,500m).

Westerberg et al. (2011) conducted a choice experiment with a wide scope on the effect of offshore wind farms on tourism in Languedoc Rousillon, France. The authors use 3 distinct latent class models to evaluate the preference heterogeneity of respondents. The first model assumes that there is heterogeneity in the socio-economic characteristics of the respondents. The second model assumes heterogeneity in the opinions respondents have on energy issues and the third model assumes that heterogeneity in the activities respondents participate in affect WTP. Weighting WTP by the size of each segment revealed that respondents were WTP between €87.20 per household, per year and €109.90 per household, per year to have the municipality form a 'coherent environmental policy' involving the creation of bicycle lanes, energy efficiency and improved public transport infrastructure. Respondents were WTP between €13.10 and €54.10 per household, per year to ensure that recreational activities would be integrated into the wind farm plans. The study concludes that the tourist industry would prefer that wind farms be located at least 12 km from the shore. The external costs of locating wind farms 5, 8 and 12 km from the shore are approximately €115, €50 and €0 per household per year, on average across the 3 latent class models. These results appear to fall between the results for Ladenburg and Dubgaard (2007) and Krueger (2011).

Most recently, Krueger et al. (2011) investigated the WTP for offshore wind farms in Delaware, U.S. A choice experiment was distributed to 3 stratified random samples in different areas of the state. The attributes included in the choice experiment were: location, distance from the shore and energy company royalty payments to community fund. The paper included the results of two random parameter model specifications as well as a fixed parameter model. In each of these models, the authors find that there was no statistically significant difference in the WTP between the 3 locations off the Delaware coast. The main result of the study was that households bordering the Atlantic coast were WTP more than households bordering Delaware Bay, who in turn were WTP more than inland households. The perpetual annual cost to inland households was \$18.86, \$8.74, \$0.78 and \$0 for wind farms located 0.9, 3.6, 6 and 9 miles off the coast, respectively. The perpetual annual cost to households in Delaware Bay was \$34.39, \$11.17, \$5.83, \$2.05 for wind farms located 0.9, 3.6, 6 and 9 miles off the coast, respectively. The perpetual annual cost to households on the Atlantic coast was \$80.03, \$68.79, \$35.10, \$26.65 for wind farms located 0.9, 3.6, 6 and 9 miles off the coast, respectively. This translates into households being WTP \$12 for each 0.25 miles their home is located away from the Delaware coast. The authors note that Ladenburg and Dubgaard (2007) found that the external cost per household of wind farms was more than double the amount reported in this survey with turbines located approximately 5 miles from the shore in Denmark. However, the external cost in Ladenburg and Dubgaard (2007) fell more rapidly as the turbine distance from shore increased. This could be caused by the larger turbines used to illustrate potential projects in the Ladenburg and Dubgaard (2007) study. Krueger et al. (2011) conclude that the magnitude of the decrease in external costs imposed as the turbines are moved from 6 to 9 miles off the coast suggest that it may be cheaper to compensate households for the visual disamenity at 9 miles off the coast than it would be to move the turbines further off the coast so that they are not visible.

The study by Krueger et al. (2011) covers many of the same topics addressed in the second paper of this thesis. Unfortunately, the advances in this paper could not be incorporated into the second paper because the choice experiment had been designed and distributed prior to the publication of Krueger et al. (2011).

4. Conclusions

Section 2 outlined many reasons which justify the support for infant technologies. None of the reasons outlined in Section 2 are contradicted by the findings in this thesis. However, in addition to the reasons given in Section 2, learning curves have been used in the energy industry, much more so than any other industry, to justify support for new technologies due to the potential to foster cost reductions which arise from learning-by-doing. The first paper in this thesis develops a patent-based knowledge stock which corroborates the findings of Klaassen et al. (2005), who found that learning curves, which model cost using only cumulative capacity, leads to the over-estimation of cost reductions from learning-by-doing and the failure to capture cost reductions resulting from innovation. This suggests that over-reliance on one-factor learning curves will result in governments placing too much emphasis on support policies which are designed to accelerate the deployment of infant technologies; policies such as feed-in tariffs and renewable obligations. Instead, the two-factor and multi-factor learning curves developed in the first paper in this thesis, suggest that more resources should be devoted to the support of technological innovation. However, it should be noted that this thesis does not attempt to derive the optimal amount of resources to support technological innovation. Barreto and Kypreos (2004) have attempted to conduct this research by including learning rates in a bottom-up energy system model; however, this analysis is considered to be beyond the scope of this thesis.

The second finding from the learning curve paper is that unit roots exist in the key variables included in learning curve analysis: cumulative capacity, the cost of the technology and knowledge stock. The failure to reject the null hypothesis that these variables are not cointegrated implies that learning curves produce spurious results, which has major consequences for government policy as it suggests that learning curves should not be used to justify support for infant technologies. This does not mean that increasing cumulative capacity and increasing knowledge stock do not cause decreases in the cost of a technology. Instead, it implies that it is not possible to prove with any degree of confidence that these variables are causative.

Section 3 outlined the most relevant literature on the stated preferences of households towards electricity generation, which the research in this thesis attempts to build upon. The objective of the second paper was to establish how much Scottish households are willing to pay, through increased electricity charges, to increase the proportion of renewable sources in Scotland's electricity supply such that the Scottish Government's 2020 energy targets are achieved.

The presentation of multiple discrete choice models reveals that this is not a straightforward question, as it is demonstrated that preference heterogeneity significantly affects WTP calculations. A latent class model is used to allow for the presence of preference heterogeneity, while also overcoming the potential collinearity problems which may affect the multinomial logit model that interacts socio-economic characteristics with the alternative specific constants (ASCs). The latent class model reveals that the preferences of the majority of Scottish households (76.5%) are reflected well by the multinomial logit model which does not include socio-economic characteristics. This suggests that these households are WTP an additional £89 - £196 per year to increase the proportion of renewable sources in the electricity supply. The results also demonstrate that, ceteris paribus, there is no statistically significant difference in the WTP between the renewable energy sources included in the choice experiment: wave power, offshore wind and onshore wind. This suggests that higher subsidies for one renewable technology over the other cannot be justified unless they are accompanied by other statistically significant improvements, such as an improvement in environmental outcomes relative to the alternatives.

Crucially, the latent class model illustrates that there is a sizeable minority of households (23.5%) which do not wish to pay anything to increase the proportion of renewable sources in the electricity supply. Indeed, their opposition is so strong that they are WTP to avoid the increased use of renewable electricity. Respondents who fall into this latter category are likely to believe that CO_2e output is not an important attribute in choosing between energy sources and are also more likely to be older than the average respondent. This group may prefer that conventional sources, such as coal, oil and gas should be used to generate electricity, or they may prefer that Scotland retains its nuclear power capacity, as is suggested by questions relating to general viewpoints on Scotland's energy strategy. While only 16.2% (21.2% of respondents who had an opinion) of respondents stated that they prefer nuclear power over renewable technologies, it is particularly notable that 54.1% (67.2% of respondents who had an opinion) of respondents stated that they would prefer that Scotland retain nuclear capacity while also pursuing renewables. This is contrary to the Scottish Government's rejection of nuclear power, suggesting that the policy does not have popular support. The result is particularly surprising since the survey was sent out six weeks after the tsunami induced nuclear disaster in Fukushima, Japan.

It is notable that the coefficients on wildlife variables remain fairly stable throughout the models presented in this paper, with respondents WTP between £3 and £10 to improve wildlife outcomes. This corroborates findings from previous literature on the topic, particularly the study by Bergmann et al. (2006), also conducted in Scotland, which found almost identical WTP for improvements to wildlife outcomes. The questions relating to the importance of each attribute in the choice experiment also supports these results since respondents indicated that wildlife impact was the most consistently important attribute in choosing between energy sources.

A novel approach to include actual house values as part of the socioeconomic characteristics which are interacted with the ASCs reveals that house value is significant and negative at the 5% level. This could suggest that respondents with high value properties are concerned with the possibility that their house value may decrease due to the installation of renewable power sources or that their electricity bills may increase disproportionately due to the positive correlation of house size and house prices.

Throughout the model estimations it was evident that respondents had no statistically significant WTP to avoid renewable electricity generators from being placed in their own region, which corroborates the findings of Ek (2005) and Ladenburg (2008), that no statistically significant NIMBY effect is evident. However, the regions included in the survey were very large geographic areas so it is possible that NIMBY characteristics may exist at a more local geographic level.

There are clearly trade-offs to be made when choosing the scope of a choice experiment. The analyst can design a choice experiment with a wide scope, which could give greater insights into overall energy preferences compared to a narrowly focussed choice experiment. However, the narrowly focussed choice experiment is likely to produce more precise parameter estimates of the environmental good it is evaluating. The choice experiment conducted in the second paper is designed to have a wide scope, in order to address issues relating to Scotland's energy strategy to the year 2020. It is notable that the analysis of this paper finds that households do not generally have a statistically significant WTP to move offshore wind turbines or wave power generators further from the coast. This contradicts the results of papers which are focussed solely on this issue such as Ladenburg and Dubgaard (2007) and Krueger et al. (2011). It is likely that these opposing results are simply due to the less precise parameter estimates produced due to the wide scope of this study.

The third paper in this thesis focuses on overcoming the escalating methodological problem of conducting cost-effective choice experiments in the UK due to declining response rates to mail surveys. A novel method of eliciting choice experiment responses from online advertising was tested and compared to an identical mail-based choice experiment, which was used in the second paper in this thesis. It is demonstrated that Internet advertising is a cost-effective method of eliciting responses to choice experiments. The elicitation method has the potential to reach younger age groups which are difficult to reach by traditional elicitation methods. Generally, the socio-economic characteristics of the respondents to the Internet based choice experiment were representative of the population under study and were similar to those of the mail-based choice experiment. However, the one major exception is that respondents were statistically significantly more likely to be male in the internet-based choice experiment, so appropriate sample weights must be applied during model estimation.

Overall, the third paper indicates that caution should be exercised when interpreting the results of a choice experiment which elicits responses using Internet advertising. It is observed that the pseudo R^2 of the Internet-based sample is lower than the mail-based sample and that the mean respondent to the Internet-based choice experiment is willing to pay significantly more for renewable electricity than the mean respondent to the mail-based choice experiment at the 5% level of significance. Furthermore, the mean willingness to pay estimates in the Internet-based choice experiment appears to be unrealistically high when socio-economic characteristics are included in the model estimation.

Without knowing in advance whether anyone would complete a choice experiment based on seeing an online advertisement, this project devoted approximately 90% of the project funds to advertising costs and 10% to the prize fund. Having found that a significant number of people are prepared to click on an online advertisement and complete an online survey, it is probable that a greater number of responses would have been received by increasing the prize fund relative to advertising costs. Future research investigating the elasticity of survey responses to the prize fund on offer would be valuable in identifying the most cost-effective strategy to obtain responses. Higher prize funds are likely to lessen self-selection bias as the marginal respondent will be less interested in the survey topic and more interested in the prize fund.

4. References

Barreto, L. and Kypreos, S. (2004), Endogenizing R&D and market experience in the “bottom-up” energy-systems ERIS model, Technovation, Vol. 24, Issue 8, pp. 615-629, 10.1016/S0166-4972(02)00124-4.

Bergmann, A., Hanley, N., Wright, R. (2006), Valuing the attributes of renewable energy investments. Energy Policy 34 (9), pp. 1004–1014.

Clément, A., McCullen, P., Falcão, A., Fiorentino, A., Gardner, F., Hammarlund, K., Lemonis, G., Lewis, T., Nielsen, K., Petroncini, S., Pontes, M.T., Schild, P. Sjöström, B., Sørensen, H.C. and Thorpe, T. (2002), Wave energy in Europe: current status and perspectives, Renewable and Sustainable Energy Reviews, Vol. 6, Issue 5, pp. 405-431, ISSN 1364-0321, 10.1016/S1364-0321(02)00009-6

Cumberland, J. (1979), Interregional Pollution Spillovers and Consistency of Environmental Policy, Regional Environmental Policy: The Economic Issues, H. Siebert et al. eds. New York: New York University Press, pp. 255 – 281.

DECC (2011a), Digest of UK Energy Statistics, DUKES Chapter 5: Electricity, Plant capacity: United Kingdom (DUKES 5.7), http://www.decc.gov.uk/media/viewfile.ashx?filepath=statistics/source/electricity/dukes5_7.xls&filetype=4&minwidth=true, last accessed 12th December 2011.

DECC (2011b), UK Renewable Energy Roadmap, July 2011, http://www.decc.gov.uk/assets/decc/11/meeting-energy-demand/renewable-energy/2167-uk-renewable-energy-roadmap.pdf, last accessed 12th December 2011.

DECC (2011c), Special feature – Renewable energy in 2010, June 2011, http://www.decc.gov.uk/assets/decc/11/stats/publications/energy-trends/articles/2082-renewable-energy-2010-trends-article.pdf, last accessed 12th December 2011.

Douglas, N. and Saluja, G. (1995), Wind energy development under the U.K. non-fossil fuel and renewables obligations, Renewable Energy, Vol. 6, No. 7, pp. 701-711, doi:10.1016/0960-1481(95)00072-R

DTI (2003), Department of Trade and Industry, Energy White Paper: Our Energy Future – Creating a Low Carbon Economy, http://webarchive.nationalarchives.gov.uk/+/http://www.berr.gov.uk/files/file10719.pdf, last accessed 12th December 2011.

DTI (2007a), Department of Trade and Industry, Wave energy – Current use in the UK, http://webarchive.nationalarchives.gov.uk/+/http://www.dti.gov.uk/energy/sources/renewables/renewables-explained/wave-and-tidal/wave-energy/current-use/page17048.html, last accessed 12th December 2011.

DTI (2007b), Department of Trade and Industry, Tidal power – Current use in the UK, http://webarchive.nationalarchives.gov.uk/+/http://www.dti.gov.uk/energy/sources/renewables/renewables-explained/wave-and-tidal/tidal/current-use/page17055.html, last accessed 12th December 2011.

EEA (2004), European Environment Agency, Energy subsidies in the European Union: A brief overview, EEA Technical report – 1/2004.

Elkins, P. and Baker, T. (2001), Carbon Taxes and Carbon Emissions Trading. Journal of Economic Surveys, Vol. 15, pp. 325–376, doi: 10.1111/1467-6419.00142

Ek, K.. (2002), Valuing the Environmental Impacts of Wind Power: A Choice Experiment Approach, Licentiate Thesis, Lulea University of Technology.

Ek, K. (2005), Public and private attitudes towards "green" electricity: the case of Swedish wind power, Energy Policy, Vol. 33, Issue 13, pp.1677-1689, http://dx.doi.org/10.1016/j.enpol.2004.02.005

Eurostats (2011), Electricity generated from renewable sources, http://epp.eurostat.ec.europa.eu/tgm/table.do?tab=table&init=1&plugin=1&language=en&pcode=tsien050, last accessed 12th December 2011.

EU (2009), Directive 2009/28/EC of The European Parliament and of The Council of 23 April 2009 on the promotion of the use of energy from renewable sources and amending and subsequently repealing Directives 2001/77/EC and 2003/30/EC, http://eur-lex.europa.eu/LexUriServ/LexUriServ.do?uri=OJ:L:2009:140:0016:0062:en:PDF, last accessed 12th December 2011.

Firestone, J. and Kempton, W. (2009), Public opinion about large offshore windpower: underlying factors, Energy Policy, Vol. 35, pp. 1584–98.

Hensher, D. A., Rose J. and Greene W.H. (2005), Applied Choice Analysis: A Primer, Cambridge University Press: Cambridge.

HM Government (2009), The UK Renewable Energy Strategy. TSO, London, http://www.renewableseast.org.uk/uploads/TheUKRenewableEnergyStrategy2009[1].pdf, last accessed 12th December 2011.

HM Government (2010), Severn Tidal Power: Feasibility Study Conclusions and Summary Report, October 2010, http://www.decc.gov.uk/assets/decc/what%20we%20do/uk%20energy%20supply/energy%20mix

/renewable%20energy/severn-tp/621-severn-tidal-power-feasibility-study-conclusions-a.pdf, last accessed 12th December 2011.

Intergovernmental Panel on Climate Change, Working Group I (IPCC) (2007a), Climate Change 2007: The Physical Science Basis: Summary for Policymakers.

Intergovernmental Panel on Climate Change, Working Group II (IPCC) (2007b), Climate Change 2007: Impacts, Adaptation and Vulnerability.

Klaassen, G., Miketa, A., Larsen, K., Sundqvist, T. (2005), "The Impact of R&D on Innovation for Wind Energy in Denmark, Germany and the United Kingdom, *Ecological Economics*, Vol. 54, pp. 227-240, doi:10.1016/j.ecolecon.2005.01.008

Kouvaritakis, N., Soira, A., Isoard, S. (2000), "Modelling Energy Technology Dynamics: Methodology for Adaptive Expectations Models with Learning by Doing and Learning by Searching", *International Journal of Global Energy Issues*, Vol. 14, pp. 104-115, http://inderscience.metapress.com/link.asp?id=3uqf8dv46mur3yrq

Krueger, A.D., Parsons, G.R. and Firestone, J. (2011), "Valuing the Visual Disamenity of Offshore Wind Projects at Varying Distances from the Shore", *Land Economics* 87.2 pp. 268-283. Available at: http://works.bepress.com/george_parsons/7

Ladenburg, J. and Dubgaard, A. (2007), Willingness to pay for reduced visual disamenities from offshore wind farms in Denmark, Energy Policy, Vol. 35, Issue 5, pp. 4059-4071, http://dx.doi.org/10.1016/j.enpol.2007.01.023

Ladenburg, J. (2008), Attitudes towards on-land and offshore wind power development in Denmark; choice of development strategy, Renewable Energy, Vol. 33, pp. 111 – 118, http://dx.doi.org/10.1016/j.renene.2007.01.011

Louviere, J. J. Hensher, D. A. and Swait, J. D. (2000), Stated choice methods: analysis and application, Cambridge University Press, New York.

Meyerhoff, J., Ohl, C., Hartje, V. (2010), Landscape externalities from onshore wind power, Energy Policy, Vol. 38, Issue 1, pp. 82-92, http://dx.doi.org/10.1016/j.enpol.2009.08.055

Nordhaus, W, (2011), Designing a friendly space for technological change to slow global warming, Energy Economics, Vol. 33, Issue 4, pp. 665-673, 10.1016/j.eneco.2010.08.005

Oates, W. (1999), An Essay on Fiscal Federalism, Journal of Economic Literature, Vol. 37, No. 3, pp. 1120 – 1149.

Pelamis (2009), Pelamis Wave Power Ltd: Statement on Portuguese Aguçadoura Project, http://www.pelamiswave.com/media/statement_on_aguadoura_project.pdf.

Romer, P. (1990), Endogenous Technological Change, The Journal of Political Economy, Vol. 98, No. 5, Part 2: The Problem of Development: A Conference of the Institute for the Study of Free Enterprise System (Oct., 1990), pp. S71 – S102.

Solomon, B.D. (1987), Optimal subsidies to new energy sources, Energy Economics, Vol. 9, pp. 183 – 189, doi:10.1016/0140-9883(87)90025-9.

Söderholm, P. and Sundqvist, T. (2007), "Empirical Challenges in the Use of Learning Curves for Assessing the Economic Prospects of Renewable Energy Technologies, *Renewable Energy*, Vol. 32, pp. 2559-2578, doi: 10.1016/j.renene.2006.12.007.

Stern, N. (2007), The economics of climate change: the Stern review. Cambridge University Press, Cambridge.

UK Parliament (2008), Climate Change Act 2008, London: HMSO; http://www.legislation.gov.uk/ukpga/2008/27/pdfs/ukpga_20080027_en.pdf, last accessed 12th December 2011.

Yokell, M.D. (1979), The Role of the Government in Subsidizing Solar Energy, The American Economic Review, Vol. 69, No. 2, pp. 357 – 361.

Westerberg, V.H., Jacobsen, J.B and Lifran, R. (2011), Offshore wind farms in the Mediterranean Seascape – A tourist appeal or a tourist repellent?, International Conference on Landscape Economics, July 2011.

Multi-Factor Learning in Renewable Energy Technology: Evidence from Patent Data

Neil Odam [a]

[a] *University of Stirling, Stirling, FK9 4LA, Scotland, UK*

December 2011

Abstract

Learning curves are frequently cited to justify government subsidies for relatively new technologies in order to facilitate the movement of the technology down the learning curve and towards market competitiveness. Recent literature has focussed on improving the specification of the basic learning curve model by augmenting it with a measure of innovation. We utilise patent counts, an output-based measure of innovation, as an alternative proxy to input measures such as public R&D expenditure, which has been utilised in the past. We have used the PATSTAT database, a comprehensive record of worldwide patents, to estimate a learning curve using a panel data framework. We investigate the presence of unit roots in learning curves and caution of the possibility that learning curves produce spurious results.

Keywords: Learning, Innovation, Renewable energy, Patents, Cost assessment, Unit roots

---

1. Introduction

Basic one factor learning curves (1FLC) model the relationship between cost and cumulative capacity and are frequently cited in policy debates to justify subsidization of renewable energy technologies (Philibert, 2011; IEA, 2000). Recent academic literature on the subject has focussed on improving the specification of the 1FLC by including additional explanatory variables. Learning curves have evolved from a simple linear regression to a two-factor learning curve (2FLC), attempting to capture the contribution of innovation towards cost reduction, and further to a multi-factor learning curve (MFLC), attempting to fully encompass the variables that contribute to technological cost reduction.

One potential drawback of the MFLC is that innovation is considerably more difficult and imprecise to measure than cumulative capacity. Prior literature on the topic has utilised public R&D expenditure as a proxy for innovation (Klaassen et al., 2005; Söderholm and Sundqvist, 2007). The use of public R&D expenditure as a proxy for innovation has led to criticism that the MFLC fails to account for private sector R&D, which is likely to have different impacts on the cost of a technology compared to public R&D (Yeh and Rubin, 2011). This paper investigates the use of patent counts as an alternative measure of innovation, designed to capture the returns to private sector innovation. Patent counts can be viewed as an output-based measure of innovation while R&D expenditures provide an input-based measure of innovation. This paper seeks to compare the impact of these two innovation metrics on the 2FLC. Popp (2005) explains that patent counts, as a measure of innovation, compare favourably to R&D expenditures because they can be collected in highly disaggregated forms, which can help to identify when and where innovative activities have taken place. However, utilising patents as a measurement of innovation is controversial because it has been observed that a large fraction of patents are frivolous (Lanjouw et al., 1998).

The PATSTAT database, a comprehensive record of worldwide patents, is pivotal to this research as it has the capacity to identify valuable patents by distinguishing between low cost initial patent filings and higher cost claimed priority filings, which have been claimed in at least one foreign country. Restricting the measurement of innovation to these higher cost claimed priority filings should avoid the issue of frivolous patents which could affect the findings of a similar study by Jamasb (2007), which uses an unrestricted count of patents. In combination with data on the cost of generating electricity from on-shore wind farms in Germany, Denmark, the UK and Spain, a panel data framework is utilised to model the MFLC using this output-based measure of innovation. The prior hypothesis of this research was that an output-based measure of innovation would improve the MFLC specification and increase the precision of the parameter estimates of innovation and cumulative capacity. The results of this alternative estimation of the MFLC are not significantly different from the results produced by Klaassen et al. (2005), thus the prior hypothesis is rejected. Instead, the results corroborate the findings of Klaassen et al. (2005), suggesting that the MFLC is robust to alternative specifications of innovation. MFLCs show that the cost reductions from cumulative capacity are overestimated in the 1FLC and suggest that governments could allocate funds for renewable energy more efficiently by fostering innovation, instead of using only feed-in tariffs which are used to accelerate the installation of cumulative capacity.

Further, as increasingly sophisticated techniques have been used to improve the specification of the MFLC, it has also become apparent that there are many potentially serious econometric problems relating to the estimation of learning curves, including the impact of scale effects on the MFLC (Söderholm and Sundqvist, 2007) and the potential presence of unit roots (Lindman and Söderholm, 2011). This paper attempts to address both of these issues. Scale effects are addressed through the collation of yearly average capacity of wind turbines in each country under study which should provide a superior measure of scale effects in the MFLC. The results suggest that the inclusion of these scale effects does improve the specification of the MFLC; however, the inclusion of scale effects results in further econometric problems. It is found that scale effects are collinear with innovation, implying that the parameter estimates for both scale effects and innovation are likely to be inaccurate when estimated simultaneously.

The potential presence of unit roots is addressed by the attempt to detect the presence of non-stationarity in the cost of wind turbines, cumulative capacity and each specification of innovation. The implications of non-stationarity are critical to the use of learning curves since the failure to control for unit roots could result in the reporting of spurious results. The analysis in this paper fails to reject the hypothesis that each of these variables is non-stationary. Furthermore, the analysis fails to reject the hypothesis that costs and cumulative capacities are not cointegrated, thereby suggesting that learning curves produce spurious results. The econometric problems described here suggest that learning curves should be fundamentally revised before any reliance is placed on their results for policy formation.

Section 2.1 introduces the literature on learning curves, while section 2.2 introduces the literature on the use of patents as a measure of innovation, in order to establish the motivation for this study. Section 3 describes the patent data used in this study. Section 4 outlines the data used in this paper and specifies the models which are to be empirically tested in this paper. Section 5 presents the empirical estimates based on the models contained in section 4. Section 6 considers the limitations of the model and potential areas of future research. Conclusions and implications will be discussed in section 7.

2.1 Motivating theory – Learning curve literature review

Learning curves originated over 70 years ago when Wright (1936)[1] used the concept to forecast the decrease in cost for each marginal aircraft manufactured. Little evidence exists of their use in other industries until the Boston Consulting Group (1972) promoted their use more generally within other industries. More recently, public bodies and academics have applied learning curves to technologies at the industry level; particularly the energy industry as demonstrated by the International Energy Agency (IEA) (2000, p24):

> Experience curves remain under-developed tools for public energy policy... [they] can become powerful instruments for strategic analysis during most of the phases of policy making. They support the identification of technology areas where intervention is necessary to avoid lock-in, the selection of realistic policy targets in these areas, and the design and monitoring of policy measures to reach the targets. Specifically, experience curves help the design and monitoring of portfolios of CO_2 benign technologies.[2]

The 1FLC for an electricity generating technology is given as:

$$SPC_{nt} = A.\,CC_{nt}^{\alpha}$$

where SPC_{nt} is the specific investment cost of an energy technology per MW in country n, for a given year t, A is the cost of the first unit of capacity, CC_{nt} is the cumulative capacity in MW and α is the learning index.

---

[1] Bryan and Harter (1899) have an earlier claim relating to telegraph operators, but Wright is generally credited for bringing learning curves to a mainstream audience.

[2] While some authors do make minor distinctions between experience curves and learning curves, such varied definitions of both terms has arisen that there is little significant informational content derived from one name over the other. In this paper, we refer to learning curves throughout.

The basic concept of the learning curve is that as cumulative capacity doubles, the investment cost falls by a certain percentage, known as the learning rate ($1-2^{\alpha}$), and this percentage decrease in cost remains constant for each doubling of cumulative capacity. The reason that learning curves have continued to gain in popularity is that this relationship has been observed to hold for a wide range of technologies (IEA, 2000).

A note of caution should be introduced at this stage regarding the effectiveness of learning curves. Neij (1997, p2) warns that:

> The concept of the experience curve cannot be considered an established theory or method, but rather a correlation phenomenon which has been observed for several different technologies…Only after many doublings of experience can the underlying pattern or trend be distinguished.

The 1FLC is basically a backward looking instrument. While some scholars (Varian, 1994) advocate the use of the simplest possible model, it is important to understand why this should not necessarily apply to learning curves. Learning curves have not been derived from a sound theoretical analysis, where irrelevant details have been removed, but instead evolved from the realisation that the simple relationship between cumulative capacity and cost has been observed in many technologies, where cumulative capacity happens to capture the effects of the underlying determinants of the cost relationship. Despite its success at showing that the costs fall by a similar percentage with each doubling of cumulative capacity, the under-specification of the model means that it would be reckless to rely on these trends being extrapolated into the future.

Without studying the effect of the underlying variables affecting the cost of a technology, learning curves cannot be considered a viable tool for cost prediction. For instance, Junginger et al. (2005) assemble a meta-analysis of past studies into wind power learning rates and conclude that learning rates vary between 15 and 23 percent depending on the country and time period being analysed. While some of this discrepancy can certainly be attributed to a lack of standardisation concerning the methodology used to compile and analyse the data used in these studies, the magnitude of the variation between different studies have significant influences on the policy implications for wind power's contribution to our future energy mix, given many governments' ambitions for the amount of power wind farms are envisaged to provide.

Kouvaritakis et al. (2000) extended the 1FLC framework by adding a 'knowledge stock' variable – proxied by cumulative public R&D expenditure - in an attempt to identify more clearly the relationship between learning and cost reduction by separating learning into two main effects: learning-by-doing and learning-by-searching. This framework is known as the 2FLC. Learning-by-doing is designed to capture the reduction in the cost of a technology caused by the experience gained in replicating the same production process multiple times, which is described by the cumulative capacity of the technology. Learning-by-searching is designed to capture the reduction in the cost of a technology caused by improvements in the quality of the technology or more efficient production processes, as represented by the knowledge stock. Klaassen et al. (2005) subsequently modified the 2FLC to make it more practical for policy-making purposes by widening the scope of knowledge stock from a narrow focus on cumulative R&D expenditures to one which is designed to realistically model the process by which R&D expenditure results in innovation. Furthermore, they also include time lags, to recognise that R&D expenditure does not result in immediate innovation, and depreciation of cumulative R&D expenditure, with the assumption that R&D expenditures lose their value over time.

Using R&D expenditure as a proxy for knowledge stock, Klaassen et al. (2005) construct the following functional specification:

$$KS_{nt} = (1 - \delta).KS_{n,t-1} + RD_{n,t-x}$$

where KS_{nt} is the knowledge stock in country n, for a given year t; $RD_{,}$ is the amount of R&D expenditure in dollars; x is the time lag in years between incurring R&D expenditure and obtaining the benefits in the form of innovation; δ is the annual knowledge stock depreciation rate.

With this knowledge stock, the 2FLC can now be formulated as:

$$SPC_{nt} = A.CC_{nt}^{\alpha}.KS_{nt}^{\beta}$$

where SPC_{nt} is the specific investment cost of an energy technology per MW in country n, for a given year t; CC is cumulative capacity in MW; A is the specific cost at one MW of cumulative capacity and one dollar of knowledge stock; KS is the R&D-based knowledge stock; α is the learning-by-doing index; β is the learning-by-searching index. Learning rates are now defined for the knowledge stock (learning-by-searching rate: $1–2^{\beta}$) as well as for cumulative capacity (learning-by-doing rate: $1–2^{\alpha}$).

In the 1FLC framework, *CC* is implicitly capturing any cost reductions from innovation. The 2FLC uses the knowledge stock variable to explicitly capture the cost reductions from innovation. By explicitly modelling innovation in this fashion, the interpretation of learning-by-doing is modified so that it relates more specifically to Smith's (1776) famous example of cost reduction from specialisation in a pin factory.

Klaassen et al. (2005) utilise their 2FLC in a fixed effects panel data study of wind power generation in Denmark, Germany and the UK. They conclude that both learning-by-doing, the cost reduction resulting from increased cumulative capacity, and learning-by-searching, the cost reduction resulting from innovation, are statistically significant; with rates of 5.4% and 12.6% respectively. Furthermore, they find that there is a statistically significant common slope between the countries but that the common intercept is not statistically significant, implying that learning is technology-specific rather than country-specific, as would be expected from a learning curve model.

While the authors find that their 2FLC model is mostly robust with respect to alternative depreciation rates as well as time, they do find that learning-by-searching does not remain statistically significant using a 10 percent depreciation rate combined with a two year time lag. While this lack of robustness is not concerning by itself, when combined with the small sample size in the study, providing only 34 degrees of freedom, the need for further robustness tests is apparent. Söderholm and Sundqvist (2007) performed many of these robustness tests on the 2FLC by testing a wide range of learning curve specifications, which has given rise to the MFLC. These specifications included additional variables such as feed-in tariffs and scale effects in an attempt to reduce the omitted variable bias present in learning curves, which had previously been identified by Neij et al. (2003). Söderholm and Sundqvist (2007) extended the MFLC to include a measure of scale effects and tested the effect of including a time trend in each specification to determine whether previous learning models have overestimated learning rates by attributing cost reductions from exogenous technological progress to endogenous learning. Furthermore, instrumental variables, such as coal prices, electricity prices and the age structure of coal-fired power plants, were used to address issues of endogeneity[3]. This paper attempts

[3] Learning curves assume that increases in cumulative capacity cause the cost of a technology to fall. While this is likely to be accurate, it is also likely that reductions in the cost of a technology will result in more cumulative capacity being installed, suggesting reverse causality.

to build on the foundations of these recent developments using much of the same data, while augmenting the dataset with patent counts and a more accurate measurement of scale effects.

2.2 Motivating theory – Patent literature review

The knowledge stock is designed to capture technological improvements which occur through invention, innovation and diffusion as originally theorised by Schumpeter (1934). There are a number of ways to measure the knowledge stock that contributes to the three stages of technological change; however, all are imperfect. R&D expenditures and an absolute count of scientists and engineers engaged in research activities provide input measures which are likely to capture the process by which innovation occurs and, to a lesser extent, the process by which invention occurs. However, innovation per R&D dollar spent varies between firms and industries and is also subject to diminishing returns (Griliches et al., 1989).

An alternative approach to these input-based measures is to use patent counts as an output measure of innovation and invention. Patents provide monopoly protection for novel inventions and innovations which encourage firms to self-identify their innovative and inventive output. Popp (2005) remarks that patents are particularly useful for studying technological change because of the detailed information they contain on the innovation or invention, the inventor country and the country where the patent is registered. This allows the data to be collected in highly disaggregated forms which compares favourably to R&D expenditures. Amongst the main drawbacks of patent counts is that the value of a patent can vary widely and that there are major differences in patent regulations and cultures between different countries, making international comparisons difficult (Kinmonth, 1987; Lanjouw et al., 1998). It is debatable whether patent counts are superior to R&D expenditure as a proxy for innovation. However, data limitations have limited prior research on learning curves to rely on public R&D expenditure as a proxy for innovation (Klaassen et al., 2005; Söderholm and Sundqvist, 2007). Griliches (1990) documents that there exists a strong relationship between patent counts and overall R&D expenditure, which leads us to contend that patent counts are a superior proxy for overall R&D expenditure than public R&D expenditure because patents are likely to capture the returns to both private and public R&D expenditure.

There are two primary reasons for including the knowledge stock in the 2FLC. The first is simply to improve the fit of the learning curve by adding a variable which is likely to be a significant determinant of future product costs within an industry, or company (depending on which level is being analysed). The second reason is to increase the usefulness of learning curves in forming policy. Klaassen et al. (2005) argue that the cumulative capacity of a product is largely demand driven. It is difficult and expensive for a government to foster this demand for a new technology. However, governments frequently attempt to develop policies to encourage R&D due to its positive public good externality. Yokell (1979) contends that this positive public good externality means that R&D spending left purely to market forces will be less than socially optimal, which justifies government intervention. By adding knowledge stock to the basic learning curve, governments can make better informed decisions about which industries to focus their attention, in order to maximise the benefits of its policies. Barreto and Kypreos (2004) include learning rates in an energy system model in order to derive the optimal allocation of R&D funds between competing technologies; however, this is beyond the scope of this paper.

3. Description of patent data and patent-based knowledge stock

Patent counts were extracted from the PATSTAT database by researchers at the OECD to obtain patent counts by inventor country for a range of energy technologies. The special property of the PATSTAT database lies in the user's ability to specify that the extraction of patents should only include claimed priority filings (i.e. inventions for which protection has been sought in at least one country, in addition to the country of the priority office), along with the patent class and the country from which the patent application originated or the country where the application was filed. In order to extract the relevant patents from the database, it was necessary to search the European Patent Office's (2010) user interface (esp@cenet) to locate the patent classes containing the patents which are likely to result in cost reductions for wind power. The root classes that were used are contained in Table 1. It is important to note that these patent classes largely relate to the manufacturing process of wind turbines. Patents relating to the placement and assembly of wind turbines are unlikely to be fully covered by these patent classes. While the patent classes could have been expanded to encompass these patents, the trade-off is an increasing likelihood of incorrectly including patents which are not directly related to the actual development of wind power.

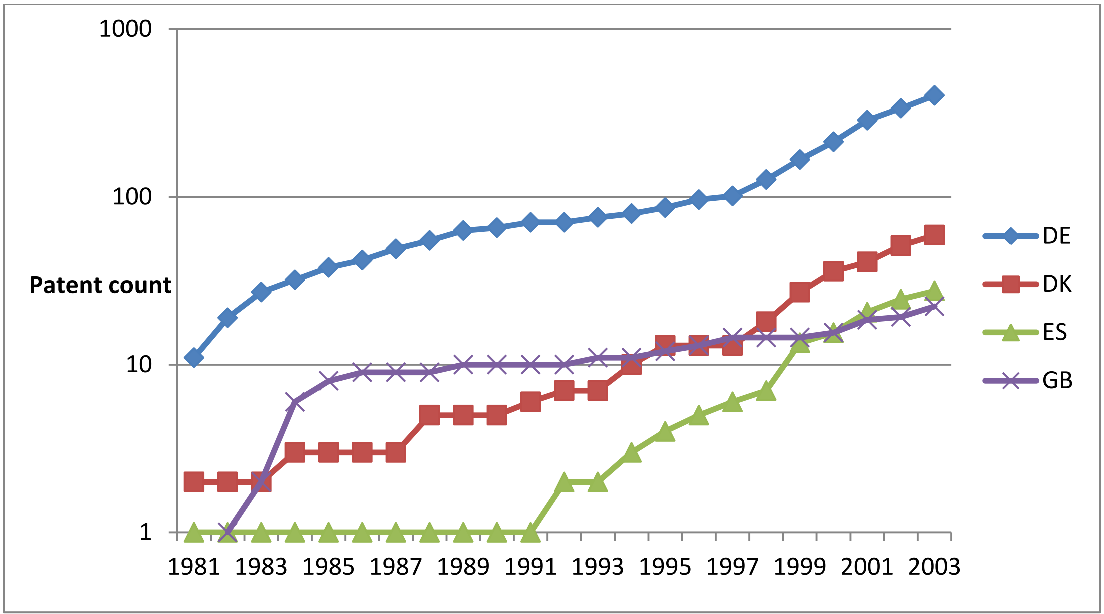
Table 1: Patent classes extracted for wind power knowledge stock

Patent class	Description
FO3D	Wind motors
FO3D 1/00-06	Wind motors with rotation axis substantially in wind direction
FO3D 3/00-06	Wind motors with rotation axis substantially at right-angles to wind direction
FO3D 5/00-06	Other wind motors
FO3D 7/00-06	Controlling wind motors
FO3D 9/00-06	Adaptations of wind motors for special use
FO3D 11/00-06	Details, component parts, or accessories not provided for in preceding groups

Source: European Patent Office (2010)

Counts of claimed priority patents by inventor country were extracted. The use of claimed priority patents rather than all patent applications, minimises the inclusion of low value patents because firms have a one year period in which they can evaluate whether their initial patent is valuable enough to justify the cost of extending their patent protection to countries other than the country where the patent was initially filed (Popp et al., 2011). A graphical representation of cumulative patent counts from 1981 to 2004 for the four countries which have cumulative cost and price data availability: Germany, Denmark, UK and Spain are presented in Figure 1.

Figure 1: Cumulative patent counts (claimed priorities worldwide) for Germany, Denmark, Spain and the UK from 1981 to 2003



Source: European Patent Office (2010)

Table 2 displays the absolute number of claimed priority patents filed by each country as well as a column which normalises the number of wind technology patents by 1,000 overall patents for each country. Normalising patents in this way has been used by Johnstone et al. (2010) to control for country-specific patenting behaviour and to recognise that smaller countries often specialise in specific industries more than large countries.

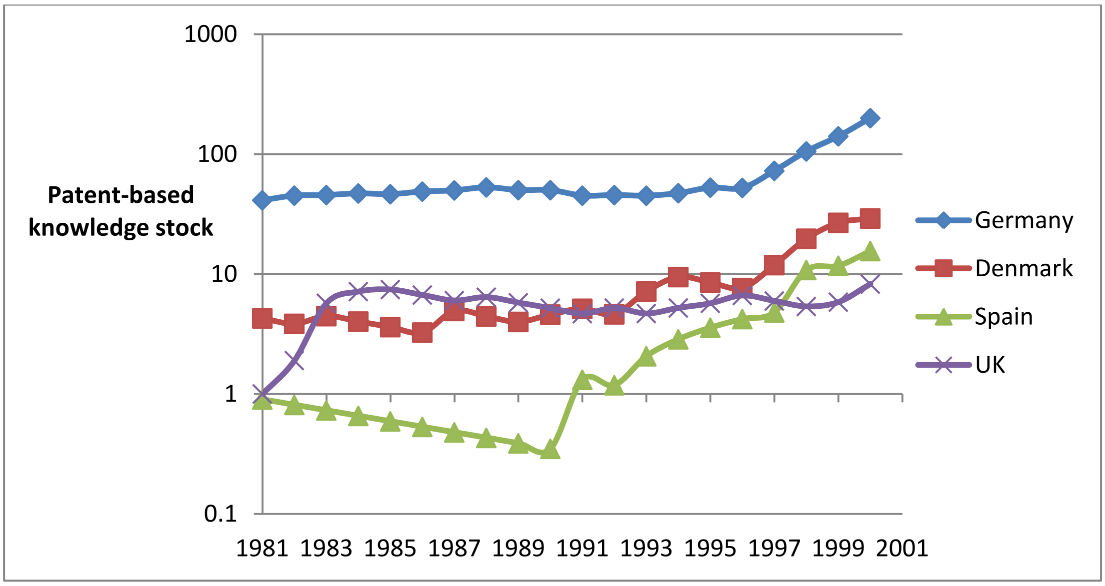
Table 2: Descriptive statistics of cumulative patent counts (claimed priorities worldwide) for Germany, Denmark, Spain and the UK from 1981 to 2003

Cumulative patents	Germany	Denmark	UK	Spain
Observations	29	29	29	29
Mean	115.35	15.22	4.88	8.62
St. Dev	106.99	16.26	7.71	6.62
Min	1.80	1.00	0.00	0.00
Max	436.05	63.25	27.50	22.25
Year	1975-2003	1975-2003	1975-2003	1975-2003
Normalised cumulative patents				
Observations	29	29	29	29
Mean	0.53	2.83	1.95	0.37
St. Dev	0.18	1.19	1.91	0.24
Min	0.17	1.58	0.00	0.00
Max	1.02	6.00	7.76	0.78
Year	1975-2003	1975-2003	1975-2003	1975-2003

Source: European Patent Office (2010)

It is necessary to adjust this raw data to better represent how the development of intellectual capital enters into the production process. The concept that the knowledge stock, derived from R&D, would depreciate over time was developed by Griliches (1979). His theory has subsequently been empirically tested (Griliches, 1990) and from this point onwards it has been standard practice in literature referencing technological innovation to include a depreciation rate for R&D expenditures. Hall et al. (1986) demonstrated that R&D expenditures have a lagged effect on technological improvement. While Klaassen et al. (2005) utilise a depreciation rate of 3 percent and a time lag of 2 years as their baseline assumption, it is unlikely that this specification would realistically describe the relationship between patent counts and innovation due to the different processes by which R&D and patents interact with innovation. R&D is an input measurement of innovation so there is little doubt that R&D lags behind the knowledge stock used in the production process. However, because patent counts are an output measurement of innovation, it is likely that a reduced time lag exists. This paper therefore assumes a scenario with a time lag of 1 year and, following Klaassen et al. (2005), a depreciation rate of 3 percent. The conversion from raw patent counts to the patent-based knowledge stock is shown in Figure 2. It could be argued that intellectual property which has been patented will enter the production immediately, in which case there would be no time lag. It is even possible that a negative time lag could exist if firms do not immediately patent their intellectual property due to trade secrecy, a lack of awareness or a prolonged patent filing period. Indeed, Griliches (1990) notes that the date on which the application for the priority filing of a patent is made closely follows the date of invention. A wide variety of robustness tests using different specifications for the knowledge stock have been conducted. This includes a range of positive and negative time lags as well as a range of depreciation rates to accommodate the range of 1-10 percent as suggested by Nordhaus (2002). These robustness tests did not produce significantly different results than the central model reported in this paper.

Figure 2: Knowledge stock Germany, Denmark, Spain and the UK from 1981 to 2001. 1 year time lag, 10% depreciation rate.



Source: European Patent Office (2010)

4. Outline of data and model specification

This paper uses cumulative capacity figures and average yearly wind power project prices obtained from Söderholm and Sundqvist (2007) for Denmark from 1986 to 1999, Germany from 1990 to 1999, the UK from 1991 to 2000 and Spain from 1990 to 1999. All price data is denoted in U.S. dollars using 1998 as the base year. Descriptive statistics of the data used to estimate the models in this paper are included in Table 3.

Table 3: Descriptive statistics of data used in panel data estimation.

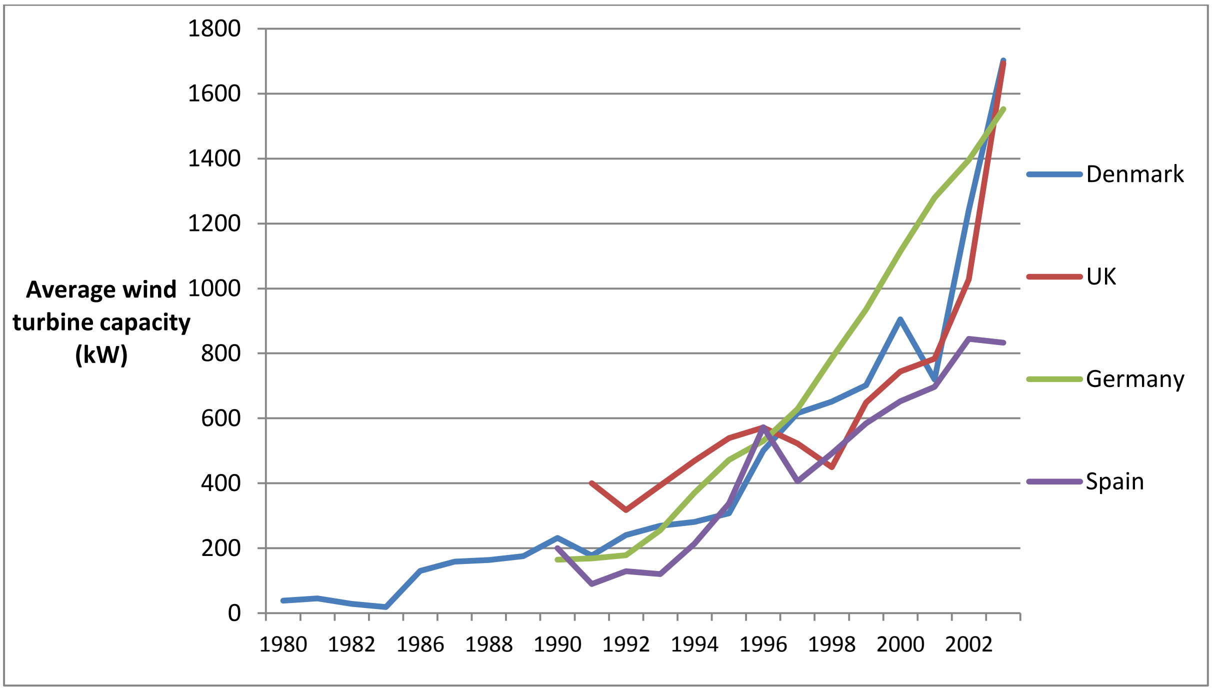
Specific investment cost	Denmark	Germany	UK	Spain
Observations	14	10	10	10
Mean	1,406.00	1,628.70	1,750.70	1,593.40
St. Dev	240.22	288.91	320.97	354.45
Min	1,039.00	1,338.00	1,306.00	1,202.00
Max	1,828.00	2,070.00	2,193.00	2,268.00
Years	1986-1999	1990-1999	1991-2000	1990-1999
Cumulative capacity				
Observations	14	10	10	10
Mean	618.46	1,317.17	212.51	348.10
St. Dev	499.33	1,425.79	137.41	509.02
Min	82.60	59.80	4.00	0.01
Max	1,744.00	4,400.00	406.00	1,584.00
Years	1986-1999	1990-1999	1991-2000	1990-1999
Feed-in tariff equivalent				
Observations	14	10	10	10
Mean	10.28	11.08	13.41	9.34
St. Dev	1.14	1.34	7.28	1.73
Min	8.38	8.89	5.00	7.09
Max	12.31	12.78	21.47	12.30
Years	1986-1999	1990-1999	1991-2000	1990-1999
Scale effects				
Observations	15	11	10	11
Mean	367.37	509.50	505.61	345.45
St. Dev	243.51	326.69	127.69	207.44
Min	130.00	164.30	317.50	90.00
Max	904.76	1,113.80	744.10	653.00
Years	1986-2000	1990-2000	1991-2000	1990-2000
IMF commodity index				
Observations	12	12	12	12
Mean	294.45	294.45	294.45	294.45
St. Dev	525.57	525.57	525.57	525.57
Min	1.14	1.14	1.14	1.14
Max	1,744.00	1,744.00	1,744.00	1,744.00
Years	1986-2000	1986-2000	1986-2000	1986-2000

Sources: Specific investment cost, cumulative capacity and feed-in tariffs: Söderholm and Sundqvist (2007), Scale effects: See Figure 4. IMF commodity index: IMF (2011).

It is important to emphasise the diverse range of cost reductions which contribute to the learning curve to avoid excessive focus on the most intuitive cost reduction: those relating only to manufacturing the product. The IEA (2000) assert that cost reductions related to improved site selection, tailoring devices to the individual site, maintenance and power management should be included in learning curves, while Neij (1997) stresses the importance of other sources of cost reduction, such as scaling effects, product standardization and input prices. Neij (1997) finds that the learning rate for Danish wind turbines between 1982 and 1995 was a relatively modest 4 percent while the learning rate of wind-generated energy in Denmark was 9 percent, demonstrating the importance of these additional cost sources. While our paper has used data relating to wind power projects, it is possible that the use of patent counts would be more suited solely to wind turbines, since it is difficult to find patent counts relating to installation, maintenance and power management. Data constraints have prevented this application at this point in time.

The distinction between learning-by-doing and economies of scale also needs to be noted. Economies of scale are simply the dilution of overhead costs over a larger number of units, thus reducing the cost per unit, whereas learning-by-doing refers to cost reductions through increased efficiency or innovation. It is vital to separately account for the economies of scale effect in learning curves since this component is unlikely to share the same cost reduction percentage over multiple orders of magnitude. Failure to account for this will result in an overestimate of the potential cost savings which could be achieved from innovation or enhancement in cumulative capacity. In this paper, economies of scale were taken into account by calculating the average power output of wind turbines installed in Denmark, Germany, the UK and Spain. This is shown in Figure 4. While this is unlikely to fully account for cost reductions from economies of scale, it can be calculated accurately and is likely to capture much of the scale effect. An attempt has also been made to encompass input prices for wind power projects; this has been accomplished by using the IMF (2011) industrial material index. It has been assumed that input prices have a time component but not a country-specific component.

Figure 3: Average wind turbine capacity in Denmark, the UK, Germany and Spain from 1979 to 2003.



Source: Danish Energy Agency (2008), Renewable UK (2011), Molly – DWEI (2007), Spanish Wind Energy Association (2008)

Table 4 presents the model specifications which are reported in Section 5. In total, seven specifications are tested. In order to enable comparisons with the previous key literature, the most informative specifications from Söderholm and Sundqvist (2007) are analysed with the new scale effect and patent data. Where the models are directly comparable to models in Söderholm and Sundqvist's (2007) paper, the model number which they used is given in square brackets in roman numerals and preceded with S&S.

The first model [S&S: Model I] represents the basic 1FLC model with only learning-by-doing effects. The second model [S&S: Model IV] is a re-estimation of an MFLC with scale effects given by the average capacity of wind turbines installed by country and year instead of electricity generated by wind power generators, used by Söderholm and Sundqvist (2007). The third model [S&S: Model VI] is a 2FLC, which corresponds to the model used by Klaassen et al. (2005), comparing the patent-based knowledge stock with the public R&D knowledge stock. The fourth model [S&S: Model VII] adds scale effects to the 2FLC while the fifth model [No direct comparison] adds feed-in tariffs. The sixth model [No direct comparison] adds a commodity index to the 2FLC model. The seventh model [S&S: Model VIII] includes both scale effects and feed-in tariffs in the 2FLC. An eighth model would have been included to add the commodity index to model 7. However, model 6 demonstrates that commodity prices do not affect the price of wind power in the way expected since our null hypothesis, that commodity prices should be positively related to wind power cost, is rejected. Instead, the coefficient on the commodity index is either negative or statistically insignificant, depending on which KS is used. Adding the commodity index to model 7 produces the same results and does not improve the model estimation.

Each model was subjected to the Hausman test (1978) and the Breusch-Pagan Lagrange Multiplier test (Breusch and Pagan, 1980) to determine whether fixed or random effects should be included. Both tests confirmed that random effects were not appropriate and so each model specification included fixed effects.[4] It should be noted that by using a fixed-effects model, with domestic cumulative capacity and knowledge stock, that we are implicitly assuming no international learning spillovers. Ek and Söderholm (2010) discuss the theoretical implications of learning spillovers but also find that it is not a simple task to empirically estimate the effect of spillovers in learning curves.

To ensure consistency between approaches and the availability of only very weak instruments, none of the models from Söderholm and Sundqvist (2007) which include instrumental variables have been

[4] Stata 11 (StataCorp, 2009) was used to perform all of the econometric analysis in this paper.

included due to lack of data. For instance, one instrument proposed by Söderholm and Sundqvist (2007) is coal prices, which has a correlation of -0.11 with cumulative capacity, suggesting that the instrument is unlikely to improve model estimation. However, it should be noted that endogeneity is likely to remain a problem for the cumulative capacity variable, feed-in prices and possibly knowledge stock.

Table 4: Learning curve model specifications

Model	Estimated learning equation	Description
1	$\ln SPC_{nt} = \ln \beta_0 + \beta_1 \ln CC_{nt} + \varepsilon_{nt}$	1FLC
2	$\ln SPC_{nt} = \ln \beta_0 + \beta_1 \ln CC_{nt} + \beta_3 \ln Scale_{nt} + \varepsilon_{nt}$	MFLC with cumulative capacity and scale effects. 2.1 Söderholm and Sundqvist (2007) scale from M_{toe} electricity produced by wind turbines. 2.2 Scale from average wind turbine capacity.
3	$\ln SPC_{nt} = \ln \beta_0 + \beta_1 \ln CC_{nt} + \beta_2 \ln KS_{nt} + \varepsilon_{nt}$	2FLC with KS 3a Söderholm and Sundqvist (2007) KS 3b Updated IEA public R&D KS 3c Patent KS 3d Normalised patent KS
4	$\ln SPC_{nt} = \ln \beta_0 + \beta_1 \ln CC_{nt} + \beta_2 \ln KS_{nt} + \beta_3 \ln Scale_{nt} + \varepsilon_{nt}$	Model (3) plus scale effects from average turbine size.
5	$\ln SPC_{nt} = \ln \beta_0 + \beta_1 \ln CC_{nt} + \beta_2 \ln KS_{nt} + \beta_4 \ln Feed\text{-}in_{nt} + \varepsilon_{nt}$	Model (3) plus feed-in tariffs
6	$\ln SPC_{nt} = \ln \beta_0 + \beta_1 \ln CC_{nt} + \beta_2 \ln KS_{nt} + \beta_5 \ln Commodity_t + \varepsilon_{nt}$	Model (3) plus commodity index
7	$\ln SPC_{nt} = \ln \beta_0 + \beta_1 \ln CC_{nt} + \beta_2 \ln KS_{nt} + \beta_3 \ln Scale_{nt} + \beta_4 \ln Feed\text{-}in_{nt} + \varepsilon_{nt}$	Model (4) plus feed-in tariffs.

5. Results

Table 5 displays the results of model 1 and 2. Models 1 and 2.1 have been replicated precisely from Söderholm and Sundqvist (2007) to provide a starting point of comparison. Model 2.2 demonstrates that the scale variable created from the average capacity of wind turbines installed by country and year, which was identified as the preferred measurement of scale effects by Söderholm and Sundqvist (2007), appears to improve the fit of the model compared to the variable they used for scale effects: M_{toe} electricity produced by wind power, which is shown in model 2.1. This finding justifies the use of this new measure of scale effects in the remaining models where scale effects are included.

Table 5: Summary results of 1FLC and MFLC with scale effects (excluding knowledge stock).

Dependent variable: ln SPC Coefficient (t statistic)	Model 1	Model 2.1	Model 2.2
Constant	7.7423***(140.72)	7.2314***(45.07)	8.6265***(53.98)
β_1 ln CC_{nt}	-0.0735***(-7.66)	-0.0257(-1.55)	-0.0397***(-4.29)
β_3 ln $Scale_{nt}$	-	-0.0777***(-3.34)	-0.1836***(-5.72)
R^2 (adjusted R^2)	0.671 (0.637)	0.746 (0.713)	0.823 (0.800)
Learning by doing rate (%)	4.97	1.77	2.71
*, ** and *** denote statistical significance at the 10, 5 and 1% levels, respectively.			

Models 3 – 7, each contain 4 variants of knowledge stock, as set out in Table 4. Model Xa uses the public R&D-based knowledge stock from Söderholm and Sundqvist (2007). Model Xb uses the same public R&D-based knowledge stock, but with updated values from the IEA database (IEA, 2011). Model Xc is the patent-based knowledge stock as outlined at end of Section 3. Model Xd uses the same assumptions as Xc, but normalises the patent count as described in Section 3.

Table 6 reports the 2FLC using different measures of knowledge stock. In each model, it is observed that the knowledge stock coefficient is significant at the 1% level. The prior hypothesis of this paper was that an output-based measure of knowledge based on claimed priority patent counts would provide a superior proxy for innovation than an input-based measure of knowledge stock based on public R&D expenditure. The results of this paper reject this hypothesis. Instead, alternative knowledge stock specifications appear to produce broadly similar results, hence corroborating previous 2FLC specifications. Model 3d suggests that the use of normalised patent counts produces the best model fit; however, Section 6 discusses the implications of modelling the knowledge stock in this way and cautions against its use without further empirical evidence.

Table 6: Summary results of 2FLC.

Dependent variable: ln SPC Coefficient (t statistic)	Model 3a	Model 3b	Model 3c	Model 3d
Constant	8.7434***(31.99)	8.9086***(29.05)	7.9609***(87.36)	8.3608***(56.89)
β_1 ln CC_{nt}	-0.0559***(-5.85)	-0.0555***(-5.86)	-0.0369**(-2.38)	-0.0460***(-4.59)
β_2 ln KS_{nt}	-0.2589***(-3.72)	-0.2630***(-3.85)	-0.1577***(-2.88)	-0.2816***(-4.42)
R^2 (adjusted R^2)	0.759 (0.727)	0.763 (0.732)	0.730 (0.695)	0.783 (0.754)
Learning by doing rate (%)	3.80	3.77	2.53	3.14
Learning by searching rate (%)	16.43	16.67	10.35	17.73
*, ** and *** denote statistical significance at the 10, 5 and 1% levels, respectively.				

Table 7 demonstrates that the knowledge stock variable is sensitive to the specification of the MFLC. Including a measure of scale effects, based on the average capacity of wind turbines installed, suggests that learning-by-searching does not significantly affect the cost of wind power projects at the 5% level of significance. The learning-by-doing rate is almost half that reported in model 1, which suggests that learning-by-doing is over-estimated even if innovation is not included in the model. The volatility of the knowledge stock coefficients in Table 7 suggests that scale effects could be collinear with knowledge stock. Belsley (1991) proposed a method to detect collinearity by testing the effects of small random changes to parameters in the model. The perturb module (Hendrickx, 2004) in Stata was used to confirm that knowledge stock and scale are collinear. Collinearity does not affect the overall model but does mean that individual parameter estimates can be misestimated. This problem could be remedied by the addition of more data; however, in the absence of this the individual parameter estimates of knowledge stock and scale in model 4 should not be relied upon. Since the learning-by-searching rate is dependent on the knowledge stock coefficient, this means that the rates from previous models are likely to be more accurate than those reported in Table 7.

Table 7: Summary results of MFLC with knowledge stock and scale effects.

Dependent variable: ln SPC Coefficient (t statistic)	Model 4a	Model 4b	Model 4c	Model 4d
Constant	8.7795***(37.40)	8.8347***(33.24)	8.6261***(51.34)	8.6531***(53.89)
β_1 ln CC_{nt}	-0.0394***(-4.24)	-0.0394***(-4.26)	-0.0396***(-3.12)	-0.0374***(-3.97)
β_2 ln KS_{nt}	-0.0693(-0.89)	-0.0760(-0.98)	-0.1834(-0.01)	-0.0961(-1.18)
β_3 ln $Scale_{nt}$	-0.1598***(-3.82)	-0.1568***(-3.72)	-0.1834***(-4.42)	-0.1453***(-3.19)
R^2 (adjusted R^2)	0.827 (0.799)	0.828 (0.800)	0.823 (0.795)	0.830 (0.802)
Learning by doing rate (%)	2.69	2.69	2.71	2.56
Learning by searching rate (%)	4.69	5.13	11.94	6.44
*, ** and *** denote statistical significance at the 10, 5 and 1% levels, respectively.				

Table 8 reports the results of adding feed-in tariffs to the 2FLC. Every parameter in these models is found to be statistically significant at the 5% level. Feed-in tariffs have positive coefficients which are significant at the 1% level. Söderholm and Sundqvist (2007) identified two reasons why feed-in tariffs would have a positive coefficient. The primary reason is that feed-in tariffs incentivise power firms to develop increasingly marginal wind power sites. These sites may either have more expensive grid connections or wind conditions which are worse than the average wind power site, which raises the average price of wind power projects. The second reason that Söderholm and Sundqvist (2007) identify does directly relate to the increase in wind power costs. They argue that feed-in tariffs act to reduce competition with other energy sources which is likely to reduce innovation incentives. It is likely to be difficult to identify the relative weights of these two effects on learning curves and no attempt has been made to do so in this paper.

Table 8: Summary results of MFLC with knowledge stock and feed-in tariffs.

Dependent variable: ln SPC Coefficient (t statistic)	Model 5a	Model 5b	Model 5c	Model 5d
Constant	8.1773***(26.76)	8.3246***(24.92)	7.477***(43.73)	7.9044***(34.48)
β_1 ln CC_{nt}	-0.0505***(-5.74)	-0.0502***(-5.76)	-0.0339**(-2.44)	-0.0445***(-4. 72)
β_2 ln KS_{nt}	-0.2208***(-3.46)	-0.2246***(-3.58)	-0.1335**(-2.69)	-0.2296***(-3.63)
β_4 ln Feed-in_{nt}	0.1601***(3.13)	0.1583***(3.12)	0.1720***(3.22)	0.1309**(2.49)
R^2 (adjusted R^2)	0.809 (0.778)	0.813 (0.782)	0.789 (0.755)	0.814 (0.784)
Learning by doing rate (%)	3.43	3.42	2.32	3.04
Learning by searching rate (%)	14.19	14.42	8.84	14.71
*, ** and *** denote statistical significance at the 10, 5 and 1% levels, respectively.				

Model 6 added a commodity price index to model 3. Our null hypothesis is that commodity prices should be positively related to wind power cost. Contrary to expectation, the null hypothesis is rejected. The commodity price index had a negative coefficient, which would suggest that the cost of wind power projects decreases as input costs rise. However, the coefficient was not statistically different from zero. It is surprising that the coefficient is not statistically significantly positive and further investigation will be required. It would be particularly desirable to test the models on more recent wind power prices to identify whether the result holds when rising wind power prices occur, as has been the case during the last few years.

Table 9: Summary results of MFLC with knowledge stock and commodity index.

Dependent variable: ln SPC Coefficient (t statistic)	Model 6a	Model 6b	Model 6c	Model 6d
Constant	9.1479***(14.01)	8.3246***(24.92)	9.2237***(13.74)	7.9044***(34.48)
β_1 ln CC_{nt}	-0.0567***(-5.85)	-0.0563***(-5.86)	-0.0339**(-2.22)	-0.0454***(-4. 68)
β_2 ln KS_{nt}	-0.2486***(-3.47)	-0.2530***(-3.60)	-0.1732***(-3.23)	-0.2902***(-4.71)
β_5 ln $Commodity_t$	-0.1013 (-0.68)	-0.1003 (-0.68)	-0.2831* (-1.90)	-0.2550* (-1.93)
R^2 (adjusted R^2)	0.762 (0.723)	0.766 (0.728)	0.754 (0.714)	0.803 (0.771)
Learning by doing rate (%)	3.85	3.83	2.32	3.10
Learning by searching rate (%)	15.83	15.83	11.31	18.22
*, ** and *** denote statistical significance at the 10, 5 and 1% levels, respectively.				

Model 7 attempts to develop a comprehensive MFLC by including knowledge stock, scale effects and feed-in tariffs. Model 7 produces the best fitting models, which corroborates a result from Söderholm and Sundqvist (2007), who also found that this specification was one of the best fitting. Feed-in tariffs remain positive and significant at the 5% level, as is the case in model 5. The only coefficient which is not statistically significant in this model is the knowledge stock; however, this is caused by collinearity between knowledge stock and scale effects, as discussed in model 4. The higher learning-by-searching rates reported in models 3, 5 and 6 should therefore be considered more reliable than those reported in model 7.

Table 10: Summary results of MFLC with knowledge stock, scale effects and feed-in tariffs.

Dependent variable: ln SPC Coefficient (t statistic)	Model 7a	Model 7b	Model 7c	Model 7d
Constant	8.3196***(30.81)	8.3709***(28.47)	8.1712***(36.59)	8.2127***(36.64)
β_1 ln CC_{nt}	-0.0372***(-4.35)	-0.0373***(-4.37)	-0.0370***(-3.16)	-0.0363***(-4. 15)
β_2 ln KS_{nt}	-0.0642 (-0.90)	-0.0702 (-0.99)	-0.0035 (-0.07)	-0.0545(-0.71)
β_3 ln $Scale_{nt}$	-0.1382***(-3.53)	-0.1357***(-3.45)	-0.1585***(-4.06)	-0.1396***(-3.30)
β_4 ln $Feed\text{-}in_{nt}$	0.1287***(2.82)	0.1284***(2.82)	0.1298***(2.82)	0.1230**(2.63)
R^2 (adjusted R^2)	0.858 (0.831)	0.859 (0.832)	0.855 (0.827)	0.857 (0.829)
Learning by doing rate (%)	2.55	2.55	2.53	2.48
Learning by searching rate (%)	4.35	4.75	0.24	3.71
*, ** and *** denote statistical significance at the 10, 5 and 1% levels, respectively.				

The most important result of these analyses is that learning-by-doing rates are consistently lower in every model than is suggested by the simple one factor learning curve in model 1. These model specifications suggest that learning models which fail to include a measure of innovation over-estimate the learning-by-doing rate and potentially mislead renewable energy policy.

Söderholm and Sundqvist (2007) found that most of the results from their MFLC specifications did not hold when a time trend was added. The idea of adding a linear time trend was to try to control for exogenous technological change, when little other exogenous technological data was available. A time trend was fitted to each model in Table 4. Instead of adding a linear time trend, yearly dummies were added to the models. This confirmed Söderholm and Sundqvist's (2007) findings that the inclusion of a time trend is pivotal as the majority of coefficients are not significant at the 5% level. Wald tests were performed on the year dummies and were found to be jointly significant at the 5% level in models 1, 3, 5 and 6: the models which did not include scale effects. This is particularly problematic because the scale effects have been demonstrated to introduce collinearity to the model, which suggested that models 3, 5 and 6 should be used for reliable parameter estimates of the knowledge stock. The consequence of adding the year dummy variables is to reduce the learning-by-doing and learning-by-searching rate, or even reverse the coefficient. These results should encourage great care to be taken when relying on estimates of learning-by-doing from one-factor learning curve models. The perturb tool, as discussed in relation to model 4, suggests that the inclusion of a time trend may cause similar collinearity problems with the knowledge stock variable. However, the results are not robust, implying that it is not certain whether collinearity is the cause of the volatile coefficient estimates.

One of the main criticisms of learning curves is that they are unable to separate out the effects of endogenous technological change and exogenous technological change. For instance, Nordhaus (2009) argues that if the exogenous technological rate of progress is not equal to zero, and it is not included in the model specification then it will lead to biased results, which will most likely over-estimate the learning-by-doing rate. The criticism applies equally to MFLC's, where it may be the learning-by-searching rate that is over-estimated, or both the learning rates. The result of adding year dummy variables significantly alters the results, raising concerns that learning curves which do not include these variables are over-estimating learning-by-doing and learning-by-searching rates. It adds credence to Nordhaus' (2009) claim that it is not possible to separate out exogenous and endogenous learning due to multicollinearity problems. Further investigation into this topic will be necessary before too much emphasis is placed on the results of any learning curve.

One benefit of using patent counts in this paper is that it is possible to create an index of exogenous technological progress by counting all patents by country and year. Adding this index to the models outlined in Table 4 produces results which are similar to the addition of a time trend above. Again, the perturb module suggests that the exogenous technological progress index is collinear with other independent variables; however, in common with the time trend, the results are not definitive. This adds further empirical evidence to Nordhaus's (2009) claim that it is not possible to separate out exogenous and endogenous technological progress.

During the analysis of these models it became apparent that cumulative capacity and the knowledge stock embody data generating processes which are likely to produce data containing a unit root. If the data generating process of cumulative capacity is non-stationary then it is possible that all learning curves produce spurious results. In the past two decades, unit root tests have been devised specifically for panel data (Harris and Tzavalis, 1999). More recently tests have been devised for this purpose which is more robust to small sample sizes in panel data. The Breitung unit root test (Breitung and Das, 2005) appears to the most appropriate for limited sample size in this study. However, the Im-Pesaran-Shin test (Im et al., 2003) is also suitable for small sample sizes and offers the option to choose the Augmented Dickey Fuller (ADF) lag structure using goodness of fit tests, such as the Akaike Information Critera (AIC). The null hypothesis of the Breitung test is that the panels contain unit roots, while the null hypothesis of the Im-Pesaran-Shin test is that all the panels contain unit roots. The Breitung test requires a strongly balanced panel, meaning that the data set was reduced to 4 panels with 9 periods each. Table 11 contains the results of a variety of specifications testing for unit roots in cumulative capacity. Each specification of the Breitung test suggests that cumulative capacity contains a unit root. The Im-Pesaran-Shin test produces the same results, except where the ADF lag term is chosen by the AIC. It is likely that cumulative capacity is non-stationary and trend non-stationary. Only if the AIC determined ADF lag structure can be justified should it be concluded that learning models are valid in their current form.

Table 11: Unit root test of $lcap_{nt}$

P-values	**Breitung**	**Im-Pesaran-Shin**
No trend	0.9989	0.6681
Trend	0.8505	0.3925
Lag (1)	0.5405	0.7979
Lag (AIC) **(AIC lag length)**	-	0.0000*** (0.25 lags)
Trend and lag (1)	0.2241	0.0001***
Trend and lag (AIC) **(AIC lag length)**	-	0.0001*** (0.75 lags)
*, ** and *** denote statistical significance at the 10, 5 and 1% levels, respectively.		

Table 12 contains the results of the same tests applied to the investment cost data used in this paper. On this occasion, each specification fails to reject the hypothesis that the investment cost contains a unit root. The presence of unit roots in time series variables have been shown to produce spurious results in linear regression analysis (Granger and Newbold, 1974). However, as noted by Lindman and Söderholm (2011), if cumulative capacity and investment costs share a common stochastic trend then the two variables would be cointegrated, dispelling the problem of spurious results.

Table 12: Unit root test of $linv_{nt}$

P-values	Breitung	Im-Pesaran-Shin
No trend	0.9118	0.7427
Trend	0.1470	0.2193
Lag (1)	0.6587	0.7339
Lag (AIC) **(AIC lag length)**	-	0.8192 (0.00 lags)
Trend and lag (1)	0.5462	0.3548
Trend and lag (AIC) **(AIC lag length)**	-	0.3372 (0.50 lags)
*, ** and *** denote statistical significance at the 10, 5 and 1% levels, respectively.		

Table 13 displays the results of the Westerlund (2007) test for cointegration. Gt and Ga test for cointegration in the group means. Pt and Pa test for cointegration in the panel as a whole. Both tests have the null hypothesis that there is no cointegration. Gt and Pt set the number of leads and lags in the test based on the number of years in the data, while Ga and Pa set the number of leads and lags in the test based on the AIC. Given that Gt has failed to estimate results, it is clear that the low sample size may impact the overall test results. The panel test, Pt, with leads and lags based on the number of years in the data, does indicate that cumulative capacity and investment costs are cointegrated. However, given that the Gt test failed to estimate, it is likely that the number of leads and lags used for the Pt test are not optimal. Both the group mean and panel test, using AIC to choose the leads and lags in the test, both fail to reject the null hypothesis that there is no cointegration and given the concern about the lead and lag structure in Gt and Pt, these results should take precedence. With the sample size currently available for wind power, it appears that investment costs and cumulative capacity are both non stationary and cannot be said to be cointegrated, thus suggesting that learning curves are highly likely to produce spurious results.

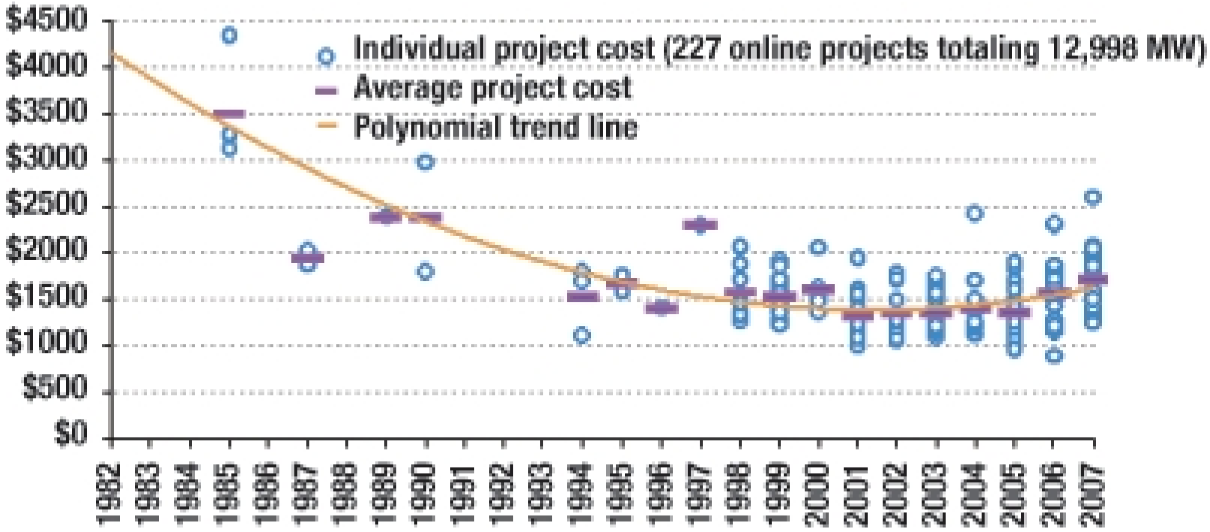
Table 13: Westerlund test for cointegration

Statistic	Value	Z-value	P-value
Gt	-	-	-
Ga	-10.564	0.401	0.656
Pt	-44.405	-46.800	0.000***
Pa	-10.304	-0.452	0.326
*, ** and *** denote statistical significance at the 10, 5 and 1% levels, respectively.			

6. Discussion

The analysis in this paper has concerned only Denmark, Germany, the UK and Spain. Given that the U.S. has become an increasingly important market for wind power in the last two decades, it will be important to extend the analysis to the U.S. and for an extended time period; this will be particularly important given the current small sample size. The data constraints on the time period have been particularly concerning given that there is evidence that the basic 1FLC for wind power have broken down from 2001 onwards, which is demonstrated in Figure 5, where the investment costs of wind power has started to increase despite increases in the cumulative capacity. Part of the motivation for this paper is that the 1FLC had become ineffective at modelling wind power costs. However, by incorporating a patent count knowledge stock, scale effects, feed-in tariffs and a proxy for input prices, it is anticipated that this modified learning framework will have more success at modelling the atypical price relationship which has been experienced in the last 5 years.

Figure 4: U.S. wind power specific investment cost from 1982 to 2007



Source: Wiser and Bolinger (2008)

The reason that model 6 has been included in this paper's analysis is that one potential explanation for the price rises, shown in Figure 5, is that commodity prices have been rising rapidly during this period. The results of model 6 reject this hypothesis; however, the time period analysed in this paper did not include the commodity boom years from 2003 onwards, which coincides with rising wind power costs in Figure 5.

One issue which has not been addressed sufficiently in the existing literature is the distinction between the cost and the price of wind power. While learning curves are designed to model the cost of wind power, virtually all prior analysis has used price data for the simple reason that firms are not willing to share commercially valuable confidential cost data. In order to model the last five years, where prices have been rising (see Figure 5), it will be necessary to take this distinction into account. Monopoly power in the market, or in the more recent case where the increase in demand for wind power has quite simply outpaced the increase in supply, has resulted in most wind turbine producers being unable to expand production to meet short-term demand (Balibouse, 2008). Clearly in this situation firms will increase their prices, resulting in profits driving an increasingly large wedge between the price and the cost of wind power. It is anticipated that in the future this analysis will be able to be performed either by analysing the market share of the largest wind turbine producers or by analysing financial statements or share price changes. The latter method may prove problematic since it will be difficult to separate profits from wind turbine production and other operations in a global conglomerate like General Electric, which is currently the largest supplier of wind turbines in the U.S.

In addition to the drawbacks of using patents already alluded to by Kinmonth (1987) and Lanjouw et al. (1998); Pakes (1984) show that a large fraction of patents are frivolous or do not retain value for a long period of time. However, we are in agreement with the conclusion from Hall et al. (1986) that aggregated patents can confer valuable information regarding the innovative output of research and development despite the fact that individual patents often contain little useful information. One major concern relating specifically to this study is that fewer patents (see Figure 1) registered by Danish inventors were found than was expected given their position as market leaders in wind power during the last two decades. One potential explanation is that firms have used other methods of protecting their intellectual property rights; trade secrecy for instance. This could introduce a source of bias which would lead to imperfect analysis. This problem has been addressed in this paper by the inclusion of models which base knowledge stock on normalised patent counts by country. Table 2 identified that countries such as Sweden, Spain and especially Denmark had a greater proportion of their total patents in wind power than would have been suggested by their relatively low absolute number of patents relating to wind power. The use of normalised patents implicitly values patents from these countries higher than countries with more diverse patent portfolios. This is a contentious assumption which should not be relied upon in the absence of empirical support.

One further problem relating to patents is that their expected influence on costs is not as unambiguous as the influence of R&D. This is because patents create monopoly protection for the patent holder and thus could potentially drive up industry costs; this concern is heightened if firms use patents as a way of blocking competitors from patenting related innovations (Cohen et al., 2002). It could be considered that in industries where these problems are pervasive that public R&D would provide a superior measure of innovation.

7. Conclusion

This paper has demonstrated that learning curves which attempt to encompass the theoretical foundations for technological cost reduction can be specified effectively and can perform better at capturing the sources of cost reduction for wind power generation than the basic 1FLC. The results have corroborated the findings from Klaassen et al. (2005), that by failing to include a measure of innovation in learning curve models, the result is likely to be an over-estimation of the learning-by-doing rate, which could lead to sub-optimal energy policy being implemented if too much confidence is placed in the basic 1FLC.

The prior hypothesis of this paper was that an output-based measure of knowledge based on claimed priority patent counts would provide a superior proxy for innovation than an input-based measure of knowledge stock based on public R&D expenditure. However, the results of this paper reject this hypothesis. Instead, the results suggest that the output-based knowledge stock produces similar results to those based on public R&D expenditure.

It should be noted that Ek and Söderholm (2010) found that public R&D did not significantly affect the cost of wind power. They attempted to endogenise knowledge stock by developing a model in which public R&D is determined by cost of wind power, the opportunity cost of public R&D and the country's debt to GDP ratio. In this model, public R&D was assumed to be pooled into a common knowledge stock applicable to all European countries. While it is possible that the attempt to endogenise knowledge stock may have produced this outcome it is notable that their central model contained a measure of scale effects. As demonstrated by model 4 and 7 in this paper, scale effects appear to be collinear with knowledge stock, meaning that while the overall model is valid, the individual coefficient estimates for knowledge stock and scale are not reliable when estimated in the same model.

Unit root tests have been used to demonstrate that learning curves based on cumulative capacity are likely to be spurious. This has major policy implications for many emerging technologies, particularly in the energy industry. It is important to note that a spurious relationship does not mean that learning-by-doing or learning-by-searching is not an important determinant of cost reductions. These variables may be causative, but cannot be proven with the current limited data available for learning curve analysis. If these results are confirmed with larger data sets then it suggests that great caution should be exercised when using current learning curves models for energy policymaking.

Subsidies to emerging technologies can be justified by other means, but it is likely that many current subsidy schemes are more generous than is justified by the evidence. Any subsidy which relies upon learning curves as a justification falls into this category. Existing subsidies should be monitored with greater transparency to ensure that public money is not wasted on technologies which are not developing as expected, or promised by learning curves.

8. Acknowledgements

Neil Odam would like to thank the Economic and Social Research Council (ESRC) for funding this research. The authors gratefully acknowledge Ivan Hascic and Nick Johnstone of the OECD Secretariat who provided the patent data, based upon search strategies developed as part of the OECD Project on 'Environmental and Technological Innovation' (**www.oecd.org/env/cpe/firms/innovation**). Data obtained from Asami Miketa, Thomas Sundqvist, Kristina Ek and Lena Neij has also been instrumental in this research. The views expressed in this paper are the author's alone and he is solely responsible for any errors.

9. References

Baliboûse, D. (2008), "Vestas cites huge order book in wind turbines", International Herald Tribune, Reuters: Bloomberg News, August 15th 2008, last accessed 10th November 2010.

Barreto, L. and Kypreos, S. (2004), Endogenizing R&D and market experience in the "bottom-up" energy-systems ERIS model, Technovation, Vol. 24, Issue 8, pp. 615-629, 10.1016/S0166-4972(02)00124-4

Belsley, D.A. (1991). Conditioning diagnostics, collinearity and weak data in regression. New York: John Wiley & Sons.

Breusch, T. S. and Pagan, A. R. (1980), The Lagrange multiplier test and its applications to model specification in econometrics, *Review of Economic Studies,* Vol. 47, pp. 239-253.

Boston Consulting Group (1972), "Perspectives on Experience", Boston, MA.

Breitung, J. and Das, S. (2005), Panel unit root tests under cross-sectional dependence, Statistica Neerlandica, Vol. 59, nr. 4, pp. 414 – 433.

Bryan, W. L. and Harter, N. (1899), "Studies on the Telegraphic Language: The Acquisition of a Hierarchy of Habits", *Psychology Review*, Vol. 6, pp. 345 – 375.

Cohen, W. M., Goto, A., Nagata, A., Nelson, R., Walsh, J. P. (2002), "R&D spillovers, patents and the incentives to innovate in Japan and the United States", *Research Policy*, Vol. 31, pp. 1349-1367, doi:10.1016/S0048-7333(02)00068-9

Danish Energy Agency (2008), Stamdataregister for vindkraftanlæg ultimo maj 2008, http://www.ens.dk/sw34512.asp, last accessed 10th November 2010.

Ek, K. and Söderholm, P. (2010), Technology learning in the presence of public R&D: The case of European wind power, *Ecological Economics*, Vol. 69 (12), pp. 2356-2362. http://dx.doi.org/10.1016/j.ecolecon.2010.07.002

European Patent Office (2010), esp@cenet user interface (http://www.espacenet.com/), last accessed 10th November 2010.

Granger, C. W. and Newbold, P. (1974), Spurious regressions in Econometrics, Journal of Econometrics 2, pp. 111 – 120.

Griliches, Z. (1979), "Issues in Assessing the Contribution of Research and Development to Productivity Growth", *The Bell Journal of Economics*, Vol. 10, pp. 92-116, http://www.jstor.org/stable/3003321

Griliches, Z., Nordhaus, W. And Scherer, F. M. (1989), "Patents: Recent Trends and Puzzles, Brookings Papers on Economic Activity", *Microeconomics*, Vol. 1989, pp. 291-330, http://www.jstor.org/stable/2534723

Griliches, Z. (1990), "Patent Statistics as Economic Indicators: A Survey", *Journal of Economic Literature*, Vol. 28, No. 4, pp. 1661-1707, http://www.jstor.org/stable/2727442

Hall, B. H., Griliches, Z., Hausman, J. A. (1986), "Patents and R and D: Is there a lag?, *International Economic Review*, Vol. 27, No. 2, pp. 265-283, http://www.jstor.org/stable/2526504

Harris, R. and Tzavalis, E. (1999), Inference for unit roots in dynamic panels where the time dimension is fixed, Journal of Econometrics, Vol. 91, Issue 2, pp. 201-226, http://dx.doi.org/10.1016/S0304-4076(98)00076-1

Hausman, J.A. (1978), "Specification Tests in Econometrics", Econometrica, Vol. 46, pp. 1251-1271.

Hendrickx, J. (2004), PERTURB: Stata module to evaluate collinearity and ill-conditioning, Statistical Software Components, S445201, Boston College Department of Economics, revised 9th December 2004.

IEA, International Energy Agency (2000), Experience Curves for Energy Technology Policy, OECD/IEA, Paris.

IEA (2011), IEA Guide to Reporting Energy RD&D Budget/Expenditure Statistics, June 2011 Edition, OECD/IEA 2011: Paris, http://www.iea.org/stats/RDD%20Manual.pdf, last accessed 10th November 2010.

Im, K. S., Pesaran, M. H. and Shin, Y. (2003), Testing for unit roots in heterogeneous panels, Journal of Econometrics, Volume 115, Issue 1, pp. 53-74, http://dx.doi.org/10.1016/S0304-4076(03)00092-7

IMF, International Monetary Fund (2010), IMF Primary Commodity Prices, http://www.imf.org/external/np/res/commod/External_Data-110410.csv, last accessed 10th November 2010.

Jamasb, T. (2007), Technical Change Theory and Learning Curves: Patterns of Progress in Electricity Generation Technologies, The Energy Journal, Vol. 28, No. 3.

Johnstone, R., Hascic, I., Popp, D. (2010), Renewable Energy Policies and Technological Innovation: Evidence Based on Patent Counts, Environmental and Resource Economics, 45: 133 – 155, DOI: 10.1007/s10640-009-9309-1

Junginger, M., Faaij, A., Turkenburg, W.C. (2005), “Global Experience Curves for Wind Turbines”, *Energy Policy*, Vol. 33, pp. 133-150, doi:10.1016/S0301-4215(03)00205-2

Kinmonth, E. H. (1987), “Japanese Patents: Olympic Gold or Public Relations Brass”, *Pacific Affairs*, Vol. 60, No. 2, pp. 173-199, http://www.jstor.org/stable/2758131

Klaassen, G., Miketa, A., Larsen, K., Sundqvist, T. (2005), "The Impact of R&D on Innovation for Wind Energy in Denmark, Germany and the United Kingdom, *Ecological Economics*, Vol. 54, pp. 227-240, doi:10.1016/j.ecolecon.2005.01.008

Kouvaritakis, N., Soira, A., Isoard, S. (2000), "Modelling Energy Technology Dynamics: Methodology for Adaptive Expectations Models with Learning by Doing and Learning by Searching", *International Journal of Global Energy Issues*, Vol. 14, pp. 104-115, http://inderscience.metapress.com/link.asp?id=3uqf8dv46mur3yrq

Lanjouw, J., Mody, A. (1996), Innovation and the international diffusion of environmentally responsive technology, Research Policy, Vol. 25, pp. 549 – 571, http://dx.doi.org/10.1016/0048-7333(95)00853-5

Lanjouw, J., Pakes, A. and Putnam, J. (1998), "How to Count Patents and Value Intellectual Property: The Uses of Patent Renewal and Application Data", *The Journal of Industrial Economics*, Vol. 46, No. 4, pp. 405-432, http://www.jstor.org/stable/117497

Levin, A., Lin, C. and Chu, C. J. (2002), Unit root tests in panel data: asymptotic and finite-sample properties, Journal of Econometrics, Vol. 108, Issue 1, pp. 1-24, http://dx.doi.org/10.1016/S0304-4076(01)00098-7

Lindman, A. and Söderholm, P. (2011), Wind power learning rates: A conceptual review and meta-analysis, Energy Economics, In Press, http://dx.doi.org/10.1016/j.eneco.2011.05.007

Molly, J.P. (2007), DWEI GmbH, Ermittlung der deutschen Wertschopfung im weltweiten Windenergiemarkt fur 2007, http://www.wind-energie.de/fileadmin/dokumente/statistiken/WE%20Deutschland/DEWI-Statistik_1HJ_2008.pdf, last accessed 10th November 2010.

Neij, L. (1997), “Use of Experience Curves to Analyse the Prospects for Diffusion and Adoption of Renewable Energy Technology, *Energy Policy*, Vol. 23, No. 13, pp. 1099-1107, doi:10.1016/S0301-4215(97)00135-3

Neij, L., Anderson, P. A., Durstewitz, M., Helby, P., Hoppe-Kilpper, M., Morthorst, P. E. (2003), “Experience Curves: A Tool for Energy Policy Assessment (EXTOOL), IMES/EESS Report No. 40 Department of Technology and Society, Environmental and Energy Systems Studies, Sweden.

Nordhaus, W.D. (2002), “Modeling Induced Innovation in Climate Change Policy”, In: Nakicenovic, N., Grubler, A., Nordhaus, W.D. (Eds.), Induced Technological Change and the Environment. Resources for the Future, Washington.

Nordhaus, W.D. (2009), “The Perils of the Learning Model for Modelling Endogenous Technological Change”, Cowles Foundation Discussion Paper No. 1685.

Pakes, A. (1984), “Patents as Options: Some Estimates of the Value of Holding European Patent Stocks”, *Econometrica*, Vol. 54, No. 4, pp. 755-784, http://www.jstor.org/stable/1912835.

Philibert, C. (2011), Solar Energy Perspectives, International Energy Agency.

Popp, D. (2005), “Lessons from Patents: Using Patents to Measure Technological Change in Environmental Models, *Ecological Economics*, Vol. 54, pp. 209-226.

Popp, D., Hascic, I. and Medhi, N. (2011), Technology and the diffusion of renewable energy, Energy Economics, Vol. 33, Issue 4, pp. 648-662, http://dx.doi.org/10.1016/j.eneco.2010.08.007

Renewable UK (2011), UKWED, Operational wind farms, http://www.bwea.com/ukwed/operational.asp, last accessed 10th November 2010.

Schumpeter, J. (1934), The Theory of Economic Development, Cambridge: Harvard University Press.

Smith, A., (1776), An Inquiry into the Nature and Causes of the Wealth of Nations, Glasgow Edition, (1976) Oxford: Liberty Fund.

Söderholm, P. and Sundqvist, T. (2007), "Empirical Challenges in the Use of Learning Curves for Assessing the Economic Prospects of Renewable Energy Technologies, *Renewable Energy*, Vol. 32, pp. 2559-2578, doi: 10.1016/j.renene.2006.12.007

Spanish Wind Energy Association (AEE) (2008), Wind Power 2008, Sector's Yearbook: Analysis and Data, http://www.aeeolica.es/doc/AEE_anuario_ingles08.pdf, last accessed 10th November 2010.

StataCorp. (2009), *Stata Statistical Software: Release 11*, College Station, TX: StataCorp LP.

Varian, H.R. (1994), How to Build an Economic Model in Your Spare Time, Szenberg, M. Ed., Passion and Craft. Economists at Work, University of Michigan Press, Ann Arbor.

Westerlund, J. (2007), Testing for error correction in panel data. Oxford Bulletin of Economics and Statistics 69: 709-748.

Wiser, R. and Bolinger, M. (2008), Annual Report on U.S. Wind Power Installation, Cost, and Performance Trends: 2007, May 2008, US Department of Energy: Energy Efficiency and Renewable Energy.

Wright, T. P. (1936), "Factors Affecting the Cost of Airplanes", Journal of Aeronautical Sciences, Vol. 3, No. 4, pp. 122 – 128.

Yeh, S. and Rubin, E.S. (2011), A review of uncertainties in technology experience curves, Energy Economics, In Press, http://dx.doi.org/10.1016/j.eneco.2011.11.006.

Yokell, M.D. (1979), "The Role of the Government in Subsidizing Solar Energy", *The American Economic Review*, Vol. 69, No. 2, pp. 357-361.

Electricity in Scotland: A choice experiment

Neil Odam [a]

[a] *University of Stirling, Stirling, FK9 4LA, Scotland, UK*

December 2011

Abstract

The Scottish Government has set a target to increase renewable electricity generation from 28% of total electricity generated in 2010 to 100% of domestic consumption by 2020. As well as meeting self-imposed targets, Scotland's two remaining nuclear power plants will reach the end of their intended lifecycles by 2016 and 2023, respectively. Scotland's energy policy is therefore at a crossroads, which will result in new long-term commitments.

Discussions regarding alternative energy sources tend to focus primarily on their cost per kWh and more recently on the externality cost of their CO_2e lifecycle output. While this latter development should improve our energy policy strategy, there are many other attributes of each energy source which are neglected. This could lead to sub-optimal energy choices especially when long-term major projects are being considered as part of a national energy policy. This paper attempts to incorporate these attributes by utilising a choice experiment to obtain stated preference (SP) responses relating to a more complete range of attributes corresponding to several energy sources.

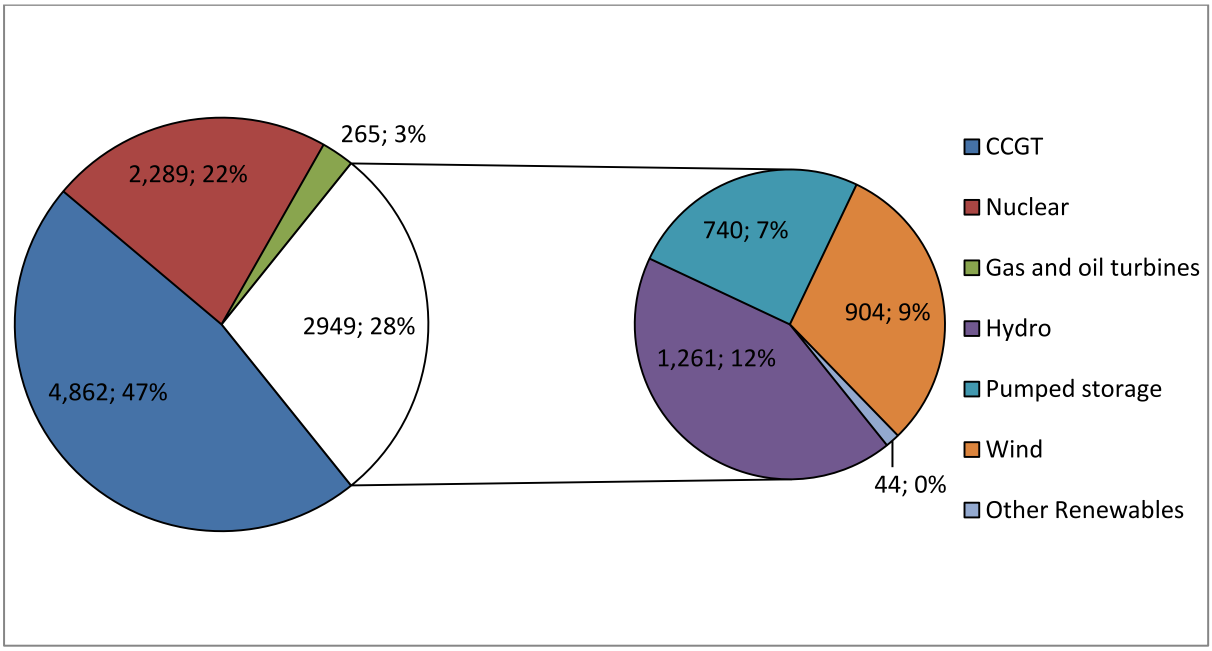
Keywords: Choice experiment, Renewable energy, Wind power, Latent class model.

1. Introduction

In 2009, Scotland generated 23.5% of its electricity from renewable sources, rising from 11.1% in 2000 (BERR, 2011). In 2010, wind power became the largest source of renewable electricity for the first time, increasing from 4.4% of renewable sources in 2000 (BERR, 2011) to 51.1% in 2010 (DECC, 2010). It replaced hydro power as the largest renewable electricity source, which generated 34.3% of Scotland's renewable electricity in 2010. The current Scottish Government administration has committed not to build any new nuclear plants. Scotland's two remaining nuclear plants: Hunterston B (850 MW) and Torness (1.4 GW) are expected to operate until 2016 and 2023, respectively. These two plants amounted to 22% (2.3 GW) of Scotland's electricity capacity in 2010 (DECC, 2011).

The Scottish Government has a target to produce 100% of Scotland's domestic electricity demand from renewable sources by 2020. In 2010, Scotland's total capacity was 10.4 GW (Figure i), with 2.9 GW of renewable capacity (DECC, 2011). Since 2006, plant capacity has grown by an average compound rate of 1.6%. Extrapolating this rate to 2020 projects Scotland's capacity to be 12.1 GW. This figure requires simplifying assumptions that load factors will remain constant, which will not be accurate if nuclear plants are replaced by renewable sources. However, this rough approximation suggests that Scotland will have to install 9.2 GW of additional renewable capacity, an increase of 312%, to meet the Government's target. It should be noted that the Government does not intend for Scotland to rely on intermittent renewable energy sources for 100% of its electricity consumption. Instead, the Scottish Government plan to build capacity equal to 200% of Scotland's domestic electricity demand and to export excess power to England or continental Europe, should a 'super-grid' come into existence.

Figure i: Scotland's electricity plant capacity in 2010 (MW)



Source: DECC (2011)

Scotland has the highest average wind speed in Europe and is estimated to have 206 GW of practical offshore wind potential, which is approximately 25% of Europe's total potential (Scottish Government, 2011a). Relatively low levels of sunshine hours mean that solar power is less viable in Scotland than most countries. Scotland is at the forefront of developing wave and tidal power devices, with the European Marine Energy Centre (EMEC) situated in Orkney, one of the most abundant wave and tidal sources in the world. It should be noted that the developmental cycle of new renewable energy sources generally take several decades and so it is unlikely that wave power will be able to contribute substantially to Scotland's renewable electricity target by 2020. However, Scotland is estimated to possess 10% of Europe's wave energy potential and sites with a total potential capacity of 1.6 GW (including tidal power sites) have been identified (Scottish Government, 2011a). Since the vast majority of practical hydro power sites have already been developed, the remainder of Scotland's renewable electricity target will likely have to be met by onshore and offshore wind power as well as marine power. If the target is met entirely by wind power then it will be necessary to increase the capacity of wind power by approximately 26% per annum. While this is a major challenge, the annual growth rate of 27% from 2007 to 2010 (DECC, 2011) suggests that it is not entirely unrealistic.

This paper reports the results of a choice experiment (CE) which was designed to elicit preferences from Scottish households concerning what attributes are most important to them in the context of Scotland's 2020 energy target and the current Government's commitment not to pursue nuclear power. A labelled CE was used to compare preferences between electricity generating technologies, with wave power included as an option for the first time. Area location dummy variables have been used to elicit preferences over spatial attributes. These location dummies were also used to identify any 'Not in my back yard' (NIMBY) effects by creating an additional NIMBY dummy which took the value of 1 if the proposed development would occur in the same region as the household and 0 otherwise. A unique feature of the choice experiment is that the survey was sent to households which had purchased a home in the past 7 years. It was therefore possible to interact the household's actual house price, adjusted for inflation to the third quarter of 2010, with their choices to determine how their house value data influences willingness to pay (WTP). House price data can also be used to overcome problems related to the disclosure of household income and could also reveal potential differences between wealth and income. The CE has been analysed using multinomial logit models and latent class models, estimated using NLogit (Greene, 2007).

2. Method

Initially, the CE was designed to offer the choice between onshore wind, offshore wind, wave, nuclear and an opt-out option resulting in missing the 2020 target by building conventional power plants to replace the soon to be decommissioned nuclear power plant, Hunterston B. However, multiple focus groups determined that five options, combined with the relevant attributes describing these technologies, was too difficult for recipients to complete. Since CEs looking at preferences between renewable, conventional and nuclear sources already exist (Fimereli et al., 2008); the decision was made to focus solely on preferences between renewable technologies in Scotland: offshore wind, onshore wind and wave power. Tidal power was also considered as a stand-alone option or as a combined option with wave power. However, adding tidal power as a stand-alone option presented the same problem as including nuclear power. Combining wave and tidal power made it more difficult to describe each technology's attributes realistically. The decision to use wave power instead of tidal power was made because the attributes between offshore wind power and wave power are more homogenous, facilitating the identification of preferences between the technologies.

Restricting the choice set to wave, offshore wind, onshore wind and an opt-out of conventional power plants, such as coal and gas is likely to attract protest responses from respondents in favour of nuclear power. In order to mitigate these protest responses, three questions were asked before the choice cards portion of the survey. These questions were designed to allow respondents to share their wider viewpoints on energy sources and therefore assure the respondent that their choices in the choice scenario section would not misrepresent their overall views. The results of these pre-survey questions are included in the discussion section of this paper.

Ngene (ChoiceMetrics, 2011) was used to generate a Bayesian efficient design with 24 choice scenarios. The design had four labelled alternatives to choose from, as listed above, to replace the power output from Scotland's oldest nuclear power station, which is due to be decommissioned in 2016. The payment vehicle, represented by an annual increase in a household's electricity bill, included six levels ranging from £0 to £120 per year. A wildlife deterioration attribute with four levels was included for each renewable power option. A visual representation of wave power devices and offshore wind turbines was included to demonstrate the visual impact these technologies had, depending on what distance they were placed from the shore. This attribute contained four levels ranging from 1-12km. An effects coded dummy variable was included to represent 4 distinct regions of Scotland, where the proposed development would take place. The content of the CE and the attributes in the choice scenarios was initially tested on two focus groups, both of which suggested that this choice card was challenging to complete and so the design was blocked into 4 groups, such that each respondent was asked to complete 6 choice scenarios. The attributes included in the design are described in greater detail in Section 3.

Efficient designs have become increasingly prevalent in recent years (Rose et al., 2008) with the recognition that it is generally likely that at least some information will be known about the model parameters prior to the design of a CE. Previous studies by Ek (2002), Bergmann et al. (2006) and Ladenburg (2008) have covered similar topics, on renewable energy, which meant that several parameters could be estimated prior to the design. However, this paper did not attempt to replicate any of these previous papers, which means that there is uncertainty about the accuracy of these prior parameter estimates. Bayesian models can be used to incorporate this uncertainty into the design by including both the mean of the normally distributed parameter estimate and the standard deviation of the parameter. Standard deviations from the aforementioned previous papers were used to formulate initial values for the Bayesian model; however, these standard deviations were widened to acknowledge the uncertainty in applying parameter estimates in a different context to the initial studies. A pilot study with 132 observations was then conducted and analysed using this initial design.

The results from the pilot study were used to generate updated priors for the Bayesian efficient design.[5]

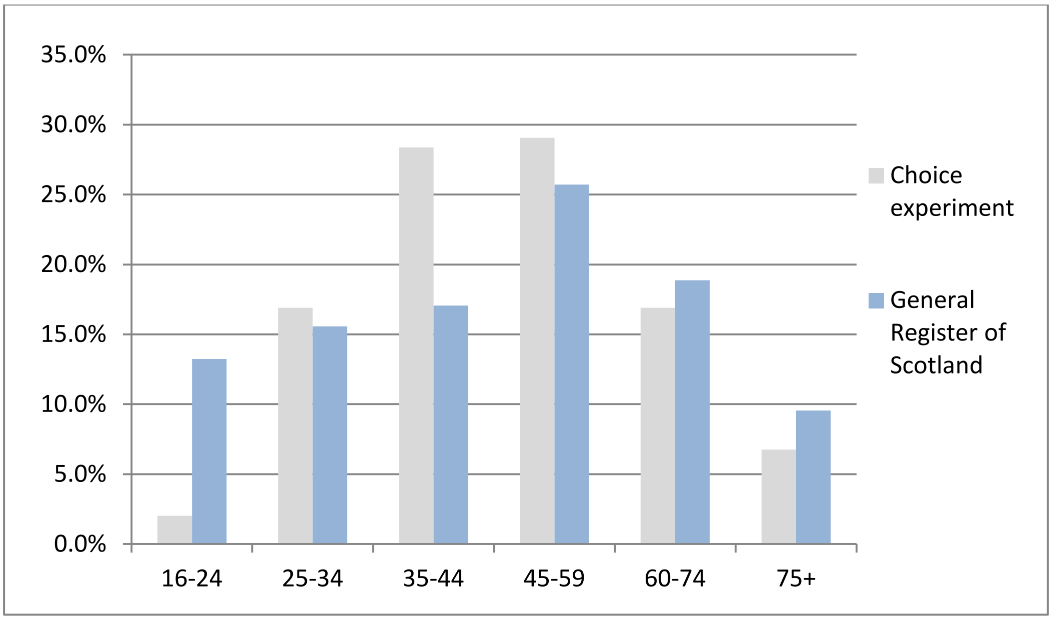
The CE was sent to 1,200 households from the UK's edited electoral roll. Appendix A displays the total number of households in each council area of Scotland in 2009. In order to achieve a geographically representative sample of the Scottish population, addresses were selected at random from each council area in accordance with its proportion of Scottish households. Appendix A also displays the resulting number of households which were sent CEs. 172 responses were received, of which 24 were not fully completed, leaving 148 surveys for the final analysis. 62 surveys were unable to be delivered, giving a response rate of 15.1% and a completed response rate of 13%. This response rate is on the lower side of expectations, even in the context of British CEs, which have generally seen lower response rates than continental Europe and particularly Scandinavia. Odam (2011) investigates diminishing response rates in the UK and examines alternative methods of stated preference elicitation, using a novel internet advertising approach. Despite the low response rate, the sample size is sufficient for the CE, suggested by the design's s-error.

[5] Final design

```
;alts = Wave, Offshore, Onshore, Opt
;eff = (mnl,d,mean)
;rows = 24
;block = 4
;alg=mfederov
;model:
U(Wave) = bWave[(n,4.11,3.00)] + LocOff.effects[(n,-0.15,0.350)|(n,0.2,0.440)|(n,-0.1,0.400)] * LocOff[0,1,2,3]
+ bCost[(n,-0.036,0.01)] * Cost[0,10,20,40,80,120] + bWildlife[(n,-0.16,0.08)] * WildWave[-10,0,10,20]
+ bShore[(n,0.285,0.272)] * ShoreWave[1,4,8,12]  /
U(Offshore) = bOff[(n,4.15,2.98)]  + LocOff.effects[(n,-0.15,0.350)|(n,0.2,0.440)|(n,-0.1,0.400)] * LocOff[0,1,2,3]
+ bCost[(n,-0.036,0.01)] * Cost[0,10,20,40,80,120] + bWildlife[(n,-0.16,0.08)] * WildOff[-10,0,10,20]
+ bShore[(n,0.285,0.272)] * ShoreOff[1,4,8,12]  /
U(Onshore) = bOn[(n,3.01,2.98)]+ LocOn.effects[(n,-0.15,0.350)|(n,-0.1,0.400)] * LocOn[0,1,2]
+ bCost[(n,-0.036,0.01)] * Cost[0,10,20,40,80,120] + bWildlife[(n,-0.16,0.08)] * WildOn[-10,0,10,20]$
```

While the sample distribution can be controlled for prior to the administration of the survey, very little control can be exerted on the socio-economic characteristics (SECs) of the respondents to a mail survey. In this CE, both age and gender were not statistically different from the Scottish population, with 49.4% of responses being from females compared to 52.1% of the Scottish population. The average age of respondents was 48.1 compared to the average age of 47.2 of Scottish adults (over 16) (GROS, 2011a). Figure ii reveals that the CE age distribution had greater kurtosis than Scotland's population, meaning that the youngest and oldest groups were under-represented, particularly the group between 16 and 24 which did not include a single female respondent.

Figure ii: Age distribution – Comparison of choice experiment sample and Scotland's population



Source: GROS (2011b)

In 2010, there were 5.22 million people in Scotland living in 2.36 million households (GROS, 2011b), resulting in an average household size of 2.213 (including adults and children). The average household size in the sample was 2.601, which is significantly higher than the population average of 2.213, at a 5% level of significance. During model estimation, the data was weighted to mitigate the bias caused by this non-representative sample.

One addition to the CE was the careful selection of households to ensure that the house price of each recipient was known. This approach was taken to test how much explanatory power house prices have compared to household income, which is normally used in academic surveys. Household income introduces a number of issues, which are particularly prevalent in mail surveys. Even official government surveys have difficulty in identifying household income. Reasons for this include: lack of knowledge of each residents income, poor record keeping, inconsistent reporting of net and gross income, inaccurate reporting of household income and refusal to divulge personal information. This is demonstrated by the largest Scottish government survey: the Scottish Household Survey (SHS) (2011), which states that its methodology does not allow for the estimation of the average income in Scotland because the survey asks for the income of the two main earners in the household, regardless of how many adults are in the household. The SHS advises readers to use the Department for Work and Pensions (DWP) (2011) Family Resource Survey for the best estimate of household income in Scotland. However, the values used in the DWP survey have not been updated to keep up with inflation. The DWP survey divides respondents into 11 mutually exclusive income groups, with the highest income group having no upper bound. As a consequence of not raising these income bands with inflation, 17% of respondents state that they are in the highest income group, earning "over £1,000" net income per week as a household. Even a uniform distribution would imply that only 9% of respondents should be in each category. The problem is magnified further if a more realistic normal distribution is assumed. There is no information regarding the average net income of this group of households earning over £52,000 per year making it difficult to determine the average household income in Scotland with any accuracy. Assuming that the average weekly earnings of this highest income group are £1,500, this would result in the average net annual household income in Scotland being just under £32,000. The sample annual household net income in this survey is approximately £42,000, which is significantly greater than the DWP estimate at the 5% level of significance. An alternative estimate of the average annual household income in Scotland can be found by dividing Scotland's GDP by its number of households. Excluding oil and gas, the Scottish Government (2011b) estimates Scotland's GDP in 2010 to be £111bn. Dividing this by the number of households results in an average annual household income in Scotland of £57,000 (this assumes that taxes and government transfers net to 0). This much higher figure is just within the 95% confidence interval of the sample average household income. It also highlights how large the margin for error can be, depending on which source is used, and suggests that the sample average household income should not be assumed to be statistically different from the population average household income. However, it should be noted that the effort to ensure that each house price was known results in council house tenants being excluded from the pool of potential respondents, which could introduce a source of sample bias. The SHS (2011) finds that 22% of Scottish households live in this type of social housing. Those living in privately rented accommodation would not have been excluded because the CE was addressed to the occupier instead of the homeowner.

The benefit of using house prices is that there is considerably more confidence in the reliability and accuracy of the data. For this study the website www.zoopla.co.uk was used to identify the last recorded transaction of particular house. This website holds data on every UK house transaction in the last seven years. Appendix A displays the average house price of each council area in Scotland in the third quarter of 2010 from the Registers of Scotland (RoS) (2011). The average house price of sampled households was normalised to the third quarter of 2010 and is also included in Appendix A for comparative purposes. It can be seen that the unweighted normalised average house price of our sample is approximately 6% higher than the average RoS house price. However, the sampled average house prices in high population areas such as Glasgow and Edinburgh were statistically significantly higher than the RoS house prices. Weighting the house prices by the proportion of total houses results in an average sampled house price of £174,074 compared to the RoS average weighted house price of £153,734. While the percentage difference rises to 13% when the data is correctly weighted, the difference is not statistically significant due to the high standard deviation in house prices.

Obtaining names and addresses of households which were on both the UK's edited electoral roll and which had a transaction in the last seven years was challenging and laborious. A variety of different methods were used to identify households which were on both databases. One drawback of sending the survey to only households which have been sold in the last seven years is that households renting from the government, making up 23% of Scottish households, will be omitted from the survey. This is likely to introduce some bias and may result in the lowest income strata being under-represented.

3. Description of attributes

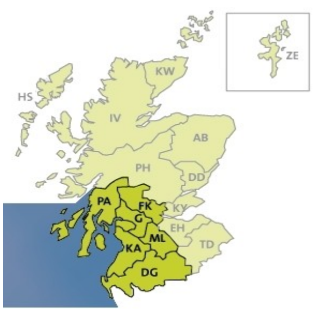
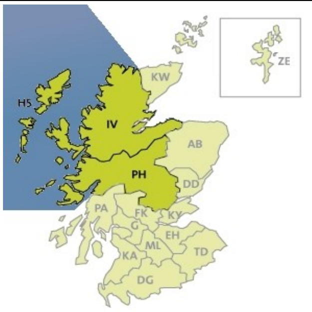
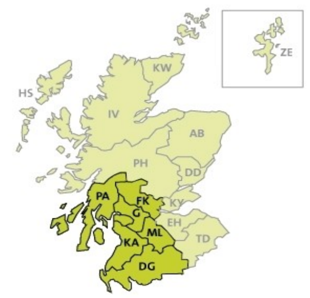
Detailed pictures of each technology were included in the introduction of the CE. Similar to a study by Ladenburg and Dubgaard (2007), pictures of wave and wind power generators, on a standard background, were scaled to give respondents a visual representation of what each technology would look like from the shore at distances of 1km (Near), 4km (Medium), 8km (Far) and 12km (Out of sight). The generators were intentionally almost invisible at the furthest distance on the choice cards. A sample choice card demonstrating these pictures is included in Figure iii. A website (http://www.electricitysurvey.com/[6]) was created to give much more detail about each technology featured in the CE, including additional pictures and videos. The website also included more detail about the CE method and the motivation behind this survey method. This was designed to assure respondents that the CE was legitimate and to provide further information to anyone who was interested in the topic beyond the essential information contained in the hard copy of the CE. 19% of respondents stated that they visited the website before completing the survey. The website also contained a link to the identical online version of the survey to increase the options available to potential respondents. A prize draw of £100 was available to all respondents to incentivize the completion of the CE.

Following Bergmann et al.'s (2006) finding that respondents had a statistically significant WTP for wildlife improvements, this study included four levels of wildlife as an attribute. These levels were described as follows, relative to the current reality:

- Positive - great care is taken in identifying sites which will not harm wildlife. Wildlife may adapt to new technologies so well that wildlife indicators improve.
- No change - some regulation is imposed on the placement of generators to ensure that the most important locations for wildlife are protected.
- Negative - little regulation is imposed on the placement of generators, resulting in new generators being placed in areas which are damaging to wildlife.
- Very negative - no regulation is imposed on the placement of generators, resulting in new generators being placed in areas which are very damaging to wildlife. Unforeseen negative impacts on wildlife caused by the inability of wildlife to adapt to new technologies.

[6] This domain name will not be renewed indefinitely. The following address should provide a more permanent source for the website: https://sites.google.com/site/energysurvey2011/

Figure iii: Sample choice card

	Wave	Offshore wind	Onshore wind
Distance from shore	 Far (8km)	 Near (1km)	 Onshore
Increased cost of electricity per year per household	£120 (30% increase)	£120 (30% increase)	£40 (10% increase)
Wildlife Impact	No change	Positive	Very negative
Location			
Choice			
None of the above - No additional renewable electricity. New gas, coal or oil generators built instead. Electricity cost remains the same. Higher air pollution and carbon output.			

Respondents were also informed that different types of wildlife are likely to be affected depending on what type of technology is adopted. For example, birds and bats are most likely to be affected by wind turbines whereas marine species are most likely to be affected by wave power. Furthermore, the respondents were informed that conventional and nuclear technologies are less likely to have direct impacts on wildlife, but could affect much greater numbers indirectly through medium to long-term pollution. In order to allow for the possibility that respondents would value different types of wildlife being affected by each technology, the attribute was modelled with alternative specific parameters so that any difference in WTP could be identified.

The payment vehicle in the CE was an increase in electricity bills. This payment vehicle was timed fortuitously to coincide with newspaper headlines connecting Renewable Obligation Certificates (ROCs) with rising electricity bills. As advised by Carlsson et al. (2005), respondents were given a cheap talk script informing them that it is important to carefully consider the cost of each scenario while taking into account your household budget and by considering what you would have to trade off to pay for any increased electricity bill, whether it is something you consume or a reduction in your planned savings.

Another novel addition to the CE was the inclusion of location dummies representing distinct areas in Scotland. The first objective of the location dummies was to ascertain preferences for where new electricity generation should take place. The second objective was to combine the location dummies with the post code of the respondent to determine if any NIMBY effect existed.

The distribution of Scotland's population and long-standing political and council boundaries facilitates the creation of dummy variables. Most of Scotland's population (approximately 70%) is based in the central belt which is split into the western central belt, where Glasgow is situated, and the eastern central belt, where Edinburgh is situated. Further distinct regions can be identified in southern Scotland, northern Scotland and the Northern Isles. The North of Scotland can be further divided between the sparsely populated mountainous region in the West and the coastal areas in the East which is more populous and prosperous due to the concentration of energy resources in the North Sea. Initially, it was anticipated that all six of these areas could be represented by dummy variables. However, during the design phase it became apparent that the sample size requirement would be prohibitively large using this specification. It was necessary to restrict the design to four dummy variables to ensure that the sample size requirement was reasonable. The final design preserved the Northwest and Northern islands (denoted by Orkney hereafter) as distinct regions because these two regions hold much of Scotland's renewable energy potential. The populous region of Scotland was split between the West, centred on Glasgow, and the East, containing Edinburgh, Aberdeen and Dundee. The respondents were informed that the shaded area of the maps in each choice card represents where the generators would be located to replace the nuclear power plant at Hunterston B, but that renewable technologies would not be limited to these locations, signifying that there would be a higher concentration of generators in the shaded areas.

4. Opinions on electricity generation

Respondents were asked to state the importance of each attribute included in the choice experiment on a scale from 1-5 (lowest – highest). The results in Table i show that wildlife was the most important attribute included in choice experiment, surprisingly even more important than cost. Respondents indicated that the choice between technologies was the next most important attribute. Location and the distance from the shore of wave and offshore wind projects were of medium importance, but both were significantly lower than the top three attributes at the 5% level. Respondents were also asked to make a binary choice about whether they considered each of the other attributes included in Table i to be important in deciding Scotland's energy strategy. CO_2 output was the most important attribute which was not included in the choice experiment, with 58% of respondents stating that it was important. Each of the other attributes were seen to be more important to over 50% of respondents, with the exception of the aesthetic impact of electricity generation, which only 21.7% of respondents found important.

Table i: Electricity generation attribute importance

Attribute (n = 141)	Scale from 1 - 5
Wildlife	3.745
Cost	3.596
Technology	3.177
Location	2.730
Distance from shore	2.436

Attribute (n=141)	Binary choice
CO_2 emissions	0.580
Security of supply	0.559
Safety	0.538
Impact on jobs	0.524
Air pollution	0.524
Aesthetic	0.217

Table ii displays the results of the pre-survey questions. While only 16.2% (21.2% of respondents who had an opinion) of respondents stated that they prefer nuclear power over renewable technologies, it is particularly notable that 54.1% (67.2% of respondents who had an opinion) of respondents stated that they would prefer that Scotland retain nuclear capacity while also pursuing renewables. This is contrary to the Scottish Government's rejection of nuclear power, suggesting that the policy does not have popular support. The result is particularly surprising since the survey was sent out six weeks after the tsunami induced nuclear disaster in Fukushima, Japan.

Table ii: Opinions on Scottish energy strategy.

Statement (n = 119)	**Yes (%)**	**No (%)**	**Don't know / No opinion (%)**
I generally favour nuclear power over renewable power generation.	16.2	60.1	23.6
I generally favour conventional energy sources such as gas, coal or oil over renewables.	15.5	62.2	22.3
I think that Scotland should maintain nuclear capacity while also expanding renewable power generation.	54.1	26.4	19.6

5. Multinomial logit model

CEs are based on two economic principles. The first is Lancaster's (1966) characteristics theory of value which states that goods do not have innate value but instead consumers derive utility from the attributes of the good. The second is random utility theory, which enables the estimation of a consumer's utility based on the choices they are observed to make.

The multinomial logit model (MNL) is a good starting point for CE analysis if it can be shown that the IIA property is not violated. Given a consumer's utility function for a number of alternatives:

$U(alternative\ 1) = \beta_1' x_{i1},$

$U(alternative\ 2) = \beta_2' x_{i2},$

…

$U(alternative\ J) = \beta_J' x_{iJ}.$

The probability of choosing option j is given by:

$$\mathrm{Prob(choice\ j)} = \mathrm{Prob}\left(\mathrm{U_j} > \mathrm{U_q}\right), \forall \mathrm{q} \neq \mathrm{j}$$

$$= \frac{\exp\,(\beta_j' x_{ij})}{\sum_{q=0}^{J} \exp\,(\beta_q' x_{iq})}, j = 0, \ldots, J.$$

The Hausman-test of IIA was applied to both MNL models presented in Table ii and Table iii to determine whether the IIA property was violated. The Hausman-test evaluates whether the ratio of any two alternatives remains constant despite the presence or absence of any other alternative with the set of alternatives included in the CE (Hensher et al., 2005). The Hausman-test failed to reject the hypothesis that IIA was not violated, thus suggesting that MNL is sufficient for this CE. Therefore a random parameter model which relaxes the IIA assumption was not necessary in this study. Table ii shows the results of the CE based on a MNL with SECs excluded from the model. This model can be seen as a baseline, which can be compared to more advanced models, such as the multinomial logit model which includes interactions with SECs and the latent class models which follow in Section 6. Both of these latter models relax the implicit assumption of the basic MNL model that respondents have uniform preferences.

The marginal WTP gives a measure of the change in welfare due to a marginal change in a given attribute and is defined as the maximum amount an individual is willing to pay in exchange for what they perceive to be an improvement in the level of a given attribute. It can be derived from the result tables using the following formula:

$$MWTP = -\frac{\beta.attribute}{\beta.price}$$

It should be noted that in the latent class model, contained in Section 6, the MWTP is calculated separately for each class segment because each segment may have different price coefficients.

The results of the basic MNL model presented in table ii suggest that households are WTP an additional £132 to £183 per year if their electricity came from renewable sources instead of conventional sources, such as coal and gas. While the results show that households are WTP £50 more per year for offshore wind than onshore wind and wave power, the 95% confidence interval shows that there is no significant difference in the WTP for any of the three renewable technologies.

The basic MNL model also suggest that Scottish households are willing to pay (WTP) between £4 and £5 per year to improve the impact on wildlife by one level, as described in attributes section. In the design phase, each technology was given an alternative specific parameter for wildlife because to allow for differing wildlife impacts. This means that separate WTP coefficients can be calculated for each technology. However, the 95% confidence interval reveals that respondents were not WTP significantly more to improve the wildlife outcome of any particular technology compared to another.

Table iii also reveals that respondents were not WTP significantly more than 0 to increase the distance (by one level of 3 - 4km) wave generators and offshore generators are located from the shore. While the coefficient on wave power shore distance was positive and significant at the 10% level, the coefficient on offshore wind power shore distance was negative, but not significant. This result contradicts the results of recent papers by Ladenburg and Dubgaard (2007) and Krueger et al. (2011), both of which found statistically significant WTP to reduce the visual impact of offshore wind farms by locating the turbines further from the shore. Both of those studies focussed narrowly on the visual disamenity of offshore wind farms and the contradictory results displayed in this paper may indicate that CEs are not suited to addressing a wider topic with many disparate attributes, which may result in respondents ignoring attributes due to the overwhelming amount of information. Alternatively, it is possible that the contradictory results stem from the different populations which were sampled, since both of the aforementioned papers concentrated on households near specific offshore projects, while this paper sampled the whole of Scotland, where the majority of residents are unlikely to be directly affected by offshore renewable developments.

Somewhat surprisingly, table iii also reveals that households do not exhibit any NIMBY behaviour, as they are not WTP a statistically significant amount to ensure that renewable developments occur outside their region. This result is contrary to Firestone and Kempton (2009), who found that residents nearby a proposed development in the Cape Cod region of the U.S. were strongly opposed to the development. However, the lack of a statistically significant NIMBY effect has been documented in several past valuation studies such as: Krohn and Damborg (1999), Ek (2005) and Ladenburg (2008). Ladenburg (2008) found that the attitude of respondents to wind farms was not statistically significantly affected by whether they can see wind turbines from their property. It is also possible that the location dummies used in this CE were not small enough to cause respondents to worry that they would be affected by choosing the option that would result in renewable development in their local area. Indeed, studies which have identified a NIMBY effect have contextualised their studies by referring to local projects, which respondents can more readily visualise.

The variables: Orkney, North and East in the table refer to three of the four areas represented in the CE, with the west of Scotland serving as the base level. The MNL model shows that respondents are WTP approximately £18 per year to locate renewable technologies in Orkney instead of western

Scotland; however, this coefficient was significant at the 10% level only. Respondents were WTP £26 per year to locate renewables in the west of Scotland instead of east Scotland. This result is surprising because both the west and east of Scotland are heavily populated. It is possible that this result indicates that respondents had a preference to locate renewables in the west of Scotland because the west is better suited to renewable electricity generation due to stronger and more consistent winds which predominately come from the Atlantic.

Table iii: WTP derived from multinomial logit models, excluding socio-economic characteristics.

Multinomial logit model	**n=**792	**Pseudo $R^{2:}$** 0.188	
Variable	**Coefficient**	**Implicit price**	**Implicit price – 95% confidence interval**
Price	-0.014***	-	-
Wave constant	1.883***	£138.67	£108.89 - £168.45
Offshore constant	2.488***	£183.22	£153.81 - £212.62
Onshore constant	1.799***	£132.50	£107.46 - £157.54
Wave wildlife	0.069***	£5.08	£3.83 - £6.34
Offshore wildlife	0.064***	£4.73	£3.6 - £5.86
Onshore wildlife	0.058***	£4.28	£3.13 - £5.43
Wave shore distance	0.038*	£2.82	£-0.05 - £5.69
Offshore shore distance	-0.018	-£1.35	£-4.69 - £1.98
Wave NIMBY	0.230	£16.93	£-15.52 - £49.39
Offshore NIMBY	-0.105	-£7.74	£-44.13 - £28.65
Onshore NIMBY	0.007	£0.48	£-28.39 - £29.35
Orkney	0.244*	£17.98	£-0.28 - £36.23
North	-0.122	-£9.02	£-29.23 - £11.2
East	-0.352**	-£25.92	£-46.56 - £-5.27
*, ** and *** denote statistical significance at the 10, 5 and 1% levels, respectively.			

Table iv displays the results of an MNL model which interacts the SECs of each respondent with the alternative specific constants (ASC) for each technology option. By recognising that respondents' SECs are likely to influence their preferences on electricity generation, it can be seen that the main result of the basic MNL model no longer applies. That is, when SECs are interacted with the ASCs, households are not WTP any amount statistically significantly greater than 0 to generate electricity from renewables compared to conventional sources. The WTP for improved wildlife outcomes remains almost identical to the basic MNL model, which suggests that this result is robust to alternative utility specifications. The inclusion of SECs also removes the surprising result from table iii, which had suggested that households would be WTP to place renewable projects in the west of Scotland instead of the East of Scotland. The coefficient on Orkney remains positive and significant at the 10% level.

The coefficients on the SECs provide valuable insights into how each characteristic impacts the average household's WTP for renewable electricity. Every SEC, except a dummy indicating that the respondent is employed full-time and income, which is significant at the 5% level only, is significant at the 1% level. The age coefficient reveals that the older a respondent is, the less likely they are to be WTP for renewable energy. The gender coefficient indicates that males (dummy coded 1) are more likely to favour renewable energy than females. Likewise, the education coefficient shows that additional years of education increase the probability that the respondent will support renewable electricity generation. The negative income coefficient surprisingly reveals that increasing income decreases the probability that a respondent will favour renewable electricity. The dummy variable indicating that the respondent lives near to an existing wind farm, denoted 'Wind farm near home' in the result tables, is surprisingly important as the relatively large coefficient reveals that respondents living near to an existing wind farm are statistically significantly more likely to support renewable electricity generation. This suggests that respondents who live near wind farms have come to accept them, while those who do not live close to wind farms are fearful of their impact. This result is particularly striking because similarly robust results were found by Krueger et al. (2011), while a potential explanation is identified by Eltham et al. (2008), who studied the opinions of a local population both before and after the installation of a wind farm, finding that some attitudes towards wind farms improved after in the years following installation. The coefficient associated with the

'Work in energy industry' variable reveals that those who work in the energy industry are statistically significantly less likely to support electricity from renewable sources. From the data obtained for this CE, it is not possible to determine whether this result is caused by these respondents having a greater knowledge of the energy industry, or if they have a conflict of interest from working with conventional energy sources. Finally, the 'residents' coefficient shows that WTP for renewable energy is positively correlated with the number of residents living in the respondent's household.

Table iv: WTP derived from multinomial logit models, including socio-economic characteristics.

Multinomial logit model		**n**=690	**Pseudo R^2:** 0.262
Variable	**Coefficient**	**Implicit price**	**Implicit price – 95% confidence interval**
Price	-0.013***	-	-
Wave constant	-0.507	-£38.71	£-229.34 - £151.92
Offshore constant	0.003	£0.24	£-189.75 - £190.23
Onshore constant	-0.648	-£49.41	£-238.87 - £140.05
Wave wildlife	0.071***	£5.41	£4.00 - £6.83
Offshore wildlife	0.067***	£5.08	£3.80 - £6.37
Onshore wildlife	0.057***	£4.35	£3.07 - £5.64
Wave shore distance	0.033	£2.49	£-0.73 - £5.71
Offshore shore distance	-0.017	-£1.29	£-5.08 - £2.50
Wave NIMBY	0.163	£12.44	£-24.26 - £49.13
Offshore NIMBY	0.028	£2.15	£-38.32 - £42.63
Onshore NIMBY	-0.025	-£1.88	£-34.27 - £30.51
Orkney	0.248*	£18.89	£-1.46 - £39.24
North	-0.090	-£6.89	£-29.90 - £16.12
East	-0.203	-£15.45	£-38.63 - £7.72
Age	-0.046***	-	-
Gender	0.985***	-	-
Education	0.674***	-	-
Income	-0.200**	-	-
Wind farm near home	3.165***	-	-
Work in energy ind.	-1.770***	-	-
Residents	0.832***	-	-
Full-time employment	0.204	-	-
*, ** and *** denote statistical significance at the 10, 5 and 1% levels, respectively.			

Table v replicates the model from table iv, but actual house prices are interacted with the ASCs, as well as the SECs which were included in table iv. It should be noted that the sample size decreases in this table because not all respondents' house transactions could be identified. However, the results remain fairly similar to those in table iv. On average, respondents are still not WTP an amount statistically significantly greater than 0 for renewable energy. The critical result from table v is that the inclusion of house prices has resulted in the income coefficient becoming statistically insignificant, while the coefficient on each house price variable, interacted with each technology's ASC, is negative and significant at the 5% level. Possible interpretations of this result are that households are concerned about renewable energy developments devaluing their homes or that more expensive homes are correlated with larger homes, meaning that any increase in electricity prices will disproportionately affect homeowners of larger houses.

Table v: WTP derived from multinomial logit models, including socio-economic characteristics and house prices based on actual house price transactions.

Multinomial logit model		**n=**492	**Pseudo R^2:** 0.314
Variable	**Coefficient**	**Implicit price**	**Implicit price – 95% confidence interval**
Price	-0.012***	-	-
Wave constant	-2.591	-£222.25	£-584.35 - £139.85
Offshore constant	-2.124	-£182.13	£-544.45 - £180.19
Onshore constant	-2.648	-£227.11	£-588.52 - £134.3
Wave wildlife	0.089***	£7.63	£5.62 - £9.63
Offshore wildlife	0.067***	£5.79	£4.05 - £7.53
Onshore wildlife	0.072***	£6.21	£4.36 - £8.06
Wave shore distance	0.037	£3.20	£-1.22 - £7.62
Offshore shore distance	-0.038	-£3.28	£-8.51 - £1.96
Wave NIMBY	0.058	£5.01	£-41.65 - £51.68
Offshore NIMBY	-0.051	-£4.36	£-54.29 - £45.57
Onshore NIMBY	0.037	£3.17	£-39.13 - £45.46
Orkney	0.191	£16.36	£-12.76 - £45.49
North	-0.324*	-£27.78	£-59.68 - £4.12
East	-0.375**	-£32.19	£-64.3 - £-0.07
Age	-0.031	-	-
Gender	1.405***	-	-
Education	0.729***	-	-
Income	0.049	-	-
Wind farm near home	4.200***	-	-
Work in energy ind.	-2.315***	-	-
Residents	1.320***	-	-
Full-time employment	-0.111	-	-
House price - wave	-0.005**	-	-
House price - offshore	-0.005**	-	-
House price - onshore	-0.006**	-	-
*, ** and *** denote statistical significance at the 10, 5 and 1% levels, respectively.			

6. Latent class models

The models presented in tables iv and v allow for preference heterogeneity amongst respondents to be recognised. However, interacting SECs with the ASCs in MNL models imposes the analyst's assumptions about the source of heterogeneity on the model. Latent class models allow for greater flexibility in recognising preference heterogeneity, as no prior knowledge about the potential sources of heterogeneity is required. As such, latent class models assume that a number of a priori unknown segments exist in a population, each with a different preference structure (Meyerhoff et al., 2010). Furthermore, latent class models avoid potential collinearity problems, which commonly arise when adding multiple independent variables which are highly correlated. This is particularly likely to apply to variables such as age, income and house value.

Table vi displays the results of the various information criteria which are commonly used to evaluate how many segments should be estimated in the latent class model.

Table vi: Information criteria for optimal number of latent class segments.

Segments	**2**	**3**	**4**
Number of parameters	38	60	82
Log likelihood function	-744.062	-681.665	-637.325
AIC	2.086	1.978	1.918
BIC	2.320	2.347	2.423
HQIC	2.176	2.120	2.113

As is common in previous applied latent class models, the information criteria do not form a consensus regarding the optimal number of segments (Meyerhoff et al., 2010); (Westerberg et al., 2011). Meyerhoff et al. (2010) note that the AIC tends to over-estimate the number of segments which should be included, while the log likelihood function is expected to decrease as the number of parameters in the model is increased. Increasing the number of segments to 4 produces results where one class's attributes are all statistically insignificant. This appears to be a particular problem with relatively small sample sizes. The BIC finds that a 2 segment model is optimal and since the other information criteria recommend a model with 4 segments, the results in this paper will focus on the 2 segment model.

The SECs which were used to form the segment membership are outlined in table vii. These results show the coefficients on each attribute relating to segment 1, relative to segment 2 which is set to 0 as a baseline. As well as regular SECs, such as age, gender and a dummy variable for high income; two opinions on energy sources were included. The two energy opinions resulted from the following questions:

Do you generally favour conventional energy sources such as gas, coal or oil over renewables?

Do you consider CO_2 to be an important attribute in determining Scotland's energy strategy?

Table vii: Socio-economic characteristics used to form segment memberships

Segment 1	Coefficient	Standard error	Z stat	P value
Constant	3.823	1.613	2.369	0.018
Age	-0.060	0.025	-2.442	0.015
Gender	-0.226	0.645	-0.350	0.726
High income	-0.681	0.659	-1.034	0.301
Conventional energy sources	-0.001	0.001	-0.752	0.452
CO_2 output	1.303	0.606	2.151	0.032

Table vii shows that only the constant, age and the respondent's opinion regarding the importance of CO_2 output were significant at the 5% level. This means that respondents in segment 1 are statistically significantly more likely to be younger than the average sample population and to believe that CO_2 reduction is an important issue. The signs on the other coefficients reveal that respondents in segment 1 are marginally more likely to be female, have lower incomes than average and dislike conventional energy sources. While it might have been expected that more SECs would be statistically significant, the previous literature has shown that this is a common occurrence as Meyerhoff et al. (2010) reports that the SECs in his study had a weak influence on segment membership. The results in table vii are strikingly similar to the findings of Colombo et al. (2009), which reported that only age and belonging to an environmental organisation statistically significantly influenced segment membership in their study.

Tables viii and ix display the WTP for renewable energy of segment 1 and 2, respectively. It is important to note that segment 1 describes 76.5% of the respondents, while segment 2 only describes the remaining 23.5% of respondents.

Table viii: Segment 1 of 2 - WTP derived from latent class models.

Latent class model **Segment 1**	**n=750** 76.5%	**Pseudo R^2** 0.286	
Variable	**Coefficient**	**Implicit price**	**Implicit price – 95% lower confidence interval**
Price	-0.019***	-	-
Wave constant	2.379***	£128.44	£89.06 - £167.82
Offshore constant	2.902***	£156.66	£117.23 - £196.09
Onshore constant	2.568***	£138.60	£101.87 - £175.32
Wave wildlife	0.091***	£4.89	£3.53 - £6.26
Offshore wildlife	0.080***	£4.32	£3.17 - £5.46
Onshore wildlife	0.074***	£4.00	£2.88 - £5.12
Wave shore distance	0.025	£1.36	£-1.45 - £4.17
Offshore shore distance	-0.040	-£2.17	£-5.5 - £1.15
Wave NIMBY	-0.130	-£7.03	£-39.84 - £25.78
Offshore NIMBY	-0.185	-£9.96	£-48.28 - £28.36
Onshore NIMBY	-0.175	-£9.47	£-35.66 - £16.73
Orkney	0.137	£7.39	£-10.58 - £25.37
North	-0.190	-£10.25	£-30.37 - £9.87
East	-0.366*	-£19.78	£-39.96 - £0.39
Wind farm near home	1.380***	-	-
*, ** and *** denote statistical significance at the 10, 5 and 1% levels, respectively.			

Table viii shows that the respondents in segment 1 view renewable energy favourably, as they are WTP an additional £130 to £160 per year to obtain their electricity from renewable sources instead of conventional sources. The 95% confidence intervals reveal that there is no significant WTP for one renewable technology over the other. The most striking aspect of table viii is how closely it resembles the results of the basic MNL model reported in table iii. The latent class model suggests that the preferences of 76.5% of respondents would have been represented accurately by the basic MNL model.

Table ix: Segment 2 of 2 - WTP derived from latent class models.

Latent class model **Segment 2**	**n=750** 23.5%	**Pseudo R^2** 0.286	
Variable	**Coefficient**	**Implicit price**	**Implicit price – 95% lower confidence interval**
Price	-0.006***	-	-
Wave constant	-3.958***	-£633.42	£-793.66 - £-473.17
Offshore constant	-3.282***	-£525.12	£-694.75 - £-355.49
Onshore constant	-7.284***	-£1,165.52	£-1461.42 - £-869.63
Wave wildlife	0.041***	£6.63	£2.29 - £10.97
Offshore wildlife	0.028*	£4.53	£-0.05 - £9.11
Onshore wildlife	0.128*	£20.52	£-3.41 - £44.45
Wave shore distance	0.087**	£13.93	£3.21 - £24.66
Offshore shore distance	0.053	£8.54	£-5.66 - £22.74
Wave NIMBY	1.223***	£195.68	£73.15 - £318.22
Offshore NIMBY	0.644	£103.13	£-38.28 - £244.55
Onshore NIMBY	0.668	£106.94	£-295.39 - £509.27
Orkney	0.792***	£126.80	£47.44 - £206.17
North	0.820**	£131.18	£24.53 - £237.83
East	0.120	£19.17	£-63.01 - £101.35
Wind farm near home	4.915***	-	-
*, ** and *** denote statistical significance at the 10, 5 and 1% levels, respectively.			

However, table ix displays a very different set of preferences. The results here are the extreme opposite of the results displayed in table viii. The most interesting result is that the 20% of respondents who make up group 2 would be WTP substantial amounts to avoid installing renewable electricity generators. The average respondent in segment 2 is WTP between £525 and £1165 per year to receive electricity from conventional sources, instead of renewable sources. These respondents are particularly opposed to onshore wind power, which has a statistically significantly lower coefficient than wave power and offshore wind power. This may mean that the respondents in segment 2 are attaching attributes which are not included in the CE to the labels, or as is more likely the case, they may simply represent protest responses. The robustness of the wildlife coefficient is again evident as the respondents in segment 2 still have a positive WTP to improve wildlife outcomes, although only at the 10% level of significance in the case of wildlife affected by offshore and onshore wind farms. It is also notable that these respondents are WTP approximately £125 per year to ensure that any renewable energy projects are built in the north of Scotland or on Orkney, which are the two most sparsely populated regions of Scotland. Prior to the distribution of the CE it was expected that the majority of respondents would prefer renewable energy projects to be placed in these remote regions. However, it appears that the respondents in segment 1 view renewable energy favourably regardless of its location, unless it negatively affects wildlife.

Interestingly, the 3 segment model produced similar results to the 2 segment model. The respondents in segment 1 were split fairly evenly into two segments. 33.5% of respondents primarily favour positive environmental outcomes for wildlife, while also moderately supporting renewable energy. 43.8% of respondents heavily favour renewable energy and are less concerned about wildlife. The protest group shrinks slightly to 22.8% in the 3 segment model. While the coefficients on the technology constants remain heavily negative, it is also revealed that the price coefficient is no longer statistically significant for this group. This provides evidence that the respondents in segment 2, of the two segment model, did not pay attention to the price of their choices and it is therefore likely that the majority were simply protest responses.

7. Conclusion

The objective of this paper was to establish how much Scottish households are willing to pay, through increased electricity charges, to increase the proportion of renewable sources in Scotland's electricity supply such that the Scottish Government's 2020 energy targets are achieved. The presentation of multiple discrete choice models reveals that this is not a straightforward question, as it has been demonstrated that preference heterogeneity significantly affects the WTP calculation at the 5% level of significance.

The latent class model, reported in section 6, overcomes the potential collinearity problems which may affect the multinomial logit model, reported in section 5, which interacts SECs with the ASCs. The latent class model reveals that the preferences of the majority of Scottish households (76.5%) are reflected well by the multinomial logit model which does not include SECs. This suggests that these households are WTP an additional £89 - £196 per year to increase the proportion of renewable sources in the electricity supply. The results also demonstrate that, ceteris paribus, there is no statistically significant difference in the WTP between the renewable energy sources included in the CE: wave power, offshore wind and onshore wind. This suggests that higher subsidies for one renewable technology over the other cannot be justified unless they are accompanied by other significant improvements, such as an improvement in environmental outcomes relative to the alternatives.

Crucially, the latent class model illustrates that there is a sizeable minority of households (23.5%) which do not wish to pay anything to increase the proportion of renewable sources in the electricity supply. Indeed, their opposition is so strong that they are WTP to avoid the increased use of renewable electricity. Table vii indicates that households who fall into this latter category are likely to believe that CO_2e output is not an important attribute in choosing between energy sources. This group may prefer that conventional sources, such as coal, oil and gas should be used to generate electricity, or they may prefer that Scotland retains its nuclear power capacity, as is suggested by table ii.

It is notable that the coefficients on wildlife variables remain fairly stable throughout the models presented in this paper, with respondents WTP between £3 and £10 to improve wildlife outcomes by one level, as described in section 3. This corroborates findings from previous literature on the topic, with near identical WTP identified by Bergmann et al. (2006), and also the results of the questions relating to the importance of each attribute in the CE, which stated that wildlife impact was the most important attribute in choosing between energy sources.

A novel approach to include actual house values as part of the SECs which are interacted with the ASCs reveals that house value is significant and negative at the 5% level. This could suggest that respondents with high value properties are concerned with the possibility that their house value may decrease due to the installation of renewable power sources or that their electricity bills may increase disproportionately due to the positive correlation of house size and house prices.

Throughout the model estimations it was evident that respondents had no statistically significant WTP to avoid renewable electricity generators from being placed in their own region. This supports much of the previous research on the topic; however, the regions included in the survey were very large geographic areas so it is possible that NIMBY characteristics may exist at a more local geographic level.

8. Acknowledgements

Neil Odam would like to thank the Marine Alliance for Science & Technology Scotland (MASTS) and the Economic and Social Research Council (ESRC) for funding this research. Special thanks are due to Sergio Colombo, Dugald Tinch, Elena Tinch, Mirko Moro, Mikolaj Czajkowski and Kati Torres for their help during this research. The views expressed in this paper are the author's alone and he is solely responsible for any errors.

10. References

Bergmann, A., Hanley, N., Wright, R. (2006), Valuing the attributes of renewable energy investments. Energy Policy 34 (9), pp. 1004–1014.

BERR (2011), Business, Enterprise and Energy, High Level Summary of Statistics Trends, http://www.scotland.gov.uk/Topics/Statistics/Browse/Business/TrendData, last accessed 13/10/2011.

Carlsson, F., Frykblom, P. And Lagerkvist, C. J. (2005), Using cheap talk as a test of validity in choice experiments, Economic Letters, Vol. 89, Issue 2, pp. 147-152, http://dx.doi.org/10.1016/j.econlet.2005.03.010

ChoiceMetrics (2011), Ngene 1.1 User Manual and Reference Guide, the Cutting Edge in Experimental Design, http://www.choice-metrics.com, last accessed 13/10/2011.

Colombo, S., Hanley, N. and Louviere, J., (2009), Modeling preference heterogeneity in stated choice data: an analysis for public goods generated by agriculture, Agricultural Economics, Vol. 40, pp. 307–322.

DECC (2010), Department of Energy and Climate Change, Energy Trends, September 2011, https://restats.decc.gov.uk/cms/regional-renewable-statistics/#Data, last accessed 13/10/2011.

DECC (2011), Department of Energy and Climate Change, Digest of United Kingdom Energy Statistics 2011, http://www.decc.gov.uk/assets/decc/11/stats/publications/dukes/2312-dukes-2011--full-document-excluding-cover-pages.pdf, Page 145, last accessed 13/10/2011.

DWP (2011), Department for Work and Pensions, Clay, S., Herring, I., Metcalf, S., Sullivan, J., Vekaria, R., Family Resources Survey: United Kingdom, 2009-10, May 2011, http://research.dwp.gov.uk/asd/frs/2009_10/frs_2009_10_report.pdf, last accessed 12/11/2011.

Eltham, D. C., Harrison, G. P. and Allen, S. J. (2008), Change in public attitudes towards a Cornish wind farm: Implications for planning, Energy Policy, Vol. 36, Issue 1, pp. 23-33, 10.1016/j.enpol.2007.09.010.

Ek, K. (2002), Valuing the Environmental Impacts of Wind Power: A Choice Experiment Approach, Licentiate Thesis, Lulea University of Technology.

Ek, K. (2005), Public and private attitudes towards “green” electricity: the case of Swedish wind power, Energy Policy, Vol. 33, Issue 13, pp.1677-1689, http://dx.doi.org/10.1016/j.enpol.2004.02.005

Fimereli, E., S. Mourato and P. Pearson. (2008), Measuring Preferences for Low-Carbon Energy Technologies in South-East England: The Case of Electricity Generation, ENVECON, London, http://www.webmeets.com/files/papers/EAERE/2008/800/Paper_EAERE_2008.pdf

Firestone, J. and Kempton, W. (2009), Public opinion about large offshore windpower: underlying factors, Energy Policy, Vol. 35, pp. 1584–98.

Greene, W. H. (2007), LIMDEP Version 9.0/NLOGIT Version 4.0 Econometric Modelling Guide, Econometric Software, New York: Plainview.

GROS (2011a), General Register Office for Scotland, Population Estimates Time Series Data, http://www.gro-scotland.gov.uk/statistics/theme/population/estimates/mid-year/time-series.html, last accessed 15/10/2011.

GROS (2011b), General Register Office for Scotland, Scotland's Population 2010: The Registrar General's Annual Review of Demographic Trends 156th Edition, Chapter 9: Households and Housing, http://www.gro-scotland.gov.uk/files2/stats/annual-review-2010/j176746-11.htm, last accessed 12/11/2001.

Hensher, D. A., Rose J. and Greene W.H. (2005), Applied Choice Analysis: A Primer, Cambridge University Press: Cambridge.

Krohn, S. and Damborg, S. (1999), On public attitudes towards wind power, Renewable Energy, 16, pp. 954-960.

Krueger, A.D., Parsons, G.R. and Firestone, J. (2011), "Valuing the Visual Disamenity of Offshore Wind Projects at Varying Distances from the Shore", *Land Economics* 87.2 pp. 268-283. Available at: http://works.bepress.com/george_parsons/7

Ladenburg, J. and Dubgaard, A. (2007), Willingness to pay for reduced visual disamenities from offshore wind farms in Denmark, Energy Policy, Vol. 35, Issue 5, pp. 4059-4071, http://dx.doi.org/10.1016/j.enpol.2007.01.023

Ladenburg, J. (2008), Attitudes towards on-land and offshore wind power development in Denmark; choice of development strategy, Renewable Energy, Vol. 33, pp. 111 – 118, http://dx.doi.org/10.1016/j.renene.2007.01.011

Lancaster, K. J. (1966), A new approach to consumer theory, Journal of Political Economy74, pp. 132-157.

Meyerhoff, J., Ohl, C., Hartje, V. (2010), Landscape externalities from onshore wind power, Energy Policy, Vol. 38, Issue 1, pp. 82-92, http://dx.doi.org/10.1016/j.enpol.2009.08.055

Odam (2011), Comparison of Choice Experiment Elicitation Methods: Online Advertising compared to mail shot, University of Stirling, Working paper.

Registers of Scotland (2011), Quarterly Statistics Time Series, Residential Property, http://www.ros.gov.uk/public/news/quarterly_statistics_time_series.html, last accessed 12/11/2011.

Scottish Government (2011a), 2020 Routemap for Renewable Energy in Scotland, http://www.scotland.gov.uk/Resource/Doc/917/0118802.pdf

Scottish Government (2011b), Government Expenditure & Revenue: Scotland 2009-2010, June 2011, http://www.scotland.gov.uk/Resource/Doc/352173/0118332.pdf, last accessed 12/11/2011.

SHS (2011), Scottish Household Survey, Scotland's People – Annual report: results from 2009/2010, http://scotland.gov.uk/Topics/Statistics/16002/PublicationAnnual, last accessed 16/10/2011.

Westerberg, V.H., Jacobsen, J.B and Lifran, R. (2011), Offshore wind farms in the Mediterranean Seascape – A tourist appeal or a tourist repellent?, International Conference on Landscape Economics, July 2011.

Appendix A

Council area	Total households	Sampled households	Average of all house prices (Q3 2010)	Average of sampled house price (Normalised to Q3 2010)
Aberdeen City	103,438	53	£185,502	£184,115
Aberdeenshire	102,626	53	£210,364	£177,389
Angus	50,343	26	£143,528	£105,152
Clackmannanshire	22,967	12	£117,951	£99,610
Dundee City	69,228	35	£124,171	£146,813
East Ayrshire	53,459	27	£120,549	£149,363
East Dunbartonshire	42,915	22	£216,644	£352,452
East Lothian	42,385	22	£215,705	£216,021
East Renfrewshire	35,799	18	£201,177	£222,996
Edinburgh, City of	218,774	112	£216,597	£277,520
Eilean Siar	11,893	5	£95,429	£67,433
Falkirk	68,223	35	£128,709	£142,147
Fife	160,372	82	£133,388	£120,405
Glasgow City	281,743	144	£135,441	£205,104
Highland	100,906	27	£155,392	£185,758
Inverclyde	36,595	19	£119,115	£173,166
Midlothian	34,820	18	£173,208	£147,069
Moray	38,954	20	£145,454	£114,478
North Lanarkshire	143,896	74	£111,962	£163,721
Renfrewshire	79,026	47	£123,546	£166,606
Scottish Borders	51,640	26	£170,744	£117,175
South Ayrshire	51,255	26	£157,474	£216,361
South Lanarkshire	136,389	70	£135,460	£156,056
Stirling	37,789	19	£194,328	£168,259
West Dunbartonshire	41,471	21	£114,800	£158,718
West Lothian	72,569	37	£140,288	£183,351
Argyll and Bute	41,422	19	£153,731	£98,410
Dumfries and Galloway	68,161	29	£137,207	£65,102
North Ayrshire	61,814	32	£118,323	£102,013
Orkney Islands	9,206	13	£110,814	£98,909
Perth and Kinross	64,654	50	£180,069	£176,455
Shetland Islands	9,704	7	£125,522	£139,741
Scotland	**2,344,436**	**1,200**	**£150,393**	**£159,308**

Total households and average household price are from Registers of Scotland (2011)

A comparison of choice experiment elicitation methods

Neil Odam [a]

[a] *University of Stirling, Stirling, FK9 4LA, Scotland, UK*

Abstract

Odam (2011) conducted a choice experiment into different renewable energy scenarios which would enable Scotland to meet its target of generating 100% of its electricity from renewable sources by 2020. Two methods were used to elicit responses for the choice experiment. A traditional mail shot was sent to 1,200 Scottish households. Online advertising was used to generate a similar number of responses to the mail shot.

This paper undertakes a comparison between the two elicitation methods and discusses the strengths and weaknesses of each approach.

Keywords: Choice experiment, Power generation, Renewable energy

---

1. Introduction

Choice experiment (CE) elicitation methods have traditionally fallen into the following three categories: in-person interview, telephone interview and mail survey. In recent years, online surveys have expanded in use, but are still relatively unconventional.

Table A outlines the features of each CE elicitation method.

Table A: Summary of the strengths and weaknesses of each choice experiment elicitation device.

Method	Cost	Response rate	Ease of implementation
In-person	High	High	Moderate
Telephone	↓	↓	Difficult
Mail			Moderate
Internet	Low	Low	Easy

The 'Ease of implementation' column refers to the ease of distributing the survey, the ease of completing the CE for potential respondents and the ease of inputting results. After a CE is designed, a great deal of work is required to distribute the survey to the sample population. In-person interviews and telephone surveys require a large amount of labour to physically conduct the CE. Mail surveys involve many hours of labour to print, fold, label and pack envelopes. Internet surveys require a fraction of this labour to distribute the CE. Most CEs are designed on computers, which mean little additional work is required to develop the Internet-based survey, although it should be noted that some time is required to become familiar with online survey software.

In-person interviews are generally considered to be the ideal CE elicitation method because a well-informed interviewer can generally identify any problems which a survey respondent is experiencing and help to ensure that the CE is completed as intended. A telephone interviewer should also be able to offer instant assistance to the respondent; however, the ease of completing the survey is diminished by the lack of visual cues and the potential difficulty in understanding the verbal questions posed by the interviewer. Both of these methods introduce human interaction into the survey taking process, which adds the possibility that the respondent will be biased by the interviewer. Internet-based CEs allow the analyst to create interactive questionnaires, which can include hyperlinks to further information, video, high resolution pictures, contingent questions and automated piping of respondents into different CE groups.

Conventional survey methods require many hours of labour to manually input CE results, increasing the probability of data entry error. The results from Internet-based surveys can be exported directly into econometric software; however, it will generally be necessary to derive algorithms to modify the raw data into a useable form, meaning that error can still be introduced at this stage. Most of these problems can be mitigated by the use of Computer Assisted Personal Interviews (CAPI) during in-person interviews. However, this will generally require the use of a professional survey organisation, which can be very costly.

Olsen (2009) compares the use of a pre-made Internet panel to a mail survey and concludes that there is not a statistically significant difference in willingness to pay (WTP) between the survey methods. However, the author does report that the mail based CE produces a higher degree of precision compared to the online CE. Similarly, Lindhjem and Navrud (2011) have found that there is no statistically significant difference in WTP between a nationwide face-to-face interview and online survey in Norway. It is for this reason that this paper assumes no a priori reasons that an internet-based elicitation method should generate different results than a mail-based elicitation method, assuming that SECs are weighted appropriately. However, there were indications from respondents' open-ended comments about the CE that the internet-based elicitation method was more likely to attract respondents with either extremely positive or negative views on renewable energy.

Olsen (2009) described the main benefits of pre-made Internet panels as: reduced cost, automatic data input, faster response times, reduction in accidental question omission and the ability to use contingent questions and multimedia in questionnaires. Olsen (2009) identifies the main drawbacks of Internet surveys as: sampling bias due to lack of Internet access and self-selection of respondents.

One further advantage of Internet survey distribution is the increased economic efficiency compared to other methods. The vast majority of the cost of conventional CEs relates to the delivery of the CE to the potential respondent (including material and labour costs), while a small fraction is reserved to compensate the respondent, generally by means of a prize draw. As a result, CEs essentially rely on the charity of the respondent. The introductory paragraphs in CEs tend to become marketing exercises in attempting to persuade the potential respondent that the topic is important enough to warrant the volunteering of their time. As socially beneficial as CEs may be, it is possible that the greatest beneficiary of respondents' time are the analysts themselves, who gain potentially valuable publications. Due to their very low marginal distribution costs, Internet-based surveys offer the possibility of compensating the survey respondent more directly for their time. Compensating respondents in this way is also likely to increase response rates, since James and Bolstein (1992) found that offering a payment of $5 or $10 to complete a survey resulted in the response rate more than doubling after one mailing.

While many Scandinavian countries continue to enthusiastically participate in academic surveys, with response rates upwards of 60%, the UK has never had such a willing population, with response rates generally below 50%. Furthermore, response rates have been steadily declining as alluded to by the following response rates to similar CEs distributed by mail on electricity generation in the UK, which are listed in chronological order: Bergmann (2003) received 43%, Fimereli et al. (2008) received 31% and Odam (2011) received approximately 15%. No other choice experiments on similar topics, which have been distributed by mail in the UK, have been published in recent years. Clearly three data points is insufficient to establish a trend; however, declining response rates have also been observed amongst colleagues in several studies which are currently in progress. Response rates, for similar valuation studies, between 20% and 30% are currently perceived as being good in the UK.

One potential cause for this declining response rate is that it is becoming increasingly difficult to obtain up-to-date and representative names and addresses of households in the UK. From 1832 to 2002, the full electoral roll could be purchased for a nominal fee. Following successful litigation against a local authority selling personal data from the electoral roll (Robertson v City of Wakefield Metropolitan Council, 2001) the UK split the electoral roll into two distinct rolls (Representation of the People Act, 2002). The full electoral roll is used for electoral purposes only, while the edited electoral roll can be purchased by any individual or organisation. Concurrently, an option to opt-out of the edited electoral roll was offered for the first time. This has meant that steadily more households are opting out of the edited electoral roll. Thomas and Walport (2008) report that 40% of households in the UK had opted-out of the edited electoral roll by 2008. It is very unlikely that households will return to the electoral roll once they have opted-out; since their choice to opt-out becomes the default option in future electoral rolls. This means that there will be a steadily declining population to survey in the UK. Furthermore, as the population of eligible households shrinks, it is likely that direct mail will be increasingly concentrated on these remaining households, further incentivizing households to opt-out of the electoral roll.

Thomas and Walport (2008) were commissioned by the UK Government to undertake a review for the use of personal information in both the public and private sectors. One recommendation that they made to the Government was to cease the sale of any electoral roll data to any party, with the exception of political parties and credit reference agencies. Terminating the edited electoral roll will not prevent mail surveys completely because it will still be possible to purchase names and addresses from firms which have permission from their customers to share their details with 3rd parties. However, it is likely that the cost of accessing the edited electoral roll is currently below what the market rate would be without government interference. Removing the edited electoral roll is therefore likely to increase the cost of purchasing names and addresses from legitimate sources and may reduce the representativeness of the sample. In combination with the recent strengthening of consumer rights' to prevent unsolicited mail (DEFRA, 2011), it appears that mail based CEs may soon not be such a cost attractive option in the UK.

Olsen (2009) noted that in Denmark the most severe disadvantage of using Internet surveys relates to the sampling procedure, caused by the lack of access to the Internet for some people. Although this should be a concern, it is important to note that steadily increasing Internet access in much of the world means that this problem could be less severe than other survey methods. For instance, 77% of households in the UK have access to the Internet (ONS, 2011), which compares favourably to the 60% of households that remain on the electoral roll in the UK (Thomas and Walport (2008)). Indeed, the Electoral Commission (2010) reports that up to 80% of households have opted-out of the electoral roll in some regions of the UK.

This paper focuses on the sample selection problems relating to Internet surveys. Survey respondents self-select themselves into the sample population no matter what elicitation method is used. However, mail and Internet surveys are most susceptible to this potential bias due to their relatively low response rates. Olsen (2009) notes that members of an Internet panel have gone through at least two self-selection processes, first by signing-up for the Internet panel and then by signing up for the topic area. Two potential reasons for self-selection are that the survey respondent feels strongly about the topic or that the respondent is knowledgeable about the topic. Both of these reasons are likely to bias the result compared to a true random sample of the population. It should also be noted that respondents who self-select due to knowledge of the subject may provide a more informed opinion than the average respondent. However, it is not obvious that this bias is negative, particularly if the latter reason has caused self-selection.

One disadvantage which is unique to the Internet panel method is that respondents may alter their responses as a direct result of being a member of an Internet panel. If respondents have signed up to an Internet panel for monetary reward then they may have developed strategies to maximise their return by frequently completing surveys with limited engagement with each survey. While it is possible to screen respondents based on the time they took to complete a survey, a respondent may try to evade detection by this screening process in order to remain eligible for other surveys. The very act of completing multiple surveys may alter the way a respondent thinks about surveys and could introduce further bias. In order to avoid the problems specific to Internet panels this paper takes a novel approach to eliciting CE responses via the Internet. Google Adwords, referred to as Adwords henceforth, was used to place advertisements inviting viewers to complete the CE. A £100 prize draw was offered as an incentive to complete the online version of the survey. The paper will compare this method to an identical mail survey, which had a separate £100 prize draw. It will show that despite the social economic characteristics (SECs) being similar across the samples, that the CE results are statistically significantly different and that the aggregate Internet response appears to be WTP unrealistically high amounts for renewable energy technologies. This suggests that the average Internet respondent did not weight their budget constraint, or the trade-offs necessary to pay for improved environmental outcomes, sufficiently.

2. Method

CEs are based on two economic principles. The first is Lancaster's (1966) characteristics theory of value which states that goods do not have innate value but instead consumers derive utility from the attributes of the good. The second is random utility theory, which enables the estimation of a consumer's utility based on the choices they are observed to make. The CE method was used to establish the value which Scottish households place on environmental goods associated with renewable electricity generation, for which no market currently exists, in order to determine the average WTP for wave, onshore and offshore wind generators.

Ngene (ChoiceMetrics, 2011) was used to generate a Bayesian efficient design with 24 choice scenarios. The design had four labelled options to choose from to replace the power output from Scotland's oldest nuclear power station, which is due to be decommissioned in 2016. These options were: wave power, offshore wind power, onshore wind power and an opt-out, from the renewable energy options, of conventional energy sources such as coal and gas, which would not meet the Scottish Government's 2020 renewable energy target. The payment vehicle, represented by an annual increase in a household's electricity bill, included six levels ranging from £0 to £120 per year. A wildlife deterioration attribute with four levels was included for each renewable power option. A visual representation of wave power devices and offshore wind turbines was included to demonstrate the visual impact these technologies had, depending on what distance they placed from the shore. This attribute contained four levels from ranging from 1-12km. An effects coded dummy variable was included to represent 4 distinct regions of Scotland, where the proposed development would take place. The content of the CE and the attributes in the choice scenarios was initially tested on two focus groups, both of which suggested that this choice card was challenging to complete and so the design was blocked into 4 groups, such that each respondent was asked to complete 6 choice scenarios. Odam (2011) describes the CE attributes in greater detail.

Efficient designs have become increasingly prevalent in recent years (Rose et al., 2008) with the recognition that it is generally likely that at least some information will be known about the model parameters prior to the design of a CE. Previous studies by Ek (2002), Bergmann (2006) and Ladenburg (2008) have covered similar topics, on renewable energy, to this paper, which meant that several parameters could be estimated prior to the design. However, this paper did not attempt to replicate any of these previous papers, which means that there is uncertainty about the accuracy of these prior parameter estimates. Bayesian models can be used to incorporate this uncertainty into the design by including both the mean of the normally distributed parameter estimate and the standard deviation of the parameter. Standard deviations from the aforementioned previous papers were used to formulate initial values for the Bayesian model; however, these standard deviations were widened to acknowledge the uncertainty in applying parameter estimates in a different context to the initial studies. A pilot study with 132 observations was then conducted and analysed using this initial design. The results from the pilot study were used to generate updated priors for the Bayesian efficient design[7].

[7] Final design

```
;alts = Wave, Offshore, Onshore, Opt
;eff = (mnl,d,mean)
;rows = 24
;block = 4
;alg=mfederov
;model:
U(Wave) = bWave[(n,4.11,3.00)] + LocOff.effects[(n,-0.15,0.350)|(n,0.2,0.440)|(n,-0.1,0.400)] * LocOff[0,1,2,3]
+ bCost[(n,-0.036,0.01)] * Cost[0,10,20,40,80,120] + bWildlife[(n,-0.16,0.08)] * WildWave[-10,0,10,20]
+ bShore[(n,0.285,0.272)] * ShoreWave[1,4,8,12] /
U(Offshore) = bOff[(n,4.15,2.98)] + LocOff.effects[(n,-0.15,0.350)|(n,0.2,0.440)|(n,-0.1,0.400)] * LocOff[0,1,2,3]
+ bCost[(n,-0.036,0.01)] * Cost[0,10,20,40,80,120] + bWildlife[(n,-0.16,0.08)] * WildOff[-10,0,10,20]
+ bShore[(n,0.285,0.272)] * ShoreOff[1,4,8,12] /
U(Onshore) = bOn[(n,3.01,2.98)]+ LocOn.effects[(n,-0.15,0.350)|(n,-0.1,0.400)] * LocOn[0,1,2]
+ bCost[(n,-0.036,0.01)] * Cost[0,10,20,40,80,120] + bWildlife[(n,-0.16,0.08)] * WildOn[-10,0,10,20]$
```

An almost identical version of the survey was sent to 1,200 households across Scotland, although it should be noted that images demonstrating the visual impact of each technology were included in the survey and these images were higher resolution in the online version than the mail version. Labao et al. (2008, p11), found that “colored photographs positively influenced the overall perception of respondents on the good being valued, translating to higher WTP for the good in question”. This finding could equally apply to higher resolution images and this effect was not controlled for in this experiment.

Adwords was used to elicit responses to the CE. A website was developed for the CE, which was used as a gateway to the survey. This website contained additional information about the CE, which was intended to allay the fears of any respondent who thought that the information contained in the CE itself was insufficient. The online version of the CE was hosted by Survey Gizmo. The software available to design surveys was more than sufficient to present the CE in the desired format, to provide easy accessibility and to provide relevant information to the survey respondent. Features that were particularly helpful include the ability to reveal questions which are contingent on previous answers and the ability to randomly assign each respondent to one of the four CE blocks.

Both search and display advertisements were used to elicit responses. The strict character limit applied to search advertising resulted in the advertisement presented in Figure A being used, while the display advertisement is shown in Figure B. The search advertisement was displayed in the paid result section of Google’s search engine, next to regular search engine results when one of a large list of terms was entered. These terms related to energy, such as ‘Energy Scotland’ or ‘Electricity’, as well as to many Scottish news and discussion sites, such as ‘The Glasgow Herald’ or ‘The Courier Dundee’, both of which are Scottish newspapers. The display advertisements were displayed in the advertising banner spaces of 3rd party websites. A list of Scottish news and discussion sites were specified, such that the display adverts would have a chance of being displayed on these sites, which was also tailored to specific pages on those sites. However, Adwords contextual display network was more successful at eliciting advert clicks. This is where the display adverts were placed on websites based on the search term which had resulted in the user viewing the website, if the site was part of Google's display network.

Figure A: Search advertisement used to elicit responses for choice experiment.

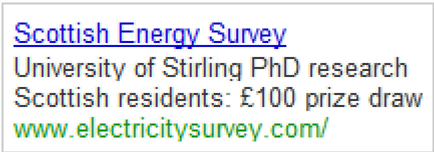


Figure B: Display advertisement used to elicit responses for choice experiment.

Display advertisements are much more flexible than search advertisements because more information can be conveyed. The design was animated to catch the viewer's attention and five different advertisement sizes were made so that they could be displayed on a large variety of websites.

One of the greatest challenges in eliciting responses through online advertising is tailoring the survey to the standards which are set by Adwords. The criterion used by Adwords to display advertisements is not simply based on the highest bid. Instead, each advertisement is rated based on its relevancy to users. Adwords refers to this as the advertisement quality score, which is based on relevancy to the keyword and also to the click through rate. Quality scores are used by Google to ensure that the advertisements which generate the most clicks and therefore revenue are displayed most often. It also avoids abuse of the software by discouraging firms attempting to gain free advertising by having their advertisement viewed, but not clicked.

The advertisement quality score is also based on the relevancy of the target website of the advertisement to the contents of the advertisement. This meant that the website that was set up to accompany the survey was vital to the success of the campaign. It is possible to link advertisements directly to the survey on a survey hosting site such as Survey Gizmo or Survey Monkey. However, Adwords will detect that this website is about surveys, rather than the topic of the survey and it will therefore receive a low quality score. The web domain www.electricitysurvey.com was purchased as the address for the website accompanying the CE. This website was given a much higher quality score by Adwords, because the contents of the site were relevant to the words used in the advertisements. It is more desirable to direct advertisement clickers directly to the survey so that they do not potentially get distracted before getting to the survey, therefore two different campaigns were used to test whether one website was more successful than the other. The higher quality score for www.electricitysurvey.com was reflected in a much higher display frequency, which is displayed in Table B. This table shows that the search adverts had a superior click-through rate and lower cost per click than the display adverts. This result should be expected because it is more likely that someone searching for key words related to the subject of the CE will be more interested in the CE than an average person. The problem with this technique is that CEs tend to investigate topics which are more narrowly focussed than a mass audience is likely to search for, hence resulting in a comparatively low number of impressions and therefore clicks directing the potential respondent to the CE. The main advantage of using display adverts is striking in this table as it is observed that the display adverts were shown more than 20 times as often as the search adverts, in the same period.

Table B: Summary of Google Adwords campaign

Adverts	Impressions	Clicks	Click-through rate	Cost per click
Search	46,850	69	0.15%	£0.56
Display	1,109,289	722	0.07%	£0.94

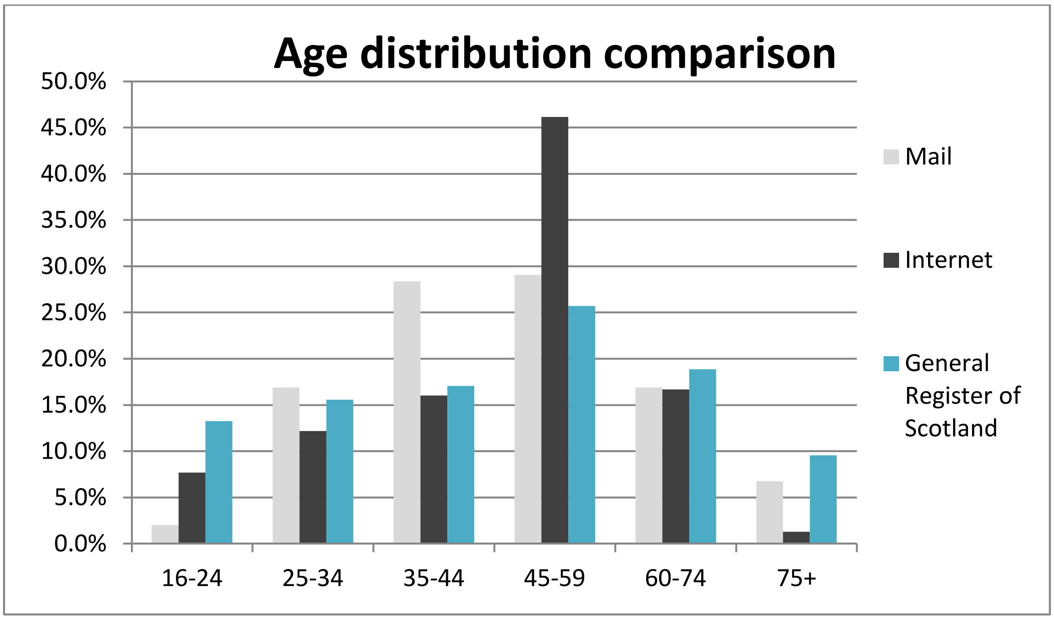
The survey focussed only on Scotland, so online advertisements were targeted at Scottish residents only. This geographic filtering by IP address appeared to work effectively since 100% of respondents reported valid Scottish post codes. In total, advertisements placed on Adwords received 1,156,139 impressions. Impressions simply count the number of times the advertisement is shown. It does not count the number of individuals who have seen the advertisements as it is likely that the advertisements were displayed numerous times to the same web user. The campaign ran from the 20th of May to the 17th of July 2011. 791 of those impressions resulted in a click through to survey, equal to a 0.07% click through rate. 127 of these clicks resulted in fully completed responses. It is difficult to evaluate whether this click through rate was above or below average because Google does not publicise what the average click through rate is. Even if this figure was published, it would be difficult to adjust to the unique circumstances of an academic CE.

It is possible to integrate code from Adwords into web-pages to track which advertisement has resulted in a conversion (i.e. a completed survey). However, it was not possible to integrate this code into specific pages of the survey software, which meant it was not possible to track which advertisement resulted in a conversion.

3.1 Results – Comparison of Socio Economic Characteristics

The average age of respondents to the mail CE was 48.1, while the average age of respondents to the Internet CE was 47.5. The average age is not statistically different from the population average of 47.2 for either sample. However, Figure C reveals that there relatively large differences between the age bands involved in the survey methods. As expected, respondents in the youngest age group were more likely to be included in the Internet CE than the mail CE. Interestingly, this group's representation was still only half what would be expected by a nationally representative sample, suggesting that this age-group is particularly difficult to reach. Integrating the CE with social media is one potential solution to this under-representation. It is clear that Internet-based surveys will have difficulty reaching the 75+ age group since 85.3% of this age group in Scotland did not use the Internet in 2010, compared to only 27.8% of the overall population (SHS, 2011). The over-representation of online respondents between the ages of 45 and 59 is not supported by the Internet usage statistics recorded by the ONS (2011), since this group is no more likely than average to discuss or take part in civic or political discussions online. This suggests that the age group from 45-59 are either more interested in the topic of renewable energy or are more likely to engage with online surveys than other age groups.

Figure C: Age distribution – Comparison of choice experiment mail sample, choice experiment Internet sample and Scotland's population



Source: GROS (2011)

One major difference between the Internet CE and the mail CE is that male representation in the Internet CE was statistically significantly higher than the mail CE proportion. Males make up only 47.9% of the Scottish population (GROSa, 2011). However, 64.1% of Internet respondents were male, compared to 50.7% of mail respondents. While males are still over-represented in the mail CE, this difference was not statistically significant at the 5% level. Males were significantly over-represented in the Internet CE at the 5% level. Weights were applied to the responses for the CE analysis, in order to account for this non-representative sample. Female respondents were weighted more heavily than male respondents so that a representative sample was approximated.

In 2010, there were 5.22 million people in Scotland, living in 2.36 million households (GROS, 2011); resulting in an average household size of 2.213 (including adults and children). The average household size in the mail sample was 2.601, compared to 2.654 in the Internet sample. While there is no statistically significant difference between these samples, both of these samples are significantly higher than the population average of 2.213 at a 5% level of significance. During model estimation, the data was weighted to mitigate the bias caused by this misrepresentative sample. Odam (2011) describes the difficulties in determining the net average household income in Scotland. Differing methods of measuring household income means that the net average household income is within the wide range of £32,000 to £57,000 per year. The net average household income in the mail survey is approximately £42,000 per year, while the equivalent figure is approximately £34,000 per year in the mail survey. The wide range in Scotland's net average income means that both of the sampled average incomes are not statistically different from the national net average household income. However, it is accurate to state that the average net household income in the mail survey is significantly higher than the Internet sample net average household income at the 5% level of significance. This is somewhat unexpected due to the high percentage of Internet survey respondents in the peak earning age category of 45-59. Furthermore, the SHS (2011) shows that there is a strong positive correlation between household income and the probability of having an Internet connection, ranging from only 46% of households in the lowest income band, below £6,000, to 97% in the highest income band, above £40,001. This could suggest that the average income of the mail survey was biased downwards due to the exclusion of council house residents or that lower income respondents are self-selecting into the CE because of the prize draw featured in the advertisements. Council house residents were excluded from the mail survey because Odam (2011) attempted to include house prices as an explanatory variable. Further research on this topic, by varying the expected value of the prize draw on offer, could provide insight into the criteria respondents use when deciding whether to participate in the CE.

3.2 Results – Comparison of opinions on electricity generation.

Table C displays the importance, on a scale of 1-5, which respondents placed on each of the 5 attributes that were included in the choice scenarios. Respondents were given a binary choice for each of the bottom 6 energy opinion questions that were not included in the choice experiment. The two samples displayed broadly similar preferences for the 5 attributes included in the choice scenarios. However, it is notable that the mail survey respondents ranked wildlife as the most important attribute, with cost ranked second, while the two rankings were reversed in the Internet sample. The only significant difference, at the 5% level of significance, between the two samples was that technology was rated significantly more important in the Internet sample than by mail-based respondents. However, it remained the 3rd highest ranked attribute in both samples. A greater proportion of the mail survey respondents stated that CO_2 emissions, safety, impact on jobs and air pollution were important factors affecting the generation of electricity in Scotland compared to the Internet respondents. However, only CO_2 emissions were chosen by a significantly higher proportion compared to the Internet respondents at the 5% level of significance. A greater proportion of the Internet survey respondents stated that security of supply and aesthetics were important aspects compared to the mail respondents. However, only aesthetics were chosen by a statistically significantly higher proportion compared to the mail respondents and it should be noted that aesthetics remained the least important aspect in both samples.

Table C: Comparison of electricity generation attribute importance between mail-based survey and internet-based survey.

Attribute	Mail (n = 141) Scale from 1 - 5	Internet (n = 153) Scale from 1 - 5
Wildlife	3.745	3.526
Cost	3.596	3.562
Technology	3.177	3.493
Location	2.730	2.850
Distance from shore	2.436	2.309
Energy opinions	**Mail Binary choice**	**Internet Binary choice**
CO_2 emissions	0.580	0.481
Security of supply	0.559	0.583
Safety	0.538	0.468
Impact on jobs	0.524	0.494
Air pollution	0.524	0.417
Aesthetic	0.217	0.301

The lower proportion of Internet respondents stating that CO_2 emissions are important combined with the higher proportion stating that security of supply is an important attribute indicates that the Internet sample is less likely to favour renewable electricity generating technologies. This is confirmed by the results in Table D, which compares the views of each sample towards different energy strategies. A significantly higher percentage of the Internet survey respondents agreed with all three statements in Table D, at the 5% level of significance; however, the majority of respondents disagree with the first and second statement in both samples. Odam (2011) demonstrated that the majority of mail survey respondents favoured the retention of nuclear capacity as well as expanding renewable energy generation, which is contrary to the Scottish Government's rejection of nuclear power. The Internet survey respondents corroborate this finding which suggests that the Scottish Government's policy has even less popular support than was suggested by the mail survey respondents. The result is particularly surprising since the survey was sent out six weeks after the tsunami induced nuclear disaster in Fukushima, Japan.

Table D: Comparison of opinions on Scottish energy strategy between mail-based survey and internet-based survey.

Energy attitudes	**Mail (%) (**n = 119)			**Internet (%) (**n = 147)		
Statement	**Yes**	**No**	**Don't know / No opinion**	**Yes**	**No**	**Don't know / No opinion**
I generally favour nuclear power over renewable power generation.	16.2	60.1	23.6	36.5	50.6	12.8
I generally favour conventional energy sources such as gas, coal or oil over renewables.	15.5	62.2	22.3	23.1	71.2	5.8
I think that Scotland should maintain nuclear capacity while also expanding renewable power generation.	54.1	26.4	19.6	62.2	26.3	11.5

3.3 Results – Comparison of WTP for environmental goods from choice experiment analysis.

The multinomial logit model (MNL) is a good starting point for CE analysis if it can be shown that the IIA property is not violated. Given a consumer's utility function for a number of alternatives:

$U(alternative\ 1) = \beta_1' x_{i1}$,

$U(alternative\ 2) = \beta_2' x_{i2}$,

...

$U(alternative\ J) = \beta_J' x_{iJ}$.

The probability of choosing option j is given by:

$$\mathrm{Prob(choice\ j)} = \mathrm{Prob}\left(\mathrm{U_j} > \mathrm{U_q}\right), \forall \mathrm{q} \neq \mathrm{j}$$

$$= \frac{\exp\,(\beta_j' x_{ij})}{\sum_{q=0}^{J} \exp\,(\beta_q' x_{iq})}, j = 0, \ldots, J.$$

The Hausman-test of IIA was applied to both MNL models presented in Table ii and Table iii to determine whether the IIA property was violated. The Hausman-test evaluates the ratio of any two alternatives remains constant despite the presence or absence of any other alternative with the set of alternatives included in the CE (Hensher et al., 2005). The Hausman-test failed to reject the hypothesis that IIA was not violated, thus suggesting that MNL is sufficient for this CE. Therefore a random parameter model which relaxes the IIA assumption was not necessary in this study.

Table E compares the WTP estimates generated by the MNL models for mail and Internet respondents when only no SECs are included in the model. The marginal willingness to pay (WTP) gives a measure of the change in welfare due to a marginal change in a given attribute and is defined as the maximum amount an individual is willing to pay in exchange for what they perceive to be an improvement in the level of a given attribute. It can be derived from the result tables using the following formula:

$$MWTP = -\frac{\beta.attribute}{\beta.price}$$

Each alternative specific constant (ASC) is significant at the 5% level in both samples. However, respondents to the mail survey were willing to pay significantly more for offshore wind than for wave or onshore wind power, at the 5% level of significance, while respondents in the Internet survey were willing to pay significantly more for wave power than offshore or onshore wind, at the 5% level of significance. The only significant difference between the ASCs of the two samples is that the Internet respondents were willing to pay significantly more for wave power than the mail survey respondents at the 5% level of significance. One source of bias which could potentially explain this result is that respondents had to select their choice slightly differently in the Internet survey than in the mail survey. It is best practice to vary which alternative is placed first in the survey to avoid bias arising from respondents selecting the first option. However, this was not done in this CE due to the complexity of the choice card and because of the two elicitation methods used. In the mail survey the respondents were asked to mark the box directly below the technology they preferred. In the internet survey, it was not possible to display the check boxes in exactly the same way. Instead, 4 radio buttons were presented beneath the choice cards. This could explain the preference for wave power in the internet survey since this was the first radio button presented.

Both samples were willing to pay very similar amounts to improve wildlife outcomes by one level, as described in Odam (2011). The only significant difference in preferences for wildlife protection was that the Internet respondents were willing to pay statistically significantly more to protect wildlife from offshore wind turbines compared to onshore wind turbines. This could suggest that Internet respondents were more concerned about migratory birds, which are relatively more likely to encounter offshore wind turbines than domestic birds. However, it should be noted that the difference is small in magnitude, at £1.50 per household per year.

Internet respondents were willing to pay statistically significantly more to increase the distance that offshore wind turbines are placed from shore compared to the mail respondents who were not prepared to pay significantly more than 0 to increase the distance offshore wind turbines are placed from shore. However, the mail respondents were willing to pay £2.82 per household per year to increase the distance that wave generators would be placed from shore, although only at the 10% level of significance. This is in sharp contrast to the Internet-based respondents who the model suggests are willing to pay a positive value to place wave generators closer to the shore. This result is not rational and in combination with the low importance placed on this variable in Table C, it appears likely that many respondents ignored this attribute for wave power.

No statistically significant willingness to pay was observed for the location of renewable technologies in the Internet sample. However, the mail sample was prepared to pay significantly more to have renewable technologies placed in Orkney or the west, compared to the east at the 5% level of significance.

Table E: Comparison of WTP derived from multinomial logit models for mail-based choice experiment and internet-based choice experiment, excluding socio-economic characteristics.

Multinomial logit model	Mail Pseudo R^2	n=792 0.188		Internet Pseudo R^2	n=882 0.126	
Variable	**Coefficient**	**Implicit price**	**Implicit price– 95% confidence interval**	**Coefficient**	**Implicit price**	**Implicit price– 95% confidence interval**
Price	-0.014***	-	-	-0.012***	-	-
Wave constant	1.883***	£138.67	£108.89 - £168.45	2.799***	£243.28	£209.62 - £276.93
Offshore constant	2.488***	£183.22	£153.81 - £212.62	1.973***	£171.50	£136.27 - £206.73
Onshore constant	1.799***	£132.50	£107.46 - £157.54	1.773***	£154.12	£124.81 - £183.43
Wave wildlife	0.069***	£5.08	£3.83 - £6.34	0.049***	£4.30	£3.04 - £5.56
Offshore wildlife	0.064***	£4.73	£3.6 - £5.86	0.059***	£5.09	£3.8 - £6.39
Onshore wildlife	0.058***	£4.28	£3.13 - £5.43	0.041***	£3.59	£2.31 - £4.86
Wave shore distance	0.038*	£2.82	£-0.05 - £5.69	-0.041***	-£3.60	£-6.53 – £-0.68
Offshore shore distance	-0.018	-£1.35	£-4.69 - £1.98	0.062***	£5.42	£1.57 - £9.26
Wave NIMBY	0.230	£16.93	£-15.52 - £49.39	-0.251	-£21.80	£-54.22 - £10.62
Offshore NIMBY	-0.105	-£7.74	£-44.13 - £28.65	0.201	£17.50	£-16.16 - £51.16
Onshore NIMBY	0.007	£0.48	£-28.39 - £29.35	-0.140	-£12.16	£-41.47 - £17.15
Orkney	0.244*	£17.98	£-0.28 - £36.23	-0.055	-£4.82	£-25.25 - £15.61
North	-0.122	-£9.02	£-29.23 - £11.2	-0.037	-£3.20	£-25 - £18.61
East	-0.352**	-£25.92	£-46.56 - £-5.27	-0.064	-£5.57	£-27.29 - £16.16
*, ** and *** denote statistical significance at the 10, 5 and 1% levels, respectively.						

Table F re-estimates the MNL model with SECs included. This has a major effect on the model as the ASCs are no longer statistically significant in the mail sample, while the ASCs are significantly higher for the Internet sample. Within each sample, no significant difference in WTP between the renewable technologies is identified at the 5% level of significance. The central estimates for Internet respondents' WTP for renewable energy technologies appear to be unreasonably high. In combination with the substantially lower pseudo R^2 in the Internet-based CE, it appears likely that the mail-based CE provides more reliable WTP estimates.

Both samples retain their WTP to protect wildlife; however, the mail survey respondents were willing to pay significantly more to protect wildlife from wave generators and onshore wind turbines than the Internet survey respondents, at the 5% level of significance. Including the SECs in the MNL model did not resolve the unexpected negative co-efficient for distance from the shore for wave power generators, which again suggests that some respondents ignored this attribute during completion of the CE.

It is notable that the Not-in-my-back-yard (NIMBY) coefficients were not statistically significant in either sample group under both specifications. The NIMBY coefficient was calculated by setting each respondent's NIMBY dummy variable to 1 if their household resided in the same region as the proposed renewable energy development. This result is contrary to Firestone and Kempton (2009), who found that residents nearby a proposed development in the Cape Cod region of the U.S. were strongly opposed to the development. However, the lack of a NIMBY effect is consistent with Ladenburg (2008) and Ek (2005).

Table F: Comparison of WTP derived from multinomial logit models for mail-based choice experiment and internet-based choice experiment, including socio-economic characteristics.

Multinomial logit model		Mail	n=690	Internet	n=804	
		Pseudo R^2	0.262	Pseudo R^2	0.153	
Variable	**Coefficient**	**Implicit price**	**Implicit price – 95% confidence interval**	**Coefficient**	**Implicit price**	**Implicit price– 95% confidence interval**
Price	-0.013***	-	-	-0.013***	-	-
Wave constant	-0.507	-£38.71	£-229.34 - £151.92	5.104***	£407.73	£251.47 - £564.00
Offshore constant	0.003	£0.24	£-189.75 - £190.23	4.273***	£341.39	£184.38 - £498.41
Onshore constant	-0.648	-£49.41	£-238.87 - £140.05	3.992***	£318.96	£163.5 - £474.42
Wave wildlife	0.071***	£5.41	£4.00 - £6.83	0.047***	£3.78	£2.56 - £4.99
Offshore wildlife	0.067***	£5.08	£3.80 - £6.37	0.059***	£4.74	£3.49 - £5.99
Onshore wildlife	0.057***	£4.35	£3.07 - £5.64	0.038***	£3.02	£1.80 - £4.24
Wave shore distance	0.033	£2.49	£-0.73 - £5.71	-0.055**	-£4.36	£-7.22 - £-1.51
Offshore shore distance	-0.017	-£1.29	£-5.08 - £2.50	0.060	£4.80	£1.05 - £8.54
Wave NIMBY	0.163	£12.44	£-24.26 - £49.13	-0.207	-£16.51	£-47.73 - £14.7
Offshore NIMBY	0.028	£2.15	£-38.32 - £42.63	0.117	£9.32	£-23.48 - £42.12
Onshore NIMBY	-0.025	-£1.88	£-34.27 - £30.51	-0.164	-£13.11	£-41.28 - £15.07
Orkney	0.248*	£18.89	£-1.46 - £39.24	-0.071	-£5.68	£-25.4 - £14.05
North	-0.090	-£6.89	£-29.90 - £16.12	0.021	£1.69	£-19.47 - £22.84
East	-0.203	-£15.45	£-38.63 - £7.72	-0.028	-£2.21	£-23.19 - £18.77
Age	-0.046***	-	-	-0.026**	-	-
Gender	0.985***	-	-	-0.673**	-	-
Education	0.674***	-	-	0.041	-	-
Income	-0.200**	-	-	-0.035	-	-
Wind farm near home	3.165***	-	-	-0.688**	-	-
Work in energy ind.	-1.770***	-	-	-0.499	-	-
Residents	0.832***	-	-	-0.240*	-	-
Full-time emp	0.204	-	-	1.877***	-	-
*, ** and *** denote statistical significance at the 10, 5 and 1% levels, respectively.						

Table G displays the results of a multinomial logit model which pools the mail-based and Internet-based samples. This shows that the average respondent in the combined sample is WTP an additional £161-£215 per year for renewable electricity. The average respondent is WTP approximately £4 per year to improve wildlife outcomes by one level, which is almost identical to the WTP for improvements to wildlife outcomes identified by Bergmann et al. (2006). These results are largely consistent with those reported in Odam (2011), which used a latent class model to identify that the majority of respondents (76.5%) are well represented by the basic multinomial logit model. However, the low pseudo R^2 of the Internet-based sample lowers the overall pseudo R^2, compared to the results presented in Odam (2011).

Critically, table G includes a dummy variable (‘Mail’) which takes the value of 1 if the respondent was part of the mail sample. If the preferences of both samples were equal then the coefficient on this variable should not be significantly different from 0 at the 5% level. However, table G shows that this coefficient is significantly less than 0 at the 5% level, which corroborates the results from table F. This indicates that mail-based respondents are less likely to favour renewable electricity compared to Internet-based respondents.

Table G: Pooled multinomial logit model of mail and Internet responses, including socio-economic characteristics.

Multinomial logit model		**n=**1494	Pseudo R^2: 0.173
Variable	**Coefficient**	**Implicit price**	**Implicit price – 95% confidence interval**
Price	-0.013***	-	-
Wave constant	2.722***	£215.36	£106.61 - £324.11
Offshore constant	2.484***	£196.47	£87.47 - £305.47
Onshore constant	2.036***	£161.03	£52.91 - £269.15
Wave wildlife	0.055***	£4.39	£3.47 - £5.3
Offshore wildlife	0.063***	£4.96	£4.06 - £5.85
Onshore wildlife	0.046***	£3.67	£2.79 - £4.55
Wave shore distance	-0.018	-£1.40	£-3.52 - £0.71
Offshore shore distance	0.026	£2.02	£-0.63 - £4.67
Wave NIMBY	-0.057	-£4.54	£-28.17 - £19.1
Offshore NIMBY	0.059	£4.67	£-20.45 - £29.78
Onshore NIMBY	-0.131	-£10.36	£-31.46 - £10.75
Orkney	0.076	£6.00	£-8.11 - £20.11
North	-0.051	-£4.03	£-19.55 - £11.5
East	-0.099	-£7.82	£-23.29 - £7.66
Age	-0.028***	-	-
Gender	-0.193	-	-
Education	0.320***	-	-
Income	-0.121**	-	-
Wind farm near home	0.770***	-	-
Work in energy ind.	-0.888***	-	-
Residents	0.025	-	-
Full-time employment	1.363***	-	-
Mail	-0.443**	-	-
*, ** and *** denote statistical significance at the 10, 5 and 1% levels, respectively.			

4. Discussion

CEs commonly split the number of choice cards into several blocks, so as to avoid over-burdening respondents with too many choice scenarios. The survey software is particularly adept at dealing with the problem of randomizing which block is seen by each respondent. Traditional CEs will use a database of prospective respondents. The blocks have to be randomized before the CE is delivered. Mail surveys have uncertain response rates and the rate may differ substantially between blocks, which could result in analytic problems. The online survey software randomly assigns each survey respondent to each block. This is still likely to produce different response rates to each block, but the difference will be less systematic.

Adwords is focussed on generating sales for businesses. There are many tools available through Adwords which allow businesses to monitor the performance of their advertising campaigns. It is evident that there are no tools which can be used to evaluate survey participation and it becomes quickly obvious that the software is not set up to accommodate academic surveys. Adwords offers a free consultation with an Adwords advisor. The advisor who called regarding the campaign for the CE was helpful in suggesting more effective keywords and was pivotal in getting the campaign off the ground by increasing the maximum bid per click. It was only after the maximum bid per click was increased from £0.50 to £1.50 on June 22nd that the advertisements were picked up properly. Between the 20th of May and the 22nd of June the advertising campaign received 68,876 impressions with 67 of these resulting in a click through to the survey and 4 fully completed responses being received. The average cost per click was £0.50 during this period which means that each survey response cost £8.95. Between the 22nd of June and the 17th of July the advertisements were displayed 1,080,646 times with 720 clicks through to the survey and 123 fully completed responses being received. While the cost per click increased to £0.94 during this period, the increased conversion of clicks to responses meant that the cost of each survey during this period fell to £5.53. It is important to note that a low click through rate is not necessarily bad for this type of research because it is possible to pay per click, as well as by 1,000 impressions. However, with such a low click through rate it is like that paying per 1,000 impressions would have been more expensive than paying per click.

Online respondents were asked to forward the survey to family and friends, which generated a further 29 responses. For every response generated through Adwords, 0.23 additional responses were generated from respondents forwarding the survey. This study did not include any social media interaction, yet the willingness to share the CE by respondents suggests that social media may facilitate a substantially higher response rate. However, one particularly damaging source of bias was introduced by inviting respondents to share the CE. One respondent concluded that the CE was designed to further the 'anthropogenic global warming myth' and chose to forward the CE to 3 like-minded respondents, all of whom chose the opt-out option for every choice scenario. If groups with very strong preconceived beliefs about the topic are over-represented in the sample then the overall results could be severely biased towards the viewpoints of this group, instead of the population as a whole. Fortunately, it is relatively easy to identify this type of group because the survey software includes the time when the survey was taken, the approximate location of the IP address of the respondent and the time taken to complete the survey. This group was identified and excluded from the CE results by identifying their similar geographic locations, the short time interval between responses, the declaration that the survey was shared by another respondent and the survey duration, which was approximately half the time of the average respondent.

The total cost of this method was £855.44, which resulted in 156 responses, compared to the total cost of the mail survey, which was £1,922.37 for 148 responses. While the cost of the mail survey could have been roughly halved by using only black and white printing, research by Labao (2008) has demonstrated that the valuation of goods can be significantly affected by the choice of whether to use colour images or black and white images.

5. Conclusion

This paper has demonstrated that Internet advertising is a cost-effective method of eliciting responses to choice experiments. Additionally, the elicitation method has the potential to reach younger age groups which are difficult to reach by traditional elicitation methods. Generally, the socio-economic characteristics of the respondents to the Internet-based choice experiment were representative of the population under study and were similar to those of the mail-based choice experiment. However, the one major exception is that respondents were significantly more likely to be male in the internet-based choice experiment at the 5% level of significance.

Overall, this paper indicates that caution should be exercised when interpreting the results of a choice experiment which elicits responses using Internet advertising. It can be observed that the pseudo R^2 of the Internet-based sample is lower than the mail-based sample and that the mean respondent to the Internet-based choice experiment is willing to pay statistically significantly more for renewable electricity than the mean respondent to the mail-based choice experiment. Furthermore, the mean willingness to pay estimates in the Internet-based choice experiment appears to be unrealistically high when socio-economic characteristics are included in the model estimation.

Without knowing in advance whether anyone would complete a choice experiment based on seeing an online advertisement, this project devoted approximately 90% of the project funds to advertising costs and 10% to the prize fund. Having found that a significant number of people are prepared to click on an online advertisement and complete an online survey, it is probable that a greater number of responses would have been received by increasing the prize fund relative to advertising costs. Future research investigating the elasticity of survey responses to the prize fund on offer would be valuable in identifying the most cost-effective strategy to obtain responses. Higher prize funds are likely to lessen self-selection bias as the marginal respondent will be less interested in the survey topic and more interested in the prize fund.

6. Acknowledgements

Neil Odam would like to thank the Economic and Social Research Council (ESRC) and MASTS for funding this research. The views expressed in this paper are the author’s alone and he is solely responsible for any errors.

7. References

Bergmann, A., Hanley, N., Wright, R. (2006), Valuing the attributes of renewable energy investments. Energy Policy 34 (9), pp. 1004–1014.

ChoiceMetrics (2011), Ngene 1.1 User Manual and Reference Guide, the Cutting Edge in Experimental Design, http://www.choice-metrics.com, last accessed 13/10/2011.

DEFRA (2011), Responsibility Deal between the UK, Scottish and Welsh Governments and the direct marketing sector, Department for Environment, Food and Rural Affairs, http://www.defra.gov.uk/publications/files/direct-mail-responsibility-deal-pb13668.pdf, last accessed 21/11/2011.

Ek, K.. (2002), Valuing the Environmental Impacts of Wind Power: A Choice Experiment Approach, Licentiate Thesis, Lulea University of Technology.

Ek, K. (2005), Public and private attitudes towards "green" electricity: the case of Swedish wind power, Energy Policy, Vol. 33, Issue 13, pp.1677-1689, http://dx.doi.org/10.1016/j.enpol.2004.02.005

Electoral Commission (2010), http://www.electoralcommission.org.uk/__data/assets/pdf_file/0005/86927/Response-to-the-Ministry-of-Justice-consultation-final.pdf, last accessed 20/09/2011.

Fimereli, E., S. Mourato and P. Pearson 2008, Measuring Preferences for Low-Carbon Energy Technologies in South-East England: The Case of Electricity Generation, ENVECON, London (2008), http://www.webmeets.com/files/papers/EAERE/2008/800/Paper_EAERE_2008.pdf.

Firestone, J. and Kempton, W. (2009), Public opinion about large offshore windpower: underlying factors, Energy Policy, Vol. 35, pp. 1584–98.

GROS (2011), General Register Office for Scotland, Scotland's Population 2010: The Registrar General's Annual Review of Demographic Trends 156th Edition, Chapter 9: Households and Housing, http://www.gro-scotland.gov.uk/files2/stats/annual-review-2010/j176746-11.htm, last accessed 12/11/2001.

Hensher, D. A., Rose J. and Greene W.H. (2005), Applied Choice Analysis: A Primer, Cambridge University Press: Cambridge.

James, J. M. and Bolstein, R. (1992), Large monetary incentives and their effect on mail survey response rates, Public Opinion Quarterly, Vol. 56, Issue 4, pp. 442 – 453, doi: 10.1086/269336.

Labao, R. Francisco, H., Harder, D. And Santos, F. I. (2008), Do Colored Photographs Affect Willingness to Pay Responses for Endangered Species Conservation?, Environmental and Resource Economics, Vol. 40, No. 2, pp. 251 – 264, DOI: 10.1007/s10640-007-9151-2

Ladenburg, J. (2008), Attitudes towards on-land and offshore wind power development in Denmark; choice of development strategy, Renewable Energy, Vol. 33, pp. 111 – 118, http://dx.doi.org/10.1016/j.renene.2007.01.011

Lancaster, K. J. (1966), A new approach to consumer theory, Journal of Political Economy74, pp. 132-157.

Lindhjem, H. and Navrud, S. (2011), Are Internet surveys an alternative to face-to-face interviews in contingent valuation?, Ecological Economics, 70: 1628 – 1637, doi:10.1016/j.ecolecon.2011.04.002

Odam, N. (2011), Electricity in Scotland: A choice experiment, University of Stirling, Working paper.

Olsen, S.B. (2009), Choosing Between Internet and Mail Survey Modes for Choice Experiment Surveys Considering Non-Market Goods, Environmental Resources Economics, 44: 591 – 610, DOI: 10.1007/s10640-009-9303-7

ONS (2011), Internet Access – Households and Individuals, 2011, http://www.ons.gov.uk/ons/publications/re-reference-tables.html?edition=tcm%3A77-226727, last accessed 24/09/2011.

Robertson v City of Wakefield Metropolitan Council, 2001, http://www.bailii.org/cgi-bin/markup.cgi?doc=/ew/cases/EWHC/Admin/2001/915.html&query=Brian+and+Robertson+and+privacy&method=boolean.

Rose, J. M., Bliemer, M. C. J., Hensher, D. A., Collins, A. T. (2008), Designing efficient stated choice experiments in the presence of reference alternatives, Transportation Research Part B: Methodological, Vol. 42, Issue 4, pp. 395-406, http://dx.doi.org/10.1016/j.trb.2007.09.002

SHS (2011), Scottish Household Survey, Scotland's People – Annual report: results from 2009/2010, http://scotland.gov.uk/Topics/Statistics/16002/PublicationAnnual, last accessed 16/10/2011.

Thomas, R. and Walport, M. (2008), Data Sharing Review Report, UK Ministry of Justice, http://www.justice.gov.uk/reviews/datasharing-intro.htm, last accessed 15/09/2011.

White, I. (2008), Supply and Sale of Electoral Register, House of Commons Library, http://www.parliament.uk/documents/commons/lib/research/briefings/snpc-01020.pdf, last accessed 15/09/2011.

Help shape Scotland's energy future

UNIVERSITY OF STIRLING

Dear <First name, Last name>,

As part of a project investigating the choices facing Scotland relating to electricity generation, the University of Stirling is conducting a survey on the public's preferences for alternative technologies.

The Scottish Government has set an ambitious target to generate 80% of electricity from renewable sources by 2020. As well as meeting self-imposed targets, Scotland's two remaining nuclear power plants will reach the end of their intended lifecycles by 2016 and 2023 respectively. Scotland's energy policy is therefore at a crossroads, which will result in long-term commitments.

Please let us know your opinion about Scotland's energy future by completing this survey. It has been sent to over 1,000 households selected at random from the electoral roll. It would be very much appreciated if you are able to complete this survey, no matter your previous experience with the topic, and post it in the pre-paid envelope provided. Alternatively, the survey can be completed online at www.electricitysurvey.com. Each additional response increases the confidence which can be expressed in the results of the survey so every response is of great value to the study.

If you have any questions about the survey or the project please contact Neil Odam at the University of Stirling by email at N.J.Odam@stir.ac.uk or by telephone on 01786 466 408.

In order to make the survey as short and quick as possible, only essential details are included here. Detailed information is available online at www.electricitysurvey.com. Results will be posted on the website in July 2011. Privacy is taken very seriously; responses will be used only for this research project and no personally identifiable information will be published.

Thank you for your time.

Yours faithfully,

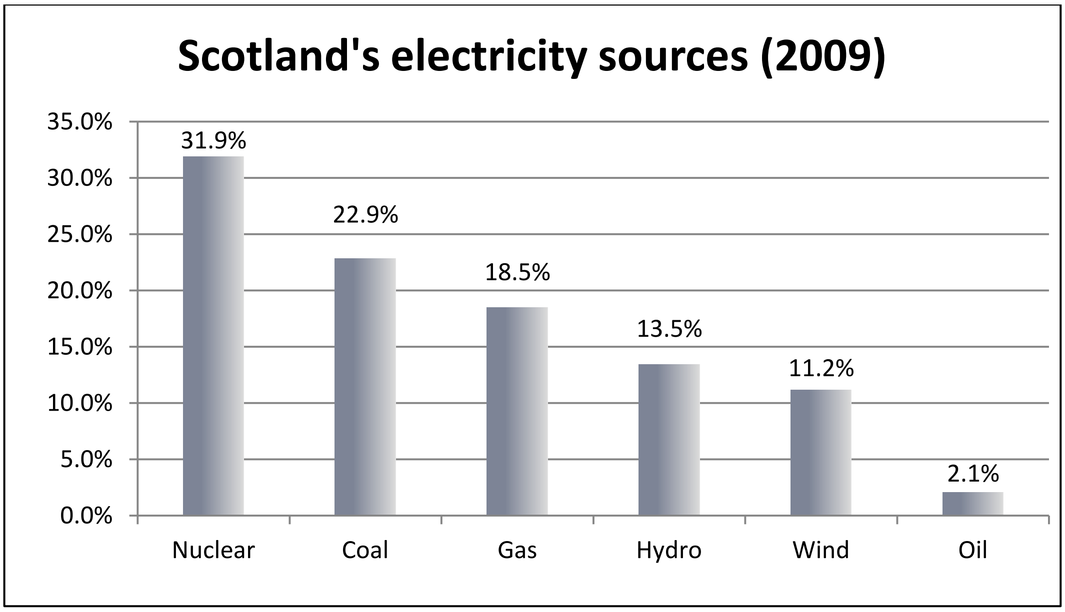
Neil Odam

P.S. Please let us know your opinion about Scotland's energy future by completing this survey and returning it in the pre-paid envelope by **13/05/2011**. As a small token of my appreciation, each respondent is invited to enter a £100 prize draw at the end of the survey.

Introduction

Scotland is in a unique position due to its inherent strong renewable energy resources. As well as having access to some of the best conditions to generate power from the wind in the world, Scotland is also at the forefront of developing renewable technologies such as wave and tidal power. However, these technologies are still in their infancy and many uncertainties exist regarding their performance, cost and impact on the environment.

The graph below shows the energy sources used to generate electricity in Scotland in 2009 (the most recent data available). The Scottish Government's current policy is that no further nuclear power stations will be built in Scotland.



This survey focuses on the expected decommissioning of Hunterston B nuclear power station in North Ayrshire in 2016. Hunterston B currently produces approximately 840MW of power, or 10% of Scotland's total electricity. You will be presented with 6 choice cards, in each of which you will be asked to choose your favourite option. Each scenario will offer the choice between three renewable technologies which could be used to replace the power output from Hunterston B.

The attributes of each technology varies in each scenario, reflecting uncertainties in the cost of each technology and the differing environmental impacts which could result depending on which device is installed and which location is chosen. While some scenarios are more likely to be accurate than others, you are asked to make your decisions as if the attributes in each scenario are true at the point in time when Hunterston B is replaced.

The next two pages contain information about the different attributes which may influence your choice of what technology you would prefer is pursued. A brief summary of each electricity generating technology is also included.

The survey concludes with some questions relating to your circumstances as well as questions relating more generally to your opinions on the topic.

Replacing Hunterston B with wind turbines could involve either onshore or offshore wind farms. This picture shows Europe's largest onshore wind farm, with 140 turbines at Whitelee, just south of Glasgow.

Approximately 750 more onshore wind turbines would be required to replace Hunterston B's annual power output.

One significant cost of replacing fossil fuel plants with wind turbines or wave generators is their intermittency, due to variable wind speed and sea conditions. The main cost of intermittency is that backup power plants, which can be activated quickly, need to be maintained. In the choice cards, the cost of this backup capacity is included in the cost of the renewable energy options.

This picture shows an offshore wind farm with 60 turbines at Robin Rigg, off the Dumfries coast.

Approximately 550 more offshore wind turbines would be required to replace Hunterston B's annual power output.

Offshore turbines generally produce more power than onshore turbines because of more consistent wind conditions and the use of larger turbines.

This picture shows a Pelamis wave power generator situated at the European Marine Energy Centre's test site in Orkney.

Approximately 2,200 more wave generators would be required to replace Hunterston B's annual power output.

The primary challenge for wave generators is to survive the harsh sea conditions which exist in the best areas for power generation. The joints of wave power devices resist each wave to generate power.

Wave power is still relatively early in the development cycle. As with most new technologies, wave power is currently significantly more expensive than more mature technologies, such as wind power. However, the cost per unit is likely to fall as more units are added to the electricity grid.

Cost

It is important that you carefully consider the cost of each scenario while taking into account your household budget and by considering what you would have to trade off to pay for any increased electricity bill, whether it is something you consume or a reduction in your planned savings.

In the choice cards, cost is expressed as a change from the current cost of electricity for the average household in Scotland. The average electricity bill in Scotland is approximately £400. This will vary depending on whether gas is also used and on the number of rooms and occupants in the household.

Impact on wildlife

Conventional and nuclear technologies are less likely to have direct impacts on wildlife, but could affect much greater numbers indirectly through medium to long-term pollution.

Impact on wildlife has been split into four levels relative to the current situation:

- Positive - great care is taken in identifying sites which will not harm wildlife. Wildlife may adapt to new technologies so well that wildlife indicators improve.
- No change - some regulation is imposed on the placement of generators to ensure that the most important locations for wildlife are protected.
- Negative - little regulation is imposed on the placement of generators, resulting in new generators being placed in areas which are damaging to wildlife.
- Very negative - no regulation is imposed on the placement of generators, resulting in new generators being placed in areas which are very damaging to wildlife. Unforeseen negative impacts on wildlife caused by the inability of wildlife to adapt to new technologies.

Different types of wildlife are likely to be affected depending on what type of technology is adopted. Birds and bats are most likely to be affected by wind turbines whereas marine species are most likely to be affected by wave power.

Distance from the shore

This attribute includes a picture giving a visual representation of four different distances from the shore for both wave and offshore wind devices. The 'far' alternative contains devices which are only just visible on the horizon while the 'out of sight' alternative relates to any distance beyond which can be seen from the shore.

Location

The shaded area of the maps represent where the generators would be located for this specific project. While renewable technologies would not be limited to these locations, the shaded areas indicate where generators are assumed to be located to replace the nuclear power plant at Hunterston B.

Choice cards

While I am interested in all of your views on energy sources, a good amount of information already exists on preferences for major energy sources, such as between nuclear, oil, gas and renewables. In this survey, I am particularly focusing on options available to Scotland to meet its 2020 renewable electricity target.

As such, the detailed energy scenarios only look at alternative renewable energy sources. I am not advocating these technologies; instead, I am trying to obtain data on the public's preferences between these technologies since little is currently available.

The following three questions give you an opportunity to state that you would prefer Scotland to pursue an alternative energy strategy.

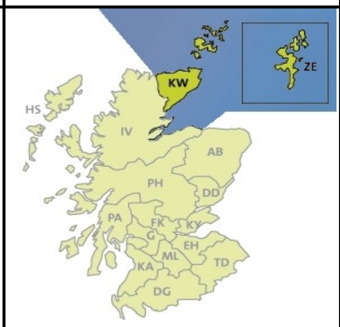
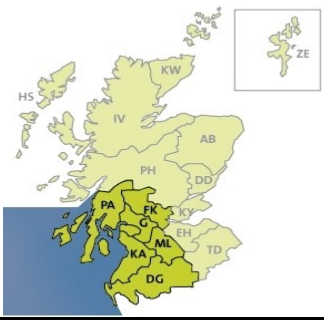
I generally favour nuclear power over renewable technologies.	☐ Yes	☐ No	☐ Unsure
I generally favour conventional energy sources such as gas, coal or oil over renewables.	☐ Yes	☐ No	☐ Unsure
I think that Scotland should maintain nuclear capacity while also expanding renewable power generation.	☐ Yes	☐ No	☐ Unsure

Example scenario

The table below presents an example of a potential scenario facing Scotland.

There are many factors which may affect your decision. In this scenario wave power is the most expensive option. If you are particularly in favour of wave power or prefer that power generators are built in the north of Scotland and around the Northern Isles, or you place a high value on preserving wildlife then this may be a good choice. Onshore wind is the cheapest renewable option in this scenario but has a highly negative wildlife impact and may cause higher visual impacts depending on your preferences.

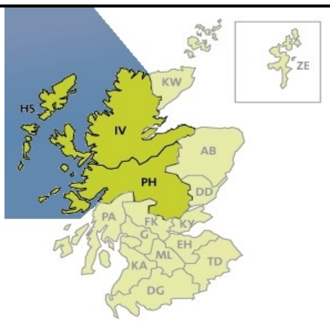
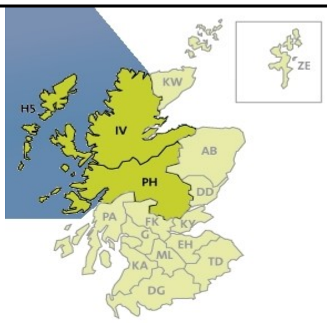
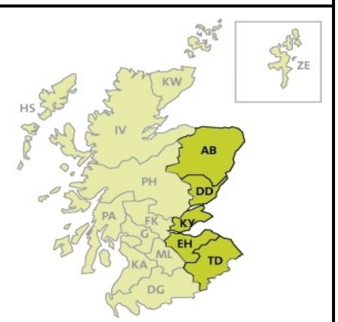
Finally, there is an option to state that you would prefer Scotland to drop its renewable energy targets and instead build more coal, oil or gas power plants. This is the lowest cost option in this scenario but would result in higher CO_2 emissions and higher air pollution.

Sample card	Wave	Offshore wind	Onshore wind
Distance from shore	 Medium (4km)	 Near (1km)	 Onshore
Increased cost of electricity per year per household	£80 (20% increase)	£40 (10% increase)	£20 (5% increase)
Wildlife Impact	Positive	No change	Very negative
Location			
Choice	☐	☐	☐
None of the above - No additional renewable electricity. New gas, coal or oil generators built instead. Electricity cost remains the same. Higher air pollution and carbon output.	☐		

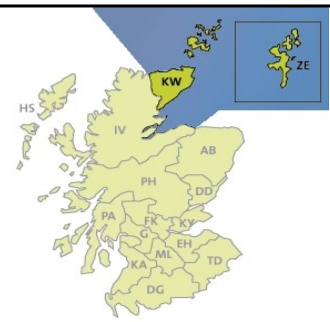
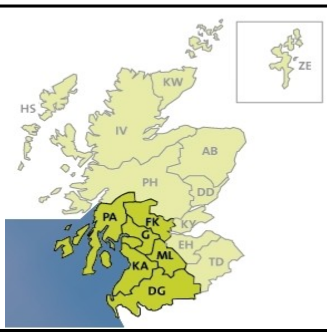
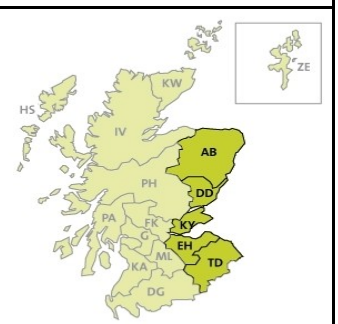
Your responses are not being judged in any way. Every attempt has been made to phrase questions in such a way to avoid introducing bias to your answers to ensure that you can express your real preferences. **There are no right or wrong answers.**

Each choice card should be considered independently. The attributes in each scenario change to reflect uncertainty in the development of renewable technologies.

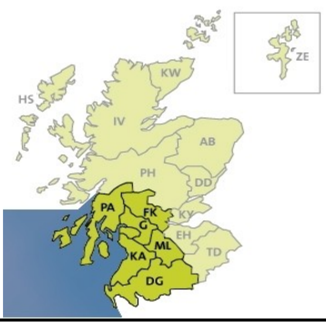
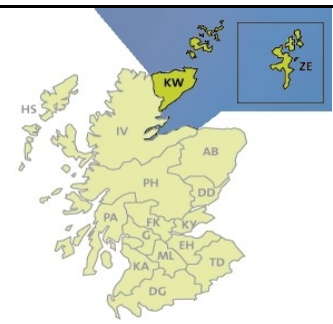
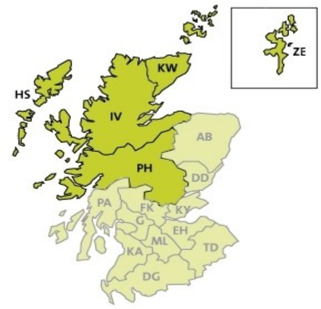
Choice card A

	Wave	**Offshore wind**	**Onshore wind**
Distance from shore	 Near (1km)	 Far (8km)	 Onshore
Increased cost of electricity per year per household	£120 (30% increase)	£120 (30% increase)	£0 (no change)
Wildlife Impact	⇩ ⇩ Very negative	⇩ Negative	⇧ Positive
Location			
Choice	☐	☐	☐
None of the above - No additional renewable electricity. New gas, coal or oil generators built instead. Electricity cost remains the same. Higher air pollution and carbon output.	☐		

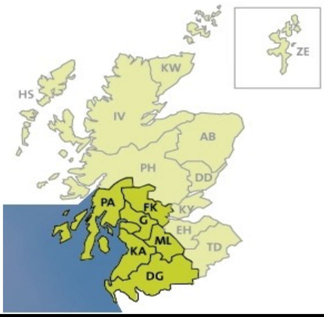
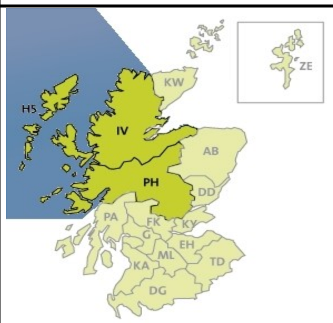
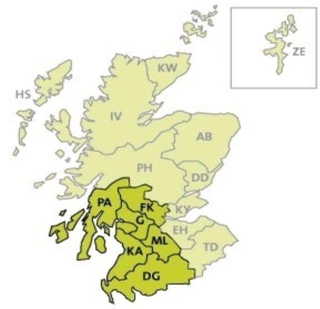
Choice card B

	Wave	**Offshore wind**	**Onshore wind**
Distance from shore	 Medium (4km)	 Near (1km)	 Onshore
Increased cost of electricity per year per household	£80 (20% increase)	£80 (20% increase)	£40 (10% increase)
Wildlife Impact	⇩ Negative	⇧ Positive	⇩ Negative
Location			
Choice	☐	☐	☐
None of the above - No additional renewable electricity. New gas, coal or oil generators built instead. Electricity cost remains the same. Higher air pollution and carbon output.	☐		

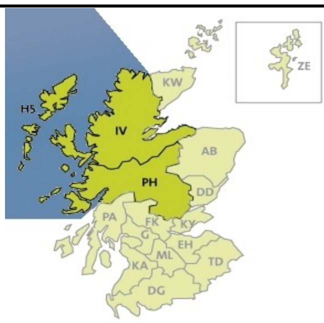
Choice card C

	Wave	Offshore wind	Onshore wind
Distance from shore	 Out of sight (>12km)	 Far (8km)	 Onshore
Increased cost of electricity per year per household	£0 (no change)	£80 (20% increase)	£80 (20% increase)
Wildlife Impact	⇩ ⇩ Very negative	⇩ Negative	⇔ No change
Location			
Choice	☐	☐	☐
None of the above - No additional renewable electricity. New gas, coal or oil generators built instead. Electricity cost remains the same. Higher air pollution and carbon output.			☐

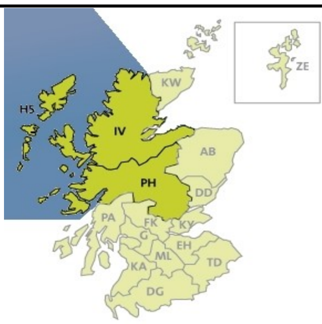
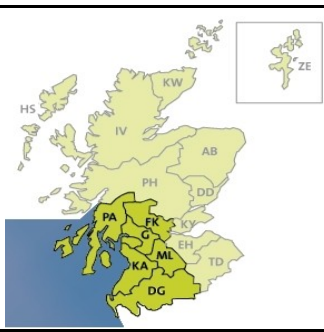
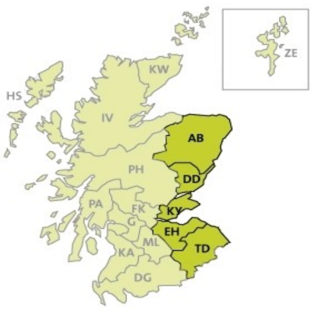
Choice card D

	Wave	Offshore wind	Onshore wind
Distance from shore	 Far (8km)	 Near (1km)	 Onshore
Increased cost of electricity per year per household	£120 (30% increase)	£120 (30% increase)	£40 (10% increase)
Wildlife Impact	⇔ No change	⇧ Positive	⇩ ⇩ Very negative
Location			
Choice	☐	☐	☐
None of the above - No additional renewable electricity. New gas, coal or oil generators built instead. Electricity cost remains the same. Higher air pollution and carbon output.			☐

Choice card E

	Wave	Offshore wind	Onshore wind
Distance from shore	 Near (1km)	 Near (1km)	 Onshore
Increased cost of electricity per year per household	£20 (5% increase)	£10 (2.5% increase)	£20 (5% increase)
Wildlife Impact	⇩ Negative	⇩ Negative	⇩ Negative
Location			
Choice	☐	☐	☐
None of the above - No additional renewable electricity. New gas, coal or oil generators built instead. Electricity cost remains the same. Higher air pollution and carbon output.			☐

Choice card F

	Wave	Offshore wind	Onshore wind
Distance from shore	 Near (1km)	 Out of sight (>12km)	 Onshore
Increased cost of electricity per year per household	£0 (no change)	£40 (10% increase)	£10 (2.5% increase)
Wildlife Impact	⇧ Positive	⇩ ⇩ Very negative	⇔ No change
Location			
Choice	☐	☐	☐
None of the above - No additional renewable electricity. New gas, coal or oil generators built instead. Electricity cost remains the same. Higher air pollution and carbon output.			☐

Demographic questions
Why is this information necessary?

These questions serve two vital purposes. Firstly, the answers are used to ensure that all the respondents, taken together, provide a representative sample of the Scottish population or allow any sample bias to be taken into account.

Secondly, a major component of the survey is the cost involved in each electricity scenario. Household income is likely to affect a respondent's willingness to pay for electricity.

Any information provided by respondents will be:
- stored securely.
- used solely for the purpose of this research into people's preferences towards energy sources.
- subject to strict confidentiality.

A detailed privacy policy can be found on www.electricitysurvey.com/privacy-information

1. I am ☐ Female ☐ Male

2. I am ______ years old.

3. What is your postcode? ________

4. How many people reside in your house (including yourself)? ______

5. What is your status at this house? ☐ I own the property. ☐ I live in the property rent free.

☐ I rent the property privately or through a letting agency. ☐ I rent the property from a council.

6. Did you visit the website (www.electricitysurvey.com) accompanying the survey? ☐Yes ☐ No

7. What is your highest level of education?

☐ Primary school ☐ College ☐ Postgraduate degree

☐ Secondary school ☐ University ☐ Other

8. I am currently?

☐ Working full-time ☐ Studying ☐ Retired

☐ Working part-time ☐ Unemployed ☐ Other

9. My household (**all household residents)** income in the past year before taxes is:

☐ Less than £10,000 ☐ £30,000 - £39,999 ☐ £60,000 – £69,999

☐ £10,000 - £19,999 ☐ £40,000 - £49,999 ☐ £70,000 - £79,999

☐ £20,000 - £29,999 ☐ £50,000 - £59,999 ☐ More than £80,000

10. Are you a member of an environmental organisation? ☐ Yes ☐ No

11. Are you a member of the Royal Society for the Protection of Birds (RSPB)?☐ ☐es
No

12. Do you work in/study the energy industry? ☐ Yes ☐ No

£100 Prize draw entry: Email address ____

On receipt of this survey, at the University of Stirling, this section will be cut off and stored securely, separately from your survey, to preserve anonymity. The prize draw will be made in July 2011.

Attitude to energy sources and climate change

In making your decision, how important were the following attributes?

	Ignored	Not important				Very important
	0	1	2	3	4	5
Cost						
Technology						
Wildlife impact						
Location						
Distance from shore						

Are there any other attributes which are important to you? (You may choose more than one.)

☐ CO_2 emissions ☐ Impact on jobs ☐ Air pollution ☐ Security of supply

☐ Aesthetics ☐ Safety ☐ Other ____________________

	Yes	No
Do you think that climate change is a problem which should be taken seriously?	☐	☐
Do you think that humans are the primary cause of accelerating climate change?	☐	☐
Do you think that Scotland should significantly reduce its CO_2 emissions?	☐	☐

The nuclear problems in Fukushima, Japan, have affected my views on energy sources.

Not at all						Very much	Don't know / No opinion
1	2	3	4	5	6	7	8
○	○	○	○	○	○	○	○

The nuclear problems in Fukushima, Japan, have:

Negatively affected my view of nuclear power			Had no impact on my view of nuclear power			Positively affected my view of nuclear power	Don't know / No opinion
1	2	3	4	5	6	7	8
○	○	○	○	○	○	○	○

Are there any wind farms where you live? ☐ Yes ☐ No ☐ Don't know

If yes: How many wind turbines do you see on an average day?

☐ 0-1 ☐ 2-5 ☐ 6-10 ☐ 11-20 ☐ 21+

Can you see wind turbines from your home? ☐ Yes ☐ No

Do you experience nuisances in relation to the wind turbines in your area?

	Major	**Minor**	**Not at all**	**Don't know**
Visual nuisances				
Noise				
Light effects (shadow, flicker)				

Thank you for completing the survey.