Demand response of domestic consumers to dynamic electricity pricing in low-carbon power systems

by

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Abstract

The ability for domestic consumers to provide demand response to dynamic electricity pricing will become increasingly valuable for integrating the high penetrations of renewables that are expected to be connected to electricity networks in the future. The aim of this thesis is to investigate whether domestic consumers will be willing and able to provide demand response in such low-carbon futures. A broad approach is presented in this thesis, with research contributions on subjects including data privacy, behavioural economics, and battery modelling. The principle argument of the thesis is that studying the behaviour of consumers with grid-connected photovoltaic ('PV') systems can provide insight into how consumers might respond to dynamic pricing in future low-carbon power systems, as both experience irregular electricity prices that are correlated with intermittent renewable generation. Through a combination of statistical and qualitative methods, this thesis investigates the demand response behaviour of consumers with PV systems in the UK. The results demonstrate that these consumers exhibit demand response behaviour by increasing demand during the day and decreasing demand during the evening. Furthermore, this effect is more pronounced on days with higher irradiance. The results are novel in three ways. First, they provide quantified evidence that suggests that domestic consumers with PV systems engage in demand response behaviour. Second, they provide evidence of domestic consumers responding to irregular electricity prices that are correlated with intermittent renewable generation, thereby addressing the aim of this thesis, and supporting the assumption that consumers can be expected to respond to dynamic pricing in future markets with high penetrations of renewables. Third, they provide evidence of domestic consumers responding to dynamic pricing that is similar to real-time pricing, while prior evidence of this is rare and confined to the USA.

Keywords: demand response; flexible demand; low-carbon electricity; dynamic pricing; photovoltaic; feed-in tariff; data privacy; behavioural economics; battery model.

List of publications

Journal papers:

Eoghan McKenna, Ian Richardson, Murray Thomson, **Smart meter data: Balancing consumer privacy concerns with legitimate applications**, Energy Policy 41 (2012), pages 807-814.
http://dx.doi.org/10.1016/j.enpol.2011.11.049 (see Appendix A).

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1. Introduction

1.1. Central research question

Is it valid to assume that domestic consumers will be willing and able to provide demand response to facilitate the integration of high penetrations of renewables into future low-carbon power systems?

1.2. Low-carbon power systems, system balancing and the value of flexible demand

To achieve targeted reductions in greenhouse gas emissions (European Commission, 2010), the electricity supply industry needs to become decarbonised (Committee on Climate Change, 2009). In the UK, this will likely involve connecting a large amount of wind power to the electricity network (DECC, 2010a). The 2020 targets, for example, include a third of UK electricity being generated from renewables, with the majority coming from wind power (Committee on Climate Change, 2008). By 2050, wind power could supply more than half of annual electricity demand (DECC, 2010a).

The deployment of wind power at this scale, however, will pose considerable challenges to the electricity supply industry (National Grid, 2009). Uncertainty in wind output, for example, could increase system balancing costs due to additional requirements for power stations providing balancing reserve (Gross et al., 2006).

Due to intermittency, the probability that wind power can contribute towards meeting peak demand, which is known as the capacity credit, is considerably lower than it is for traditional fossil-fuel plant. To maintain the same level of reliability, therefore, systems with high penetrations of wind need to adopt measures to deal with periods when wind output is low and demand is high (Freris and Infield, 2008b).

Furthermore, as the installed wind capacity increases, there is likely to be an increasing number of occasions when there is too much wind power being produced, and not enough demand on the system to make use of it. During these situations, wind power generation would need to be constrained and, under the current economic framework, wind farm operators would receive payments for the lost generation. Constraints on wind farms already occur regularly in the UK: in 2011 over 58.7 GWh of wind power was constrained at an average price of £218/MWh (Renewable Energy Foundation, 2012).

These challenges can be expected to grow as the amount of wind power connected to the electricity network increases towards the targets described previously, and are equally relevant to other intermittent renewables, such as solar and wave power.

The conventional response to the challenge of intermittent renewables is to use fossil-fuel power stations to provide balancing and capacity reserve. The UK Energy Bill 2012 (HM Government, 2012), for example, proposes legislation to enable a capacity market that will support investment in flexible generating plant to be used during periods when demand is high and supply from renewables is low.

In practice, however, this refers to gas-fired power stations that have not been fitted with carbon capture and storage technology. This raises the concern that the development and extensive use of a new generation of gas-fired plant in the UK might be incompatible with the government's carbon targets (Committee on Climate Change, 2012).

To address these challenges, there is considerable interest in the use of large-scale storage (Committee on Climate Change, 2008; Black and Strbac, 2007) to capture surplus power that might otherwise be wasted in systems with high penetrations of intermittent renewables, such as wind (Grünewald et al., 2011) or solar power (Solomon et al., 2010). The surplus power is then released back to the grid at a later time, when it is needed.

There are, however, considerable challenges in deploying storage technology at a large scale. Pumped hydro, such as the Dinorwig power station in the UK (First Hydro, 2012), offers fast response, and potentially a large amount of storage, but can only be built in the few locations with the appropriate geography to allow the creation of the necessarily large storage lakes at altitude. The few locations that are suitable tend to also be areas of considerable natural beauty, which stakeholders are often reluctant to see affected.

Batteries are another storage technology option that could be considered (Grünewald et al., 2011). The challenges with batteries are associated with their often considerable negative environmental impact (McManus, 2012). Battery lifetimes and efficiencies can also be adversely affected by deep cycling and rapid discharging respectively (BP Solar, 2001) – facts which can limit their operational use for system balancing purposes. Finally, large-scale battery storage solutions remain at the research and demonstration stage.

The role of storage in the above is to act as a buffer between supply and demand. An altogether different approach is to make the demand itself more flexible, reducing the need for a storage buffer, or indeed flexible back-up generation. 'Flexible demand' consists of discouraging demand during the periods when supply is scarce and expensive, and encouraging it during the periods when supply is plentiful and cheap.

Flexible demand is not a new concept to the electricity supply industry. The Economy 7 tariff has, for example, been used for decades in the UK to increase domestic demand during the night (McCartney, 1993), and thereby flatten the national demand profile. It is fair to say, however, that due to the historic availability of cheap fossil fuels, flexible demand has generally not been a priority for the industry.

The situation is changing now, and stakeholders are recognising that flexible demand will be increasingly valuable in managing the intermittency of renewables in the future (Committee on Climate Change, 2008; National Grid, 2009; Ofgem, 2010).

1.3. Flexible demand and distribution network constraints

In addition to the system balancing issues described previously, low-carbon futures can be expected to put increasing strains on local electricity distribution networks. High penetrations of microgeneration for example, such as domestic solar photovoltaic (PV) systems, can cause network voltages to rise outside of the statutory limits (Thomson and Infield, 2007).

The possible electrification of the domestic transport and heating sectors (DECC, 2010a) is also of concern, as accommodating high penetrations of electric vehicles and heat-pumps could require considerable new investment in the distribution network to cope with the resulting increases in peak demand (Strbac et al., 2010).

Flexible demand, however, could also help to address these concerns. Voltage rise, for example, might be avoided by encouraging demand to coincide with peaks in microgeneration output. Likewise, the times when electric vehicles are charged, or heat pumps switched, could be managed in order to minimise the peaks in aggregated demand on the network (Strbac et al., 2010; Pudjianto et al.; Strbac, 2008). Flexible demand can therefore also contribute towards operating the distribution network nearer to its limits, avoiding or deferring the need for network reinforcement.

1.4. Securing flexible demand in the domestic sector using dynamic pricing

Flexible demand can be encouraged in the industrial (Roos and Lane, 1998), commercial (Álvarez Bel et al., 2009), and domestic sectors (Owen and Ward, 2010). From a technical perspective, compared to the industrial or commercial sectors, the domestic sector has a considerably greater number of individual consumers, with relatively small loads per individual. This necessitates that domestic flexible demand measures in the domestic sector be relatively inexpensive on a 'cost per individual' basis. Historically, this ruled out many technology solutions, with the result that currently there is relatively little flexible demand that has been secured in the domestic sector (Ofgem, 2010).

Cost reductions in the field of information and communication technology, however, have meant that it is increasingly feasible to deploy technology to enable flexible demand in the domestic sector. Smart meters are perhaps the most obvious example of this trend, and at least 80% of domestic consumers in the European Union can now expect to have smart meters installed in their homes by 2020 (CEC, 2009).

Smart meters are viewed as a key enabling technology for flexible demand because they can facilitate the introduction of dynamic electricity pricing ('dynamic pricing') to domestic consumers (Faruqui et al., 2010). Dynamic pricing refers to any demand tariff with electricity prices that vary throughout the course of the day. Dynamic pricing is one of the principal tools that is expected to secure large amounts of flexible demand in the future (Faruqui et al., 2010). 'Demand response' refers to flexible demand where consumers time-shift demand, either manually or through automation, in response to dynamic pricing (Ofgem, 2010; Owen and Ward, 2010; Albadi and El-Saadany, 2008).

Looking forward, there is an expectation that dynamic pricing will play a key role in securing a low-carbon power system (Committee on Climate Change, 2008). Electrical engineers, concerned with the secure operation of such power systems, emphasise in particular the value of consumers responding to real-time pricing (Roscoe and Ault, 2010). Real-time pricing consists of electricity prices that vary on an hourly, or sub-hourly, basis and which reflect the real cost of electricity in the wholesale market (Albadi and El-Saadany, 2008).

In summary, this leads to the vision of a low-carbon power system where domestic consumers support the integration of high penetrations of renewables by responding to real-time pricing with wholesale market variability (Kockar et al., 2011). As the importance and value of demand response increases, however, so too does the need to question and test the validity of the assumptions that underlie this vision of a low-carbon future.

1.5. Consumer behaviour in demand response schemes

Dynamic pricing is based on the concept that demand is price-elastic (EPRI, 2008): an increase in price will produce in a decrease in demand, and vice-versa. This is the economists' 'law of demand'. Demand for electricity is assumed to obey the law of demand, because consumers in electricity markets are assumed to behave as rational economic actors (Lutzenhiser, 1992; Devine-Wright, 2007), who seek to maximise utility (value or satisfaction) according to their self-interested preferences, and individual budget constraints.

It is important to note however that this simplistic model of consumer behaviour is increasingly being questioned within economics (Rabin, 2002). There is indeed a growing literature that demonstrates that people do not behave as rational economic actors (Dellavigna, 2009; Camerer and Loewenstein, 2004), and that policies and interventions that are designed with human 'irrationality' in mind can have greater successes than those that are designed purely for rational economics actors (Thaler and Benartzi, 2004).

There is, as a result, increasing attention being given to the application of behavioural sciences and insights to energy policy and research (Allcott and Mullainathan, 2010). The UK government, for example, has set up a 'Behavioural Insights Team' as part of the Cabinet Office with the task of applying the insights from behavioural sciences to public policy making, and in particular to energy policy (Behavioural Insights Team, 2011).

The problem, therefore, is that the understanding of consumer behaviour in dynamic pricing schemes is simplistic and, by consequence, potentially unsound. This leads to the following two research questions:

Research question 1: Do domestic consumers respond to dynamic pricing?

Research question 2: What are the factors that influence the ability or willingness of consumers to respond to dynamic pricing?

The first question is explored in chapter 2 through a literature review of current demand response schemes, and the second question is addressed in chapter 3 with an analysis of consumer behaviour in real-time pricing schemes.

A further concern is that the dynamic pricing schemes that are investigated in these chapters are in markets where generation is supplied by flexible fossil-fuel plant. As discussed in chapter 4, this results in price profiles that are regular because the periods of high and low prices occur during the same times of day, day after day. Markets with high penetrations of renewables, however, can no longer be expected to have regular prices (Cox, 2009; Green and Vasilakos, 2010), due to the irregular variability of renewables. This leads to the requirement for a third research question, as follows:

Research question 3: Can domestic consumers be expected to respond to irregular dynamic pricing?

1.6. Investigating demand response behaviour of occupants of dwellings with PV in the UK

In order to address this third research question, there is a need to investigate the response of domestic consumers to electricity pricing with irregular variability. One approach to achieve this investigation would be to conduct a field experiment to test how domestic consumers respond to the kinds of prices that could be expected in a low-carbon future. A range of tariffs could be tested, combined perhaps with a range of technology interventions, such as informative billing, or 'smart' controls. Such experiments, however, can require a large number of participants, as well as long periods of monitoring. A recent trial of time-of-use tariffs in Ireland, for example, required over 5,000 participants, and monitoring for one and a half years (Commission for Energy Regulation, 2011). The costs involved in such an experiment are clearly considerable.

A novel approach, however, is presented by this thesis. The approach is based on the argument that studying the behaviour of consumers with grid-connected PV systems can provide insight into how consumers might respond to real-time pricing in future low-carbon power systems, as both experience irregular electricity prices that are correlated with intermittent renewable generation. From a practical perspective, the focus here is on PV rather than micro-wind, as the former has considerably more domestic installations (DECC, 2012a), as well as a greater availability of data for study.

In simple terms, for consumers in the UK with grid-connected PV systems, electricity is less expensive when they are producing more electricity than is being consumed, and expensive when the opposite is true. Consider, for example, the Energy Saving Trust's advice that occupants of dwellings with PV in the UK should 'use any appliances during the day when the solar PV modules are generating the electricity' (Energy Saving Trust, 2011) in order to maximise their return on investment. For this to be true there must be an economic benefit for the occupants in shifting their demand in order to coincide with the periods when their PV is generating. In the UK at least, it can be said that PV systems produce a price signal which is influenced by the intermittent output of the PV system (Keirstead, 2006), and which encourages demand response behaviour.

1.7. Benefits of the approach over the study of real-time pricing

For the purposes of investigating consumer response to dynamic pricing in low-carbon futures, the study of consumers with PV offers a number of advantages over the study of dynamic pricing in current markets. Firstly, consumers with PV experience a price signal that is correlated with a low-carbon, renewable resource, while consumers with dynamic pricing in current markets experience a price that is correlated with the time of day and, in some cases, temperature. Consumers with PV therefore experience a price that has seasonal variability, variability over periods of several days, as well as within-day variability. Consumers with PV experience a price signal that is more stochastic than consumers in current markets, and this is more in line with what might be expected in future low-carbon markets.

There are, furthermore, some unusual characteristics of the PV price signal, which makes the study of consumers with PV insightful, such as the fact that consumers with PV in the UK can benefit from free electricity, or the fact that the price is determined, in part, by the dwelling's power consumption, and not energy consumption.

1.8. Limitations of the approach

It is important, however, to mention why an understanding of consumers with PV might not be suitable for gaining understanding about how consumers might respond to irregular prices in a future power system with high penetrations of wind. Firstly, consumers with PV experience irregular pricing that is linked to their local solar resource, while consumers in markets with high penetrations of wind power would be likely to experience irregular pricing that is influenced by the wind resource at a national scale, at least for system balancing purposes.

For the purposes of managing local distribution network constraints, however, it is possible that consumers in systems with high wind penetrations might experience prices that are correlated with the local wind resource, for example where the local wind farms would otherwise need to be constrained, in which case the approach taken in this thesis has more relevance.

Another possible limitation is that due to the stochastic nature of the wind resource, consumers in systems with high penetrations of wind might conceivably experience high or low prices at any time of the day. Consumers with PV, by contrast, generally can expect a more or less consistent 'opportunity window' of low prices with a start and finish defined by the sunrise and sunset times. While this opportunity window does vary in duration seasonally, as well as in magnitude on a day-to-day basis depending on the level of cloud cover, it is nonetheless different to the case with high penetrations of wind.

An important exception to this is the case of consumers with PV who also have time-of-use pricing. Take, for example, consumers with PV in the UK with Economy 7. During the summer months, these consumers will experience a low price period during the middle of the day, while during the winter months, the low price period will be at night. These consumers experience a reversal of price signals that is correlated with the solar resource, and which makes the price signal they experience more relevant to the case for systems with high penetrations of wind.

Furthermore, consumers with PV can experience extended periods of several days with an abundant availability of cheap electricity, or by contrast very little due to bad weather. Flexible demand over periods of several days is of particular value to systems with high penetrations of wind power due to the possibility of persistent periods of calms in the wind resource. Insight into how consumers with PV respond to these situations is therefore also relevant to systems with high penetrations of wind power.

While the above has considered the potential limitations of applying the insight from consumers with PV to consumers in systems with high penetrations of wind, there are fewer limitations in applying the insight to systems with high penetrations of solar power. The results presented in this thesis are therefore of particular relevance to countries that might expect high penetrations of solar power in the future, for example Australia, or Spain.

1.9. Contributions of the thesis

In order to investigate demand response behaviour in consumers with PV systems, one of the contributions of this thesis has been the development of the novel concept of a variable 'effective price' for domestic grid-connected PV systems. The 'effective price' describes the variation of the price that occupants of dwellings with PV pay for the electricity they consume – even if they have a flat-rate electricity demand tariff. Though somewhat unusual, the effective price formalises the PV 'price signal', and conceptually aligns it with the real-time pricing used in demand response schemes. The effective price concept is useful as it allows the various feed-in tariff and metering configurations to be unified by a single variable. Chapter 4 describes the factors that influence the effective price, and confirms that the effective price is correlated with PV generation. This confirms in turn that consumers with PV experience dynamic pricing with irregular variability.

As there is no quantified evidence of occupants with PV showing demand response behaviour, chapter 5 presents a statistical regression analysis of demand data from dwellings with PV in the UK. The results provide quantified evidence that suggests that occupants with PV do respond to an irregular electricity price. The results indicate that, on an average weekday, occupants with PV exhibit an increase in demand during the daytime of approximately 8% of their mean daily demand, and show a corresponding reduction in demand during the evening.

Having quantified the effect of PV on domestic demand profiles in the UK, chapter 6 investigates what the occupants are doing to produce this response, and, indeed, why they do it. This work is important because it complements the statistical work and provides qualitative data that suggests the underlying causes for the quantitative data described in chapter 5. These questions are addressed through the analysis of an internet forum used by occupants with PV in the UK to discuss the changes they make to their behaviour in order to maximise the benefit from their PV systems. The internet forum provides a rich source of information, and reveals that there is considerable flexibility available in domestic dwellings, with occupants making wide-ranging behavioural changes in order to time-shift their demand.

The evidence from these two chapters suggests that the response to PV can be characterised in terms of a routine response and an opportunistic response. The routine response consists of occupants making changes to their daily routines to consistently run appliances during the day. The opportunistic response consists of occupants responding to the intermittent variability in PV generation associated with variable sunshine levels, for example by conserving electricity on cloudy days and using more electricity on sunny days. The opportunistic response is of particular value for supporting the integration of high penetrations of renewables in the future.

The forum study also reveals that while the main motivation for these changes appeared to be an economic one – recouping the cost of the PV system as quickly as possible – there were also other important positive drivers such as the fact that some participants found demand response behaviour to be fun, or similar to a hobby.

Building on these findings, chapter 7 discusses the relevance of the behaviour of occupants with PV to the broader topic of demand response in low-carbon power systems. The behavioural factors that appear to be most important in influencing the decisions of occupants with PV are identified, and the possibility of tailoring future demand tariffs in low-carbon power systems to address these factors is discussed. The conclusion is that price is an important, and very likely necessary, driver for flexible demand in low-carbon power systems. There are, however, also other important, positive motivating factors that can increase the effectiveness of the price signal, and the potential application of these factors to demand response schemes in general is discussed.

2. Literature review

The literature review of this thesis has the aim of addressing the first research question presented in the previous chapter:

> Research question 1:
>
> Do domestic consumers respond to dynamic pricing?

To address this question, this chapter presents a review of existing demand response schemes. The objectives are to learn about how demand response is achieved today, and to highlight the main challenges.

Sections of this chapter are derived from the two following papers: a journal paper co-authored with Sarah Darby at the Environmental Change Institute, Oxford University, published in Energy Policy volume 49 (Darby and McKenna, 2012), and a conference paper that was presented at the 2nd International Conference on Microgeneration and Related Technologies in Glasgow, UK (McKenna et al., 2011). The full papers are provided in appendices D and E respectively.

2.1. Dynamic pricing and wholesale market prices

A range of demand response schemes is presented in this chapter in order to demonstrate the different approaches used to achieve demand response. Several types of dynamic pricing tariff are considered, some of which are illustrated in Figure 1. A note on terminology: 'tariff' is used to refer to a set of electricity prices that is agreed between the consumer and the utility. 'Price' refers to the value or cost of a unit of electricity in p/kWh, and is used in preference to the term 'rate'.

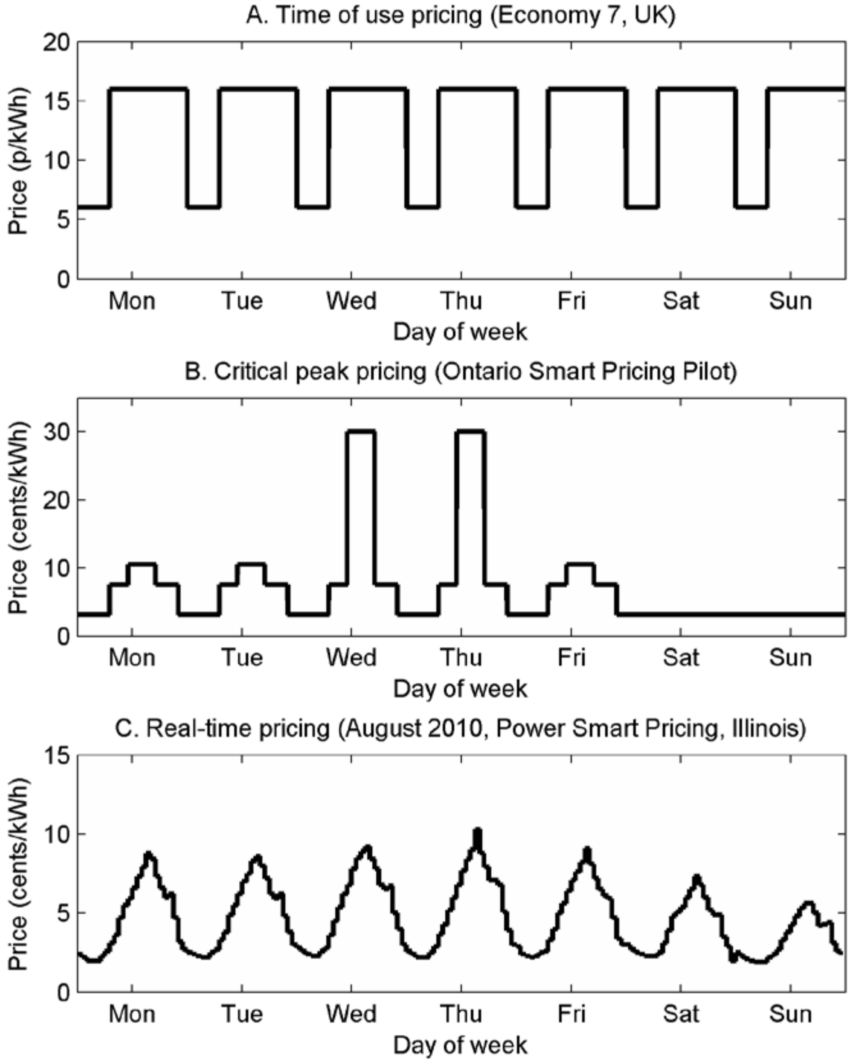


Figure 1 – Examples of dynamic pricing tariffs.

Figure 1A shows 'time-of-use pricing', in this case the Economy 7 tariff in the UK. The day is divided into high and low prices periods, also called 'peak' and 'off-peak' periods. Time-of-use pricing is highly predictable – the periods of high or low price do not change, and prices during these periods are known in advance.

Figure 1B shows an example of 'critical peak pricing', in this case from the Ontario Smart Price Pilot. Compared to time-of-use pricing, the day is divided into more periods, in this case peak, off-peak, and 'shoulder' periods. Furthermore, on certain 'critical peak' days the peak price is considerably increased. Consumers are notified about critical peak days in advance, and the number of critical peak days per year is restricted. Critical peak pricing has been widely introduced by utilities in North America to help manage generation capacity shortages aggravated by high penetrations of air-conditioning units (Faruqui and Sergici, 2010).

Figure 1C shows 'real-time pricing', in this case from the Illinois Energy Smart Pricing Plan. In contrast to the static predictability of time-of-use pricing, real-time pricing has prices that vary hourly, or sub-hourly, reflecting the variability of prices on the wholesale market (Albadi and El-Saadany, 2008).

Indeed, it can be said that all of the price profiles shown in Figure 1 reflect wholesale market price variability, at varying degrees of resolution. Wholesale prices provide a means for system balancing and, as a result, so to do the dynamic pricing tariffs described above. The important point is that for dynamic pricing to contribute effectively towards system balancing, it must reflect wholesale market variability. While this is explored in greater detail in chapter 4, for the moment it can be said that wholesale price profiles in current markets are regular, as they tend to follow the aggregated consumer demand profile. As will be discussed later, this regularity of prices has an impact on how consumers respond, and so it is important to consider the factors that affect wholesale prices in future low-carbon markets. This is investigated in more detail in Chapter 4. The following presents the demand response case-studies.

2.2. Radio Teleswitch, United Kingdom

Radio Teleswitch is a radio-operated control link between the electricity supply industry and domestic electricity meters on the Economy 7 tariff in the UK. Economy 7 is a type of time-of-use pricing that provides seven hours of cheap, off-peak electricity during the night. Prices during the rest of the time are, by contrast, relatively expensive. Figure 1A illustrates what this looks like. Historically, Economy 7 was associated with the presence of electric storage heaters and electric immersion water heating, as these could be switched on at night when the price of electricity was cheap.

Radio Teleswitch achieves two things. Firstly, it controls when the meter switches from one price to the other, thereby avoiding the need for conventional time clocks in the meter, which were unreliable and inflexible. Secondly, it controls when the electric storage heaters and electric water heaters are switched on or off.

By controlling the switching of the electric heaters, Radio Teleswitch provides a demand response service to the supply industry (Woolner and Hannon, 1996). Peaks in demand, for example, can be avoided by staggering the switching times of groups of heaters (McCartney, 1993).

Electric storage heaters, however, have proven not to be popular with consumers. While there were 2.2 million houses in the UK with electric storage heating in the 90's, these numbers have been steadily declining, with today's figures closer to 1 million (DECC, 2010b). Indeed, a survey commissioned by Ofgem found that electric storage heating was the least popular method of shifting electricity usage to the off-peak period (Ofgem, 2010), especially among the older generations, while electric water heating was the most popular.

2.3. Ripple Control, Czech Republic

Similar to Radio Teleswitch, Ripple Control provides centralised control over the electric heating appliances of domestic consumers on time-of-use pricing in the Czech Republic (Neuberg, 2009), though Ripple Control uses power line communication to control the heaters rather than radio. Ripple Control is associated with two tariffs: the first is an 8 hour off-peak time-of-use pricing tariff similar to Economy 7, while the second is a 20 hour off-peak time-of-use pricing tariff. The first tariff is associated with electric storage heaters, while the second is associated with direct (non-storage) electric heaters. Furthermore, the Ripple Control system has some flexibility with regards to the timing of the off-peak periods of the two tariffs. While consumers received advance notification of the timings of the off-peak period, this was not popular with consumers, as it meant they had to adapt their behaviour.

Up until 2005, Ripple Control provided an effective demand response service, with approximately 20% of consumers in the Czech Republic participating in the system. After this date, however, the Czech energy market was deregulated, and ownership and control of the system passed to the distribution network companies. This effectively removed the use of Ripple Control for system balancing purposes, though it is still used for the purposes of managing distribution network constraints.

2.4. LIPAedge, Long Island, USA

The LIPAedge system consists of the centralised control of domestic and commercial air-conditioning units via a two-way pager communication network (Kirby, 2003; Long Island Power Authority, 2001). LIPAedge does not include any form of time-of-use pricing. In 2003, LIPAedge was the largest domestic load control program in the US (Kirby 2003), with control over around 17,000 air-conditioning units. LIPAedge allows the utility to adjust the temperature set-point of the air-conditioning units of participating consumers. It was developed in order to reduce summer peak demand on the Long Island network, as well as to provide a fast reserve service in case of sudden loss of generation on the network. Control over consumers' air-conditioning units can only occur between the hours of 2pm and 6pm, on pre-notified critical peak days. Consumers are able to manually over-ride the control over their air-conditioning unit, except during network emergencies. During a typical control period, on average 15% of consumers would manually over-ride the control. This is a relatively low number, and indicates that the majority of domestic consumers either did not notice the fact that their air-conditioning units were being controlled, or were not inconvenienced enough to engage the manual over-ride.

2.5. Smart Price Pilot, Ontario, Canada

The Smart Price Pilot consisted of a trial of three dynamic pricing tariffs in Ontario (Strapp et al., 2007). Participants were enrolled into three tariff test groups: a three-tiered time-of-use pricing tariff with peak, off-peak and shoulder periods, and two critical peak pricing tariffs that superimposed either a critical peak price or critical peak rebate on top of the time-of-use pricing. The critical peak pricing is illustrated in Figure 1B. The times of the peak periods varied seasonally in order to reduce both winter and summer demand peaks. Participants were informed of critical peak days in advance. The trial lasted seven months, and included one summer and one winter.

The results of the trial are shown in Table 1. Out of the seven critical peak days that were called, only the first two produced statistically significant reductions in peak demand, and one of the winter critical peak days produced an increase in peak demand – the opposite of the expected response.

Table 1 – Peak demand reductions for all tariff groups on critical peak days for the Smart Price Pilot (Strapp et al., 2007)**. 'n/s' denotes results that were not statistically significant.**

Critical peak day	**SUMMER**
Friday, August 18	27.7%
Tuesday, August 29	10.1%
Thursday, September 7	n/s
Friday, September 8	n/s
	WINTER
Tuesday, January 16	n/s
Wednesday, January 17	−7.2%
Friday, January 26	n/s

Table 2 shows the results for the individual tariff groups. The critical peak pricing groups produce statistically significant reductions in peak demand, though only during the summer period. On non-event days (results not shown here), where all three test groups were effectively on the same time-of-use tariff, no statistically significant shifting occurred in the test groups with the exception of one of the critical peak test groups, which demonstrated an increase in on-peak demand – again the opposite of the expected result. On average, there was a conservation effect of 6% across the test groups for the full test period.

Table 2 – **Demand reductions for the individual tariff groups** (Strapp et al., 2007).

SUMMER			
Period	**Time-of-use**	**Critical-peak**	**Critical-peak rebate**
Critical peak hours (3-4 hours during peak)	n/s	25.4%	17.5%
Entire on-peak period	n/s	11.9%	8.5%
Mid-peak	n/s	n/s	n/s
Off-peak	n/s	n/s	n/s
WINTER			
Period	**Time-of-use**	**Critical-peak**	**Critical-peak rebate**
Critical peak hours	n/s	n/s	n/s
Entire on-peak period	n/s	n/s	n/s
Mid-peak	n/s	n/s	n/s
Off-peak	n/s	n/s	n/s

The Smart Price Pilot included participant surveys. These revealed strong customer satisfaction, a preference for time-of-use pricing over critical peak pricing, and that participants valued clear, concise and durable information about how prices could be expected to vary throughout the day and seasons.

2.6. Energy Smart Pricing Plan, Illinois, USA

The Energy Smart Pricing Plan was the first trial of real-time pricing in the domestic sector and ran from 2003 to 2006 in Illinois, USA (Summit Blue Consulting, 2007; Star et al., 2010b). Prices varied each hour and reflected the prices on the wholesale electricity market, as illustrated in Figure 1C. Participants were notified about prices on a day-ahead basis. This meant that they received estimates of the hourly prices 24 hours in advance, but they paid the actual price on the day, as determined by the wholesale market. As a result, participants were taking on board a certain amount of uncertainty in terms of the prices they paid, and this was a factor that discouraged people from participating (Star et al., 2008). People preferred to know for certain what prices would be in advance, and the program organisers subsequently decided to change the scheme so that the day-ahead prices were firm.

The Energy Smart Pricing Plan evaluated the response of the participants to the real-time pricing by estimating the elasticity of demand (Summit Blue Consulting, 2007), and the results are shown in Table 3. The elasticity of demand refers to the percentage change in demand associated with a 100% increase in price. The trial found that the elasticity stayed relatively constant throughout the course of the trial, and that elasticity increased on days when a high-price notification was sent to the participants. The trial found that the response of the participants reduced on consecutive high price days, and a period without notifications was needed in order to for the response to return to previous levels.

Table 3 – Annual elasticity of demand for the Energy Smart Pricing Plan (Summit Blue Consulting, 2007).

Year	Elasticity of demand
2003	-4.2%
2004	-8.0%
2005	-4.7%
2006	-4.7% (<0.13c/kWh) -8.2% (>0.13c/kWh)

2.7. Gridwise™ Olympic Peninsula Project, Washington, USA

The Olympic Peninsula Project tested a number of innovative 'smart grid' concepts in the domestic sector, and a 'local marginal energy market' – an electricity market in which domestic appliances could bid for their demand and distributed generators could offer to supply power (Hammerstrom, 2007).

In total, 112 homes participated in the project, and had energy-management systems installed that allowed their air-conditioning units and electric water heaters to interact with the local marginal energy market. Participants were assigned to a control group, a flat-rate group, a standard two-tier time-of-use pricing group, and a real-time pricing group, with only the latter actually participating in the market. The home energy-management systems allowed the real-time pricing participants to choose how much they wanted their appliances to interact with the market price, based on the participants' preference for 'economy' or 'comfort'.

The project did not publish exact figures for peak demand reduction for the different tariff groups, however indicative values have been estimated from the published load profiles (Hammerstrom, 2007) and are given in Table 4. The time-of-use pricing participants achieved greater reductions in peak and total demand than the real-time pricing group. There was no conservation effect for the real-time pricing group (those that participated in the real-time energy market).

Table 4 – Demand reduction results from the Olympic Peninsula Project (Hammerstrom, 2007).

	Time-of-use	Real-time pricing
Total reduction in demand	-17%	0%
Peak demand reduction (winter week day)	-24%	-9%

Although the real-time pricing participants were put on a 'balanced economy/balanced comfort' preference setting as a default, 39% of the participants changed their water heater settings to 'no price reaction', and 22% did the same for their air-conditioning. The project organisers believed that this may have been due to a problem that occurred with the home-energy management systems early in the project, and which caused participants to disallow any further control by the project.

2.8. Customer Behaviour Trial, Ireland

The time-of-use pricing was recently trialled in Ireland (Commission for Energy Regulation, 2011). Four time-of-use pricing tariffs were tested, with each tariff having a different ratio of peak to off-peak price (1.7:1, 2.4:1, 3.2:1 and 4.2:1). While these ratios show a clear trend, this was not nearly so apparent in the results, with peak demand reductions of -7.2%, -9.8%, -9.0%, and -10.9% observed for the respective tariff groups. The result is important, as it demonstrates that peak demand can be quite inelastic to price increases. This poses a challenge to the assumption that price might be an effective means of achieving the large reductions in peak demand that might be necessary in low-carbon futures. A possible explanation for this is that the participants viewed prices simply as a type of 'traffic light' scheme, where prices are either high or low, not absolute values. If this were the case, then one would expect the response to this simplified high/low price signal to have been quite similar from group to group.

2.9. Discussion and further research questions

As mentioned in section 2.1, one of the main purposes of demand response schemes is to contribute towards system balancing. The review of existing demand response schemes described above reveals that there is a distinction between schemes where the response is being delivered by the consumer, and schemes where the response is being delivered by automated technology on behalf of the consumer. These approaches are discussed further in the following.

2.9.1. Acceptance of automation

Automation featured prominently in several of the above case-studies. In order for automation to work, however, it must be accepted by the consumer. This is not trivial, as people can react negatively to automation for two reasons. Firstly, even when an automated system works perfectly, there is still the matter of consumers being inconvenienced. This was the case for participants in the Ripple Control system, who disliked the timings of the off-peak periods being constantly changing. This is also the case for Radio Teleswitch in the UK, as electric storage heaters are in decline because consumers prefer other forms of heating. Secondly, there is the further matter of inconvenience caused by an automated system that works imperfectly. This was the case for the Olympic Peninsula Project, where participants disallowed control over their appliances, due to a fault arising in the control equipment.

Automated control strategies need to be sympathetic to consumers' needs, and not over-complicated. The Olympic Peninsula Project concept, where customers can choose their preferences on a scale between 'economy' and 'comfort', fits well with this notion of 'customer-friendly' automation. The challenge with automated technology is therefore whether it will prove to be acceptable to the consumer.

2.9.2. Smart meters and data privacy concerns

As mentioned previously, smart meters are viewed as a key technology for enabling demand response in the domestic sector and, as a result, there is a considerable need for consumers to accept this form of smart technology. There are, however, considerable negative reactions to smart meters which, if left unresolved, could severely reduce the uptake and acceptance of smart meters around the world (Quinn, 2009). These negative reactions are principally based on the concern that smart meter data could be used to infer private activities that occur within the dwelling. Although this data is classified as personal data, and so protected under existing data protection laws, there are relevant exceptions to this, for example where the data is required for legitimate applications associated with regulated duties (Ofgem and DECC, 2011).

One of the contributions of this thesis has been to examine the data requirements of the proposed applications of smart meter data within the electricity supply industry, with the purpose of investigating whether the use of personal data can be reduced or avoided. This work was published in a paper in volume 41 of Energy Policy (McKenna et al., 2012), and is contained in full in Appendix A. The results of the work indicate that, for most of applications considered, personal data use can indeed be minimised or avoided by appropriate 'privacy friendly' techniques. The use of such techniques will go some way towards minimising any negative reactions to smart meters, and reduce the risk that they are rejected.

2.9.3. People respond to prices in a limited, complex way

The question posed at the beginning of the literature review was 'do domestic consumers respond to dynamic pricing?' The literature review allows us to say that there is some evidence of consumers responding to dynamic pricing, though this comes mainly from North America. It is also clear that domestic consumers respond to price in a limited and complex way. The variability of the results of the Smart Price Pilot are, for example, of concern. The results from the Energy Smart Pricing Plan also reveal that consumers' response can vary in time, for example by decreasing on consecutive high price days, as well as varying with context, for example by having a greater response on days when a high price notification had been sent out.

This highlights the fact that there is currently a general lack of understanding about consumer behaviour in demand response schemes. Demand response schemes appear to be designed based on a simplified concept of consumers that classifies them in a rigid economic context. Fundamentally, however, it is not clear how or why the consumers in these schemes reviewed above responded in the way they did. There is growing recognition that existing models of consumer behaviour in energy can be improved or complemented using the insights from the behavioural sciences and psychology (Allcott and Mullainathan, 2010; Wilson and Dowlatabadi, 2007).

This thesis is therefore concerned with improving the understanding of consumer behaviour in demand response schemes, in particular in determining the why and how of consumer response, to complement the existing quantitative data that is the focus of many of the existing demand response schemes. More specifically, there is particular value in improving the understanding of consumer behaviour in real-time pricing schemes, as these are an important component of the low-carbon future vision.

This confirms the value of the second central research question described in chapter 1, which is therefore re-stated here, with the focus now on real-time pricing, rather than dynamic pricing. This question is addressed in the following chapter.

Research question 2: What are the factors that influence the ability or willingness of consumers to respond in real-time pricing schemes?

2.9.4. Dynamic pricing in markets with high penetrations of renewables

The literature review revealed that there is some evidence of consumers responding to dynamic pricing. The schemes that have been considered are however in current markets where power is supplied by flexible fossil-fuel generation. It is important therefore to question whether these findings are also valid within the context of a future low-carbon power systems where power is supplied by intermittent generation from renewables, and wholesale prices might become less regular.

This confirms the value of the third research question presented in chapter 1, which is re-stated here, and which will be investigated in chapter 4.

Research question 3: Can domestic consumers be expected to respond to irregular dynamic pricing?

3. Behavioural economics and demand response: consumer inattention in real-time pricing schemes

3.1. Introduction

The aim of this chapter is to address the following research question, which was presented in section 2.9.3.

Research question 2:   What are the factors that influence the ability or willingness of consumers to respond in real-time pricing schemes?

The chapter therefore investigates the models of consumer behaviour that are used to characterise the observed behaviour of consumers in real-time pricing schemes, and discusses whether behavioural economics can provide a useful framework for improving the understanding of consumer behaviour in real-time pricing schemes, and indeed, demand response in general.

3.2. Rational consumer behaviour

The idea that people behave as self-interested, rational actors has been the dominant model of consumer behaviour in neo-classical economics for decades (Camerer and Loewenstein, 2004). In order to provide context for what follows, it is useful to be specific about what the term 'rational' implies. In order to do this, the following briefly describes one of the dominant formal characterisations of rational choice theory within economics: expected utility theory.

According to expected utility theory, which will be referred to here as the 'standard model', people make decisions which maximise the utility that they can expect over their lifetimes (Dellavigna, 2009; Kahneman and Tversky, 1979). A 'rational' actor is one who, given a set of alternatives, ranks them according to preferences, chooses the most preferred option, and whose preferences are assumed to be consistent in time, affected only by their own self-interest, and independent of the framing of the decision (Dellavigna, 2009). The standard model is widely applied in economics as a descriptive model of consumer decision-making in situations involving both risky and riskless choice (Tversky, 1991). In theory, reasonable people should want to behave as utility-maximisers, and furthermore neo-classical economics assumes that most people, most of the time, actually do.

The simplicity of the standard model is, in part, its strength, as it can be applied to almost any form of economic situation (Camerer and Loewenstein, 2004), yet the question of interest here is whether the standard model is an effective characterisation of the behaviour of participants of real-time pricing schemes.

3.3. Behavioural economics and demand response

It is increasingly acknowledged within economics, that the standard model's assumptions about consumer rationality are often inconsistent with observed behaviour (Rabin, 2002). Research into this area, is commonly referred to as 'behavioural economics'. It can be said that behavioural economics has the aim of identifying the ways in which actual consumer behaviour differs from the assumptions of the standard model, and showing that this behaviour is of economic importance. Furthermore, behavioural economics tries to explain 'irrational' behaviour in terms that are understandable – making what appears to be irrational, less so. This chapter describes examples from the literature which should serve to illustrate this, and considers whether behavioural economics can provide a better understanding of consumer behaviour in real-time pricing schemes than the standard model.

The scope of behavioural economics is broad, and the aim here is not to provide an exhaustive treatment of the subject. Instead, the approach will be to focus the discussion on the types of behaviour which appear to be most relevant to demand response. In particular, the discussion will focus on heuristic (or 'rule of thumb') behaviour, and consumer inattention. Further types of behaviour, including social preferences, and self-control problems, are also discussed, though in less detail.

In order to provide context for the forthcoming discussions, the following section gives a brief background to behavioural economics. Further reading on the subject can be found in the academic reviews by Dellavigna (2009), Camerer and Loewenstein (2004), and Mullainathan and Thaler (2000).

3.4. Background on behavioural economics

Early behavioural economics research focussed on documenting evidence on how people systematically deviated from the standard model (Rabin, 2002), as well as proposing alternative models of behaviour. More recently, there has been a greater emphasis on applied behavioural economics research, in which these findings are then applied to real-world problem situations.

A good example of a successful real-world application of behavioural economics research is given by the work of Thaler and Benartzi (2004) who, inspired by behavioural explanations of why many people failed to save enough for their retirement, performed an experiment which aimed to increase savings rates. They introduced a new savings scheme which worked by getting people to commit, in advance, to allocating a portion of their future salary increases towards their retirement savings plan. The scheme succeeded in raising average savings rates from 3.5% to 13.6% over the course of 40 months, helping to prove that behavioural economics could be used to aid consumer decision-making in matters of economic importance.

The insights from behavioural economics have also been applied to energy-related issues. Motivated by behavioural research which demonstrated that revealing information about social norms can induce people to conserve energy (Nolan et al., 2008), a company called Opower has achieved persistent energy reductions of between 1% and 3% for 600,000 households, simply by providing them with a comparison of their monthly consumption against that of their neighbours (Allcott, 2011a).

The initial successes of applied behavioural economics are starting to make an impact on energy policy. For example, in the UK, two recent government publications discuss how behavioural insights can be applied to energy policy in the UK (Behavioural Insights Team, 2011; Chatterton and Anderson, 2011).

The preceding examples demonstrate that behavioural economics can be useful and relevant to energy research. While there has been some work in applying this research to the study of demand reduction (Greene, 2011; American Council for an Energy Efficient Economy, 2007), to date there has been no systematic effort to do the same for demand response. Addressing this gap is one of the contributions of this thesis.

3.5. Heuristics and consumer inattention

3.5.1. Background

Herbert Simon was one of the earliest critics of the standard model (Simon, 1955), proposing instead the alternative concept of 'bounded rationality': due to natural constraints such as limited cognitive power, limited time and attention, people were often unable, or unwilling, to reach optimum decisions. They were not decision optimisers but rather 'satisficers', saving time and effort by making choices that met minimum levels of satisfaction. In order to reach these satisfactory decisions, people often adopted heuristics, or 'rules of thumb'. Such time-saving rules of thumb are not recognised in the standard model, but have been proven to produce systematic biases in decision-making that are therefore important to take into account.

Table 5 gives examples of several documented types of heuristics. The rest of this section will focus on one of these in particular: consumer inattention.

Table 5 – Heuristics: examples of how people make decisions that are satisfactory but not necessarily optimum.

Description of behaviour	Referenced examples
Inattention Attention is a limited resource, this can lead people to overlook or ignore non-salient factors when making decisions.	In a study of consumer inattention to shipping costs on eBay, Hossain and Morgan (Hossain and Morgan, 2006) auctioned CDs with either A: \$4 reserve price and no shipping cost, or B: \$0.01 reserve price and \$3.99 shipping cost. The average revenue raised for B was \$1.79 higher than for A (\$10.16 versus \$8.37), showing that bidders were not attentive to shipping costs. Dellavigna and Pollet (2009) found that even investors in stock markets suffered from limited attention: earnings announcements that are released on Fridays generally exhibit lower immediate response and higher delayed response than the norm.

Anchoring Judgements can be influenced by irrelevant or arbitrary factors.	After spinning a wheel of fortune which randomly landed on a number between 0 and 100, Tversky and Kahneman (1974) asked subjects whether the number of African nations in the UN was greater or less than the random number. Subjects were then instructed to guess the actual number. Surprisingly, the guesses were significantly correlated to the wheel of fortune number, even though the subjects could clearly see that it had no relationship to the questions. See Ariely, Loewenstein and Prelec (2003) for more examples of this effect.
Menu-effects Heuristics involved with choosing amongst a multitude of possibilities.	Results from a study by Barber and Odean (2008) suggest that individual stock market investors deal with the overload of stock market information by picking companies that stand out from the rest e.g. companies with unusually high or low performance the previous day, or companies in the news. In this case investors are taking a complex problem, and reducing it to something simpler. The result is that they only purchase stocks that most caught their attention. Iyengar and Lepper (2000) found that people were more likely to purchase an item if the choice of different items was not excessive (a choice of 6 versus a choice of 24). When there were too many options available, people often 'chose not to choose'.

3.5.2. Models of inattention

The standard model assumes that individuals make decisions using all relevant information that is available to them (Dellavigna, 2009). By extension, individuals also have the skill to be able to reject information that is irrelevant. Yet a moment of self-reflection will reveal that this is not entirely true all of the time. As demonstrated in the examples in Table 5, people can often ignore relevant information (like shipping costs on eBay), and even give undue attention to information that is entirely irrelevant (the wheel-of-fortune example). Indeed, the evidence from psychology is that people have limited attention (Norman and Bobrow, 1975) and, for example, can often struggle to perform two different tasks simultaneously.

As a result, efforts have been made by economists to develop new models of behaviour that aim to account for inattentive behaviour. The following therefore describes two different models of attention, prior to discussing the relevance of this behaviour to demand response. Note that the two models offer different interpretations, or ways of explaining, the same thing – inattentive behaviour.

3.5.3. Limited attention model

The first model will be referred to as the 'limited attention model'. This states, that, while information may be readily accessible to an individual, they may fail to consciously register it due to a lack of attention. For example, an individual may find that they have difficulty in following two different conversations simultaneously at a dinner party, even if they want to and are trying hard to listen to both.

Economists characterise this type of behaviour by proposing that attention is a limited resource that is dependent on three factors (Dellavigna, 2009). Firstly, a given piece of information (take for example the value of a second-hand car) is determined by the sum of two components: a 'visible' component and an 'opaque' component. The terminology here can be confusing and so will be clarified. The terms 'visible' and 'opaque' do not indicate opposites – opaque in this context simply refers to something that an individual has difficulty in seeing, and that the degree of difficulty depends on factors which will be described shortly.

The visible component of the information is available to the individual – there are no barriers to access. The opaque component of the information is, however, less easily accessible. Taking the example of the value of a second-hand car, the visible component might be the value associated with the aspects of the car that are easily accessible. The make, model, and year of manufacture, for example, should normally be readily available to a prospective purchaser, and can be used to determine the going rate for a car of the same make, model and year in the market place. On the other hand, the opaque component would be associated with those aspects of the car that contribute (or detract) from its value which might be harder for a purchaser to access. The condition of the car's engine is perhaps a useful example. When taking the car for a test drive, the purchaser might not notice an unhealthy sounding engine – they might have been concentrating on the traffic instead.

Returning to the factors that determine how easily an individual sees the opaque component of the information: it has been proposed that this is a function of the 'salience' of the opaque information (i.e. how obvious it is); and the number of competing stimuli being experienced by the individual. Continuing the previous example, a loud bang from the car's exhaust would be highly salient information to a prospective purchaser. If, however, this occurred while driving next to a noisy construction site, then it is possible that these distracting noises could provide competing stimuli that could obscure the exhaust's bang.

3.5.4. Information costs model

The second model of inattention that is considered here will be referred to as the 'information costs model'. This model proposes that information which needs more attention to be registered has a higher 'cost of acquisition' (Gabaix et al., 2006). An individual may therefore decide that the costs of acquiring the information outweigh the potential benefits that the information may bring. Continuing the dinner party conversation example, listening to only one of the conversations would have a low cost of acquisition, whereas following both would have a high cost. In this context 'cost', can refer to explicit financial costs, but also to costs associated with time and effort spent in order to accomplish a task.

3.5.5. Irrational or 'boundedly' rational?

It is interesting to note that these two models of inattentive behaviour offer different views of consumer rationality. The information costs model can be viewed as a direct alternative to the limited attention model described previously: less salient information, which can be overlooked by 'irrational' individuals, can be described instead as information that has a higher acquisition cost, which 'boundedly rational' individuals can choose to be inattentive to. From a boundedly rational viewpoint, behaviour that initially appeared to be irrational can be made to look rational, by attaching an acquisition cost to information.

A discussion of the validity of one model over the other is, however, out of scope. For the purposes of this chapter, both models serve as useful characterisations of inattentive behaviour.

3.5.6. Inattention and the use of proxy information

If one accepts that individuals can be inattentive to some information, whether through its obscurity, or due to the costs involved in acquiring it (or both), then it follows that people can resort to heuristics to save themselves the trouble of accessing the obscure/costly information. For example, instead of making decisions based on accurate, 'higher cost' information, an individual can instead make decisions based on a 'proxy' for this information. The proxy would be accessible at lower cost (or would be more salient), but might, as a result, also be a relatively inaccurate substitute for the costly information. Returning to our dinner party example, instead of trying to follow the second conversation, the individual could instead choose to observe the body language of the people engaged in the conversation. In this case, the body language would act as a proxy for the topic of the conversation, though one that might be relatively inaccurate.

3.6. Evidence of inattentive behaviour in real-time pricing schemes

This section considers therefore whether inattention is relevant to consumer behaviour in real-time pricing schemes. The approach is to analyse the behaviour of participants of the 'Power Smart Pricing' real-time pricing program conducted in Illinois (Star et al., 2010a). This program was a direct successor of the Energy Smart Pricing Plan that was described in 2.6.

The Power Smart Pricing program was evaluated over a number of years through a series of reports (Summit Blue Consulting, 2009; Navigant Consulting and Summit Blue Consulting, 2010; Navigant Consulting, 2011). One of the objectives of the reports was to quantify the response of the participants to real-time pricing using statistical analysis of the participants' demand data.

The statistical analysis that was used in the first evaluation report was based on the following demand function (Summit Blue Consulting, 2009).

$$\ln y_{it} = \alpha_i + \rho \ln price_t + \beta x_{it} + \varepsilon_{it}$$

Equation 1

Where:

$\ln y_{it}$:	the natural log of electricity consumption for house i during hour t.
α_i :	the estimated constant term ("fixed effect") for household i .
ρ :	the price elasticity of demand.
$\ln price_t$:	the natural log of the price of electricity during hour t.
β :	a vector of estimated coefficients.
x_{it} :	a vector of weather variables (e.g. temperature).
ε_{it} :	econometric error term for household i during hour t.

A demand function is an equation that specifies the variables which the consumer demand is assumed to depend upon. This type of specification, with price, weather and 'fixed effect' variables, is commonly used in the evaluation of dynamic pricing programs (Faruqui and Sergici, 2011). It will be referred to as the 'standard demand function' here. The coefficients of the demand function are estimated by performing a regression analysis using the observed data from the program under evaluation.

The standard demand function shown above implies that, for a particular household, and a particular hour of the day, the factors that determine the household's consumption are: the price during that hour, the outdoor climate during that hour, plus a constant term for that household. The implicit assumption is that people know what the price is during each hour of the day, and that this has an effect on the amount of electricity they consume. From a behavioural point of view, this is a simplistic view of how people behave. Though the specification of the demand function is limited by what can be reasonably observed for each household, it is nonetheless important to stress that this simplistic view of how people behave is implicitly assumed in its specification.

The standard demand function was, however, dropped from subsequent evaluation reports (Navigant Consulting and Summit Blue Consulting, 2010; Navigant Consulting, 2011), because the program evaluators believed that it was not an accurate characterisation of the observed behaviour. It was proposed that the model's assumptions were too restrictive. These assumptions were therefore relaxed, and new demand functions were developed.

The new approach that was adopted in subsequent reports recognised two distinct forms of response: a 'medium run' response, and a 'short run' response. It was proposed that in the medium run, the demand during each hour was dependent on the average price for that hour of the day over a long period (e.g. several months). This response would capture broad shifts in behaviour that were associated with the general average shape of the price profile throughout the day.

In the 'short run' response, participants could also benefit by responding to deviations of the hourly price from the average hourly price. It was proposed that the extent of this response was dependent on the extent of the deviation from the average, and the 'cost of short-term behavioural adjustments, including the cost of closely monitoring prices' (Navigant Consulting, 2011). The short run model was proposed to be only relevant to days when participants received an alert that indicated when prices were expected to be unusually high ('high price alert day').

The new demand functions therefore explicitly recognised the inattention of participants. Firstly, by accepting that there was a cost involved in checking prices, and that participants would generally not want to incur this cost, except on high price alert days. Secondly, by assuming that participants developed a rule of thumb understanding of the general shape of prices throughout the day, around which they based their routines.

One of the reasons why the standard demand function in the first report was less accurate than the new demand functions, was because it simply did not reflect the reported behaviour of the participants. For example, when the program organisers surveyed participants about how often they checked prices, only a minority (30%) of participants reported that they checked prices 'every day or almost every day' (Navigant Consulting, 2011). The majority checked prices less frequently: at least once a week (29%), at least once a month (24%), or only after received a high price alert (17%). The standard demand function was not correct because it assumed that participants knew the price during each hour of the day, and yet this simply was not the case for the majority of the participants.

Furthermore, the program's marketing material included material that described how prices would vary on a typical day, including colourful figures of the price curve throughout a typical day. It also included the recommendation to 'keep the price pattern in mind'. This information would likely have encouraged participants to develop a rule of thumb understanding of prices, so that they would not have to check prices every day.

3.7. Rules of thumb and real-time pricing

Once a participant had learned the general price shape, then this would have been quite effective at predicting relative hourly prices, because the shape of the daily price profile for real-time pricing schemes in Illinois did not change much on a day-to-day basis (Allcott, 2011b). In other words, any changes in price are more likely to be associated with shifts in the entire price curve up or down, rather than changes in its shape. Once a participant had learned the general shape of the price profile over a typical day, then this rule of thumb understanding could be used to determine high and low price periods for most days, without needing to check actual prices. This would be useful for consumers contemplating shifting consumption within a day, as it gives them an understanding of relative costs within a day.

The challenge for participants was therefore not in determining when the low or high prices periods occurred during the day, but rather the day's overall level of price i.e. whether it was a high or low priced day. It is possible that heuristics could also have been used to determine the overall level of price for the day. Firstly, the marketing material sent to participants also emphasised the connection between temperature and overall price – low price days being typically cool, and high price days being typically hot (Navigant Consulting, 2011). It is possible therefore that in addition to developing a general understanding of the price pattern during the day, temperature was used by participants as a proxy for the overall level of price from one day to the next.

Further evidence to support this claim comes from an internet user-group set up for participants of a concurrent, and broadly similar, real-time pricing program also based in Illinois, by the utility ComEd (ComEd, 2012). In several discussions, participants express their concerns about unexpectedly high prices during days that were not particularly hot:

'Wow! What is with the high prices that have kicked in several times the last week or two. It's hot out, but not as hot as back in June. […]' (Participant 1)

'The rate hit twenty cents per kWh twice in the past week and the temperature here has just barely gone over 80 degrees. Just even look at today's predicted prices and it looks like a 95 degree day from last August. […]' (Participant 2)

'[…] I was wondering if you could please provide some insight into the volatility that has been seen on days like yesterday and some of the hotter days in August? […] Obviously, I understand that temperature plays a big part, but yesterday was not all that hot […]' (Participant 3)

These exchanges reveal instances where the participants' rule of thumb about the relationship between temperature and price was not accurate. The fact that temperature was not an accurate proxy for price during these days, and that participants were concerned about it, demonstrates that it was, however, a relatively good proxy the rest of the time. The link between temperature and price was clearly well-established in the minds of these participants, and this supports the notion that participants had adopted the heuristic behaviour of using temperature as a proxy to infer the overall level of price that could be expected for a given day.

Two distinct heuristic behaviours are therefore evident. Firstly, participants learn the general pattern of prices throughout the day. Secondly, the overall level of price during a day is inferred using temperature as a proxy. This is supported by evidence from participant surveys and discussion groups, and from the econometric analysis reported by the program evaluators.

3.8. Participant rationality

Which of the two models of inattention discussed previously (limited attention, or information costs) best describes this type of behaviour? The acquisition costs involved in checking prices were arguably quite low – prices could be checked through the program website, a range of internet browser applications, by phone, and even on Twitter during the later years (Navigant Consulting, 2011). Where acquisition costs are low or negligible this generally makes the limited attention model the more plausible option (Dellavigna, 2009). It is, however, inconclusive whether the participants were resorting to heuristics because of limited attention, or the due to the acquisition costs associated with checking prices.

What is clear, though, is that the regular prices made heuristic behaviour a satisfactory option for participants. Regular here refers to the fact that the times when prices were high or low occurred at the same times of day, day after day. The participants knowledge of the general price profile, and the use of temperature as a proxy for the overall level of price, made prices predictable, and so greatly reduced the need for them to check prices.

Similar to the example of investors in stock markets in Table 5, this demonstrates that people tend to simplify complex information. In the participants' heads, the real-time pricing scheme could be satisfactorily interpreted as a tariff with more or less fixed periods of high and low prices, and with an overall level of price that would vary according to the temperature.

3.9. Use of enabling technologies

Another important point to note is that the organisers who are implementing dynamic pricing programs seem to have recognised the importance of inattention, and evidently strive to reduce the information costs involved in checking prices. Numerous 'enabling technologies' were introduced to the Illinois program that allowed prices to be more visible to participants. This included internet sites and applications, high price alerts (via text, phone, or email), as well as a 'PriceLight' – a glowing light-orb that changes colour depending on the current price. These technologies could work by reducing the acquisition costs involved in checking prices, or by making prices more salient (or indeed both). The PriceLight is especially useful in this regard as people can get a feel for the current price without needing to be right next to the object (unlike an in-home display), or necessarily be particularly attentive either – as they can see the PriceLight's colour from a distance, or while performing other tasks. Similar to the body language in the dinner party conversation mentioned previously, the PriceLight acts like a proxy signal for the price, people can get a feel for the price without needing to know the specifics. Indeed, participants with PriceLights had significantly greater elasticity of demand (an additional 6.0%) compared to those without (Summit Blue Consulting, 2009). This is an impressive result considering the relative simplicity of the technology.

3.10. Discussion of other behavioural factors

Evidence therefore suggests that participants in real-time pricing programs resort to heuristics, due to inattention. This suggests that behavioural factors, should be incorporated into models of consumer behaviour in real-time pricing schemes and, possibly, to demand response schemes in general. Given the above, it is possible that other behavioural factors that are already recognised by behavioural economics could equally play an important role. This following therefore briefly summarises and discusses several further types of behaviour.

3.10.1. Framing effects

'Framing effects' describe how decisions can be influenced by context and the way that choices are framed. A classic example of a framing effect was demonstrated by Kahneman, Knetsch and Thaler (1990). They performed a laboratory experiment whereby subjects in a group were randomly allocated a mug. Subjects with a mug were then asked to state how much money they were willing to accept in exchange for the mug they had just been given, and the remaining subjects were asked to state how much money they would be willing to pay to receive a mug. Under the standard model, there should be no difference between the subjects' stated willingness to pay and willingness to accept. In fact, the median willingness to accept was $5.75 and the median willingness to pay was $2.25. This asymmetry between willingness to pay and willingness to accept is known as the 'endowment effect' – the simple act of conferring ownership of an item to a person alters the value they place in the item. The endowment effect has been extensively researched and demonstrates the fact that people are generally loss averse, insofar as losses are felt more strongly than gains. This and other well-known framing effects are summarised in the following table.

Table 6 – Framing effects: how people evaluate outcomes and choices based on the framing of information

Description of behaviour	Referenced examples
Reference-dependent preferences People evaluate outcomes relative to a reference point.	A group of 70 participants is asked the following problem (Kahneman and Tversky, 1979): 'In addition to whatever you already own, you have been given 1000. You are now asked to choose between A: (1000, .50) and B: (500)' where (1000, .50) indicates a 50% probability of winning 1000 and a 50% chance of winning 0. Another group of 68 participants is offered a different problem: 'In addition to whatever you own, you have been given 2000. You are now asked to choose between C: (-1000, .50) and D: (-500)'. In the first group 84% chose B over A, and in the second group 69% chose C over D, even though, in terms of outcomes, B and D are identical, as are A and C. People's decisions are therefore often influenced by changes in wealth, rather than final wealth. If told that an item they have decided to buy is on sale at \$5 cheaper in another shop 20 minutes drive away, most people will say they are willing to travel to save the \$5 when the item costs \$15, but not when it costs \$125 (Tversky and Kahneman, 1981).
Certainty effect People overweight certain outcomes compared to risky outcomes.	Faced with the choice between A: (4000, .80) and B: (3000), 80% chose B (Kahneman and Tversky, 1979). By contrast when the same choice was framed as a choice between negative outcomes, A:(-4000, .80) and B:(-3000), 92% chose A, the riskier option. Due to the certainty effect, people are risk averse for gains and risk seeking for losses.
Loss aversion Losses are felt more strongly than gains.	The 'mug' example above illustrates loss aversion in a laboratory setting, while several other studies have demonstrated it in the real-world, including sports card trading, the housing market, finance, labour supply and insurance (Dellavigna, 2009).

Ignoring opportunity costs Whenever a choice is made, there is always a cost incurred that is associated with the value of the alternative choices, and people often fail to factor this cost into their decisions.	The following was asked to a group of wine collectors (Thaler, 1999): 'Suppose you bought a case of a good [wine] in the futures market for $20 a bottle. The wine now sells at auction for about $75 a bottle. You have decided to drink a bottle. Which of the following best captures your feeling of the cost to you of drinking this bottle? $0, $20, $20 plus interest, $75, and -$55.' Only 20% of respondents chose the economically correct answer ($75), while 30% felt that it cost them no money, and 25% that it actually saved them money (-$55).
The value of 'free' People perceive the benefits of free (zero price) products to be greater than the benefits of the same products at low (non-zero) prices.	Shampanier, Mazar, and Ariely (Shampanier et al., November/December 2007) contrasted the demand for two products across conditions that maintained the price difference between the products, but varied the cost of the cheaper product between a low and zero price. As the price difference between the two products was maintained, the standard model predicts that demand should not change, yet for the zero-price option, there was dramatically more demand for the free product.

In a rare example of behavioural economics applied to demand response, Letzler has proposed that framing effects could be used to improve the adoption of critical peak pricing tariffs in the US (Letzler, 2010). The adoption of such tariffs remains low, despite the fact that consumers who are on them are generally satisfied, and save on their bills. Focussing on the consumer's choice of tariff stage, Letzler argues that consumers over-weight the impact of high price periods, and neglect the fact that, for most of the year, they would be paying less than they would under the standard flat-rate tariff. In order to counter this effect, Letzler proposes the introduction of an 'Incentive Preserving Rebate' tariff – effectively a critical peak tariff that has been modified slightly to minimise the risk of consumers rejecting the tariff due to loss aversion. Under the rebate tariff, consumers pay a fixed amount at the beginning of each month, which gives them the right to purchase a fixed amount of energy during critical events at the standard, non-critical price. Customers that use less than this amount receive a rebate, and customers that use more than their allowance pay the critical price. By adopting a rebate structure, critical peak periods are framed as opportunities to gain rebates (by reducing consumption below certain reference levels), rather than periods when high losses can occur. Fundamentally however, the rebate tariff is the same as a critical peak tariff: consumers have the option of reducing their bills by consuming less during peak periods. A practical implementation of such a tariff is needed now in order to demonstrate whether it succeeds in increasing adoption rates, or indeed has an effect on people's response during critical peak periods.

3.10.2. Self-control problems

Even if people do manage to reach an optimum decision, there is still the matter of carrying it out. A moment of honest self-reflection will reveal that we can be prone to procrastination, and avoiding difficult decisions altogether. Often we know that something will be good for us in the long run (exercising, giving up smoking, eating less, etc.), but because of the immediate or short-term sacrifices it involves, we put it off until tomorrow. Some of the relevant factors that contribute to these self-control problems are summarised in Table 7.

Table 7 – Self-control problems

Description of behaviour	Referenced examples
Status quo bias People tend to stick to the default option.	In a striking example that indicates the importance of status quo bias, consider the different levels of organ donation in European countries. In countries where people need to opt-out of organ donation, almost 100% of the population are organ donors. Whereas in countries where people need to opt-in, the percentage of the population who are organ donors ranges from 4% to 27.5% (Johnson and Goldstein, 2004).
Hyperbolic discount rates People value immediate rewards (and dislike immediate costs) much more than they value distant rewards (and dislike distant costs) (Houde and Todd, 2010).	In a laboratory experiment, Thaler (1981) found that the median subject was indifferent between \$15 now and \$20 in one month and between \$15 now and \$100 in ten years. This implied discount rates of 345% for the first option and 19% for the second. While discount rates should in theory be consistent, at least in the minds of the participants, discounting appears to be steeper in the immediate future than in distant future. This shows that as the period of time increases, people's discount rates approach values that are economically realistic (though still high in this case). When the period of time is short, or immediate however, people's discount rates reflect a strong preference for immediate gratification.

Status quo bias highlights the importance of assigning the correct default option. It is for this reason that in California and Ontario, customers that have smart meters installed are by default put onto a time-of-use tariff (Industrial Fuels and Power, 2011; Rowlands and Furst, 2011). Though customers are allowed to subsequently opt-out of the tariff, it is highly likely that this policy will achieve a higher enrolment rate than a reliance on people opting-in (though it does not guarantee that people will respond). Where certain behaviours are viewed to be socially desirable (such as with the organ donation example in Table 7), it would seem sensible to make the default option that which is most beneficial to society – and this logic applies equally well to mandatory participation in demand response schemes.

Improving adoption rates is however, only part of the challenge, as it is also necessary to ensure that people actually respond when needed. The preference for immediate gratification might act to discourage people from responding, and so it is important to understand the relevance of this effect, and how it might be mitigated.

Looking to the study of energy efficiency, it has been shown that consumers consistently undervalue the energy-savings associated with investments in efficiency (American Council for an Energy Efficient Economy, 2007). Hyperbolic discounting has been suggested as one possible explanation for this type of behaviour (Greene, 2011). For example, investments in some home improvements, such as improving loft insulation, can have relatively high rates of return, and as such would appear to make economic sense. Yet consumers with hyperbolic discounting will considerably undervalue the expected energy savings, particularly in the short-term, making such investments less attractive. Considering demand response, while there is a clear economic motive for people to shift consumption outside of peak hours, a strong preference for immediate gratification might oppose this.

One of the possible ways of reducing the impact of people's self-control problems is to use commitment mechanisms and goal setting. Indeed people often use commitment mechanisms to overcome their tendency to procrastinate, for example by purchasing gym memberships, or by putting disposable income into bank accounts which cannot be accessed until a certain date. Goal setting has also been shown to help consumers reduce their energy consumption (Becker, 1978). For demand response, the obvious way of achieving this is to get people to sign up in advance to making future shifts or reductions in demand, and then using automation to ensure that it happens. Even if people are given a manual override button, the fact that the default is to respond will considerably improve the chances of it happening.

3.10.3. Incentive Effects

A dynamic pricing program is an incentive scheme in its entirety, and so it is important to realise that financial incentives can have a profound effect on people's behaviour, and can even produce results that are opposite to what was intended. The reason for this is that people often base their actions on the principles of social-exchange, where favours or gifts are exchanged between people without money changing hands. In market-exchange, by contrast, money is used to pay for goods or services. As it turns out, there are quite different rules that govern behaviour for these two types of exchange. Imagine for example, offering your mother-in-law a cash payment in exchange for the family meal she just made. People would generally frown upon this type of behaviour, because they expect social-exchange behaviour – a gift, such as a box of chocolates of bouquet of flowers, would be more appropriate in these circumstances. Market-exchange and social-exchange are therefore quite separate, and introducing monetary incentives to a social-exchange environment can have unexpected consequences, as illustrated in the example given in the table below.

Table 8 – Incentives and their effects in market-exchange or social-exchange environments.

Description of behaviour	Referenced examples
Market exchange vs. social exchange People can be strongly motivated by social exchange (e.g. favours, non-monetary gifts, feelings of guilt). Introducing market exchange principles (i.e. monetary incentives) can produce counter-intuitive results.	Gneezy and Rustichini (2000) tested the effectiveness of imposing a fine on parents who were late in picking up their children from an Israeli day-care centre – thereby forcing a teacher to work late. Instead of reducing tardiness, the effect of the fine was to increase the number of tardy parents significantly. Furthermore, when the fine was subsequently removed several weeks later, no reversion to pre-fine levels was observed. The feelings of guilt that had previously been motivating the majority of non-tardy parents, had been removed with the introduction of the fine, in turn making it more acceptable to be late.

There is unfortunately little research on the relationship between social exchange and market exchange in demand response. Strengers (2010) has however conducted a qualitative study of household practices in response to critical peak pricing in Australia, and found that, while there was some evidence of rational behaviour in response to price increases during critical peak periods, for many households the increased cost did not feature in their explanations of how and why they responded. Indeed, in most cases, households expressed a sense of social responsibility in reducing consumption during peak periods, and that it was the notification of an impending critical peak period that created this feeling. Strengers concluded that while most demand response schemes are designed with the objective of shifting *demand* given the right *price signals*, greater results might be achieved by considering how to shift social *practices* given the right *notifications*.

It seems therefore that people might adopt beneficial behaviours even when not financially incentivised, provided they know that it is socially desirable to do so. Indeed, EnergyAustralia conducted an 'information-only' trial, where participants received notifications of critical peak periods, but no change in tariff, but still achieved a reduction in peak consumption of 13% (Strengers, 2010). Compared to the results from price-based schemes, this result is still very impressive. The role of social factors in demand response could therefore prove to be important, and the next section discusses this idea further.

3.10.4. Social preferences and norms

Humans are social animals, and have evolved to function effectively as part of a social group. Our preferences and decisions are not dictated solely by selfish motives, and as a result, people will often go to some lengths to act selflessly, or indeed to punish selfish behaviour in others. A number of these social preferences are described below.

Table 9 – Social preferences and norms

Description of behaviour	Referenced examples
Social pressure People can be strongly motivated to conform to a group identity.	In an early experiment on social pressure, Asch (Asch, 1951) asked subjects to compare the lengths of lines drawn on cards. When subjects performed the experiment in isolation 98% gave correct answers. When in a group of four to eight people however, one third of subjects gave incorrect answers when the other subjects, who were actually confederates of the experimenter, unanimously gave the wrong answer (Dellavigna, 2009). The subjects purposely gave incorrect answers, to not appear to disagree with the other members of the group.
Selflessness, and the punishment of selfish behaviour People will make sacrifices to punish selfish behaviour in others, and will act more selfishly if unobserved by others.	In 'Ultimatum Game' experiments, a participant 'the proposer' is given a certain amount of money, and they then have to decide how much of it they will share with another, usually anonymous, participant – the 'responder'. Once the offer is made, the responder then decides to accept it or not – if they choose not to, neither of the participants keeps any of the money. While the standard model would predict that proposers would offer very little, and that responders would always choose to accept whatever was offered to them, in fact proposers usually offer at least 30% of the sum to be divided, and responders usually reject anything below 30% (Lunn, 2010, p. 104). Mazar, Amir and Ariely (2008) performed six experiments that provided evidence that most people will cheat or be dishonest if they believe they can get away with it (e.g. if their actions are unobserved), but that this dishonesty will usually be small enough so that people are able to delude themselves into thinking that their self-integrity has not been compromised.

Social norms People form estimates of socially undesirable behaviour and use this as a reference for their own behaviour.	Schultz et al. (2007) tested the effect of normative messages on domestic energy consumption. A descriptive normative message, containing details of average neighbourhood energy use, was sent to households and produced either a desirable conservation effect in households that consumed more than the average, or an undesirable 'rebound effect' on households that consumed less than the average. The researchers also found that the rebound effect could be eliminated by providing an 'injunctive message' which conveyed social approval to low energy usage (in this case smiley faces for low-usage households).

The Opower example, described previously in section 3.4, provided consumers with information about how much energy they consumed in relation to their neighbours. This provided a social reference for consumers to compare their energy consumption, with lower levels of consumption framed as more socially desirable. The intervention worked by altering consumer's reference points about the social norms for energy consumption. The Opower reports were found to be a cost-effective way of achieving small but persistent energy reductions, in the order of 1-3% (Allcott, 2011a). It is likely that this type of intervention could be usefully extended to demand response programs, for example by providing neighbour energy comparison reports about on and off-peak energy use.

Another consideration raised in Table 9 was that people's behaviour can depend upon whether they are observed or not. People might act selflessly when they think they are being observed by others, yet selfishly when they think they are unobserved. A possible intervention that builds on this idea is to make energy use more publicly visible. Houde and Todd (2010) give the example of creating public leader-boards, or lists of people that have made particular conservation efforts. In theory, the same principle could be used with demand response in mind.

Table 9 also highlights the notions that fairness, transparency, and trust are important to people. If people perceive others to be dishonest or selfish then they will punish them, even if this incurs a cost. This is relevant to demand response as currently consumers in many countries have a low level of trust with their energy suppliers, and if people feel that they are making sacrifices by changing their energy consumption behaviours, only for others to profit from it, then this might result in a backlash of opinion against suppliers and their demand response schemes. The relatively successful real-time pricing programs in Illinois owe some of their success to the fact that they were administered by an independent, community cooperative that had good ties with the community. Including this kind of trusted independent third party to demand response schemes might therefore be worth considering in other schemes more generally.

3.11. Summary

This chapter has investigated the results of a real-time pricing scheme in Illinois and has argued that it shows evidence of two distinct consumer heuristic behaviours. Firstly, participants learn the general pattern of prices throughout the day, and so develop rules of thumb about when prices can be expected to be high or low – rather than actually checking prices every day. Secondly, temperature is used as a proxy for the overall level of price during the day. This is supported by evidence from participant surveys and discussion groups, and from the statistical analysis of the program evaluation reports.

Referring back to the research question presented at the beginning of this chapter, it can be said that heuristics and inattention are relevant to explaining consumer behaviour in real-time pricing schemes: consumers are not willing to constantly check prices and, by consequence, use their ability to create rules of thumb to simplify the price signal instead.

This is how consumers respond to prices in current markets, yet there is still the matter of considering whether prices can be expected to continue to be regular in future low-carbon markets. This is explored in the next chapter.

4. Variability of electricity prices in current and future markets

4.1. Introduction

The following research question was presented in the overview, and re-stated at the end of the literature review.

Research question 3: Can domestic consumers be expected to respond to irregular dynamic pricing?

The rationale for this question was based on the concept that current wholesale markets have regular price profiles due to the large amount of flexible fossil fuel connected to the system. In the future, however, we can anticipate more wind power on the system, and this might be expected to have a considerable effect on the regularity of wholesale prices. As the purpose of dynamic pricing is to reflect wholesale price variability, this calls into question the assumption that the results from existing demand response schemes can be extrapolated into a future where prices become less regular.

While this rationale was mentioned previously in the thesis, this chapter provides a fuller discussion. Section 4.2 investigates prices in current markets, and includes a statistical analysis of the regularity of wholesale prices. Section 4.3 then compares this with the case of future markets with high penetrations of renewables. Section 4.4 investigates the variability of electricity prices with domestic grid-connected PV systems. This identifies that consumers with PV experience irregular electricity prices, and so are an appropriate group to investigate in order to address the research question above.

4.2. Electricity prices in current markets

One of the fundamental challenges of electrical power systems engineering is the requirement to maintain a continuous balance between electricity supply and demand (Wildi, 2000), referred to as system balancing. Historically, this was achieved by a central system operator through 'optimum economic dispatch' (Freris and Infield, 2008a) – demand is forecasted into the future, and generators are dispatched according to a merit order determined by the generators' running costs.

With the aim of promoting competition and reducing costs for consumers, however, the electricity supply industries of many countries have been, or are in the process of being, liberalised, and a centralised approach to system balancing is increasingly being replaced by a market approach (Freris and Infield, 2008a).

In such markets, one way of determining electricity prices is through a process of supply and demand bids. Generators bid to supply a certain amount of power at a certain price, for each hour or half-hour for the day ahead. The market price is set by the most expensive generation bid required to meet the forecasted demand. To this price would normally be added any additional costs incurred by the system operator in maintaining adequate reserve for system balancing and security of supply. Note that there exist other methods for determining prices in wholesale markets (Freris and Infield, 2008a).

In markets where power is supplied predominantly by fossil fuel plant, wholesale prices tend to follow the pattern of the daily demand profile. Figure 2, for example, shows demand and prices for the Californian PX Day-ahead market for one week in 1999 (University of California Energy Institute, 2003). Daily maximum air temperature is also shown alongside the price profile. The market price clearly follows the pattern of the demand profile. As the demand profile of large aggregations of domestic consumers tends to be regular in nature, the price also tends to follow a similar pattern from day to day, with hotter days also tending to have higher prices.

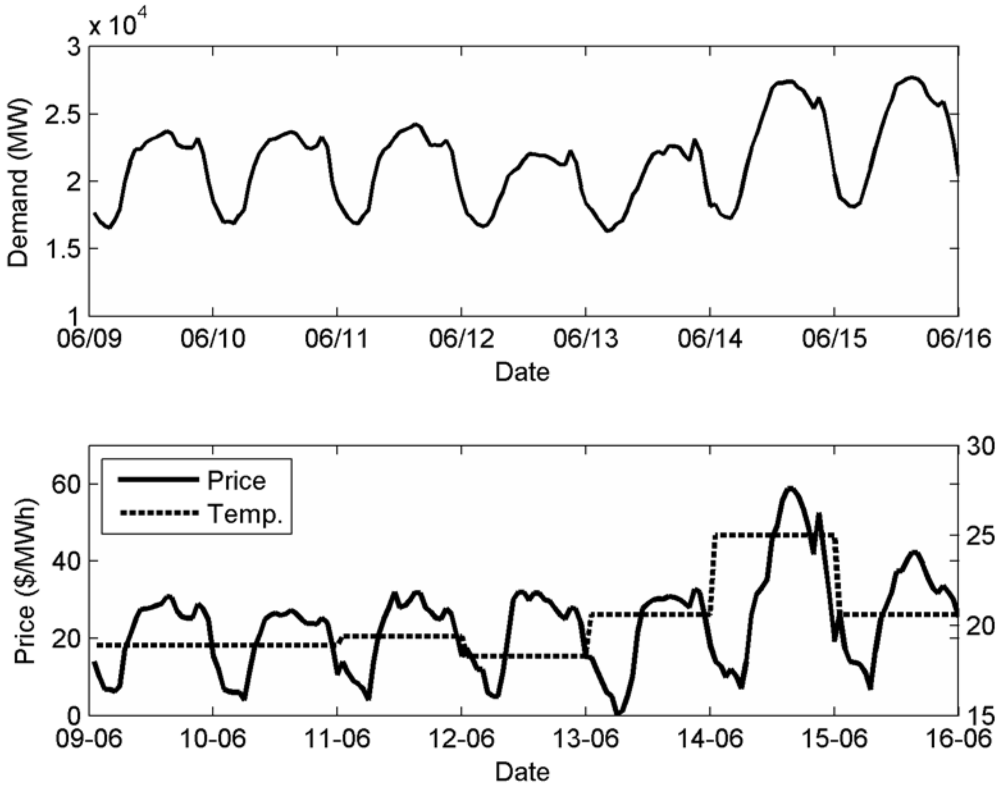


Figure 2 – Market demand, prices and daily maximum air temperatures for one week in 1999 for the Californian PX Day-ahead market.

There would appear to be a positive correlation between demand and price in this market, and this is explored further in Figure 3, which shows hourly market price against hourly market demand for the same California PX Day-ahead market, using data for the whole of 1999. The data has been 'binned', with the bin-colour illustrating the number of data points within it. While there is some scatter to the data, especially during periods of high demand, there is clearly a positive relationship between price and demand. Pearson's correlation coefficient is 0.63 for the data shown in Figure 3, which is statistically significant at the 99% confidence level.

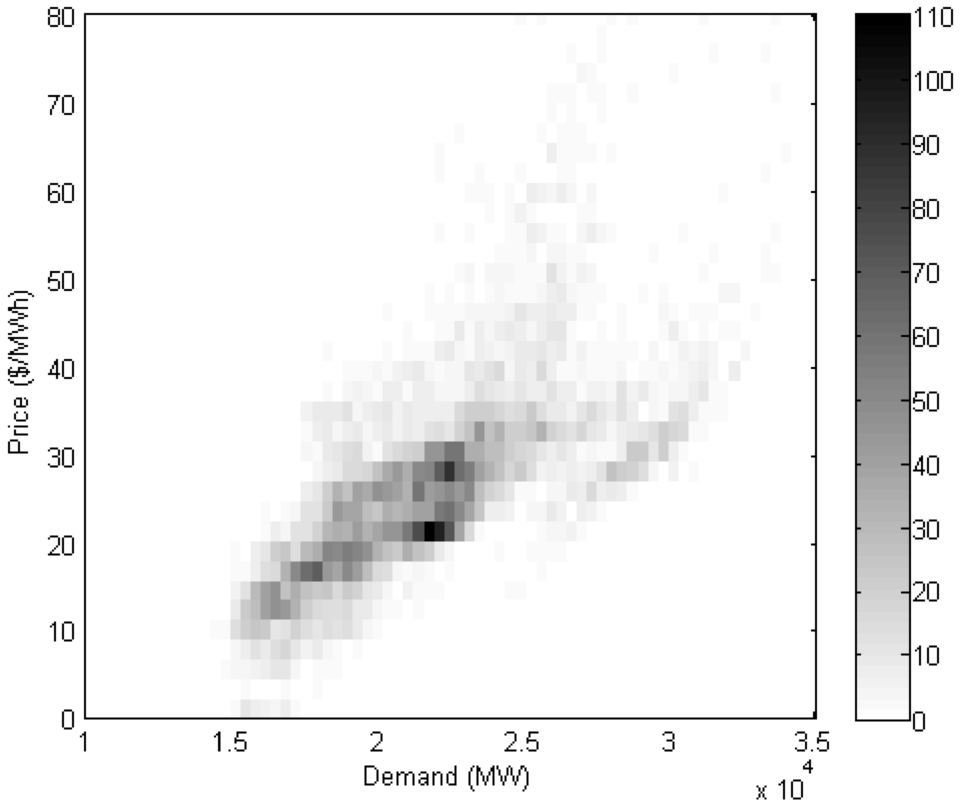


Figure 3 – Hourly market demand and price data in 1999 for the Californian PX Day-ahead market.

4.2.1. Regression analysis of the effectiveness of consumer heuristics given current market prices

The previous figure demonstrates that wholesale prices, and by extension, real-time prices in current markets are correlated with the demand. Prices are regular, therefore, because the demand profile is regular. Referring back to the previous chapter, it was suggested that consumers in real-time pricing schemes use two heuristics: first, they learn the general pattern of prices throughout the day, and second, the overall level of price during a day can be inferred using temperature as a proxy. It was argued that these two heuristics were effective because prices are regular. In order to test the effectiveness of these heuristics, a regression was performed on the market data shown in Figure 3, with the purpose of identifying how much of the price variation can be explained by the two heuristics.

This is tested by regressing hourly price onto hour of day binary or 'dummy' coefficients, and a coefficient representing the daily maximum air temperature. The hour of day coefficients capture the accuracy of the first heuristic, by associating a mean price for each hour of the day. Referring back to Figure 3, this is similar to testing whether the shape of the price profile is repeated each day.

The temperature coefficient captures the accuracy of the second heuristic, by associating an overall increase or decrease in the price for all hours of the day that is dependent on the daily temperature. Temperature data was sourced from the University of California (University of California, 2012), and daily maximum air temperature data for Los Angeles was used in the regression. Referring back to Figure 3, this is similar to testing whether the temperature has a significant effect on the overall level of price during the day.

The regression function is therefore as follows:

$$p_i = \beta_1 + \sum_{n=2}^{24} \beta_n D_{n,i} + \beta_{25} T_{max,i} + u_i$$

Equation 2

Where

p_i : hourly market price for hourly observation i (MW).

β_m : is the mth coefficient estimated by the regression.

$\sum_{n=2}^{24} \beta_n D_{n,i}$: binary 'dummy' terms for each hour of the day.

$T_{max,i}$: daily maximum air temperature for hourly observation i (°C).

u_i : econometric error term associated with observation i.

This regression function was applied to the data shown in Figure 3. Separate regressions were performed for each month of data. The result of interest here is the coefficient of determination, or the 'R^2' value, for each month's regression. The R^2 value 'measures the proportion or percentage of the total variation in [price] explained by the regression model' (Gujarati, 1992c). The R^2 value is a measure of how well a regression function fits the data. A value of 1 indicates a perfect fit, while a value close to 0 indicates a bad fit.

Figure 4 shows the results. Prices throughout the whole year are shown in Figure 4A, and the monthly R^2 values are shown in Figure 4B. The results show that for over half the year, the heuristic method of knowing the general shape of the price curve throughout the day, and the effect of temperature on overall level of price, can explain over 50% of the total variation in price (i.e. the R^2 value is greater than 0.5). For some months, it explains over 70% of the price variation. It can be seen that the R^2 values are low during months that appear to have unusually variable and high prices.

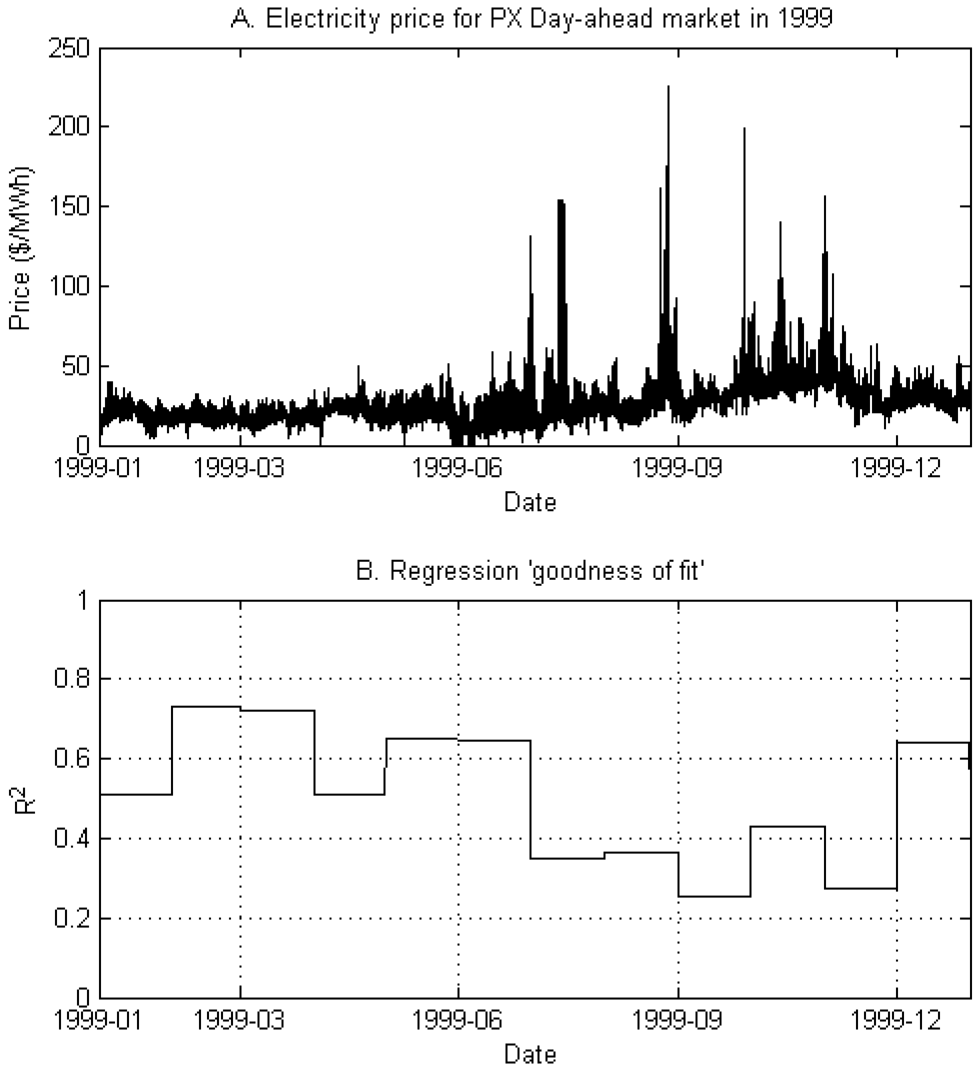


Figure 4 – Market prices and monthly R^2 values for the regression.

This illustrates an important point: electricity prices in current markets are characterised by regular price profiles, with overall levels of price affected by temperature. The term regular refers to the fact that the shape of the price profile is similar from day to day, and that the periods when prices can be expected to be high or low remain broadly unchanged. In such markets, the consumer heuristics described previously are effective, and consumers do not need to check prices regularly on real-time pricing schemes. The next section considers whether this regularity of prices can be expected to change with high penetrations of renewables.

4.3. Electricity prices in future low-carbon markets

4.3.1. Wind power

Out of the intermittent renewables, wind is expected to supply the largest amount of electricity in the period 2015 to 2030 (International Energy Agency, 2008). The effects of large-scale wind penetration are of particular interest to the UK, e.g. one of the DECC 2050 pathways shows over one half of the nation's electricity demand being met by wind power (DECC, 2010a).

Figure 5 shows an estimate of what wholesale prices might be expected to look like in the UK given the anticipated levels of wind power in 2030, using historic weather data from 2000. This data has been re-drawn from (Cox, 2009). This study estimates that prices can be expected to become more variable, with extreme prices of well over £1000/MWh (£1/kWh), as well as periods of negative prices, where consumers might be paid to increase demand, or wind farm operators paid to curtail generation.

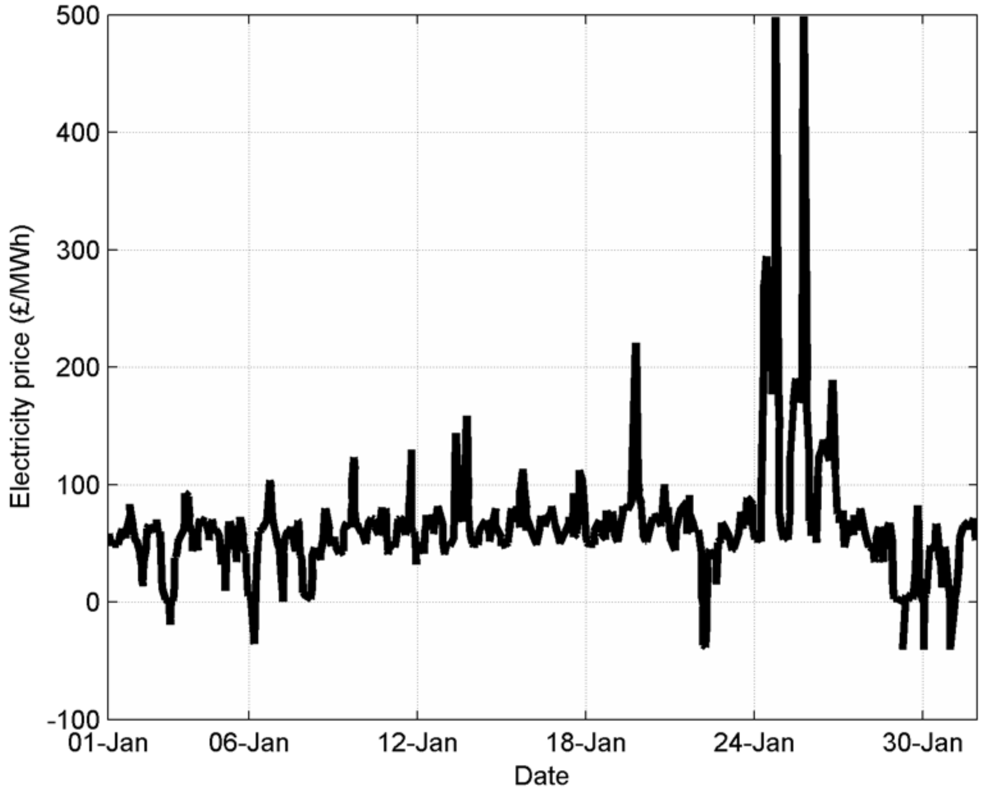


Figure 5 – Anticipated wholesale prices given 2030 projects for wind power in the UK. Re-drawn from (Cox, 2009).

Similar conclusions were reached by another study, which estimated the effects of wind power on market prices given 2020 projects (Green and Vasilakos, 2010): increasing penetrations of wind power can be expected to result in a wider range of prices, and daily price profiles that are less regular than at present.

The increased price variability is caused by the natural variability of wind power, which can be described as having three components: within-day variability, variability over periods of several days, and seasonal variability. Within-day variability reflects the distribution of wind power throughout the course of the day. In the UK, on average, wind produces approximately 50% more electricity during the daytime than at night, with its maximum during the afternoon (Freris and Infield, 2008b). These are, however, average figures, and it is still possible for wind output to be high or low at any time of the day. By consequence, with high penetrations of wind power, there will no longer be the certainty that prices will be consistently high in the evening or consistently low at night.

Variability over periods of several days reflects the influence of passing weather systems on wind generation. Of particular concern is the price variability caused by calms or swells of wind power caused by persistent weather systems, as these are likely to cause prices to remain very high or low, possibly for days on end (Cox, 2009), as illustrated in Figure 5 by the extreme prices towards the end of the month.

Finally, the seasonal variability of wind has two consequences. Firstly, wind power produces on average twice as much electricity during winter than in summer (Freris and Infield, 2008b), which is useful as this matches the seasonal variability in demand. The second consequence, however, is that there will be greater variability in wind generation during the winter, with the result that prices during the winter months can also be expected to be more variable than prices during summer months (Green and Vasilakos, 2010).

This variability of wholesale prices, and by extension, real-time prices that can be expected in the future raises several concerns. Firstly, the previous sections have described how domestic consumers respond to real-time pricing by resorting to heuristics. It is not obvious, however, that these same heuristics will be effective for responding to prices that are linked to intermittent wind output. Furthermore, it is not obvious whether this kind of irregular pricing could be usefully simplified in order to accommodate consumer heuristics.

The result is that we should be wary of assuming that consumers responding to prices linked to wind output variability will have the same level of response as consumers responding to regular price profiles in current markets.

The above has discussed the expected effect of wind power variability on market prices. It stands to reason, however, that large penetrations of other intermittent renewables will also have an impact on market price variability. Some of these are considered in the following.

4.3.2. Solar power

Solar electricity generation (both PV and concentrating solar power) is of interest, as it is expected to become the second largest source of electricity generation from an intermittent renewable source in the period 2015-2030 (International Energy Agency, 2008). Similar to wind power, solar power also has seasonal variability, variability over periods of several days, and within-day variability:

- The seasonal variability of solar power is opposite to that for wind, with higher output in summer compared to winter.
- The variability over periods of several days is influenced by passing weather systems, as the presence of clouds will affect irradiance levels. In this case, there are similarities with wind power's variability over periods of several days.
- The within-day variability of solar power is, however, somewhat different to wind power, due to the fact that the sun rises and sets at predictable times. Some solar power can always be expected during the daytime, therefore, the uncertainty is associated with how much can be expected due to, for example, cloud cover.

The variability of solar power is naturally suited to some national demand profiles e.g. anywhere in the world that experiences summer peaking demand associated with air-conditioning.

4.3.3. Other intermittent renewables

Tidal and wave power, while not expected to make large contributions at the global level (International Energy Agency, 2008), are relevant to the UK where they could meet 5-10% of energy demands in 2050 (DECC, 2010a). Tidal power benefits from being a completely predictable source of power, though it should be stated that the peak in tidal power output is determined by the timing of the tides, which can be expected to change on a day-to-day basis. Wave power is mainly driven by the wind resource, and so could accentuate system balancing issues caused by high penetrations of wind power.

While the different types of renewables have been considered separately in the above, it should be noted that power systems with combinations of high penetrations of renewables will experience market variability that is influenced by the aggregation of the variability of the different renewables.

In summary, wholesale prices in current markets are correlated with the time of day and the temperature, and are regular in nature. Wholesale prices in future markets with high penetrations of renewables will be irregular and correlated with the intermittent generation from the renewables at a national scale. The demand response needed to respond to dynamic pricing in these two markets will be quite different, and it is not valid to assume that future schemes will be effective based on the evidence from current demand response schemes.

In order to address the research question presented at the beginning of this chapter, there is a requirement to investigate the response of domestic consumers to irregular pricing, in particular where this irregularity is caused by intermittent renewable generation. The following section considers whether consumers with grid-connected PV systems are an appropriate group to study.

4.4. Electricity prices with domestic grid-connected PV systems

In some countries, consumers with grid-connected PV systems can benefit financially by time-shifting their demand in relation to the times that their PV is generating. In the UK, for example, consumers can increase their financial benefit by shifting their demand to the daytime when the PV is generating (Energy Saving Trust, 2011). In Germany, the same advice appears to be true, though only for relatively recent systems built after 2009 (Braun et al., 2009).

This thesis presents the argument that consumers with grid-connected PV systems in some countries experience an 'effective price' of electricity that is similar in nature to real-time pricing, and which encourages demand response behaviour. As this is a novel concept, this section first presents the effective price in more detail. Subsequently, similar to the way that previous sections explored price variability in current and future markets, the variability of effective prices is analysed by calculating its correlation with PV generation using data from real domestic PV systems in the UK.

The following sections are derived from a paper that has been accepted for publication subject to minor revisions in IET Renewable Power Generation. The full paper, including revisions, is provided in Appendix B.

4.4.1. Variable effective prices for domestic PV systems

The effective price describes the price that consumers with grid-connected PV systems pay for the electricity they consume. While the paper provides a full description and mathematical calculation of the effective price, a summary is provided here. The effective price is determined by a number of variables. Firstly, it depends on the amount of power that a dwelling is importing from the grid. The cost of imported power is determined by the import price of the dwelling's demand tariff. Secondly, the effective price depends on the amount of power that is being generated by the PV system and which is being consumed within the dwelling, known as 'self-consumption'. The cost of self-consumed power is an 'opportunity cost', as it reduces the income from export payments associated with the dwelling's feed-in tariff, where this is applicable. The effective price is a then calculated as the weighted average of the import cost and the opportunity cost. This can be written as:

$$\boldsymbol{p_{eff}} = \frac{(\text{Opportunity cost} + \text{Import cost})}{\text{Total consumption}} = \frac{\boldsymbol{p_e P_{self}} + \boldsymbol{p_i P_i}}{\boldsymbol{P_d}}$$

Equation 3

Where the variables are described in Table 10.

Table 10 – Description of variables.

Variable	Description
P_{pv}	PV generation (kW).
P_e	PV output exported to grid (kW).
P_i	Electricity demand imported from the grid (kW).
$P_{net} = P_e - P_i$	Dwelling's net power flow (kW).
$P_d = P_{pv} - P_{net}$	Consumer electricity demand (kW).
$P_{self} = \min(P_{pv}, P_d)$	'Self-consumed' power i.e. PV generation that is consumed on-site within the dwelling (kW).
P_{pv}/P_d	PV fraction (>1 when exporting, < 1 when importing).
p_i	Price paid for a unit of electricity imported from the grid, 'import price' (p/kWh).
p_e	Price paid for a unit of electricity exported to the grid, 'export price' (p/kWh).
p_{eff}	Effective price of electricity (p/kWh).

For a fully metered PV system, as shown in Figure 6, the effective price can then be expressed in terms of the consumer demand (P_d) and the PV generation (P_{pv}) as derived below. A fully metered system is one where a generation meter, export meter, and import meter are present, and so where all the power flows are accounted for. The effective price for other metering configurations will be summarised later.

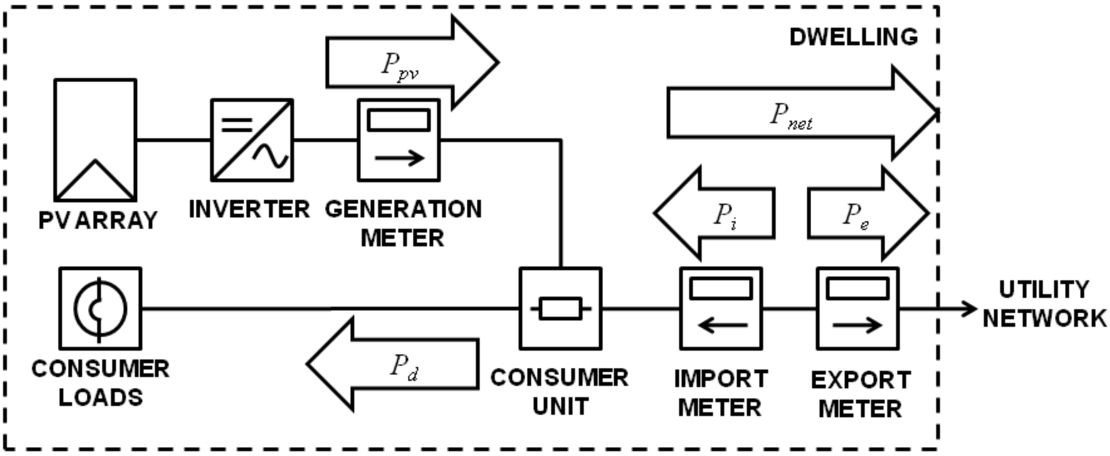


Figure 6 – A 'fully metered' domestic PV system

When exporting:

$$P_{pv} > P_d \text{ therefore } P_{self} = P_d \text{ and } P_i = 0$$

$$p_{eff} = \frac{p_e P_d + p_i 0}{P_d} = p_e$$

When importing:

$$P_{pv} \leq P_d \text{ therefore } P_{self} = P_{pv} \text{ and } P_i = P_d - P_{pv}$$

$$p_{eff} = \frac{p_e P_{self} + p_i P_i}{P_d} = \frac{p_e P_{pv} + p_i\left(P_d - P_{pv}\right)}{P_d} = \frac{p_i P_d + (p_e - p_i) P_{pv}}{P_d}$$

$$p_{eff} = p_i - (p_i - p_e)\frac{P_{pv}}{P_d}$$

$$\boldsymbol{p_{eff}} = \begin{cases} \boldsymbol{p_e} \text{ when exporting} \\ \boldsymbol{p_i} - (\boldsymbol{p_i} - \boldsymbol{p_e})\dfrac{\boldsymbol{P_{pv}}}{\boldsymbol{P_d}} \text{ when importing} \end{cases}$$

Equation 4

Equation 4 shows that the effective price is a function of the ratio P_{pv}/P_d, known as the 'PV fraction'. Figure 7 shows this relationship in graphical form for typical metering and tariff configurations in the UK and Germany.

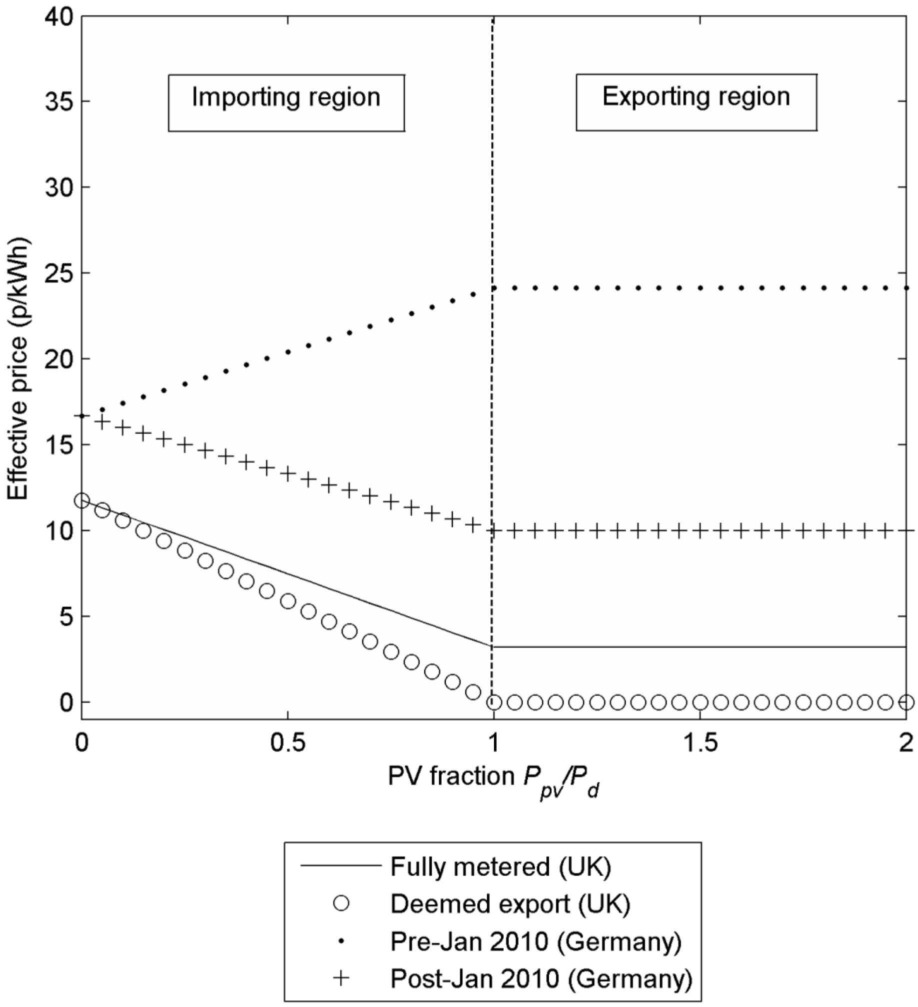


Figure 7 – Relationship between effective price and PV fraction, for some typical PV configurations.

For all the configurations, the effective price is equal to the export price when the dwelling is exporting power (the right hand side of the figure). The effective price is different for the various configurations because they have different export prices. In the UK, export prices are generally low, compared to the typical import price, whereas in Germany export prices can be either high or low depending on when the PV system was installed: systems installed before January 2010 have high export prices, whereas systems installed after this date have low export prices. The left hand side of the figure shows the importing region, where the effective price varies linearly with the ratio of PV generation and demand: the PV fraction.

Figure 8 shows an example of what the effective price looks like in practice for a real domestic PV system of 2.03 kW_{peak} located in Gloucestershire, UK, for a single day in June 2006. The day can be seen to be divided broadly into two periods where prices are different. During the day, when the PV is generating, prices are generally low, though never lower than the 'floor' price set by the export price (3.2 p/kWh in this example). Prices are variable during the times when the dwelling has to import from the grid. Outside the daytime period, prices are high, and are set by the 'ceiling' price which is given by the import price (11.8 p/kWh in this example).

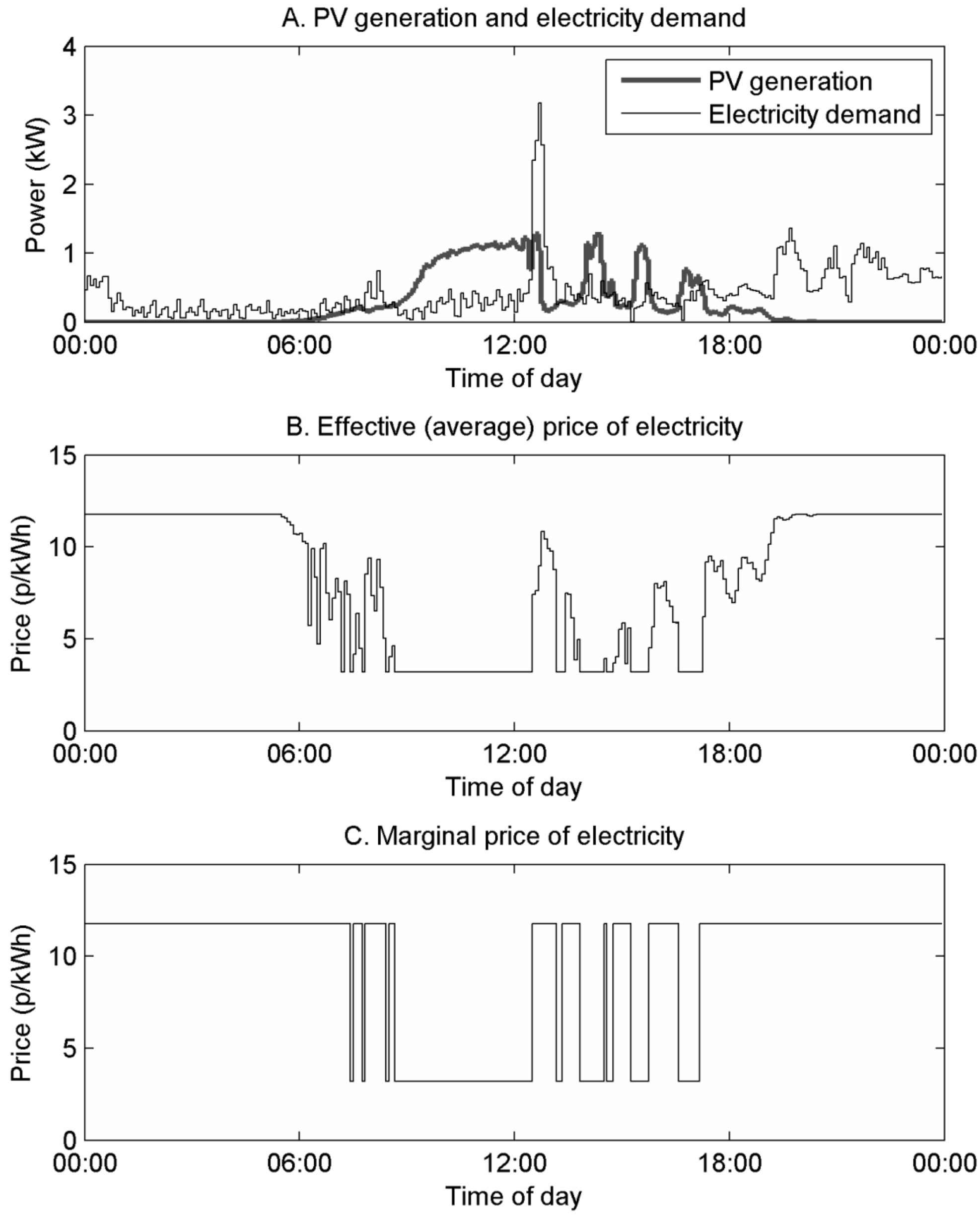


Figure 8 – PV generation, dwelling demand for a single domestic PV system (2.03 kW_{peak}) for a single day in June 2006, and the resulting price profiles.

An important point to note is that the price range presented in Figure 8B is similar to the range of prices that can be found in existing dynamic pricing tariffs, for example those that were presented in Figure 1. Occupants with PV in the UK therefore experience a price differential between high and low prices that is similar to that which is experienced by consumers on say an Economy 7 tariff, or a real-time pricing tariff in Illinois. The variability of prices in Figure 8B is also similar to that for real-time pricing.

4.4.2. Weighted mean average effective price versus marginal effective price

As an alternative to the weighted mean average effective price described above, it is interesting to consider the marginal effective price, which describes the price associated with an incremental increase in electricity demand, such as for example the price associated with switching on a small low energy light bulb. The marginal price for consumers without PV is determined by the import price, and as such for most consumers is a fixed amount, and so equal to the average price. For consumers with PV, however, the marginal price is determined by the status of the dwelling's net power flow. When the dwelling is importing, then the marginal price is equal to the import price, while when the dwelling is exporting the marginal price is determined by the export price.

Figure 8C shows what the marginal price looks like compared to the average effective price for the same day. It is interesting to note that there are occasions when the marginal price is high, but the average effective price is low. This illustrates that the PV price signal is complex, and it raised the question of whether consumers understand and respond to a price signal of this complexity. This will be explored in detail in chapter 6 through an analysis of an internet discussion forum for consumers with PV in the UK.

4.4.3. Correlation of effective price and intermittent generation

The previous section formally described the equations that determine the effective price, for a fully metered system in the UK, and demonstrated one of the determining variables was the PV generation. The correlation between price and PV generation is of interest here, as this is an important determining factor in deciding whether consumers with PV systems experience irregular dynamic pricing. While the correlation between the effective price and PV generation is implied in the equations described previously, this section investigates whether this correlation occurs in practice by analysing the effective price using measured data from 15 dwellings with PV systems in the UK taken from the Photovoltaic Domestic Field Trial (Munzinger et al., 2006). All systems were assumed to be fully metered systems, with import rates of 11.8 p/kWh, and export rates of 3.2 p/kWh. The full analysis of this dataset is provided in the paper in appendix B, while the following considers the correlation of effective price and PV generation.

Figure 9 plots hourly average effective price against hourly average PV generation for the 15 dwellings with PV mentioned previously. The figure shows data for the year 2006, for the hours of 09:00 through to 15:00, and where hourly PV generation values were greater than zero. The data has been binned, with the bin colour indicating the number of data points contained. The figure shows that for low generation, prices tend to be clustered near the import price (11.8 p/kWh). With increasing generation, the effective price decreases until the export price (3.2 p/kWh) is reached, at which point the data clusters again.

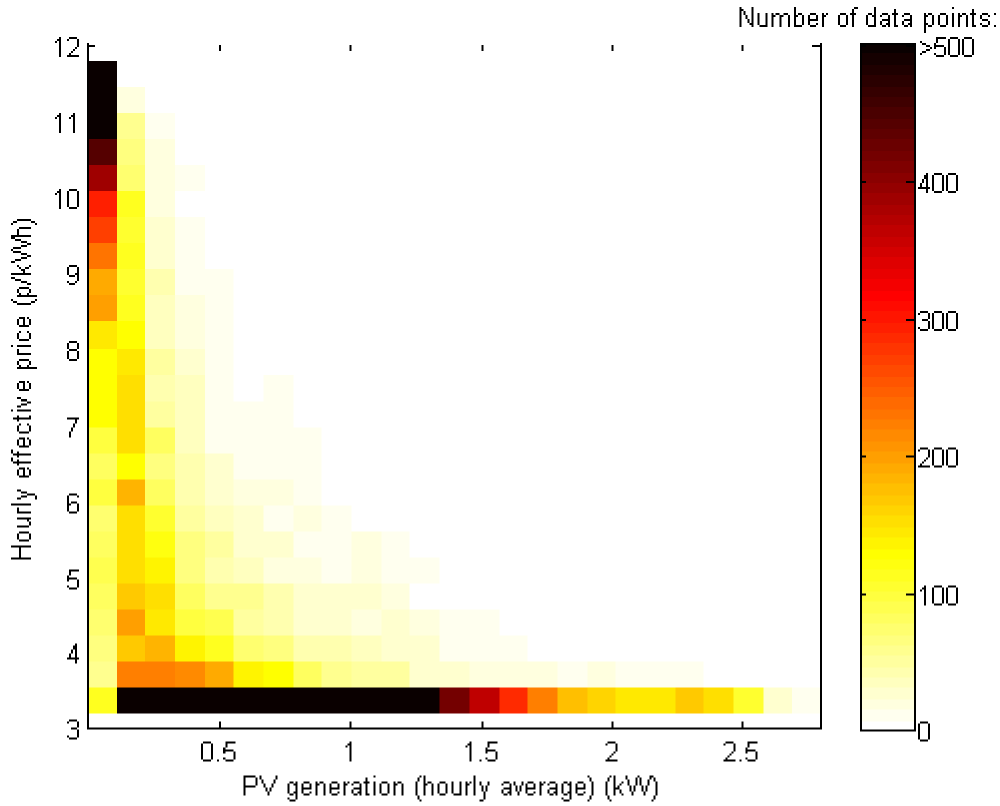


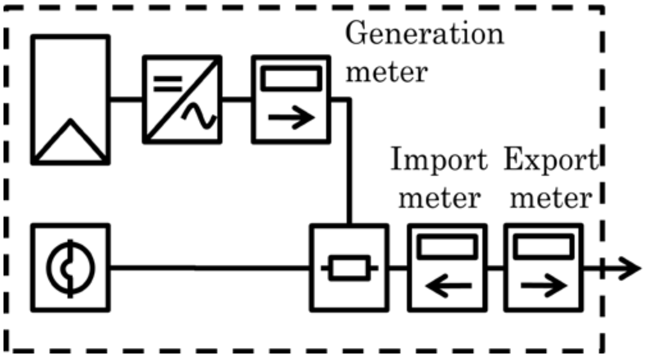
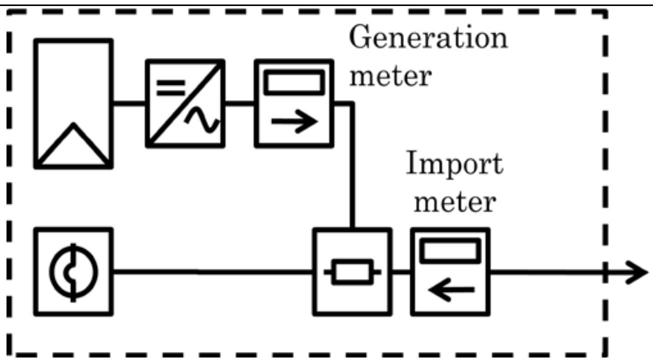
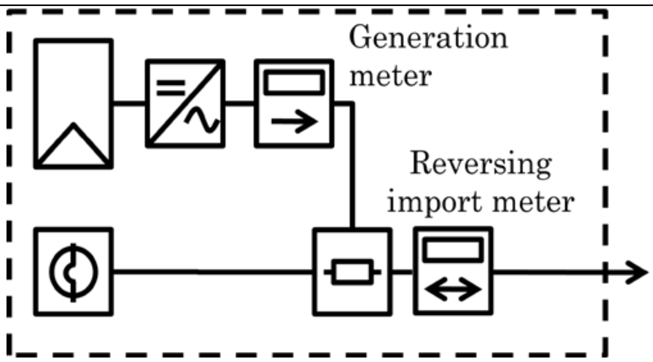
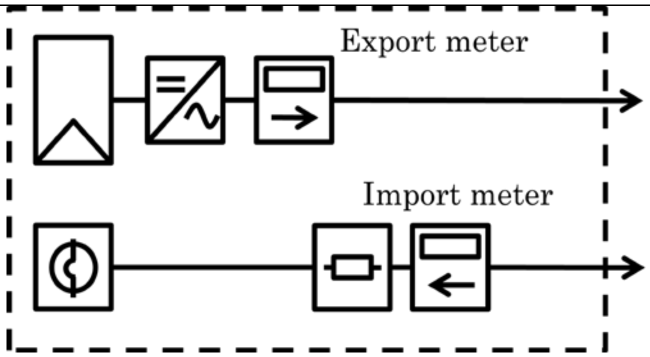
Figure 9 – Hourly effective price against hourly average of PV generation for 15 dwellings for 2006.

The data is non-linear, and polarised, with a high number of data points at the 'floor' and 'ceiling' prices. There is, however, a clear negative relationship between price and PV generation. In terms of the correlation between these two variables, Pearson's product-moment correlation coefficient is −0.59 for the data shown in Figure 9, while Spearman's rank correlation coefficient is −0.77. Both coefficients are significant at the 99% confidence level.

This allows us to say, with some certainty, that the effective price is correlated with PV generation and confirms that occupants with PV in the UK experience an effective price with an appropriate variability for them to be a relevant group to study for the purpose of this thesis.

4.4.4. Typical metering and tariff configurations and their effect on price

Previous sections have considered the effective price for fully metered systems. This section considers the effective price for the typical metering and tariff configurations in the UK, Germany, and the USA. These are shown in Figure 10. The following is a summary, full details are provided in the paper in appendix B.

Row number	Configuration name		Effective price
1	Fully metered UK (uncommon)		Varies
2	Deemed export UK (common)		Varies
3	Deemed export reversing import UK (uncommon)		Constant
4	Separate connection Germany		Constant

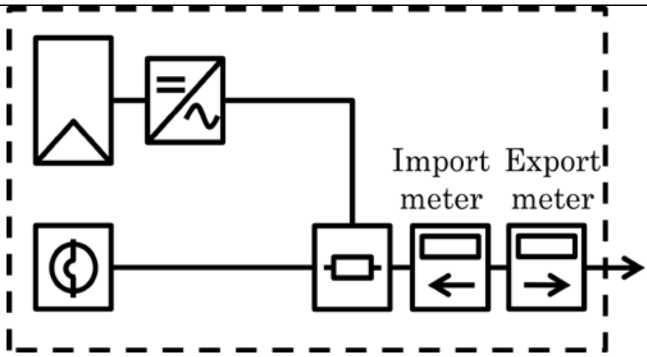
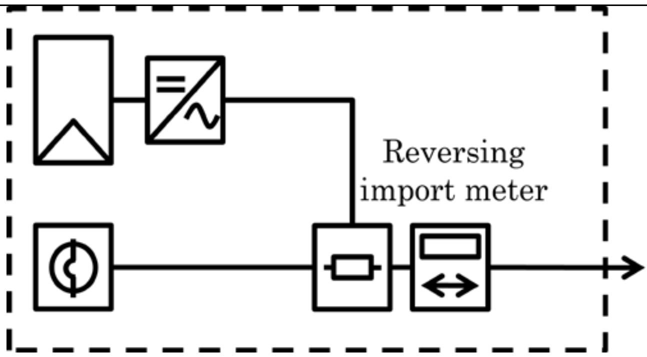
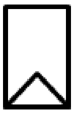
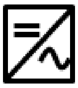
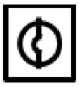
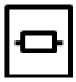
5	Import/export Germany		Varies
6	Net metering USA		Constant
	Key:  PV array  Inverter  Loads  Consumer unit → To grid		

Figure 10 – Typical PV system connection and metering configurations.

4.4.4.1. Feed-in tariff (UK)

The UK feed-in tariff consists of a high generation price paid for units of electricity generated by the PV system, and a low export price paid for units that are exported to the grid (Ofgem, 2012). Both the generation and export prices are changing over time: for PV systems installed on existing domestic properties and with installed capacity of 4 kW_{peak} or less, the generation price was 45.4 p/kWh in 2010 and dropped to a value of 21.0 p/kWh in 2012. The export price has, by contrast, been increasing: it started at a value of 3.2 p/kWh, and from 1st August 2012 was raised to 4.5 p/kWh. The top row of Figure 10 shows the fully metered system, which was considered in previous sections. The effective price for this system was given as:

$$p_{eff} = \begin{cases} p_e \text{ when exporting} \\ p_i - (p_i - p_e)\dfrac{P_{pv}}{P_d} \text{ when importing} \end{cases}$$

Equation 5

Fully metered systems are relatively uncommon in the UK, as most PV systems do not have an export meter fitted. In which case, these are known as 'deemed export' systems as shown in the second row in Figure 10. Exports are 'deemed' to be 50% of the PV generation (DECC, 2012d). As exports are not metered, the export price is zero, and the effective price is given by:

$$p_{eff} = \begin{cases} 0 \text{ when exporting} \\ p_i - p_i\dfrac{P_{pv}}{P_d} \text{ when importing} \end{cases}$$

Equation 6

The line of circles in Figure 7 shows the variation in effective price as a function of the PV fraction for a deemed export system. Prices for deemed export systems can be seen to be lower than those for fully metered systems. Furthermore, it is important to note that electricity is 'free' for occupants with deemed export systems, though only up to the limit set by the PV generation.

The third row of Figure 10 shows a 'deemed export reversing import' system, which is again relatively uncommon. In this case the import meter is a legacy meter that 'reverses' when the dwelling is exporting. For these systems, the export price is equal to the import price, in which case the effective price does not vary at all:

$$p_{eff} = p_i \text{ when importing and exporting}$$

Equation 7

4.4.4.2. Feed-in tariff (Germany)

There are two typical metering configurations for Germany, shown by the fourth and fifth rows of Figure 10 (VWEW Energeiverlag, 2001), and which are referred to as 'separate connection systems' and 'import/export systems'. With a separate connection system, the occupant does not experience a variable effective price because the PV is connected directly to the grid, bypassing the consumer unit and import meter.

Occupants with the import/export systems have the same effective price functions as for the fully metered system, as the generation meter has no effect on the effective price.

Furthermore, Germany has two variants of feed-in tariff (German Federal Law, 2010). For systems installed pre-January 2010, the feed-in tariff consists of a high export price (~30 c€/kWh-40 c€/kWh). There is no generation price. Occupants with import/export systems in Germany are incentivised therefore to maximise their exports to the grid. This is the opposite to the case for occupants in the UK, and is illustrated by the dotted line in Figure 7, which slopes in the opposite direction to the line for the fully metered system.

Systems installed after January 2010 have a different feed-in tariff: they receive a payment for any electricity that is generated and consumed on-site – self-consumption (German Federal Law, 2010). The result is that the effective price for these occupants is similar to that for UK occupants, this is again illustrated in Figure 7, where it can be seen that the slope of the line is now similar to that for the fully metered system.

The effective price for Germany PV systems post January 2010 is given by:

$$p_{eff} = \begin{cases} p_e - p_{self} \text{ when exporting} \\ p_i - (p_i - p_e + p_{self})\dfrac{P_{pv}}{P_d} \text{ when importing} \end{cases}$$

Where p_{self} is the self-consumption payment.

4.4.4.3. Net metering

'Net metering' is shown in the last row in Figure 10. Net metering is common in the USA, and the occupant is charged only for their net electricity consumption. Net metering is achieved either with a reversing import meter, or through separate import and export meters. Occupants with net metering do not experience a variable effective price.

4.4.5. Summary

This section has demonstrated that occupants with PV in the UK experience a variable effective price of electricity that is correlation with PV generation. The effective price has a price range that is similar to existing dynamic pricing tariffs. Furthermore, due to the correlation with PV, the effective price can be classified as irregular dynamic pricing. This section therefore confirms that occupants with PV in the UK are a useful group to study for the purposes of addressing the research question presented at the beginning of this chapter.

In order to benefit financially from the variable effective price, occupants with PV can engage in demand response behaviour. This is investigated in subsequent chapters. As described in chapter 1, storage is a common solution to the problems associated with balancing intermittent renewables and demand. An alternative for the occupants with PV is therefore to use battery storage to facilitate their demand response behaviour. The following section therefore considers the economic impact associated with the use of lead-acid batteries in domestic grid-connected PV systems under current feed-in tariff arrangements.

A paper based on the following work has been accepted for publication in Applied Energy. The paper is provided in full in appendix C. The following provides a brief summary of the work, for full details please refer to the paper in the appendix. The paper was a collaboration with Marcelle McManus and Sam Cooper from the University of Bath. The main contributions of these authors was on the environmental impact assessment of the battery. The environmental impact work is therefore not included in this thesis, but can be found in the paper.

4.5. Economic impact of the use of lead-acid batteries in domestic grid-connected PV systems

This work considers the economic impact of the use of lead-acid batteries in domestic grid connected PV systems under current feed-in tariff arrangements. The specific commercial opportunity to the occupant under these circumstances is to charge the battery system during the day to reduce exports, at an opportunity cost of 3.2 p/kWh, and to discharge the battery during the evening in order to reduce imports from the grid, at a benefit of 11.8 p/kWh. In trading exported electricity during the day for imported electricity during the evening, losses in the battery need to be considered. Furthermore, the costs and lifetimes of the equipment (batteries and inverter) also need to be considered.

The approach taken to quantify these impacts was to develop a realistic model of a lead-acid battery, and apply this to measured data from a group of domestic dwellings with PV in the UK, in order to simulate hypothetical power flows for the PV system with battery.

The battery model developed for this study is novel and is described in full in the paper in appendix C. Equipment costs were estimated from an internet search, and battery lifetimes were estimated using published empirical models. Three battery and inverter options were considered and are described in Table 11 alongside the estimated costs.

Table 11 – Details of the batteries used in the study.

	Battery option 1	Battery option 2	Battery option 3
Capacity	210 Ah	430 Ah	570 Ah
Voltage	48 V	48 V	48 V
Energy capacity	10.08 kWh	20.64 kWh	27.36 kWh
Estimated battery cost	£1280	£2621	£3475
Inverter size	2.02 kW	4.13 kW	5.47 kW
Estimated inverter cost	£1222	£2502	£3316

The battery model was applied to a year's worth of measured data on 37 dwellings with PV systems located in the UK. This consists of data from two of the sites that were monitored for the Photovoltaic Domestic Field Trial (Munzinger et al., 2006). In order to ensure the results of the study were robust, the study also considered the impact of a perfect lossless battery and inverter.

Figure 11 illustrates the effect that the modelled battery has on the power flows for a single dwelling with PV over the course of a single day. The top figure shows the PV generation and dwelling demand – these are un-changed from the measured data. The lower figure shows the net dwelling demand with and without battery. On this day, the battery had been used the previous evening and so started the day at minimum state of charge. As the PV starts to generate and exceed the dwelling demand, the battery is charged. There is a limit to the battery's charge current, which explains why there are still some exports during the middle of the day. During the evening, the dwelling demand exceeds the PV generation, and so the battery is discharged until minimum state of charge is reached again at around 23:00.

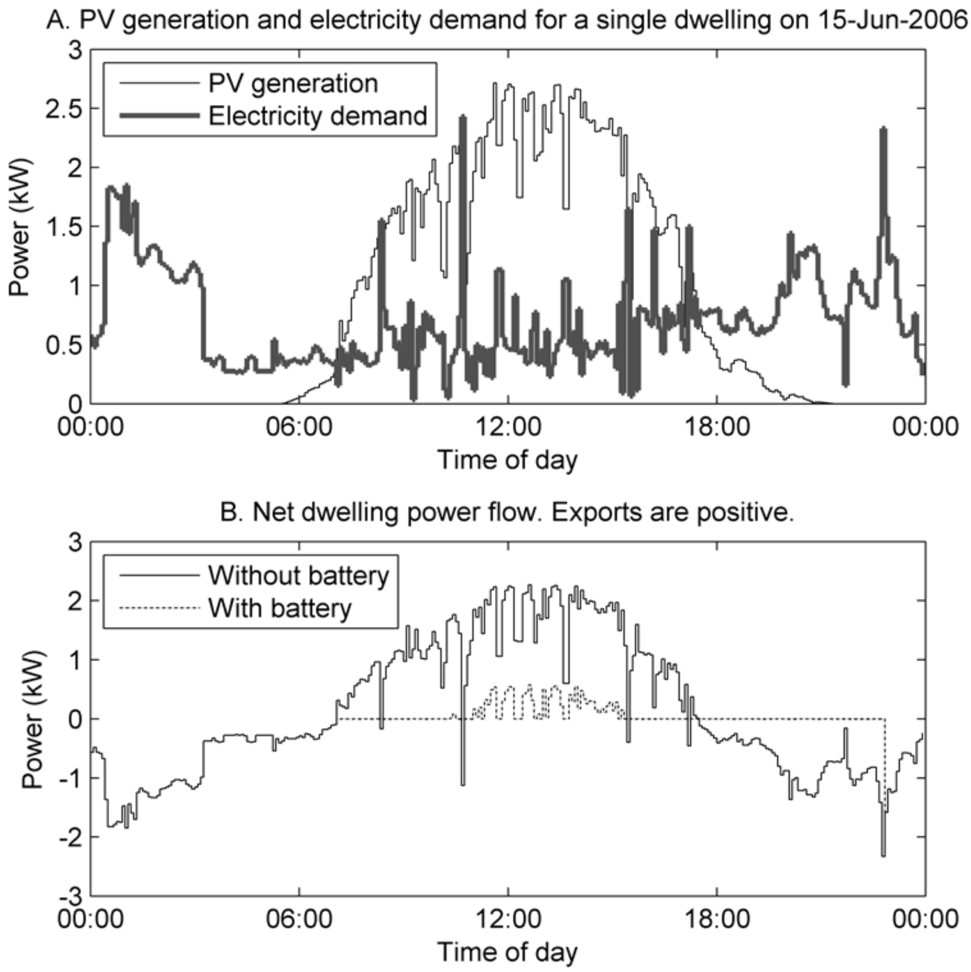


Figure 11 – PV generation, dwelling demand, net power flow to the grid, before and after battery.

Figure 12 shows the battery state of charge and efficiency for the same day. In the model, charging efficiency depends on the rate of charge and state of charge, with higher rates of charge and higher states of charge both adversely affecting efficiency. The discharge efficiency is based on rate of discharge, again with higher rates resulting in lower efficiencies. The model uses existing data as input to calculate these efficiencies.

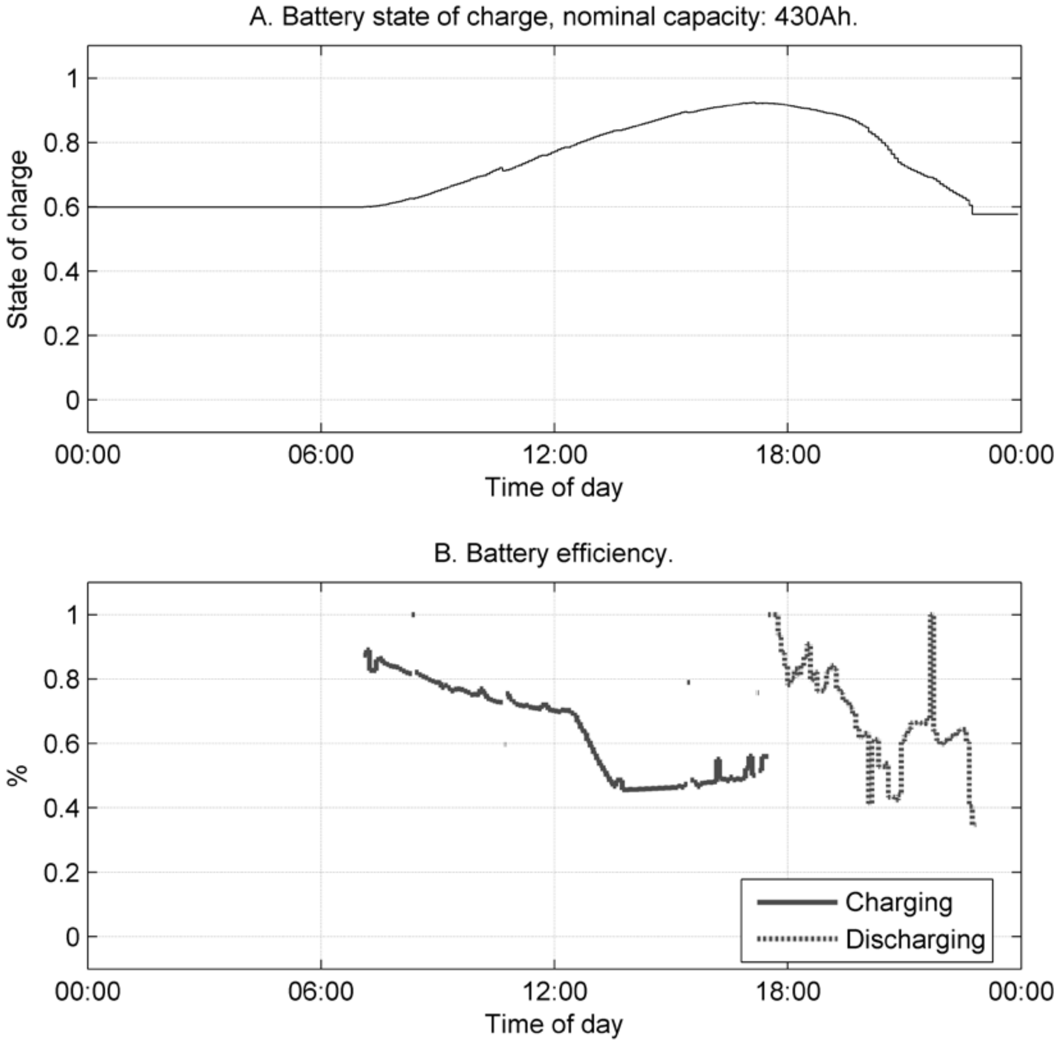


Figure 12 – Battery state of charge and efficiency.

For the same day, Figure 13 shows the financial impact of the battery. An opportunity cost is incurred during the day as exports are reduced, and a benefit is achieved in the evening as imports are reduced. The total benefit for the day was modest: approximately 10 p.

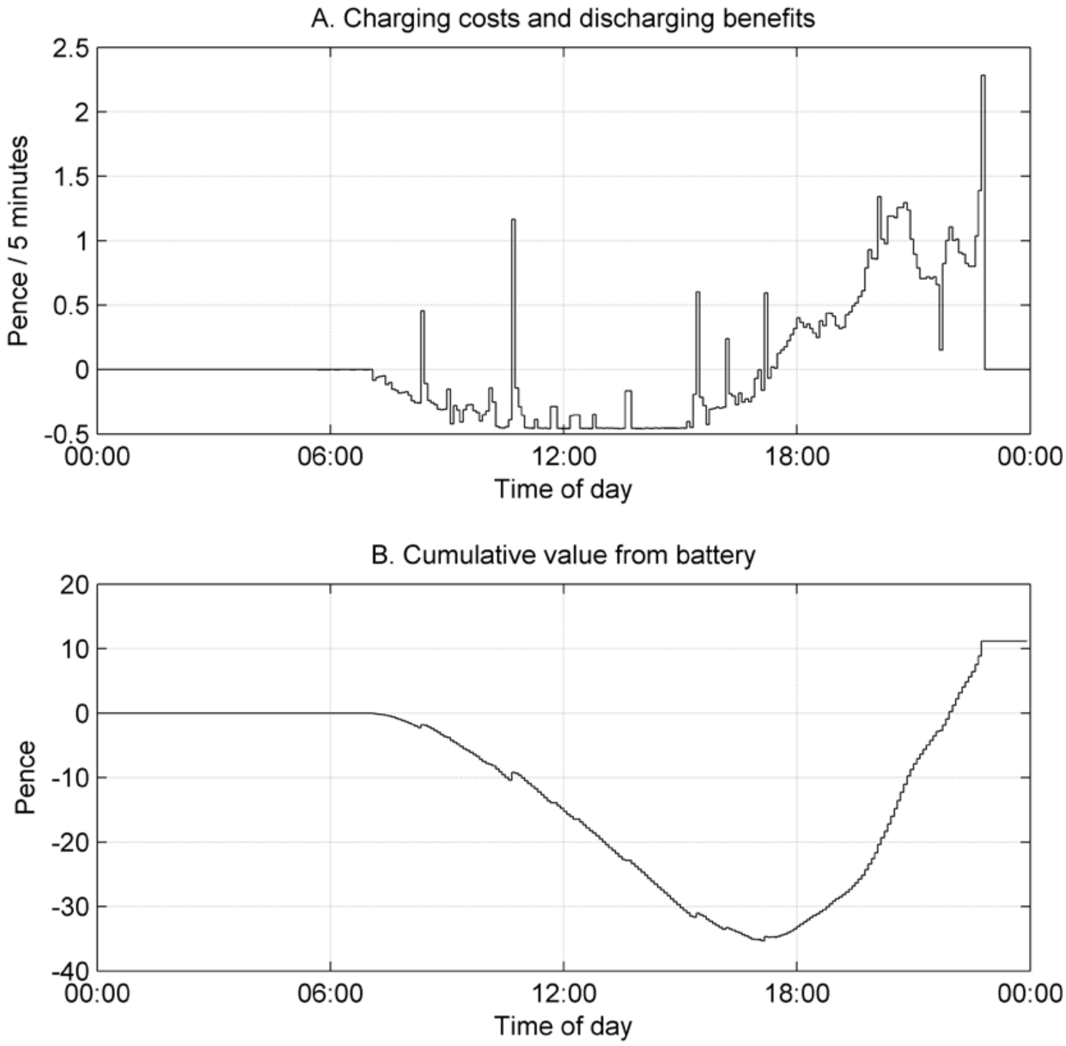


Figure 13 – Cost benefit over the course of a single day.

The previous figures illustrated the effect of the battery for a single dwelling over a single day. The model performs the same process for 37 dwellings using data for a whole year, and balances the benefit against the costs associated with the equipment given realistic wear and lifetimes. The results in terms of net benefit for the 37 dwellings and three battery systems considered here are shown in Figure 14. The case for realistic batteries is shown alongside idealised lossless batteries. It can be seen that the net benefit for both cases is negative, and there is no business case for the use of lead-acid batteries for the specific commercial opportunity presented by the UK feed-in tariff. These results are extrapolated for the case of feed-in tariffs in other countries in the paper in appendix C and show that this conclusion is equally valid for PV systems in Germany and Australia.

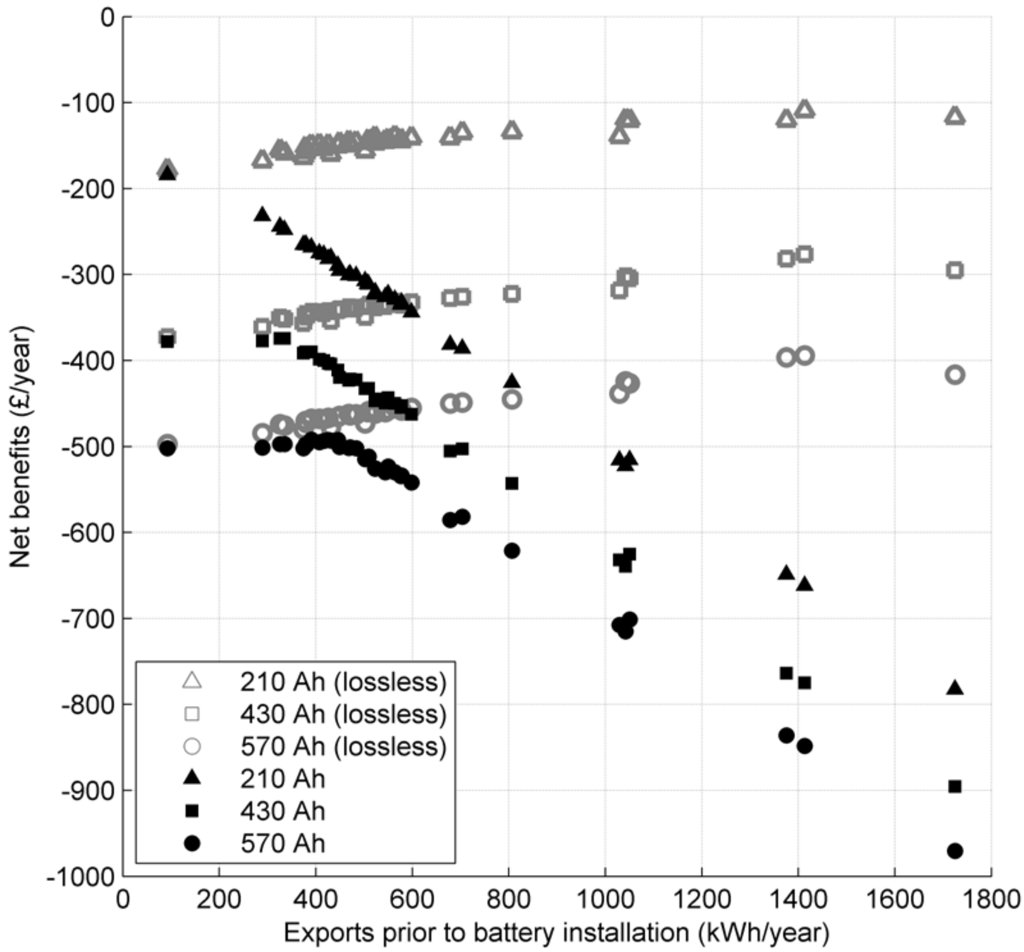


Figure 14 – Annual net benefits for lossless and realistic batteries for multiple dwellings with PV in the UK.

5. Quantifying the effect of PV on domestic consumer electricity demand profiles

5.1. Introduction

The previous chapter described how occupants of dwellings with PV in the UK experience a variable effective price of electricity. Regression is a common method for evaluating the response of consumers to dynamic electricity pricing schemes. In such evaluations, the purpose of the regression analysis is to identify and estimate the effect that price variations have on demand. The aim of this chapter is therefore to perform a regression analysis on the electricity demand of dwellings with PV in order to quantify the effect of the PV price signal on the occupants' demand.

As this work is statistical in nature, it can be useful for the reader to have in mind the final outcome of the work, as this provides context and can help to explain why certain approaches were taken. The following section therefore provides a brief preview of the results. Subsequent sections then review the literature on demand response behaviour of occupants with PV, discuss the use of regression applied to electricity demand data, describe the data limitations and the regression that was used in the analysis, and finally present the results of the regression.

5.2. Preview of the work

The regression analysis was performed on demand data from dwellings with PV in the UK, taken from the UK Photovoltaic Domestic Field Trial (Munzinger et al., 2006). This consisted of demand data for 130 dwellings with PV systems ranging in size from 1 kW_{peak} to 4 kW_{peak}. This group is called the 'PV group' in the following.

The purpose of the regression is to identify and estimate the response of the PV group to the effective price described previously in section 4.4. This can be expected to have two effects on the PV group's demand. Firstly, the PV group will make changes to their daily routines and consistently run appliances during the day. This is called the 'routine response'. The second effect that can be expected is for the PV group to be responsive to the irregular PV generation associated with variable sunshine levels. Cloudy days might encourage the PV group to conserve electricity, while sunny days might encourage opportunistic consumption. This is called the 'opportunistic response'.

The routine response is identified in the regression by comparing the PV group's demand with the demand of another group of dwellings that have similar characteristics, though who do not have PV – a 'control group'. As there was no control group in the Domestic Field Trial, one was created using data from the Irish smart meter Consumer Behaviour Trials (Commission for Energy Regulation, 2011). One of the limitations in this approach was that the PV group had a number of dwellings on Economy 7 tariffs, while the control group were all on flat-rate tariffs. These limitations are discussed further in section 5.5.

The regression results for the routine response on weekdays are shown in Figure 15. The line shows the estimate of the difference in hourly demand between the PV group and the control group. The results show that the PV group has higher demand than the control group during the night, and during the middle of the day. The higher nighttime demand is due to the dwellings on Economy 7 tariffs in the PV group. The result of interest here is, however, the increase in daytime demand that is evident for the PV group, which provides evidence of a routine response. The PV group has considerably lower demand than the control group in the evenings, and so it would appear that demand is being shifted from the evening to the day.

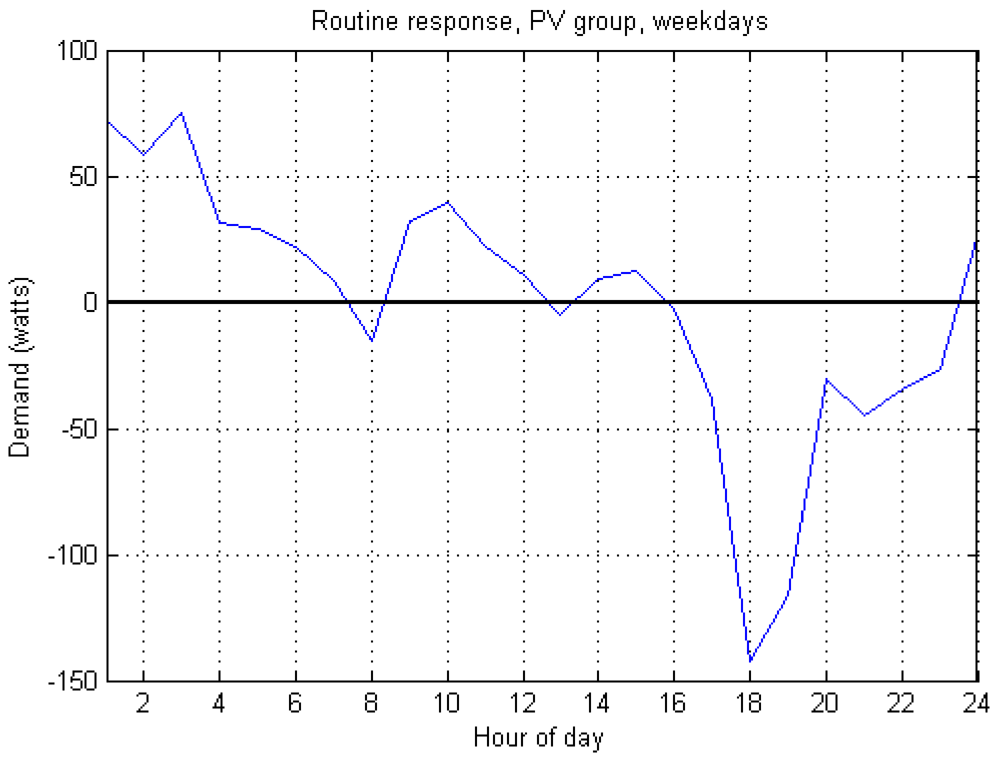


Figure 15 – Estimate of the routine response in the PV group for weekdays.

The above shows the routine response, and we now move on to consider the opportunistic response, which is also identified by comparing the PV group with the control group, in this case by comparing the effect that daily irradiance levels have on the demand for the two groups.

Irradiance can be expected to have two effects on demand. Firstly, increasing irradiance will tend to reduce demand for heating and lighting. This is the 'base response', and will be experienced by both the PV and control group. Because of the opportunistic response, however, the PV group should also have an opposing tendency to consume more on days with higher irradiances.

The presence of the control group is important because it allows these two factors to be isolated from each other. The control group will only experience the base response, while the PV group should experience both the base response and the opportunistic response. In simple terms, the difference in the effect of irradiance between the two groups can be interpreted as the opportunistic response that is of interest here.

Figure 16A shows the estimates of the base response to irradiance for weekdays. The y-axis of the figure shows a coefficient which, when multiplied by a daily irradiance, results in an estimate of the change in hourly demand that is associated with that level of irradiance. Taking an example off the graph, at 18:00 the coefficient is approximately $-3\text{x}10^{-5}$, which corresponds to a change in demand of −75 W on an average day with an irradiance of 2500 Wh/m^2. The results show that increasing irradiance tends to be associated with lower demand – the expected result. Note that the peak in reduction occurs during the evening, and is not coincident with the peak in irradiance, which occurs around noon. This could be associated with a lag in internal temperatures associated with the dwelling's thermal mass, as well as reduced lighting requirements in the evening. The base response is present in both the PV and control groups.

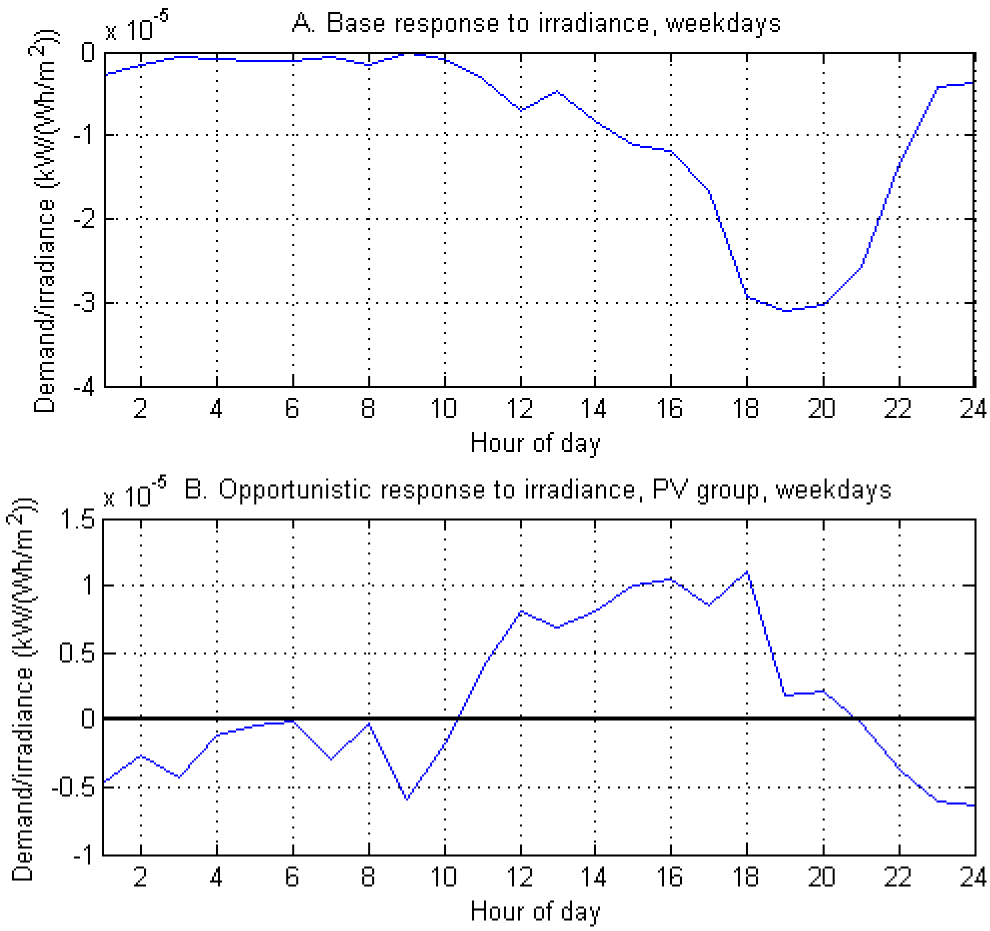


Figure 16 – Base response (both groups) and opportunistic response (PV group) to irradiance for weekdays.

Figure 16B shows the results for the opportunistic response to irradiance, present in the PV group only. The units of the y-axis are the same as those in Figure 16A, and are interpreted in the same way. The results show that the opportunistic response tends to increase demand during the day in the PV group. This would be associated with the PV group running appliances during the day in order to take advantage of the availability of cheap electricity. To re-iterate, the PV group experiences both the base response, and the opportunistic response – these are assumed to be independent effects, which the regression has isolated from each other.

This is significant because it provides quantified evidence that occupants of dwellings with PV are demonstrating demand flexibility associated with the irregular output from the PV system, and that this response can be characterised by a routine response and an opportunistic response. With this in mind, the following discusses how the regression was performed in practice, starting with a literature review of existing studies of demand response behaviour of occupants with PV.

5.3. Previous studies of demand response of consumers with PV

This section now considers the literature on demand response in dwellings with PV. The small amount of literature on demand response in dwellings with PV comes from the UK. The attention it has received, however, has often been as a part of a broader study of behavioural response to PV in domestic dwellings, often with a focus on whether installing PV results in occupants reducing their overall energy consumption.

Keirstead conducted interviews with occupants of 63 dwellings with PV in the UK in 2005 (Keirstead, 2007). The goal of the interviews was to investigate behavioural response to PV in the domestic sector. Though the overall focus of the interviews was on the possible conservation effect of PV, some of the questions were concerned with any time-of-use changes made by the occupants. 43% of the participants described changes in the time that they used electricity, and that this was primarily associated with large loads such as the dishwasher or washing machine. While this does provide evidence that these occupants were responding to the PV price signal, it was taken from a small sample, and furthermore does not quantify the response empirically.

Bahaj discusses the value of time-shifting demand in dwellings with PV in the context of the potential 'added value' that PV systems can offer to occupants in fuel poverty in terms of reducing their electricity bills (Bahaj and James, 2007). 'Load matching' is discussed to minimise exports and imports in order to obtain maximum value from the PV array. This is studied in terms of percentage figures for exported electricity to the grid. The findings were that low energy users receive less financial gain from PV systems than high energy users (£75 vs. £114 savings per year), principally because high energy users have higher base-load demand than low energy users. The study, however, did not indicate whether the occupants were responding to the PV price signal by time-shifting demand and, again, did not quantify this response empirically.

Dobbyn and Thomas investigated how microgeneration affected attitudes and behaviours through interviews of occupants of dwellings that had various microgeneration technologies installed, including PV (Dobbyn and Thomas, 2005). The focus of the study was mainly on whether the occupants were motivated to conserve energy after having microgeneration installed. Nonetheless, the study mentions how some interviewees had developed an understanding of which behaviours were 'free' or 'self-provided'. For example, one occupant with a micro-wind turbine mentioned that they turned on their electric heaters when the wind was blowing, presumably because this was 'free'. Washing machines are also mentioned being used by interviewees during times of peak generation. Similar to previous studies mentioned above, however, the research does not quantify the demand response behaviour, nor indeed focus on it in detail. This confirms the novelty of the present work.

Note that the studies mentioned above were focussed mainly on the effect of PV systems on reducing total demand. This is a separate consideration than the effect that PV systems have on encouraging time-shifting behaviour in occupants. It is important to emphasise therefore that the focus of this thesis is the time-shifting effect of PV systems, and not the demand reduction effect.

5.4. Regression in dynamic pricing evaluation

The aim of this chapter is to quantify the response of occupants to the variable effective price of electricity produced by UK grid-connected PV systems. Regression is a common method for evaluating the response of consumers to dynamic electricity pricing schemes. It is useful therefore to review the use of regression in such evaluations, in order to determine the appropriate approach for the present study.

A regression analysis generally involves the specification of a regression function, which is then applied to the observed data, in order to estimate regression coefficients which serve to indicate the presence of any statistical dependencies between the regression variables. In specifying the regression function, consideration should be given to the purpose of the regression, as well as to the limitations of the data that is available. Data limitations are discussed in section 5.5, while the regression's purpose is considering in the following.

Consider, for example, the evaluation time-of-use pricing, where the day is divided into fixed periods of high and low price. The simplest forms of time of use pricing consist of just two periods, such as Economy 7 in the UK. More complex time of use pricing might consist of three or four distinct periods during the day, possibly with different pricing during the weekend.

When evaluating such tariffs, the purpose is often the calculation of the price elasticity of demand (Faruqui and Sergici, 2011). Price elasticity of demand refers to the percentage change in demand given a 100% change in price, which serves as a useful quantification of the effect that price has on the demand.

The 'constant elasticity of substitution' model is a common regression function used for calculating price elasticity of demand for time of use tariffs (Faruqui and Sergici, 2010; Faruqui and Sergici, 2011). For a two-tier time of use tariff, the constant elasticity of substitution model consists of a regression function of the following general form.

$$\log\left(\frac{P_i^{peak}}{P_i^{off}}\right) = \beta_1 + \beta_2 \log\left(\frac{p^{peak}}{p^{off}}\right) + \beta_3 x_3 + \cdots + \beta_n x_n + u_i$$

Equation 8

Where:

$\log\left(\frac{P_i^{peak}}{P_i^{off}}\right)$: peak to off-peak ratio of demand for dwelling *i*.

$\log\left(\frac{p^{peak}}{p^{off}}\right)$: peak to off-peak ratio of price.

β_n: *n*th regression coefficient, which is estimated by applying the regression function to the observed data.

x_n : other relevant independent variables which are observed and are expected to have an influence on dwelling *i*'s demand e.g. temperature, presence of electric heating (note that qualitative variables such as this are represented by a binary variable).

u_i: residual error term for dwelling *i*. Simplistically, the regression estimates the 'best' fit to the data by minimising these residual error terms.

The function expresses the peak to off-peak ratio of demand as a function of the peak to off-peak ratio of price. β_2 is the price elasticity of substitution, in this case indicating the percentage change in the ratio of peak to off-peak demand given a percentage change in the ratio of peak to off-peak price. The regression function is applied to the observed data, yielding estimates of the coefficients, β_1 to β_n. A negative value of elasticity, β_2, would be expected – as the peak price increases one would expect demand to be shifted to the off-peak period. Other independent variables, illustrated by the x_n terms are included where appropriate. The subscript i stands for observation i, indicating that the regression function is performed on a data set of multiple observations of the independent and dependent variables. The error term u_i accounts for the residual error associated with observation i.

While the constant elasticity of substitution model is appropriate for variable pricing with distinct price periods, like the Economy 7 tariff, it is less suitable for the present study because the variable price experienced by occupants of dwellings with PV does not have well-defined periods of fixed price changes. Rather, both the duration of the periods, and price experienced during them, varies from season to season, and day to day depending on the weather.

It is more appropriate therefore to consider regression functions used in the evaluation of real-time pricing tariffs, as such tariffs have similar characteristics to the effective price. Allcott proposed the following regression function in the evaluation of the Illinois real-time pricing program (Allcott, 2011b):

$$P_{ihd} = \beta_{1hd} + \beta_2 \bar{p}_{hs} + \beta_3(p_{hd} - \bar{p}_{hs}) + \cdots + u_{ihd}$$

Equation 9

Where:

P_{ihd}: demand during hour h of day d for dwelling i.

$\bar{p}_{hs}$: average price for hour h of season s.

$(p_{hd} - \bar{p}_{hs})$: deviation of price during hour h of day d during season s.

The specification of this function has two important characteristics that are relevant to the present study. Firstly, the regression considers the hours of the day separately. This identifies the variation in the influence of the independent variables throughout the day, and allows a detailed demand profile to be re-constructed. As the current work is interested in identifying changes in demand profiles, an hourly resolution to the regression will also be chosen.

The second point is that there is a term that indicates a routine behaviour change to average prices, $\beta_2 \bar{p}_{hs}$, and a second term for identifying responses to deviations from the average price, $\beta_3(p_{hd} - \bar{p}_{hs})$. This is useful in the present context because two types of behaviour can be expected to be observed with occupants of dwellings with PV. Firstly, a routine behaviour change, whereby routines are changed in order to shift demand to the day-time, regardless of availability of solar resource. And secondly, opportunistic behaviour whereby occupants respond directly to an availability of cheap electricity, specifically time-shifting demand to take advantage of this.

Allcott, and other studies (Navigant Consulting, 2011), have found that characterising the response to real-time pricing in terms of a routine behaviour response and an opportunistic response provides a good fit to observed data from real-time pricing schemes. Given the similarities between real-time pricing and PV price signals, it would seem reasonable to pursue a similar strategy here, and to specify the regression function accordingly.

5.4.1. Problems with the use of price as an independent variable

While the functional form of the regression function has been suggested by the preceding section, there is a problem with using price as an independent variable in the regression: the price experienced by the occupants is itself a function of the demand.

For example, as described in section 4.4.4.1, the effective price for a deemed export PV system is as follows:

$$p_{eff} = \begin{cases} 0 \text{ when exporting} \\ p_i - p_i \dfrac{P_{pv}}{P_d} \text{ when importing} \end{cases}$$

Equation 10

As a result, a regression of demand on price is equivalent to a regression of demand on a function of itself. This will cause problems in the regression. For example, because price is a function of demand, this means that, by definition, low demands produce low prices, and high demands produce high prices. This implies that there is a positive association between price and demand that would be identified using the regression and would lead to the spurious conclusion that occupants of dwellings with PV respond to increases in price by increasing their demand. For PV systems therefore, it is clearly not useful to regress demand on price.

Price is however also a function of PV generation, and, as PV generation is proportional to irradiance, price is also correlated to irradiance (this is proven in the paper in appendix B). Instead of regressing demand on price, therefore, demand could equally be regressed on PV generation, or irradiance. These variables would act as a proxy for price, but would not have problems associated with using price itself, as they are independent of demand.

The option chosen here is to regress demand on irradiance. Firstly, this is because irradiance is a more intuitive metric for occupants with PV to determine when is a good time to consume electricity than the effective price described in previous chapters.

Secondly, it is useful to use irradiance because the control group also experiences an irradiance 'signal', and so it is useful for seeing if the effect of irradiance on the PV group is different from its effect on non-PV dwellings. Irradiance would be expected to have an association with demand because it influences demand for lighting, as well as heating due to solar gain. This is therefore an interesting experiment because it would be expected that irradiance would be negatively correlated with demand for lighting and heating, but that there would be a positive correlation with demand in the PV group associated with the availability of cheaper electricity. Correct specification of the regression function will allow these two effects to be isolated from each other and quantified.

In summary, the approach to be taken is a regression analysis for each hour of the day for UK dwellings with and without PV using irradiance as the independent variable and demand as the dependent variable. This approach will sometimes be called an 'experiment' in the following. With this in mind, the next section describes the data that was used to perform the regression.

5.5. Description of data

The aim of this thesis is to investigate the demand response behaviour of consumers with PV, and to apply the results of this investigation more generally. In performing this investigation, it is important to understand the challenges involved in extrapolating results from a specific group, in this case consumers with PV, to a broader population, for example domestic consumers more generally in the UK.

Ideally, a 'randomised field experiment' framework would be used (Allcott and Mullainathan, 2010; Allcott, 2011b). This would involve recruiting a group of consumers to participate in an experiment, and assigning some of the participants with PV systems, this would be the PV group, while the remaining participants would comprise the control group. In assigning participants to the PV and control groups, it is important that both groups are representative of each other (with the exception of one group now owning PV systems), as well as being representative of the broader nation. In this way, it would be possible to identify changes in the behaviour of the PV group compared to the control group, and hypothesise that these changes could be attributed to the presence of the PV system in the PV group, as well as being able to extrapolate the results more generally to the broader national population.

The approach used in this thesis is however reliant on secondary data, which introduces challenges in both identifying the demand response behaviour of consumers with PV, as well as in extrapolating the results more generally. These issues are described graphically in Figure 17, which shows the different data groups that are used in the thesis, and some of the challenges involved in comparing them. This is discussed in the following section.

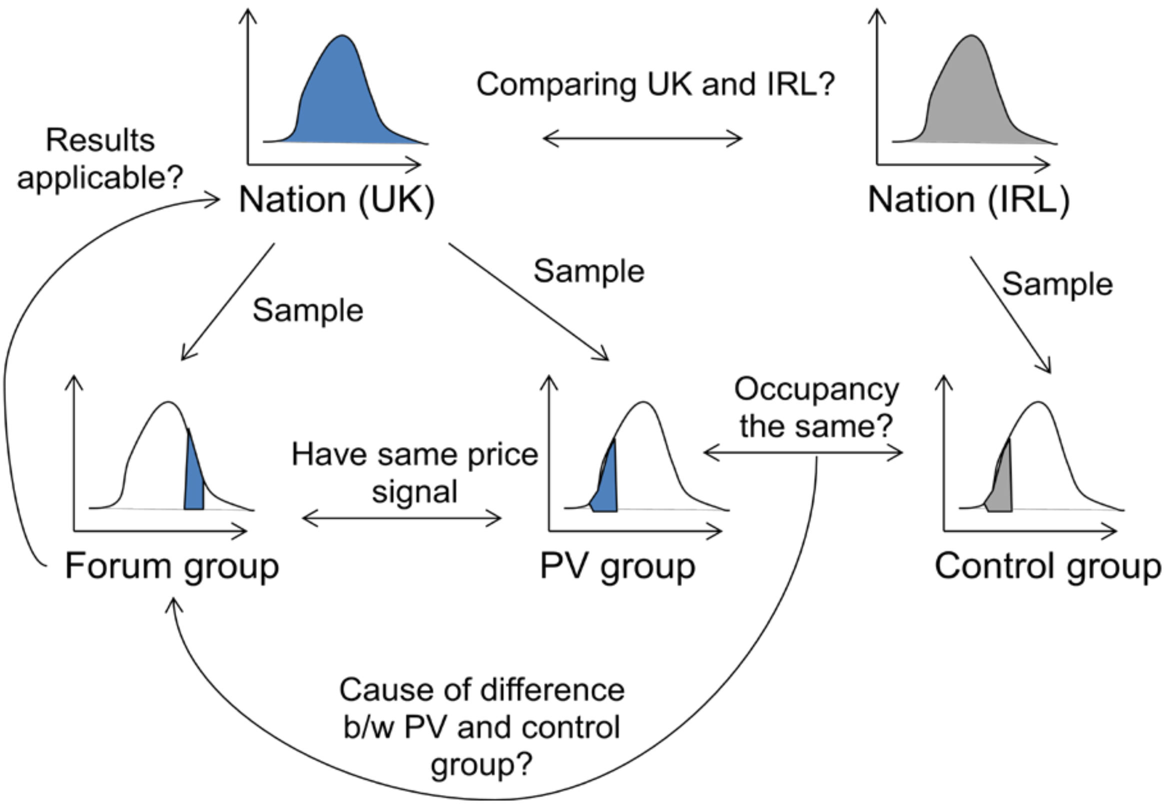


Figure 17 – Sampling issues involved in comparing the different data groups used in the thesis.

5.5.1. Sampling issues involved in creating the PV group and control group

Data on dwellings with PV was obtained from the UK Photovoltaic Domestic Field Trial (Munzinger et al., 2006). The Domestic Field Trial consisted of an extended campaign of installation and monitoring of grid-connected domestic PV systems in the UK. The trial ran from 2002 to 2006, and its purposes were to evaluate the performance of domestic PV systems in the UK, and to identify best practice in system installation.

The trial focussed on recording a wide range of variables associated with the performance of the PV systems, described in section 5.5.4. Data was recorded at high resolution (5 minute) for up to two years for each system. No data was available before the PV systems were installed.

The participants of the Domestic Field Trial were anonymous, and there was no published data on the occupants of the dwellings that were monitored, nor details about the dwelling construction, demand tariff, or information such as presence of electric heating.

It is, however, unlikely that the PV group is representative of UK consumers in general, and this is important because this introduces bias to the results. Firstly, the published reports do make clear that many of the dwellings consisted of social housing. It is possible therefore that this could result in day-time dwelling occupancy that is different from the general population. This could possibly lead to a 'false-positive' result in the regression, because higher daytime consumption is also what is expected as a response to the PV price signal. This means that that care must be taken in extrapolating insights gained about the PV group to the general population.

Secondly, another significant detail from the DFT report is that many of the PV systems were installed as part of new building developments, or social housing refurbishment. It is therefore also likely that the PV group consists of dwellings that are newer and therefore more energy efficient than the average UK dwelling.

Finally, it should be noted that the PV group has significantly lower energy consumption than the UK national average. This can be seen in Figure 18 and Figure 19 by comparing the PV group demand profile (green line) with the Elexon demand profile (red line). The Elexon demand profile shows the Elexon class 1 demand profile (Electricity Association, 1997). The Class 1 demand profile is representative of the UK national average for domestic consumers, who are not on an Economy 7 demand tariff (Elexon, 1997).

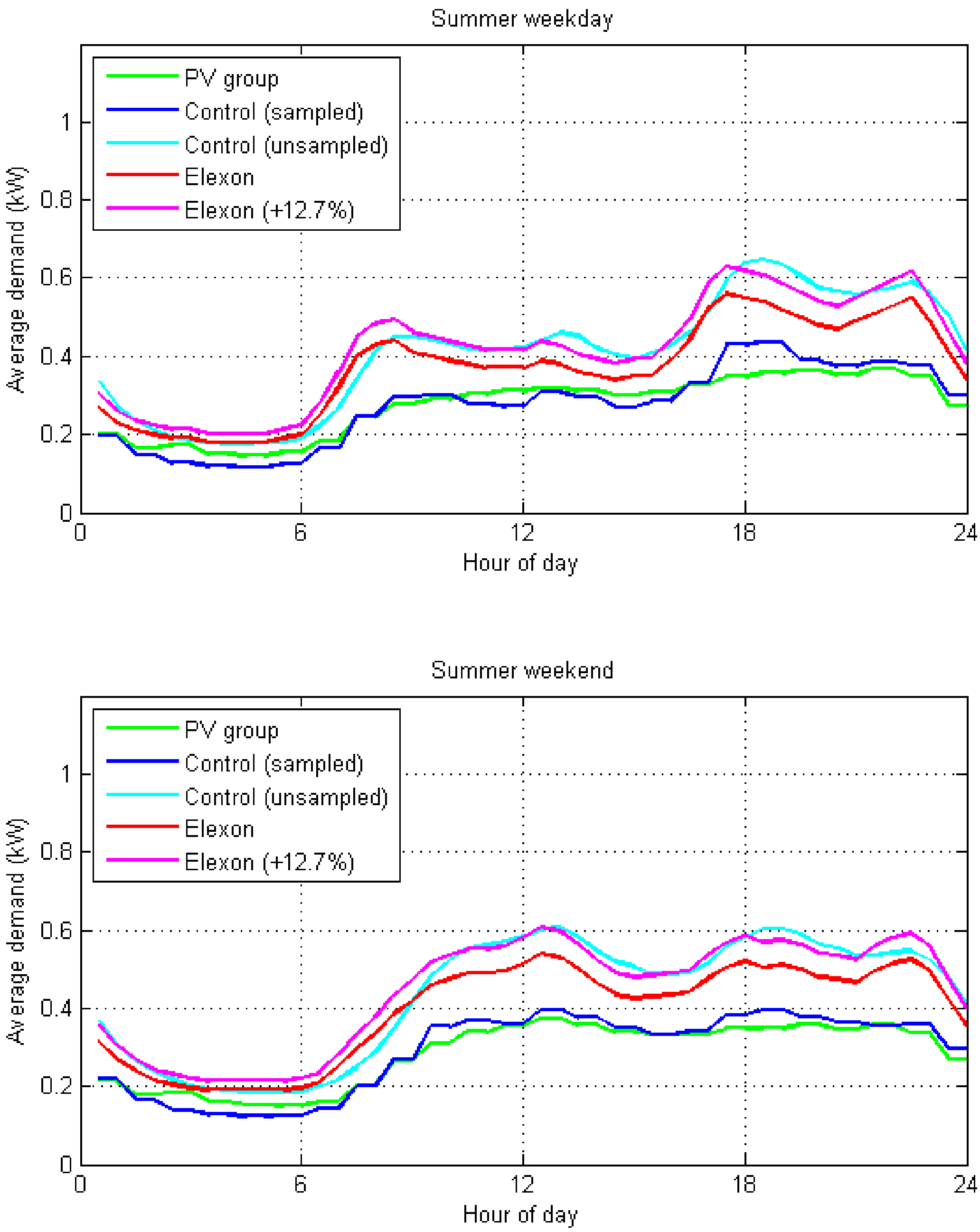


Figure 18 – Comparison of summer demand profiles

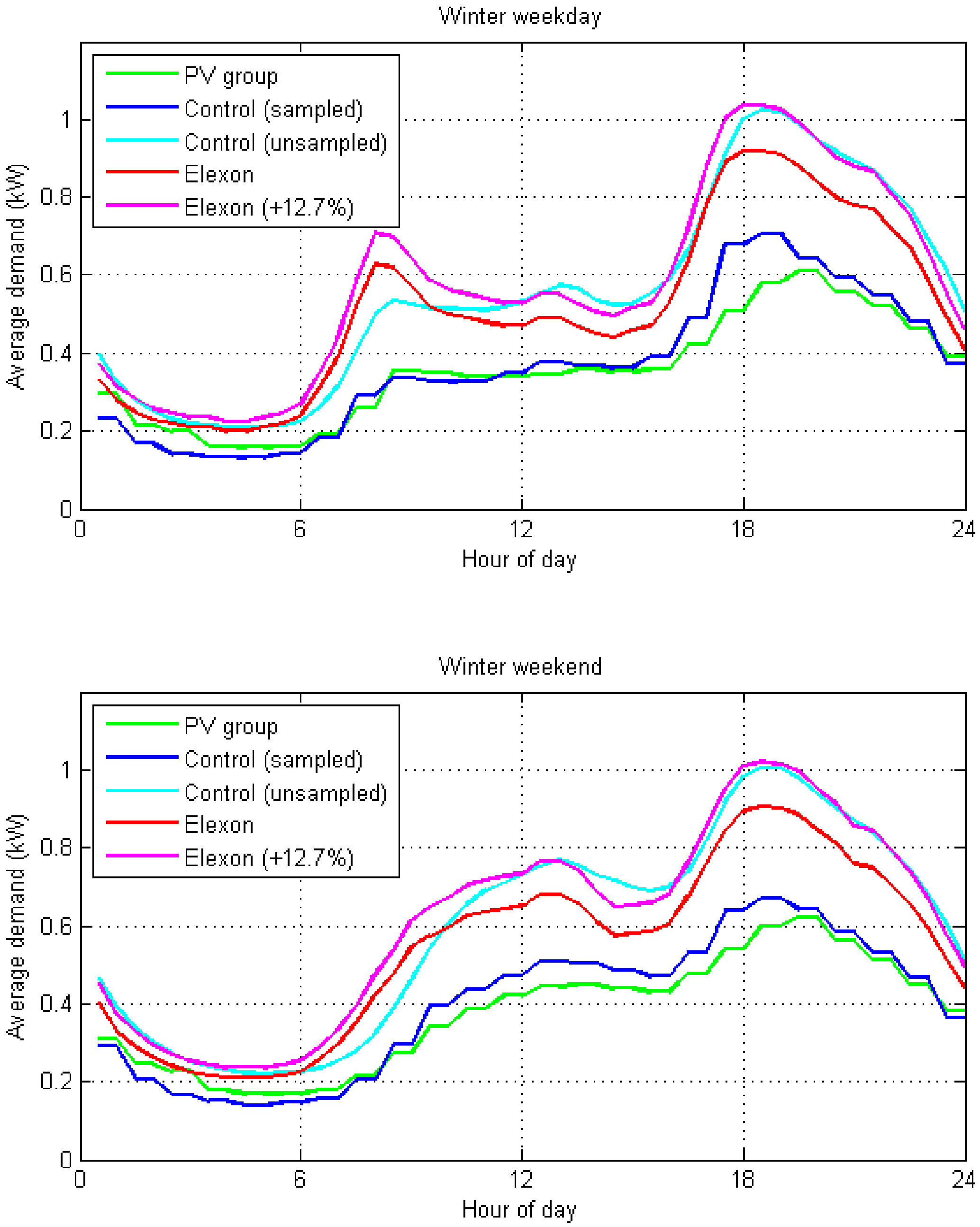


Figure 19 – Comparison of winter demand profiles

The next challenge involves identifying the response of the PV group to their PV systems. As mentioned previously, under ideal circumstances a control group would be used that had identical characteristics to the PV group, with the exception of not having PV systems. The purpose of the Domestic Field Trial was not, however, to estimate the effect of PV on occupant electricity demand, and so it did not include a control group.

For the purposes of this experiment therefore, a control group was created from a separate dataset. Data was instead used from the Irish Commission for Energy Regulation's 'Customer Behaviour Trial' for electricity smart meters, which ran from 2009 to 2010 (Commission for Energy Regulation, 2011). The Customer Behaviour Trial was one of the largest and most statistically robust trials of smart metering, demand response initiatives and time of use pricing. Of particular interest was the trial's large control group, which was recruited in order to be representative of the national average. The control group for the present study has been sampled from the Customer Behaviour Trial control group.

This leads the important question of whether it is valid to compare UK and Irish domestic consumers? The CBT control group was chosen specifically in order to be representative of the Irish national average. In order to address the question above, it is useful to compare the control group demand profile with the elexon class 1 demand profile. This will indicate whether the electricity demand practices of the Irish and UK consumers are similar. The demand profiles are compared in Figure 18 and Figure 19. The control group is shown by a light blue line, while the elexon demand profile is shown by a red line.

A visual inspection of the figures reveals that the control group demand profile displays lower consumption during the morning 'peak' than the Elexon class 1 demand profile, as well as higher day-time and evening consumption. It should be noted however that the class 1 profiles are from data taken in the 1990's, while the CBT is from 2009-2010. Annual demand in the UK has increased since the 90's, for example annual demand per dwelling in 2007 was 12.7% greater than in 1997 (DECC, 2012b). As a result, Figure 18 and Figure 19 also display an elexon demand profile which has been uniformly increased by 12.7% throughout the day (magenta line).

The shape of the control group and the revised class 1 demand profiles are, in fact, quite similar. This indicates two things. Firstly, that it is reasonable to compare Irish consumers to UK consumers. Secondly, it is reasonable to compare demand data for these groups even across a considerable number of years. This suggests that the use of CBT participants in the control group is an acceptable compromise, given this experiment's data limitations.

5.5.2. Creating a useful control group for comparison to the PV group

While the control group demand profile is broadly similar to the elexon demand profile, the same cannot be said about the control group and the PV group: the PV group evidently has much lower demand throughout the entire day. It was necessary therefore to sample the control group, in order to create a new control group that could be usefully compared to the PV group, as described in the following.

The Domestic Field Trial dataset contained data on 229 dwellings with PV, across 17 different geographic locations. Due to erroneous or missing data, however, data from six sites could not be used, bringing the total number of dwellings assigned to the PV group to 130. The distribution of annual electricity consumption for the PV group is shown below in Figure 20A.

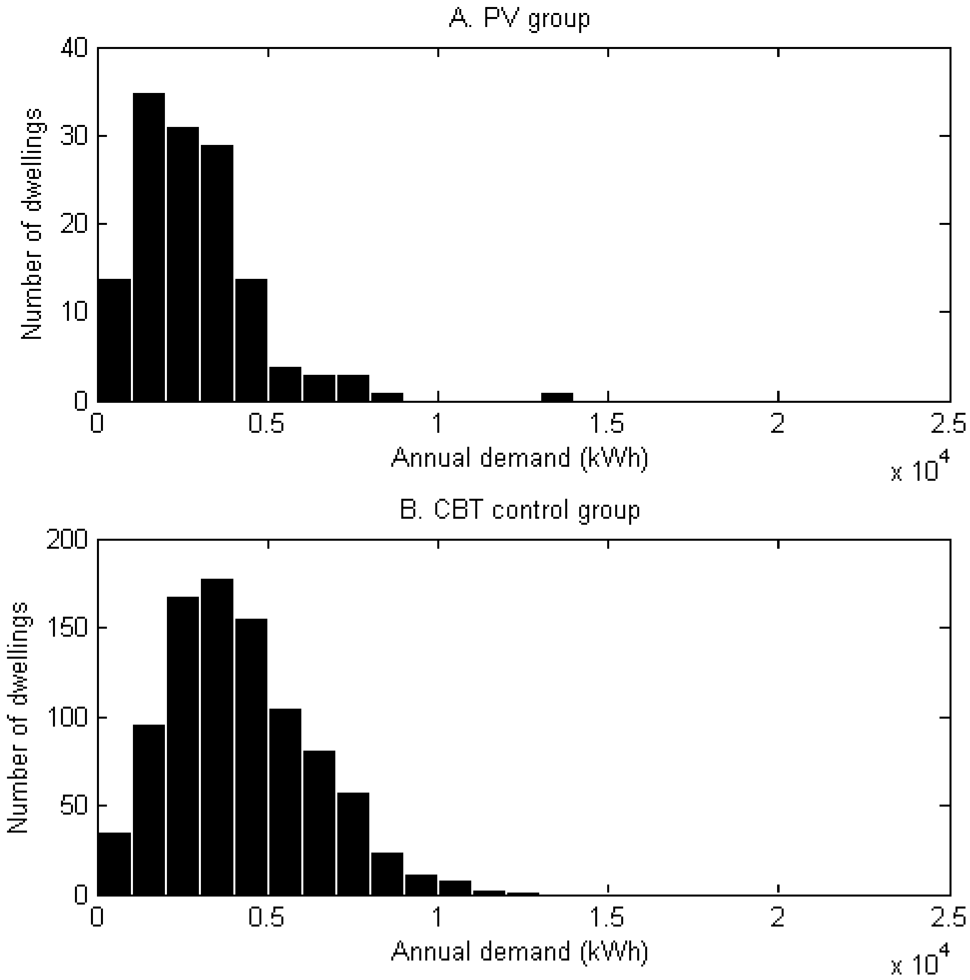


Figure 20 – Distribution of annual electricity consumption for PV and control groups

The control group of the Customer Behaviour Trial dataset consisted of 929 dwellings. The distribution of annual energy consumption of the CER control group is shown above in Figure 20B. The Customer Behaviour Trial control group has a considerably different distribution of annual energy consumption compared to the PV group. A visual inspection reveals that the PV group has an over-representation of lower consumption dwellings and an under-representation of higher consumption dwellings. It is noted that the Customer Behaviour Trial control group was recruited to achieve a nationally representative diversity in dwelling demand's, whereas the Domestic Field Trial did not have this goal.

This is problematic for the regression as the PV and control groups should be statistically similar in order for the regression to be able to identify the trends that are of interest. If the demand distribution of the PV and control groups are not identical, then the regression results will identify differences in overall level of consumption, which will obscure the results of interest: the difference in the shape of the demand profiles of the two groups.

This problem was mitigated by selecting a random sample of dwellings from the CBT control group that had the same distribution of annual energy consumptions as the PV group. This was done by counting the number of dwellings in bins of 100 kWh (annual electricity consumption) and ensuring that there were equal numbers of dwellings in both the PV and control groups. Dwellings with annual consumption below 600 kWh were removed from the sample under the assumption that they were unoccupied. Dwellings with annual consumption above 7300 kWh were also removed because of the lack of such dwellings in the DFT database.

After sampling, both the PV and control groups consisted of 130 dwellings each. The resulting distribution of dwelling demands is shown below in Figure 21. The distributions are identical for both groups. The mean annual demand for the PV group is 2782.7 kWh, and 2783.4 kWh for the control group.

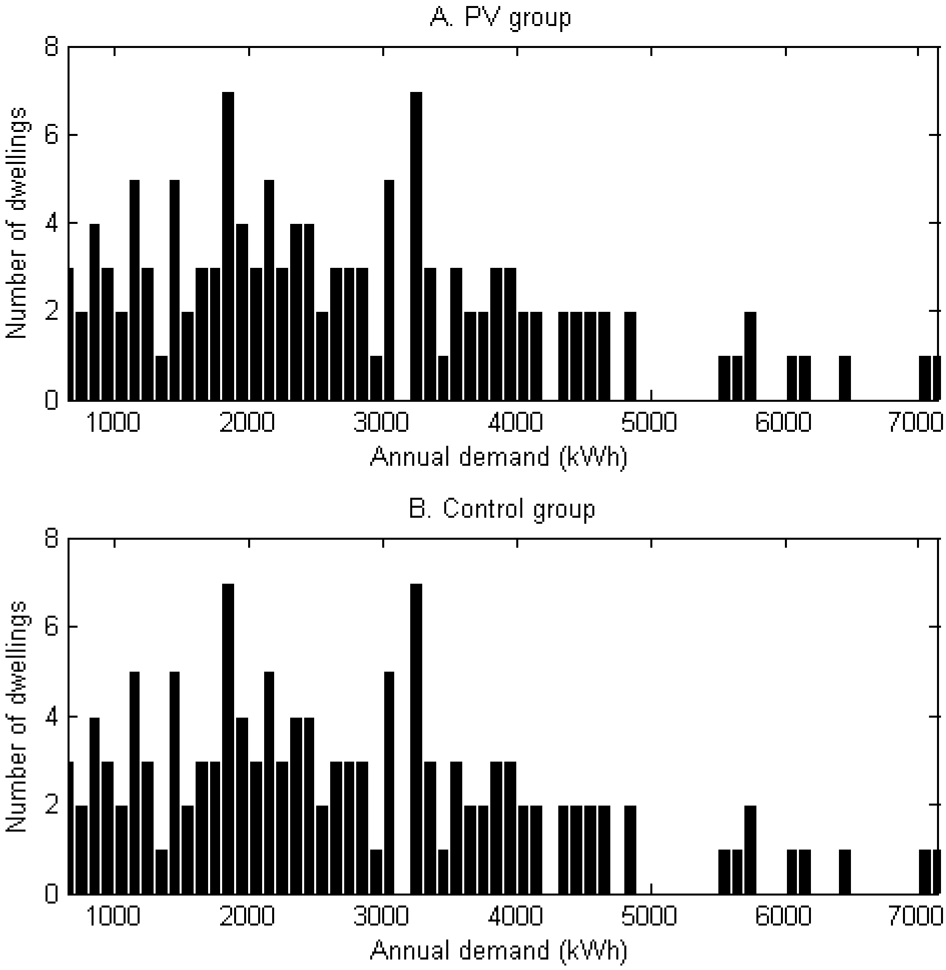


Figure 21 – Distribution of annual electricity demands for PV and control group after sampling

The other distribution that needs to be considered is the temporal distribution of the data. The Domestic Field Trial contains either one or two years of data for each dwelling, which implies an even distribution of data over the whole year. The Customer Behaviour Trial, however, started in July 2009 and finished in December 2010. There is therefore an under-representation of data for the control group for the months January through to June. This could lead to biases in the data which would obscure the regression results. The solution is therefore to use only the 2010 data for the control group.

The temporal distribution of data in terms of numbers of dwelling-days is therefore shown below in Figure 22, where only the data from 2010 has been used in the control group. There is twice the amount of data in the PV group because most DFT dwellings were monitored for two years, compared to one year for the control group. It can be seen that the distribution is reasonably uniform over the whole of the year for both PV and control groups. This indicates that there should be no bias in the regression results associated with a mismatch in temporal distribution of data between the two groups. The demand profiles for the sampled control group are shown in Figure 18 and Figure 19 (dark blue line) alongside the PV group demand profile for comparison. In the following sections, any mention of the 'control group' can be taken to mean the sampled control group.

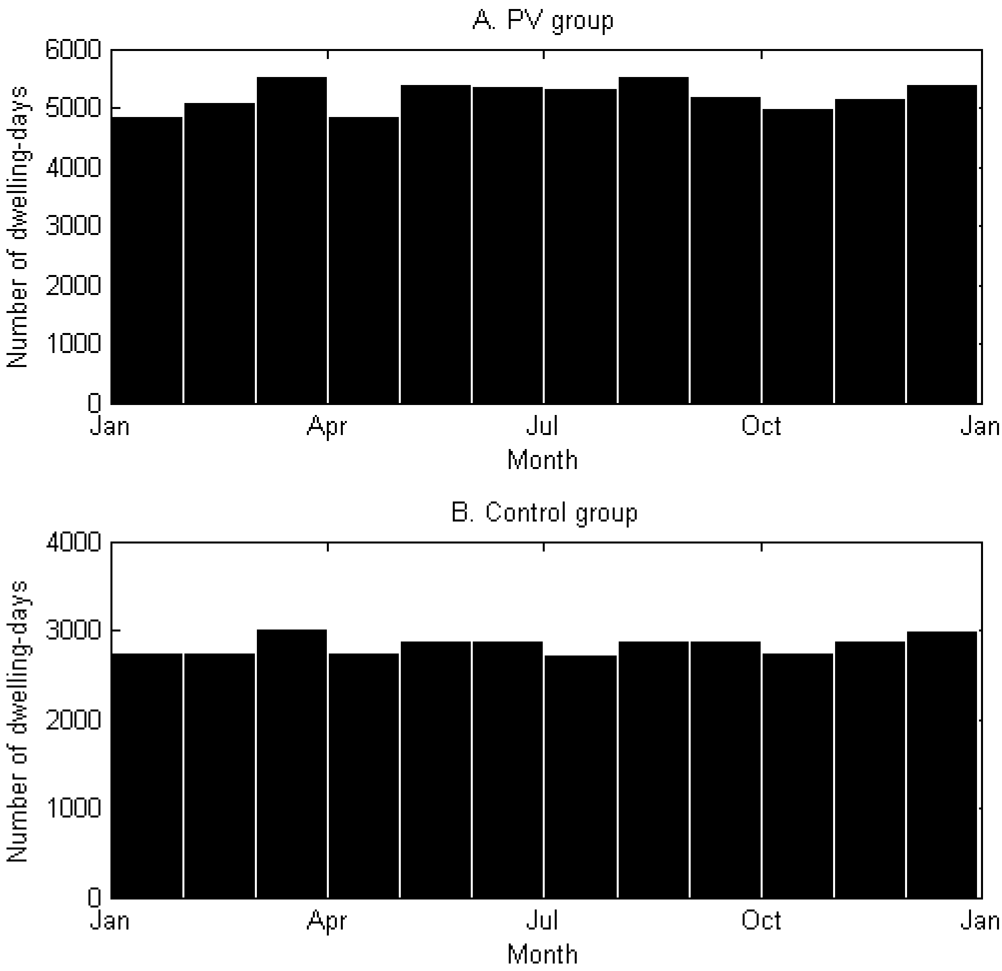


Figure 22 – Temporal distribution of data for PV and control groups.

5.5.3. Statistical association and causation

Given these steps, the consumption and temporal distribution of the PV and control groups are therefore very similar. The regression will now identify differences in the shape of the demand profiles of the two groups, and not differences in overall level of consumption. It is important to note, however, that while the regression will identify differences in the demand profiles, it does not reveal what causes the differences, and this issue is compounded by the problems associated with creating a control group from a different data group.

For example, assume that the regression identifies a statistically significant difference in demand profiles between the PV and control groups that shows that the PV group consumes more during the day and less in the evening than the control group. The actual cause of this difference, however, is not revealed by the regression, and could in fact be caused by three factors. Firstly, it could be that the PV group does not in fact respond to the PV price signal, but simply has higher occupancy during the day than the control group. If this was the case then the increase in day-time consumption revealed by the regression would be a false-positive, and it would be incorrect to assume that this was proof that the consumers were responding to irregular pricing.

Secondly, it could be that the PV group is responding to the irregular pricing but that they also are at home during the day more than the control group, and so able to respond manually to the variability of the PV generation. Thirdly, it could be that the PV group is responding to the irregular pricing, and has similar occupancy to the control group, and for example are utilising automation such as timers if they are away during the day. Finally, it is also possible that the difference in demand profiles are caused by a combination of all three of the above factors.

This is, however, an unavoidable limitation in statistical analysis. The regression can prove statistical association or dependence between variables, but cannot say that one is the cause of the other. It is for this reason that it is important to back up the quantitative statistical work with qualitative research, in order to determine the 'how' and 'why' of the association. The work presented in this chapter is therefore complemented and supported by qualitative research on consumers with PV (the 'forum group' shown in Figure 17) that is presented in the following chapter, which has the aim of revealing some of the underlying causation for the quantified response presented in this chapter.

5.5.4. Differences in environmental variables between the two data sets

Returning to a discussion of comparison of the PV group and control group data sets, it is important to control for changes in environmental variables such as temperature, as it is not obvious that these will be consistent or similar between the two data sets.

The regression function should include parameters for all of the variables that are observed and that are expected to have an effect on demand. Ideally, this would include structural data on the dwellings such as electric heating, number of appliances, occupancy, as well as environmental variables such as temperature. There is good structural data available for the control group through the surveys conducted during the Customer Behavioural Trials, but no environmental data. The opposite is true for the PV group, where the only structural variable observed with any confidence is the presence of PV. While the lack of structural data cannot be addressed here, the lack of environmental data for the control group can, however, by using other data sets as detailed as follows.

The Domestic Field Trial monitored the variables described in Table 12 at 5 minute resolution. Dwelling demand was calculated from these variables as follows:

$$P_d = P_i + P_g - P_e$$

Equation 11

Table 12 – Observed variables for the Domestic Field Trial.

Symbol	Quantity	Units
	Date	
	Time	
	Horizontal Irradiation	Wh/m^2
	In-plane Irradiation	Wh/m^2
	Ambient temperature	^oC
	Module temperature	^oC
	DC output of system	Wh
P_g	AC output of system	Wh
P_i	Electricity imported from grid	Wh
P_e	Electricity exported to grid	Wh

The Domestic Field Trial experienced considerable faults in monitoring equipment (Munzinger et al., 2006), which is why data from several sites could not be used in this experiment. An effort was made here to filter out erroneous data. Observations were ignored where import values were negative or greater than 2.2 kWh, as this is equivalent to a current greater than approximately 110 A sustained over five minutes – 110 A is greater than the limit of most domestic main fuses (Central Networks, 2006). Observations were also removed where exports exceeded generation. This combination was found to be satisfactory at removing any obviously faulty data from the DFT dataset.

Environmental variables were not observed for the Customer Behaviour Trial, and so this data was instead obtained from the MIDAS database with permission from the UK Meteorological Office (UK Meteorological Office, 2012). Temperature data was also obtained from the same source. As the geographic location of the control group dwellings was not known, the approach taken was to calculate average temperature and irradiance values using data from all available weather stations in Ireland. Hourly irradiance data was available from three weather stations in Ireland, while hourly temperature data was available from 28 weather stations. MIDAS data is quality checked by the Met Office, so no effort to filter data for errors was made beyond using the quality-checked data only.

The use of temperature data was important due to the temperature variations in the two datasets. Figure 23 displays daily average temperature and irradiance data for the control and PV groups. The control group data corresponds to the years 2009 and 2010 and are averaged values for the whole of Ireland. The PV group data corresponds to temperature and irradiance data for the 10 UK sites that are used in the PV group recorded over the time range 2002 to 2006.

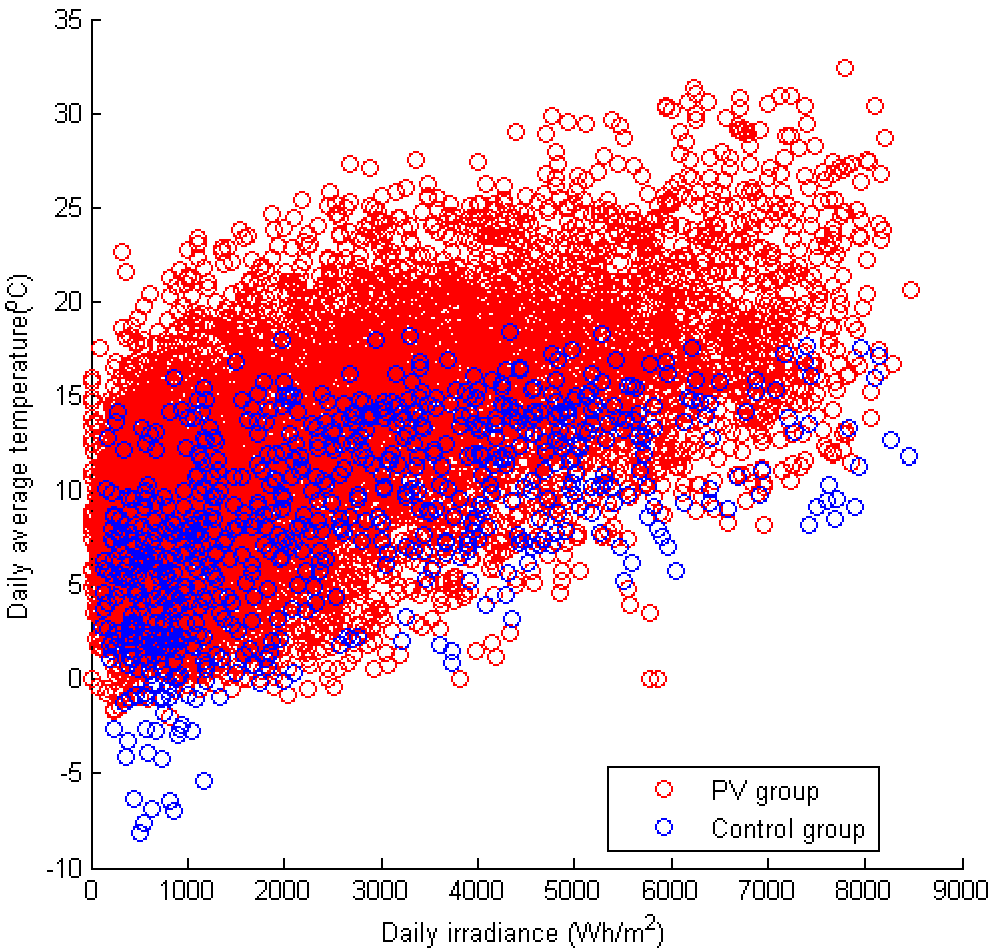


Figure 23 – Daily values of temperature and irradiance for the PV and control groups.

Visual inspection of Figure 23 reveals that there is a considerable difference in temperature readings for the two sites. The average of the temperature values for the PV group is 12.46 °C, and the average of the irradiance values is 2.56 kWh/m^2. For the control group, the average of the temperature values is 8.69 °C, and the average of the irradiance values is 2.63 kWh/m^2. This indicates that while irradiance values were similar across the datasets, the control group experienced considerably colder weather than the PV group.

This discrepancy in temperature distributions could be accounted for by the difference in years between the data sets (2002-2006 for DFT and 2010 for CBT). In addition, however, the instrumentation used to measure temperature could have been different. In particular, it is likely that the temperature measurements of the Domestic Field Trial would have been roof-mounted, while Met Station instruments would have been ground mounted.

This discrepancy in temperature distributions, if not probably accounted for, could introduce a 'temperature bias' to the regression which could obscure the results. This is because the control group was sampled in order to have an identical demand distribution to the PV group. The problem is that this involves comparing the demands from two groups with non-identical temperature distributions. If the control group had experienced temperatures more similar to the PV group, then their demands would have been lower, and a different sampling would have been taken. What can be said is that, while sampling has ensured identical demand distributions between the two groups, because of the temperature bias, the PV group are actually higher consumers than the current sampled control group. As a result, the regression function needs to be specified in order to account for this temperature bias, for example by using separate temperature variables for each group in the regression function.

5.5.5. Electricity price

The PV systems in the DFT dataset correspond to 'fully metered' systems, as high resolution generation, import and export meters were fitted as part of the trials. The price function for such dwellings was detailed in section 4.4, and it follows that it is important to consider the import and export prices for the PV group.

The Domestic Field Trials were conducted between 2002 and 2006, before the introduction of the feed in tariff. Keirstead interviewed suppliers in 2005 to find out types of microgeneration tariff in the market (Keirstead, 2006). The interviews revealed that 150 out of 580 consumers (26%) with micro-generation were paid the same price for exports as for imports, and so did not experience a time variable electricity price. The remaining 74% would have experienced a variable price similar to a deemed export system i.e. self-consumed electricity would be free.

Bearing this in mind the assumption is made here that the PV group is experiencing a variable effective price, and that this would be the same type of price signal as more modern PV systems on deemed export feed-in tariffs.

In terms of making the comparison between the DFT systems and more modern PV systems, the main difference is that import prices were lower in 2002-2006. Keirstead for example uses 7.64 p/kWh as a typical import price for the time (2005). By comparison, a typical import price today is nearer to 12 p/kWh. This compares with the control group who are on a flat rate tariff of 14.1 c€/kWh, ~11.2 p/kWh (Commission for Energy Regulation, 2011).

A further consideration is that it is likely that some of the PV group were on an Economy 7 tariff. Considering the demand profiles of the PV group in Figure 18 and Figure 19, there is evidence of peaks in demand during the night, suggestive of loads being switched on using timers to take advantage of cheap nighttime import prices. No effort was made to correct for this or to omit these dwellings. A consequence therefore is that the PV group is likely to have higher demand during the night than the control group.

Economy 7 is often associated with electric night-time storage heaters (McCartney, 1993), and ideally the presence of electric heating would have been observed for the PV and control groups. The presence of electric heating was observed in the control group, but not in the PV group, which is unfortunate as electric heating will obviously have a significant effect on demand profile and it would have been useful to be able to isolate its effect. Because this was not possible, the underlying assumption is that the distribution of electric heating was equal between the PV and control groups.

5.5.6. PV systems

The distribution of PV system sizes that are in the PV group is shown below. Current domestic PV system installations in the UK tend to be near the 4 kW_{peak} cut-off. By contrast, the figure below shows that the Domestic Field Trial PV systems are relatively small.

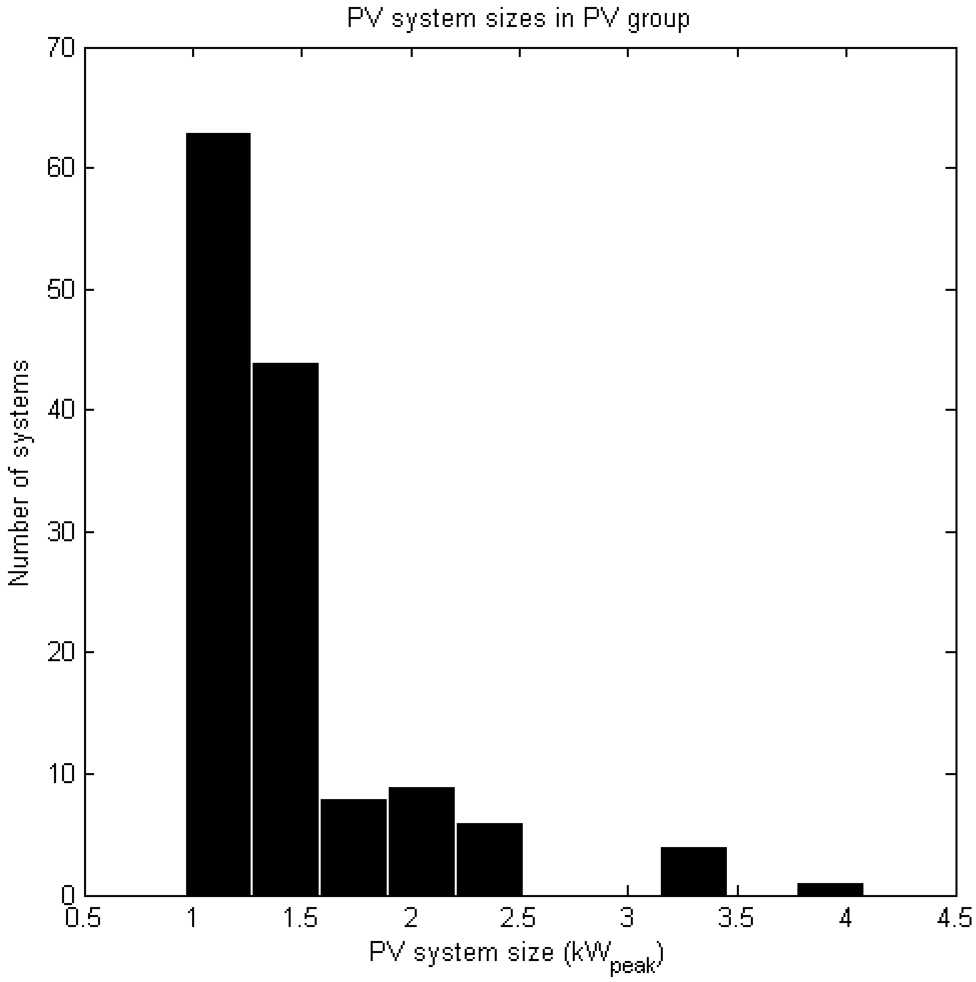


Figure 24 – Installed capacities of PV systems in the PV group.

This is of significance because PV system size will be proportional to the availability of cheap electricity for the occupants of the dwelling. Occupants with a small PV system will as a result have less cheap electricity than those with larger PV systems. It might be expected therefore that the PV group would have less reason to be responsive to their PV price signal than occupants of dwellings with larger PV systems.

5.6. Regression function

The regression function used is as follows:

$$P_{ihd} = \beta_1 + \beta_2 D_i^{PV} + (\beta_3 + \beta_4 D_i^{PV})G_{id} + (\beta_5 + \beta_6 D_i^{PV})T_{id} + \beta_7 D_d^{mon} + \beta_8 D_d^{wed} + \beta_9 D_d^{thu} + \beta_{10} D_d^{fri} + u_{ihd}$$

Equation 12

Where:

P_{ihd}: electricity demand for dwelling *i* during hour *h* (kW) of day *d*.

β_n: the coefficients of the model which are to be estimated by the regression

D_i^{PV}: binary or "dummy" variable indicating the presence of a PV system for dwelling *i*.

G_{id}: daily irradiance for dwelling *i* on day *d* (Wh/m^2).

T_{id}: average temperature for dwelling *i* on day *d* (^{o}C).

D_d^{mon}: dummy variable indicating the day of the week for day *d* (only applicable to weekdays). Separate dummy variables are used for each day of the week.

u_{ihd}: error term.

The above regression function was applied separately to data for each hour of the day, using data for the PV and control groups. Separate regressions were run for weekdays and for weekends.

The first six terms in the regression function are the most important. These consist of three pairs of terms, and each pair will be described together in the following.

The first pair of terms, $\beta_1 + \beta_2 D_i^{PV}$, allows the identification of the 'routine response' of the PV group. β_1 captures the average hourly demand for the control group. The $\beta_2 D_i^{PV}$ term identifies the difference in demand between the control and PV group – the 'routine response'. This term will also pick up any other differences between the two groups. The most significant of these have been mentioned already: the PV group is likely to have dwellings with Economy 7, more social housing occupants, and newer more efficient dwellings.

The second pair of terms $(\beta_3 + \beta_4 D_i^{PV})G_{id}$, allows the identification of the opportunistic response in the PV group. The β_3 term captures the 'base response' to irradiance that will be present in both PV and control groups. A negative correlation is expected as higher irradiances will be associated with lower demand for heating and lighting. The $\beta_4 D_i^{PV}$ term captures the opportunistic response to irradiance that is present only in the PV group. A positive correlation is expected as higher irradiances should be associated with increased use of appliances during the day.

Note that daily rather than hourly temperature and irradiance values were used. The main purpose for this was to eliminate problems in the regression when the irradiance was zero during the night. Regressing onto a variable consisting only of zeros will results in an error – it is analogous to drawing a straight line through a scatter of data points that all lie on the y-axis. The gradient of this line is not a number.

The third pair of terms $(\beta_5 + \beta_6 D_i^{PV})T_{id}$ are equivalent to the second pair, though capturing the influence of temperature on the demand of the two groups, rather than irradiance. As discussed in section 5.5.4, it is important to include separate terms for each control group because of the considerable difference in temperature distributions for the two groups.

The final terms in the regression function capture any differences in average hourly demand associated with the different days of the week. There is no dummy variable for Tuesday to avoid a 'dummy variable trap' (Gujarati, 1992e), whereby one of the independent variables is a linear combination of one or more of the other independent variables, known as 'perfect multicollinearity'.

The regression coefficients were estimated in Matlab using ordinary least squares regression. Ordinary least squares is the basic approach to regression and is valid provided the data meets certain statistical criteria, notably that there is no presence of multicollinearity, heteroscedasticity, or autocorrelation. The validity of these assumptions is discussed in section 5.7.1 of the results.

5.7. Results

The results of the regression are shown below in Figure 25 to Figure 27. These figures show the estimated hourly coefficients for the three pairs of terms described the previous section. Results are shown separately for weekdays and for weekends, and 95% confidence intervals are shown.

The constant term β_1 is shown for weekdays in Figure 25A, and for weekends in Figure 25C. This indicates the average hourly demand for the control group for these two types of day, ignoring the effects of irradiance and temperature on this group's demand.

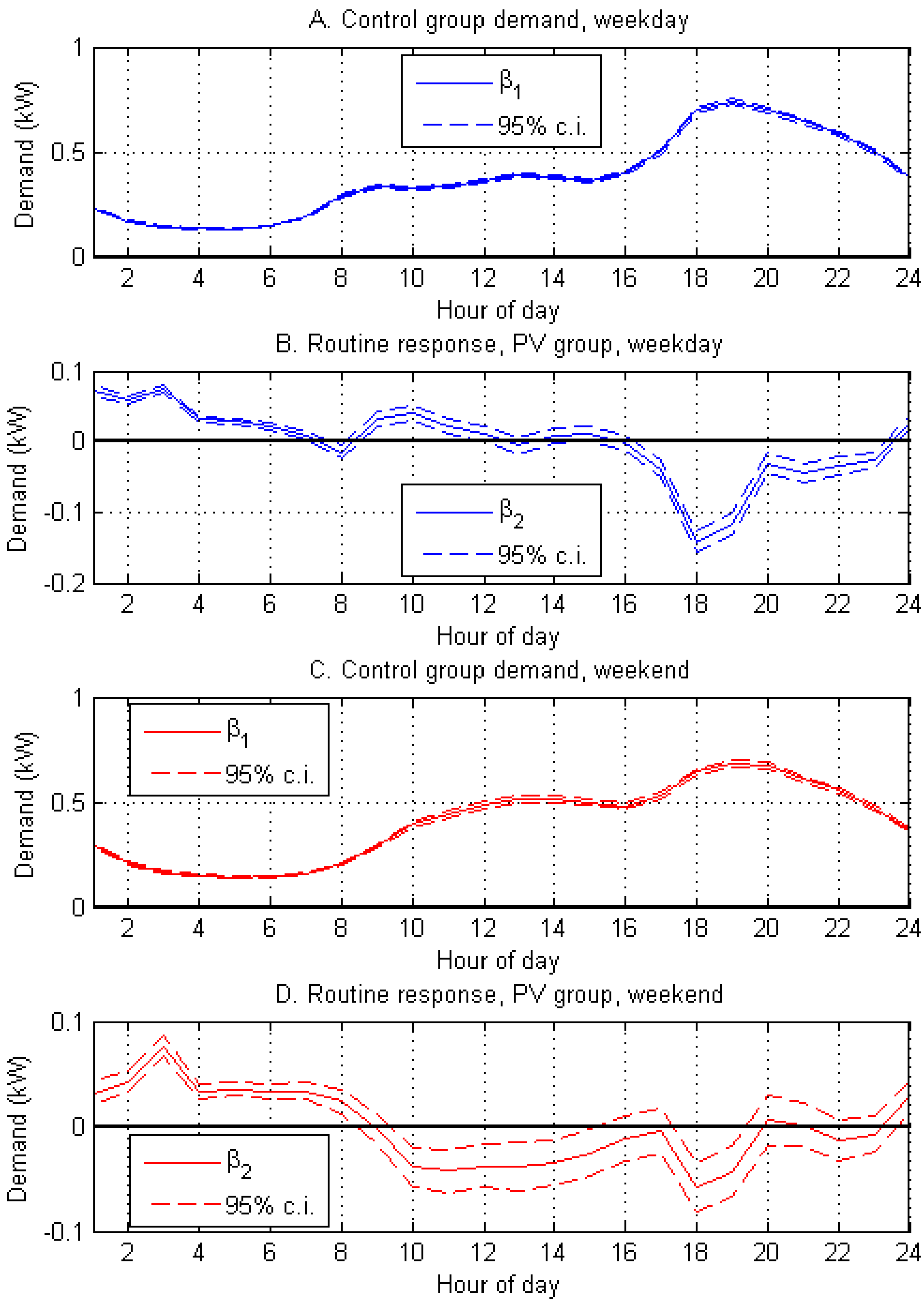


Figure 25 – Regression results for the first two terms.

The second term, $\beta_2 D_i^{PV}$, is shown in Figure 25B and D. This indicates the hourly 'routine response' for the PV group, in terms of a deviation from the control group's demand profile. It shows the times of day when the PV group's demand is higher or lower than the control groups, ignoring the effects of irradiance and temperature.

Looking at the weekday results, the PV group tends to consume more than the control group during the middle of the day, more at night, and considerably less during the evening. The higher night-time demand for the PV group is likely due to the presence of some dwellings on Economy 7 tariff. It is, however, the higher day-time consumption that is of interest here. The lower evening peak demand for the PV group would suggest that demand is being shifted from evening to the day or night. As discussed previously in section 5.5.3, this could be due to higher day-time occupancy in the PV group compared to the control group and no response to PV, higher day-time occupancy in the PV group and a response to PV, similar day-time occupancy and a response to PV, or a combination of all three of these factors.

The results are similar for weekends, with the notable exception that there is a decrease in day-time consumption rather than an increase. People are generally at home and consuming during the day on weekends anyway, and so it is not unexpected that the PV group does not consume more than the control group during the daytime on weekends.

Figure 26 shows the deviations to hourly demand associated with variations in daily irradiance for the control group and PV group on weekdays and weekends. Figure 26A and C shows the results for base response, present in both the PV and control groups. The values of the coefficients are multiplied by the daily irradiance in order to produce the average hourly deviation in demand from the demand profiles shown above in Figure 25. To put this into perspective a coefficient of $2x10^{-5}$ corresponds to a change in demand of approximately 50 W on an average day with irradiance of 2500 Wh/m^2. It can be seen that the results are similar for both weekdays and weekends, with increasing irradiance associated with a reduction in demand centred around the evening peak. The reduction in demand could be associated with passive solar gain requiring less electric heating, or less demand for lighting due to brighter evenings.

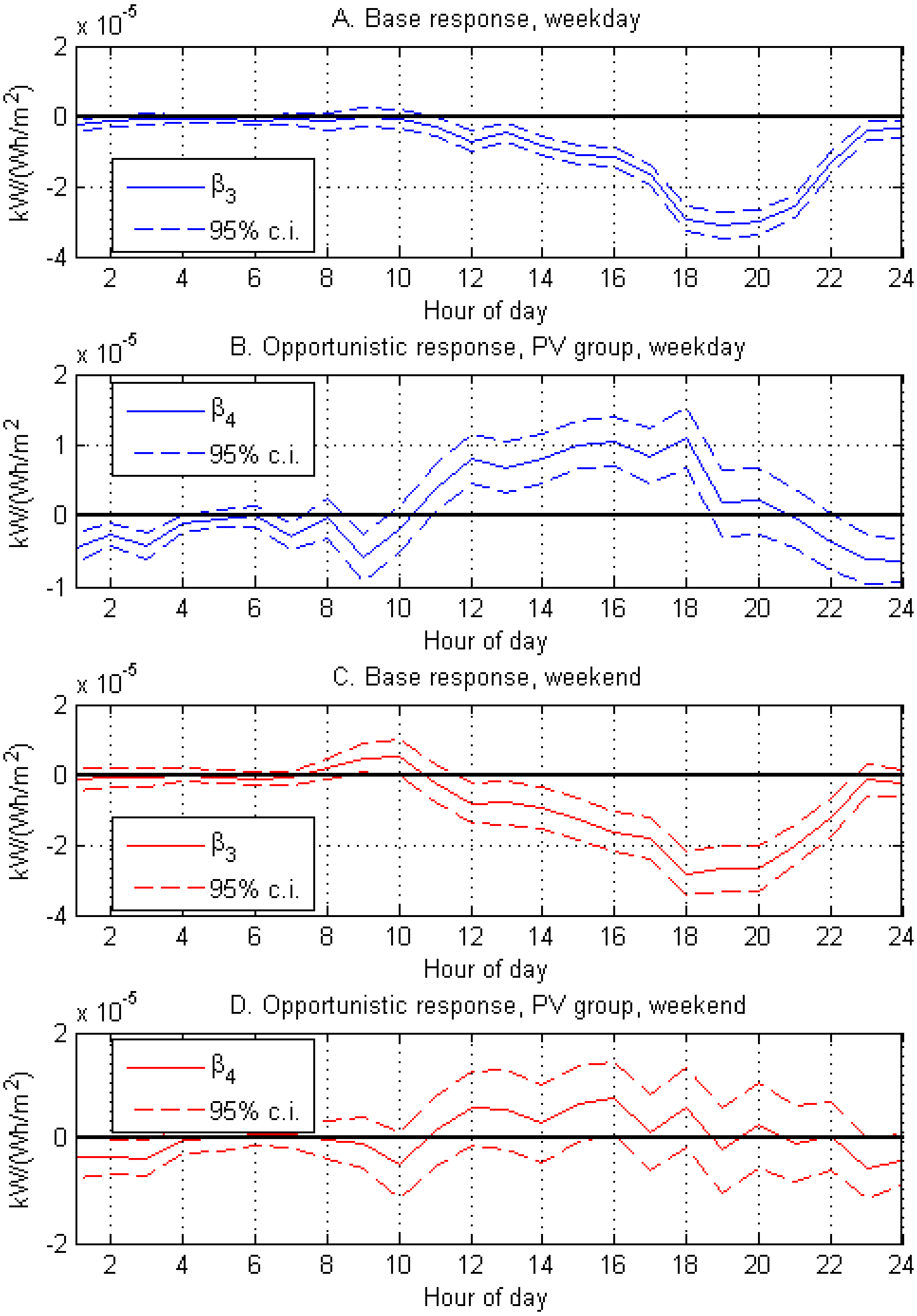


Figure 26 – Regression results for the base response and opportunistic response to irradiance.

Figure 26B and D shows the opportunistic response to irradiance present in the PV group only. The results indicate that, in addition to the base response detailed above, the PV group also experiences an increase in demand during the daytime. This has quite a pronounced effect for weekdays, but is not statistically significant at the 95% level for weekends. Similar to the previous discussion of the routine response, this effect could be caused by multiple factors. Firstly, it could be caused by the PV group responding to variable irradiance levels with opportunistic behaviour, most likely involving running appliances during the day.

Secondly, it could be caused by dissimilarities between the PV group and control group, that are not associated with a response to the PV system. For example, note that the base response and opportunistic response happen to be very similar in magnitude during the day: the two terms broadly cancel each other out during the day. This means that on sunnier days, the control group experiences a drop in demand, while the PV group does not. This could also be explained if the two groups had different levels of electric heating. If the control group had a greater proportion of electric heating than the PV group, then they would be less likely to need to use electric heating on sunnier days, and would therefore see a larger drop in demand compared to the PV group. Another explanation could be that the PV group have more efficient dwellings and so show less of a response to changes in temperature and irradiance. Again, the results need to be interpreted given the limitations associated with the sampling issues discussed in section 5.5.

With these limitations in mind, and acknowledging that the statistical work cannot prove causation, the assumption will nonetheless be made in the following that the results can be attributed to a routine response and an opportunistic response by the PV group to the PV system. The qualitative analysis include in the following chapter will help to validate this assumption.

Returning to the results, Figure 27 is similar to Figure 26 and shows the results for the temperature coefficients instead of irradiance. The same logic applies in terms of how they translate into deviations in demand profiles for the two groups. Firstly, it can be seen that the temperature results for the control group mirror those for irradiance. This is unsurprising as hotter days tend to be days with higher irradiance. The coefficients for the PV group are smaller than those for the control group and have positive values in the evening.

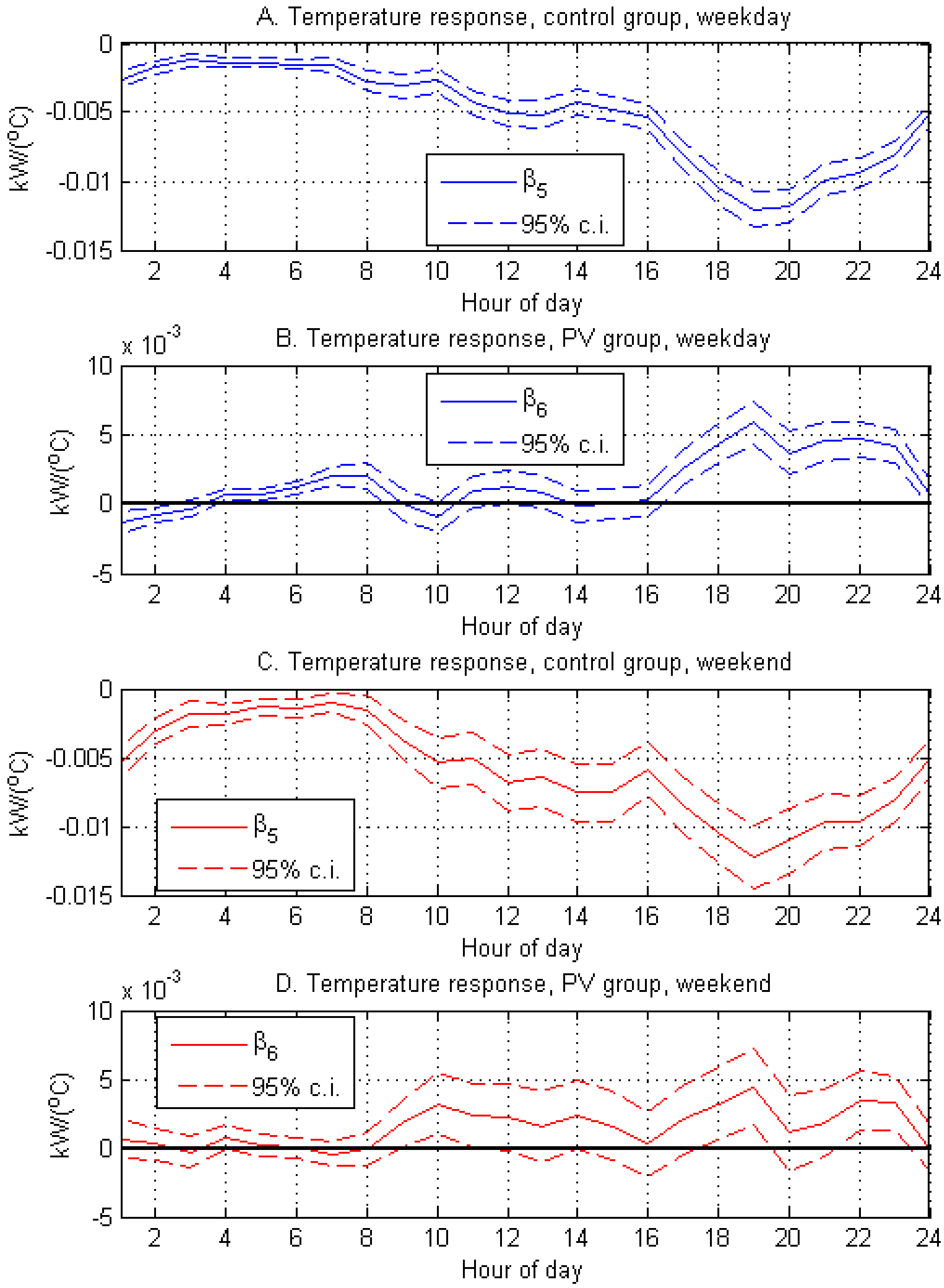


Figure 27 – Results for temperature terms for weekday and weekends.

The fact that the temperature coefficients are negative for the control group and positive for the PV group is a side effect of the fact that the control group and PV group had different temperature distributions. As expected, the fact that the PV group has positive coefficients indicates that this group actually has higher demands than the control group. If this had not been accounted for in the regression then this temperature bias could have obscured the results that are of interest above.

Using the above results, Figure 28 combines the terms for the PV group to indicate the difference in demand profile between the PV and control groups that could be expected on an average day. The routine response and opportunistic response are included, but not the temperature response due to the 'temperature bias' discussed previously.

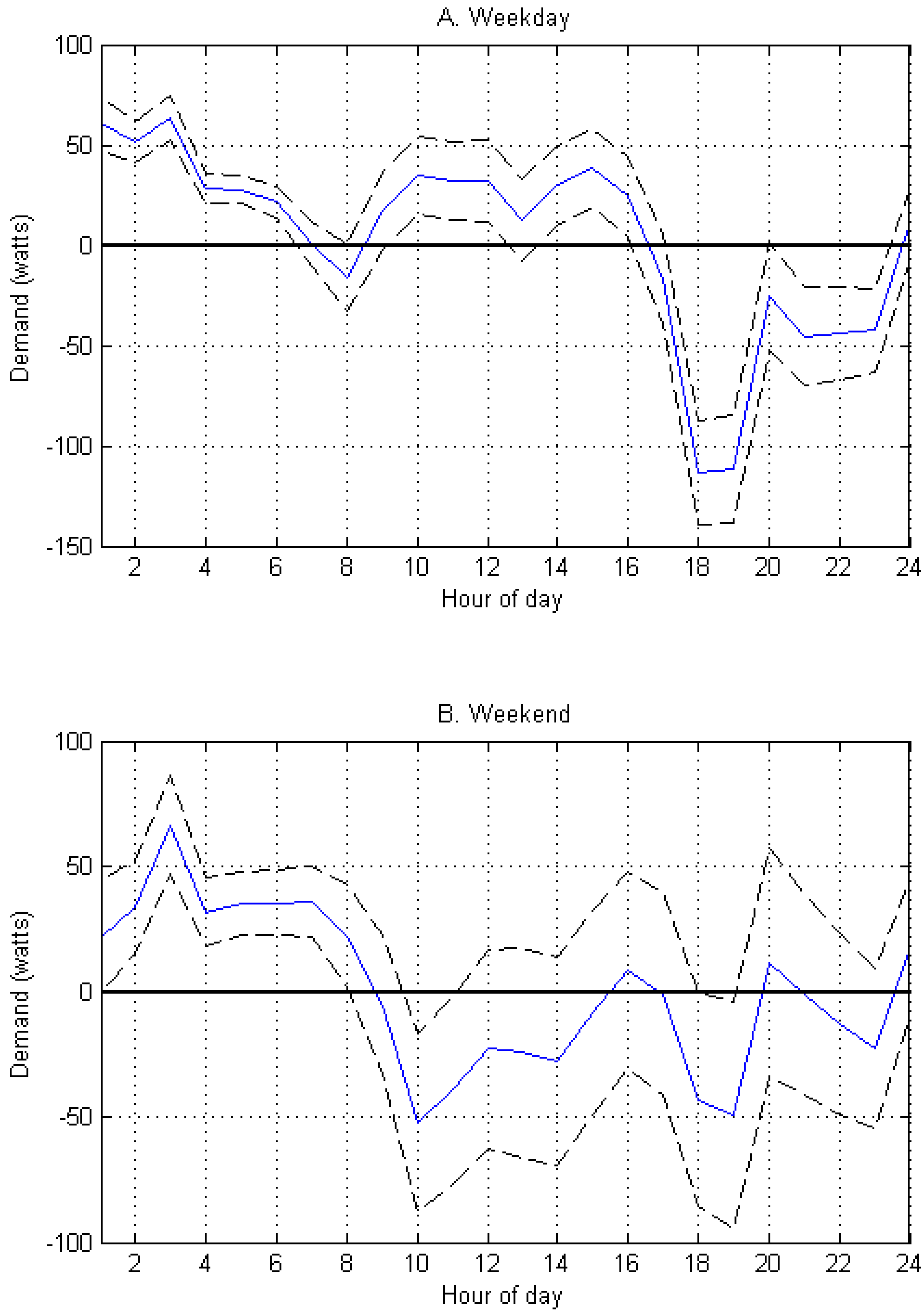


Figure 28 – Combination of terms for the PV group for a typical day.

The most obvious result is that PV dwellings are shifting demand from evening peak to the daytime and night during weekdays. The nighttime shift will be due to the presence of Economy 7 tariffs in the PV group, while the day-time shift is likely due to the presence of PV.

It can be said that on average demand is higher by approximately 25 W between 9:00 and 17:00 in the PV group compared to the control group. This is approximately 8% of the average daily demand for the PV group of 311 W. The maximum difference in day-time demand occurs around 15:00 and is approximately 40 W, or 13% of the daily average demand.

Assuming that this is in response to the marginal price signal, which would be 0 p/kWh compared to a typical import price at the time of ~8 p/kWh, this shows that a reduction in price of approximately 8 p/kWh can produce a shift of approximately 40 W. By comparison, Allcott found US consumers reduced day-time usage by a maximum of 50W for an increase of about 3p/kWh. While a direct comparison of these results is not valid due to the differences in the experiments, it is at least interesting to note that the responses are of the same order of magnitude.

Returning to Figure 28, it is interesting to note that the increase in day-time demand is similar in size to the increase in night-time demand that is also evident in the PV group, and which is likely to be a result of flexible demand in response to the Economy 7 tariff.

In summary, these results provide quantified evidence that occupants of dwellings with PV do in fact respond to a price signal that is linked to an intermittent renewable technology, and that this response can be characterised through a routine response and an opportunistic response.

5.7.1. Statistical validity of the regression

As mentioned previously, ordinary least squares regression was used to estimate the coefficients of the regression shown previously. Ordinary least squares regression is appropriate provided the data contains no multicollinearity, heteroscedasticity, or auto-correlation (Gujarati, 1992d). These will be discussed in the following.

Multicollinearity is a concern when some of the independent variables are correlated. For example, as mentioned previously, if a dummy variable had been included for Tuesday as well as the other weekdays, this would have introduced 'perfect multicollinearity' as the Tuesday dummy term would have been a perfect linear combination of the other weekday terms. This is illustrated by the following equation.

$$D_i^{tue} = 1 - D_i^{mon} - D_i^{wed} - D_i^{thu} - D_i^{fri}$$

Equation 13

While this illustrates the case of perfect multicollinearity, imperfect multicollinearity is also possible. This is where independent variables are correlated, just not perfectly so. A visual inspection of Figure 23 indicates that there is a positive correlation between the independent variables for daily irradiance and daily temperature. It is therefore likely that there is the presence of imperfect multicollinearity in the regression.

The consequences of this imperfect multicollinearity, however, are not likely to be important for the regression results. Firstly, the correlation between daily irradiance and daily temperature is modest, not strong, and the large amount of scatter visible in plots of this data (Figure 23) will help to minimise any adverse effects. Secondly, note that one of the main concerns with multicollinearity is that it results in wider confidence intervals (Gujarati, 1992d). The results of the regression shown in Figure 28 are however quite good in terms of having reasonably small confidence intervals, and so it is reasonable to assume that multicollinearity is not of major concern here.

The next potential concern is heteroscedasticity, which occurs when the error variance is nonconstant (Gujarati, 1992b). The consequences of heteroscedasticity are more serious than those for multicollinearity, because the estimates of confidence intervals are unreliable. A common method for identifying the presence of heteroscedasticity is by visual examination of the square of the residuals of the regression.

Figure 29 plots the square of the first 10,000 residual errors against daily irradiance for the regression for weekday hour 10. There would appear to be slight negative correlation between the residuals and the independent variable. The Park Test for heteroscedasticity (Gujarati, 1992b) consists of regressing the logarithm of the square of the residuals onto the explanatory variable (irradiance in this case). If a statistically significant correlation exists then there is heteroscedasticity in the data. The Park Test was therefore performed on the data shown in Figure 29 and confirmed that the presence of a statistically significant negative correlation (-3.86×10^{-6}) between the residuals squared and the explanatory variable.

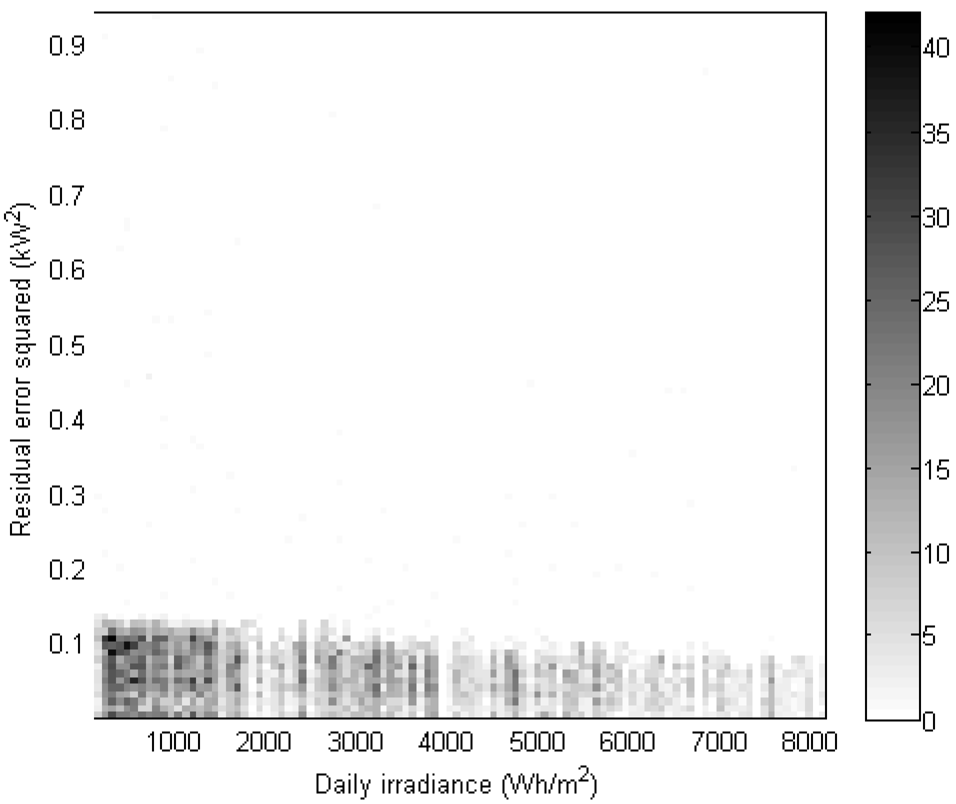


Figure 29 – Residual errors plotted against daily irradiance for weekday hour 10 regression.

While this indicates that heteroscedasticity is present in the data, the negative relationship is close to zero. When for example the same test was performed on the first 1,000 data points the presence of heteroscedasticity could not be confirmed as the negative correlation was not statistically significantly different from zero at the 95% confidence level. It can be said therefore that there is only a limited presence of heteroscedasticity in the data, which is only identifiable due to the large amount of data used in this study. Heteroscedasticity is only worth correcting when the problem is severe (Fox, 1997), which is not the case here.

Autocorrelation occurs when the error terms themselves are correlated (Gujarati, 1992a), and it often an issue in time-series analysis. The consequences of autocorrelation are similar to those for heteroscedasticity. The presence of autocorrelation can however be detected using a Durbin-Watson test. The Durbin-Watson d statistic was close to 2 for the regression results, which suggests that autocorrelation was not present in the data.

Having considered these criteria, the use of ordinary least squares can be said to be valid, and the results of the regression statistically robust.

5.8. Summary

The aim of this chapter was to perform a regression analysis on the electricity demand of dwellings with PV in order to quantify the effect that the PV system has on the occupants' demand. This chapter has described a regression analysis of the demand data of occupants of dwellings with PV in the UK. The results of the regression have provided quantified evidence that occupants with PV do respond to the irregular variability of the PV system, and that furthermore this can be characterised in terms of a routine response and an opportunistic response. On an average irradiance day, occupants with PV exhibit an increase in demand during the daytime of approximately 8% of mean daily demand, with a corresponding reduction in demand during the evening.

It should be noted that this study has not tried to quantify the potential demand reduction effect of PV systems. This does not negate the results, however, as the control group was sampled in order to have the same distribution of annual consumptions as the PV group.

This study has provided a quantification of the effect that PV systems have on demand response behaviour of occupants in the UK. The following chapter builds on this work by investigating what occupants with PV are doing to produce this response, and indeed why they do it.

6. Learning about demand response behaviour from an internet discussion forum for occupants with PV in the UK

6.1. Introduction

The statistical analysis described in the previous chapter identified trends in the data that indicated whether the demand of occupants with PV was statistically dependent on the presence of PV and the outside irradiance levels. This analysis indicated that the response could be characterised as a routine response and an opportunistic response. The aim of this chapter is to support and complement the previous chapter's work by investigating the demand response behaviour of occupants with PV in the UK. To complement the previous chapter, which was quantitative in nature, the following work will be qualitative, and concerned with understanding how and why occupants with PV time-shift their demand.

6.2. Method: analysis of an internet discussion forum

The approach taken here was to analyse an internet discussion forum entitled 'So now I have a solar PV system how do I make the most of it?' on the website MoneySavingExpert.com (MoneySavingExpert.com, 2012a). The forum was started in January 2011 with the aim of providing a platform for occupants with PV in the UK to discuss tips and techniques for reducing electricity bills by making changes to behaviour. The forum is very active, with over 180,000 views. In total over 2,370 posts from this forum were analysed for this chapter, resulting in relevant data being captured on 105 forum participants. The forum has proven to be a rich source of information: for example, there were 45 participants who mentioned engaging in demand response behaviour, and 114 unique mentions of appliances used to time-shift demand.

The approach was to read through the forum and to look for posts that are relevant to this chapter's focus. For ease of reference, the entire forum was copied verbatim to a word document. Figure 30 shows the coding framework that was used to provide a logical structure to the analysis of the forum posts, and enable the results to be quantified. Whenever a relevant post was found, then the post was tagged given the appropriate code, and an entry was made in a spreadsheet against the contributor's forum alias. The entries are a mixture of direct quotations from the forum, or an interpretation of the posts. In order to link this chapter's findings with the work described chapter 3, the 'factors affecting demand response' codes have been grouped according to the behavioural economics factors as described previously.

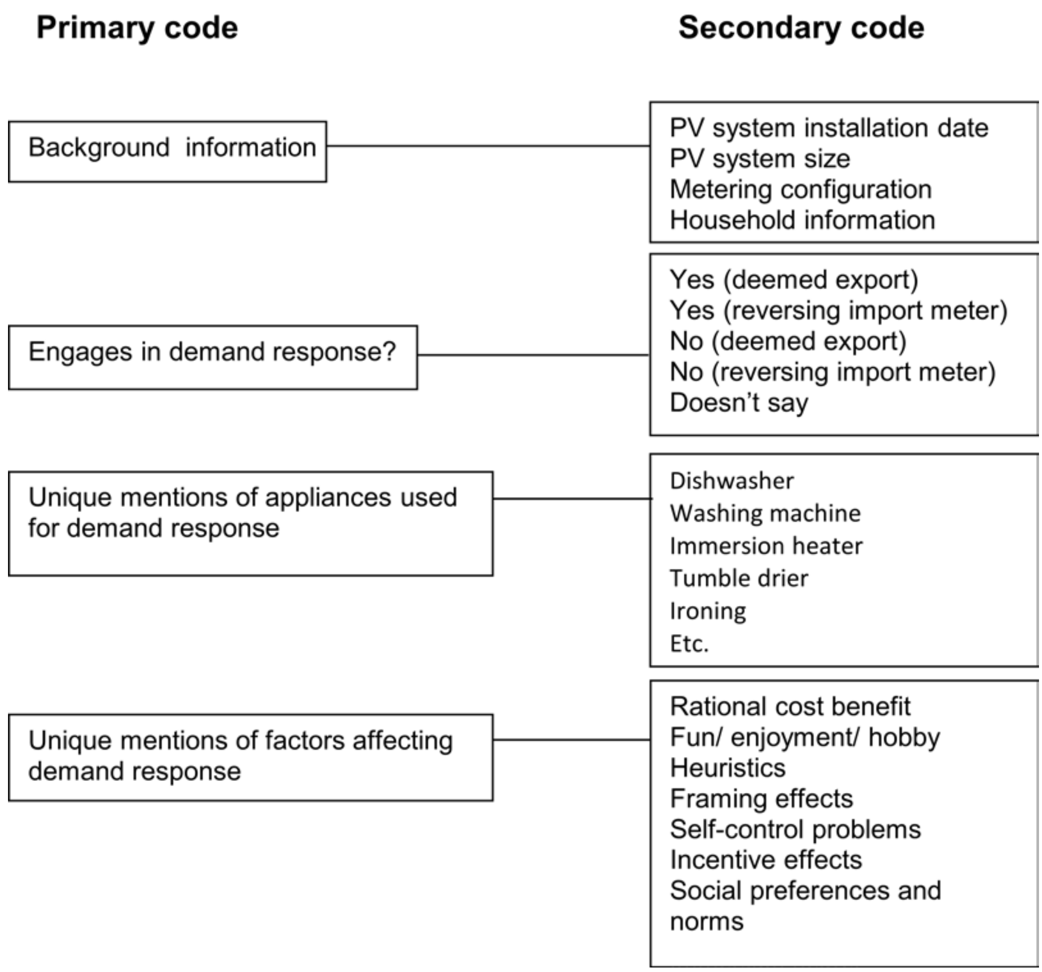


Figure 30 – Coding framework used in the forum analysis.

6.2.1. A note on copyright and privacy

The contents of the forum is owned by MoneySavingExpert.com and is protected by UK copyright laws (MoneySavingExpert.com, 2012b). The contents of the forum are used here according to the website's terms and conditions: the use is non-commercial, and a single copy of extracts from the discussion forum has made on a single computer for personal, individual use only.

None of the data from the discussion forum can be classified as personal data, as it cannot be used to identify an individual. The participants use aliases when making posts, and furthermore the information that is on the forum has been knowingly made available to the public by the participants. Nonetheless, where data was collected on a participant, they were assigned an abbreviated alias, and any quotations that appear in the following text are referred to using the abbreviation, not the participant's forum alias.

6.3. Reducing electricity bills: reviewing the general guidelines for the UK

Before presenting the analysis of the forum, it is useful to review the general guidelines for how to reduce electricity bills with a PV system for occupants in the UK. The advice that occupants should be most familiar with is from the Energy Saving Trust which states that occupants should 'use any appliances during the day when the solar PV modules are generating the electricity' (Energy Saving Trust, 2011). This provides the guiding principle behind the occupants' demand response behaviour.

The paper provided in appendix B reviewed this advice, in light of the paper's analysis of the effective price for a group of dwellings with PV. The advice can therefore be expanded upon as follows:

- The EST advice is broadly true, and applies even during the winter, and for days with low irradiance.
- On average, occupants can expect effective prices to be reduced by two-thirds during the day in summer. In winter, on average the effective price is reduced during the day by about one-third.
- In order for occupants to achieve the lowest effective price, demand should be kept below generation. 'Spikes' in demand should therefore be avoided, for example, by running larger appliances consecutively, rather than at the same time.
- The effective price of electricity is negatively correlated with the outside irradiance. By considering the level of sunshine outside, therefore, as well as the direction of the sun, occupants can determine when it is a good time to use electricity.

The above has summarised the guidelines for occupants with PV in the UK. The following presents the analysis of the internet forum, in order to determine how occupants actually behave in practice.

6.4. Background information

6.4.1.1. PV installation date and installed capacity

In total, data was collected on 105 participants. The selection criteria for these participants was that they had something useful or relevant to say for the purposes of the aims of this chapter.

For example, of this total, 47 stated the date when they had their PV system installed. The distribution of installation dates is shown in Figure 31. All of the reported installation dates are after the start of the introduction of the feed-in tariff scheme (April 2010). It would seem reasonable therefore to assume that the majority, if not all, of the participants were on the UK feed-in tariff. The number of installations has a peak towards the end of 2011, which can be explained by the reduction in the feed-in tariff generation price from 45.4 p/kWh to 21 p/kWh that occurred at this time (Ofgem, 2012).

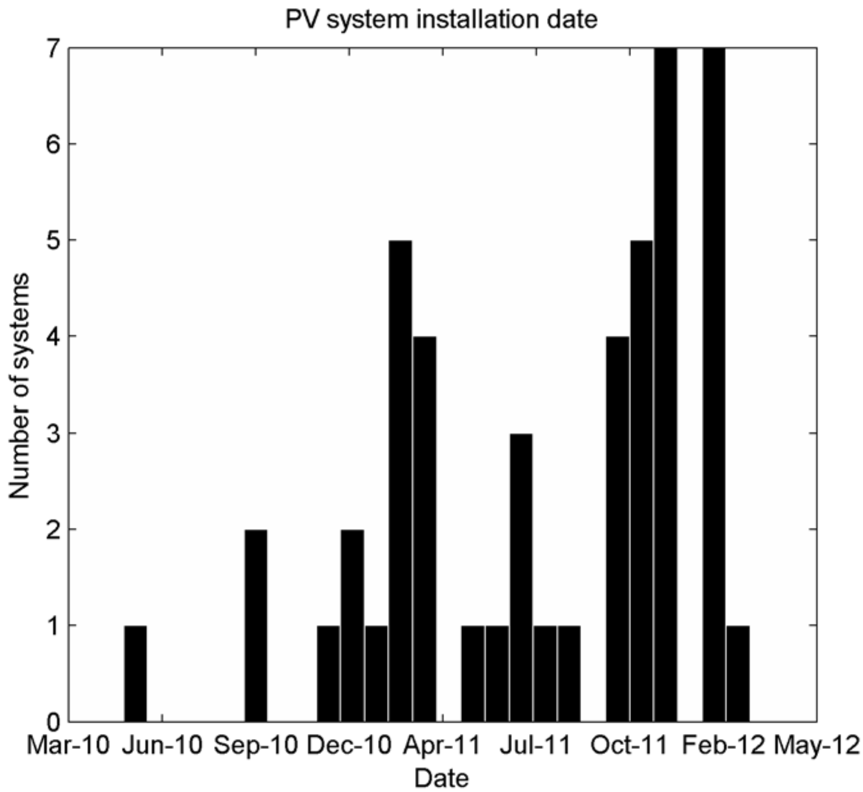


Figure 31 – Installation dates of forum participant PV systems

Out of the 105 participants, 65 stated the installed capacity of their PV systems, and the resulting distribution is shown in Figure 32. This information was mentioned by the participants because it was useful for comparing system performance with other participants. Furthermore, as most of the participants had PV installed recently, they generally knew the exact size of their system. It is clear from Figure 32 that the majority of installations are grouped near the 4 kW_{peak} threshold. Installations over 4 kW_{peak} have a more onerous connection arrangement, and also incur lower feed-in tariff payments (DECC, 2012c). The fact that most of the systems are near the 4 kW_{peak} mark is again a good indicator that the systems were installed for the purposes of benefiting from the feed-in tariff.

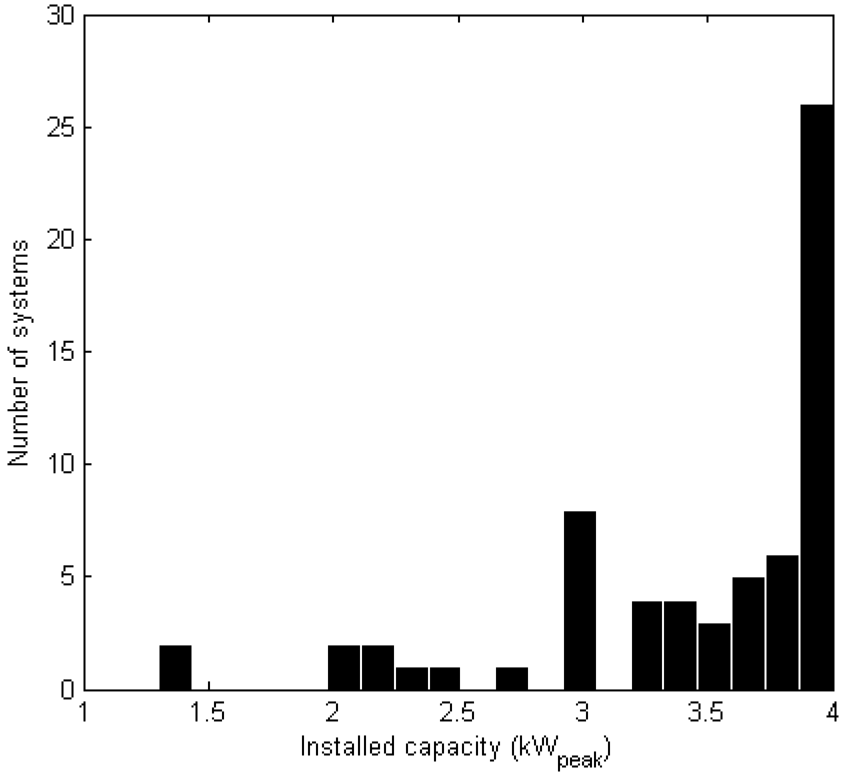


Figure 32 – Size of PV system reported by forum participants.

6.4.1.2. Metering configuration

In terms of metering configurations, none of the participants mentioned having an export meter fitted, and it is likely therefore that all participants had 'deemed export' PV systems, described in section 4.4.4.1, where exports are not metered but deemed to be 50% of the electricity that is generated by the PV.

Participants with this type of system will experience an effective price as described in section 4.4.1, consisting of a variable effective price with a 'floor' price of 0 p/kWh when the PV generation exceeds dwelling demand, and a 'ceiling' price equal to the import price when the PV generation is zero.

Deemed export with non-reversing import meter is the standard metering configuration for domestic PV systems in the UK, and so it has been assumed that this is also the standard metering configuration for the forum participants. This is significant because it means that the majority of the forum participants experienced the same effective price as the occupants with PV that were analysed in the statistical work described in chapter 5.

Out of the 105 participants, therefore, all are assumed to have deemed export systems with non-reversing import meters with the following exceptions: 17 participants who reported that they had reversing import meters. As described in 4.4.4.1, the participants with reversing import meters would not have experienced a variable effective price of electricity, meaning that there was no financial benefit for them in time-shifting their demand.

A further three participants indicated that they had 'faulty' import meters that added exported electricity to the cumulative import register. These participants were therefore charged the import price for any electricity that was exported. It should be noted, however, these meters were not faulty but in fact designed to do this to prevent fraud, specifically the reverse wiring of the meter.

6.4.1.3. Household information

There was little information in the forum concerning the participants' lifestyle and household. It appeared, however, that the majority of participants were an adult member of an owner-occupier household, who also owned the PV system. Some of the participants indicated that their household was occupied during the day, and indeed occupancy during the day was an important factor in how people changed the way they used electricity, as discussed later.

An important exception to the above were four participants who indicated that they had 'rent-a-roof'' systems. In these cases, the participant owned their home, but leased the roof to a private company, who in turn install, own, and receive the feed-in tariff profits from the PV system. The benefit to the occupant is that they can reduce their electricity bills by using PV electricity for 'free' instead of paying for imports from the grid. Note that occupants of dwellings with rent-a-roof PV systems experience a variable effective price of electricity that is identical to a deemed export system.

6.5. Comparing the forum group to the PV group

The aim of this chapter is to learn about the behaviour of consumers with PV in the UK, and one of the reasons for doing so is to complement the results of the previous chapter, in particular by investigating whether the quantitative results are likely to be attributable to a response to PV, or rather some other factor such as differences in day-time occupancy between the PV and control groups. This chapter does not however analysis the PV group, but rather a separate 'forum group' which is likely to have different demographics and so deserves discussion.

While the PV group was likely to be over-representative of social housing, the forum group is likely to be over-representative of wealthy families, owner-occupiers, and elderly retirees. The forum group will most likely be 'early-adopters' of PV systems, while the PV group (if social housing), will not.

The forum group is also self-selected, as they chose to participant in the forum discussion, while the PV group, if social housing, is not self-selected, as it would have been the social landlord's decision to install the PV system. This self-selection means that it would be prudent to assume that the forum group would be over-representative of PV owners would are already interested in engaging in demand response behaviour to save on their bills.

Nonetheless, both groups experience the same variable price signal, and it could be said that the PV group could be more enthusiastic about taking advantage of cheap electricity if the assumption can be made that social housing equates to a higher likelihood of fuel poverty. Indeed the potential savings in electricity bills afforded by the PV system consists of the entirety of the financial benefit for the PV group, while this benefit is in fact small compared to the greater benefit to the forum group afforded by the feed-in tariff generation payments.

The assumption is made here therefore that if demand response behaviour is observed in the forum group, then this provides evidence supporting the assumption that the results from the previous chapter can, at least in part, be attributed to demand response behaviour.

6.6. Evidence of demand response behaviour

This section describes evidence of demand response behaviour for the forum participants. Of the 105 participants, 45 (43%) reported engaging in some form of demand response behaviour. The selection criteria for this was if the participant mentioned having engaged in time-shifting behaviour, for example by specifically mentioning that they used an appliance in order to benefit from the available PV generation. The following is an illustrative quotation from one of the participants.

'Great generating day today, best since mid-october. Managed 2 lots of washing, 2 tumble dryer loads, cooked lunch (electric hob), boiled kettle twice, pc on, TV on and had the oil heater at varing levels all day.' (R.D)

The remaining 60 participants (57%) did not mention engaging in demand response behaviour, but posted other relevant information, for example, the size of their PV system. This provides an indication of the level of interest in demand response behaviour of the forum participants and indicates that while the group is self-selected, this does not necessarily mean that they all engage in demand response behaviour.

Out of the 45 who mentioned engaging in demand response behaviour, Figure 33 indicates the number of unique mentions of appliances that were used by the participants to engage in demand response behaviour. The washing machine and dishwasher were the most commonly mentioned appliances, followed by electric space and water heating. It is worth noting that some of the appliances that were mentioned provide novel evidence of demand response behaviour for example the kettle, and cooking appliances. As will be discussed in more depth later, demand response of these appliances represents participants making changes to their expectations, such as changing when a hot meal is eaten during the day. This presents evidence of considerable flexibility above that which is commonly associated with demand response, such as delaying when the dishwasher runs.

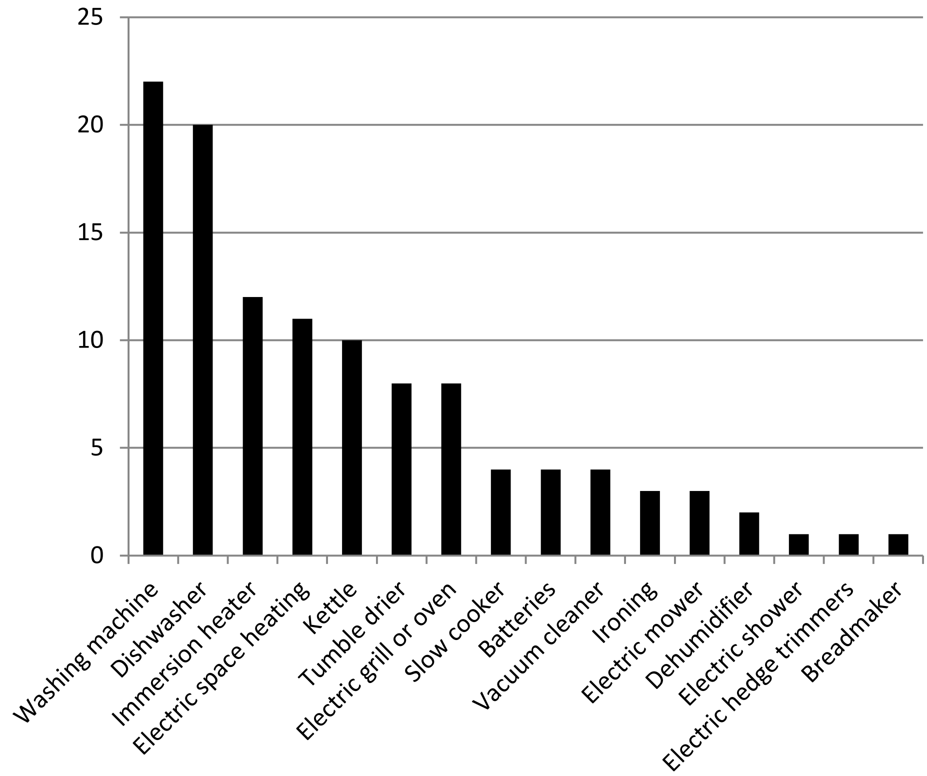


Figure 33 – Number of unique mentions of appliances used for demand response by participants.

These results therefore support the assumptions of the previous chapter, by providing evidence that domestic consumers with PV in the UK change their demand in response to their PV systems.

Of the 45 who mentioned engaging in demand response behaviour, six of these reported having reversing import meters, and so were incorrect in their behaviour. Of the remaining participants, five specifically mentioned that they did not engage in demand response behaviour, all of whom had reversing import meters, and so were correct in this behaviour. The following section considers how the forum participants went about making demand response changes.

6.7. How do occupants with PV time-shift their demand?

6.7.1. What information are participants using to respond to?

Most of the participants monitored PV generation and the dwelling's net power flow, and used this to inform decisions about when they should run appliances. Clip-on monitors such as the 'Owl' (2 Save Energy Ltd., 2012) were commonly mentioned, though some participants were able to monitor PV generation through their computer. The following quotations provide examples.

'[The monitor is in the kitchen and] usually consulted when we're thinking of switching something on' (E.R.I.)

'Not a huge amount of work to estimate how much power each major appliance needs and make sure that total usage is below generation output whenever possible' (E.R.I.)

'We have a generation monitor and a consumption monitor next to each other in the kitchen so that we can try to get the most out of what we produce' (N.A.M.)

'I generally monitor how much power is being generated by the panels, and try to match the load to the supply.' (P.R.)

Many of the participants, however, expressed frustration because the clip-on monitors could not be used to monitor household demand, only the magnitude of net power flow, as these devices cannot determine the direction of current flow. Some of the participants mentioned that if they wanted to know whether they were exporting or importing, they would quickly switch on a high power appliance, such as an oven hob, and see how the power reading of the clip-on monitor would change.

Ideally, the participants wanted a monitoring system that could allow them to directly compare PV generation with household demand, and so determine how much spare PV generation there was. Instead, however, most participants only had PV generation and the absolute value of net dwelling power flow, which many found difficult or confusing to work with.

Several participants who did not have clip-on monitors would instead rely on checking their import meter to determine if they were exporting.

'If I am exporting electricity the [import] meter is on permanent red.' (J.P)

'First look at the meter wheel on your [import meter]. Stopped = good' (S.T.)

There were fewer difficulties associated with monitoring generation, and many of the participants spent a lot of time comparing PV outputs. Indeed, it can generally be said about the forum participants that they became very knowledgeable about their PV output. This included understanding the variation in daily output throughout the year, how and when shading would affect output, the effect of panel orientation and slope, and the effect of passing clouds. The following quotations from the forum demonstrate how some participants developed a very sophisticated understanding of the variability of their PV output.

"[…] I've been surprised by the variation in generation on a realtime basis - it's not only 1.4kW one second, then 100w a second later when a cloud passes over, but even in the sunny weather we've had for a couple of days since my installation, the generation varies between 1.2kW and 1.4kw second by second even with no perceptable 'clouds' or haze. Any slight dimming perception knocks the output by 500W, and normal clouds knock it by 1,3kW in my case. There is also a variation in ouput caused by the inverter searching for the maximum power point every six seconds" (G.H.)

"Today is tracking yesterday but about 100 watts lower, the sky has a milky looking quality to it" (F.J.)

"After a while of checking the [monitor], you will be able to estimate the generation by looking at the sky and feeling the sun's strength" (P.R.)

"Shading from a tree for 45 minutes at peak time 1130-1215 - 110 deg facing" (M.V.R.)

The process of monitoring PV output was seen by some as a being similar to a game, hobby, obsession, and even an addiction. For some this was due in part to the relative novelty of the PV system: for example one participant mentioned that initially she monitored her system on a daily basis, but that after 9 months, she 'doesn't look so much' (T.G.). This was likely due to the fact that this participant was now familiar with the PV output and as a result did not need to monitor it regularly.

The process of monitoring and comparing PV output also helped many participants to improve their understanding of the technical aspects of energy. For example, while many participants initially confused kW and kWh, or even kW/h, this seemed to improve over time as they became more familiar with the technical terms.

One participant mentioned that he had found it useful to have a clip-on monitor for some time before having PV, because it allowed him to build a good prior understanding of the power consumption of many of his appliances. Implicit in this last statement is the notion that it is more difficult to build up this awareness if the PV system is already installed.

Previous chapters introduced the concept of a variable effective price that occupants with PV respond to, yet it is important to note that the forum participants seem to respond to a variety of different signals. Some respond to irradiance, while others seem to respond to PV generation, net dwelling power flow, or even a 'traffic light' signal from the lights of their import meter.

It is interesting to note that those that respond to PV generation and net dwelling power flow could be said to be responding to something similar to the weighted mean average effective price, while those responding to a traffic light signal from their import meter appear to be responding to something closer to the marginal effective price as introduced in section 4.4.2. The determining factor in whether a participant appears to respond to one or the other would appear to be the type of monitors and display equipment present in the dwelling. Those with clip-on monitors correspond to those responding to the average effective price, while those without who rely on their import meter are responding to the marginal effective price.

From the perspective of this thesis, all of these variables are closely correlated, and can be viewed as proxies for each other. It is for this reason that they are used interchangeably in this thesis, though it is noted that this is a simplification of the actual response of occupants with PV.

6.7.2. How do participants respond to this information?

With a good knowledge of their PV generation, and a technique for determining when and how much electricity was available from the PV, the participants could then concentrate on taking advantage of this using their available appliances. As indicated in Figure 33, above, the washing machine and dishwasher were the most commonly mentioned appliances on the forum, and so it is useful to analyse in detail how these were used.

6.7.2.1. Washing machines and dishwashers

Typically participants mentioned switching on the washing machine and dishwasher during the middle of the day when their PV was generating, in order to take advantage of the cheap electricity offered by the system. The following quotations provide examples:

'Now (10:20) nudging 2.5kw so I'm running dishwasher - not quite 'free' as [the dishwasher] (in heating cycle) + base load exceed generation by 200w but still a lot cheaper than an E7 load.' (E.R.I.)

'[The monitor is] telling me I've got a surplus of almost 2KW so off to switch on washing machine' (E.R.I.)

Participants appeared to be well aware of the advice described in section 6.3 that it is important to stagger the use of the larger appliances, in order to minimise the possibility of importing electricity from the grid. And indeed, the washing machine and dishwasher were often mentioned being run in this manner in order to avoid demand spikes. For example, one participant mentioned that they tended to switch on their dishwasher 30 minutes after their washing machine, in order to stagger the heating cycles of the machines.

Both the dishwasher and washing machine benefit from having a form of storage that enables people to be flexible in the times when they need to be used. Dirty plates can be placed in the dishwasher, and dirty clothes can be allowed to build up in the laundry basket. Provided there were sufficient clean plates or clothes, and sufficient space in the machines themselves, participants could be flexible about when the appliances were run. It was also clear, however, that participants were able to be more flexible with their dirty washing than their dirty dishes. For example, many participants mentioned that they saved their dirty washing for a sunny day, but that they were less able to wait for a sunny day in order to do the dirty plates.

Other cleaning appliances were also mentioned. For example, one participant mentioned that if the sun was not out then neither was the ironing board. Another participant mentioned only doing the vacuuming when the sun shines. The tumble drier was also mentioned relatively often as being used during the middle of the day – with one participant mentioning that she enjoyed 'fluffing' the towels when the sun was shining.

6.7.2.2. Heating appliances

Most participants had electric immersion water heaters, and also had a year-round need for hot water. As a result, the conversion of PV electricity into hot water was mentioned by several participants as being a convenient method of using 'excess' or 'surplus' PV generation.

"The best practical way to store surplus energy - in the sense of being able to utilise it when the sun isn't shining - is as hot water" (O.G.R.)

The problem that many participants mentioned was that their existing immersion heater was a 3 kW device which, when switched on, would typically draw some, or most, of its electricity from the grid. As a result, many of the participants mentioned purchasing custom-built 1 kW immersion heaters, which were much less likely to import power when switched on. One participant mentioned using a 1 kW immersion heater to 'super-heat' the water in the hot water tank to 75 °C, so that on following days without much sun, he still had hot water. Again, this shows that participants clearly understood the advice described in section 6.3 that they should try to keep demand below PV generation.

Other participants mentioned using PV electricity to power electric space heaters, usually in the form of portable oil-filled or radiant heaters, though some mentioned purchasing air-source heat pumps, and one even mentioned purchasing an electric AGA oven. The small portable electric heaters seemed to be convenient to participants particularly if they had multiple power settings, and were typically mentioned being used in the autumn or spring, as a replacement for gas central heating.

6.7.2.3. Cooking appliances

Indeed the low-power immersion heater is an example of what the participants called a 'PV friendly' appliance: a low-power version of an appliance that would be less likely to import power from the grid. Many participants therefore had replaced their traditional 2 kW or 3 kW kettles with a low-power 500 W travel kettle, particularly during the winter months. Others mentioned using a 'super-kettle', or 'keep warm' kettle, which keeps water permanently hot and had a demand of around 700 W (not continuous). The following is a quotation from a participant regarding the use of a low powered kettle:

'I do of course realise that a 500w kettle for 12 mins is using exactly the same as a 3kw one for 2 mins. As I wrote that, my Wattson meter was telling me I had a 500w excess so the little kettle cost absolutely nothing to run, the bigger one would have been working at '17% off'. [...] Other things being equal, I'm happy to wait a few minutes for a slow kettle rather than paying 0.06p (or whatever) for the instant gratification of a hot drink before I've had time to prepare the sandwich to go with it. Do that 150 times (and I'm sure I would most months) and there's a pound less on the next electricity bill' (E.R.I)

This quotation reveals that the participant was aware that the benefit of being more flexible in this case was very small indeed (0.06p), and yet they were still content to make considerable changes: sacrificing 'instant gratification' for the long term prospect of reducing the bill at the end of the month.

Many participants mentioned changing how or when they cooked meals. Some simply moved their hot meal from the evening to lunchtime, in the hope of running their electric grill or oven when their PV generation was high. Others mentioned cooking during the day, and re-heating the meal using a microwave oven in the evening. Quite a few used 'slow cookers' to cook meals during the day, to be ready for their evening meal. The slow cooker is another example of a 'PV friendly' device, because its power consumption is relatively low compared to an electric oven.

It was also mentioned that most microwave ovens were not PV friendly because their peak power demand at a low-power setting was the same as that on a high-power setting (the appliance pulses on and off in order to achieve a lower average power demand). Some modern microwave ovens are able to modulate their power demand without pulsing, and these were felt to be a more PV friendly choice.

6.7.3. An appetite for automation

The purchase of PV friendly appliances indicates that the participants were willing to make capital investments in order to facilitate their demand response behaviour. Beyond the PV friendly appliances mentioned previously, the participants also demonstrated an appetite for automation to help deal with the practicalities of time-shifting demand. Timers that can delay when appliances are switched on were, for example, often mentioned by participants who were not at home during the day, as illustrated by the following quotations:

'As I work some distance from home (like a lot of people) I look out the window in the morning and set washing machine / dishwasher to come on at about lunchtime or earlier if bright and sunny already. Not an exact science as stated elsewhere but if I wait until I get home there is the CERTAINTY that there will be no generation at this time of year.' (D.U.C.)

'Our washing machine and dishwasher come with a timer, which I find really useful to achieve this. So you can leave the dishwasher full and ready and program it to run at a suitable time.' (N.S.B.)

The use of timers is an example of the participants using technology to allow them to benefit from the cheap electricity provided by their PV, while minimising the effort required to do so. Beyond timers, there was also a certain amount of appetite for more sophisticated automation that could reduce the effort involved in switching appliances and loads on and off depending on the output of their PV system.

'The whole system really needs to be smoother with a smart way of diverting the "free" energy around the house to where it's needed without importing.' (M.V.R.)

'I've concluded that anything other than using solar to power things that you would have run anyway is a waste of time (notwithstanding some intelligent control system to do it).' (O.R.R.)

One of the automation technologies that was most often mentioned was a device to automatically switch on the electric immersion heater whenever there was adequate PV generation, and automatically switch off the heater when there was not enough. The lack of a cheap device that could do this was frustrating to many of the participants. A device called an 'Emma' (Coolpower Products UK, 2012) that could do this was mentioned but at an expected installation cost of around £1000, it was deemed far too expensive. One participant said that he would invest in a device that did this if it cost £150 or less.

Some participants expressed an interest in storing excess PV generation in batteries, and wondered if there were affordable systems available to do this. Indeed, two participants created systems themselves to do this, using leisure batteries that they charged during the day using PV electricity, and discharged at night. One participant used two 80 Ah batteries (~2 kWh), which they used to power a 50 inch TV at night. The second participant charged a 110 Ah battery (~1.2 kWh), that was fed through an inverter to run the house lights in the evening. On a smaller scale, some participants mentioned that they tried to charge devices that used rechargeable batteries during the day e.g. laptops, electric toothbrushes, etc. Finally, it should be noted that several participants expressed an interest in electric vehicles, mainly because of the possibility of charging them cheaply during the day using their PV generation.

The previous sections are therefore encouraging because they demonstrate that the participants were quite willing and able to engage in demand response behaviour, and that this even extended to purchasing appliances and technologies specifically with the view of facilitating this behaviour. It is also important to note, however, that given the potentially very low savings associated with the demand response behaviour, these investments in appliances are not entirely rational, as their payback period is likely to be very long, as illustrated for the case of batteries in PV systems in section 4.5.

6.7.4. Developing habits

It appears that the forum participants were going through the process of learning about their 'price signal', in this case by learning about the variable output of their PV system, as well as the power consumption of their appliances, and how these could be matched in order to reduce their bills. This learning process was facilitated by the forum, which was a place where participants could exchange advice with other people in similar situations. After the initial learning phase, whereby new behaviours are tried out, and concepts learned, the new behaviours became habits. The following quotations give some examples:

'The majority of people who invest what is effectively the value of a new car on glazing their roof attempt to recoup their fixed investment as quickly as possible and the only way this can be achieved/influenced is through changing personal energy usage profiles. It actually become quite fun/obsessive for a while as people play with their new toy to maximise the return, then it just becomes habit' (Z.P.)

'I'm still getting used to only putting on one appliance at a time and not using them in the evenings. Means I have to be slightly more organised than usual.' (S.P.A.)

'If it's sunny (and likely to stay that way) do the washing and dishwashing and put on any other high-energy appliances that stay on for a while. If it isn't sunny, consider delaying them until it is, provided it's convenient to do so.' (D.O.C.)

'I don't let the solar panels rule my life, and although I was a little obsessive [...] when the panels were initially fitted, we now generally use a common sense rule of thumb to maximise efficiency, and try to use heavy load appliances wherever possible when it's sunny, timing the dishwasher, clothes washer etc. for around midday.' (P.R.)

'We make the simple changes; use dishwasher, washing machine in turn during daylight hours but don't worry if overcast; if an evening meal can be pre cooked , say a chilli, hotpot, beef in red etc, if panels cover the usage then fine, if not, then that's fine as well given we are trousering cash' (S.T.U.)

'I say that with around 18 months experience. It really isn't worth all the hassle trying to achieve some kind of PV 'perfection'. You won't manage it, and you need a life! […] A bit of experience and a degree of commonsense should enable most people to maximise the use of the 'free' power, without turning their lives upside down in the process.' (D.O.C.)

'I'd never go to ridiculous extremes - e.g. when convenient we try to have main meal of day at lunchtime if it's sunny but haven't yet got to the stage of not eating for three days in case sun comes out on fourth' (E.R.I.)

'[…] if you just use [solar power] by setting a timer at midday to run the washing machine etc. (if you're not on e7 that is), then you'll probably pay about £25 more per year than someone who continually tries to match solar generation with usage (and who's good at it).' (G.H.)

These quotations indicate that the participants would weigh the perceived benefits against the perceived costs (in terms of time and effort) of making changes to their behaviour. The balance between perceived cost and perceived benefit determines the extent of the behaviour change. It is useful therefore to analyse how participants perceived costs and benefits in more detail.

6.7.5. Perception of costs or 'hassle' factor

The previous quotations reveal that the main perceived cost was the potential 'hassle' or time and effort involved in changing behaviour and trying to maximise the use of PV electricity. This was particularly so when trying to achieve a close match between PV generation and demand.

'I've tried to roughly match my solar power to my usage by turning on small medium and large loads at my disposal. It is impossible to even get near matching.' (G.H.)

Some participants, however, found the process of trying to maximise self-consumption to be a fun challenge, almost a hobby.

'But if we're having fun, what's the problem? A lot of this is just people running through some mental exercises over what can or could be done. I've already found, that it's become second nature, not really a chore anymore, just a new way to do things. […] I've had PV for 8 months and find it neither a chore nor hard work to get more out of it. In fact it's already becoming second nature, and is still remarkable fun. If at any point it stops being fun, or un-rewarding I'll follow [D.O.C.]'s advice and move on to something else.' (M.T.N)

It appears therefore that what some participants viewed as a chore, others viewed as being 'remarkable fun'. As this had a bearing on the extent to which they appeared to adopt demand response behaviour, it can be said that encouraging this positive perception of demand response behaviour would be beneficial to demand response schemes more generally.

6.7.6. Perception of financial benefits

In general, the participants had a relatively good grasp of the potential benefits of self-consumption. There was a general agreement amongst those with non-reversing import meters that self-consumed electricity was 'free', and that savings could be achieved by replacing imported electricity with free electricity.

The situation was complicated, however, if the self-consumed electricity was replacing gas usage. An example of this that was much discussed on the forum concerned using electric immersion heaters during the middle of the day to use free PV electricity. Some participants wrongly assumed that this saved them the equivalent of 10 p/kWh (the import price), even though most of them would have used gas to heat the water instead, at a rate nearer to 3 p/kWh. Some participants, however, recognised this:

'There is not a lot of money you can save be replacing gas or economy 7 electricity with "free" daytime electricity.' (J.P.)

This was especially important when considering situations where the immersion heater drew some of its electricity from the grid, with one participant correctly pointing out that if anything more than one third of the immersion heater's demand came from the grid, then it would result in an overall increase in people's bills. Another similar example that was mentioned previously of participants using portable electric space heaters to replace gas central heating during the spring and autumn months.

6.7.6.1. Effect of introduction of smart meters on financial benefits

Smart meters are due to be rolled out in the UK over the next few years, and when this happens the participants' exports will be metered, and they will have fully metered systems. The consequence will be that self-consumption will no longer be free, but instead have an opportunity cost determined by the export price (e.g. 3.2 p/kWh).

As a result, considering the case of the immersion heater replacing gas usage mentioned above, the ~3 p/kWh of saving from displacing gas consumption will effectively disappear, because the export price is 3.2 p/kWh. This means that there will be no financial benefit to using the immersion heater to use surplus PV generation, if it is replacing gas usage, and that people with PV who have invested in new PV friendly 1 kW immersion heaters are even less likely to recoup their investment costs.

This transition to smart meters, and metered exports was discussed by some participants. One participant correctly pointed out that once exports were metered that savings from self-consumption would need to be compared against the 3.2 p/kWh export price. Regarding the incentive to time-shift, another participant incorrectly thought that this would disappear once smart meters were installed 'since you would then get paid only for what you export' (C.R.).

One rent-a-roof participant rightly pointed out that even with a smart meter, it would not change their situation, because any income from exported electricity was paid to the company who owned the PV system, and not the participant. With rent-a-roof schemes, the occupant will still get free electricity from the PV system, even when smart meters are installed.

6.7.6.2. Reversing import meters

Interestingly, there were six participants who seemed to believe that they could benefit from time-shifting behaviour, even though they had a reversing import meter, and so could not. Indeed one participant even seemed to continue to time-shift, even after she had it pointed out to her that it did not make a difference to her bills, and even after she acknowledged that this was true. This would appear to be completely 'irrational' behaviour, with similarities to the 'mug' experiment described in section 3.10.1, which demonstrated that the value that people place in objects changes depending on whether they own it or not. Accordingly, these 'irrational' forum participants would place a greater value on the electricity produced by their PV system compared to electricity imported from the grid, even though they actually have the same financial value.

Regarding reversing import meters in general, several participants felt that having a reversing import meter was a big advantage because the timing of their electricity-use was not a factor. The concept of exports being 'banked' by the grid for future use was mentioned several times. The following are quotations from several participants explaining what having a reversing import meter means for them:

'If your meter goes backwards, then it makes no odds whatsoever when you use your electricity'(G.H.)

"If your meter is running backwards then it is totally irrelevant what you switch on when as your net usage is going to be exactly the same no matter when your appliances are switched on" (J.B.)

6.7.6.3. Reversing price signals with Economy 7 and PV systems

There were a number of participants who were on an Economy 7 tariff. These participants were in an unusual position because, in addition to the cheap electricity afforded by the PV system during the day, they also could take advantage of cheap electricity at night, typically from 11pm to 6am. While self-consumed electricity during the day would be cheaper than off-peak Economy 7 consumption at night, these participants also had to consider the limited capacity of free electricity provided by the PV system, especially during the winter months. Indeed, it would seem that these participants experienced a reversal of price signals that was seasonally dependent. During the summer, these participants would aim to run appliances during the day, but during the winter they would run appliances during the night. The following quotation provides an example.

'Although we have Solar PV we use Economy 7 so still try to run things at night as unless very sunny day in summer' (B.E.Z.)

Another interesting observation is that the combination of cheap day-time electricity, and cheap night time Economy 7 electricity results in prices that are expensive during the evening, starting after the PV system has stopped generating, say around 5pm, and ending around 11pm when the Economy 7 off-peak price starts. The following quotation illustrates how one participant perceived this evening peak.

'I am now very aware that the evening is now my most expensive time of day for consuming electricity and find myself looking round trying to spot what is increasing [grid imports].' (J.P.)

These findings are important because they strengthen the applicability of the thesis' findings for systems with high penetrations of wind, which was one of the limitations of this research approach as discussed in section 1.8. The fact that this thesis has found instances of domestic consumers who experience and say they respond to a reversing price signal is therefore encouraging from the point of view of securing demand response in future power systems with high penetrations of wind where periods of high or low prices could conceivably occur at any time of day.

6.8. Behavioural factors affecting demand response behaviour

Of the 45 who mentioned engaging in demand response behaviour, Table 13 shows the strength of the factors that affected the participants demand response behaviour. The factors have been grouped according to the structure of behavioural economics factors that were described in chapter 3. Additional factors have also been included: 'Rational cost benefit' indicates that the participant weighed the benefits of demand response against the costs involved in terms of time and effort spent as would be expected under a rational model of consumer behaviour. 'Fun/ enjoyment' indicates the participant gained additional benefits from engaging in demand response behaviour as they found it to be an enjoyable activity. 'Did not say' indicates that while there was evidence that the participant engaged in demand response behaviour, they did not mention any specific factors that affected their behaviour. The strength of the factors is shown as a count of the number of unique mentions by the 45 participants who mentioned engaging in demand response behaviour. Unique mentions are determined by interpretation of participant forum posts, and examples of relevant quotations are given in the following text, along with a discussion of the various factors.

Table 13 – Unique mentions of factors affecting demand response behaviour by the 45 participants who engaged in demand response behaviour.

Factor		**Count (% out of 45)**
Rational cost benefit		28 (62%)
Enjoyment or fun factor		7 (16%)
Heuristics / rules of thumb	Inattention	24 (53%)
	Anchoring	0
	Menu-effects	0
Framing effects	Reference dependent preferences	0
	Certainty effect	0
	Loss aversion	5 (11%)
	Endowment effect	6 (13%)
	Ignoring opportunity costs	3 (7%)
	The value of 'free'	14 (31%)
Self-control problems	Status quo bias	0
	Discount rates (hyperbolic)	0
	Discount rates (irrationally low)	6 (13%)
Incentive effects	Market exchange vs social exchange	0
Social preferences and norms	Social pressure	0
	Selfishness/ punishment of selfish behaviour in others	0
	Social norms	0
Did not say		8 (18%)

6.8.1. Rational cost benefit analysis

Rational cost benefit analysis was assumed to affect the demand response behaviour of the participants if they mentioned either the perceived benefits of the behaviour in terms of reduced electricity bills, or the costs involved in changing behaviour, for example in terms of the time and effort involved. 28 out of 45 (62%) of the participants who mentioned engaging in demand response indicated that rational cost benefit analysis affected this behaviour, making this the most common factor. The following quotations provide examples of quotations that were taken to indicate that rational cost benefit analysis affected the behaviour of the participants.

'Just a word of advice from someone who's had panels up and running since the summer of 2010 - you can waste an awful lot of time fussing over what will prove to be quite small amounts of money if you're not very careful.' (D.O.C.)

'I've tried to roughly match my solar power to my usage by turning on small medium and large loads at my disposal. It is impossible to even get near matching.' (G.H.)

6.8.2. Enjoyment or fun factor

Seven out of 45 (16%) of the participants expressed that their demand response behaviour was affected by an enjoyment or fun factor. This acts as an additional benefit to the participant that motivates them to change their behaviour, on top of the existing financial benefit. The following are example quotations.

'It actually become quite fun/obsessive for a while as people play with their new toy to maximise the return, then it just becomes habit' (Z.P)

'I don't let the solar panels rule my life, and although I was a little obsessive [...] when the panels were initially fitted, we now generally use a common sense rule of thumb to maximise efficiency [...]' (P.R.)

'I've had PV for 8 months and find it neither a chore nor hard work to get more out of it. In fact it's already becoming second nature, and is still remarkable fun.' (M.T.N.)

6.8.3. Rules of thumb and inattention

24 out of 45 (53%) of the participants indicated that inattention was an important factor affecting their demand response behaviour. For example, participants commonly mentioned using sunshine as a proxy for when they could expect electricity to be cheap. Sunshine was a useful proxy because it consisted of information that was relatively easy to acquire and an accurate indicator of whether electricity prices could be expected to be low. The following provides example quotations.

'Dishwasher goes on in the morning 9ish, water 12, washer in the afternoon if sunny of course! I packed in work last year so most cleaning and ironing is done in the day, if the sun is not out neither is the ironing board!' (P.I.C.)

'Weather forecast is good so getting the dishwasher and washing machine on now.' (S.L.Y.)

6.8.4. Loss aversion

As discussed previously, the majority of the participants had deemed export systems, in which case if the electricity generated by the PV system is not consumed in the dwelling, then it is exported and 'lost', insofar as the participant does not get compensated and loses the opportunity to use the electricity. Loss aversion would act to motivate participants to avoid such losses. Loss aversion was judged to be applicable if the participant mentioned electricity exports in terms of being 'lost', 'unused', 'surplus', or 'an excess' to them in some way. Loss aversion appeared to affect five out of 45 (11%) of the participants, with the following quotations providing examples.

'[The portable electric heater] uses excess energy which would normally go to the grid and you would lose it.' (A.N.T.)

'We need to use the electric before it hits the meter which is quite difficult at the moment.' (F.D.)

6.8.5. Endowment effect

Of the 45 participants who mentioned engaging in demand response behaviour, six had reversing import meters, and so were incorrect in this behaviour as it had no financial benefit. Their behaviour could be explained by a lack of knowledge, and not understanding that having a reversing import meter removes the financial incentive to time-shift. There is also the possibility, however, that the endowment effect could be a contributing factor to their behaviour. The participants owned the electricity their PV systems produced, and the endowment effect could act to increase the value of self-consumed electricity over imported electricity. It is possible that this could be a contributing factor for the six participants with reversing import meters who nonetheless engaged in demand response. An example is given by the following quotations from a participant with a reversing import meter, who appeared to understand that there was no financial benefit in engaging in demand response behaviour and yet persisted in this activity.

'Actually I have [an importing meter] too. […] Just realising though why my meter makes [a] difference. […] I don't really have to save my jobs for a sunny day. […] I do set the washing machine on timer through the week.' (T.G.)

In a post eight days later:

'It is very difficult to [maximise self-consumption] although some of us have good fun trying' (T.G.)

In a post the following month:

'On these very productive days I am struggling big time to use all the electricity I make. […] We have turned off the gas heater and are using the immersion twice a day.' (T.G.)

6.8.6. Ignoring opportunity costs

Three out of 45 participants (7%) appeared to ignore opportunity costs associated with their demand response behaviour. One example concerns the introduction of smart meters, where a participant stated 'it is financially way better to use the [electricity] that you generate for free, and not get any export tariff, rather than buy it in at say, 12 p/kWh, and sell the odd bit back for 3.2 p/kWh' (C.L.R.). The quotation shows that the participant wrongly considers self-consumption to be free, even though there is an opportunity cost associated with reducing their income from metered exports.

Another example is given by the following quotation from a participant who had a reversing import meter:

'To my reasoning if [my reversing import meter] winds back 10 units then I have to use 10 units to end up were I started from so the 10 units are free' (D.E.G.)

This quotation indicates faulty reasoning on the part of the participant, who believes that the exports that are 'banked' by the grid can be consumed for free, whereas in fact the effective price of electricity for this participant has an opportunity cost that is equal to the import rate.

6.8.7. The value of free

14 out of 45 participants (31%) appeared to find pleasure in the fact that self-consumed electricity was free. This would suggest that the fact the electricity was free was having a disproportionate effect on the value the participants associated with it. The following provides example quotations.

'Today I had the luxury of using the tumble dryer for free.' (J.P.)

'I get great satisfaction out of seeing 3kW+ on the [monitor] and putting the kettle on for a nice brew for free :D' (D.O.N.)

6.8.8. Irrational discount rates

The behavioural economics literature on self-control problems presented in section 3.10.2 described how people are inclined to value immediate rewards (and dislike immediate costs) much more than they value distant rewards (and dislike distant costs), known as 'hyperbolic discount rates'. This would act to discourage demand response behaviour as the reward is in the future (reduced bill) while the cost is in the present. What is remarkable about some of the forum participants was that they appeared to have the opposite of hyperbolic discount rating, and rather valued distant rewards over immediate gratification. A good example of this was given in section 6.6.2.3 where a participant justified the use of a low-powered kettle because it saved 0.06 p each time it was used. This is an example of participants demonstrating very low discount rates, perhaps even irrationally low. This also appears to apply to the participants who invested in equipment to facilitate demand response, as the pay back for these investments are likely to be long, such as for installing battery systems, or low-powered immersion heaters. Six out of 45 (13%) of the participants therefore appeared to be affected by irrationally low discount rates.

6.9. Summary

This chapter has analysed the contents of an internet discussion forum in order to investigate the demand response behaviour of occupants with PV in the UK. The analysis finds that occupants with PV in the UK try to shift their demand to the daytime, and do so principally in order in an effort to maximise the financial benefit of the PV system.

The analysis has further revealed what and how appliances are used when making changes in demand. Referring back to the statistical work of chapter 5, it was proposed that consumer response to PV systems could be characterised in terms of a routine response, and an opportunistic response. Many of the quotations that have been presented in this chapter have revealed examples of these two responses. Given the assumption that the behaviour of the forum group studied here is representative of the behaviour of the PV group studied in the previous chapter, it can be said that the quantitative results of the previous chapter can at least be partly attributed to demand response behaviour.

Participants developed habits based on behaviours that reached an acceptable compromise between costs and benefits. Costs were generally associated with the time and effort involved in changing behaviour and trying to maximise the use of available PV generation, while the benefits were generally understood to be associated with trading imported electricity for self-consumption.

While the participants used financial reasoning to justify their actions, it is also clear that the financial benefits involved were small, and certainly not large enough to justify capital investments in appliances or technologies that facilitated demand response behaviour. The fact that many participants nonetheless expressed interest in, and purchased, such equipment, is therefore evidence of potentially unsound, or irrational, financial reasoning. The prime example of this were the participants who used batteries to increase self-consumption, even though this is likely to result in a negative net benefit as demonstrated in section 4.5.

Ultimately, however, the results of this chapter are encouraging from a demand response perspective, as they have shown that the participants were willing and able to engage in demand response behaviour, even so far as to change routines or expectations, as well as to make capital investments, even when the financial benefits of doing so were small. The following chapter considers the relevance of these findings to the thesis' central research focus of demand response in low-carbon futures.

7. Discussion

Section 2.9.4 presented the following research question.

Research question 3: Can domestic consumers be expected to respond to irregular dynamic pricing?

Given the results of the previous chapters, the next section discusses whether the research question above can now be answered. Subsequent sections will then consider the broader relevance of the thesis' findings.

7.1. Is there evidence of domestic consumers responding to irregular dynamic pricing?

The results of chapters 5 and 6 allow us to say, with some confidence, that occupants with PV in the UK do respond to the irregular variability of the PV system, in particular by increasing demand during the day and decreasing demand in the evening, compared to occupants without PV. Furthermore, this effect is more pronounced on days with higher irradiance.

The results allow us to say that the increase in daytime demand can be characterised as a combination of a routine response and an opportunistic response. It is important to stress that the opportunistic response provides evidence of occupants' time-shifting demand over periods of several days. This represents demand response behaviour that is of value in the future context of high penetrations of renewables, in particular wind, where the prospect of calms in wind output for several days are of concern.

The result is that we are now in a considerably better position to address the research question presented at the beginning of this chapter. It can now be said that domestic consumers can be expected to respond to dynamic pricing in future markets with high penetrations of renewables, because this thesis has provided evidence of domestic consumers responding to dynamic pricing with similar variability today.

These results are furthermore also relevant to the first research question:

Research question 1: Do domestic consumers respond to dynamic pricing?

This question was investigated in the literature review which revealed that while there is some evidence of domestic consumers responding to dynamic pricing, much of the evidence comes from the USA, in particular for real-time pricing. The results of this thesis therefore have the additional value of providing evidence of domestic consumers responding to dynamic pricing that is similar to real-time pricing, who are outside of the USA, and who do not have air-conditioning units.

7.2. Are occupants with PV in this study representative of domestic consumers in general?

It is important to note that while this thesis has found evidence of demand response behaviour in domestic consumers with PV systems, this group is not representative of the UK population as a whole. Owners of PV systems, for example, tend to be older, more educated, richer, and more likely to own their own home than the national average (Keirstead, 2006). They are more likely to be retired, therefore, and occupy their dwellings during the day. Indeed, this seemed to be confirmed by the forum study in chapter 6, with many of the participants appearing to be at home during the daytime. Furthermore, as mentioned previously, the PV group analysed in chapter 5 is likely to be over-representative of social housing tenants, as well as newer, more efficient buildings than the national average.

It should be noted therefore that care should be taken when extrapolating the results to the broader population. Nonetheless, the results of this study have provided insight into demand response behaviour of domestic consumers, and the statistics and forum chapters complement each other because they deal with different social groups, and this broadens the applicability of the results.

7.3. People have limited time and attention

This section considers the broader conclusions that can be drawn from the thesis' results, in particular by re-considering the second research question, which was presented in section 2.9.3.

Research question 2: What are the factors that influence the ability or willingness of consumers to respond in real-time pricing schemes?

The first point to note is that the results of the previous chapters have demonstrated that domestic consumers can be quite willing and able to engage in demand response behaviour, and in some cases going to considerable lengths in order to recoup what often amounts to quite a small financial benefit. In this regard, the results are encouraging because they support the notion that people can be expected to respond to irregular dynamic pricing in the future.

Nonetheless, one of the overarching conclusions to emerge from this thesis has been the fact that people have limited time and attention to devote to everyday tasks and decisions such as demand response. People do not make optimum decisions based on a perfect understanding of all the relevant information, but instead use heuristics to make satisfactory decisions, based on the information that is most salient, or that is most easily acquired. Chapter 3 gave examples of this from the behavioural economics literature, such as the fact that individual stock market investors deal with large amounts of market information by focussing their attention on companies that appeared in the news, or that had unusually high or low performances on previous days.

Chapter 3 further argued that heuristics were relevant to demand response schemes. Evidence suggested, for example, that consumers on real-time pricing schemes simplified the price signal by learning the consistent shape of the price profile, as well as understanding the influence that temperature has on the overall level of price. Indeed, it was shown in section 4.2.1 that these heuristics could be effective at explaining the variation in market prices – for some months they could explain over 70% of the variation in hourly prices of the Californian day-ahead wholesale market. These heuristics therefore can allow consumers in real-time pricing schemes to save time and attention, because they do not need to check prices every day, and yet still have a satisfactory understanding of prices.

7.4. Heuristics and occupants with PV

It is perhaps not surprising therefore that the results of this thesis have shown that occupants with PV also resort to heuristics in order to reduce the time and effort involved in making complex decisions – in this case how to best make use of the available PV generation and reduce their electricity bills. In this way, occupants with PV are no different from consumers in Illinois on a real-time pricing scheme, or indeed individual investors in the stock market.

While consumers on real-time pricing schemes learn the general shape of the price profile, occupants with PV learn about the variability of PV generation, and how they can use their appliances to take advantage of this. While occupants with PV do not receive an explicit price signal, they nonetheless learn the times of day and behaviours that result in lower costs of electricity.

The process of learning cumulates with the development of habitual behaviour. It was clear from many of the quotations presented in the previous chapter that the occupants with PV were developing 'rule of thumb' behaviours that could save them money without the 'hassle' of trying to achieve a perfect balance between PV generation and demand.

For example, one heuristic that was mentioned was to use irradiance as a proxy or indicator of the times when surplus PV generation was available for use. Over time, occupants with PV would learn to be able to estimate their PV generation given the current irradiance levels, without needing to check the monitors. For many of the participants, irradiance acted as a signal, or trigger, that would prompt them to switch appliances on.

Another heuristic example is the case of occupants using their import meter to determine when they were exporting and therefore should be switching appliances on. Some occupants relied upon the import meter displaying a red light when they were exporting, while others got the same information by observing whether their meter disc had stopped rotating. In either case, the occupants were reducing the complexity of the PV price signal into something more like a 'traffic light' signal, with the meter light or disc acting as an indicator for when demand should be increased or decreased.

Evidence suggests therefore that occupants with PV simplify the effective price into a more basic price signal, with a low price period during the day when the PV is generating, with an additional influence of irradiance, with sunny days offering greater capacity to consume cheap electricity. In this way, there is a similarity between the occupants with PV and the consumers on real-time pricing schemes in Illinois. Both seem to interpret a complex price signal into a more basic price signal, with periods of high and low price determined by heuristic learning, and with an added influence on overall level of price determined by a weather variable – temperature in Illinois, and irradiance for occupants with PV. These results also echo the findings of the Irish Customer Behaviour Trial, described in 2.8, which suggested that participants of the various time-of-use pricing tariffs simplified the tariffs into 'high' and 'low' price periods.

7.5. Automation to facilitate demand response

While consumers are keen to simplify price signals in order to develop convenient habits and routines, this thesis has shown that occupants with PV are nonetheless open to the concept of adopting technology that can provide a more optimum response on their behalf. These people are aware that they are experiencing a highly dynamic price signal, one that is too inconvenient for them to respond to manually, and appear to be happy with the idea of automated technology responding for them. Examples included a control for electric hot water heating, battery systems that charge during the day to reduce exports and discharge during the evening to reduce imports, and electric vehicles.

This is therefore encouraging news for proponents of 'smart' technologies and appliances (Timpe, 2009), as evidently this is something that consumers are interested in and see a potential value in. The challenge, however, will be in creating technology solutions that are cost effective, as the additional benefits of 'optimum' response compared to the consumer's 'rule of thumb' response are not large. This was exemplified by the battery study described in section 4.5, which showed how equipment costs can far outweigh the benefits, given today's prices and incentives.

Automation in demand response is often discussed in terms of extremes: with either the consumer completely 'out of the loop' and smart technology controlling everything remotely; or alternatively with the consumer rejecting technology intrusions in their home and any form of control that goes with it. This thesis has shown that neither of these extreme views is accurate. Instead consumers are willing to engage in demand response, but are also interested in the benefits of automation in terms of facilitating their response, in particular when they are not at home, or to minimise the 'hassle' of the response. The point is that in a future with high penetrations of wind it is likely that both consumer engagement and automation will be valuable, and this thesis supports the notion that both will be available.

7.6. Beyond price: developing appropriate future tariffs for low-carbon power systems

This section considers how the findings of this thesis can be applied to the development of future electricity tariffs in low-carbon power systems with high penetrations of wind or solar power, in particular by considering the factors beyond price that can affect demand response behaviour in domestic consumers.

7.6.1. Balancing accurate price signals with consumer's need for simplicity

Firstly, it is important to consider how dynamic pricing could be simplified for consumers in low-carbon markets, in particular with high penetrations of wind power. This could be a challenge given the potential variability of wind power and its influence on market prices. Tariff designers will therefore need to think carefully about balancing the need for an accurate price signal that reflects the variability of the wind output, with the consumers' need for simplicity and habitual routines.

With the aim of achieving this balance in mind, an important finding of this thesis is that consumers with PV in the UK experience a price of electricity that depends on the instantaneous levels of PV generation and demand, resulting in a tariff that is dependent on power rather than energy consumption. The price is cheap provided demand is kept within a capacity limit determined by the PV generation. This is equivalent to a 'power banding' tariff, where prices are expensive when demand exceeds a variable power capacity limit. The important point is that this thesis finds that even though this type of power banding tariff is actually quite complex, it was nonetheless understood by the forum participants analysed in chapter 6.

It is conceivable therefore that similar power banding tariffs could be used in future low-carbon power systems, for example by linking the variable capacity limit with the generation of local or national renewables resources. Given this thesis' findings, it is also conceivable that domestic consumers could be expected to understand such tariffs. It stands to reason that gaining such understanding is a useful first step in terms of encouraging an response.

Another important finding from chapter 6 is that consumers with PV are aware of the correlation between the availability of cheap electricity and their local solar resource. This is an association between a variable price and a variable renewable resource. It is important to point out that the consumers with PV analysed here are considering a local resource, while consumers in systems with high penetrations of wind might be more concerned with the national wind resource. Ultimately, however, the value in both cases is in consumers being aware of the link between weather and electricity price, and in them responding to this price. This is exactly the type of behaviour that this thesis has found with the consumers with PV analysed in chapter 6.

7.6.2. Use of gaming concepts to encourage demand response

The role that technology can play is to reduce the 'hassle' of performing demand response behaviour for the occupant. The forum work showed, however, that for some occupants the process of trying to make the most of the available PV generation was not a hassle, but rather something that they enjoyed. In the context of demand response behaviour this is quite remarkable – the concept of consumers enjoying demand response is certainly not something that is traditionally associated with dynamic pricing schemes. Given that the enjoyment that some occupants admitted to appeared to be an important factor in motivating them to change behaviour, it would seem to be a useful concept to try to develop in demand response schemes more generally.

By way an analogy, consider how modern vehicles with digital dashboards are incorporating software applications with the aim of improving fuel economy, or driver safety. For example, the dashboard of the Chevrolet Volt, a plug-in hybrid vehicle, includes a 'driver efficiency display', which shows a ball which moves up or down in relation to the vehicle's speed, acceleration, and braking. By keeping the ball in the middle of the display, the driver can ensure they are driving at optimal efficiency. This is an example of an emerging concept of 'gamification' (Deterding et al., 2011), whereby gaming concepts are applied to real-world problem situations, in order to encourage beneficial consumer behaviour.

Here the applicability of the 'gamification' concept to demand response is suggested, given the evidence that some occupants with PV found this behaviour to be fun, challenging, or like a hobby. This concept could also be linked with the behavioural economics work on self-control problems described in section 3.10.2 where, for example, goal setting has been proven to help people reduce their energy consumption.

Continuing with the behavioural economics theme, it is possible that several of the framing effects that were introduced in section 3.10.1 could be relevant to the behaviour of occupants with PV, notably the endowment effect, loss aversion, and the value of free.

7.6.3. Endowment effect

The endowment effect describes how people value things that they own more than things that they do not. Occupants with PV generally own their PV system, and so do actually own the electricity that is produced by the system. And indeed some of the forum participants did seem to enjoy the concept of producing and consuming their 'own' electricity. This could have been what motivated some of the participants to engage in demand response behaviour even when they had no financial benefit in doing so, as discussed in section 6.7.5.

The concept of producing your own electricity being a pleasurable thing is also suggested by the work by Dobbyn and Thomas in their interviews with owners of microgeneration (Dobbyn and Thomas, 2005). One of the key concepts that their report focuses on is the potential of creating your own energy to be a pleasurable experience, with one of the interviewees saying that it similar to growing your own vegetables.

The concept of ownership of electricity can help explain a lot of the enthusiasm for small-scale renewables like PV systems, and it also possibly provides additional motivation for occupants with PV to engage in demand response behaviour. It is therefore interesting to question whether the endowment effect could also be used in future tariffs in low-carbon power systems.

The problem with this scenario is that the renewables that can be expected are likely to be pre-dominantly large offshore wind farms, not small-scale systems connected to dwellings. It would be useful therefore to explore whether the concept of ownership can be extended to such large-scale, offshore wind farms.

It is perhaps more conceivable, however, to imagine that the endowment effect could be encouraged in communities that are local to on-shore wind farms, or large solar installations. This could be fostered by offering local consumers an electricity tariff with power banding that is linked to the output of the local renewable resource. Not only could this be useful for potentially avoiding wind farm curtailment, but it could also foster community goodwill and perhaps facilitate planning permission for the development.

7.6.4. The value of free

The second framing effect that could be present with the occupants with PV is the disproportionate effect on demand that is produced when goods become free. The occupants with PV had the opportunity to consume electricity at zero cost, and indeed many of them expressed satisfaction in this concept.

This is not something that is normally associated with dynamic pricing – prices may end up being quite low during some periods, but never free. Yet, while the concept of free electricity may seem improbable in present markets, it might be less so in future markets with high penetrations of renewables. Section 4.3.1, for example, revealed that markets with high penetrations of wind power can expect market prices to reach zero or negative prices. Furthermore, there is already a considerable amount of wind power that is constrained in the UK, at considerable cost to the system operator (Renewable Energy Foundation, 2012). Instead of constraining wind power, consumers that were located near the wind farms could have equally been paid to increase demand, or at least benefitted from free electricity.

The point is that it may well be possible in the future to offer dynamic pricing tariffs to consumers that might include the possibility that electricity might be free on occasions, due to a high availability of wind power, for example. Even if the expected savings associated with such a tariff were small, as indeed the savings are small for the occupants with PV analysed in previous chapters, the prospect of free electricity provides a fundamental shift in how consumers would perceive the financial benefits of adopting such a dynamic pricing tariff. This might also motivate a much broader segment of the population to adopt such a tariff, as it seems that the simple prospect of lower electricity prices is not enough to motivate large numbers of consumers to adopt real-time pricing in current markets (Star et al., 2010a). In addition, the prospect of free electricity on some occasions might also help make consumers more tolerant of other periods where prices might be extremely high.

Free electricity could also be readily associated with a power banding tariff, such that electricity is free up to a capacity limit that could be variable and, for example, linked with the output from renewables at a national scale. This combination of free, but capacity limited, electricity can offer a powerful demand response message to consumers, as shown by the forum participants in chapter 6. Finally, the prospect of free, but limited, electricity could help to mitigate the possible adverse impacts that future dynamic pricing tariffs might have on the fuel poor, and help to address the equity implications that such tariffs may have (Darby, 2012).

7.6.5. Loss aversion

The final framing effect that could be present with occupants with PV is the concept of loss aversion. This describes how people are loss averse, and feel losses more strongly than equivalent gains. For the occupants with PV studied in this thesis, the electricity exported by the PV was either not being metered, or was not being remunerated. This meant that self-consumed electricity was free. However if they did not use the electricity at the times when it was generated then they lost the opportunity to consume the free electricity.

If occupants did not use their free electricity, then they lost it, and this could have had an additional motivating factor that encouraged them to engage in demand response behaviour. The effect is analogous to the use of limited-time offers or sales on goods: it is likely that some of the people buying during the sales are doing so partly because of the prospect that the opportunity to purchase goods at a reduced rate was for a limited time only. The world of marketing is full of examples of 'buy one get one free' offers that 'bargain hunters' find irresistible, even if they do not really need the items.

It would appear therefore that part of what motivated some of the participants to engage in demand response behaviour could have been linked to a desire to take advantage of a 'bargain' while it lasted. This concept could be readily extended to demand response schemes more generally, and there are many marketing techniques that could prove useful in encouraging people to time-shift their demand. The prospect of smart meters and in-home displays being installed in people's homes will mean that time-sensitive messages could be transmitted into people's homes in order to inform them of demand response 'offers'. For example, during a critical peak period, when consumers would normally be charged a high price, they could instead be offered free electricity provided they keep their demand below a certain threshold. There is also the prospect of tailoring these kinds of offers to specific appliances in a future 'smart home' scenario, for example, if wind output was low for several days on end, then consumers could receive benefits if they avoided the use of deferrable appliances such as dishwashers and washing machines.

7.6.6. Instant gratification versus long-term savings goals

Finally, it is interesting to note that some of the occupants with PV investigated in chapter 6 appeared to have a long-term savings goal in mind that they wanted to achieve as soon as possible: recouping the cost of their investment in the PV system. This long-term goal seemed to have the effect of providing the motivation to make changes in behaviour that helped justify the relatively small individual savings that each demand response action could produce. Each demand response action could be seen as an investment decision. The self-control problems described in section 3.10.2, however, reveal that most people do not act in this way and do not have long-term savings goals in mind, but instead are more inclined to value instant gratification.

The critical point here is that the participants had a long-term goal in mind, the fact that it was linked to recouping the cost of their PV system is a detail. The concept of long-term goals is already being introduced to demand reduction schemes such as the Opower examples described in section 3.10.4 and have been proven to achieve small but persistent reductions in demand. The concept of goal-setting for demand response could be readily introduced in a similar way, for example by providing neighbour comparison reports.

In summary, it would seem therefore that while price is an important motivating factor for encouraging flexible demand in domestic consumers there are many ways in which we can go beyond price. Indeed many of the factors that have been identified here are in fact well known to the behavioural sciences and are commonly used to influence consumer behaviour in other markets. Ultimately, this is encouraging as it shows that consumer demand response behaviour is very similar to other forms of consumer behaviour, insofar as it is open to being influenced by a wide range of factors beyond price, and this considerably expands the range of techniques available for developing future tariffs and securing demand response in low-carbon futures.

8. Conclusions

8.1. Dynamic pricing in current markets

There is considerable value in securing demand response in low-carbon power systems. One of the ways in which domestic consumers can provide demand response is by responding to dynamic pricing that reflects the variability of prices on the wholesale electricity market. Many of the existing examples of dynamic pricing schemes are based in North America, and focus primarily on shifting the usage of air-conditioning units.

A literature review of such schemes addressed the first research question of this thesis:

Research question 1: Do domestic consumers respond to dynamic electricity pricing in current markets?

While there is some evidence of domestic consumers responding to dynamic pricing, it is clear that this response is limited and complex. There is a general lack of understanding about consumer behaviour in demand response schemes and fundamentally it is not clear how or why the consumers respond in the way they do.

8.2. Demand response to regular dynamic pricing

In current markets, electricity is supplied predominantly by flexible fossil fuel plant and, as a consequence, wholesale prices are correlated with the demand. Wholesale prices are, as a result, regular in nature, with periods of high and low prices that occur at the same times of day. Furthermore, due to the influence of temperature on air-conditioning usage, wholesale prices are also correlated with temperature, with hotter days experiencing higher prices throughout the day.

Due to the regular nature of wholesale prices in current markets, dynamic pricing can be simplified to aid consumer demand response in two ways. Firstly, the utility can present a simplified version of the variability of wholesale prices to the consumers, for example, time-of-use pricing, where the periods of high and low prices are static. Secondly, where the consumer receives a relatively complex price signal such as real-time pricing, then the consumer can use rules of thumb to simplify the price signal and avoid the need to check prices regularly. Evidence from existing real-time pricing schemes suggests that two rules of thumb are used: firstly, the general shape of the price profile is learned, and secondly, temperature is used as a proxy for the overall level of price during the day.

In current markets, these heuristics can be effective: a statistical analysis of the Californian PX day-ahead market indicates that over 50% of the variation in price can be explained using the two heuristics, for much of the year.

This work addresses the second research question of this thesis:

Research question 2: What are the factors that influence the ability or willingness of consumers to respond to dynamic electricity pricing?

In identifying that consumers in current dynamic pricing schemes use heuristics to save time and effort, this thesis finds that behavioural economics provides a useful framework for characterising consumer behaviour in demand response schemes and understanding the factors that influence their ability and willingness to respond to dynamic pricing in general.

8.3. Dynamic pricing in future low-carbon markets

Wholesale prices in future markets with high penetrations of renewables cannot be expected to be regular in nature, as prices will be correlated with the intermittent generation from renewables. Dynamic pricing in such futures will therefore also need to be irregular in nature. The challenge for tariff designers will be in creating a dynamic pricing tariff that accurately reflects the irregular variability of the wind generation, and yet accommodates the consumers' need for simplicity and habitual routines.

The demand response needed to respond to irregular prices is fundamentally different from the demand response that is needed in current markets where prices are regular. There is little evidence of domestic consumers responding to irregular prices, and it is not valid to extrapolate the findings of current demand response schemes to future situations with irregular prices.

8.4. Variable effective prices with grid-connected PV systems

It has been shown that consumers with grid-connected PV systems experience a variable effective price of electricity that depends on the dwelling's metering configuration, feed-in tariff, and instantaneous levels of dwelling demand and PV generation.

The effective price concept is novel, unifies the various metering configurations using a single variable, and aligns the demand response behaviour of consumers with PV to the demand response behaviour of consumers in dynamic pricing schemes.

Consumers with PV in the UK experience an effective price that is correlated with PV generation, that has a range of prices that is similar to Economy 7, and a dynamic resolution that is similar to real-time pricing.

Studying the demand response behaviour of consumers with PV in the UK therefore provides insight into how consumers might be expected to respond to real-time pricing in future markets with high penetrations of renewables, as both experience irregular dynamic pricing.

8.5. Demand response to irregular dynamic pricing

By performing a statistical analysis of demand data from 130 dwellings with PV in the UK, it was found that on an average weekday, consumers with PV show an increase in demand during the day of approximately 8% of mean daily demand, with a corresponding reduction in demand during the evening. Furthermore, this effect is more pronounced on days with higher irradiance.

This response can be characterised in terms of a routine response and an opportunistic response. It is suggested here that the routine response consists of consumers consistently running appliances during the day, regardless of the level of PV generation, and the opportunistic response consists of consumers responding to the irregular variability of the PV generation, for example by shifting demand over periods of several days.

These results provide, for the first time, quantified evidence that suggests that consumers with PV in the UK do engage in demand response behaviour by responding to the variable output of their PV systems.

Furthermore, these results also suggest evidence of domestic consumers responding to dynamic pricing that is similar in its variability to real-time pricing. The results are valuable in this regard, because evidence of domestic consumers responding to real-time pricing is rare, generally associated with consumers with air-conditioning units, and confined to the USA.

The demand response behaviour of consumers with PV was analysed qualitatively by examining an internet discussion forum. This work supports the statistical work by also finding evidence that consumers with PV in the UK engage in demand response behaviour.

This work furthermore demonstrated that domestic consumers can be quite willing and able to engage in demand response behaviour, and that this extends to making changes to their lifestyle and routines, as well as making capital investments in equipment that facilitates this behaviour, even though the financial benefits involved are small.

The results also indicate that, while willing and able, consumers ultimately seek a balance between the costs (in terms of effort) and the benefits involved in demand response behaviour. In this, consumers with PV are no different from consumers with real-time pricing in Illinois, insofar as both seek a compromise between reducing bills and convenience.

8.6. Use of lead-acid batteries in domestic grid-connected PV systems

It can be said that consumers with PV base demand response behaviour on financial reasoning, specifically the aim of recouping the investment in their PV system. In this regard, the consumers appeared to be quite 'rational' in their decisions, however there was also considerable evidence of unsound financial reasoning, and this applied in particular to capital investments in equipment that could facilitate their response. The prime example of this was the use of battery storage as an alternative to manual demand response behaviour. The specific commercial opportunity involves charging the battery during the day when the PV generation exceeds demand, and discharging during the evening when the demand exceeds PV generation.

A novel lead-acid battery model was developed and applied to recorded data from 37 dwellings with PV in the UK in order to simulate hypothetical power flows for the PV systems with battery. An economic analysis of the results indicates that there is no business case for the use of lead-acid batteries for this specific commercial opportunity in the UK, even for an idealised lossless battery system. These results are also valid for recent PV systems in Australia and Germany.

8.7. Insight into demand response in low-carbon futures

By investigating demand response behaviour of consumers with PV, this thesis has provided insight into how consumers might be expected to respond to real-time pricing in future low-carbon power systems with high penetrations of renewables, thereby addressing the third research question of this thesis.

Research question 3: Can domestic consumers be expected to respond to irregular dynamic electricity pricing in future low-carbon markets with high penetrations of renewables?

This thesis has provided evidence of domestic consumers responding to irregular dynamic pricing, and it can now be said with more confidence that consumers can be expected to respond to irregular dynamic pricing in future low-carbon systems also.

Of particular relevance is the evidence of consumers shifting demand over periods of several days, which is of particular value in the context of high penetrations of wind power and the possibility of persistent calms in wind output.

Furthermore, this thesis finds that not only are consumers willing and able to engage in demand response, but they are also interested in the use of automation that can respond on their behalf – particularly where responding involves too much 'hassle', or when they are not at home. Consumers are willing to make capital investments in such equipment, even though in current markets the financial benefits are small, and payback periods long. In a future with high penetrations of wind power, it is likely that both consumer engagement and automation will be valuable, and this thesis supports the notion that both will be available.

Finally, it is important to note that while it would appear that price is a necessary driver for demand response, there is evidence that demand response behaviour can be influenced by a number of factors beyond price. Some of these additional factors could prove to be powerful motivators that could fundamentally change how consumers engage with demand response, for example the prospect of free electricity in futures with high penetrations of wind power, or by encouraging the potential for consumers to enjoy demand response behaviour. It is encouraging to note that these additional factors are in fact already well known to the behavioural sciences, and are commonly applied in other markets. Expanding the understanding and use of these factors offers the prospect of considerably increasing the range of techniques available for securing demand response in low-carbon futures.

8.8. Claims for originality

This thesis has made novel research contributions in the following areas:

- Concept development and derivation of variable effective price in grid-connected domestic PV systems.
- Concept development of investigation of consumers with PV to yield insights into demand response behaviour of consumers in future low-carbon power systems.
- Elaboration and refinement of Energy Saving Trust advice for maximising financial benefit of PV systems for consumers in the UK.
- Quantitative data analysis based on secondary data sources to yield results suggesting demand response behaviour in consumers with PV in the UK.
- Qualitative research based on analysis of internet forum to yield findings of how and why consumers with PV in the UK engage in demand response behaviour.
- Application of behavioural economics literature to demand response behaviour.
- Application of behavioural factors beyond price-response to guide development of future demand tariffs in low-carbon power systems.
- Development of novel lead-acid battery model.

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Appendix A

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