The Value of Lost Load (VoLL) for Electricity in Great Britain

Final report for OFGEM and DECC

Prepared by

London Economics

July 2013

About London Economics

London Economics is one of Europe's leading specialist economics consultancies. With our head office in London, we also have offices in Dublin, Brussels, Cardiff and Budapest, and associated offices in Paris and Valletta. We advise clients in both the public and private sectors on economic and financial matters, policy development and evaluation, business strategy, regulatory and competition policy. Our consultants are highly-qualified economists with experience in applying a wide variety of analytical techniques to assist our work, including econometric modelling, forecasting, choice experiments, cost-benefit analysis, multi-criteria analysis, policy simulation, scenario building, statistical analysis and mathematical modelling. We are also experienced in using a wide range of data collection techniques including literature reviews, survey questionnaires, interviews and focus groups and applying the resulting data to complex economic policy problems and analysis.

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Acknowledgements

We would like to acknowledge the useful guidance and feedback provided by Ofgem and DECC throughout this research, especially the inputs from Grendon Thompson, Emma Burns, and Nat Martin. Ofgem/DECC also provided input data for the estimation for industrial and commercial consumers. The research also benefited at a number of stages from suggestions by Professor Iain Fraser, Kent University. We would also like to thank OMB Research and YouGov for key inputs in the survey development and administration stages. Responsibility for the contents of this report remains with London Economics.

Contents

Page

Contents

Page

Tables, Figures & Boxes

Page

Tables, Figures & boxes

Page

Tables, Figures & Boxes

Page

Tables, Figures & boxes

Page

Tables, Figures & Boxes

Page

Tables, Figures & boxes

Page

Tables, Figures & Boxes

Page

Executive summary

This report by London Economics estimates the value of lost load (VoLL) for domestic, small and medium sized businesses (SMEs) and industrial and commercial (I&C) electricity consumers in Great Britain (GB). VoLL represents the value that electricity users attribute to security of electricity supply and the estimates could be used to provide a price signal about the adequate level of security of supply in GB. The report is commissioned jointly by Ofgem and the Department of Energy and Climate Change (DECC). The research is based on a variety of methods, but the major work element involved estimation of VoLL using choice experiments (CE). The fieldwork for the CEs was carried out by YouGov and OMB Research, and CE experimental design by London Economics and by Professor Iain Fraser.

Background

The UK and Europe are facing many challenges including climate change, the need to make energy markets more competitive and efficient, and improving security of supply. The medium-term future of energy policy in the UK will see a need to incorporate into the generation mix up to circa 30GW of renewable energy, mostly wind, as well as a need to replace retiring coal and nuclear capacity. At the same time, new rules for European electricity market integration will be coming into effect. Given these challenges, Ofgem as energy regulator, and DECC as policy maker, are reviewing and reforming various aspects of GB energy policy, including legislating for the introduction of a Capacity Market (DECC) and a significant code review of the balancing regime (Ofgem).

The VoLL will likely play a significant role in a number of these emerging areas of GB energy policy and market design. For the Capacity Market, the amount of electricity generating capacity that GB requires and that will be contracted through a Capacity Market is likely to be informed by the VoLL. For balancing and cash-out, the VoLL could represent the cost of disconnections to consumers. VoLL will therefore be used in a variety of policy and market design contexts.

Methods

This study uses a variety of methods. A stated preference choice experiment (CE) is used to estimate the VoLL in terms of willingness-to-accept (WTA) payment for an outage and willingness-to-pay (WTP) to avoid an outage for domestic and SME electricity users. The CE approach allows us to examine the WTA and WTP of electricity outages of different lengths, seasons, days of the week and times of the day. Econometric estimation and standard statistical techniques are then used to convert the CE results into £/MWh VoLL figures and confidence intervals. The study also includes open-ended contingent valuation (CV) questions where respondents were simply asked to state their pound-value for an outage in WTA or WTP terms. The CE method is preferred to the CV method as it allows us to examine outages that are multi-dimensional, reduces the possibility of 'strategic responses' and allows us to examine preferences for attributes over a range of price/payment levels; the CV method nonetheless is included as a broad cross-check.

For I&C customers, we used a value-at-risk approach and econometric techniques to estimate VoLL.[1] These methods are based on sector-level gross value-added and electricity use statistics.

Finally, we studied the potential cost of system operator-directed demand reductions. During an emergency supply shortfall, voltage reduction can be the first step to balance supply and demand before disconnection. We considered the potential costs to consumers from shutdowns associated with voltage sags and surges, the cost of household protection equipment, the potential for damage to devices and equipment and other factors, using existing and desk-based research.

Domestic electricity users results

We present our main VoLL results for domestic users in £/MWh below. The results show a range of VoLLs for domestic customers based on the different times and seasons for the hypothetical outage. This is as expected as domestic users will typically have a different value for an electricity outage depending on its timing. Our preferred model is the WTA model which indicates that the levels of VoLL range from £6,957/MWh to £11,820/MWh. The highest payment for the provision of involuntary demand side response (hereafter 'payment') would be required if an electricity outage occurred during the winter, at peak times (3pm - 9pm), and on the weekend.

Using the WTP method, four of the eight values are significant and range from £1,651/MWh to £2,766/MWh. However, there are some electricity outage scenarios that indicate respondents would not be willing to pay a value that is statistically different from £0 to avoid these outages.

Table 1: Comparison of WTA and WTP £/MWh estimates by time of outage – domestic customers, based on a time varying electricity demand profile

	Not Winter Not Peak Weekend	Not Winter Not Peak Weekday	Not Winter Peak Weekday	Not Winter Peak Weekend	Winter Not Peak Weekend	Winter Not Peak Weekday	Winter Peak Weekday	Winter Peak Weekend
WTA (£/MWh)	**9,550**	**6,957**	**9,257**	**11,145**	**10,982**	**9,100**	**10,289**	**11,820**
WTP (£/MWh)	**2,766**	(101)	(105)	**1,805**	**2,240**	315	208	**1,651**

Note: The figures are based on figures for a one hour electricity outage. Converted based on an assumed annual electricity consumption of 3.934 MWh per annum but the numbers have been adjusted for different electricity demands across outage scenarios. This is discussed in Annex 12. Estimates in bold indicate statistical significance at the 95% confidence interval.
Source: London Economics analysis

[1] We also used a real options approach to estimate VoLLs for very large electricity users.

Our WTA estimates are larger than the comparable WTP estimates. This is as expected. When consumers are used to enjoying a service that they pay for, they typically want a greater payment in order to bear a loss of that service than they are willing to pay to retain it. This is because individuals feel a sense of ownership for something they already have (in this case as a reliable electricity service). Psychologically, the loss from giving something up feels greater than the gain from keeping it and avoiding the loss, and thus WTA is often empirically greater than WTP.

For this noted 'ownership' effect, and from the policy implications of it, we believe that using the WTA estimates is most appropriate in the context of valuing security of supply for electricity; the WTA indicates consumers' inconvenience value if the reliable service they already enjoy were interrupted. Consumers will typically not be willing to pay more to improve the service (i.e., avoid the outage) but when an outage occurs may feel that the involuntary disruption is worth some form of payment for the service they provide.[2] However, in terms of setting energy policy, we believe the degree of 'consumer impact' an outage would cause is the most important factor, and this points to the WTA estimates. Further, the WTP results show apparent lower degree of statistical accuracy.

SME electricity users

A very similar choice experiment is used to estimate the WTA and WTP for SME electricity users. The results are broadly consistent with the domestic experiment and prior expectations. The results indicate that SMEs are most sensitive to an outage that occurs on a typical work day during winter in either WTP or WTA terms. The figures in bold in the table show statistical significance.

The results are less conclusive than the domestic results regarding peak times. The WTA SME model indicates that SMEs' valuation of an outage is mainly driven by whether it occurs on a workday, rather than precisely the time of day, but this is consistent with SMEs likely having different peak business/usage times than domestic consumers or heavy industry. The non-workday WTA figures are not significant.

As with the domestic experiment, the WTA results are typically larger than the WTP estimates.

[2] Pearse, D. (2002) "The Role of 'Property Rights' in Determining Economic Values for Environmental Costs and Benefits" Report to the Environmental Agency

Table 2: Comparison of WTA and WTP £/MWh estimates by time of outage – SMEs – using a time varying demand profile

	Summer Not Peak Non-work	Summer Not Peak Work day	Summer Peak Work day	Summer Peak Non-work	Winter Not Peak Non-work	Winter Not Peak Work day	Winter Peak Work day	Winter Peak Non-work
VoLL WTA (£/MWh)	37,944	**36,887**	**33,358**	34,195	44,149	**39,213**	**35,488**	39,863
VoLL WTP (£/MWh)	**21,864**	**19,271**	**20,048**	**24,175**	**26,346**	**21,325**	**21,685**	**27,859**

Note: This is converted to £/MWh using an assumed annual consumption of 29.35 MWh. This annual estimate is then adjusted then to account for time varying electricity demand. This is discussed in Annex 12. Estimates in bold indicate statistical significance at the 95% confidence interval.
Source: London Economics analysis of SME survey

Some of the WTA estimates are not statistically significant for SMEs. These outage scenarios are associated with outages that occur on non-work days. While it is difficult to interpret these results, they seem to indicate that there may be significant VoLLs for some SMEs in non-work days, but the pattern in the sample is too irregular to be conclusive.

Our VoLL estimates are roughly three to four times higher for SMEs in comparison to domestic users. We believe this is reasonable and intuitive, and there are a number of possible explanations for this. One of these may be that SMEs have less flexibility regarding replacement of lost hours and input costs, as staff may only work designated hours and it may be not be possible to make up for lost sales. In contrast, households may be able to postpone the tasks that require electricity or use alternatives that may suffice as short-term substitutes. Domestic users could further reallocate their time to leisure or other leisure activities not requiring electricity. Further, it is likely SMEs have a larger value at risk[3] during a peak time of an outage, but in many cases may not use significantly more electricity than households.

Industrial and commercial electricity users

We also examine the VoLL for industrial and commercial (I&C) users using the gross value added (GVA) or value-at-risk (VAR) approach. This analysis is also done using a detailed sectoral breakdown of GVA and electricity consumption. The headline results of this analysis are shown in the table below. These are estimated by dividing GVA by electricity consumption. Additional detailed breakdowns by sector are found in the Annexes.

[3] This concept has to do with Gross Value Added (GVA) per unit of electricity. GVA for an SME during peak times could easily be £20-£100 in some small business, which would make the VoLL quite a bit larger than the VoLL for a household user.

Table 3: Estimate of electricity VoLL, (based on 2011 data)			
	Total GVA £/yr. (millions)	Total Electric use (GWh)	VoLL (£/MWh)
Total	177,395	107,228	1,654
Total (manufacturing - 10-32)	148,028	98,248	1,507

Note: data from DECC and ONS
Source: London Economics analysis

While the 'plain vanilla' GVA/VAR approach provides useful insights to VoLL, another aspect of this study was to examine the limitations and weaknesses of the GVA/VAR approach and improve upon the method if possible. A variety of weaknesses in the GVA/VAR approach have been identified, such as potential aggregation and substitution biases,[4] and the possibility that electricity is not critical to production (London Economics 2011). We have thus also examined possible improvements to the GVA/VAR model that may give superior estimates of electricity VoLL for I&C customers. These techniques are based on accounting for 'critical' electricity and possible differences in capacity utilisation across sectors. We also used various econometric techniques to examine predictions and estimates of electricity VoLLs. These techniques specified both a Cobb-Douglas and translog GVA production function and then predicted the VoLL or the GVA based on the econometric prediction, in order to estimate the VoLL. The results of these approaches are found in the table below.

Table 4: Comparable analysis of VoLLs using the GVA/VAR method		
Method	**VoLL (£/MWh)**	**% share of VAR approach**
GVA/VAR approach	1,654	100%
'Critical' electricity consumption	1,075	65%
Capacity Utilisation	1,505	91%
Econometric production function (Cobb-Douglas)	1,290	78%
Econometric production function (Translog model)	1,472	89%

Note: The VoLL estimates presented in this table are the average of all sectors considered. Details analysed at a more disaggregated breakdown are provided in the Annexes (A13.1.3).
Source: London Economics

Overall, the VoLLs for I&C customers are about £1,400/MWh taking the simple arithmetic mean of the figures above (at a sector level, as detailed in Annex 13, the average I&C VoLLs show a broader range; however, the vast majority are around £6,000/MWh or lower). The results are the average VoLL for the most recent year (2011) of full comparable data from the various techniques. As can be seen, there is a range of average VoLLs from the techniques, and all the adjustment tend to reduce the VoLL estimate relative to the GVA/VAR approach. This is somewhat as expected as the

[4] Aggregation bias refers to when two or more very different sectors are combined together and the result shows the average of two different sectors rather than the individual sector. Substitution bias refers to the bias that may be apparent when certain firms are able to 'substitute' energy inputs in the event of an electricity outage.

limitation of the GVA/VAR approach was that it gave implausibly high VoLLs for some sectors with low electricity use relative to GVA, such as construction.

The VoLLs for I&C customers are significantly lower than for SMEs. This is intuitive as a) large users use more electricity per unit of GVA than small business, and this impacts the VoLL/MWh. In essence, large industry tends to be more intensive on energy use, and less intensive on labour use, with the former driving up the denominator in the VAR VoLL calculation and the later driving down the numerator. Further, large customers may engage in action to limit the impacts of outages or manage security of supply, such as self-supply, engaging in demand-side response, or have onsite back-up equipment when production is load-critical, and this will limit the VoLL for large customers. Finally, when assessing various policy parameters and the impacts of VoLL, the importance of industry would in some cases be best weighted by load, so larger users, although having lower VoLLs, would get a larger weight in calculations such as estimating efficient levels of aggregate capacity.

Estimating a cost for voltage reduction

As a further aspect of our study, we were asked to examine the cost in £/MWh of SO-directed demand-reducing actions such as voltage reduction. The results of our analysis indicate that, given the statutory range of voltages, the expected voltage reductions are unlikely to cause significant costs to household and SME consumers. We nonetheless studied a range of possibilities and estimates, and this is reflective, in part, of the uncertainty surrounding the estimated values. Our best estimates based on the available evidence are that cost of the SO-directed actions could be very low/close to zero, as the maximum voltage reduction is unlikely to have significant long-term impact on machines or equipment and most modern equipment can ride through (not shut down) low voltage situations.

However, an element that is missing from our analysis is whether other power quality reductions, such as short term sags, other transient voltage and power quality problems, (surges, the shape and phase angle of voltage distortions, etc.) would be greater or more likely as a consequence of SO-directed voltage reductions during a power emergency. In some cases, the impacts of these power quality reductions could be additive with the standard voltage reduction, which would then have greater impacts on equipment.

The results of the SO-directed actions should thus be viewed with caution and seen as a first step in a relatively unexplored field for a variety of reasons. While there is a growing body of qualitative and quantitative research on the impacts of low voltages on household equipment and devices, there has been to our knowledge no published research on the precise types of voltage sags and power quality disturbances that would occur during the typical power emergency and whether these would be additive or interact with the SO-directed reduction. In addition, if the conclusion that the impacts were indeed zero were definitive, one might ask the question why SOs the world over do not avail of voltage reduction more frequently. We would therefore urge further research in this area.

Use of VoLL and narrowing the range of VoLL figures

As part of our project, we were asked to give our opinions on how to narrow the range of VoLL figure estimates across time periods and customer types to more aggregate headline figures. Narrowing down VoLL depends in part on how VoLL will be used; the ultimate use of VoLL is up to

Ofgem and DECC, and we are only offering illustrative scenarios. However, we suggest that since VoLL is likely to be used as a substitute for a market price for security of supply and has applications for both capacity and balancing markets, then a single simplified VoLL may be the most important figure.

In theory, VoLL is a demand-side concept that is no different from more familiar supply-side concepts; market supply and demand are symmetric. The stack of plant from least to highest marginal cost that makes up the supply side, and symmetrically, the stack of least to highest marginal value or willingness to pay makes up the demand side. If a market maker could indeed order and stack consumers in the same way as the market stacks generation plants, and consumers could respond to the resulting price signals, then security of supply would always be achieved via prices.

A major challenge with VoLL and energy policy for security of supply is that it is often difficult to determine precisely who has been disconnected and for how long during power emergencies. Thus the VoLL, while in theory a marginal concept, is in practice a weighted-average approximation of the marginal impact on a group of customers. The VoLL is thus the weighted-average of the consumer surplus plus market revenue from a typical group of customers that might be disconnected.

Further decisions about how to aggregate VoLL and which are the most appropriate figures to use were driven by discussions among the LE, Ofgem and DECC teams. In concert with the project teams from Ofgem and DECC, it was agreed that as the future energy policy landscape evolves, large customers will increasingly be able to participate in demand-side response, and should face market price signals from the energy markets directly. Therefore, our focus is on domestic and SME customers. Further, we discussed that the marginal impact on security of supply should be with reference to typical winter peak demand periods. Finally, we agreed that from a policy perspective, using the WTP figures, which suffer from the well-known downward bias due to 'entitlement' and strategic responses from consumers, would risk setting a security of supply standard that is too low; we concluded that the WTA method was the better approach.

Therefore, we concluded that we should calculate a headline VoLL figure using the willingness to accept (WTA) CE results, as a load-share weighted average across domestic and SME users for the winter peak weekday figures (see Table 5 below).

Table 5: Load-share weighted average across domestic and SME users for winter, peak, weekday

VoLL (£/MWh)
16,940

Note: We have derived this weighted average using a 74:26 weighting for domestic: SME
Source: London Economics analysis

Overall conclusions

We have estimated the value of lost load (VoLL) for electricity consumers in Great Britain. We used a variety of methods, but the focus of our work was based on choice experiments where domestic and SME consumers stated their willingness to accept (or pay to avoid) an electricity outage by choosing between two scenarios. These results indicated a peak winter workday VoLL of £10,289/MWh for domestic users and £35,488 for SME users based on willingness-to-accept. Our best judgment is that the WTA results are both more statistically robust and more appropriate (than the WTP results) in policy[5] terms for setting a VoLL as an input to security of supply. The higher value of the WTA VoLL estimates for SMEs is intuitive, in our opinion, because SMEs relative to households likely have a higher time-value of output and fewer possibilities to substitute into other non-electricity-using activities during peak times.

For I&C customers, a variety of GVA/MWh Value-at-risk approaches suggested an average VoLL of about £1,400/MWh. This lower value of I&C is intuitive as well given the high levels of electricity input in some industry.

The results of our analysis of the potential costs of voltage reductions indicates that given the statutory range of voltages, and the maximum 6% reduction, this is unlikely to cause significant costs to household and SME consumers.

Because VoLL is likely to be used to input into security of supply calculations, such as for setting capacity levels and calculating costs in cash-out, but customers who experience an outage cannot in general be identified or ordered in terms of preference/WTA (stacked), we believe that a weighted-average winter peak workday VoLL is the most appropriate single number for these purposes. Further, given that large I&C customers may now, or will in the future, have the option of demand-side response, self-supply, and other types of protections, we further based our VoLL estimate on an average of the VoLLs across domestic and SME customers only. Doing these calculations yields a headline weighted-average VoLL figure of £16,940/MWh for peak winter workdays in GB.

[5] The policy rationale has been suggested by DECC/Ofgem. The rationale is that WTA corresponds better with the concept of an ‘outage’, which represents taking away a good that consumers already enjoy.

1 Introduction

This section provides a short background for this current study as well as a description of its scope.

1.1 Background for the study

This study by London Economics has been commissioned jointly by Ofgem and DECC. The value of lost load (VoLL) fits into the wider context of the UK's[6] energy and climate change mitigation policy, and it is important to understand the background for these.

In the near and medium term future, the GB electricity market will face a number of challenges and changes. About one fifth of total currently available capacity is due to be decommissioned before 2020. In addition, with ever greater amounts of wind and renewable generation on the system, the electricity system will see a significant rise in intermittent and less flexible generation. Further policy objectives of increasing use of electricity in vehicles and other areas, given the increasing green content of the generation mix, will further spur demand and put pressure on the supply-demand balance in GB.

Current UK policy goals for energy and climate change mitigation naturally include both security of supply, reduced GHG emissions, while minimising the cost of achieving stated targets. The main legislative tool for achieving these goals is the Energy Bill, and the Electricity Market Reform (EMR). The Energy Bill, introduced into Parliament in November 2012, seeks to implement the main elements of Electricity Market Reform (EMR) as well as a range of other measures.

The main initiatives of EMR for electricity which are likely to be adopted are:[7]

- A mechanism to support investment in low-carbon generation: the Feed-in Tariffs with Contracts for Difference (CfD);
- A mechanism to support security of supply, if needed, in the form of a Capacity Market; and
- The institutional arrangements to support these reforms.

The design of the capacity market and setting the policy-maker-generated levels of security of supply are of key interest, and the estimates of VoLL have direct implications for this. Simplistically, the economically efficient levels of security of supply are found by equating the marginal cost of added capacity with the marginal social cost of electricity outages (VoLL). The efficient level of security of supply is not 100%, as the cost of this would be too high. DECC is one of the key agencies involved in design of these policy objectives and initiatives.

The efficient levels of security of supply, and minimising the cost of running the system, are also important to study in terms of a wider range of more technical aspects of the functioning of the electricity system, and it is these elements which fall under Ofgem's remit. Ofgem is considering attributing the price of consumers' VoLL to firm-supply customer disconnections in the Electricity cash-out arrangements as part of its Electricity Balancing Significant Code Review. The growth in intermittent renewables generation is perhaps one of the most important elements of these

[6] While our study covers GB, naturally wider policy goals and objectives cover the UK.

[7] This section draws from public information available from DECC. UK Capacity Market: Gaming and Consistency Assessment Tender No: 600/04/2013.

policies, as the increased intermittency will most likely have implications for the electricity sector, which will likely include enhanced payments for generators and demand-side users providing capacity/demand reduction, balancing energy, reserves, and other security of supply related services.

More specifically, one of Ofgem's major study areas is the Electricity Balancing Significant Code Review. Balancing involves the matching of supply and demand in real time. Any real-time mismatch between generation and demand may cause the system operator to take balancing actions.

It is Ofgem's view that the current balancing regime may not working as well as it can for the market and for consumers, and thus it is considering a wide range of policy initiatives. A key element of balancing is the value of energy not served, and this will likely be where VoLL is needed. VoLL represents the value that electricity users attribute to the security of electricity supply. There are indeed other aspects and potential uses of VoLL, such as paying consumers in the case of an outage, and using a willingness to accept measure may be akin to the level of adequate payment that is required in the event of an electricity outage.

1.2 Purpose and scope of this study

The purpose of the study is to undertake quantitative research to derive estimates of VoLL for domestic, SME and I&C electricity users, respectively. The study provides:

- Estimates of VoLL for domestic consumers and SMEs using a non-market valuation survey with a choice experiment;
- Estimates of VoLL for industrial and commercial (I&C) consumers using a value-at-risk (VAR) approach; and
- Desk research regarding the potential cost for voltage reduction.

The remainder of the study is structured as follows:

- Section 2 discusses the VoLL estimates, derived from the Choice Experiment approach, for domestic and SME users.
- Section 3 discusses the VoLL estimates, derived from the Value-at-Risk (VAR) approach, for Industrial and Commercial (I&C) users.
- Section 4 examines the potential cost to consumers of System Operator (SO) directed action to reduce demand, as well as the potential costs to consumers resulting from voltage reductions as directed by the SO.
- Section 5 presents our overall conclusions.

Annexes contain survey results, data, quantitative modelling results and a literature review.

2 VoLL for domestic and SME electricity users

This section presents VoLL estimates for domestic and SME electricity users. These estimates are derived from a choice experiment (CE) approach. This section briefly discusses the overall rationale and methodological approach to estimate VoLLs for domestic and SME electricity users.

2.1 Methodological approach

This study uses stated preference methods to elicit an estimate of the Value of Lost Load (VoLL) for domestic and SME electricity users. Stated preference methods involve asking consumers their valuations or preferences among goods, situations, and prices or payments. The two most frequently used stated preference techniques are:

- Choice Experiments (CE); and
- Contingent Valuation (CV).

In essence, a choice experiment involves asking a consumer to choose between alternatives of situations or purchases with a set of attributes—in our case the situation will be electricity outage scenario and prices to pay or receive to avoid or experience the outage. The CV method, on the other hand, asks consumers directly what they would be willing to pay (accept) to avoid (experience) the outage.

Stated preference methods, in general, have both advantages and disadvantages in contrast to other methods (e.g., revealed preference), however, we believe stated preference methods are best suited to studying VoLL in the context of the project and question presented to LE by Ofgem/DECC via the terms of reference. In large part, the driving feature towards stated preference over revealed preference methods is that consumers in GB will have had very limited experience with actual electricity outages[8]. Further, even if it were feasible to obtain a representative sample of consumers who had experienced an outage, aspects such a limited information or cash constraints would typically suggest that revealed changes in economic behaviour might still not yield good estimates of VoLL. Thus our preferred methodology involves using choice experiments. The CE method allows us to consistently estimate the VoLLs for a range of outage scenarios and for a wide range of consumers and a range of seasons, times of day, etc. We also, however, included CV questions in our survey as a cross check, but only for peak winter outages.[9]

The choice experiment has a number of advantages over the CV approach. The main benefits of the CE approach include:

[8] Further, even for those who had experienced outages, the time and cost of trying to identify and collect data from such customers, let alone glean VoLL estimates would have made such methods unsuitable for our terms of reference and proposal.

[9] For this reason, the contingent valuation questions were placed after the choice experiment to ensure that the responses would not be able to influence the results of the choice experiment which was the main purpose of the survey. As a consequence of this, the results of the contingent valuation questions may have been influenced by the attribute levels set for the choice experiment. The CV questions asked respondents to value a 1 hour outage of this type.

- Capacity to examine changes that are multi-dimensional (i.e., peak, season, day, etc.), as well as interactions among attributes;
- Reduce 'strategic response' possibilities, where the respondent gives a biased answer in the hope of influencing the policy;
- The possibility for respondents to express their preference for attributes over a range of payment amounts; and
- Overcomes the 'zero response' problem in WTP CV preference models.

It must be noted that the estimated values of WTA and WTP are stated preference measures. These are not based on actual economic behaviour in the market (i.e., revealed preference).

We included both willingness-to-accept (WTA) and willingness-to-pay (WTP) CEs in our surveys and modelling. In theory, WTA and WTP will be equal if a consumer would pay the same amount to receive a good as they would be willing to receive in payment for not receiving the good. However, empirically WTP=WTA is not typically the case and WTA tends to exceed WTP in most stated preference survey based studies. This is especially true when the respondent may feel that they have an entitlement to the good or when the good may be described as a 'public good'[10] such as secure electricity supply. Two main reasons put forward for this gap are loss aversion[11] and the endowment effect.[12] When consumers are used to enjoying a service that they pay for, they typically want greater payment in order to bear a loss of that service than they are willing to pay to retain it. This is because individuals feel a sense of ownership (property rights) for something they already have (in this case a secure electricity service). Psychologically, the loss from giving something up feels greater than the gain from keeping it and avoiding the loss.

A brief overview of these methods and how they lead to willingness-to-pay estimates can be found in the recent report for the Competition Commission.[13] Further discussion of the existing literature on why choice experiments have been applied to estimating electricity VoLLs is given in Annex 1.

2.2 Designing the choice experiment

This section briefly describes the design of the choice experiment. The key components of the CE design are as follows:

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[10] While there is a range of factors defining public goods, in essence, because one consumer's enjoyment of secure electricity supply does not reduce the available security of supply available to others, we can think of secure electricity supply as a public good. This topic can get more technical and more debateable, since at some point, the demand added by one customer is on the margin and thus may impact the security of supply of others. But for most small consumers, we can think of their consumption as being negligibly small.

[11] Loss Aversion refers to people's tendency to strongly prefer avoiding losses to acquiring gains. Further explanation of this can be found in Pearse, D. (2002) "The Role of 'Property Rights' in Determining Economic Values for Environmental Costs and Benefits" Report to the Environmental Agency.

[12] The endowment effects refers to the hypothesis that a person's WTA for a good is greater than their WTP for it once their property right to it has been established. Further useful background material on this can be found in Kahneman, D., Knetsch, J. L., & Thaler, R. H. (2009). Experimental Tests of the Endowment Effect and the Coase Theorem. In E. L. Khalil (Ed.), The New Behavioral Economics. Volume 3.

[13] Competition Commission, 2010, "Review of Stated Preference and Willingness to Pay Methods" http://webarchive.nationalarchives.gov.uk/+/http://www.competition-commission.org.uk/our_role/analysis/summary_and_report_combined.pdf

- Attribute levels and attribute selection; and
- Inclusion of a no-choice option.

These components have been analysed and implemented following examination of comparable previous research and London Economics' prior experience in this area. The attribute levels were also developed in partnership with the market research teams from YouGov and OMB, Prof Fraser, and the Ofgem and DECC project teams.

2.2.1 Selection of attributes and attribute levels

A first step in the survey design was to consider attributes and their levels. A detailed literature review (see the Annexes) and discussion with Ofgem and DECC informed the process including policy priorities. As part of our main choice experiment design, we use four attributes.

The number of attributes that can be tested in a CE is limited due mostly to the difficulty consumers might encounter with weighing complex choices. According to Hanley *et al.* (2001) the number of attributes that can be tested depends on the sample size. However, as a rule of thumb no more than four or five attributes should be tested. Various research[14] from the behavioural economics field suggests that respondents to experiments have difficulty making complex calculations and this is likely to increase as the number of possible calculations (attributes) increases.

The selected attribute levels for non-price attributes are shown in Table 6. The attributes chosen for the CE were: duration, time of day, day of week, season, and price.

Electricity outages of this type are typically different from gas outages. They are typically of shorter durations and this is reflected in the duration lengths chosen in the choice cards.[15,16] The duration outages were chosen based on analysis of previous outages of this type and discussions with the Ofgem and DECC project team.[17]

The time of the day variable is split into peak (3pm – 9 pm) or non-peak (10pm – 2pm). These times were chosen to reflect the peak demand for electricity[18] which typically occurs between 3pm and 9 pm. It was felt that the peak demand should be over a longer time period than the actual peak (i.e. 6pm – 7pm). A very narrow 'peak' may create 'noise' in the experiment. For example, someone who arrives home at 7.30pm may feel that a peak at 6pm – 7pm has no impact on them.

In the CV question, we have allowed respondents to choose what they think is their peak electricity demand.

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[14] See for example Tversky and Kahneman (1974) "Judgment under Uncertainty: Heuristics and Biases" for one of the seminal works in this area.

15 National Grid (2008) Available at (http://www.nationalgrid.com/NR/rdonlyres/E19B4740-C056-4795-A567-91725ECF799B/32165/PublicFrequencyDeviationReport.pdf)

16 Ofgem (2012) www.ofgem.gov.uk/Markets/WhlMkts/CompandEff/Documents1/2013%20Electricity%20Cap%20Assessment%20Consultation%20Methodology.pdf

17 CERR Guidelines on Estimation of Costs due to electricity interruptions and voltage disruptions.

[18] See Figure 41 in Annex 12 for a graphical illustration of the demand profile for electricity by month and time of the day.

One small difference between the SME and domestic choice experiments was in relation to the weekday variable. For SMEs this was specified as a 'working' day or a 'non-working' day. In the domestic experiment the day variable is either that the outage occurs on a 'weekday' or a 'weekend'.

The final attribute chosen was the season of the electricity outage. In the domestic survey, this was split between winter and 'not winter'. This was chosen to reflect the higher levels of electricity demand that typically occur during the winter months which are reflected in the electricity demand profile.

Overall, attribute selection was typically based on analysis of the electricity demand profile and recent evidence along with discussions with the Ofgem and DECC project team.

Table 6: Selected attributes and attribute levels for non-price attributes

Attribute	Attribute levels
Duration of interruption	20 minutes[19]
	1 hour
	4 hours (5 hours for SMEs)
Season of interruption	Not Winter
	Winter
Time of Day	Peak (3pm-9pm)
	Non-Peak (10pm-2pm)
Day of Week	Weekday (work day for SMEs)
	Weekend/Bank holiday (Non-work day for SMEs)

Source: London Economics

The levels of payment are shown in Table 7 for domestic and SME electricity users. Both willingness to pay (price) and willingness to accept (payment) were phrased as 'once-off' payments. This simplifies the interpretation of the choice experiment. It also negates the possibility that respondents do not apply proper discounting when analysing future payments. This makes the WTA and WTP estimates directly comparable. Our primary rationale was to set the experiment up as if an outage occurred tomorrow and how much you should pay/receive to avoid or accept.

In the domestic experiment, the price attribute levels were set as (£1, £5, £10, £15). These amounts were in part informed by our previous study on Gas VoLL, and discussion with the Ofgem and DECC teams, and consultation with Professor Fraser. The choices for price levels were also informed by a broad understanding that these amounts were generally in-line the opportunity cost of lost time which is typically estimated at around 50% of the average wage rate.

For SMEs, the price variable attribute levels were chosen as a percentage of the annual electricity bill. This approach is taken as electricity bills are typically more varied for SMEs than for

[19] The minimum duration for SME's was fifteen minutes. This should not impact on the modeling of WTA/WTP.

households. Thus, if we relied on set pound values, there would have been in our view a risk that SME respondents' values did not properly reflect their usage and VoLLs. In contrast, the survey data on bills for domestic consumers does not enter the VoLL calculation.

Table 7: Selected attributes and attribute levels for price attributes

Attribute	Attribute levels	
	Domestic electricity users	SME electricity users
WTP: Once-off payment	£1	1% of annual bill
	£5	5% of annual bill
	£10	10% of annual bill
	£15	15% of annual bill
WTA: Once-off payment	£1	1% of annual bill
	£5	5% of annual bill
	£10	10% of annual bill
	£15	15% of annual bill

Note: The payments are classified as 'once-off' payments
Source: London Economics

One attribute that is frequently found in the literature, but which we did not include in our first set of surveys and headline VoLL results was frequency of outage. We did include frequency of outage as an attribute in the piloting phase[20] of the experiment but the results of this pilot indicated that this variable was complicating the experiment to the extent that consumers were having difficulty responding to the survey, and the choices were being made on only a limited number of attributes.[21]

After piloting, it was our judgment, working in close contact and consultation with Ofgem's team, DECC's team, our market research team and Professor Fraser that the CE's with five attributes were too complicated and there was a risk that respondents were responding by implicitly 'simplifying' the experiment in their responses. Thus it was our judgment to drop frequency and merely inform respondents of the typical frequency. Respondents were informed that the average interruption of this type was about once every 12 years and this was kept constant across choices.[22]

As the overall results may be sensitive to the outage frequency, we subsequently conducted an additional survey and simplified CE using only frequency, duration, and price attributes (where peak time, day of the week, and season, were defined in advance by informing consumers of the timing). This experiment was undertaken as a sense check to our primary choice experiment results. The design of this additional experiment is very similar to the main choice experiment with the duration and payment attributes taking the same levels as per the main CE. Full details of this additional choice experiment and the resulting VoLL estimates can be found in Annex 17.

[20] An online pilot survey was initially undertaken with 98 responses (98*6=588 choice card selections for WTA/WTP). A pilot SME study was also undertaken.

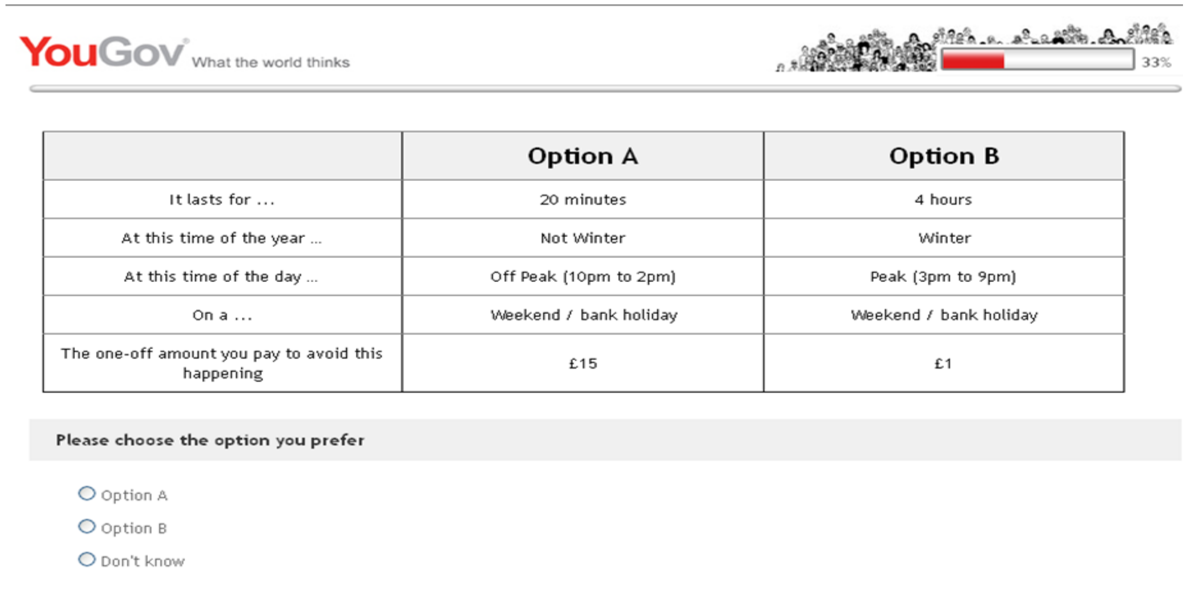
[21] Tests were carried out to determine if a limited number of attributes were determining a disproportionate number of choices, as well as if seemingly dominated or inconsistent choices were occurring.

[22] This "1 in 12" frequency estimate is based on Ofgem's recent capacity assessment that states over the next few years, 1 in 12 is the most frequent outage expectation. See Ofgem (2012) "Electricity Capacity Assessment".

2.2.2 Inclusion of a no-choice option[23]

An actual example of the choice cards as would be seen by a respondent in the online survey is shown in Figure 1 below. The cards present a consumer with the attributes down the left and the levels of the attributes vary across the choices: Option A and Option B. The example is a WTP, so the previous screen would have explained that a hypothetical choice would be presented, and the person should respond with their best choice based on their preferences.

Figure 1: Example of choice card (WTP)


YouGov What the world thinks 33%

	Option A	Option B
It lasts for ...	20 minutes	4 hours
At this time of the year ...	Not Winter	Winter
At this time of the day ...	Off Peak (10pm to 2pm)	Peak (3pm to 9pm)
On a ...	Weekend / bank holiday	Weekend / bank holiday
The one-off amount you pay to avoid this happening	£15	£1

Please choose the option you prefer

- Option A
- Option B
- Don't know

Source: YouGov

It should be noted that the choice experiment includes a 'don't know' option in addition to the two alternative scenarios presented on the choice cards. It is generally recommended that choice experiments include a no-choice option to ensure that respondents are not forced to make a choice, which ensures better estimates of WTP and WTA. However, a possible disadvantage of including a no-choice option is that no information about WTP or WTA is revealed by respondents who select the no-choice option.

There appears to have been a significant level of 'non-engagement' in the WTP domestic choice experiment. The results indicate that around 11% of respondents answered 'don't know' for all WTP choices. This appears to show that these respondents have not engaged with the experiment and including their responses in the regression analysis may bias the results. For this reason, these types of respondents have been excluded from the analysis. This problem is much smaller for the

[23] Another element of the design of the choice experiment is in relation to how the choice cards are generated. For this choice experiment, we use 'efficient' designs. An explanation and derivation of this technical aspect is provided in the Annexes (see A4.1.2).

WTA experiment (about 5%) and these types of respondents have also been excluded. A full summary of the choices made by the respondents for domestic and SMEs is provided in Annex 9.

Some respondents chose the 'don't know' option for some choice scenarios and this may mean that the respondents couldn't decide between the two choices presented to them. Excluding these types of responses would bias the results and would force respondents to choose between choices where neither is preferred. We thus assumed that only those respondents that answered 'don't know' for all of the choice cards were displaying 'non-engagement', and all others we assumed 'don't know' responses resulted from not being able to choose between the different alternatives.

2.3 Valuation survey and sample

It is generally useful to include background questions in such a survey, as this enables checking whether such variables may be explaining or add intuition about choices. Thus, in addition to the choice experiment, the survey included background questions about:

- Electricity usage characteristics such as what electricity is used for (e.g., heating, hot water, appliances etc.) , time of peak usage and annual electricity and energy spend;
- Available substitutes to electricity in the event of electricity outage (e.g., gas heating,[24] candles, torches etc.);
- Awareness of current payment arrangements;
- Background questions about the respondent. In the household survey, this included age, gender, region, income and whether the respondent felt they could keep their home adequately heated;
- In the SME survey, this included sector and size of the SME in terms of numbers of employees; and
- The impact of a one hour electricity outage at peak times in winter on a weekday (typical work day for SMEs).

The results of these background questions are presented in Annex A2.4.

Two contingent valuation (CV) questions were also included to provide a cross-check of the results from the choice experiment. For the SME survey, CV questions were also asked. These questions were phrased slightly differently to align with the attributes presented in the choice experiment. The details of the design and results of the CV questions are presented in Annex 8.

2.3.1 Domestic survey

The domestic survey consisted of an online survey with 1,524 respondents.[25]

The sample for the online survey was drawn at random from YouGov's 400,000+ strong online panel of adults. Quotas were set to ensure that the resulting sample was representative of the GB

[24] During the piloting phase, it was pointed out that a small amount electricity may be required to 'start' a gas boiler.

[25] A face-to-face survey was also undertaken. This surveyed 150 'vulnerable' domestic electricity consumers. This survey was used as a sense check for the representative online survey. A full description of this survey is provided in the Annexes (see A2.1).

population in terms of age, gender and socio-economic characteristics. It should be noted that since the online sample is a random sample, it also includes vulnerable consumers. Further details of the representativeness of the survey are presented in Annex 2 but the online sample is broadly representative of the GB population[26].

Nonetheless a face-to-face survey was conducted to supplement the online-only survey, and these results are also available in the Annexes. This face-to-face survey targeted certain types of customers[27] and the face-to-face survey over-sampled on types of customers that might have been under-represented in the online sample We'd note, explicitly, however, that the difference between the VoLL estimates with the pooled online plus face-to-face survey data did not vary significantly from the online only sample.

Our main results for domestic VoLL, however, are derived from the online only sample, as the pooled online and face-to-face sample would have over-represented certain types of customers, given that the face-to-face sample targeted vulnerable users.

Respondents to the online survey also had to be:

- solely or jointly responsible for paying the households' energy bills; and
- if they were renting their home, they had to pay their energy bills separately from their rent.

We should note that applying these criteria means that direct comparisons with a nationally representative profile are not possible. Typically between 10 and 15% of the population would not qualify to take part; often these are younger people without bill paying responsibilities.

2.3.2 SME survey

Prior experience has found that an online survey approach is in general not feasible for businesses because online business surveys yield very low response rates. Therefore, the business survey was undertaken as a computer assisted telephone interview (CATI) survey. Respondents were contacted over the phone and, when feasible, choice cards were e-mailed (via weblink) or faxed to them so that they would have the choice cards in front of them while responding to the survey. A large majority of SMEs (94%) surveyed had direct access to a computer at the time of the interview.

For the SME survey, respondents were randomly asked only either WTA or WTP choice questions (but both CV questions). It was felt that asking both WTA and WTP choices (12 choice cards) was not advisable for SMEs given that the survey was done over the telephone. The research was presented as being on behalf of Ofgem/DECC and this was disclosed in the survey introduction.

Annex 3 provides a comparison between sample and population characteristics for SMEs in GB.

[26] Further details on the methodology used by YouGov to construct their representative panel is provided in the annexes (See A2.3)

[27] A more detailed description of how the face-to-face was carried out and who was targeted to partake in this survey is included in the annexes (see A2.1)

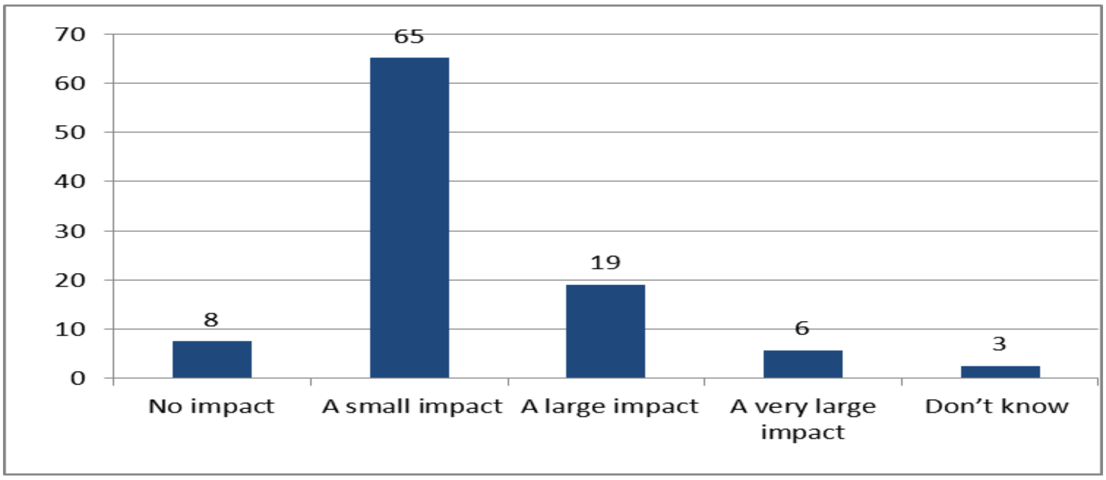
2.4 Domestic and SME electricity usage

This subsection presents the key qualitative results regarding the importance of an electricity outage. A more detailed description of the different characteristics of the survey is provided in Annex A2.4.

2.4.1 Domestic electricity importance

As part of the survey, we ask respondents a qualitative question about how much a one hour electricity outage would impact on them. The results for the online survey are shown in Figure 2 below. Around 73% of respondents to the online survey indicated that this electricity outage would have a limited or negligible impact. Twenty-five per cent of these online respondents believed that such an outage would have a 'large' or 'very large' impact on them.

Figure 2: Impact would an electricity outage of one hour have on your household (% of total number of households having participated in the survey)



Source: Online domestic survey

The majority of respondents believe that a one-hour electricity outage at an unspecified time would have a relatively low impact.

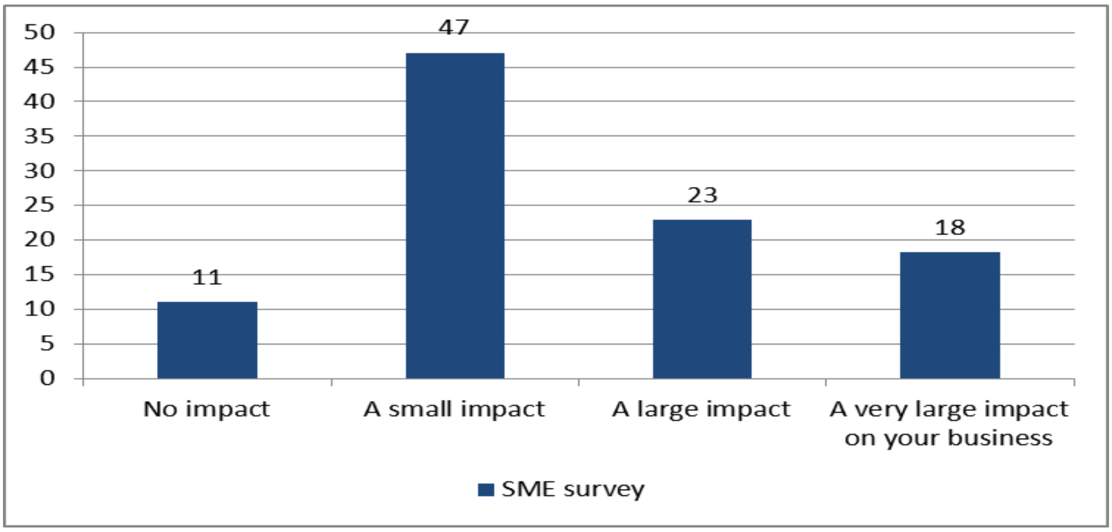
2.4.2 SME electricity usage

We also asked SMEs about their usage patterns for electricity. The vast majority of SMEs use electricity for computing and lighting. The importance of these applications will vary by the type of business of the SME. The results of the survey also indicate that only around 23% of SMEs use electricity directly in the production process. Again, this probably reflects the size of the SMEs and that around 70% of SMEs engage in service related activities. Further details of these background characteristics are provided in the Annexes (A3.3).

Similar to the household survey, SMEs were also asked to give a qualitative estimate of the impact of a one hour electricity outage on a typical working day. These qualitative results are shown in Figure 3 below. Most SMEs do not believe that an outage would have a large impact, but some do. Forty-seven per cent of SMEs say the impact would be small. Forty-one per cent of SME electricity users believe that such an electricity outage would have a large or very large impact on their business. Only around 11% say that an outage would have no impact on their business.

According to these results, SMEs believe that a one hour electricity outage would typically have a qualitatively more important impact than households. Around 41% of SMEs have indicated that an electricity outage will have a large or 'very large' impact. This compares with about 25% of households who indicated that the same impact would have a 'large' or 'very large' impact. Our prior thinking is that respondents who indicate a 'high' impact will be affected more significantly by an outage which in turn may suggest a higher VoLL.

Figure 3: Impact of a electricity outage lasting for one hour and taking place in the winter during the afternoon of a typical business day (% of SMEs having participated in the survey)



Source: London Economics analysis of SME survey

Annual SME electricity bill

The payment levels in the choice experiment for SMEs are in percentage terms of annual electricity bill. Thus, it is important that we examine estimates of the annual average electricity bill as this is needed to convert the results of the choice experiment into monetary values. As there is no official 'average' SME electricity usage or bill data, we also use information from the SME survey on the annual electricity bill to derive an estimate of average annual SME electricity consumption.

Table 8 illustrates how the average changes as more observations are excluded from the estimation of the average annual electricity bill for SMEs. Fifty-nine respondents were unable to give an exact estimate of their annual electricity bill. Instead, these respondents chose an electricity bill band. These were appended to our sample using the midpoint of these bands.

The rationale for using this table is that some very large SMEs may have very large electricity bills which may make the arithmetic mean electricity bill from the survey somewhat unrepresentative of typical SMEs. In the table the maximum number of observations that are removed is ten and this decreases the average from £4,976 to £2,166, thus indicating the survey sample was indeed skewed-right by a distribution with a few very high values.

Table 8: Average size of annual electricity bill for SMEs (in £)

Sample	Avg. (£)	Med. (£)	Max. (£)	Min. (£)	Std. Dev.	Sample %[1]
Full sample	4,976	1,200	500,000	100	31,025	100%
Limited sample: Mean +/-3 std. dev.	2,500	1,200	40,000	100	4,233	99%
Limited sample: Mean +/-2 std. dev.	2,500	1,200	40,000	100	4,233	99%
Limited sample: Mean +/-1 std. dev.	2,421	1,200	32,000	100	3,889	99%
Limited sample: Mean +/-0.5 std. dev.	2,166	1,200	20,000	100	2,937	98%

Note: 1. Refers to the number of observations in the sample as a share of the full sample. The lowest estimate removes the 10 highest observations from the sample.
Source: London Economics analysis of survey data

Based on the analysis above, we use £2,500 as our estimate of the average SME electricity bill. This amount is used to convert the derived percentage estimates of the choice experiment into monetary (£) amounts.

2.5 Estimating WTP and WTA

In this subsection, we give a brief overview of how the results from the choice experiment are converted into estimates of WTP and WTA for domestic and SME customers. Additional details are available in the Annexes. This involves a number of steps as follows:

- Choice of estimation method;
- Description of model and explanatory variables; and
- Calculation of WTA/WTP from estimation results.

The choice experiment is based on the concept of a utility model. The concept is that if respondents choose one choice over another, then this choice must have higher 'utility' or value to the respondent. This is the core idea behind the neoclassical economic model of consumer behaviour. More formal derivations of the utility function approach and the choice of functional form for the estimation of willingness to pay/accept from the choice experiment data are included in the Annexes (see A4.1.3).

2.5.1 Choice of estimation method

The conditional logistic regression (logit) is the econometric method used in our analysis. The conditional logit model is a standard limited dependent variable estimation method and is a well-known method for choice experiment modelling. The results of the survey are zero-one data of 'choices' between the alternatives A and B presented. It is standard to estimate choice experiments with a no-choice option using a conditional logit model.[28] The conditional logit estimation method does not restrict the variation in attribute levels between alternatives and estimates the probability that a scenario is selected given the attributes.[29] The marginal impacts of attributes are the model-estimated parameters.

The choices made in the choice experiment reflect not only the attributes of the chosen option but also reflect the attributes of the not chosen option. Thus, the chosen option is 'conditional' on the attributes of the not chosen option.[30]

The attribute levels for the 'don't know' options are set to zero and a dummy equal to 1 for the 'don't know' option is included as suggested by Ryan *et al.* (2008), Vermeulen *et al.* (2005) and Haaijer *et al*. (2001).[31]

In summary, each choice card has three options; choice A, choice B and 'don't know'. One of these options will be a 'don't know' option which has all explanatory attributes set to zero. The econometric model estimates the marginal impact of the levels of the attributes on the likelihood of any given choice. A dummy variable approach (a zero-one explanatory variable) is used to model the 'don't know' choice.

2.5.2 Description of model and explanatory variables

In order to estimate WTP and WTA for different attribute levels, it is necessary to include both price and non-price attributes as explanatory variables in the regression. WTA and WTP cannot be converted into monetary (pound) amounts unless at least one of the explanatory variables provides information on price or payments.

As shown in Table 6, most of the attributes have only two levels and thus can be modelled as zero-one (dummy) variables. For example, winter will be equal to 1 if the outage occurs in winter and zero otherwise. The same is true of time of the day (peak or non-peak) and day of the week (weekday or weekend). In our model, duration is specified as a continuous variable. In theory, the model could also be set up with duration as a set of two dummy variables.[32] Such a model would tell us the difference between duration of four hours and the base case (20 minutes). However, this would not allow us to estimate the actual level of VoLL and only tells us the difference in VoLL

[28] Also sometimes referred to as a multinomial logit model because the conditional logit model contains the multinomial logit model as a special case.

[29] In comparison, in multinomial logit models attribute levels generally do not vary between alternatives and these models are generally used for problems where the characteristics of the alternatives are unimportant or unavailable.

[30] Further discussion on the use of conditional logit estimators in choice experiments is provided in Vermeulen et al. (2009). Vermeulen, Goos, Scarpa and Vandebroek (2009) "Efficient and robust willingness-to-pay designs for choice experiments: some evidence from simulations" University of Leuven.

[31] Ryan, M., Gerard, K., and Amaya-Amaya, M. (2008), 'Using Discrete Choice Experiments to Value Health and Health Care', Springer; Vermeulen, B., Goos, P. and Vandebroek, M. 'Models and optimal designs for conjoint choice experiments including a no-choice option', Katholieke Universiteit Leuven; and Haaijer, R., Kamakura, W., and Wedel, M. (2001), 'The 'no-choice' alternative to conjoint choice experiments', *International Journal of Market Research*, Vol. 43(1).

[32] Duration has three possible values. Thus, there may only two dummy variables used in the model. This is known as the 'dummy variable trap'. The model would be perfectly collinear if all three dummies were included and it would not be possible to estimate the model.

between the duration dummy and the reference duration. For this reason, it is important that one of the attribute variables is included in the specification as a continuous variable (duration in this case).

A key feature of the model is the interpretation of the reference category. We use a scenario of an outage occurring not at peak times, on a weekend day and on a non-winter day as the reference category for the estimation.

It is necessary to allow for interactions between some of the attributes. For example, it is important to take account of the fact that the inconvenience (i.e., loss of utility) suffered by an electricity consumer as a result of an outage of a given duration is likely to vary according to the time or day when the event occurs. Therefore, in the estimation of the WTA and WTP, the variables "winter", "time of the day" and "day of the week" are entered in the model as dummies interacting with the "duration" variable rather than as stand-alone variables. Intuitively, this is because our baseline WTA/WTP is set such that zero-duration indicates a zero WTP/WTA.[33]

The model for the domestic users is shown in the equation below. We use the same model for both WTP and WTA:

$$\text{Pr(Choice)}_i = \alpha + \beta_1\text{*Duration}_i + \beta_2\text{*(Duration}_i\text{*Winter}_i) + \beta_3\text{*(Duration}_i\text{*Peak}_i) + \beta_4\text{*(Duration}_i\text{*Weekday}_i) + \delta\text{*Monetary Value}_i + \eta\text{*Don't know dummy} + \varepsilon_i$$

Where for the domestic survey:

- Pr(Choice) is the probability any choice is made.
- "Duration" is a continuous variable taking the values in the choice experiment of twenty minutes, one hour and four hours.
- "Winter" is a dummy variable taking the value 1, if the season attribute was 'winter' and 0 otherwise.
- "Peak" is a dummy variable taking the value of 1, if in the choice scenario, the outage was specified to occur between 3pm-9pm and a value of 0 otherwise.
- "Weekday" is a dummy variable taking the value of 1, if in the choice scenario the outage was specified to occur on a weekday, and a value of 0 on weekends or bank holidays.
- "Don't know dummy" is equal to 1 if the respondent answered 'Don't know'.
- The constant α is actually a fixed-effects alpha since the model estimated was a conditional logit.

We note that variables with insignificant parameter estimates[34] were not dropped from the model because this may imply that VoLL estimates for all attribute levels cannot be achieved. WTP and WTA estimates can be calculated when the parameter estimates are insignificant and insignificance of the parameter estimates does not necessarily lead to insignificance of the corresponding WTP and WTA estimates, since the significance of the WTA value is a function of

[33] More details on the model selection and intuition can be found in the Annexes.

[34] The 5% significance level is chosen as the test of statistical significance for all variables.

the estimated sampling standard errors of all the parameters in the calculation using the delta method.

For the WTA SME model, a nonlinear specification appears most appropriate. This result indicates that SMEs may be able to adapt to longer outage durations (the longest outage is five hours in the SME choice experiment).

$$Pr(Choice_i) = \alpha + \beta_1*Duration_i + \beta_2*Duration^2_i + \beta_3*(Duration_i*Winter_i) + \beta_4*(Duration_i*Peak_i) + \beta_5*(Duration_i*Workday_i) + \delta*Monetary\ Value_i + \eta*Don't\ know\ dummy + \varepsilon_i$$

We use a scenario of an outage occurring not at peak times, on a non-work day and on a summer day as the reference category for the estimation for both WTA and WTP SME models. As stated previously, a nonlinear term is included in the WTA model only. Further discussion on model selection is provided in the Annexes (see A4.1.4).

2.5.3 Calculating WTP and WTA from the estimation results: transformation of parameter estimates

Once the conditional logit model is estimated, the marginal WTA and WTP estimates are computed directly from the model specified. For example, the ratio of the following two coefficients yields the WTA for the attribute 'i' (if there are no squared terms or interaction terms):

$$WTA_{attribute\ i} = \frac{\beta_i}{\delta}$$

where β_i indicates the parameter of the 'ith' attribute variable. It is important to note that, if interaction effects/parameters are included in the model, then these will impact the WTA, and the prediction should be for a given level of the other variable. In the chosen estimated model we have interaction terms. To estimate the WTA payment for the reference category (not peak, not weekday and not winter), we apply the formula below (ratio of duration and payment coefficients).

$$WTA_{20\ mins,not\ winter,not\ peak,not\ weekday} = \frac{\beta_1}{\delta}$$

In the previous equation, β_1 indicates the parameter of "duration". However, as another example, consider the case of a 20-minute outage occurring in the summer at peak time on a weekday. In this case, the following parameter transformation is made:

$$WTA_{20\ mins,not\ winter,peak,weekday} = \frac{\beta_1 + \beta_3 + \beta_4}{\delta}$$

Where β_3 and β_4 are the parameters of the interaction terms between peak, weekday and the duration terms. β_1 is the coefficient on the duration term. Note that if there is a negative relationship between choice and one of these attributes, then these terms will be subtracted in the above formula. For this particular transformation, we have chosen 'not winter' and thus the coefficient on the interaction between duration and winter is not included in this particular transformation.

As indicated above, the WTA and WTP estimates are a function of estimated parameters, and so the standard errors and confidence intervals from the parameter estimates must be transformed. Thus standard errors and confidence intervals for the WTP and WTA estimates are calculated using the delta method[35,36] for parameter transformations used to generate WTP and WTA estimates.[37] This means that the standard errors depend on the variance and covariance of the parameter estimates.[38]

2.6 VoLL estimates for domestic electricity users

The online sample is largely representative of the GB population, and the online-only sample we believed was the more representative sample compared with the pooled online and face-to-face sample. Therefore we use this sample to obtain our baseline VoLL estimates for domestic electricity users in GB (see Annex 2).[39]

The summary econometric estimation results for the linear model are provided for WTA and WTP in Figure 4 and Figure 5, respectively.[40] The overall model fits are given by Pseudo-R-squared statistics, which are about 34% for WTA model and 25% for WTP model. These values are generally considered appropriate for logistic models.[41]

The interpretation of the coefficients in all the conditional logit regressions should be done in terms of the sign and levels. The coefficients indicate, broadly, the marginal impact on the likelihood of the respondent choosing one set of attributes over another.

The sign of a particular parameter estimate indicates whether an attribute increases or decreases the likelihood (probability) that an alternative scenario is chosen by the respondent. Thus, a negative sign indicates that this variable is less likely to lead to the choice being chosen. Further details of the regression diagnostic tests are provided in the technical Annex (see Annex 5).

The interpretation of the levels of the coefficients should be generally qualitative, as the coefficient levels are meaningful only in relation to the WTA/WTP calculations as given in the previous subsection. In other words, the coefficient estimates are used to calculate the

[35] When parameter transformations are nonlinear, as is the case when WTP and WTA are calculated, the delta method can be used to estimate the variance of the transformed variable. The delta method expands the function used to transform the parameter estimates around its mean, usually with a one-step Taylor approximation, and then takes the variance.

[36] When parameter transformations are non-linear, as is the case when WTP and WTA are calculated, the delta method can be used to estimate the variance of the transformed variable. The delta method expands the function used to transform the parameter estimates around its mean, usually with a one-step Taylor approximation, and then takes the variance.

[37] All confidence intervals are included in the Annex.

[38] The delta method is implemented in Stata using the nlcom command. This method is used when the transformation is nonlinear (such as ratios) and does directly relate to whether the functional form of the regression is linear or nonlinear.

[39] We note that, by adding the face-to-face results to the dataset, vulnerable groups would be overrepresented in the sample, unless the observations were to be reweighted and the weight given to vulnerable groups reduced to construct a representative sample. Nonetheless the results from the two sampling possibilities were not very different.

[40] Analysis of model selection including the results from various statistical tests are included in the technical Annex (see Annex 5). The results show that the model generally fits to an adequate level for a typical conditional logit model.

[41] Additional details can be found in the Annexes (see Annex 5).

WTA/WTP. WTA and WTP are ratios and sums of the parameter estimates. These are based on marginal rates of substitution between choices.[42]

In both the WTP and WTA regressions it is the case that a longer duration of the outage reduces the likelihood that a 'choice scenario' is chosen (hence resulting in a negative sign on the "duration" variable). In both cases it is also the case that alternatives occurring in the winter are less likely to be chosen by respondents (a negative sign on the "duration*winter" variable).

It is also clear in both WTA and WTP estimations that respondents prefer outages to occur on a weekday (a positive sign on the "duration*weekday" variable). This result is statistically significant for both models. This is intuitive if household activity is more likely to be interrupted on the weekend.

The final variable is related to time of day of the outage. In the choice cards, peak time has been defined as between 3pm and 9pm and non-peak between 10pm and 2pm. The results for this variable differ between the two models. In the WTA model, this variable is negative and significant. This indicates that respondents prefer an outage not to occur at peak times (a negative sign on the "duration*peak" variable). In the WTP model it appears that respondents prefer an outage to occur at peak times. However, this duration*peak variable is not statistically significant and the coefficient is almost zero. This indicates that respondents do not place a significant value on an outage occurring at peak times over non-peak times.

Finally, the estimation results are as expected with regard to the price to be paid (WTP) and payment to be received (WTA) variables. The results show that respondents are more likely ("positive sign on the compensation variable") to choose an alternative if there is a higher level of payment to be received associated with that alternative (Figure 4) and that they are less likely ("negative sign on the price variable") to choose an alternative if there is a higher price to pay associated with that alternative (Figure 5). Further interpretation of the regression coefficients is provided in the technical Annex (see A5.1).

The duration coefficient tells us about the impact of an electricity outage in the base scenario (i.e. not winter, not peak, not weekday). The magnitude of the coefficient is based on 20 minute units and thus, the coefficient on duration can be interpreted such that an increase in the length of outage by one unit (20 minutes) decreases the probability that the option is chosen by around 5% (holding all other variables constant). Thus, for a one-hour outage increase, the probability of choice decreases by around 15%. However, it must be noted that interpretation of these coefficients should be viewed with caution, especially in the case of interaction variables.

[42] Additional details can be found in the Annexes.

Figure 4: Baseline estimation results of the model for willingness to accept (online survey)

	Coef.	Std. Err.	z	P>|z|	Lower	Upper
duration	-0.053	0.007	-7.64	0.00	-0.07	-0.04
duration_winter	-0.039	0.004	-9.12	0.00	-0.05	-0.03
duration_peak	-0.040	0.004	-9.35	0.00	-0.05	-0.03
duration_weekday	0.013	0.004	3.22	0.00	0.01	0.02
comp	0.058	0.004	15.79	0.00	0.05	0.06
dont_know	-3.013	0.076	-39.43	0.00	-3.16	-2.86

Note: The results do not report an 'alpha' estimate. This is a feature of the conditional logit model where observations are grouped. The constant alpha is actually in all the models but since it is the same in all groups it is dropped in the STATA estimation.
Source: London Economics analysis of the online household survey results

Figure 5: Baseline estimation results of the model for willingness to pay (online survey)

	Coef.	Std. Err.	z	P>|z|	Lower	Upper
duration	-0.019	0.008	-2.36	0.018	-0.034	-0.003
duration_winter	-0.004	0.005	-0.876	0.381	-0.013	0.005
duration_peak	0.000	0.005	0.086	0.931	-0.009	0.009
duration_weekday	0.019	0.004	4.358	0.000	0.011	0.028
price	-0.070	0.005	-14.937	0.000	-0.079	-0.061
dont_know	-2.852	0.081	-35.115	0.000	-3.011	-2.693

Source: London Economics analysis of the online household survey results

For the derivation of the WTA and WTP estimates under the various different circumstances, it is important to note the formulas outlined in Section 2.5.3.

- The estimated coefficient of the duration variable when it is not winter, not peak and not weekday (reference category) is given by the coefficient of "duration".
- In contrast, the estimated coefficient of the duration variable when it is winter, peak and weekday is given by the sum of the coefficients of "duration", "duration*winter", "duration*peak" and "duration*weekday".
- These coefficients are converted into WTA and WTP estimates by dividing by the appropriate payment variable.

WTA estimates

Table 9 shows the WTA figures for each of the possible choice scenarios. The figures in the table provide estimates of how much payment in pounds consumers would be willing to accept if a specified outage occurs. For example, for a one-hour outage occurring during the week at peak times (3pm-9 pm) in winter, consumers would on average require a payment of £6.16. In the regression results, we found that respondents would prefer an outage to occur during the week rather than at the weekend. Thus, the WTA for a one hour outage that occurs at the weekend, at peak and in winter may be higher than the comparable weekday estimate. This is indeed the case and the WTA estimate for a one hour outage of this type is £6.84.[43]

[43] The difference is, however, statistically significant.

Table 9: Estimates of WTA in £ for various outages in different circumstances, – domestic customers

	Not Winter Not Peak Weekend	Not Winter Not Peak Weekday	Not Winter Peak Weekday	Not Winter Peak Weekend	Winter Not Peak Weekend	Winter Not Peak Weekday	Winter Peak Weekday	Winter Peak Weekend
20 mins.	**0.92**	**0.69**	**1.39**	**1.61**	**1.59**	**1.36**	**2.05**	**2.28**
1 hour	**2.76**	**2.08**	**4.16**	**4.84**	**4.77**	**4.09**	**6.16**	**6.84**
4 hours	**11.06**	**8.33**	**16.63**	**19.35**	**19.07**	**16.35**	**24.64**	**27.37**

Note: All values in bold indicate statistical significance at the 95% confidence interval (statistical significance is calculated using the Delta Method).

Source: London Economics analysis of online household survey

As noted previously, these WTA estimates are based on the representative online sample[44].

WTP estimates

Table 10 provides estimates of how much consumers would be prepared to pay to avoid electricity outages of the specified duration, season, time of day and type of day. As expected these are lower than the average WTA payment levels derived previously.

The largest estimate of WTP derived using the choice experiment is around £4 for a four hour outage occurring at non-peak time, at the weekend, during winter. The pattern of the WTP estimates is broadly consistent with the WTA estimates. The big difference is that now some results for the various outage scenarios are not statistically significant. The interpretation of this is that respondents are not willing to pay an amount that is statistically different from £0 to avoid an electricity disruption of this type. This does not indicate that our best point estimate of their WTP is zero, but merely that the sampling error involved in the sample indicates that we cannot be confident the result is not the result of sampling error. In general, it is not advisable to try and interpret these results, as the derived WTP estimates are a function of parameter estimates which are both significant and insignificant.

Table 10: Estimates of WTP £ to avoid an outage by time of outage – domestic customers

	Not Winter Not Peak Weekend	Not Winter Not Peak Weekday	Not Winter Peak Weekday	Not Winter Peak Weekend	Winter Not Peak Weekend	Winter Not Peak Weekday	Winter Peak Weekday	Winter Peak Weekend
20 mins	**0.27**	(0.01)	(0.02)	**0.26**	**0.32**	0.05	0.04	**0.32**
1 hour	**0.80**	(0.03)	(0.05)	**0.78**	**0.97**	0.14	0.12	**0.96**
4 hours	**3.20**	(0.12)	(0.19)	**3.13**	**3.89**	0.57	0.50	**3.82**

[44] A comparison when the face-to-face respondents are included in the sample are shown in the annexes (See A6.1.1). The difference is very small and not statistically significant..

Note: All values in bold indicate statistical significance at the 95% confidence interval.
Source: London Economics analysis of online survey

2.6.1 VoLL per MWh estimates

The next step is to convert the monetary values per outage estimates into VoLLs in £/MWh. Conversion of the WTA estimates into VoLLs in £/MWh requires:

- A monetary value for a one hour outage (e.g., £6.84 for a one hour outage occurring on a weekend day at peak times during the winter (the value shown previously));
- Hourly electricity consumption for the consumer type and outage scenario (MWh); and
- The VoLL, in £/MWh, will simply be the ratio of these two variables.

We obtained estimates of domestic electricity usage from data provided by DECC. DECC estimates that the average (mean) domestic household uses 3.934 MWh of electricity per year.[45] This is converted into an hourly demand figure for purposes of conversion.

This hourly demand figure is then adjusted depending on the timing of the electricity outage. This adjustment is based on an assessment of domestic electricity demand profiles.[46] This conversion is described in Annex 12 and is based on the mean domestic electricity consumption (3.934 MWh) and domestic demand profiles which vary by month and time of day. For example, more electricity will be demanded at peak times rather than at non-peak times. This is accounted for in our time varying electricity demand estimates.

WTA

The exact demand profile for each of the eight electricity outage scenarios is somewhat simplified as the exact demand usage for our "not winter, not peak, weekend" scenario is an average of 16 hours on two days for nine months. Thus, our estimates using a time-varying demand profile are based on our best estimates using the available data. Table 11 shows the results of applying this time varying electricity profile to the WTA outage estimates derived previously. Applying a varying demand profile reduces the range of VoLL estimates as the scenarios with highest outage values typically have the highest electricity demand, and *vice versa*.

Table 11: Estimates of VoLL in £/MWh under different circumstances, WTA, domestic customers – time-varying demand profile

	Not Winter	Not Winter	Not Winter	Not Winter	Winter	Winter	Winter	Winter
	Not Peak	Not Peak	Peak	Peak	Not Peak	Not Peak	Peak	Peak
	Weekend	Weekday	Weekday	Weekend	Weekend	Weekday	Weekday	Weekend
1 hour £value	**2.76**	**2.08**	**4.16**	**4.84**	**4.77**	**4.09**	**6.16**	**6.84**
£/MWh	**9,550**	**6,957**	**9,257**	**11,145**	**10,982**	**9,100**	**10,289**	**11,820**

[45] DECC (2009) "DECC: Energy Trends: March 2009" http://www.decc.gov.uk/en/content/cms/statistics/publications/trends/trends
[46] Sustainability First (2012) "GB Electricity Demand Project"

Note: Converted based on time varying electricity consumption where the average annual consumption is 3.934 MWh. All estimates in bold are statistically significant at the 95% confidence interval.

Source: London Economics analysis

WTP

The results of applying the time varying demand profile to our WTP estimates are shown in Table 12.

Table 12: Estimates of VoLL in £/MWh under different circumstances, WTP, domestic customers – time-varying electricity demand profile

	Not Winter Not Peak Weekend	Not Winter Not Peak Weekday	Not Winter Peak Weekday	Not Winter Peak Weekend	Winter Not Peak Weekend	Winter Not Peak Weekday	Winter Peak Weekday	Winter Peak Weekend
1 hour £value	**0.80**	(0.03)	(0.05)	**0.78**	**0.97**	0.14	0.12	**0.96**
£/MWh	**2,766**	(101)	(105)	**1,805**	**2,240**	315	208	**1,651**

Note: Converted based on time varying electricity consumption where the average annual consumption is 3.934 MWh. All estimates in bold are statistically significant at the 95% confidence interval.
Source: London Economics analysis

2.6.2 WTA and WTP for different domestic consumer groups

As a sensitivity check, we also split our sample into different sub-groups according to various demographic and qualitative survey variables. The full analysis of this is given in Annex 10. The results of the analysis by different sub-groups are largely as expected.

Respondents who indicate that an electricity outage would have a 'high impact' tend to have the largest WTA and WTP estimates. These respondents represent only about 25% of the domestic sample and thus the baseline estimates are driven by respondents who claimed that an electricity outage would have a 'low impact'. These respondents do have a WTP that is lower than the baseline and significantly lower than the 'high impact' group.

The qualitative variable "being off the gas network" was the other qualitative variable that was used as sense check. There are intuitive priors that this group should be willing to pay more to avoid an electricity outage than households on the gas network, as they are unlikely to use gas for cooking[47] or heating. Our results (for both WTA and WTP) indicate that this is the case and this group of respondents have higher levels of WTA and WTP than the baseline.

[47] Cooking can still be done with bottled gas.

Our sensitivity analysis also indicates that income does not appear to be a key driver in explaining the differences in the levels of WTA or WTP. However, the results do indicate that respondents with 'low incomes' tend to require lower payments.

2.6.3 VoLL estimates using a contingent valuation methodology

This subsection presents a short description of the results of the contingent valuation (CV) survey. The CV survey asked respondents directly their valuation of outages. The contingent valuation method was used as a sense check for the results of our choice experiment. The CV questions were also asked after the CE as the CE was the primary method of deriving the WTA/WTP estimates. Further analysis of these results is provided in the Annexes (see A8.1).

WTA estimates

As part of our study, respondents were asked directly what payment they would require to accept a one-hour outage in the winter on weekday at peak times.[48]

Table 13 shows the results of the WTA CV question in terms of standard statistical indicators such as mean, median and standard deviation. This table also shows the importance of removing observations that are substantially higher than the average.

On average, consumers think that a fair payment would be £19.55 to experience a one-hour outage[49] at peak times on a weekday in the winter based on the CV survey. This is significantly higher than the estimate for WTA derived using the choice experiment (around £6.16-£6.84 for this type of outage). However, the average includes all observations including some very high stated values such as £2,000. It is unclear if these were so-called 'non-engagement' choices, or similar, but excluding possible high values and the impact of reducing the variation is shown below. The median is more in line with the CE estimate.

Table 13: Results fair payment to experience a one-hour outage during peak times on a weekday during Winter - domestic consumers

Sample	Average (£)	Median (£)	Max. (£)	Min. (£)	Std. Dev.	Sample %[1]
Full sample	19.55	10	2000	0	100.49	100%
Limited sample: Mean +/-2 std. dev.	12.91	10	201	0	20.66	99%
Limited sample: Mean +/-1 std. dev.	11.84	10	100	0	15.39	99%
Limited sample: Mean +/-0.5 std. dev.	10.50	10	65	0	11.06	97%
Excluding zero responses	23.13	10	2000	1	108.93	85%

Note: 1. Refers to the number of observations in the sample as a share of the full sample.
Source: London Economics analysis of online survey data.

[48] 'Peak times' are not specified in the CV questions and respondents choose their own peak consumption period.

[49] All averages calculated based on contingent valuation responses include both zero value responses and non-zero responses unless otherwise stated.

Willingness to pay

The survey also included WTP CV questions to all respondents similar to the WTA methodology. According to the WTP CV survey results, the average amount that consumers would be willing to pay to avoid a one hour electricity outage occurring at peak time on a weekday during the winter is £6.35. It should be noted that the question has specified that this is a 'once-off' payment to avoid an electricity outage of this type.

As with our analysis of WTA, the arithmetic mean CV WTP may be somewhat unduly skewed upwards by some very large stated CV WTP estimates. We show the impact of omitting some of these large values in Table 14. This brings down the arithmetic mean CV WTP and the standard deviation significantly. Dropping the one observation of £1,000 brings down the average value to £3.61. Limiting the sample further by dropping high observations (that fall outside various standard deviation criteria) leads to a range of £2.52 to £3.04. It must be noted that even the narrowed-range CV WTP results give a higher pound value than our choice experiment results, which indicated a WTP of around £1 for an outage of this type.

Well over 50% of the respondents indicated that they would not be willing to pay extra to avoid this specified electricity outage; the median value is £0. Finally, excluding the zero responses increased the average WTP to £16.74, which appears to be quite high, given our previous analysis of both the CV WTA and CE. Thus we believe the estimate of WTP using the contingent approach should include zero observations.

Table 14: Results willingness to pay for a one hour outage at peak times on a weekday during Winter- domestic consumers (bands)

Sample	Average (£)	Median (£)	Max. (£)	Min. (£)	Std. Dev.	Sample %[1]
Full sample	6.35	0	1,000	0	48.93	100%
Limited sample: Mean +/-2 std. dev.	3.61	0	100	0	9.85	100%
Limited sample: Mean +/-1 std. dev.	3.04	0	50	0	6.82	99%
Limited sample: Mean +/-0.5 std. dev.	2.52	0	30	0	4.79	98%
Excluding zero responses	16.74	5	1000	1	78.38	38%

Note: 1. Refers to the number of observations in the sample as a share of the full sample.
Source: London Economics analysis of survey data.

2.7 VoLL estimates for SME electricity users

This section provides results for estimated WTA and WTP for SME electricity users. Estimation results for baseline econometric models of WTA and WTP are provided in Figure 6 and Figure 7.

The results are largely as expected and show that as outage duration increases the likelihood that any given choice scenario is chosen decreases (shown by the negative coefficient on the duration variable). However, the positive coefficient on the duration-squared term for the WTA model shows that this effect decreases as duration increases. This implies that SMEs may find a way to adapt to an electricity outage as its length increases. This squared term is included as it improves the fit and performance of the WTA SME model.

The phrasing of the choice experiment is slightly different for SMEs and weekday is phrased as 'typical work day'. This variable is significant in both WTA and WTP regressions and the negative sign on the "duration*work day" variable indicates that SMEs are less likely to choose an outage that occurs on a typical working day. This is as expected.

In both models, respondents prefer an outage to occur in summer. This result is statistically significant and as expected. The timing of the outage appears to be insignificant in both models. As noted previously, we have specified the exact time period (3pm-9pm) that peak represents. This may not be the peak for a number of SMEs who work the typical business hours of 9am-5pm. Thus, it may not be surprising that this coefficient appears to have no predictive power in determining the choice made.

The final variable in both models is the payment variable. The results of this are as expected. Respondents appear to choose choice scenarios where they would receive a higher 'once-off' payment (a positive sign on the "comp" coefficient). For WTP, SMEs choose options that require them to pay lower additional payments (a negative sign on the "price" coefficient). Both payment variables have been asked phrased "as a % of your annual bill" and thus do not represent exact amounts as per the household survey. The reason for this is that SMEs may have much larger variation in annual electricity bills and thus setting absolute £ levels that are too low or too high could have made the choice experiment unrealistic for a certain proportion of the sample. For this reason, applying the WTA/WTP formulas will give results in percentage terms.

Figure 6: Baseline estimation results of the model for willingness to accept (SME survey)

	Coef.	Std. Err.	z	P>|z|	Lower	Upper
duration	-0.1119	0.054	-2.070	0.038	-0.218	-0.006
duration2	0.0067	0.002	3.501	0.000	0.003	0.010
duration_winter	-0.0238	0.006	-3.845	0.000	-0.036	-0.012
duration_peak	0.0007	0.005	0.134	0.893	-0.010	0.012
duration_workday	-0.0555	0.007	-8.490	0.000	-0.068	-0.043
comp	9.9642	2.146	4.643	0.000	5.758	14.171
dont_know	-3.6893	0.442	-8.344	0.000	-4.556	-2.823

Source: London Economics analysis of SME survey results

Figure 7: Baseline estimation results of the model for willingness to pay (SME survey)

	Coef.	Std. Err.	z	P>|z|	Lower	Upper
duration	-0.0445	0.014	-3.239	0.001	-0.071	-0.018
duration_winter	-0.0145	0.007	-2.140	0.032	-0.028	-0.001
duration_peak	-0.0096	0.006	-1.525	0.127	-0.022	0.003
duration_workday	-0.0222	0.007	-3.245	0.001	-0.036	-0.009
price	-9.0445	1.686	-5.364	0.000	-12.350	-5.740
dont_know	-4.4900	0.217	-20.723	0.000	-4.915	-4.065

Source: London Economics analysis of SME survey results

WTA estimates for SMEs

Estimates of WTA and WTP for SMEs from the CE are derived in the same way as for households in the previous section (i.e., adding the appropriate estimated coefficients). Table 15 provides estimates of SMEs WTA payments to experience one hour outages, on different types of day, at different times within days and for different seasons. WTA estimates that are statistically different from £0 are in bold typeface.[50]

The WTA estimates for SMEs range from not statistically different from 0% to 6.6% of annual electricity bill for an outage of one hour in different scenarios. These percentage estimates are converted to monetary values by assuming an average SME electricity bill of £2,500. The justification and basis for this average SME electricity bill was put forward in Table 8 in section 2.4.2. This implies a range of WTA monetary from £140 to around £165. The key driver is whether the outage occurs on a typical working day or not. The interpretation of the 'typical working day' is left to the individual SME respondents and may occur at the weekend for certain SMEs. These results also indicate that SMEs require higher levels of payment if the outage occurs in the winter rather than in the summer. It appears that SMEs do not require a significantly different payment if an outage occurs during peak hours (3pm – 9pm).

The estimates suggest that SMEs on average require a payment of £165.07[51] in order to accept an interruption of one hour during winter at non-peak times on a typical working day.

Table 15: Estimates of WTA in £ for a one hour outage in different circumstances, – SMEs

	Summer Not Peak Non-work	Summer Not Peak Work day	Summer Peak Work day	Summer Peak Non-work	Winter Not Peak Non-work	Winter Not Peak Work day	Winter Peak Work day	Winter Peak Non-work
1 hour	3.4%	**5.6%**	**5.6%**	3.4%	4.4%	**6.6%**	**6.6%**	4.3%
Implied £ valuation	85.41	**141.16**	**140.42**	84.67	109.32	**165.07**	**164.33**	108.58

Note: The % estimate is the % of the annual electricity bill that an SME would accept to avoid an outage of one hour under the different circumstances. These estimates are converted to monetary values using an assumption of an annual electricity bill of £2,500. All estimates in bold are statistically significant at the 95% confidence interval.
Source: London Economics analysis

WTP estimates for SMEs

This section discusses the results of the WTP experiment for SMEs. The results are largely as expected and indicate a lower level than the comparable WTA experiment. We estimate the WTP for SMEs using the same specification as used in the household WTP analysis. The results of the econometric model are as expected. In this model, we dropped observations that were 'strictly

[50] All confidence intervals (using the delta method) are provided in the Annex.

[51] Note that the difference between peak and not peak is not statistically significant.

dominated'[52] as we believe that these were a kind of 'non-engagement' response, similar to what we found in the household WTP survey.

The WTP estimates for the various choice scenarios for SMEs range from around 2% to 4% of the annual electricity bill. The level of willingness to pay is higher if the electricity outage occurs on a typical workday rather than on a non-work day. The results also indicate that SME respondents would be willing to pay more to avoid an outage that occurs during winter.

Our WTP estimates are typically lower than comparable WTA estimates. The monetary value that SME respondents would be willing to pay ranges from around £49 to £100, whereas the WTA point estimates range from £85 to £165. This is as expected as the both experiments were conducted based on the monetary payment being a 'once-off' event.

Table 16: Estimates of WTP in £ for a one hour outage in different circumstances, – SMEs

	Summer Not Peak Non-work	Summer Not Peak Work day	Summer Peak Work day	Summer Peak Non-work	Winter Not Peak Non-work	Winter Not Peak Work day	Winter Peak Work day	Winter Peak Non-work
1 hour	**2.0%**	**2.9%**	**3.4%**	**2.4%**	**2.6%**	**3.6%**	**4.0%**	**3.0%**
Implied £ valuation	**49.22**	**73.75**	**84.39**	**59.86**	**65.24**	**89.77**	**100.41**	**75.88**

Note: The % estimate is the % of the annual electricity bill that an SME would pay to avoid an outage of one hour under the different circumstances. These estimates are converted to monetary values using an assumption of an annual electricity bill of £2,500. Estimates in bold are statistically significant at the 95% confidence interval.
Source: SME survey

SME versus household VoLLs

It is not surprising that the average value of an electricity outage is significantly higher for SMEs over households. Qualitative evidence indicated that a larger proportion of SMEs felt a one-hour electricity outage would have a qualitatively high impact compared with domestic respondents. 41% of SMEs felt that a one-hour electricity outage would have a 'high impact' compared with only 25% of domestic electricity users.

We would also expect SMEs to be more affected by electricity outages than domestic users for various reasons. This can be thought of in terms of what is lost and can it be replaced. SMEs have less flexibility regarding replacement as staff may only work designated hours and it may be not be possible to make up for lost sales. In contrast, households may be able to postpone the tasks that require electricity or use alternatives that may suffice as short-term substitutes. Also, the VoLL for

[52] 'Strictly dominated' refers to a choice scenario where all attributes are 'better' for one choice compared with the other choice. For example, in a two attribute model of duration and compensation, a choice scenario with shorter outage duration and higher compensation should 'strictly dominate' the other option.

SMEs may be a function of the number of people employed who may all have individual VoLLs which should be aggregated to establish the VoLL of the SME.

In the literature review (Annex 1) we examine the VoLLs for domestic and non-domestic customers. This research indicates that non-domestic customers typically have higher VoLLs than domestic customers (see Table 35 and Table 36 for a comparison).

2.7.1 VoLL per MWh estimates

We next convert the pound value estimates for SMEs to VoLL per MWh figures. This requires estimates of SME consumption. Using the values derived from the annual average electricity bill for SMEs, we show WTA and WTP estimates in £/MWh below.

The estimation of electricity consumption for SMEs requires more steps than the estimates for domestic users. Electricity use by SMEs is typically larger than for domestic customers. As well as this, SMEs tend to pay somewhat lower prices per kWh than domestic consumers. According to our research, there does not appear to be any universally accepted annual average electricity consumption figure for SMEs. Thus, we use estimates based on our survey. We account for differences in electricity consumption across the different choice scenarios in a similar way as to the domestic estimates. The demand profile of SMEs and how it is applied to our mean estimate are discussed in the Annexes (A12.2).

WTA VoLL Estimates in £/MWh

Our estimates of WTA are converted into VoLLs in £/MWh and presented below in Table 17.

Table 17: Estimates of WTA VoLL in £/MWh, – SMEs – using a time varying demand profile

	Summer Not Peak Non-work	Summer Not Peak Work day	Summer Peak Work day	Summer Peak Non-work	Winter Not Peak Non-work	Winter Not Peak Work day	Winter Peak Work day	Winter Peak Non-work
Implied £ valuation	85.41	**141.16**	**140.42**	84.67	109.32	**165.07**	**164.33**	108.58
VoLL WTA £/MWh	37,944	**36,887**	**33,358**	34,195	44,149	**39,213**	**35,488**	39,863

Note: This is converted to £/MWh using an assumed annual consumption of 29.35 MWh. This annual estimate is then adjusted then to account for time varying electricity demand. Estimates in bold are statistically significant at the 95% confidence interval.
Source: London Economics analysis of SME survey

The winter peak SME VoLL estimates are about £35,000/MWh.[53] These estimates are larger than those obtained in the household survey (which were about £11,000/MWh). This is as expected especially in the context of electricity outages that occur during a working day. It is notable that

[53] Note that the estimates for "winter, peak" and "winter, not peak" are not statistically different from each other.

'peak' refers to peak corresponding to the electricity demand peak during the day, and it may be that SME's more likely have peak electricity needs from 9am to 2pm.

It is difficult to interpret the not-significant values, and as a rule non-significant coefficients should not be interpreted. Nonetheless, as these estimates seem reasonable, one interpretation could be that these are our best point estimates of the payment levels for outages occurring at these times, if such an estimate were needed.

WTP VoLL Estimates in £/MWh

Table 18 shows the VoLL estimates in £/MWh for WTP. These estimates range from £19,271/MWh to £27,859/MWh which SMEs are willing to pay to avoid an outage occurring on a workday during winter at peak times.

Table 18: Estimates of WTP VoLL in £/MWh, – SMEs

	Summer Not Peak Non-work	Summer Not Peak Work day	Summer Peak Work day	Summer Peak Non-work	Winter Not Peak Non-work	Winter Not Peak Work day	Winter Peak Work day	Winter Peak Non-work
Implied £ valuation	**49.22**	**73.75**	**84.39**	**59.86**	**65.24**	**89.77**	**100.41**	**75.88**
VoLL WTP (£/MWh)	**21,864**	**19,271**	**20,048**	**24,175**	**26,346**	**21,325**	**21,685**	**27,859**

Note: This is converted to £/MWh using an assumed annual consumption of 29.35 MWh. This annual estimate is then adjusted then to account for time varying electricity demand. Estimates in bold are statistically significant at the 95% confidence interval.
Source: London Economics analysis of SME survey

It is important to note that these VoLL estimates in £/MWh are based on an electricity consumption figure that is derived from our survey. There are limitations with converting this estimate into actual consumption. Firstly, we have only aggregate information on how much each SME pays for electricity on a per unit basis. Thus, individual SMEs may pay lower rates and thus have higher electricity consumption than the average would indicate. However, our results seem sensible and indicate that SMEs consume more electricity than domestic users. We have also compared our results to other recent research on SMEs[54] and our estimate of the average electricity bill for SMEs is broadly consistent with this. We also adjust this annual electricity consumption figure to account for differences in the demand profile for SMEs.

[54] Accent (2012) "Quantitative Research into Non Domestic Customer Engagement and Experience of the Energy Market" Available at http://www.ofgem.gov.uk/Markets/RetMkts/rmr/Documents1/Quantitative%20Research%20into%20Non%20Domestic%20Customer%20Engagement%20and%20Experience%20of%20the%20Energy%20Market.pdf

2.7.2 VoLL estimates for SMEs using a contingent valuation methodology

This section presents a short summary of the results of the contingent valuation questions for SME electricity users and compares the results to those of the choice experiment. This is used as somewhat of a sense check on the results derived using the choice experiment approach. A full analysis is provided in the Annexes (see A8.2).

WTA estimates

The full sample average payment level required is found to be around £612. However, this may be upwardly biased due some large observations. By removing the top 4% of the sample, the sample mean payment required drops to around £205. These results are shown in Table 19 and show the importance of some large observations. However, these large responses are not necessarily erroneous and likely reflect the type of business that an SME is doing.[55] If an electricity outage leads to a complete cessation of production,[56] then the disruption value might be quite large. For these types of SMEs where electricity is so vital, they may already have alternative ways of coping with an electricity outage and thus the payment required should be lower. This provides some justification for removing these respondents who appear to have very large annual electricity consumption.

It is worthwhile to compare these estimates with the estimates derived previously using the choice experiment. Comparable estimates from the choice experiment indicate that typical SMEs require a payment of £165 for a one-hour outage of this type. This result is broadly as expected we believe that the appropriate range of estimates from the contingent valuation approach is between £205 and £328. It must also be noted that the contingent valuation approach allows respondents to choose their own peak usage period.

Table 19: Fair payment to experience an outage lasting one hour at peak times on a working day in the Winter- SMEs

Sample	Mean (£)	Med. (£)	Max. (£)	Min. (£)	Std. Dev.	Sample %[1]
Full sample	612.13	100	65,000	0	3637.69	100%
Limited sample: Mean +/-3 std. dev.	328.49	100	5,400	0	800.18	99%
Limited sample: Mean +/-2 std. dev.	328.49	100	5,400	0	800.18	99%
Limited sample: Mean +/-1 std. dev.	241.62	100	4,000	0	481.94	97%
Limited sample: Mean +/-0.5 std. dev.	205.45	100	2,000	0	328.72	96%
Excluding zero responses	693.51	100	65,000	1	3,865.30	88%

Note: 1. Refers to the number of observations in the sample as a share of the full sample. There are around 28% of respondents who answered this question as 'don't know'.

Source: London Economics analysis of SME survey data

[55] It should be recalled the definition of an SME is by employee numbers. A modern 200MW power station might employ only about 40 FTEs.

[56] We also found that around 23% of SMEs surveyed used electricity in the production process. However, it is not possible to know how important this electricity consumption was in this process.

Willingness to pay

The maximum fair payment to avoid the electricity outage is a once-off payment of £10,000 and for the full sample of respondents who provided a number the sample mean is £104.75. Removing the highest 1% and 2% of observations reduces this mean to £46.81 and £36.04. Thirty-four per cent of SME respondents provided a non-zero response.

Table 20: Fair payment for an outage lasting one hour at peak times on a working day in the Winter- SMEs

Sample	Mean (£)	Med. (£)	Max. (£)	Min. (£)	Std. Dev.	Sample %[1]
Full sample	104.75	0	10,000	0	687.88	100%
Limited sample: Mean +/-3 std. dev.	50.91	0	2,000	0	158.49	99%
Limited sample: Mean +/-2 std. dev.	46.81	0	1,000	0	130.99	99%
Limited sample: Mean +/-1 std. dev.	38.74	0	792	0	97.58	98%
Limited sample: Mean +/-0.5 std. dev.	36.04	0	500	0	88.26	98%
Excluding zero responses	307.21	75	10,000	1	1,153.62	34%

Note: 1. Refers to the number of observations in the sample as a share of the full sample. There are around 12% of respondents who answered this question as 'don't know'.
Source: London Economics analysis of survey data

2.8 Summary of findings - VoLLs for domestic and SMEs

In this section, we have presented VoLL estimates for domestic and SME electricity users. These estimates were derived using a choice experiment approach. This section also showed the results from applying a contingent valuation (CV) approach as a sense check.

For the household sector, a number of broad findings emerged and many of these were as expected:

- WTA estimates were found to be larger than WTP estimates;
- Electricity outages of shorter duration were preferred;
- Electricity outages occurring on a weekday were preferred to outages on a weekend or bank holiday;
- For the WTA model, respondents prefer an outage to occur on non-peak times; and
- Using a CV approach appears to give larger estimates of WTA and WTP than the choice experiment.

Our headline VoLL estimates (in £/MWh) are shown again in Table 21. These estimates highlight the differences in VoLLs across the different choice scenarios.

Table 21: Comparison of WTA and WTP £/MWh estimates by time of outage – domestic customers, based on a time varying electricity demand profile

	Not Winter Not Peak Weekend	Not Winter Not Peak Weekday	Not Winter Peak Weekday	Not Winter Peak Weekend	Winter Not Peak Weekend	Winter Not Peak Weekday	Winter Peak Weekday	Winter Peak Weekend
WTA (£/MWh)	**9,550**	**6,957**	**9,257**	**11,145**	**10,982**	**9,100**	**10,289**	**11,820**
WTP (£/MWh)	**2,766**	(101)	(105)	**1,805**	**2,240**	315	208	**1,651**

Note: The figures are based on figures for a one hour electricity outage. Converted based on an assumed annual electricity consumption of 3.934 MWh per annum but the numbers have been adjusted for different electricity demands across outage scenarios. Estimates in bold indicate statistical significance at the 95% confidence interval.
Source: London Economics analysis of online survey

For the SME sector, a similar approach is adopted and the main findings are as follows:

- WTA is typically larger than WTP especially for outages that occur on a typical working day;
- As expected, SMEs prefer shorter electricity outages but there is some evidence that SMEs may adapt to longer outages;
- SMEs strongly prefer outages to occur on non-working days;
- SMEs are typically indifferent to whether the outage occurs at peak time;
- Summer outages are preferred; and
- The CV approach indicates a higher estimate of WTA but a lower WTP than the choice experiment approach.

The SME WTA results indicate the worst time for an electricity outage, in terms of the level of payment required, would be during winter on a typical working day.

The £ per outage values are converted in £/MWh by dividing by the average hourly electricity consumption of SMEs. The summary results of this conversion are shown in Table 22.

Table 22: Comparison of WTA and WTP £/MWh estimates by time of outage – SMEs, based on a time varying electricity demand profile

	Summer Not Peak Non-work	Summer Not Peak Work day	Summer Peak Work day	Summer Peak Non-work	Winter Not Peak Non-work	Winter Not Peak Work day	Winter Peak Work day	Winter Peak Non-work
WTA (£/MWh)	37,944	**36,887**	**33,358**	34,195	44,149	**39,213**	**35,488**	39,863
WTP (£/MWh)	**21,864**	**19,271**	**20,048**	**24,175**	**26,346**	**21,325**	**21,685**	**27,859**

Note: This is converted to £/MWh using an assumed annual consumption of 29.35 MWh. This annual estimate is then adjusted then to account for time varying electricity demand. Estimates in bold indicate statistical significance at the 95% confidence interval.
Source: London Economics analysis of SME survey

2.8.1 Overall conclusions domestic and SME VoLL estimates

We conclude that our choice experiments have enabled us to obtain as robust as possible estimates of VoLL for domestic and SME electricity consumers in GB.

VoLLs based on WTA for domestic consumers range from about £6,957 to £11,820/MWh, while results for VoLLs based on WTA for SMEs range from £33,358 to £39,213/MWh.

The results for both domestic and SMEs are generally as expected, with WTA estimates typically being larger than WTP figures.

It is also interesting to compare the WTP to the WTA results for each user type. The CE WTP results for SMEs are also about half as large as the WTA results for SMEs, and this pattern is broadly consistent across all time periods. This contrasts with domestic users CEs WTP results, which are on the order of 1/5 to 1/10th as large at the CE WTA results. This may be an indication of SME users taking security of supply and paying for it more seriously, or of a lower 'entitlement' effect for SMEs than for domestic users for electricity security of supply.

The SME results are significantly higher than the domestic figures. This may be down to a number of factors but a key consideration could be the typical workday against a non-working day distinction that is made in the choice experiment. SMEs may also have fewer production substitution possibilities during an outage. They may also face fixed costs that do not change as a result of an outage even though output may be affected. In contrast, households may delay their planned activities or substitute this activity (which may reduce utility but probably not as much as lost output).

3 VoLL estimates for industrial and commercial (I&C) users

This section presents estimates of VoLL for I&C customers using a number of different approaches. First, we consider the gross value added (GVA) or value-at-risk (VAR)[57] approach. This method estimates the VoLL using national statistical data. We analyse this approach making use of detailed data on electricity consumption by different process that highlight possible adjustments that should be made to GVA VoLL estimates. The possible impact of capacity utilisation on VoLL estimates is also examined. We then analyse these data using an econometric approach to adjust the predicted GVA for electricity and factor use.[58, 59]

3.1 VoLL estimates for I&Cs using VAR approach

3.1.1 Introduction

This sub-section presents VoLLs for electricity I&Cs, focusing on the Value-at-Risk (VAR) methodology in particular. This methodology is commonly used in the literature and has been applied to a number of different countries.[60]

The fundamental insight of this methodology is to assume that firms derive value from output and value-added. Firms employ labour, capital, materials and energy as inputs to the production process. In competitive industries, these inputs are paid their marginal value products, which are the market prices for inputs; absent externalities, the market prices reflect the full social value of the inputs. It is assumed that labour and capital cannot be redeployed during some delay or temporary shutdown of the production process. Therefore, the full social value of the service flows from these inputs are lost in the case of an electricity outage. This value can be estimated using Office for National Statistics ('ONS') data on gross value added (GVA). The method for calculating the VoLL is then to take GVA divided by electricity consumption for each sector.

While it is generally believed that the GVA method is a good starting point for VoLL estimation for I&C consumers, the method has recognised drawbacks as it can often give surprisingly high VoLL estimates for some industries with low electricity usage (a similar finding was found in the same approach to gas VoLL—see London Economics (2011)).

Previous value-at-risk calculations have assumed that that an electricity disruption would result in a total shut down of each industry segment and consequent loss of 100% of the Gross Value Added (GVA) generated by that sector. The present report challenges this assumption and investigates the extent to which electricity is used for critical production process applications and for less critical uses such as lighting and space heating in factories and offices. The approach has been limited to a desk top study but attempts to get beneath the level of macro GVA and

[57] This is not to be confused with the VAR methodology for measuring portfolio value risk which is used for investment funds, hedging and financial engineering applications.

[58] All results undertaken at the sectoral level are displayed in the Annexes. In this section, we present the headline numbers and how these differ to the GVA/VAR method.

[59] We also used the real-options approach which analyses VoLL for selected very large electricity users. The real options approach is similar to the real options approach used in our gas VoLL study (London Economics, 2011). These results are found in the Annexes.

[60] See De Nooji et al. (2007) for one of the first applications of this methodology in the Netherlands.

electricity consumption statistics to better understand the degree to which production is sensitive to electricity supply availability.

3.1.2 Value-at-risk (VAR) VoLL estimates

Value-at-risk (VAR) is one methodology that has been commonly used to estimate the VoLL for electricity in industry and other sectors. The VoLL for each industrial sector can be estimated as follows:

$$VoLL_i = GVA_i / EU_i * £/MWh$$

Where:

- VoLL = Value of Lost Load
- GVA = Gross Value Added (£ million per year)
- EU = Electricity Use (MWh per year)
- *i* is a subscript used to determine the different industrial sectors

The Value-at-risk methodology (or the GVA method) has the useful feature of being readily calculated from existing Office for National Statics (ONS) and DECC data. GVA data can be sourced from the ONS and energy use (including electricity use) can be sourced from the Digest of UK Energy Statistics (DUKES). These data are available from 1995-2011.

Value of Lost Load using the GVA/VAR approach

In this section, we present our unadjusted estimates of VoLL based on the value-at-risk method described previously. These estimates are based on 2011 data.

The estimates of VoLL resulting from dividing GVA by electricity consumption are shown in Table 23. The VoLL results are in £/MWh and the overall weighted average is £1,654/MWh.[61] At the sectoral level (see Table 106), this method produces a wide range of estimates. The highest VoLL is found for the Tobacco products sector which is estimated to have a VoLL of £12,336/ MWh. The lowest estimate is for the manufacture of basic metals sector and this is found to be £423/MWh. This disparity seems somewhat counterintuitive, since tobacco products production does not readily come to mind as an industry where electricity is critical to production or where VoLL should be particularly high.

Some possibly logical explanations for the counterintuitive results from the straight GVA method are highlighted by undertaking a sectoral analysis. The sector with the largest VoLL has the lowest electricity consumption. This suggests that an outage will have a bigger impact, at least per unit of electricity consumed, on this sector rather than other high electricity consuming sectors. Conversely, sectors with high levels of electricity use (e.g., basic metals) appear to have relatively low estimates of VoLL.

[61] The average figure (£1,654/MWh) is calculated by summing up all the GVA estimates and dividing by total electricity consumption.

Table 23: Estimate of electricity VoLL, 2011

	Total GVA £/yr (millions)	Total Elec. use (MWh 000s)	Unadjusted VoLL (£/MWh)
Total	177,395	107,228	1,654
Total (manufacturing - 10-32)	148,028	98,248	1,507

Source: London Economics analysis

Value of Lost Load accounting for 'critical' electricity consumption

In order to adjust the straight GVA/consumption VoLL figures, we examine possible 'critical' values for electricity consumption. The notion is that only some portion of output and thus GVA is critically dependent on electricity consumption of a certain type. These estimates are based on the best current publically available data. These 'critical' values will give an indicative estimate of how much of electricity consumption is actually critical to the production process.[62]

Every sector will typically have different processes which may be deemed 'critical' to the production process. For example, a process like refrigeration is much more important for a sector such as food manufacturing than for textiles. This point is particularly important when the source of energy for these critical processes is considered. Thus, the potential loss of output (loss of GVA with lost load) may be very close to 100% in a sector where 100% of its industrial processes are refrigeration and this refrigeration is electricity dependent. This would be especially evident for perishable food products.

Conversely, many electricity processes may not be critical to the production process. For example, 'space heating' may only be needed to keep the facility warm but this warmth does not have significant impact on output and thus on GVA. A similar argument may be made for lighting. Thus, a temporary electricity outage for an industry that only uses electricity for say, lighting, might have a very limited impact on output. We can then say the electricity is not 'critical' for production.

We quantitatively examine the 'critical' production of individual sectors making reference to the different industrial processes. We examine two different scenarios and how these impact on the estimate of 'critical' electricity consumption. The scenarios that we analyse are:

- Scenario (1) critical: All electricity consumed for space heating, lighting and 'other' purposes is assumed to be non-critical to the production process; and
- Scenario (2) critical: As per scenario 1 except we assume that 50% of electricity consumed for motors is non-critical.

Every sector may have different compositions of 'critical' electricity and thus we have adjusted the percentage of critical electricity production by sector using the data available and the two scenarios described above. The results are found in the table overleaf.

[62] These data are available by individual fuel and process type from 2006-2011.

The estimates of the 'critical' electricity consumption appear to make sense. For example, a sector with very high electricity consumption (such as the manufacture of basic metals) uses the majority of its electricity inputs for critical processes. Similarly, this is also true for sectors involved in the manufacture of food and beverages where around 80% of electricity consumption may be deemed 'critical'. Sectors like the manufacture of leather products, the manufacture of wearing apparel and the manufacture of textiles all have a 'critical' electricity consumption of around 50%.

The intuition behind this analysis is that sectors with a high level of 'critical' electricity consumption should have VoLL estimates that are close to levels derived using the GVA/VAR method.

The results of applying these two possible scenarios to our previous VoLL estimates are shown in Table 24. As discussed previously, these will reduce the estimate of VoLL unless it is found that 100% of electricity consumption is used for 'critical' industrial processes. Applying the more conservative Scenario 1 indicates that the GVA/VAR approach may overstate VoLL by around 20%. However, when we assume that 50% of electricity consumed for motors is also non-critical, it is possible that the VoLL is overstated by as much as 35%.

Table 24: VoLL Estimates range £/MWh

	Unadjusted VoLL (£/MWh)	Scenario (1) - VoLL (£/MWh)	Scenario (2) - VoLL (£/MWh)
Average	2,750	2,230	1,766

Note: The average refers to the sum of VoLLs for each sector divided by the number of sectors.
Source: London Economics analysis

Low capacity utilisation

Another possible reason put forward to indicate that the GVA/VAR method may overstate VoLL relates to capacity utilisation within the sector. The GVA/VAR method implicitly assumes that firms are operating at 100% capacity because lost load is assumed to impact GVA in proportion to the annual ratio. Thus, any loss in output cannot be made up in future periods as the firm cannot exceed 100% capacity. However, typically firms may not produce at 100% capacity and may be able to adjust capacity levels in future periods. Therefore, lost output from an outage could be simply produced later. Thus, if this is possible, then the GVA/VAR method will overstate the VoLL. An important adjustment for the VAR method could thus be for capacity utilization.

To adjust the VoLL estimates for capacity utilization, we have adopted the following method:

- We establish the maximum ratio of outputs to variable inputs in any one year of the last 10 years;
- Assuming the maximum output over variable inputs represents full capacity utilisation, a theoretical capacity figure can be estimated for the other time periods;
- The ratio of the actual output to this projected output figure will be the estimate of capacity utilization; and
- The VoLL is then adjusted downward for this percentage capacity utilisation.

Capacity utilisation will differ significantly by sector and it is often difficult to establish industries that are operating close to capacity. These estimates are based on publically available data and are indicative estimates based on data at the sectoral level rather than at the firm level. There may be significant constraints on firms that mean that they cannot realistically increase production to a level that corresponds to 100% capacity. There may also be other factors that lead a production outage becoming an unrecoverable loss in production.

Using this method, the average capacity utilisation factor is estimated to be 91%. This figure indicates that VoLL estimates using the GVA method may overstate VoLL by circa 10%.

Table 25: Estimate of electricity VoLL (applying a capacity utilisation factor)

	Unadjusted VoLL (£/MWh)	Capacity Utilisation	Adjusted VoLL (£/MWh)
Capacity Utilisation[63]	1,654	91%	1,505

Source: London Economics analysis

It should be highlighted that these figures are indicative and there may be significant variation at the firm level within sectors. The most relevant point from a VoLL perspective is that lost output (loss in GVA) may not be permanent. Firms may have means of increasing capacity in subsequent periods which can replace the loss in output due to an electricity outage. When this is the case, the value of loss load (VoLL) will typically represent an overestimate.

Regression analysis

An alternative to the previous adjustment methods is to use a statistical method to 'predict' the change in output given a change in electricity input. This would represent another alternative estimation method to calculate the change in GVA associated with a loss of electricity. Using the dataset constructed, we analysed estimates of VoLL in an econometric framework. (A more detailed analysis (including regression results) of these econometric results is presented in the Annexes (see A13.1.6).)

The key variables that we examined in our econometric analysis were employment and non-electrical energy consumption. Other possibly important explanatory variables were also considered and analysed in the Annex.

The GVA method often indicates that sectors with higher levels of employment typically have larger VoLLs. This is evident in sectors such as the construction sector. Thus, it is useful to establish the statistical relationship between employment and electricity VoLL. Using various econometric techniques, we find a positive and statistically significant relationship between employment and VoLL. This result indicates that sectors with large levels of employment appear to have larger estimates of VoLL, on average.

[63] We do not believe that it is possible to add the 'critical' electricity and capacity utilization together to form another scenario. This is because we do not have information on what portion of capacity utilization that is not being served is accounted for by 'critical' electricity or vice versa.

Industrial sectors with larger levels of non-electricity energy consumption appear to have lower estimates of electricity VoLL. This result is statistically significant across the various econometric models. This appears somewhat consistent with prior thinking. Sectors that are largely dependent on non-electrical energy for production, should be not be severely affected by an electricity outage (i.e., have a low VoLL).

Modelling of VoLL in the production function context

As discussed previously, VoLL is based on the equation (VoLL=GVA/E). The GVA component of this formula can be derived using a production function.

$$\ln(Q) = \alpha + \beta_1 \ln(M) + \beta_2 \ln(K) + \beta_3 \ln(L) + \beta_4 \ln(E)$$

The equation above is a Cobb-Douglas production function where the cost of electricity consumption has been separated from the intermediate inputs (M). This equation represents the linearized version where the log of each variable is taken. This model can be estimated using regression analysis. A key assumption of the Cobb-Douglas production is that the sum of the regression coefficients equal unity.

Econometric predictions of VoLL

We can also use this Cobb-Douglas model to 'predict' a value of VoLL for each industrial sector. The table below shows the headline predictions of a Cobb-Douglas model where electricity has been included as a separate production input. The 'unadjusted VoLL' estimates below refer to the estimate of VoLL that is derived using the GVA/VAR approach (GVA/electricity consumption).

Table 26: 'Predicted' levels of VoLL using a Cobb-Douglas production funciton approach

	VoLL (predicted) (£/MWh)	Unadjusted VoLL[64] (£/MWh)	% predicted
Total (average)	2,846	3,602	79%

Source: London Economics analysis

The results using a Cobb-Douglas production function indicate that the GVA/VAR method may overstate VoLL by around 20%. However, it is important to examine the variation by sector. For example, the econometric approach suggests that the actual level of VoLL for the Civil Engineering sector is significantly higher than the predicted estimate.

The estimate of VoLL using a production function approach may be sensitive to the choice of production function used. Initially, we have used the standard Cobb-Douglas production function which does not allow for an elasticity of substitution between inputs that differs from unity. The Cobb-Douglas production function also assumes constant returns to scale. This may be an important issue in the context of VoLL. Thus, we also estimate an alternative, the 'translog' production function model. We use this model to predict the levels of GVA using electricity as a

[64] Note that the unadjusted VoLL is simply GVA/electricity consumption for each sector overall years of the sample. It should not necessarily match the headline summary figures which use 2011 data.

production input along with labour and capital. We then divide this prediction of GVA by electricity consumption to obtain VoLL.

At the average, using a 'translog' functional form appears to indicate a better fit with the actual (unadjusted) level of VoLL.[65] On average, the model indicates that the GVA/VAR method typically overstates the level of VoLL by around 10%. In contrast, using a Cobb-Douglas function indicated the GVA/VAR approach overestimated VoLL by around 21%.

Table 27: Estimates of 'predicted' VoLL using 'translog' production function model with constraints

	VoLL (predicted) (£/MWh)	Unadjusted VoLL (£/MWh)	% predicted
Total (Average)	**3,207**	**3,602**	**89%**

Source: London Economics analysis

3.1.3 Conclusions on the use of the GVA/VAR method in estimating VoLL

In this section, we have estimated the VoLL of I&C consumers using the GVA/VAR approach. We have also examined a number of aspects that may impact on the VoLL using the GVA/VAR approach, and provided adjusted estimates accordingly. The key issues that we have assessed are:

- 'Critical' electricity consumption; and
- Capacity utilisation.

A number of key findings emerged including:

- It appears that a number of sectors with high electricity consumption relative to GVA use a large proportion of electricity for processes that are 'critical' to the production process. These types of sectors may have an actual VoLL that is very close to the VoLL estimate using the GVA/VAR method.
- Industries with lower levels of capacity utilisation may be able to 'ramp-up' production in subsequent periods to the electricity outage. If this is possible for various industries, then the VoLL using the GVA/VAR approach will be an overestimate.

Our econometric results indicated the following:

- Industrial sectors with larger levels of employment tend to have larger, on average, estimates of VoLL.
- Industrial sectors with larger levels of non-electricity energy consumption appear to have lower estimates of electricity VoLL.
- Modifying the traditional production function to include electricity consumption as an input indicates that electricity consumption has a positive impact on output. These production function models suggest that the reduction in output would be less than if using the GVA/VAR approach.

[65] In this context, 'actual (unadjusted) VoLL' refers to the estimate of VoLL derived using the GVA/VAR method.

The headline figures of this analysis are presented in the table below. The predicted percentages from the models are used to compare against the recent estimate of VoLL in 2011.

Table 28: Comparable analysis of VoLLs using the GVA/VAR method

Method	VoLL (£/MWh)	% share of VAR approach
GVA/VAR approach	1,654 (unadjusted VoLL)	100%
'Critical' electricity consumption[66]	1,075	65%
Capacity Utilisation	1,505	91%
Econometric production function (Cobb-Douglas)	1,290	78%
Econometric production function (Translog model)	1,472	89%

Note: The VoLL estimates presented in this table are the average of all sectors considered. Details analysed at a more disaggregated breakdown is provided elsewhere.
Source: London Economics

I&C versus SME VoLLs

The VoLLs for I&C customers are significantly lower than for SMEs. This is intuitive as a) large users use more electricity per unit of GVA than small business, and this impacts the VoLL/MWh. Further, large customers may self-supply or have onsite back-up equipment when production is load-critical, and this will limit the VoLL for large customers. Finally, when assessing various policy parameters and the impacts of VoLL, the importance of industry would in some cases be best weighted by load, so larger users, although having lower VoLLs, would get a larger weight in calculations such as estimating efficient levels of aggregate capacity.

Overall conclusions and I&C versus SME VoLLs

Overall, the VoLLs for I&C customers are about £1,400/MWh taking the simple arithmetic mean of the figures above. In this section, we have analysed a number of possible improvements to the GVA/VAR methodology that is typically used to estimate VoLLs for I&C customers. Although, we believe that the adjustments to the methodology improve the derivation of VoLL for I&C customers, it is not straight forward to indicate which method is the most appropriate. However, we believe that the 'translog' production function may be the most appropriate in terms of estimating the VoLL for I&C electricity customers. This method allows for the possible substitutability among production inputs which may be important in the analysis of VoLL. This model is also consistent with the theory behind VoLL. As noted previously, this model indicates that the GVA/VAR approach leads to about a 10% overestimate of VoLL for I&C electricity users.

[66] We do not believe that it is possible to add the 'critical' electricity and capacity utilization together to form another scenario. This is because we do not have information on what portion of capacity utilization that is not being served is accounted for by 'critical' electricity or vice versa.

4 Estimating a cost for voltage reduction

This section examines the potential cost to consumers of System Operator (SO) directed action to reduce demand. When the SO requires directed action to reduce power demand they will typically start with a reduction in voltage. In this chapter we will examine the potential costs to consumers resulting from such voltage reductions as directed by the SO.

4.1 Introduction to estimating a cost for voltage reduction

At the time of a power emergency or situation where there is insufficient supply versus demand, it is possible within the Grid Code that the SO may direct distribution network operators (DNOs) and other large users to reduce demand. Besides large users who might have interruptible loads, traditionally the DNOs reduce demand first by reducing the voltage and then, if necessary, by demand disconnection. According to information supplied by National Grid for Ofgem's Electricity Capacity Assessment Report 2013[67], around 500MW of demand reduction may be achieved through voltage reduction.

Great Britain, we understand from discussions with National Grid, holds statutory limits on the nominal supply voltage of +10% to -6%[68]. This means that the declared electricity supply of 230V could theoretically be anywhere from 216.2V to 253V depending on local conditions.[69]

In this section of the report we will focus on three areas of cost implications of voltage sags occurring during a power emergency:

1. Cost of power quality protective equipment found in households (surge protectors).
2. Opportunity costs arising from restarting or resetting of household appliances (PCs, clock radios/clocks) that shutdown due to voltage sags.
3. Costs associated with having to replace household appliances more often than their expected useful lifetime due to damage from voltage variations.

There is significant debate surrounding whether voltage sags cause damage to household equipment, much of the research and commentary in this area is qualitative and there is little substantial evidence proving either conclusion. It appears that it is unlikely that voltage sags experienced by households in the UK will have a significant damaging effect on household equipment, however, we will assume for the purpose of this study that there may be some small cost of voltage sags to equipment in the household. Many modern day appliances have regulating power supplies which automatically adjust their power usage for voltage variations within certain limits. However, in order to achieve this, the device needs to draw more current to compensate for any voltage reduction. The result of this can be added heating of the appliance. It is this

[67] http://www.ofgem.gov.uk/Markets/WhlMkts/monitoring-energy-security/elec-capacity-assessment/Documents1/Electricity%20Capacity%20Assessment%20Report%202013.pdf]

[68] Voltage limits (amongst other things) are set out in the Electricity Safety, Quality and Continuity Regulations (ESQCR). Paragraph 27(3)(b): In the case of a low voltage supply, a variation not exceeding 10 per cent above or 6 per cent below the declared voltage at the declared frequency;" : http://www.legislation.gov.uk/uksi/2002/2665/regulation/27/made: http://www.legislation.gov.uk/uksi/2002/2665/contents/made

[69] http://www.spenergynetworks.co.uk/power_loss_emergencies/voltage_queries.asp?NavID=14

overheating, up to certain limits, as well as repeated heating and cooling, which may cause damage to many appliances and devices.[70]

As the SO will reduce demand using directed voltage reductions, it is thus clear that the initial costs to consumers of a power emergency will not be in terms of completely 'lost load', i.e., an outage, but *could be due to* reduced 'quality' of electric power supply, e.g., via reduced voltages. However, what the exact behaviour of voltages and other power quality parameters would be during a power emergency, given that DNOs have reduced voltages by the maximum, is a relatively unexplored area. We thus provide broadly indicative analysis given what data are available. As the cost and thus value to consumers of SO directed demand reduction actions will be uncertain, we will examine the cost implications using a variety of methods.

First, we consider the cost of protective equipment installation. GB consumers have the option of installing protective equipment that would likely protect equipment in the case of voltage variations. It is noteworthy that the impact on equipment can be either from the sag in voltage or from the surge in voltage as the voltage is indeed increased.

Next, we consider the impact on consumers from the possibility that devices such as devices with a clock or computers, simply 'shut down', and must be restarted or reset by the consumer.

Finally, we consider the possibility of added wear and tear on appliances and devices of a typical household and any cost implications from such damage.

4.2 Cost of protective equipment

This subsection discusses the potential cost of SO directed actions, specifically voltage reduction by assessing the value placed by households on security of supply. Indicative estimates of these costs can be found in A15.1. There is little substantial quantitative research on this topic available and as such all estimated should be viewed with caution. The methodology employed looked at the value of surge protection per MWh by estimating the value placed on protection through the purchasing of household surge protection equipment. This approach has a number of potential issues which are discussed below.

Firstly, there is a wide range of cost and quality of power protection equipment available to consumers (both domestic and SMEs). It is possible or likely that equipment purchased may cover a range of power quality issues. Secondly, consumers may even purchase equipment that actually lowers voltages within limits as a means of energy savings. it is possible that consumers are not aware of the damage such power quality events can cause to their home appliances and equipment and therefore will not spend an appropriate amount to protect themselves. This would cause any figure based on consumer spending on protective equipment to likely underestimate the actual cost. However, consumers may tend to be more aware of potential damage from surges versus sags, and data on the cost of such equipment is also more readily available. Next, the capital costs required to set up what could be considered as adequate protection may defer consumers from investing properly is such protection. This problem would again lead our estimate

[70] http://www.sollatek.com/pdf/Poster/AVS%20Advertorial.pdf

to be undervaluing the true cost. Another area of concern is that our valuation of equipment prices has been for standard surge protection equipment. Equipment that would boost voltage or filter out sags and other power quality problems could be more expensive, but the sophistication of this equipment means that few household consumers would likely fully understand the costs and benefits, and thus would be unlikely to spend more for better power quality improving equipment. Finally, consumers may not be fully aware of the probability of such events occurring and therefore causing damage to their household appliances. In this case consumers may be taking a risk with a size that they are incorrectly valuing. It could be that consumers are overspending or under spending on protection depending on whether they are over estimating or underestimating the likelihood of such an event. Our indicative estimates of this potential cost can be found in A15.1.

4.3 Induced shut down costs

As discussed previously, SO-directed actions will cause low voltages for time periods typically twenty minutes to several hours. This may impact machinery and devices in a variety of ways. We will, in this section, investigate the possibility of low voltages causing household appliances to shut down and explore any costs associated with shutdowns of this kind.

In this subsection we will explore the voltage sags required to induce a shutdown in domestic appliances. We will explore the immunity typical household devices have to shutting down due to voltage sags. It is important to note from the offset that voltage reduction outside the statutory limits is extremely unlikely and in the event of it occurring it will unlikely be to a degree over a 6% drop.

Voltage sags will vary by either depth or duration. The depth of a voltage sag refers to the % of nominal voltage retained during the sag. For example, a voltage sag of depth 70% refers to a sag which retains 70% of the system's nominal voltage (for a 230V system this would be 161V). The duration of a voltage sag refers to length in time of a voltage sag, they are usually measured in cycles. The number of cycles per second is literally the frequency at which the grid works on (50Hz systems have 50 cycles per second). In this section we will test how voltage sags of various depths and duration will affect appliances ability to continue operation.

Further, in the case of PCs or clocks shutting down, we will assign a cost to the time spent restarting/resetting this device as a result of a voltage sag. This subsection will purely focus on the potential cost of induced shutdown while the next section will explore the damage that voltage sags can have on appliances without inducing a shutdown. The damage caused will, however reduce the useful lifetime of domestic appliances and therefore, household will incur a cost of such damage.

First we must define the size of the voltage sags that are likely to occur in managing a supply shortage emergency situation. Our understanding is that the likely voltage reduction requested by the SO will be in the range of 3-6% from the minimum statutory level of voltage. Therefore, as the statutory range of voltage is from +10% to -6% we assume that the maximum % fluctuation will be a maximum of 14% (taken from the midpoint of statutory range). As the research in this area focuses on the depth of the voltage sag (the retained % of nominal voltage) we are looking for results indicating which, if any, domestic appliances will require a restart with a retained voltage of 86%. However, it is very unlikely that this scenario will occur, most voltage reductions will be within the statutory limits and in the case that it goes below it would more likely be a maximum of

6% below. Therefore, while we will examine the effects of a voltage sag of depth 86%, a voltage sag of depth 94% is more likely and will be more relevant to a discussion of potential costs in the event of a shutdown. We will come back to this point further in our analysis. We note that the sag depth developed is merely a scenario, with the assumption that the range is made up of the statutory range plus the voltage reduction[71].

Before examining some of the research in this area it is important to note that while there are many other power quality parameters that will likely impact on device performance, we have focused on the depth and duration (in cycles) of voltage sags. Our understanding is, from the information provided in this area by National Grid, that these two parameters are most important in assessing the potential resetting/restarting costs with induced shut down due to power quality incidents.

A number of papers have studied the likelihood of shutdown for common devices due to voltage sags. The first research study we will examine is the Leonardo Energy paper, 'Effects voltage sag on single-phase domestic and office loads'.[72] The table below contains a summary of the results of the study which tested the effects of voltage sags on domestic equipment. The table below indicates, at the maximum duration contained in the study (60 cycles), the size of voltage sags required to induce a shutdown in each of the devices listed. Note that Y (shaded grey) indicates an induced shutdown and N indicates that appliance did not shut down as a result of the voltage sag.

Table 29: Summary of effects of voltage sag on domestic applicanes study

Device	Voltage sag depth (retained voltage)									
	80%	70%	60%	50%	40%	30%	25%	20%	15%	10%
Computer A	N	N	N	N	Y	Y	Y	Y	Y	Y
Computer B	N	N	N	N	N	N	N	N	Y	Y
Printer	N	N	N	N	N	N	N	N	Y	Y
LCD monitor	N	N	N	N	N	N	N	N	Y	Y
TV	N	N	N	N	N	N	N	N	N	Y
Microwave	N	N	N	N	N	Y	Y	Y	Y	Y

[71] As the scenario includes the statutory range midpoint, then the added SO-directed voltage reduction would be -4% outside the range.

[72] Effects voltage sag on single-phase domestic & office loads(2009), M V Chilukuri, Lee Ming Yong and Phang Yoke Yin.

Note: All incidents above refer to 60 cycles in duration the maximum duration tested in this study.
Source: Effects voltage sag on single-phase domestic & office loads (2009), M V Chilukuri, Lee Ming Yong and Phang Yoke Yin

The results above show that voltage sags with duration of 60 cycles (or about 1 second)[73] will not cause a shutdown in any of the appliances listed above until that sag reaches at minimum 40% of nominal voltage. As we are looking for effects occurring at retained voltage levels of 86%, this study gives indications that the probability of appliance shutdown at this level is very low.

The next study examined in this area was a study conducted in University Kebangsaan, Malaysia – 'Voltage Sags and Equipment Sensitivity: A Practical Investigation'.[74] This study sought to compare the performance of five PCs of different specifications to the latest industry used power acceptability standards. The two standards compared against are the SEMI F47 issued by the Semiconductor Equipment and Materials International (SEMI) in the year 2000[75] and the ITIC curve of the Information Technology Industry Council (ITIC).[76] Such standards, set for manufacturers of these kinds of product, set the acceptable region of voltage sag levels at which equipment must continue to operate.

The figure below contains voltage sag test results of five PCs against the industry acceptability standards. The figure represents the minimum amount (%) of retained voltage that each appliance could continue to operate under at voltage sags of varying duration (in cycles). The horizontal axis refers to the duration of the sag and the vertical axis refers to the retained voltage (%) of the sag. The curves graphed for each PC displays the minimum level of voltage acceptable for the PC to avoid shutting down at each duration (in cycles) time of the voltage sag in question.

The general result, that all PCS appear to be able to ride through indefinitely[77] if the size of the sag is less than 50% nominal voltage, is consistent with the table discussed above. Therefore, the chances of shutdown at 86% voltage for typical PCs appear to be very low. It is important to note, however, that the maximum sag length used in the study was 50 cycles, which is about one second given the standard frequency of the GB power grid is 50hz +/-1%.

[73] GB and most of Europe operates at 50Hz, whereas the USA and most of North and Central America at 60Hz. At 50Hz 60 cycles would be 1.2 seconds.

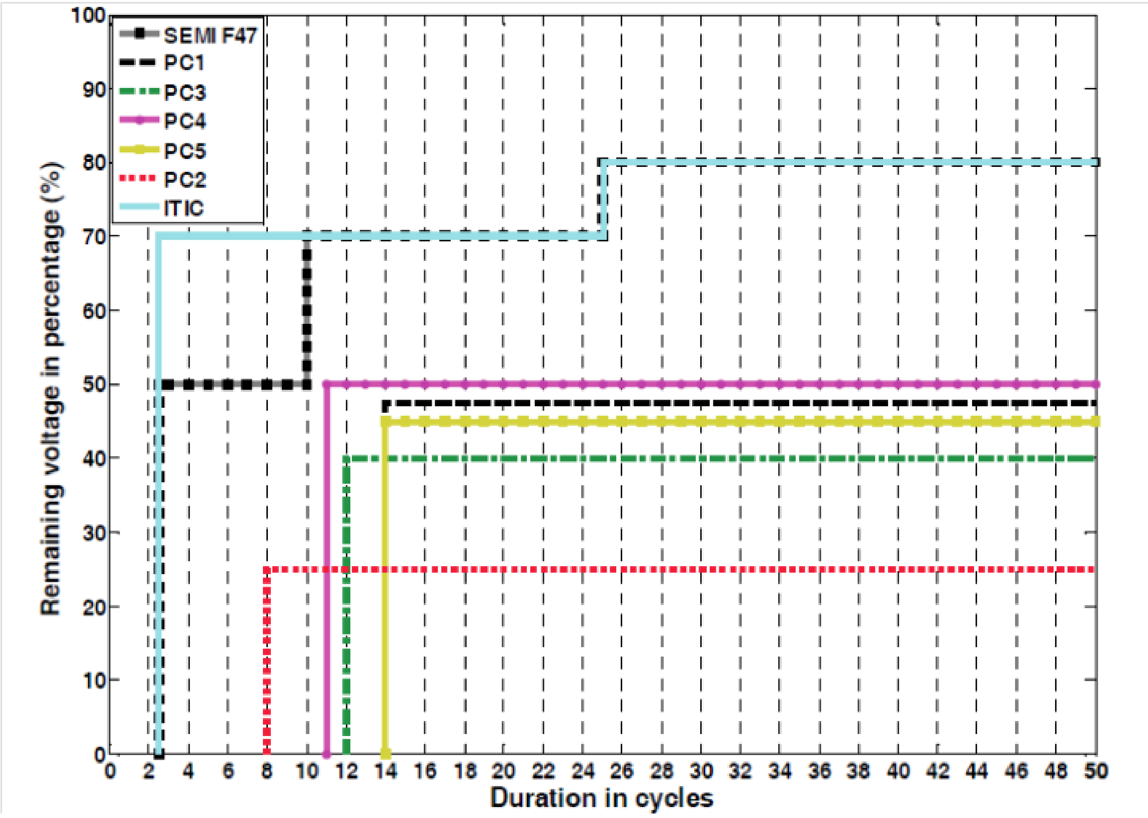
[74] Hussain Shareef, Azah Mohamed and Nazri Marzuki (2010). Voltage Sags and Equipment Sensitivity: A Practical Investigation.

[75] Djokic, S.Z.; Desmet, J. Vanalme, G. Milanovic, J.V. & Stockman, K. (2005). Sensitivity of personal computers to voltage sags and short interruptions.

[76] Kyei, J. Ayyanar, R. Heydt, G.T. Thallam, R. & Blevins, J. (2002). The design of power acceptability curves.

[77] Hussain Shareef, Azah Mohamed and Nazri Marzuki (2010). Voltage Sags and Equipment Sensitivity: A Practical Investigation.

Figure 8: Voltage tolerance curves of tested PCs - Voltage Sags and Equipment Sensitivity: A Practical Investigation



Note: Specifications for each of the PCs tested can be found in the Annex.
Source: Hussain Shareef, Azah Mohamed and Nazri Marzuki (2010). Voltage Sags and Equipment Sensitivity: A Practical Investigation

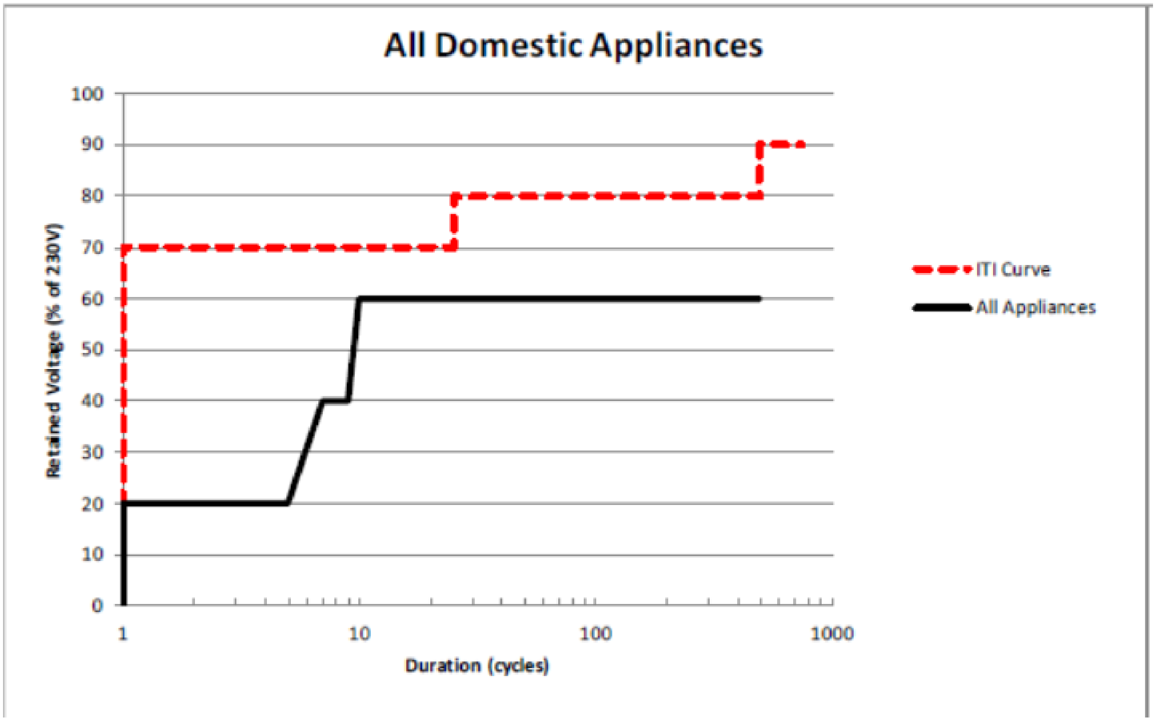
The final study in this area we discuss is the study conducted in University of Wollongong, Australia – 'The 230V CBEMA Curve – Preliminary Studies'.[78] This study, unlike the others discussed conducted voltage sag tests with duration of up to 500 cycles in length. The domestic equipment tested included:

- Televisions
- PCs
- LCD monitors
- DVD players
- Clock radios
- Microwave ovens
- Printers
- Refrigerators

[78] S. Elphick and V. Smith (2010). The 230V CBEMA Curve – Preliminary Studies.

The figure below shows results of the tests and displays a curve that represents the limits of all these domestic appliances. This curve defines the sag immunity for all appliances tested under the 230 V nominal power system. The sag immunity line refers to the minimum level of retained voltage, an appliance could withstand, at varying duration levels, without shutting down. The curves show results very similar to those of the previous studies discussed as it shows that no appliances tested would suffer a shutdown for any voltage sag over 60% of the nominal voltage. This result is strengthened due to the study implementing voltage sags of up to 500 cycles in duration. The ITI curve is a manufacturing watermark for those manufacturing electrical appliances. Therefore, all appliances must at least fit these standards.

Figure 9: Voltage tolerance curves of tested appliances - The 230V CBEMA Curve – Preliminary Studies



Source: S. Elphick and V. Smith (2010). The 230V CBEMA Curve – Preliminary Studies

4.3.1 Indicative analysis

As the results discussed above show, there appears to be little to no chance of induced shutdowns of PCs or clock/clock radio devices when voltage sags occur within the parameters of the likely SO-directed action, according to the studies discussed. This is perhaps due to the fact that most studies are probably interested in 'normal to semi-normal fluctuations' of voltage and power quality impacts for utilities operating for short periods outside of the normal bands.

We would note, however, that the studies found in the existing literature are focused more on short-duration voltage sags under normal conditions, which might last anywhere from a few to 50cycles (50cycles=1second in GB where Hz standard is 50Hz). As can be seen by the figure, the impact of the sag and the depth of the sag increases with duration. In other words, a more shallow sag can have the same impact if long enough. However, the figure seems to indicate that the curve is flat from about 100 to 1000 cycles (about 2 to 20 seconds). It is not clear whether this flat trend can be extrapolated further, but we are informed that the typical SO directed voltage reduction might be about 30 minutes and could last longer depending on the emergency situation.

It is also quite possible that other power quality parameters in general are impacted adversely during a power emergency. So for example, short term voltage sags of a few cycles could occur due to local demand on the distribution grid, as devices automatically increase the current drawn to adjust their operation and hold power constant as the voltage sags. Thus it is quite possible that deeper, very short term sags might occur more frequently or of greater depth during a SO-directed voltage reduction, but we cannot be sure of this based on the information we received from National Grid.

With the information available our best estimate is that costs in this area are very low and most likely zero, but we have included an indicative analysis of resetting/shutdown costs on two appliances that are both commonly found in households and would require time to reset the appliances after a shutdown; PCs and clocks/cock-radios. The breakdown of this indicative analysis is included in A15.2.

4.4 Cost from reduction of useful lifetime of appliances due to SO directed actions

In this final sub-section of the chapter we will explore the potential damage that SO directed actions will have on the useful lifetime of household appliances and the potential costs associated with such damage. To assess the damage voltage sags and power quality issues that come with them will cause, we will examine a range of literature on the issue. In order to assess the cost of such damage, we will use a sample of seven typical household appliances and price them accordingly. We then will use a discounted cash flow ('DCF') model to amortize the cost per year of each appliance over its lifetime. The capital value of any lifetime reduction would be the added future depreciation discounted to present value. All indicative cost calculations can be found in A15.3.

We would note that our analysis is based on a scenario approach of what might occur if power emergencies and voltage reductions were more regular in the future. This would likely be different that the case where voltage reduction was used more purely as an energy saving measure, but there was no power emergency situation.

It is reported that voltage sag events could cause damage by chipping away at the integrity of household equipment in terms of useful lifetime reduction and reduced operating efficiency.[79,80,81] However much of the research and commentary in this area is qualitative and there is little

[79] http://www.homeenergy.org/show/article/id/1002

[80] http://stereos.about.com/od/accessoriesheadphones/a/powerdisturbances.htm

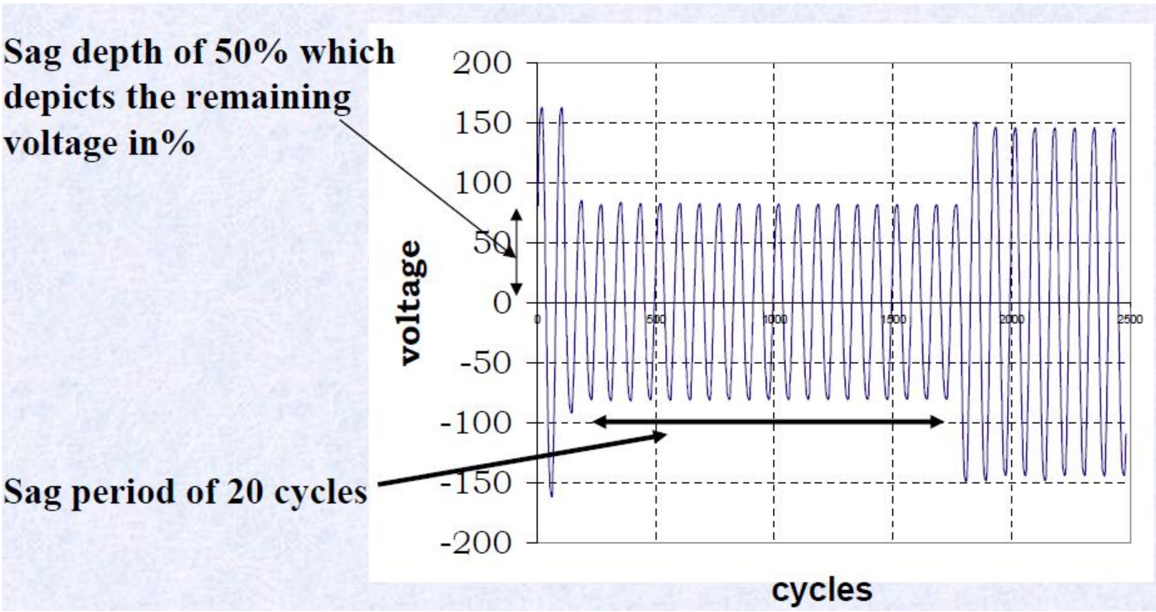
[81] Energy Community Regulatory Board, Council of European Energy Regulators ASBL (2012). 'Guidelines of Good Practice on the Implementation and Use of Voltage Quality Monitoring Systems for Regulatory Purposes'.

substantial evidence proving either conclusion. It appears uncertain that voltage sags experienced by households in the UK will have a significant damaging effect on household equipment.

It is likely that this damage will be more significant in older equipment which may not have thermo-regulators which many modern appliances have. These thermo-regulators automatically adjust their power usage for voltage variations within reasonable limits. However, in order to achieve this, the device must draw more current to compensate for any voltage reduction. The result of this can be added heating of the appliance. It is this overheating, up to certain limits, as well as repeated heating and cooling, which can cause damage to many appliances and devices.[82]

While there appears to be widespread consensus on the negative effects voltage have on induction motors (most typical loads in power system applications) there has been some literature to suggest that household equipment is not damaged by such power quality events.[83] It is possible however that what one defines as a voltage sag may determine the conclusion on the damage one could cause to household equipment. It is useful to examine the figure below which presents pictorially a voltage sag.

Figure 10:Pictorial representation of voltage sag at 50% depth and duration 20 cycles



Source: George G. Karady, Saurabh Saksena, Baozhuang Shi, Nilanjan Senroy (2005). Effects of Voltage Sags on Loads in a Distribution System

According to the *Institute of Electrical and Electronics Engineers* ('IEEE')[84] voltage sag is defined as a "decrease in RMS voltage at the power frequency for durations from 0.5 cycles to one minute,

[82] http://www.sollatek.com/pdf/Poster/AVS%20Advertorial.pdf

[83] George G. Karady, Saurabh Saksena, Baozhuang Shi, Nilanjan Senroy (2005). Effects of Voltage Sags on Loads in a Distribution System.

[84] IEEE Standard 1159-1995, IEEE Recommended Practice for Monitoring Electric Power Quality.

reported as the remaining voltage."[85] Therefore, it is possible that if the definition of a sag goes beyond 3000 cycles (one minute) as is the case of a power system at 50 Hz, the conclusions on the potential damage caused to household electrical equipment could vary. In a Chalmers University of Technology[86] paper there is acknowledgement of the fact that there is no full agreement surrounding the limit of the duration of a voltage sag.

As is clear from the discussion above there is a lot of uncertainty surrounding the damage caused to electrical equipment from voltage sags and whether there is a cost of any significance to consumers coming from having to replace domestic equipment sooner, having experienced a voltage sag. We have included an indicative analysis of these costs, assuming appliance damage from voltage sags as described. This analysis can be found in A15.3.

4.5 Conclusions on voltage control

In this section we considered the cost of SO control directions, focusing on voltage reductions , on consumers. From our discussions with Ofgem and their engineering team, along with our research, it appears that voltage reductions, which comprise of a maximum controlled voltage reduction of 6% that may be additive to a change from the midpoint statutory range (+2%)[87], are unlikely to have much impact on the lifetime or continuing operation of most household equipment. Most studies in this area have focussed on short term voltage sags and surges, which generally look at voltage incidents from 1 to 500 cycles, whereas SO-directed voltage reductions will last minutes or even hours depending on the emergency's specific needs. While it may be possible that the effects of the short term sags and the controlled voltage reductions are additive[88], it has not been possible to obtain any relevant data, as the empirical outcome of various power quality parameters to household customers during a power emergency have not been obtained--likely in part because such events are quite rare.

In addition, some power equipment will function perfectly well with a slightly lower voltage, but the measured consumption will be lower, but with potential reduction in the service provided by the appliance (e.g., dimmer lighting), and thus, in these circumstances, all else equal, there could in fact be a small cost saving to a consumer during a voltage reduction.

Further, it may be the case that as equipment and standards evolve over time, that voltage reductions may have lesser impacts on equipment and appliances. It may be for example, that if reductions become more regular, then equipment is made to operate more robustly (or course the cost then would be in the added cost of the equipment, however). Similarly, some consumers may indeed purchase voltage reduction equipment as an energy saving means. It is not clear how such equipment will operate during a power emergency when voltages are reduced, but we would suggest that such equipment would most likely be designed to deal with the ranges of 3-6%

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[85] We note that the definitions of the sag length and depth are from the study's authors. 90% remaining voltage from the midlpoint of the statutory range would be above a number of the voltages tested in these studies, and so the studies would indicate tests of voltage sags that were outside normal operating conditions.

[86] Roberto Chouhy Leborgne (2005), 'voltage sags characterisation and estimation'.

[87] In other words, (+10% - 6%)/2

[88] In other words, do the sags and other power quality variations typically add to the reductions from the SO-directed actions.

reduction from SO-directed actions. Whether this would be a net benefit then in terms of added voltage protection, energy savings to the consumer, and the cost of the equipment, we have not investigated more deeply, but these raise nonetheless interesting questions for future research.

If the cost of voltage reduction is indeed quite low, and given our previous estimates of VoLL, it would appear that voltage reduction should always be considered as part of the first response to a power emergency. While our results are very preliminary, and more work is needed, however, it might be considered whether indeed voltage reduction should or could be used as part of the more general balancing response of the system. While we are not aware of **SOs** anywhere that currently do this as a standard practice, such possibilities are beginning to be investigated at present. For example, according to DECC Electricity North West's CLASS project with the SO examines this very issue, under Ofgem's Low carbon Network Fund.[89].

With that in mind it is important to view the indicative analysis undertaken as preliminary and to view all results with caution. Empirical research in this area is very limited and needs significant further exploration. We have however identified three potential cost areas of voltage reduction and, in spite of little qualitative evidence; have developed these costs areas as much as possible. Indicative estimates of the potential cost of voltage reductions are included in Annex 15.

It is important to note that the costs estimated in this section are those focused on the power quality parameters of sag duration and sag depth (retained voltage). There are many other power quality parameters or issues such as phase angle and surges as the voltage comes back up. We did not have access to the appropriate data to include this analysis but a more detailed examination of how these parameters relate to the figures presented in this section would be beneficial in the future.

[89] According to expert commentary received by LE from DECC, it may be that DNOs do similar things regularly, but within the statutory limits. We note however, that our focus on the "Actions" are from the SO directing DNOs to reduce voltage, and when we refer to 'balancing' here we are referring more generally to the SO level system balancing.

5 Conclusions

This report provides estimates of the value of lost electricity load in GB for three broad types of consumers:

- Domestic electricity users;
- SME electricity users; and
- Industrial and commercial customers (I&C).

We also undertook desk research into the costs to consumers of System Operator (SO) directed action to reduce demand.

The estimates of VoLL for domestic and SME users are estimated using a choice experiment approach. The results show large variations in the VoLL depending on the type of electricity user and, in the case of domestic and SME electricity users, depending on the characteristics of the electricity interruption. For domestic and SME customers, our VoLL estimates using WTA are typically higher than WTP estimates. This is as expected.

The CE WTA method indicates VoLL estimates of between £6,500 and £11,800 for domestic consumers.

For SMEs, the key variable driving VoLL was workday/not workday, and VoLL on workdays was between £33,000 and £39,000 using the WTA choice experiment.

I&C customers have a wide range of VoLLs, and different sectors show a wide range of variation. Using different methods, the average I&C VoLL was about £1,400/MWh. It is notable that the largest users might have their own generation equipment, their own back-up equipment, or other equipment to ensure security of supply. The largest customers would also be less likely to face constraints for cash and capital outlays, and would likely have better information regarding outage costs, than may be the case for domestic and SME electricity consumers. Thus it is intuitive that the VoLL for larger users should be lower.

Our results also indicate that SMEs have larger VoLLs than domestic customers. These results are particularly different when the outage occurs on a typical working day. This is as expected and consistent with previous research in this area.[90] Both the estimates for domestic and SME users are considerably larger than for Industrial and Commercial (I&C) users.

From a policy perspective, using the WTP figures, which suffer from the well-known downward bias due to 'entitlement' and strategic responses from consumers, would risk setting a security of supply standard that is too low; we concluded that the WTA method was the better approach.

Finally, we calculated a headline VoLL figure using the willingness to accept (WTA) CE results, as a load-share weighted average across domestic and SME users for the winter peak weekday figures (see Table 30 below). Because VoLL is likely to be used to input into security of supply calculations,

[90] See Annex 1 for a discussion of the literature. Also, see Table 35 (domestic) and Table 36 (non-domestic) for comparable VoLL figures.

such as for setting capacity levels and calculating costs in cash-out, but customers who experience an outage cannot in general be identified or stacked, we believe that a weighted-average winter peak workday VoLL is the most appropriate single number for these purposes.

Excluding I&C customers as discussed previously, these calculations yield a headline-weighted average VoLL figure of £16,940/MWh for peak winter workdays in GB.

Table 30: Load-share weighted average across domestic and SME users for winter, peak, weekday

VoLL (£/MWh)
16,940

Note: We have derived this weighted average using a 74:26[91] weighting for domestic: SME. The derivation of this figure is further explained in the annexes (See A16.5).

Source: London Economics analysis

[91] The weight for the domestic (74%) is (total households*annual electricity consumption at winter, peak, weekday)/(total electricity consumption of SMEs and households at winter, peak, weekday). The ratio is calculated as: (total households*average annual domestic electricity consumption at winter, peak, weekday)/(total electricity consumption of SMEs and households at winter, peak, weekday). Data for total households is sourced from ONS and average electricity consumption from DECC.Data for total SME consumption is sourced from SME survey. The number of SMEs is sourced from Datamonitor's Buyer Segment Market Share Monitor (Q4 2012).

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Annex 1 Literature review

This Annex contains a review of the literature of previous non-market valuations to estimate the value of secure supply for electricity.

Firstly the Annex provides a rationale for using a choice modelling approach to analyse VoLL for domestic consumers and SMEs. Secondly, the Annex provides a review of key design features in previous studies. This literature review also includes other various estimates of VoLL in the same units as this study.

A1.1 Stated preference methods: contingent valuation methods or choice experiments

Stated preference techniques are much better suited to the estimation of the VoLL for domestic consumers and SMEs, and is endorsed by the Council of European Energy Regulators (CEER).[92,93] Stated preference techniques are able to give a comprehensive measure of the VoLL, albeit from a hypothetical scenario, even when intangible costs such as inconvenience and discomfort are some of the main costs associated with an outage. Through the use of well-designed questionnaires the complete cost to individuals and small and medium sized businesses can be better uncovered.

Most studies estimating VoLL use either a contingent valuation method (CVM) or a discrete choice experiment (DCE) (also sometimes referred to as choice modelling). CVM seeks to measure willingness to pay (WTP) or willingness to accept (WTA) through direct questions such as “What are you willing to pay?”, while DCE tries to secure rankings and ratings of alternatives from which WTP or WTA can be inferred. Both techniques have been applied in this report. The CVM approach applied in this report is a simplified version of a typical CVM approach which may contain more than one question.

The CE approach is also more appropriate than the CV approach in estimating the value of something that has many different attributes such as an electricity outage.[94] These attributes may also interact with each other and a CVM approach will not be able to capture this. As discussed in the main report, the value of an electricity outage will vary significantly depending on the timing of this outage.

Limitations of CV approach

The contingent valuation (CV) method suffers from several difficulties. Firstly, it is liable to suffer from the problem of “yea-saying”. This can occur for two reasons: either a respondent may try to please the interviewer by saying “yes”, when truthfully they should say “no”; or the individual may say “yes” to a much higher bid than his own valuation as they may feel it is in their own interest to

[92] CERR Guidelines on Estimation of Costs due to electricity interruptions and voltage disruptions.

[93] See also Hanley et al. (2003) for a discussion of why choice experiments are superior to contingent valuation methods when estimating the WTP for environmental goods.

[94] See Mogas et al. (2009) for a discussion of this with relation to forest management programs.

do this, in the safe knowledge that that amount of money will not actually be collected from them. It is also possible that respondents could respond strategically if they believe their response would influence the value placed on the object/good, and if they are reasonably assured of not having to actually pay for it. This is called the 'incentive compatibility problem'. Open-ended contingent valuation designs (e.g., how much are you willing to pay?) can avoid the "yea-saying" problem. However, experts tend to suggest that this causes the respondent to face a more difficult mental task.

A further problem with using contingent valuation in this context is that it is likely to cause some respondents to refuse to "play the game".

Advantages of choice modelling approach

Choice modelling can by-pass this problem by eliciting WTP indirectly through the use of statistical techniques rather than by asking for a direct monetary valuation. With direct monetary valuation questions, there is also the issue of how accurately respondents are able to value the good. Further, choice modelling is generally preferred for estimation of VoLL for different attributes (e.g. duration and season of outage)[95] and the methodology has also been used in many previous studies of security of supply valuations. Choice modelling allows for the estimation of a larger number of possible scenarios using econometric techniques and including interaction effects. In contrast, CVM approaches typically have to specify scenarios more directly.

A1.2 Background to VoLL estimation and various other methods

In general, there are two main ways of estimating the economic value of non-market goods, such as a secure electricity network. The first of these is a direct approach, which includes revealed preference techniques, where individuals or firms reveal their preferences through actual choices made and observed in the real world or via realistic experiments that involve actual expenditure choices. Revealed preference estimates could also use real data on alternatives to electricity used by consumers, for example, the direct cost to a residential consumer of an electricity outage may include the cost of having to use an open fire to heat their house while there is no electricity supply. This type of revealed preference example is based on the assumption that the heat from an open fire is a comparable substitute to the heat from an electric central heating system. The revealed preference may also be the monetary expenditure of an alternative (i.e., a backup generator).

The other most commonly used approach for estimating the economic value of non-market goods such as VoLL is based on stated preference techniques. This is an indirect approach, in which a hypothetical market is constructed and consumers are asked hypothetical questions in order to ascertain the value that they attach to those goods and services. The choice experiment method is

[95] Economic Valuation with Stated Preference Techniques - Summary Guide (Pearce et al (2002) Department for Transport, Local Government and the Regions : London)

one application of this stated preference approach. The benefits of this approach have been discussed above.

Additional methods to estimate VoLL exist, such as the production function approach, case studies and market based behaviour (i.e., analysing investment on backup facilities). Some studies estimate direct outage costs using case studies to estimate actual rather than hypothetical costs of energy outages. An important piece of work in this area is a study for the US Department of Energy on the consequences of the New York Blackout in 1977.[96] Extreme weather events (like the recent hurricane Sandy) can still lead to significant widespread outages. However, this approach suffers from the obvious disadvantages that large scale electricity outages in the UK are relatively rare and that data on the costs of such outages are hard to find, particularly for domestic consumers and SMEs. These outages are not the type that we are really interested in the context of this study. As well as this, outages due to adverse weather conditions are typically correlated with other service losses which also have significant economic costs.

One other approach that may be relevant is to estimate an econometric cost function for the utility operator which allows the estimation of the marginal cost of improved service quality. Such an approach is adopted using UK Data by Jamasb et al. (2012).[97] The main conclusion of this paper is that to achieve the optimal level of customer minutes (electricity outage) would require a 19% increase in the total costs of the utility companies in the UK.

There are a large number of recent studies that use the production function approach[98] to estimate VoLL for household and industrial sectors. This is a more simplistic approach based on aggregate data typically available in national accounts. As discussed previously in the report and in the Reckon[99] study, there are a number of limitations associated with this methodology. This is particularly true with relation to the household sector where this methodological approach typically centres on an assumption regarding households' valuation of leisure time. However, a variant of this approach may be useful to give indicative estimates of VoLL for the industrial sector. The results from this method typically give results that indicate the domestic and small business users have larger VoLLs than I&C (manufacturing) sectors[100]. However, to our knowledge, there is no study that uses a choice experiment to estimate VoLL of a large electricity user. The rationale regarding why I&C users are likely to have lower VoLLs has been discussed elsewhere in this report (see Section 3.1.3).

[96] SCI (1978): Impact Assessment of the 1977 New York City Blackout, SCI Project 5236-100, Final Report, Prepared for the U.S. Department of Energy, July.

[97] Jamasb et al. (2012) "Estimating the marginal cost of quality improvements: The case of the UK electricity distribution companies" Energy Economics Vol. 34 pg. 1498-1506.

[98] De Nooij et al. (2007) 'The value of supply security. The costs of power interruptions: Economic input for damage reduction and investment in networks' Energy Economics 29 pg. 277-295.

[99] Reckon (2012)'Desktop review and analysis of information on Value of Lost Load for RIIO-ED1 and associated work' Report commissioned by Ofgem; available at http://www.ofgem.gov.uk/Networks/ElecDist/PriceCntrls/riio-ed1/consultations/Documents1/RIIOED1ConResVOLL.pdf

[100] See De Nooij et al. (2007) and Leahy and Tol (2011) for analysis that provides sectoral breakdowns of VoLLs. These studies use a production function type approach to estimate all sectors.

A1.3 Advantages and disadvantages of revealed preference methods

Due to the nature and effect(s) of an electricity outage on domestic consumers and SMEs, it is unlikely to be possible to value the burden they would bear using a direct approach and/or by looking purely at other goods and services that they buy as a substitute for electricity.

This indirect VoLL estimation technique has been used in the past[101,102] and VoLL for electricity was estimated by summing the cost of averting behaviour. However, the use of revealed preferences in the present case seems a less accurate option than using stated preference techniques, as it could fail to account for the complete discomfort and inconvenience felt by individuals as a result of an electricity outage, or it might overestimate the VoLL if purchases of other goods and services, that would be useful in the case of an outage, could serve other purposes in the meantime, and the estimates did not account for this.

It is likely that, during an outage, people will be made less comfortable, but that they may do little about it. For instance, if there was to be an electricity outage for a short period of time, many may feel that it is not worth purchasing additional household items and would simply put up with the discomfort resulting from the outage. There may also be costs to consumers of an outage that cannot be mitigated because the alternatives available are not perfect substitutes of consumers' usual energy supply. For example, if consumers buy a portable gas cooker to substitute for an electric cooker, the gas cooker purchased may be intended for temporary use only and, for instance, have a more limited capacity. So, while the consumer is able to cook during the outage, he or she may not be able to cook for as many people or cook very sophisticated dishes. In this example, the gas cooker is not a perfect substitute for the electric cooker and the consumer may derive less 'utility' from using the gas cooker than they would have from using the electric cooker. This case is just one source of potential bias from the revealed preference approach. In this case, this means that the estimates of the outage cost based on revealed preferences would be lower than the true cost felt by consumers.

The direct approach is much better suited to estimating the cost to I&C users of outages, as the outage is likely to affect their production and through that, their profits. Methods, such as the production function technique (GVA/VAR approach) are likely to give a more accurate reflection of the true cost to these types of consumers of an outage, because it can be assumed that under profit maximisation lost production and thus lost gross profits are the cost to electricity users of an outage. As discussed elsewhere in the report, it is important to account for the importance of electricity in the production process when estimating the value of Lost Load using the production method. For example, in the recent Reckon study[103] it is clear that large estimate of VoLL

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101 See for example Kariuki and Allan (1996) 'Evaluation of Reliability Worth and Value of Lost Load', IEE Proceedings- Generation, Transmission and Distribution, Vol. 143, pp. 171-180, and Charles River Associates (2002), 'Assessment of the Value of Customer Reliability (VCR)'.

102 However, as part of this report, we have provided indicative estimates for the likely costs associated with electricity supply and voltage quality.

103 Reckon (2012) 'Desktop review and analysis of information on Value of Lost Load for RIIO-ED1 and associated work' Report commissioned by Ofgem; available at http://www.ofgem.gov.uk/Networks/ElecDist/PriceCntrls/riio-ed1/consultations/Documents1/RIIOED1ConResVOLL.pdf

associated with the construction sector is probably a significant overestimate of VoLL. As noted by the authors and highlighted elsewhere in this report, this is due to the fact that electricity supply has a different impact on production than other sectors in the economy. Applying the production method to sectors with low critical electricity demand typically gives overestimates of VoLL. The production function method can be interpreted as an upper bound estimate which is based on the assumption that firms cannot change their behaviour to an electricity outage. Thus, all value added lost during the outage cannot be made up through storage or increased production in subsequent periods. A more detailed discussion using UK data is included in Section 3.1 of the report.

A1.4 Estimating the value of secure energy supply

There are a number of studies (using different methods) that estimate the value of electricity security. These are summarised in detail in the Reckon study on pp. 21-28 and have been converted to 2012 £ prices for comparability purposes.

We confine our literature in this section to papers that have explicitly used a choice modelling approach as undertaken in this study.

A1.4.1 Willingness to pay or willingness to accept

Theoretically, the VoLL could be equal to both consumers' WTP to avoid electricity interruptions and consumers' WTA payment in the event of disruption. However, in practice the WTP and the WTA are not identical when estimated using survey methodologies. In general, surveys find that the WTA is higher than the WTP. In other words, the maximum amount consumers are willing to pay to achieve a better service is less than the minimum amount they are willing to accept in payment for poor service. Experience suggests that the gap between surveyed willingness to pay and willingness to accept can be very large, particularly with open-ended questions in contingent valuations.

Therefore, this raises the question of whether to design the survey to estimate WTP or WTA. The choice depends on the specific research question. In the case of utility supply, consumers generally feel that they have an entitlement to secure supply and many may be opposed to the idea of having to pay extra to secure their supply. Additionally, given the fact that electricity supply is generally seen as very reliable, consumers may oppose having to pay more to ensure the same level of reliability in the future. Therefore, if we were to base our estimates only on WTP rather than also using WTA to estimate VoLL, we could underestimate VoLL. However, at the same time, we note that WTA may overestimate VoLL in choice experiments and WTP may be seen as a more conservative estimate. Therefore, similar to Bliem (2009), Bertazzi et al. (2005), MORI (1999) and Hartman et al. (1991), we include **both** WTP and WTA for electricity VoLL in our analysis. Table 31 summarises information on which studies estimate WTP or WTA. Most studies only estimate WTP or estimate both WTP and WTA.

We expect that the estimates of WTP will provide a lower bound estimate for VoLL whereas the WTA estimates will provide an upper bound estimate of VoLL. By estimating WTP, we would not obtain a direct indication of whether consumers find the current payment levels appropriate. As shown in Figure 11 and Figure 16, there is generally a poor level of knowledge regarding payment for electricity outage disruptions.

Table 31: Use of WTP or WTA to estimate the value of secure energy supply in previous studies

Study	WTP	WTA
Hartman et al. (1991) [104]	✓	✓
MORI (1999) [105]	✓	✓
Accent (2004) [106]	✓	✓
Layton and Moeltner (2004) [107]	✓	
Bertazzi et al. (2005)[108]		
Accent (2008) [109]	✓	✓
Carlsson and Martinsson (2008) [110]	✓	
Bliem (2009) [111]	✓	✓
Carlsson et al. (2009)[112]	✓	
Hoch and James (2010) [113]	✓	
London Economics (2011) (Gas VoLL)	✓	✓

Source: London Economics

A1.4.2 Presenting price and payment levels

How WTP or WTA is reported varies across the literature (see Table 32). The payment level is usually given as either a cash value for a given time period or as a proportional change in the energy bill. In our choice experiment, we use a combination of both but specific that the additional payment is 'once-off'.

[104] Hartman, R. S., M. J. Doane, and C.-K. Woo, 1991, Consumer rationality and the status quo, Quarterly Journal of Economics 106, 141-162.

[105] MORI, (1999), Quality of Supply: Attitudes of Business and Domestic Electricity Customers, Research Study Conducted for Office of Electricity Regulation (OFFER), January – March, 1999.

[106] Accent Marketing and Research. (2004). Consumer Expectations of DNOs and WTP for Improvements in Service, London.

[107] Layton, D & Moeltner, K (2004) "The Cost of Power Outages to Heterogeneous Households – An Application of the Mixed Gamma-Lognormal Distribution".

[108] Bertazzi, A. et al (2005) The use of customer outage cost surveys in policy decision-making: the Italian experience in regulating quality of electricity supply.

[109] Accent Marketing and Research (2008). Expectations of DNOs and willingness to pay for improvements. A report to Ofgem.

[110] Carlsson, F., and P. Martinsson. (2008). "Does it Matter when a Power Outage Occurs? – A Choice Experiment Study on the Willingness to Pay to Avoid Power Outages". Energy Economics.

[111] Bliem, M (2009) "Economic Valuation of Electrical Service Reliability in Austria – A Choice Experiment Approach".

[112] Carlsson et al., 2009, The Effect of Power Outages and Cheap Talk on Willingness to Pay to Reduce Outages.

[113] Hoch and James (2010). "Valuing Reliability in the National Electricity Market". Report for Australian Energy Market Operator.

In the Beenstock (1996)[114] study, 650 households were surveyed with results given for both domestic WTP to avoid, and WTA payment for, electricity outages in terms of a value ($) per kWh. Results were reported for both WTP to avoid and WTA payment for outages in terms of dollars per minute in Hartman et al. (1991). Whereas Carlsson and Martinsson (2008) reported results as a weighted average WTP to avoid outages, giving results for planned outages and unplanned outages. This paper finds that the WTP increases with the duration of outages and also is higher if the outage occurs at the weekend and during winter months.

An Australian study of business consumers by Energy Australia reported businesses' WTP to have no more than one electricity interruption per year. This study found that 67% of small businesses would pay a fixed quarterly charge of $50 or more to and did not give the results as a proportion of total bill that consumers would be willing to pay. This is not always the case in outage experiments, however, as many studies report both a cash value and a proportion of energy bill that represents the WTP to avoid electricity outages.

For example, a 1999 study by MORI in the UK yielded businesses' WTP for an improved service as 1.5% of the bill and provided estimates of domestic consumers and business' WTA cash as payment for more power cuts. The Accent study (2004) also gave values in terms of a cash payment to avoid outages of different lengths alongside results in terms of a proportion change in the energy bill. Bliem (2009) found that households in Austria require a 16.07% reduction in their current bill to accept a four-hour power interruption. Typically, the size of businesses can vary significantly. Thus, different levels of payment may have very different impacts on different respondents. Very low (or very high) payment levels may make the experiment unrealistic. This is the main rationale put forward for using the percentage of annual electricity bill as the price/payment amount.

Table 32: Price information provided in monetary value or as percentage of energy bill

Study	Monetary value	% of energy bill
Beenstock (1996)	✓	
Hartman et al. (1991)	✓	
MORI (1999)		✓
Accent (2004)		✓
Layton and Moeltner (2004)	✓	
Plaut Economics (2007)	✓	
Carlsson and Martinsson (2008)	✓	
Bliem (2009)		✓
Carlsson et al. (2009)	✓	
Hoch and James (2010)		✓
London Economics (2011)	✓	✓ (only for WTP in SMEs)

Source: London Economics

[114] Beenstock, M & Goldin, E (1996) "Priority pricing in electricity supply: An application for Israel".

A1.4.3 Attribute selection

Choice experiments allow for estimation of the marginal WTP or WTA for different attributes. That is, the results can be used to assess how much consumers would be willing to pay or the level of payment they would require for improvement in services along different dimensions such as the timing and duration of outages. Selection of attributes and attribute levels is therefore important to the design of choice experiments. It should be noted that while a price attribute for security of supply must be included in the choice experiment in order to derive an estimate of WTP or WTA,[115] other attributes included vary significantly from study to study.

Table 33 summarises the non-price attributes included in previous choice experiments analysing the value of secure energy supply.

Table 33: Non-price attributes included in previous choice experiments analysing the value of secure energy supply

Study	Frequency	Season	Timing (time of day or week)	Duration	Planned/ unplanned
Accent (2004)	✓[1]			✓	
Layton and Moeltner (2004)		✓	✓	✓	
Accent (2008)					
Carlsson and Martinsson (2008)	✓[1]	✓	✓	✓	
Bliem (2009)	✓[1]		✓	✓	✓
London Economics (2011) - Gas	✓	✓		✓	

Note: 1) Specified as the number of outages over a fixed year period.
Source: London Economics

Among the other attributes included in the studies, Accent (2004) included improvement in resilience, change in maximum time for restoring consumer power after a storm, change in information during a power cut, and commitment to undergrounding a proportion of the network. Hoch and James (2010) looked at two different choice experiments conducted in South Australia and New Zealand. The choice experiment in South Australia included attributes associated with information provided to consumers regarding unplanned outages, information provided regarding planned outages, voltage fluctuation and future power supply improvements.

Most studies include attributes relating to the frequency, duration and timing of interruptions. It is worth noting that the duration and frequency of interruptions is quite different for gas and electricity outages. Electricity supply interruptions occur more frequently but last for a much shorter period of time. Therefore, Carlsson and Martinsson (2008), for example, allow for multiple outages over a five-year period each with duration of four, eight or 24 hours when estimating marginal WTP for unplanned power interruptions in Sweden. Bliem (2009) even considers power cuts lasting three minutes and a frequency of up to 10 times per year. As discussed in the report, it

[115] Hanley, N., Mourato, S. and Wright, R. E. (2001). "Choice modelling approaches: a superior alternative for environmental valuation?" Journal of Economic Surveys, Vol. 15, pp. 435-462.

is not feasible to include every single possible attribute in the choice experiment. Thus, there is a requirement that some potentially important attribute variables may be excluded from the choice experiment. However, these attributes may be included in the description of the outage and constitute part of the base estimates. This was the approach taken to frequency in the choice experiment used in the main report.

Table 34: Literature Summary

Study	Sample Size	Outage Attributes	Consumers and/or businesses/commercial
Beenstock (1996)	650		consumers
Hartman et al. (1991)			
Energy Australia (1999)			
MORI (1999)	2,532	Continuous/Uninterrupted Supply and Reliability of Supply	2,029 Consumers 503 Businesses
Accent (2004)	4,200	Frequency, Duration, Number, Information/Notice Provided	2,100 consumers 2,100 businesses
Layton and Moeltner (2004)			
Bliem (2009)	4,000		2500 consumers 1500 businesses
Carlsson et al. (2009)	3,500	Cost, duration, time of week, time of year	consumers
Hoch and James (2010)	1,600	Planned vs. unplanned, information provided, voltage fluctuations, undergrounding, future improvements	1000 consumers 500 businesses 100 farmers
Blass et al. (2008)[116]	557		consumers

Source: London Economics

The studies listed in the table above used a range of sample sizes, from 557 (Blass et al. 2008) to 4,200 (Accent, 2004). Duration, frequency, and notice/information provided are common attributes among the studies. Time of year (season) and time of week (workday vs. weekend) are additional variables which may be particularly significant in certain climates and for businesses, although these were not included in all studies. Most studies that included businesses surveyed fewer businesses than individual consumers. The Accent (2004) study, however, included equal numbers of consumers and businesses.

Previously, London Economics estimated the VoLL for security of gas supply in the UK.[117] A choice modelling approach was adopted which derived explicit estimates for both the WTP and WTA. One important distinction between this study and the previous study on gas is the importance of

[116] Blass, A et al (2008) "Using elicited choice probabilities to estimate random utility.
models: preferences for electricity reliability".

[117] London Economics (2011) "Estimating Value of Lost Load (VoLL)" Report commissioned by Ofgem.

time of the day in estimating the VoLL for electricity. This adds another layer of complexity to the choice experiment as discussed previously. This creates a large number of possible combinations. In order for efficient estimation, these combinations must be reduced. With an efficient design we try and find designs that are statistically as efficient as possible, measured in terms of the predicted standard errors of the parameter estimates. An efficient design will do better than an orthogonal design but accuracy of the prior parameter estimates is important. This type of approach is discussed in more technical detail in the paper by Scarpa and Rose (2008).[118]

A1.5 Comparable VoLL figures

Using the recent Reckon study, we can derive comparable estimates of VoLL based on our core assumption regarding electricity consumption. All these figures are in £2012 and are thus somewhat comparable. As noted previously, there is a degree of uncertainty regarding the exact electricity consumption for different sectors. For domestic consumers, we use a 3.934 MWh annual electricity consumption figure. For SMEs, we use a figure that is roughly eight times this amount (29.35 MWh). Comparable results from other studies (using survey based analysis) are shown in the table below.

Table 35: Literature Summary (VoLL estimates - £/MWh) – domestic consumers

Study	1 hour outage value (£)	VoLL (£/MWh)	Implied VoLL (£/MWh) based on 3.934 MWh annual consumption
Carlsson and Martinsson (2008), WTP	0.32	-	713
Kariuki and Allan (1996)	1.00	-	2,227
Bertazzi et al. (2005), WTP	1.56	3,400	3,474
Sullivan et al. (2009)	2.00	-	4,453
Accent (2008), All DNOs except LPN	2.80	-	6,235
Bertazzi et al. (2005), WTA	7.06	15,500	15,721
Bliem (2009)	26.46	-	58,920
Accent (2004)	12.40	-	27,612
Accent (2008): LPN	22.55	-	50,213
CRA (2007)	-	11,810	

Note: Based on converting figures presented in Reckon (2012) report pg.4.
Source: London Economics

The figures above show significant variety ranging from £713/MWh to around £59,000/MWh. These are estimated based on applying the constant demand profile using in this report. This is expected as the actual value of VoLL will vary significantly depending on a number of different factors.

We also examine comparable literature estimates for 'non-domestic' consumers. In our analysis, we have focused on SMEs which have very heterogeneous annual demand for electricity. Our sample focuses on the smaller SMEs who have greater reliance on electricity. Again, the results

[118] Scarpa, R. and Rose, J.M. (2008). Design Efficiency for Non-Market Valuation with Choice Modelling: How to Measure it, what to Report and Why. Australian Journal of Agricultural and Resource Economics 52: 253-282.

show significant variability. Some of this variability is due to the composition of the 'SME' sample. The result from Sullivan et al. (2009) appears to be an outlier and may be due to the choice of sampling used. Bertazzi et al. (2005) estimate both WTA and WTP for 'Business' consumers and find that the VoLL for these customers is significantly higher than for domestic customers. This study also finds that the WTA estimates exceed the WTP by a factor of around seven. Finally, a publication by the Council of European Energy Regulators[119] shows that commercial VoLLs were twelve times the size of residential VoLLs. This was based on Norwegian data using a CV approach.

Table 36: Literature Summary (VoLL estimates - £/MWh) – non-domestic

Study	1 hour outage value (£)	VoLL (£/MWh)	Implied VoLL (£/MWh) based on 29.35 MWh annual consumption
Kariuki and Allan (1996)	169	-	50,458
Bertazzi et al. (2005), WTP	-	9,700	
Sullivan et al. (2009) – small commercial and industrial	-	225,000	-
Bertazzi et al. (2005), WTA	-	72,500	
Bliem (2009)		41,000	
CRA (2007)	-	63,140	

Note: Based on converting figures presented in Reckon (2012) report pg.7.
Source: London Economics

[119] See Table 10 in CERR Guidelines on Estimation of Costs due to electricity interruptions and voltage disruptions.

Annex 2 Representativeness and further results from the domestic sample

This Annex provides further details of the online and face-to-face survey. It also includes further details on the sampling methodology along with summary statistics from both surveys.

A2.1 Face-to-face domestic survey

As discussed in the main report, the online survey is the basis for our domestic VoLL estimates. We also undertook a face-to-face survey as a sense check for our online survey. The respondents selected for the face-to-face survey were 'vulnerable consumers' as defined by satisfying at least one of the following criteria:

- Over state pension age; and / or
- They themselves or another member of their household having a long-term illness or disability; and / or
- A household income below £15,000.

In addition to these criteria participants also had to be responsible for the energy bills and to pay their bills separately if they were renting.

In the face-to-face survey interviewers physically presented each respondent with 12 choice cards. This approach was selected to ensure a high level of data quality because it is much easier for respondents to choose between alternatives in a choice experiment if they can visually see the choices in front of them. Interviews were conducted face-to-face in-street with interviewers free to find respondents that could meet the criteria above. The 150 interviews were distributed across sampling points in 9 regions covering England, Scotland and Wales.

The willingness to accept and pay choices were the same as the online survey with the exception that accept was always presented first followed by the pay choices (since order randomization was not possible in the face-to-face as it was using the online tool).For the online survey, it was possible to randomly assign respondents to answer either the willingness to accept or the willingness to pay choices first. This order of randomisation was captured within the survey system. They were then randomly assigned to one of eight blocks of six choices for both accept and pay. After an introduction to the task they made those six choices. The order of the six choices was fixed rather than randomised.

The method applied in this survey is undertaken according to best practice in the market research industry, but this research (as with survey work, in general) may be impacted by some unobservable factors. It should be noted that the econometric method used controls for random and individual-specific factors as per the standard conditional logit models and methods.

A2.2 Further background information on the domestic survey (online and face-to-face)

The timing of the choice experiment must also be noted. It was undertaken in February which may mean that respondents have just paid significantly higher than average energy bills. This may somewhat explain the level of 'non-engagement' that was found in the WTP choice experiment. However, the advantage of undertaking the experiment at this time of the year is that respondents are more aware about energy costs and may make more informed decisions about the actual value of an electricity outage described in the experiment. However, it must be noted that less respondents will use electricity for heating in comparison with gas. This will imply that the seasonal variability for electricity may be lower than for gas.

It must be remembered that respondents are also somewhat 'conditioned' before they respond to either the choice scenarios or the contingent valuation questions. The survey starts by asking people about their typical usage of electricity and then what possible alternatives they could use in the event of a disruption to their typical usage. They are also asked to give what they consider as their peak electricity consumption period.

The tables below provide detailed information on the socio-economic characteristics of the households having participated in the online or face-to-face surveys. By specifying that respondents must be electricity bill payers, the sample will underestimate the 18-24 age group. The table below shows a comparison of the online survey against national official statistics. The sample is broadly consistent. This table also shows that including the face-to-face sample would mean lead the survey to be over representative of certain groups in society.

Table 37: Comparison of the two surveys with national population statistics

		Online Consumer Survey of Energy Bill Payers (n=1,524)	National population statistics 2011 Census (except where indicated)	Face to face survey of vulnerable consumers (n=150)
Gender	Male	48%	49%	44%
	Female	52%	51%	56%
Age 1	18-24	5%	12%	-
	25-44	34%	35%	-
	45-64	40%	32%	-
	65+	21%	21%	-
Age 2	Under 50	-	-	9%
	50-59	-	-	4%
	60-64	-	-	17%
	65-69	-	-	28%
	70-74	-	-	13%
	75+	-	-	29%
SEG[120]	AB	28%	26%	3%
	C1	28%	29%	17%
	C2	14%	21%	20%

[120] National Readership Survey.

	DE	30%	24%	59%
Region	North East	4%	4%	13%
	North West	11%	11%	13%
	Yorkshire and the Humber	9%	8%	7%
	East Midlands	8%	7%	6%
	West Midlands	8%	9%	7%
	East of England	10%	9%	-
	London	11%	13%	13%
	South East	15%	14%	20%
	South West	10%	8%	7%
	Wales	5%	5%	7%
	Scotland	9%	8%	7%
Tenure	Owner Occupied	71%	65%	52%
	Social Rented	11%	16%	40%
	Private Rented	16%	17%	8%
Employment status	Employed	55%	62%[121]	-
	Unemployed	4%	4%	-
	Inactive (retired, full-time student and not looking for work)	40%	34%	-
Long-term illness or disability	Yes	21%[122]	18%[123]	86%
	No	79%	82%	14%
Do you feel that you are able to keep your home heated to a comfortable level?	Yes	74%	-	74%
	No	25%	-	22%
	Don't know	1%	-	4%

Note: For tenure, employment status and disability, census data was for England and Wales only.
Source: Online, face-to-face domestic survey and ONS

The table above shows how the online sample (and the face-to-face) sample compare with national averages (taken from the recent ONS Census). It is not possible (or indeed correct) to use a sample that is completely demographically representative for a survey such as ours, since the criteria for selection was for electricity bill payers. As noted previously, not all of the population will be electricity bill payers. As part of our research, we have confined our analysis to electricity bill payers and this selection criteria automatically leads to a particular population sample.

A2.3 Background to YouGov's online approach

This section outlines the details of YouGov's panels and panel selection methods.

Over the last ten years, YouGov has carefully recruited a panel of over 400,000 British adults to take part in their surveys. Panel members are recruited from a host of different sources, including via standard advertising, and strategic partnerships with a broad range of websites. We only engage active survey-takers. As expected, any opt-outs or invalid emails are not surveyed. More importantly, each participant is evaluated on the recency and frequency of their survey activity. As panellists become less active effort is made to re-engage them in the survey-taking process. However, if they fail to do so, they are automatically excluded from further participation.

[121] Based on those aged between 16 and 74.

[122] Either the respondent personally or someone else in the household.

[123] Limited 'a lot' or 'a little'

When a new panel member is recruited, a host of socio-demographic information is recorded. For nationally representative samples, YouGov draws a sub-sample of the panel that is representative of British adults in terms of age and gender interlocked, social class and region and invites this sub-sample to complete a survey[124].

With Active Sampling only a selected and invited sub-sample has access to the questionnaire via their username and password, and respondents can only ever answer each survey once. It is ensured that panellists are not invited too frequently. People can be excluded based on recent participation in specific surveys – or surveys in general. These exclusions can be customized on a per survey basis.

Respondents are automatically, randomly selected based on survey availability and how that matches their profile information. A typical invitation will contain only the link to a survey. The invitation will not contain any language about the subject of the survey, as this has the potential to bias responses and could encourage "cheating" in order to qualify and collect more points.

The full YouGov panel is UK-wide (the selection for our survey was however, GB), including Northern Ireland, Wales and Scotland. It is geo-demographically coded for the ONS Geographies (Urban / Town & Fringe and Rural) using the Postcode Address File. Each panellist has been coded for socio-economic classification (ABC1C2DE).

Age is captured in full rather than bands and it is common to supply age with 70+ and / or to set interlocking gender and age band quotas to ensure representative responses from those in the 70 plus category.

Highest educational attainment, the terminal age of education, ethnicity, employment status and religious affiliation are all pre-coded. There are a wide number of other pre-coded demographics including: marital status, children in the household, housing tenure, household income and others.

The YouGov panels thus represent state-of-the art market research that allows rapid and cost effect research on complex questions and survey types.

A2.4 Domestic electricity usage

The vast majority of domestic electricity users use electricity for a number of different appliances. The primary use of electricity appears to be for everyday tasks like cooking and washing with a smaller proportion using electricity for heating purposes. Over 90% of respondents have washing machines and microwaves (Table 38). Around 68% of respondents to the online survey use an electric cooker. The face-to-face survey is made up of 'vulnerable' consumers whom may have a lower income profile but there does not appear to be any significant differences in terms of electrical appliances.

[124] Further information on YouGov's panel methodology is available at http://research.yougov.co.uk/services/panel-methodology/

Table 38: Electricity usage by household having responded to the survey (% of total number of households having participated in the survey) (multiple responses possible)		
Type of electricity usage	**Online survey (in %)**	**Face-to-face survey (in %)**
Underfloor heating	4	3
Electric / oil filled radiators	15	20
Dishwasher	44	27
Tumble dryer	48	47
Electric cooker	68	60
Electric fire	15	33
Electric fan	15	25
Microwave	91	92
Washing machine	96	96
Electric shower	49	53

Note: Online sample (n=1,524) and face-to-face (n=150)
Source: Online and face-to-face domestic survey

In terms of an electricity outage, the impact of this outage will be somewhat determined by the availability of alternatives. The availability of possible alternatives to respondents is shown in Table 39. All respondents have access to some possible alternatives in the occurrence of an electricity outage. However, it must be remembered that these alternatives may not constitute comparable substitutes for electricity. For example, candles may only be a short-term fix for electrical lighting. Similarly, a barbecue will only be a substitute for an electric cooker under certain conditions.

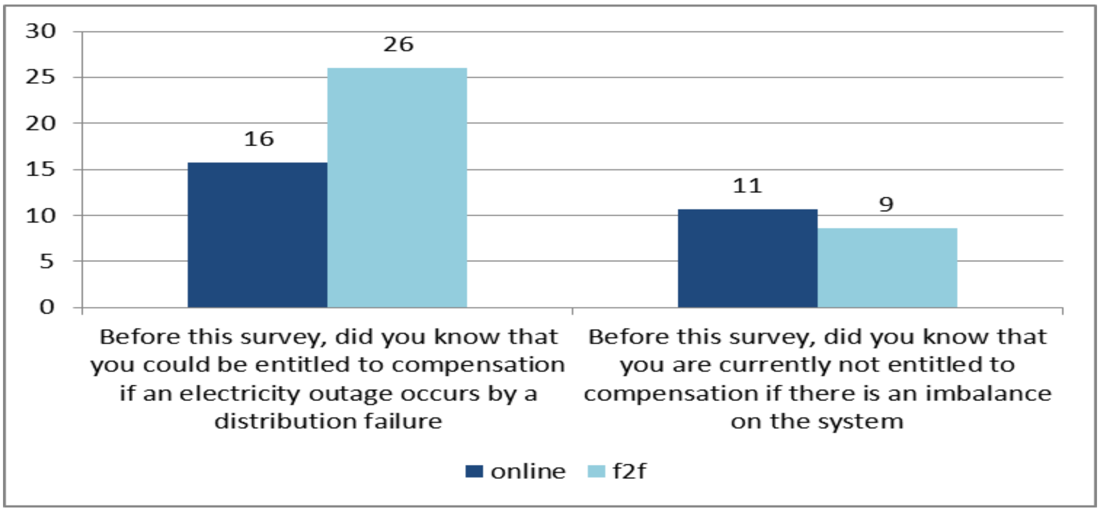
Table 39: Availability of alternatives to electricity (% of total number of households having participated in the survey) (multiple responses possible)		
Type of alternative	**Online survey (in %)**	**Face-to-face survey (in %)**
Gas central heating[125]	40	55
A gas fireplace	21	30
A gas cooker / oven	24	32
A solid fuel (coal, wood, peat) burner	10	7
A gas hob	45	27
A Calor gas / kerosene cooker	4	3
A back-up generator	1	1
Battery torch	72	60
Candles	73	72
Barbecue	16	11

Note: Online sample (n=1,524) and face-to-face (n=150)
Source: Online and face-to-face domestic survey pooled results

We also asked all domestic survey respondents about their awareness of current payments entitlements available as a result of different types of electricity outages. These results are shown in Figure 11 and indicate a general poor awareness of current entitlements.

[125] It was noted in the pilot of the survey that a small amount of electricity may be required to 'spark' the gas central heating.

Figure 11:Knowledge about entitlement to payment in the case of an electricity outage (% of households stating they 'Did Know')



Note: Online sample (n=1,524) and face-to-face (n=150)
Source: London Economics based on the online and face-to-face domestic survey

Annual domestic electricity bill

The average electricity bill from our representative online survey was £722 (Table 40). This is higher than the official Ofgem estimate. Thus, we believe it is prudent to examine the impact of the largest electricity users on the level of the average electricity bill. Removing the highest 4% of electricity users reduces the average annual electricity bill from around £722 to £641.

Table 40: Analysis of annual average electricity bill (£)

Sample	Mean	Std. Dev.	Med.	Max	Min	%
Full sample	721.82	537.15	600	5,000	52	100%
Limited sample: Mean +/-3 std. dev.	661.92	360.21	600	2,288	52	98%
Limited sample: Mean +/-2 std. dev.	641.33	321.49	600	1,680	52	96%
Limited sample: Mean +/-1 std. dev.	594.94	261.67	540	1,248	52	91%
Limited sample: Mean +/-0.5 std. dev.	530.52	197.11	520	960	52	81%

Source: London Economics analysis of online survey data

Table 41 shows analysis of electricity consumption derived using information on electricity bills in the online survey. These electricity bills are converted into consumption figures by dividing by price (£0.16/Kwh). The table below also highlights the importance of very large electricity users in determining the average electricity use. Our online sample indicates that by removing the highest 4% of domestic users, the average consumption falls from 4.49 MWh to 3.99 MWh. We show this analysis, in the context of VoLL, as the electricity consumption figure is central in the deriving VoLL estimates in £/MWh. Our analysis of the online survey indicates that the official current DECC estimate appears appropriate. In the main report, we used an annual electricity consumption figure of 3.934 MWh as the basis for our VoLL conversions. This figure was based on recent DECC research. It must be remembered that the estimates from the electricity bill question in the online survey are not used in the estimation of VoLL and are simply used as background information. Estimating exact household electricity bills is not a trivial exercise and may be influenced by a number of factors including when the survey was undertaken. As the primary focus of the research was estimating the value consumers place on electricity outages, there were restrictions on the number of questions we asked with regard to the electricity bills.

Table 41: Analysis of annual average electricity consumption (MWh)

Sample	Mean	Std. Dev.	Med.	Max	Min	%
Full sample	4.49	3.34	3.73	31.08	0.32	100%
Limited sample: Mean +/-3 std. dev.	4.11	2.24	3.73	14.22	0.32	98%
Limited sample: Mean +/-2 std. dev.	3.99	2.00	3.73	10.44	0.32	96%
Limited sample: Mean +/-1 std. dev.	3.70	1.63	3.36	7.76	0.32	91%
Limited sample: Mean +/-0.5 std. dev.	3.30	1.23	3.23	5.97	0.32	81%

Note: Excludes any respondent who claimed to have a zero electricity bill and is estimated based on an assumed price of 0.16p/kWh.
Source: London Economics analysis of online survey data

However, as noted previously, the estimates of electricity usage from our online sample appear to be broadly consistent with the national average (3.934 MWh per annum).

A2.5 More detailed sample characteristics

Table 42 below provides a detailed breakdown of the age of the household member as a percentage of the total number of responding households. The face-to-face survey sees a much higher average age while online respondents are more evenly spread between the ages of 20 and 70.

Table 42: Age of household member having responded to the survey (% of total number of households having participated in the survey)

Age group	Online survey (in %)	Face-to-face survey (in %)
under 20	0.5	8.7
20 to less than 30	13.6	
30 to less than 40	16.1	
40 to less than 50	19.4	
50 to less than 60	19.8	4.0
60 to less than 70	17.7	45.3
70 to less than 75	8.5	13.3
more than 75	4.3	28.7
Total	100.0	100.0

Note: Online sample (n=1,524) and face-to-face (n=150)
Source: Online and face-to-face domestic survey

Table 43 details the type of housing tender among those households that responded. Of those respondents that replied using the online survey, the majority either owned their home outright or were buying it with a loan. While 46% of face to face respondents owned their home outright a further 30.1% rented form a local authority. This is as expected as the face-to-face sample is made up of more pensioners and people with income below £15,000.

Table 43: Type of housing tenure of household having responded to the survey (% of total number of households having participated in the survey)

Online survey		Face to face survey	
Type of tenure	**% of households**	**Type of tenure**	**% of households**
Owned outright	35.56	Owned outright	46
Buying with a mortgage/ loan	36.81	Buying with a mortgage/ loan	6
Rented from local authority	5.51	Rented from local authority	30.67
Rented from private landlord	15.81	Rented from private landlord	8
Rented from a housing association	5.45	Rented from a housing association	9.33
Other	0.85	Other	

Note: Online sample (n=1,524) and face-to-face (n=150)
Source: Online and face-to-face domestic survey

Table 44 displays figures concerning the percentage of survey respondents and members of households surveyed that had a disability. Of those surveyed face to face 67.33% said they had a disability, whereas of those surveyed online only 14% said they had a disability.

Table 44: Members of household member having a disability (% of total number of households having participated in the survey)

Type of household member		Online survey (in %)	Face-to-face survey (in %)
Survey respondent			
	Yes	14.04	67.33
	No	80.91	32.67
	Don't know	3.67	
Other household member			
	Yes	11.02	18.67
	No	85.17	81.33
	Don't know	2.43	

Note: Online sample (n=1,524) and face-to-face (n=150)
Source: Online and face-to-face domestic survey

Table 45 below details the income breakdown of survey respondents, both online and face-to-face. Online respondents show a relatively even spread between £10,000 and £99,999 per year with £20,000 to £29,999 per year representing the mode income bracket in this group. For face-to-face respondents 26% of respondents were in the £5,000 to £9,999 per year income bracket while the majority of 56% of respondents were in the £10,000 to £14,999 per year income bracket.

Table 45: Income of household having responded to the survey (% of total number of households having participated in the survey)		
Income group	**Online survey (in %)**	**Face-to-face survey (in %)**
under £5,000 per year	3.2	3.3
£5,000 to £9,999 per year	5.8	26.0
£10,000 to £14,999 per year	9.8	54.0
£15,000 to £19,999 per year	9.0	1.3
£20,000 to £29,999 per year	15.9	6.0
£30,000 to £39,999 per year	13.1	2.0
£40,000 to £49,999 per year	8.9	0.0
£50,000 to £99,999 per year	10.7	0.0
£100,000 and over	1.7	0.0
Don't know	3.1	4.0
Prefer not to answer	18.9	3.3
Total	100	100

Note: Online sample (n=1,524) and face-to-face (n=150)
Source: Online and face-to-face domestic survey

As a further sensitivity check, we also examine the income distribution according to recent official ONS figures. These are presented in the table below (Table 46). Around 9% of our online sample have annual income below £10,000 which compares with around 10% of the national population who had an income of around this amount. Our online sample also appears to be closely representative of respondents who are in the second income decile.

Table 46: Recent Income deciles	
Income decile	**Annual Gross income (£)**
Bottom	9,622
2nd	14,635
3rd	18,365
4th	21,807
5th	25,682
6th	32,592
7th	39,933
8th	47,546
9th	59,779
Top	107,454

Source: ONS

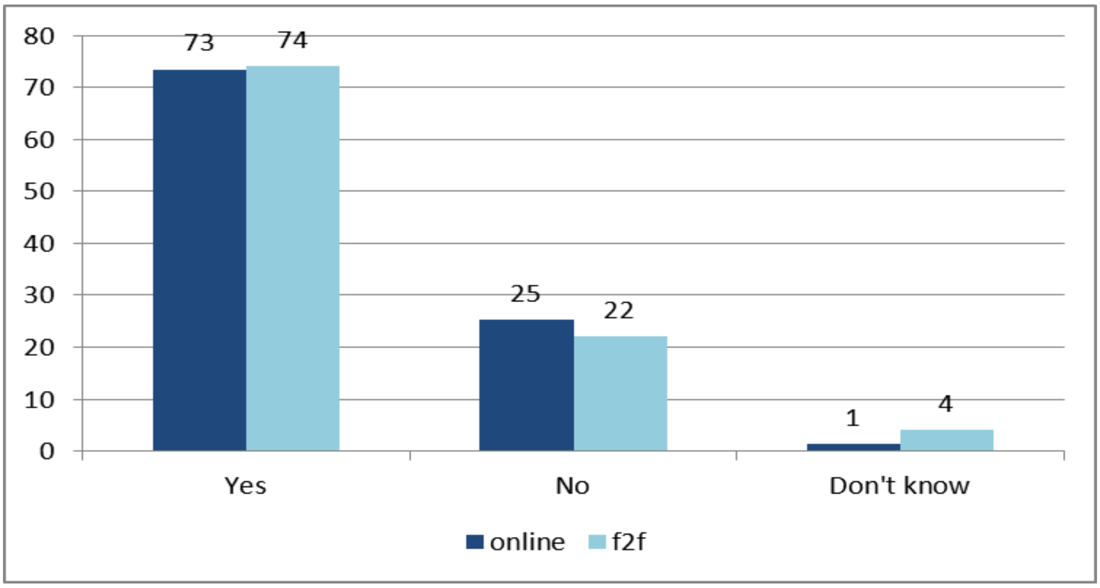
Table 47 shows the breakdown of the gender of the respondent to the survey for each household for both online respondents and face-to-face respondents. Both survey mechanisms saw a slight bias towards female respondents with 52.4% of online respondents declaring female and 56% of face-to-face respondents declaring female.

Table 47: Gender of household member having responded to the survey (% of total number of households having participated in the survey)		
Gender	**Online survey (in %)**	**Face-to-face survey (in %)**
Male	47.6	44.0
Female	52.4	56.0
Total	100	100

Note: Online sample (n=1,524) and face-to-face (n=150)
Source: Online and face-to-face domestic survey

Figure 12 details views of survey respondents on whether they are able to keep their home heated to a comfortable level. The results from both online respondents and face-to-face respondents were very similar; roughly 75% said that they were able to heat their home adequately. This tables are further analysed with relation to VoLL in A10.1.

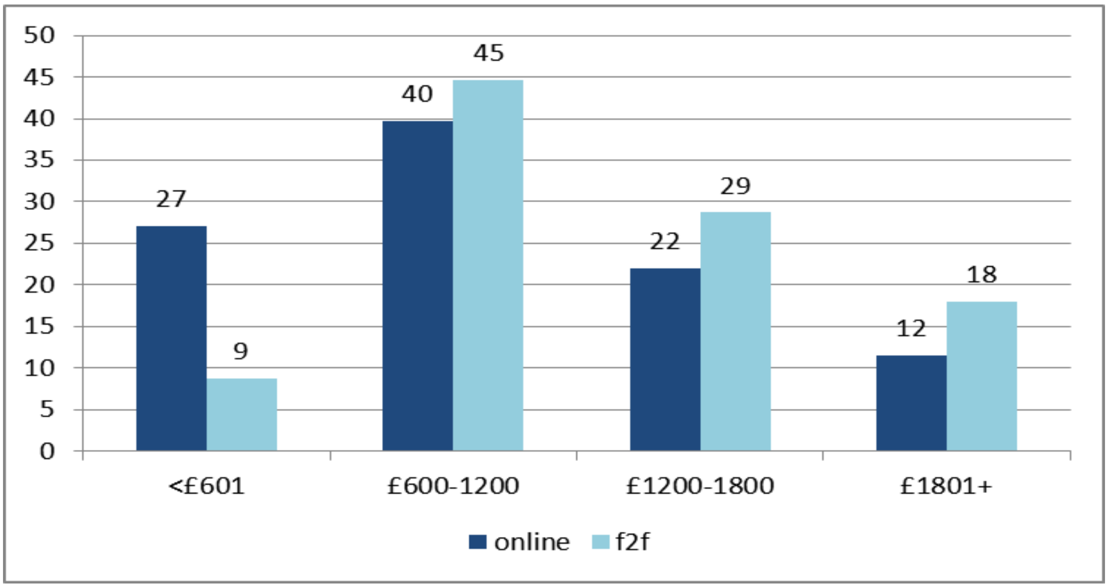
Figure 12:Households views' on whether they are able to keep their home heated to a comfortable level (% of households having participated in the survey)



Note: Online sample (n=1,524) and face-to-face (n=150)
Source: Online and face-to-face domestic survey

Figure 13 details the annual household spending on gas, electricity and fuel for survey respondents. The majority of those said, in both survey formats, that they spent £600-£1,200 per year.

Figure 13:Households' annual spending on gas ,electricity & fuel oil (% of households having participated in the survey)



Note: Online sample (n=1,524) and face-to-face (n=150)
Source: Online and face-to-face domestic survey

Table 48 below details the labour force status of survey respondents for online respondents only. Forty-six per cent said that they were working full time (over 30 hours a week) while 26.6% indicated that they were retired.

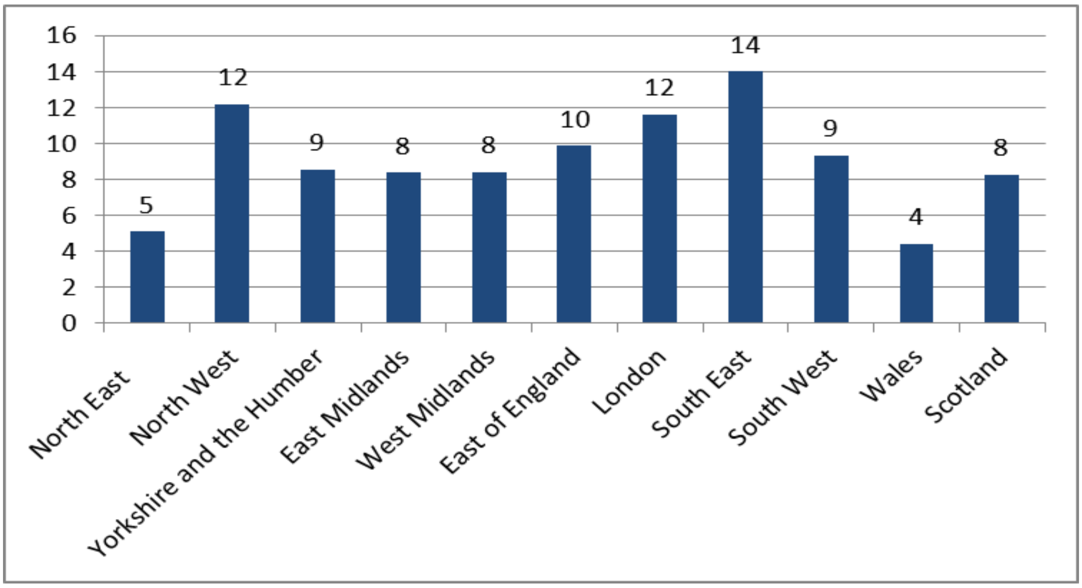
Table 48: Labour force status of survey respondent and socio-economic characteristics of households

Labour force status as % of total (online only)		Socio-economic characteristics as % of total	Online	f2f
Working full-time (30 hours a week or more)	40.7	A	10.7	3.33
Working part-time (8-29 hours a week)	13.5	B	17.1	17.33
Working part-time (fewer than 8 hours a week)	1.4	C1	28.4	20
Unemployed and looking for work	4.0	C2	13.9	59.33
Retired	26.6	D	12.9	
Looking after family or home	5.8	E	16.9	
Full time student / in school	3.1	Unknown	0.1	
Other	4.8			
Total	100	Total	100	

Note: Online sample (n=1,524) and face-to-face (n=150)
Source: Online and face-to-face domestic survey

Figure 14 shows the regional distribution of survey respondents for the online portion of the survey. London, the South East and the North West were the best represented areas each with over 12% of the total. This can be compared directly against the population which shows the online survey is very close to nationally representative in terms of geographical breakdown.

Figure 14: Regional distribution of households having participated in the online survey (% of total)



Note: Online sample (n=1,524) and face-to-face (n=150)
Source: Online and face-to-face domestic survey

Table 49 details the distribution of households by number of household members broken into children and adults for online respondents only. The majority of responses (78%) indicated that they had no children in the household, while 57% indicated that they had two adults living in the household.

Table 49: Distribution (in %) of households by number of household members– online survey only

Number of household members	Children	Adults
0	78.21	0
1	10.07	20.45
2	8.69	57.52
3+	3.03	22.03
Total	100	100

Note: Online sample (n=1,524) and face-to-face (n=150)
Source: Online and face-to-face domestic survey

Annex 3 Representativeness and further results of SME sample

A3.1 Background to the SME sample

The SME survey was conducted by telephone, using CATI (Computer Assisted Telephone Interviewing). A total of 550 interviews were conducted with a broadly representative sample of SMEs. An achieved sample of 550 will usually provide a confidence interval of +/- 4.2% at the total level. To be eligible to take part, businesses needed to pay for their electricity directly rather than being included in their rent or service charges.

The sample was sourced from Dunn and Bradstreet and ordered in proportion to the 'true' profile of the business population with broad quotas set on region, business size, and sector to ensure that the end sample was broadly representative. The quota bands used were as follows:

- Region: England / Scotland / Wales
- Size: 0-9 / 10-49 / 50-99 / 100-249
- Sector: Primary / Production / Construction / Services

The table below compares GB SME population characteristics with sample characteristics for the SME sample. The Annex also provide more detailed sample characteristics based on the survey responses. The sample approximately matches population characteristics with respect to the region, size and sector characteristics.

Table 50: Comparing population and sample characteristics for the SME sample

	SME population	Survey
Region		
England	89%	89%
Scotland	7%	7%
Wales	4%	4%
Size (number of employees)		
0-9	96%	95%
10-49	3%	3%
50-99	0.4%	0.4%
100-249	0.2%	1%
Sector		
Primary	4%	5%
Production	7%	9%
Construction	21%	18%
Services	68%	69%

Note: SME sample (n=550)
Source: SME population statistics based on BIS Population Estimates 2011

Our sample is largely representative of SMEs in the UK. The population estimates are based on recent published data from the ONS. There are some small differences in our survey in that we have surveyed slightly less construction SMEs than the population would indicate. However, these differences are small and are highly unlikely to have any impact on the results.

Comparison with previous Gas VoLL sampling approach

For the 2013 Electricity VoLL survey, the profile of the SME population was taken from recent BIS Population Estimates. However, in the earlier 2011 Gas VoLL survey, the sample was sourced from Experian and the population profile was estimated based on the profile of all SMEs on the Experian business database at that time. A comparison of the population figures used in the 2011 and 2013 studies suggests that micro SMEs were somewhat under-represented in the population estimates used for the 2011 Gas VoLL study, with 0-9 employee firms estimated to account for 83% of the population when using the Experian data compared to 96% using the more recent BIS statistics. There were also some differences in the sector profile of the two population estimates, with construction firms estimated to account for a smaller proportion of the SME population in the 2011 sampling approach.

The differences between the profile of firms interviewed in the 2011 Gas VoLL study and 2013 Electricity VoLL study are also caused by a slightly different sampling approach. In the Gas VoLL study, it emerged during the survey that smaller firms were less likely to use gas and hence the quotas were adjusted to cover a greater proportion of larger firms. In contrast, the Electricity VoLL sample was broadly reflective of the actual SME population.

A3.2 More detailed sample characteristics

The tables below provide more detailed information on the economic characteristics of the sample of SME having participated in the survey.

Table 51: Industrial sector of the SMEs having particicpated in the survey

Sector	Percentage of total sample
Agriculture, Hunting & Forestry	4.2
Fishing	0.4
Manufacturing	8.7
Construction	18.2
Wholesale & Retail	21.3
Transport, Storage & Communication	3.3
Financial Intermediation	1.6
Real Estate, Renting & Business Activities	26.7
Public Administration & Defence	0.4
Education	1.6
Health & Social Work	3.5
Other Community, Social & Personal	9.3
Private Households Employing Staff	0.9
Total	100

Note: SME sample (n=550)
Source: SME survey

Table 52: Country distribution of the SMEs having particicpated in the survey	
Country	**Percentage of total sample**
England	88.91
Scotland	6.91
Wales	4.18
Total	100.0

Note: SME sample (n=550)
Source: SME survey

A3.3 SME electricity usage

In this section, we provide background information from the SME survey.

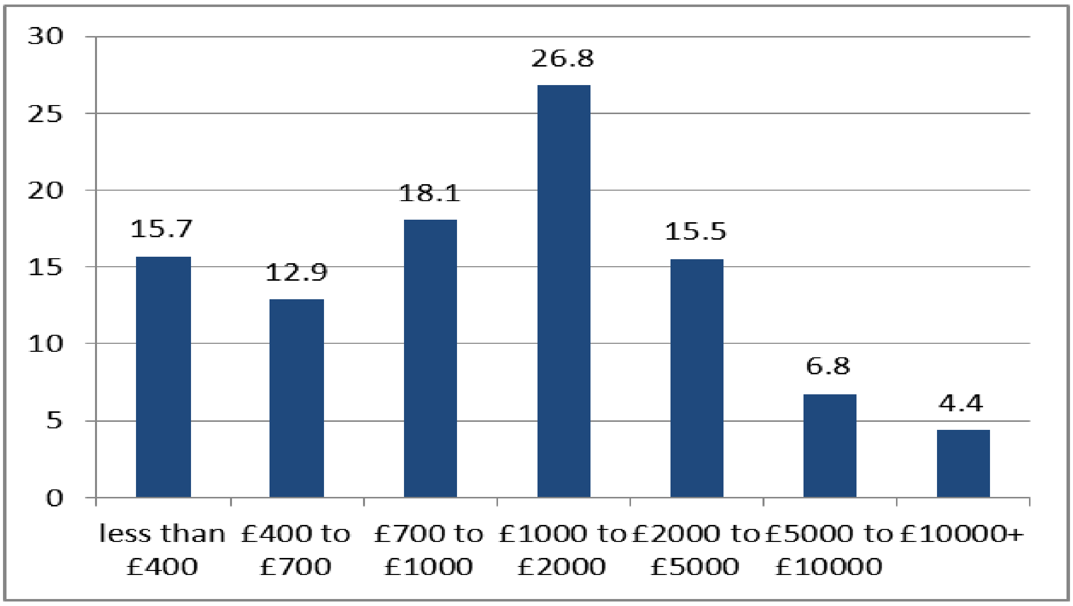
Table 53: Type of electricity usage by the SMEs having particicpated in the survey (mutilple responses were possible)	
Type of usage	**Percentage of total sample**
For heating your office/business space	68%
For cooling or ventilating your office/business	27%
For heating water	61%
For cooking/catering	44%
For computing/IT	96%
For lighting	98%
For the manufacturing or production process	23%
For compressed air	18%
For commercial refrigeration	14%
For drying or separation	6%
For transport	3%
For powering any motors your business uses	18%
For anything else	11%

Note: SME sample (n=550)
Source: SME survey

Figure 15 shows the distribution of the annual electricity bill for SMEs that use electricity in GB based on our sample. Around 47% of SMEs spend less than £1,000 on electricity per year. However, as expected, some businesses spend considerably more. Around 4.4% of SMEs spend over £10,000 annually on electricity. The largest clustering of electricity bills is in the £1,000 to £2,000 band with around 27% of SMEs in this band. It must be remembered that 95% of SMEs in our sample have fewer than ten employees. It should also be recalled that the definition of SME is based on employee numbers, so it is quite conceivable that some business with few employees could have large electricity use.

We note that it was not possible, in the context of a CATI interview of SME electricity bill payers, to ask respondents to check the accuracy of their statements by getting out their most recent bills. We would note that obtaining reasonable response rates for SMEs for complex questions is already difficult and it was our judgement that attempts to raise the accuracy of respondent's billing information, although potentially useful, in practice would have risked compromising the completion of the SME survey.

Figure 15:Annual spend on electricity (% of SMEs having participated in the survey)



Note: Around 8% of SMEs did not provide an estimate of their annual electricity bill.
Source: SME survey

Table 54 shows the percentage of SMEs who can call upon possible alternatives in the event of an electricity outage. It is clear that very few SMEs appear to have alternatives for the various business practices. However, around 9% of the sample has possible alternatives for computing/IT functions. This may be indicating the use of battery powered laptops.

Table 54: Availability of alternatives to electricity for different electricity usage by the SMEs having participated in the survey (multiple responses were possible)

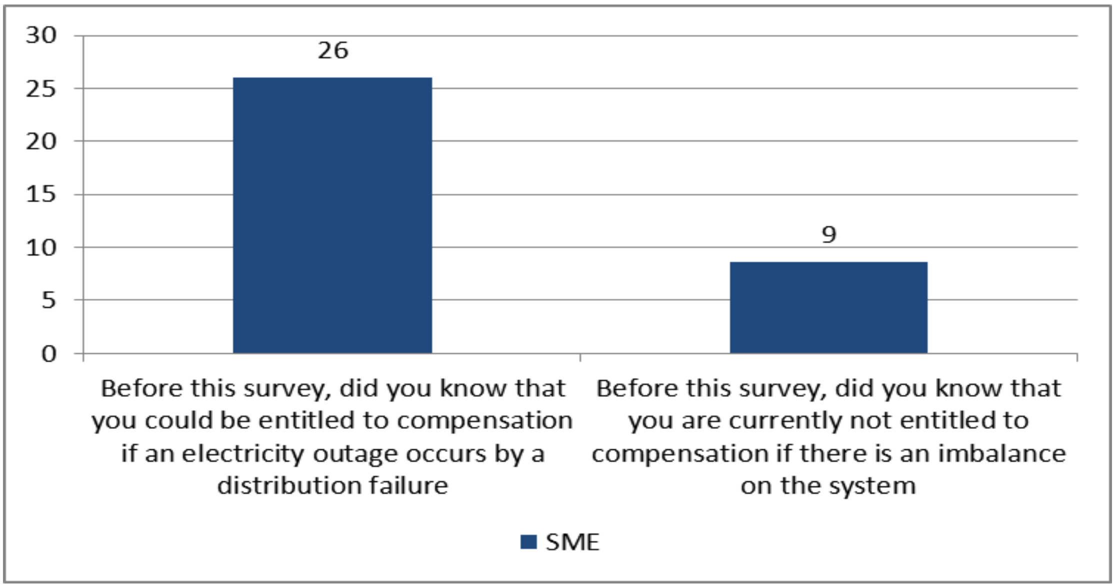
Alternative to electricity available for	Percentage of SMEs using alternative for particular usage
For heating your office/business space	4.7%
For cooling or ventilating your office/business	1.6%
For heating water	4.6%
For cooking/catering	2.0%
For computing/IT	9.3%
For lighting	7.6%
For the manufacturing or production process	2.0%
For compressed air	1.6%
For commercial refrigeration	1.1%
For drying or separation	0.7%
For transport	0.7%
For powering any motors your business uses	2.7%
For anything else	1.8%

Note: SME sample (n=550)

Source: SME survey

As part of the SME survey, we asked the respondents about their knowledge of current payment availability as a result of different types of electricity outage. The results of these awareness questions are shown in Figure 16. The results indicate there is generally a poor knowledge of current payment entitlements.

Figure 16:Knowledge about entitlement to payment in the case of a electriciy outage (% of SMEs saying 'yes, they were aware of their entitlement or otherwise to compensation)



Note: SME sample (n=550)
Source: SME survey

We also split our sample into those who indicated that an electricity outage would have a large or very large impact and those who did not. These results are shown in Table 55. The results are largely as expected. Over 17% of SMEs who thought that an electricity outage would have a low impact had electricity bills of less than £400 per annum. The comparable figure for SMEs with a 'high' impact is only around 7%. This indicates that households with a lower than average electricity bill tend to believe that an electricity outage will have a relatively 'low' impact, which is intuitive.

Table 55: Annual electricity bill and impact of outages for SMEs (%)

Bill	High impact	Low impact
less than £400	6.6	17.21
£400 to £700	10.12	16.21
£700 to £1000	12.13	13.56
£1000 to £2000	32.87	22.49
£2000 to £5000	20.74	18.86
£5000 to £10000*	10.63	7.95
£10000+*	7.11	3.63

Note: * Fewer than 30 firms in total. SMEs that were not able to provide an exact estimate of their electricity bill were asked to pick estimates in various bands. The midpoint of these bands has been used in the estimation of the annual electricity bill.

Source: London Economics analysis of SME survey

Annex 4 Background to the methodology used in the choice experiment

This Annex provides further background regarding the design and construction of the choice experiment.

A4.1.1 Further background on attribute selection (frequency)

In this section, we provide some further background regarding including frequency of outage as an attribute in our choice experiments.

Frequency is included in our choice experiment as an attribute that is constant across all choice scenarios. We did include frequency of outage as a varying attribute in the piloting phase[126] of the experiment but the results of this pilot indicated that this variable was overcomplicating the experiment and the choices were being made on only a small number of attributes.

Furthermore, there is some ambiguity about how respondents actually value frequency of outage. Typically, this attribute is described as “an outage in one out of 12 years” and improvement in this attribute may be “an outage in one out of every 20 years”. However, this type of phrasing creates possible interpretation issues. These frequency improvements occur in the distant future (possibly 20 years away) and thus some level of discounting should be applied in order to evaluate the decision based on present value terms. A further extension of this point is in what year the outage actually occurs. If the outage occurs in the first of the twenty years, then the present value of this is much different to if the outage occurred in the twentieth year. Thus, when thinking about changes in the frequency of outage, respondents really need to make at least two calculations in order to accurately judge its impact.

A further issue that may be applicable is how the payment is offered. Should the payment be paid every time there is an outage or should the payment be received (once-off) at the start? Asking the question as a once-off payment may mean that respondents do not take into account future values of this payment.

Fundamentally, after piloting, it was decided that the CE’s with five attributes were too complicated and there was a risk that respondents were responding by implicitly ‘simplifying’ the experiment in their responses. Thus it was our judgment to drop frequency and merely inform respondents of the typical frequency. Respondents were informed that the average interruption of this type was about once every 12 years and this was kept constant across choices.[127]

As noted in the main report, we subsequently carried out a simplified CE using only frequency, duration, and price attributes (where peak time, day of the week, and season, were defined in advance by informing consumers of the timing). This experiment was undertaken as a sense check

[126] An online pilot survey was initially undertaken with 98 responses (98*6=588 choice card selections for WTA/WTP). A pilot SME study was also undertaken.

[127] Ofgem (2012) “Electricity Capacity Assessment”.

to our primary choice experiment results. The design of this experiment is very similar to the main choice experiment with the duration and payment attributes taking the same levels as per the main CE. For frequency, three levels are chosen: an outage occurring once every two years, once every 12 years and once every 20 years. Respondents were only asked about their willingness to accept. In this CE, respondents are also told that they will receive payment every time the outage occurs. Further details can be found in Annex 16.

A4.1.2 Generating choice cards for the experiment

Given the four different attributes (five including price/payment) and the different possible attribute levels for each, choice cards were designed for the WTP and WTA choice experiments separately.

Each choice card was designed to consist of two alternative scenarios with one or more attributes varying across the two scenarios. Thus, there could be some choice cards that may have the same value for each attribute except one. Alternatively, some choices cards may have different values for all attributes. Each domestic respondent answered six choice cards on WTA and WTP with a total of 12 choice cards answered by each respondent. The order in which the WTA or WTP choice cards are asked was randomised. Analysis of the impact of ordering on the choices chosen is shown in Annex 9. Prior to the choice cards, respondents were informed that the frequency for an outage of this type was one in every 12 years.

The efficient choice experiment design involves reducing the number of combinations of choices, such that a maximum of information is retained, while duplication is eliminated. There were 96 different possible combinations of attribute levels (3 (duration) * 2 (peak) * 2 (season) * 2 (day of week) * 4(price)) for each of the WTP and WTA choice experiments. Each of the 96 scenarios could be paired with all the other 95 scenarios to create the complete set of choice cards. However, it is not feasible (or advisable) to ask each respondent to choose all of these choice cards. Thus, we need to reduce the number of possible combinations.

Traditionally we could have used orthogonal designs or fractional factorial designs. In this study, we instead employ "efficient" designs. What this means is that we make assumptions about the underlying data generating process and then specify the utility function (which can be attributes and interactions). This approach does require that we introduce some information about the parameters. So we can assume that the price/cost parameter will be negative.

We can give the parameters values which we think make sense - large or small depending on the scale of the data. Then using appropriate criteria (e.g., d-optimal) we generate the required number of cards using various algorithms. The algorithm will try and find the minimum or maximum of the specific criteria being used by swapping levels of attributes. So we can generate any number of choice cards less than 95 such 24, 36 or 48. Each respondent is then given a subset of cards (e.g., 6, 8, 12). Thus, the number of combinations is not an issue - as long as it is not too small.

In summary, with an efficient design we derive designs that are statistically as efficient as possible, measured in terms of the predicted standard errors of the parameter estimates for the utility function. In contrast, orthogonal designs, such as a fractional factorial design, which have been popular in the past, do not yield statistically efficient designs especially if the regression model to be estimated is nonlinear. Although fractional factorial designs work very effectively with linear regression models this is clearly not the case when estimating a Random Utility Model as is required with Choice Experiment data (e.g. conditional logit). Furthermore, with an orthogonal design there is an issue about maintaining orthogonality in relation to how the attributes are coded in the design and regression model. It is quite easy to demonstrate that if the design is effects coded as {-1,0,1} and these are replaced in a regression model as £2, £4 and £8 that the resulting data will not be orthogonal.

Within the literature it is now understood that an efficient design will do better than an orthogonal (fractional factorial) design even when we have limited information about prior parameter estimates in the utility function (Scarpa and Rose, 2008). Thus, even by employing a conservative efficient design such a multinomial logit, as has been done in this design, we can minimise the potential bias that can arise from imposing an inappropriate structure on the design and still yield a more efficient design that would be achieved if we employed a fractional factorial design. In terms of efficient design implementation there is a significant and growing literature that supports using a multinomial logit with a d-optimal criterion when we have little information about actual utility function parameter values. A good general introduction to this topic is provided by Scarpa and Rose (2008).[128]

A4.1.3 Derivation of Utility function

The heart of choice experiments is the basic neoclassical economic model of consumer behaviour and "utility". Typically, we assume that consumers[129] have a utility function, where they gain utility or satisfaction from goods and services. The approach then adds a random component, which can be interpreted as a random error, epsilon ε_i.

$$U_i = V_i + \varepsilon_i$$

For each consumer, the 'ith' alternative (the subscript i indexes the alternatives) has its own utility level, and error, although we may make assumptions about the structure of the preference sets and the error structure.

Without choosing a functional form, we assume that the non-random portion of consumers' preferences can be represented or approximated by some functional form, and that this is often a function of attributes or the characteristics of the respondent.

$$V_i = \alpha_i + \beta_{1i} f(X_{1i}) \dots \dots + \beta_{Ni} f(X_{Ni})$$

Combining the two equations gives:

$$U_i = V_i = \alpha_i + \beta_{1i} f(X_{1i}) \dots \dots + \beta_{Ni} f(X_{Ni}) + \varepsilon_i$$

where alpha and beta are parameters to be estimated.

[128] Scarpa, R. and Rose, J.M. (2008). Design Efficiency for Non-Market Valuation with Choice Modelling: How to Measure it, what to Report and Why. Australian Journal of Agricultural and Resource Economics 52: 253-282.

[129] We will use "consumers" to mean consumers of electricity services. Our study involves both domestic consumers and SMEs.

Data on the fundamental choice component in a choice experiment is discrete (we observe that the respondent has chosen choice A over choice B). Thus operationalizing the utility model above involves the logical step that utility must be higher when a choice is observed or stated to be preferred, and is represented by the probability that the consumer chooses alternative i.

Rearranging from the previous equations after substitution, we see how the error component fits into the model, i.e. the difference between the non-random elements must exceed the difference between the random elements:

$$Prob_i = |Prob\left(U_i \geq U_j\right) \forall\, j = 1 \ldots J\ (j \neq i)$$

The final step is to choose a distributional assumption for the error term and structure. A common assumption is an extreme value 1 exponential type distribution.

$$Prob(\varepsilon) = \exp(-\exp(-\varepsilon))$$

Independently identically distributed error terms (iid) is a common error structure assumption.

Then,

$$Prob_i = \frac{\exp(V_i)}{\sum_{j=1}^{J} \exp(V_i)}$$

The interpretation of the above is that for each alternative i, the probability that it is chosen is the ratio of the exponentials of the non-random V_i, to the sum over the utilities from the possible alternatives.

A4.1.4 Model selection procedure

We investigated a range of models including allowing for linear and nonlinear effects of the attributes on choice and including the attribute-type dummy variables as standalone variables. An initial analysis using dummies for peak, winter, and weekday interacted with duration to estimate WTP and WTA for different changes in the duration parameters showed that a linear model was more appropriate for domestic WTP and WTA; and, WTP for SMEs. Only in the case of WTA for businesses did a nonlinear model appear to be potentially more appropriate given the initial inspection of the data. We thus also tested a quadratic-in-duration model. Adding in quadratic terms did not improve the performance of the model significantly in terms of goodness-of-fit compared to the linear model. Typically, estimating models with fewer variables is favourable in cases where additional variables do not improve the performance of the model. The results of the various nonlinear models are provided in Annex 7.

The appropriateness of a linear functional form is not surprising given the chosen outage durations do not span days or months. In our previous work on gas, the linear form was not always chosen; but the duration range was much longer. The intuition is that over a wide range of durations, adaptations or other changes might mean that the outage impact does not change linearly with time. For example, food in a refrigerator could spoil for longer outages, over five to six hours, but if an outage was over a month, the consumer would likely have adapted and purchased food supplies not in need of refrigeration.

Electricity outages are typically expected to be much shorter than gas outages, and thus we revisited the model selection process on duration. In our choice experiment, our longest outage is four hours in duration for domestic customers. As these outages are relatively short, households may not have the time or desire to adopt alternatives, perform alternative tasks during the outage, etc. However, if there was an electricity outage of 30 days, households may adopt alternatives that would lessen the impact of the electricity outage (and indicate a possible positive and significant sign on the squared duration term). We could also include a squared term on the duration*winter variable which if significant and positive would indicate that respondents are able to adapt to an outage as it increases in the winter. The squared term is used to pick up any changes in the relationship between duration and choice as duration increases.

A4.1.5 Further details on calculating WTP and WTA from the estimation results

It must be noted that the willingness-to-pay estimate derived from the model must be multiplied by minus one. This is because typically WTP is set up so that a respondent prefers more of the 'good'. However, in this model, duration is really a 'bad' indicating that the respondents want less of this good. See Vermeulen et al. (2009)[130] for a discussion of the conversion of regression coefficients into WTP estimates.

In our WTA model for SMEs we included a nonlinear term for the duration variable. This alters the formulas needed to compute the WTA and WTP values. For example, the formula below shows the WTA estimate for the reference case including the nonlinear duration term.

$$WTA_{15\ mins, not\ winter, not\ peak, non-work\ day} = \frac{\beta_1 + \beta_2}{\delta}$$

Where β_1 and β_2 are the parameters of the duration and duration squared variables respectively.

Standard errors and confidence intervals for the WTP and WTA estimates are calculated using the delta method[131] for parameter transformations used to generate WTP and WTA estimates. It must be noted that the delta method is typically used in nonlinear transformations of variables (such as ratios) and does not require the model itself to be nonlinear.

[130] Vermeulen, Goos, Scarpa and Vandebroek (2009) "Efficient and robust willingness-to-pay designs for choice experiments: some evidence from simulations" University of Leuven.

[131] When parameter transformations are nonlinear, as is the case when WTP and WTA are calculated, the delta method can be used to estimate the variance of the transformed variable. The delta method expands the function used to transform the parameter estimates around its mean, usually with a first-order Taylor approximation, and then takes the variance of that first-order Taylor series approximation around the point.

Annex 5 Technical Annex on model selection

As part of the modelling and estimation process, detailed analysis was undertaken on model selection. We present the additional details of the econometric results and results from model selection analysis in this Annex. Detailed analysis is included in terms of verifying our preferred functional form for the model chosen—the model for which the main VoLL results are reported in the main report body and executive summary (we refer to this as 'model 1'). In our chosen econometric model (model 1), dummy variables for winter, peak, weekday only enter into the model as interactions with the duration variable (hence 'model 1').

We compare model 1 to an alternative model (model 2). In model 2, we examined a model where the standalone dummy variables were included alongside dummy variables with duration interaction terms. In this technical Annex, we examine the technical performance of the two models as well as intuition for our preferred model. It is our view that the chosen model (model 1) specification is most appropriate given our prior intuition behind what we are modelling and expectations for signs on the coefficient estimates.

A5.1 Further interpretation of the regression coefficients

As part of our detailed explanation of the econometric results, we present a more in-depth description of how to interpret the coefficient estimates. The coefficient estimates in all of our models can be interpreted in a variety of ways. It is first important to understand the general types of interpretations for coefficients in logit and probit and other similar probability-type limited dependent variable models. The coefficient estimates are the marginal impacts on the logit function. These values can then be converted to marginal probability impacts, or other values such as odds ratios. The logit function is the probability distribution function that any choice will be chosen. The choice model posits that the utility of one choice exceeds the utility of another choice based on the model as specified. The coefficients are then converted into WTA/WTP estimates based on the estimated parameters and the marginal rate of substitution between different choices.

An alternative interpretation of coefficients in logit models is as odd-ratios. Coefficients of conditional logit models can easily be converted into odds ratios.[132] Odds-ratios give an indication of the odds[133] that a choice is chosen. Figure 17 displays the regression results of our main choice experiment (see Figure 6) in terms of odds ratios. An odds ratio of 1 means that the variable has no impact on the odds of the choice being made (1:1). An odds ratio of less than 1 indicates that this variable reduces the odds of the choice being made and vice versa.

[132] See Allison (2009) 'Fixed Effects Regression Models for Categorical Data' for further description regarding the interpretation of regression coefficients in logistic models. See also http://www3.nd.edu/~rwilliam/stats3/Panel03-FixedEffects.pdf

[133] Note that odds ratios are not the same as probabilities, but have a similar interpretation for values in normal ranges.

With regard to this choice experiment, the odds ratio for duration indicates that a one-unit (20 minutes) increase in this variable decreases the odds that this option is chosen by around 5%. In contrast, if the level of payment increases, the odds of the option being chosen increase (odds ratio> 1). In the choice experiment below, the results indicate that for every £1 increase in the level of payment, the odds of this option being chosen increase by around 6%. It must be noted that this interpretation relies on the assumption that all other variables are held constant.

It must be remembered that the interpretation of interactions terms should be viewed with caution. Interpreting them based on our previous interpretation of the duration and payment variables, would indicate that a one-unit (20 minutes) increase in the duration of an outage in winter would decrease the odds of the option being chosen by around 3.8%.

We note, however, that in our particular model(s) of WTA/WTP and VoLL, we are not particularly interested in interpreting the interaction effects *per se*; rather we are purely interested in the WTA/WTP calculations. Thus we only focus on the interpretations of the coefficients as to how they impact the WTA/WTP calculations.

Figure 17:Regression results of main WTA domestic choice experiment, presented in Odds ratios

```
Conditional (fixed-effects) logistic regression     Number of obs   =      25254
                                                    LR chi2(6)      =    6237.35
                                                    Prob > chi2     =     0.0000
Log likelihood = -6129.4439                         Pseudo R2       =     0.3372
```

choice	Odds Ratio	Std. Err.	z	P>|z|	[95% Conf.	Interval]
duration	.9481992	.006604	-7.64	0.000	.9353436	.9612316
duration_winter	.9621726	.0040675	-9.12	0.000	.9542334	.9701778
duration_peak	.9608666	.0041046	-9.35	0.000	.9528553	.9689452
duration_weekday	1.013191	.0041295	3.22	0.001	1.005129	1.021317
comp	1.059434	.0038748	15.79	0.000	1.051867	1.067056
dont_know	.0491635	.0037562	-39.43	0.000	.0423262	.0571053

Source: London Economics

A5.2 Statistical tests for model selection

We conducted a range of tests as validation for our model selection. A first test is comparison of the pseudo-R-squared terms. These are useful in terms of model comparisons in logit models generally. However, the two models display very similar R-squared values, and the model with added explanatory variables (model 2) has only a slightly higher pseudo-R-squared term. This indicates that in terms of fit, the two models are virtually identical.

One typical approach to assess model selection is to use a likelihood ratio (LR) test. The likelihood ratio test is a statistical test used to compare the fit of two models, one of which (the null model) is a special case of the other (the alternative model). In this case, the null model is our chosen model (model 1) is a reduced parameter model where explanatory variables are only entered into the model as interactions with duration. The alternative model (model 2) includes the main dummy variables as well as these interactions with duration. Thus, consistent with the test, model 1 is a nested version of model 2. The likelihood ratio, or equivalently its logarithm, can then be used to compute a p-value, or compared to a critical value. The null hypothesis is that the two models are not statistically different. If the LR test statistic (a chi-squared statistic) exceeds the critical value, we can reject the null hypothesis and potentially favour the alternative model. As per standard statistical tests, a critical value of greater than around two indicates that the null model should be rejected.

Null model (model 1) with interactions on duration

Figure 18:Full regression results from chosen WTA choice experiment (model 1)

```
Conditional (fixed-effects) logistic regression   Number of obs   =      25254
                                                  LR chi2(6)      =    6237.35
                                                  Prob > chi2     =     0.0000
Log likelihood = -6129.4439                       Pseudo R2       =     0.3372
```

choice	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
duration	-.0531906	.0069648	-7.64	0.000	-.0668414	-.0395399
duration_winter	-.0385614	.0042274	-9.12	0.000	-.046847	-.0302759
duration_peak	-.0399197	.0042717	-9.35	0.000	-.0482922	-.0315473
duration_weekday	.0131046	.0040758	3.22	0.001	.0051162	.0210929
comp	.0577352	.0036574	15.79	0.000	.0505668	.0649035
dont_know	-3.012604	.0764025	-39.43	0.000	-3.16235	-2.862858

Note: The regression results presented in Figure 4 have been rounded up for clarity.
Source: London Economics analysis

Alternative model (model 2) including main effects dummies

Figure 19:Full regression results for WTA choice experiment (including the stand alone dummy variables) (model 2)

```
Conditional (fixed-effects) logistic regression   Number of obs   =      25254
                                                  LR chi2(9)      =    6438.67
                                                  Prob > chi2     =     0.0000
Log likelihood = -6028.7811                       Pseudo R2       =     0.3481
```

choice	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
duration	-.1105605	.0082839	-13.35	0.000	-.1267966	-.0943244
winter	-.4443666	.0438656	-10.13	0.000	-.5303416	-.3583916
peak	-.4236638	.0441928	-9.59	0.000	-.5102802	-.3370474
weekday	.0074942	.0439876	0.17	0.865	-.07872	.0937084
duration_winter	.0262089	.007269	3.61	0.000	.0119619	.0404558
duration_peak	.0221943	.0072048	3.08	0.002	.0080731	.0363155
duration_weekday	.0086018	.0070773	1.22	0.224	-.0052695	.0224731
comp	.0553069	.0036627	15.10	0.000	.0481282	.0624857
dont_know	-3.392553	.0836208	-40.57	0.000	-3.556446	-3.228659

Source: London Economics analysis

A5.2.1 Likelihood-ratio test

Figure 20:Likelihood-ratio test for model selection (model 1 vs. model 2)

```
. lrtest m1 m2

Likelihood-ratio test                                 LR chi2(3)  =    201.33
(Assumption: m1 nested in m2)                         Prob > chi2 =    0.0000
```

Source: London Economics analysis

Thus, adding the dummy variables winter, peak, weekday appears to give a 'better fit' in terms of the log-likelihood test, as the test statistic is larger than the null rejection level (around two). We can also interpret the result of this test in terms of its probability (P) value. The test indicates that there is a 0.000% chance that we would fail to reject a 'true' null hypothesis that the null model (model 1) is equivalent to the alternative model (model 2).

However, this test does not necessarily imply that the preferred model is actually a 'better' model and we believe that some judgement should be taken into account here. In the next section, we show that applying this test to a model with more variables typically leads to the model with the most variables being chosen.

A5.2.2 Further Likelihood-ratio testing

As a test of the test, we now apply the same test to model 2 along with a model with more explanatory variables. The regression output of model 2 (with dummy variables and dummy interactions on duration) has been shown previously.

Adding more interaction terms for winter_weekday, peak_weekday and peak_weekday offer little intuitive meaning to the model and in the regression results below lead to some of the key variables, such as peak and weekday to be statistically insignificant. However, we can apply a LR test to this new model (e.g., model 3) to see if it gives us 'better fit'. This gives an indication of the power of these tests to select the 'better' model, versus a model which is merely different.

Figure 21:Regression results of model including stand alone dummy variables along with interaction terms for all variables (model 3)

```
Conditional (fixed-effects) logistic regression   Number of obs   =      25254
                                                  LR chi2(12)     =    6451.99
                                                  Prob > chi2     =     0.0000
Log likelihood = -6022.1245                       Pseudo R2       =     0.3488
```

choice	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
duration	-.1082191	.0085357	-12.68	0.000	-.1249487	-.0914895
winter	-.5543402	.1725442	-3.21	0.001	-.8925207	-.2161597
peak	-.0559087	.1378236	-0.41	0.685	-.326038	.2142206
weekday	-.0410544	.1822672	-0.23	0.822	-.3982915	.3161827
duration_winter	.0226544	.0074148	3.06	0.002	.0081216	.0371871
duration_peak	.0242092	.0074752	3.24	0.001	.0095581	.0388602
duration_weekday	.004712	.0071872	0.66	0.512	-.0093747	.0187987
winter_peak	-.3164375	.1866982	-1.69	0.090	-.6823592	.0494842
winter_weekday	.5962953	.2870374	2.08	0.038	.0337124	1.158878
peak_weekday	-.4418824	.1902273	-2.32	0.020	-.814721	-.0690438
comp	.0549153	.0036951	14.86	0.000	.0476729	.0621576
dont_know	-3.320374	.129691	-25.60	0.000	-3.574564	-3.066185

Source: London Economics analysis

Figure 22:Log-likelihood test for different models (model 2 vs. model 3)

```
. lrtest m1 m2

Likelihood-ratio test                              LR chi2(3)  =     13.31
(Assumption: m1 nested in m2)                      Prob > chi2 =    0.0040
```

Source: London Economics analysis

Our test statistic is about 13.31 which indicates that the new model with even more dummies and interaction terms (model 3) has a ‘better fit’ than model 2, according to this log likelihood test. In probability terms, there is a 0.4% chance that the null model (model 2) is a superior model (in terms of ‘best fit’). As originally discussed, we do not see the intuition behind why these three extra variables would improve the performance of the model as it is unclear how these variables would impact on choice of electricity outage.

Another test is to look at the Pseudo-R^2 for the three models. These change very slightly between the three different models (0.337, 0.3481 and 0.3488). A pseudo R-squared should only be interpreted in comparison to another pseudo R-squared of the same model type, on the same data, predicting the same outcome. In this situation, the higher pseudo R-squared indicates which model better predicts the outcome. As we can see above, the difference between the various models is very small and we do not believe that it is advisable to base model selection on the pseudo-R^2 alone.

The pseudo- R^2 values will typically be much lower for logistic regression in comparison with time series regression. Thus, the values obtained in this choice experiment are well within acceptable ranges.[134]

Overall, we do not believe that there is any clear evidence to choose one model over another although the LR tests may indicate otherwise.

A5.3 Collinearity

A potential issue to check on the models is collinearity. It should be noted that overall problems with collinearity should be reduced by the survey design process, and also by the nonlinear nature of the logit model.

The variance inflation factor (VIF) is a widely used diagnostic for collinearity in regression based models (both OLS and probit/logit). It is called the variance inflation factor because it estimates how much the variance of a coefficient is "inflated" because of linear dependence with other predictors. Thus, a VIF of 1.6 tells us that the variance (the square of the standard error) of a particular coefficient is 60% larger than it would be if that predictor was completely uncorrelated with all the other predictors. This has been applied to our data using the 'collin' command in Stata. A certain degree of correlation between our explanatory variables is expected as we are using interaction terms of our continuous variable duration. The general rule of thumb is that a mean VIF that exceeds four warrants further investigation. However, a VIF of 10 or more needs correction.

In our chosen model (model 1), we obtain a mean VIF of 2.69 which indicates some correlation between the explanatory variables. However, this seems to be below thresholds that warrant further inspection.

Table 56: Collinearity testing for original model (model 1)

Variable	VIF	VIF SQRT	Tolerance	R-Squared
duration	5.76	2.4	0.1735	0.8265
duration_winter	2.11	1.45	0.473	0.527
duration_peak	2.23	1.49	0.4491	0.5509
duration_weekday	2.25	1.5	0.445	0.555
comp	1.86	1.36	0.5385	0.4615
dont_know	1.93	1.39	0.5171	0.4829
Mean VIF	2.69			

Note: VIF stands for variance inflation factor.
Source: London Economics analysis

The same interpretation can be applied to the model which includes the main effects dummies (model 2). In this model, we obtain a mean VIF of 4.22. This is at a threshold that may warrant

[134] However, it must be noted that there is no universally accepted figure for the Pseudo-R_2 that indicates a model of good fit. As discussed previously, the Pseudo-R_2 is very useful to compare similar models based on the same data.

further attention. However, it is still below a level which indicates that collinearity is a severe problem.

Table 57: Collinearity testing for model 2				
Variable	**VIF**	**VIF SQRT**	**Tolerance**	**R-Squared**
duration	8.5	2.92	0.1176	0.8824
winter	3.06	1.75	0.3265	0.6735
peak	3.05	1.75	0.3275	0.6725
weekday	3.09	1.76	0.3241	0.6759
duration_winter	4.58	2.14	0.2183	0.7817
duration_peak	4.8	2.19	0.2082	0.7918
duration_weekday	4.91	2.22	0.2035	0.7965
comp	1.87	1.37	0.5343	0.4657
dont_know	4.08	2.02	0.2453	0.7547
Mean VIF	4.22			

Note: VIF stands for variance inflation factor; SQRT-square root.

Source: London Economics analysis

Another test for possible collinearity in econometric models is the Condition Number Test. This is a measure of ill-conditioning in a matrix. It will indicate that the inversion of the matrix is numerically unstable with finite-precision numbers. This indicates the potential sensitivity of the computed inverse to small changes in the original matrix. The Condition Number is computed by finding the square root of the maximum eigenvalue divided by the minimum eigenvalue ($\sqrt{(4.0137)/0.0811}$). If the Condition Number is above 30, the regression is said to have significant multicollinearity. However, both our models appear to fall well below this threshold. The results are generally the same as per the VIF test with the second model having slightly more evidence of collinearity issues. However, these issues are within typically accepted thresholds.

Table 58: Further tests for collinearity (original model) (model 1)		
	Eigenvalue	**Condition Index**
1	4.0137	1
2	1.3612	1.7172
3	0.601	2.5843
4	0.5173	2.7853
5	0.3187	3.549
6	0.1071	6.1225
7	0.0811	7.0361
Condition Number	**7.0361**	

Source: London Economics analysis

Table 59: Further tests for collinearity (model 2)		
	Eigenvalue	**Condition Index**
1	5.6091	1
2	1.3656	2.0267
3	0.9355	2.4486
4	0.6906	2.85
5	0.622	3.003
6	0.4181	3.6627
7	0.1243	6.7167
8	0.1085	7.1909
9	0.0979	7.5696
10	0.0284	14.0461
Condition Number	**14.0461**	

Source: London Economics analysis

A5.3.1 Conclusions on collinearity

Overall, we do not believe that collinearity is a major concern in either of these two models. The test statistics shown previously are well within acceptable levels. However, the results would tentatively indicate that model 1 performs better than model 2 in terms of potential collinearity.

The design of the choice experiment plays a key role in alleviating the possibility of collinearity between different explanatory variables. Also, the conditional logit econometric estimator essentially puts a fixed effects dummy on every possible choice (for a given respondent) and thus any other explanatory variable (such as income) that does not vary by choice is automatically dropped due to no variation.

The net result is then that tests for collinearity do not provide any strong indications towards model selection for the models studied.

A5.3.2 Conclusions on various model selection test

Overall, we believe that the various statistical tests that we have estimated do not provide any strong evidence to choose one model over another. For this reason, we believe it is important to derive the theory and intuition for the models that are underlying the modelling process. This will be presented in the next subsection.

A5.4 Graphical Example to explain the comparison of the two models

As discussed previously, we do not believe that model selection should be based solely on statistical tests and prior intuition on the process that is actually being modelled should also be incorporated. In this section, we describe the intuition behind our choice of model using mathematical and graphical derivations.

A5.4.1 Mathematical derivation of the WTA/WTP estimates

In order to develop the explanation more fully, this subsection gives an intuitive derivation of the coefficients in the WTA models using a logit framework.

This example explains the two models - model 1 (chosen model), and model 2 (including stand-alone dummies along with duration interaction terms). The technical outputs from these models were shown previously.

1. Options are described by the duration (D) of the outage (a continuous variable), whether the outage occurs in winter (W=1), whether the outage occurs at peak time (P=1), and compensation (C) received for the outage.[135]
   Thus the choices can be given by two options:

   Option a: D_a, W_a, P_a, D_aW_a, D_aP_a, C_a

   Option b: D_b, W_b, P_b, D_bW_b, D_bP_b, C_b

2. Using a conditional logit model, model the probability that an option is chosen as a linear function of D, W, P DW, DP and C:

   P(Option a chosen) = $\beta_1 D_a + \beta_2 W_a + \beta_3 P_a + \beta_4 D_a W_a + \beta_5 D_a P_a + \beta_6 C_a = \boldsymbol{\beta X_a}$

   P(Option b chosen) = $\beta_1 D_b + \beta_2 W_b + \beta_3 P_b + \beta_4 D_b W_b + \beta_5 D_b P_b + \beta_6 C_b = \boldsymbol{\beta X_b}$

3. Then the probability that Option a is chosen from a set that includes Option a and Option b is:[136]

$$e^{\beta'' X_a} \Big/ \textstyle\sum_{i=1}^{J} e^{\beta X_i}$$

4. Similarly, the probability that Option b is chosen from that same set is:

$$e^{\beta X_b} \Big/ \textstyle\sum_{i=1}^{J} e^{\beta X_i}$$

5. If, say, option 1 is winter off peak weekend 2[137]hrs duration and option 2 is one-hour duration summer off peak weekend, That is:

[135] We have omitted weekend/weekday for simplicity, but the intuition is the same.

[136] A good discussion can be found at page 6 of this document: https://lirias.kuleuven.be/bitstream/123456789/167348/1/KBI_0809.pdf

$$e^{\beta X_a} \Big/ \sum_{i=1}^{J} e^{\beta X_i} = e^{\beta X_b} \Big/ \sum_{i=1}^{J} e^{\beta X_i}$$

6. Cancelling the denominators and taking natural logs, we get:

$$\boldsymbol{\beta X_a = \beta X_b}$$

or generally;

$$\beta_1 D_a + \beta_2 W_a + \beta_3 P_a + \beta_4 D_a W_a + \beta_5 D_a P_a + \beta_6 C_a = \beta_1 D_b + \beta_2 W_b + \beta_3 P_b + \beta_4 D_b W_b + \beta_5 D_b P_b + \beta_6 C_b$$

7. Cancelling terms of the above for the specific choice we've described as the example:

$\beta_1 D_a + \beta_2 W_a + \beta_4 D_a W_a + \beta_6 C_a = \beta_1 D_b + \beta_6 C_b$

8. Therefore:

$$\beta_6(C_a - C_b) = -\beta_1(D_a - D_b) - \beta_2 W_a - \beta_4 D_a W_a$$

9. As stated at (5) above, $D_b - D_a = 1 = D_b W_b - D_a W_a$, $W_a = 1$

10. Therefore:

$$\beta_6(C_a - C_b) = -(\beta_1 + \beta_2 + \beta_4)$$

11. Therefore:

$$(C_a - C_b) = -(\beta_1 + \beta_2 + \beta_4)/\beta_6$$

12. That is:

$$WTA = -(\beta_1 + \beta_2 + \beta_4)/\beta_6$$

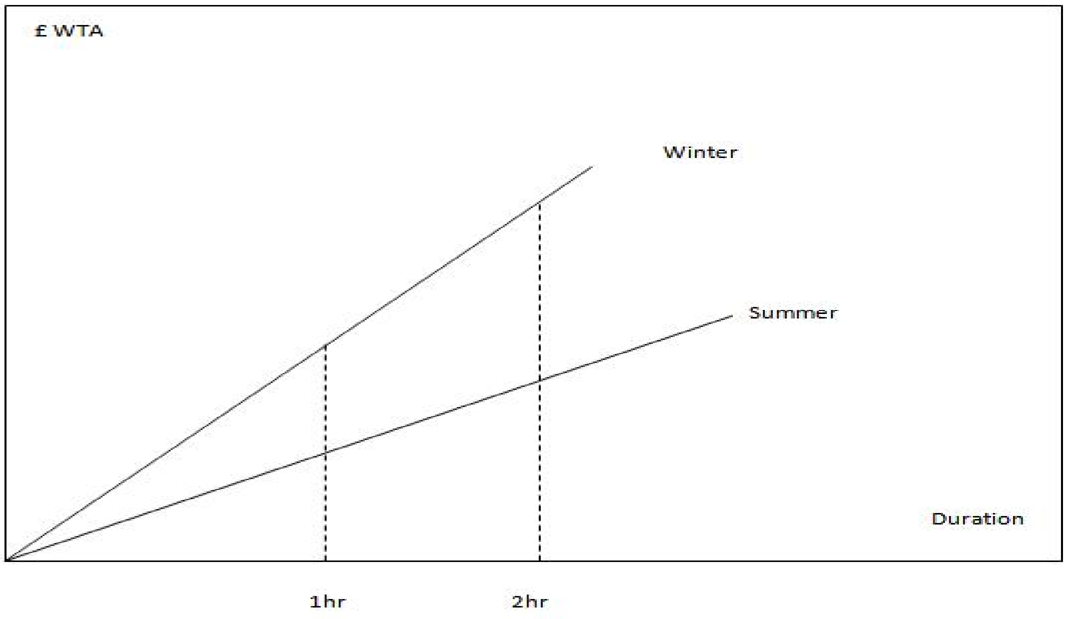
[137] The units on duration in the domestic experiment were actually 20mins, 1hr, and 4hrs, but the concept is proportional and for the example this makes the maths easier without loss of generality.

A5.4.2 Graphical illustration of the model

Thus, the above algebraic manipulation demonstrates that the underlying drivers of the choices in the CE are driven by the linear form of the model of preferences. The form of the model (e.g., model 1 and model 2) will potentially impact the estimated size of the WTA.

Since various econometric tests are not conclusive with respect to which model to use, we apply logic and reason to determine which model seems the most robust and plausible. The example is done in terms of summer[138] versus winter. The figure below shows a graphical interpretation of the WTA estimates and how the qualitatively differ between summer and winter for Model 1.

Figure 23:Model 1 (chosen model)



Source: London Economics

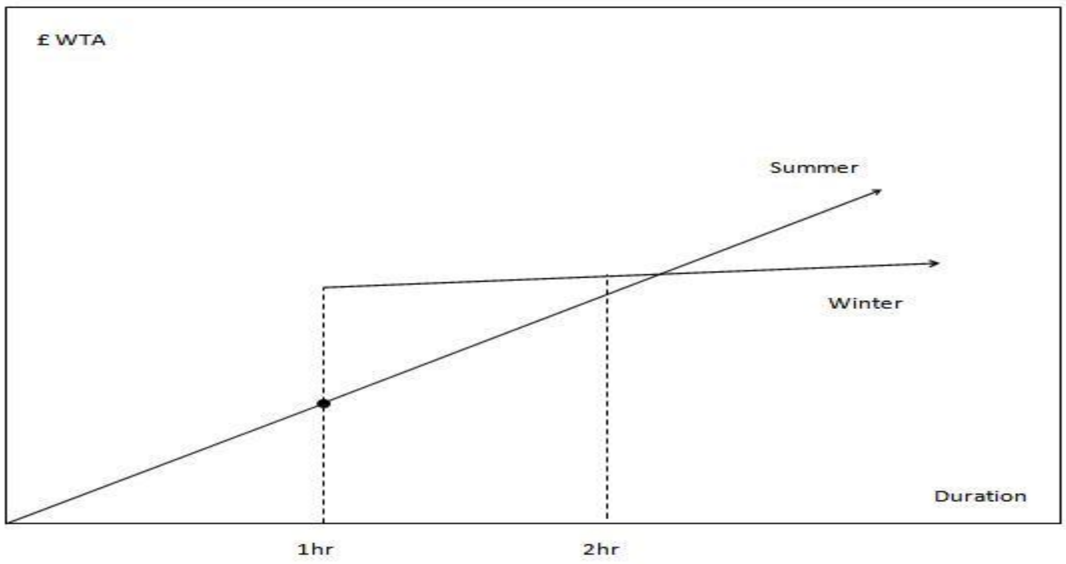
In essence, by using model 1, and given the coefficients we get, the model is constrained such that winter is always greater than summer (given the correct sign on the estimated winter coefficient), and that the value of the WTA is proportional to the time of the outage. Note that a zero-length outage must be equal to zero WTA, as by definition this is 'not an outage'.

Note that there is no chance that the model estimates that a summer outage value exceeds a winter outage, even as an outage gets long.

The next figure presents the same results graphically for model 2, the model which included both outage-duration-independent and duration interacted dummy variables for season, day of the week, and peak.

[138] In the actual choice experiment, this variable is presented as 'not winter' and winter. For the purposes of this graphical illustration we will stick to the summer winter notation for ease of interpretation.

Figure 24:Model 2 (summer winter)



Source: London Economics

Now in model 2, the structure of the model is allowed to have an intercept that is not dependent on duration, and also a slope-rotating term, the duration_winter interaction term, which changes the slope.

The winter-alpha (duration independent) value is the 'shift' variable, and is much bigger than the 'rotation' variable coefficient estimate:

Figure 25:Key regression outputs from model 2

```
winter |   -.4443666

duration_winter |    .0262089
```

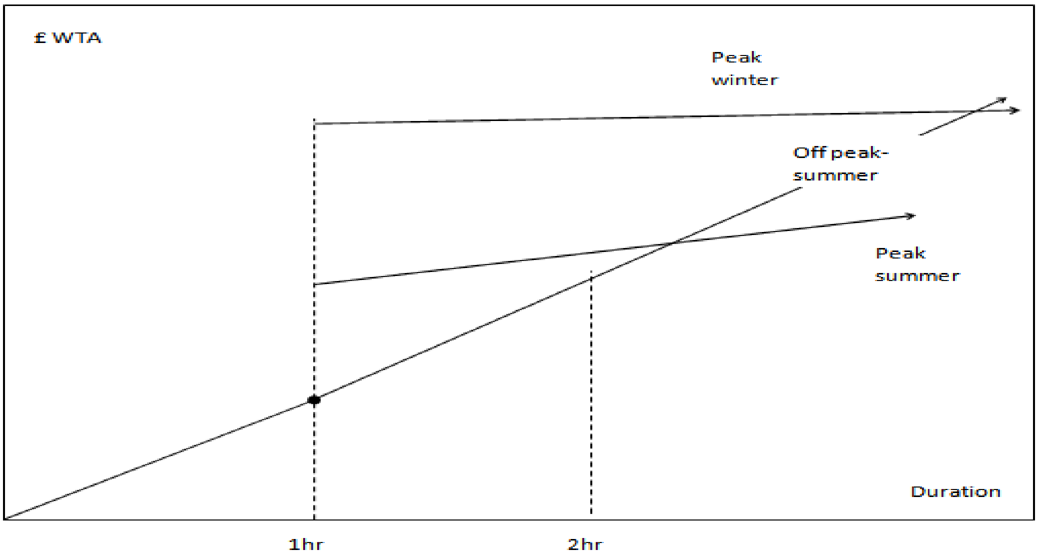
Source: London Economics

They are also of opposite sign, and significant. Thus, the effect of what this model is telling us is to shift the curve up, and flatten it out, when we have a winter outage, vìs a vìs a summer outage.

Notice that in this model, given the estimated coefficients, as the outage duration gets long, eventually the non-winter outage would become more valuable in total £WTA terms that the winter outage; this seems implausible. Further, the rate at which a winter outage increases the WTA with duration is everywhere lower for the winter outage vìs a vìs the not winter outage, which also seems implausible. In other words, why would the increase in £WTA with a longer outage be higher for not winter than in winter?

It should be noted that the size and signs of the coefficients for peak are similar. Thus the same logic would apply, i.e., we would have a situation where the model 2 estimates would imply that as an outage got longer and longer, an off-peak outage would eventually become more valuable in £WTA than a peak outage, because the impact of the coefficients is to flatten out the peak WTA curve vìs a vìs the off-peak one, as well as to shift it up. The same would happen for peak and winter. These added situations are depicted below.

Figure 26: Model 2 (summer winter and peak-offpeak)



Source: London Economics

A5.4.3 Conclusion on model selection

These implausibilities suggest that model 2 is not the best model and is not consistent with what might be considered very plausible prior beliefs about how consumers would value outages. We therefore prefer model 1 on this basis.

Annex 6 Additional results from the choice experiment

In this Annex, we provide further results using different assumptions than used in our final results which were shown in the main report.

A6.1.1 Results from the pooled sample

In this section we provide the results of the pooled sample (i.e. adding in the face-to-face observations to the online survey). As discussed in the main report, this leads to an overrepresentation of 'vulnerable' groups in the sample. However, it is useful to include this as a sense check. The results indicate a slightly higher level of WTA and WTP when the face-to-face response added to the sample. However, this is not significant as shown in the table below. Taking the weighted average of the means and standards errors of these two estimates for WTA for a 1 hour outage occurring at Winter, Peak, Weekend shows the invariance between the conclusions regarding VoLL and the inclusion or otherwise of the face-to-face survey.

Table 60: Estimates of WTA in £ for various outages in different circumstances, – domestic customers (1 hour disruption) – pooled sample

	Not Winter Not Peak Weekend	Not Winter Not Peak Weekday	Not Winter Peak Weekday	Not Winter Peak Weekend	Winter Not Peak Weekend	Winter Not Peak Weekday	Winter Peak Weekday	Winter Peak Weekend
Online only	**2.76**	**2.08**	**4.16**	**4.84**	**4.77**	**4.09**	**6.16**	**6.84**
Pooled sample	**3.00**	**2.24**	**4.24**	**5.00**	**4.99**	**4.23**	**6.23**	**6.99**

Note: Estimates in bold indicate statistical significance at the 95% confidence interval.
Source: London Economics analysis

Table 61: Confidence Intervals for a one hour outage under different circumstances, WTA – online vs pooled sample – Winter, Peak, Weekend

Type of one hour outage	Coefficient	z-stat	Std. error	Lower Bound	Upper Bound
Winter, Peak, Weekend (online)	**6.84**	**14.52**	0.47	5.92	7.77
Winter, Peak, Weekend (pooled)	**6.99**	**14.58**	0.48	6.05	7.93

Note: Estimates in bold indicate statistical significance at the 95% confidence interval.
Source: London Economics analysis

Table 62: Estimates of WTP in £ for various outages in different circumstances, – domestic customers (1 hour disruption) – pooled sample

	Not Winter Not Peak Weekend	Not Winter Not Peak Weekday	Not Winter Peak Weekday	Not Winter Peak Weekend	Winter Not Peak Weekend	Winter Not Peak Weekday	Winter Peak Weekday	Winter Peak Weekend
Online only	**0.80**	(0.03)	(0.05)	**0.78**	**0.97**	0.14	0.12	**0.96**
Pooled sample	**0.79**	(0.06)	0.02	**0.87**	**1.05**	0.20	0.28	**1.12**

Note: Estimates in bold indicate statistical significance at the 95% confidence interval.
Source: London Economics analysis

Table 63: Comparison of WTA and WTP £/MWh estimates by time of outage – domestic customers, based on a time varying electricity demand profile (pooled sample)

	Not Winter Not Peak Weekend	Not Winter Not Peak Weekday	Not Winter Peak Weekday	Not Winter Peak Weekend	Winter Not Peak Weekend	Winter Not Peak Weekday	Winter Peak Weekday	Winter Peak Weekend
WTA (£/MWh)	**10,366**	**7,482**	**9,441**	**11,518**	**11,495**	**9,419**	**10,404**	**12,076**
WTP (£/MWh)	**2,736**	(186)	41	**1,994**	**2,418**	451	462	**1,942**

Note: The figures are based on figures for a one hour electricity outage. Converted based on an assumed annual electricity consumption of 3.934 MWh per annum but the numbers have been adjusted for different electricity demands across outage scenarios. Estimates in bold indicate statistical significance at the 95% confidence interval.
Source: London Economics analysis

A6.1.2 Confidence Intervals

This section presents the confidence intervals for our headline results. The confidence intervals for a one-hour outage under the various choice scenarios are shown below. The lowest bound of the lowest estimate is found to be £1.49 with the highest bound of the highest estimate being £7.77.

Table 64: Confidence Intervals for a one hour outage under different circumstances, WTA – domestic customers

Type of one hour outage	Coefficient	z-stat	Lower Bound	Upper Bound
Not Winter, Not Peak, Weekend	**2.76**	**8.00**	2.09	3.44
Not Winter, Not Peak, Weekday	**2.08**	**6.92**	1.49	2.67
Not Winter, Peak, Weekday	**4.16**	**14.28**	3.59	4.73
Not Winter, Peak, Weekend	**4.84**	**13.63**	4.14	5.53
Winter, Not Peak, Weekend	**4.77**	**13.39**	4.07	5.47
Winter, Not Peak, Weekday	**4.09**	**14.07**	3.52	4.66
Winter, Peak, Weekday	**6.16**	**15.07**	5.36	6.96
Winter, Peak, Weekend	**6.84**	**14.52**	5.92	7.77

Note: Confidence Intervals are estimated using the Delta method.
Source: London Economics analysis

The confidence intervals for the various WTP scenarios are shown in Table 65 and show that in four of the eight scenarios, domestic respondents are willing to pay a value between £0.78 and £0.96 in order to avoid a one-hour electricity outage of different types. In the other types of electricity outages, it appears that respondents are not willing to pay a value that is statistically different from £0.

In the regression analysis, it was found that if the outage occurred on a weekday, this option was more likely to be chosen. This result was statistically significant and indicated that respondents preferred electricity outages to occur on weekdays rather than weekends. This would indicate that respondents would have a higher WTP to avoid an outage that occurs on a weekend day. This is consistent with the estimates shown above and the confidence intervals below which indicate that the WTP to avoid an outage occurring on a weekday is not statistically different from £0.

Table 65: Confidence Intervals for a one hour outage under different circumstances, WTP – domestic customers

Type of one hour outage	Coefficient	z-stat	Lower Bound	Upper Bound
Not Winter, Not Peak, Weekend	**-0.80**	**-2.470**	-1.44	-0.17
Not Winter, Not Peak, Weekday	0.03	0.090	-0.60	0.66
Not Winter, Peak, Weekday	0.05	0.160	-0.53	0.63
Not Winter, Peak, Weekend	**-0.78**	**-2.970**	-1.30	-0.27
Winter, Not Peak, Weekend	**-0.97**	**-3.190**	-1.57	-0.37
Winter, Not Peak, Weekday	-0.14	-0.530	-0.67	0.38
Winter, Peak, Weekday	-0.12	-0.550	-0.57	0.32
Winter, Peak, Weekend	**-0.96**	**-4.250**	-1.40	-0.51

Note: Confidence Intervals are estimated using the Delta method. Note that the WTP estimates are multiplied by -1 as the model is set up with more of the good (duration of outage) being negative.
Source: London Economics analysis

A6.1.3 Sensitivity analysis

In this section, we present other estimates based on different assumptions. In our headline figures, we have assumed that respondents who chose 'don't know' for all choices are not really participating with the choice experiment and should be excluded. This was much clearer for the WTP experiment. In this section we will present the comparable results from a model where these 'don't know' observations are not removed.

Table 66: Estimates of WTA in £ for various outages in different circumstances, – domestic customers, all observations included

	Not Winter Not Peak Weekend	Not Winter Not Peak Weekday	Not Winter Peak Weekday	Not Winter Peak Weekend	Winter Not Peak Weekend	Winter Not Peak Weekday	Winter Peak Weekday	Winter Peak Weekend
20 mins.	**0.82**	**0.61**	**1.41**	**1.62**	**1.60**	**1.39**	**2.19**	**2.40**
1 hour	**2.45**	**1.82**	**4.24**	**4.87**	**4.79**	**4.16**	**6.58**	**7.21**
4 hours	**9.80**	**7.26**	**16.95**	**19.49**	**19.16**	**16.62**	**26.31**	**28.85**

Note: All values are statistical significant at the 95% confidence interval.
Source: London Economics analysis online survey

As expected, removing the respondents who always chose 'don't know' has a much greater impact on the WTP estimates than for the WTA estimates. For an hour outage in winter at peak on the weekend, the highest WTA was £6.84. Including these 'don't know' respondents raises this answer to £7.21. The same choice scenario for the WTP figures moves from £0.96 to £0.61. The WTP model also had lower statistical significance when all observations were included. It must be noted that the vast majority of respondents who chose 'don't know' for all WTA choice scenarios also chose 'don't know' for all WTP choices. Thus, we believe that these respondents have not really engaged with the experiment and should be removed from both.

Table 67: Estimates of WTP £ to avoid an outage by time of outage – domestic customers, all observations included

	Not Winter Not Peak Weekend	Not Winter Not Peak Weekday	Not Winter Peak Weekday	Not Winter Peak Weekend	Winter Not Peak Weekend	Winter Not Peak Weekday	Winter Peak Weekday	Winter Peak Weekend
20 mins	0.18	(0.11)	(0.11)	**0.18**	**0.20**	(0.09)	(0.09)	**0.20**
1 hour	0.54	(0.33)	(0.32)	**0.54**	**0.60**	(0.26)	(0.26)	**0.61**
4 hours	2.14	(1.32)	(1.30)	**2.16**	**2.41**	(1.05)	(1.03)	**2.43**

Note: All values in bold indicate statistical significance at the 95% confidence interval.
Source: London Economics analysis of online survey

VoLL estimates using a constant electricity consumption across all outage scenarios

We show VoLL estimates in £/MWh in Table 68 using the chosen results from the WTA experiment. In this table, the VoLL is estimated by applying the same electricity consumption to all eight outage scenarios. The VoLL estimates range from £4,638/MWh to £15,235/MWh depending on the specific outage scenario. A significant range is expected as people are likely to value on electricity outage very differently depending on its timing.

Table 68: Estimates of VoLL in £/MWh under different circumstances, WTA – domestic customers, constant electricity demand

	Not Winter Not Peak Weekend	Not Winter Not Peak Weekday	Not Winter Peak Weekday	Not Winter Peak Weekend	Winter Not Peak Weekend	Winter Not Peak Weekday	Winter Peak Weekday	Winter Peak Weekend
1 hour	**2.76**	**2.08**	**4.16**	**4.84**	**4.77**	**4.09**	**6.16**	**6.84**
£/MWh	**6,154**	**4,638**	**9,257**	**10,773**	**10,616**	**9,100**	**13,719**	**15,235**

Note: Converted based on an assumed annual electricity consumption of 3.934 MWh per annum. All estimates in bold are statistically significant at the 95% confidence interval.
Source: London Economics analysis

We also convert our WTP estimates into VoLLs in £/MWh using the same approach as above. The results of this procedure are shown in Table 69 and as expected show a much lower value of VoLL. These estimates range from effectively zero to £2,128/MWh for an outage occurring at the weekend at peak times during winter.

Table 69: Estimates of VoLL in £/MWh under different circumstances, WTP, domestic customers, constant electricity demand

	Not Winter Not Peak Weekend	Not Winter Not Peak Weekday	Not Winter Peak Weekday	Not Winter Peak Weekend	Winter Not Peak Weekend	Winter Not Peak Weekday	Winter Peak Weekday	Winter Peak Weekend
1 hour	**0.80**	(0.03)	(0.05)	**0.78**	**0.97**	0.14	0.12	**0.96**
£/MWh	**1,783**	(67)	(105)	**1,745**	**2,165**	315	278	**2,128**

Note: Converted based on an assumed annual electricity consumption of 3.934 MWh per annum. All estimates in bold are statistically significant at the 95% confidence interval.
Source: London Economics analysis

SMEs

The confidence intervals and the estimated coefficients for a one hour outage are shown in Table 70. As mentioned previously, the coefficients in the table below are interpreted as percentages of the average electricity bill. The largest coefficients are associated with outages that occur on workdays in winter.

Table 70: Confidence Intervals for a one hour outage under different circumstances, WTA – SMEs

Type of one hour outage	Coefficient	z-stat	Lower Bound	Upper Bound
Summer, Not Peak, Non-work day	0.034	1.52	-0.014	0.082
Summer, Not Peak, Workday	0.056	**2.00**	0.006	0.113
Summer, Peak, Workday	0.056	**1.98**	0.006	0.113
Summer, Peak, Non-work day	0.034	1.50	-0.014	0.082
Winter, Not Peak, Non-work day	0.044	1.74	-0.008	0.096
Winter, Not Peak, Workday	0.066	**2.15**	0.005	0.127
Winter, Peak, Workday	0.066	**2.12**	0.004	0.128
Winter, Peak, Non-work day	0.043	1.72	-0.009	0.096

Note: Confidence Intervals are estimated using the Delta method.
Source: London Economics analysis

The confidence intervals for a one hour outage are shown below (Table 71). These results indicate that all choice scenarios are not statistically significant at the 95% confidence level. The lowest estimate is for the choice scenario where a one hour electricity outage occurs during summer at non-peak hours on a non-working day. The lower bound of this choice scenario is only marginally above zero.

Table 71: Confidence Intervals for a one hour outage under different circumstances, WTP – SMEs

Type of one hour outage	Coefficient	z-stat	Lower Bound	Upper Bound
Summer, Not Peak, Non-work day	0.0197	**2.12**	0.0015	0.0379
Summer, Not Peak, Workday	0.0295	**2.72**	0.0083	0.0507
Summer, Peak, Workday	0.0338	**2.87**	0.0107	0.0568
Summer, Peak, Non-work day	0.0239	**2.40**	0.0044	0.0435
Winter, Not Peak, Non-work day	0.0261	**2.55**	0.0060	0.0462
Winter, Not Peak, Workday	0.0359	**2.95**	0.0121	0.0597
Winter, Peak, Workday	0.0402	**3.03**	0.0141	0.0662
Winter, Peak, Non-work day	0.0304	**2.71**	0.0084	0.0523

Note: Confidence Intervals are estimated using the Delta method.
Source: London Economics analysis

VoLL estimates using a constant electricity consumption across all outage scenarios

We show SME VoLL estimates in £/MWh in Table 72 using the results from the WTA experiment. In this table, the VoLL is estimated by applying the same SME electricity consumption to all eight outage scenarios. The VoLL estimates range from £25,493/MWh to £49,046/MWh depending on the specific outage scenario. A significant range is expected as people are likely to value on electricity outage very differently depending on its timing. The key driver is whether the outage occurs on a workday or a non-workday.

Table 72: Estimates of WTA VoLL in £/MWh, – SMEs, constant electricity demand								
	Summer	Summer	Summer	Summer	Winter	Winter	Winter	Winter
	Not Peak	Not Peak	Peak	Peak	Not Peak	Not Peak	Peak	Peak
	Non-work	Work day	Work day	Non-work	Non-work	Work day	Work day	Non-work
Implied £ valuation	85.41	**141.16**	**140.42**	84.67	109.32	**165.07**	**164.33**	108.58
VoLL WTA £/MWh	25,493	**42,132**	**41,911**	25,272	32,629	**49,267**	**49,046**	32,407

Note: This is converted to £/MWh using an assumed annual consumption of 29.35 MWh. Estimates in bold are statistically significant at the 95% confidence interval.
Source: SME survey

We also convert our SME WTP estimates into VoLLs in £/MWh using the same approach as above. The results of this procedure are shown in Table 73 and as expected show a lower value of VoLL. These estimates range from effectively £14,690/MWh to £29,969/MWh for an outage occurring at the weekend at peak times during winter. As per the WTA model, the importance of whether the outage occurs on a typical working day should be noted.

Table 73: Estimates of WTP VoLL in £/MWh, – SMEs, constant electricity demand								
	Summer	Summer	Summer	Summer	Winter	Winter	Winter	Winter
	Not Peak	Not Peak	Peak	Peak	Not Peak	Not Peak	Peak	Peak
	Non-work	Work day	Work day	Non-work	Non-work	Work day	Work day	Non-work
Implied £ valuation	**49.22**	**73.75**	**84.39**	**59.86**	**65.24**	**89.77**	**100.41**	**75.88**
VoLL WTP	**14,690**	**22,011**	**25,188**	**17,867**	**19,471**	**26,792**	**29,969**	**22,648**

Note: This is converted to £/MWh using an assumed annual consumption of 29.35 MWh. Estimates in bold are statistically significant at the 95% confidence interval.
Source: SME survey

Annex 7 Nonlinear models for WTP and WTA for SME and domestic electricity users

This Annex provides alternative estimation results for a nonlinear model specification. The WTP and WTA estimates provided in this section are for outages lasting one hour and, due to the nonlinear structure, they cannot be directly scaled to outages lasting different lengths. Note also that all WTP and WTA estimates provided here should be multiplied by -1. In our model, Attribute X is minutes of outage. However, we want WTP for less outage (i.e. WTP for less X, not more). Hence we need to multiply by -1. Either way, our coefficients are in the 'right' direction – consumers prefer it when outages are shorter and when they have to pay less (accept more) – so we can write "consumers are willing to pay £x to avoid y minutes of outage", using the ratio of the coefficients to get x and y.[139]

As discussed previously, we found no evidence that a nonlinear model was more appropriate for consumers. The nonlinear model did the not significantly improve the fit of the model and the coefficient on the nonlinear duration variable was estimated to be insignificant for WTP.

A7.1 Domestic

The nonlinear model did the not significantly improve the fit of the model and the coefficient on the nonlinear duration variable was estimated to be insignificant for WTP. For the WTA, a nonlinear model led to an insignificant duration variable which was not the case in the linear model.

Figure 27:Non- Linear estimation results WTA for domestic consumers (online sample)

Choice	Coef.	Std. Err.	z	P>z	[95% Conf.	Interval]
Duration	0.119	0.100	1.180	0.236	-0.078	0.315
duration2	-0.016	0.007	-2.300	0.021	-0.030	-0.002
duration_winter	-0.254	0.024	-10.620	0.000	-0.301	-0.207
duration2_winter	0.021	0.002	9.430	0.000	0.016	0.025
duration_peak	-0.198	0.022	-9.000	0.000	-0.241	-0.155
duration2_peak	0.016	0.002	7.760	0.000	0.012	0.019
duration_weekday	0.079	0.024	3.300	0.001	0.032	0.126
duration2_weekday	-0.006	0.002	-2.790	0.005	-0.010	-0.002
comp	0.052	0.007	7.020	0.000	0.037	0.066
dont_know	-2.981	0.148	-20.090	0.000	-3.271	-2.690

Note: Standard errors and confidence intervals for WTA estimates are calculated using the delta method.
Source: London Economics

[139] Grutters et al. (2008) "Willingness to Accept versus Willingness to Pay in a Discrete Choice Experiment" Value in Health Vol. 11 No.7

Figure 28:Nonlinear estimation results WTP for domestic consumers (online sample)

	Coef.	Std. Err.	z	P>z	[95% Conf.	Interval]
duration	0.090	0.064	1.400	0.161	-0.036	0.216
duration2	-0.006	0.005	-1.370	0.172	-0.015	0.003
duration_winter	0.017	0.023	0.740	0.462	-0.028	0.062
duration2_winter	-0.002	0.002	-0.800	0.424	-0.006	0.002
duration_peak	-0.029	0.022	-1.300	0.193	-0.072	0.014
duration2_peak	0.002	0.002	1.170	0.242	-0.002	0.006
duration_weekday	0.127	0.023	5.590	0.000	0.083	0.172
duration2_weekday	-0.010	0.002	-4.790	0.000	-0.014	-0.006
price	-0.053	0.008	-7.000	0.000	-0.068	-0.038
dont_know	-2.428	0.185	-13.120	0.000	-2.791	-2.066

Note: Standard errors and confidence intervals for WTP estimates are calculated using the delta method. It must be noted that the WTP estimates should be multiplied by minus 1.
Source: London Economics

A7.2 SME

Applying a full nonlinear model led to a result where the coefficient on duration was insignificant and also the wrong sign. Also the statistical performance of the model did not improve.

Figure 29:Nonlinear estimation results WTA for SME consumers

```
Conditional (fixed-effects) logistic regression    Number of obs   =       4821
                                                   LR chi2(10)     =    1534.98
                                                   Prob > chi2     =     0.0000
Log likelihood = -997.98175                        Pseudo R2       =     0.4347
```

choice	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
duration	.1223302	.0688201	1.78	0.075	-.0125547	.2572151
duration2	-.0065179	.0030282	-2.15	0.031	-.0124532	-.0005827
duration_winter	-.1494212	.0386924	-3.86	0.000	-.2252569	-.0735855
duration2_winter	.0068467	.0019895	3.44	0.001	.0029474	.0107461
duration_peak	-.0335954	.0391235	-0.86	0.391	-.110276	.0430852
duration2_peak	.0015909	.0019967	0.80	0.426	-.0023225	.0055043
duration_weekday	-.2916247	.0356641	-8.18	0.000	-.3615252	-.2217243
duration2_weekday	.0125131	.001841	6.80	0.000	.0089048	.0161214
comp	7.793705	2.245585	3.47	0.001	3.392438	12.19497
dont_know	-3.949487	.4893362	-8.07	0.000	-4.908568	-2.990405

Source: London Economics

Applying a nonlinear model to the WTP data led to a number of insignificant regression coefficients. Thus, we felt that the linear model was more appropriate.

Figure 30:Nonlinear estimation results WTP for SME consumers

```
Conditional (fixed-effects) logistic regression   Number of obs   =      4281
                                                  LR chi2(10)     =   1271.80
                                                  Prob > chi2     =    0.0000
Log likelihood = -931.81802                       Pseudo R2       =    0.4056
```

choice	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
duration	-.0407293	.0950259	-0.43	0.668	-.2269767	.1455181
duration2	-.0004516	.004332	-0.10	0.917	-.0089422	.008039
duration_winter	-.0521762	.0434715	-1.20	0.230	-.1373788	.0330264
duration2_winter	.0025104	.0022594	1.11	0.267	-.0019179	.0069387
duration_peak	-.0463267	.0440642	-1.05	0.293	-.1326908	.0400375
duration2_peak	.0022614	.0022749	0.99	0.320	-.0021973	.0067202
duration_weekday	-.1878562	.0437033	-4.30	0.000	-.2735131	-.1021993
duration2_weekday	.0090538	.00225	4.02	0.000	.0046439	.0134637
price	-13.36745	1.933863	-6.91	0.000	-17.15775	-9.577146
dont_know	-4.946464	.2672271	-18.51	0.000	-5.470219	-4.422708

Source: London Economics

Annex 8 Results from the contingent valuation (CV) survey

This Annex provides additional analysis from the contingent valuation questions that were asked as part of the survey for domestic and SME customers.

A8.1 Domestic contingent valuation results

This section presents the results of the contingent valuation questions for domestic consumers and assesses these results with regard to the results of the main choice experiment.

The estimates and analysis are primarily based on the online sample in order to ensure that the estimates are based on a representative sample as discussed previously. Results for the face-to-face interview are presented separately at the end of this section and compared to the main results.

Contingent valuation is a more direct method to estimate willingness-to-pay (willingness-to-accept) as it is based on direct questions that have a clear interpretation. However, this directness may lead to an under estimate of WTP and an overestimate of WTA. This method is also more limited in the amount of possible scenarios that it can examine. Each CV question can really only examine one possible electricity outage scenario. Given the number of different important dimensions to an electricity outage, a CV approach would require a large number of questions and this may not be feasible in the context of an online or face-to-face survey.

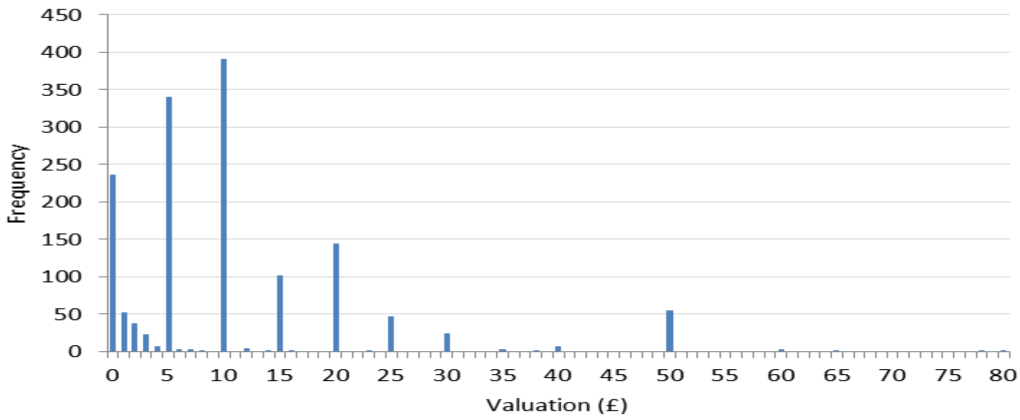
An important point to note is that the choice experiment questions were asked prior to the CV questions for domestic and SME respondents. The levels chosen in the choice experiment may have a direct influence on the levels chosen by respondents. This form of 'conditioning' may give respondents information on the appropriate level of payment that they should choose in the direct CV question. However, it must be noted, that the levels chosen in the choice experiment are not random and represent reasonable payment levels for various electricity outages. The questions asked in the contingent valuation sections are shown below:

- WTA contingent valuation question: If your electricity supply were to be interrupted for **one hour** during your peak times of usage, on a **weekday** during **winter**, how much do you think would be a fair amount of compensation?
- WTP contingent valuation question: How much would you pay as a one-off charge to avoid your electricity supply being interrupted for **one hour** during your peak times of usage on a **weekday** during **winter**?

WTA estimates

Survey respondents were asked to specify the payment they would consider fair to experience a one hour electricity outage at peak time on a weekday during in the winter. Consumers' responses to the contingent valuation questions asking respondents to state what they believe to be a fair payment to experience an hour without electricity in winter are clustered around particular values. In particular, responses were clustered around valuations of multiples of £5 (Figure 31). It must also be noted that £5, £10, £15 were three of the amounts specified in the choice experiment. The CV questions have been phrased so that respondents choose their own peak electricity usage time and this may mean that they choose a time when they are at home. This may imply higher that higher levels of payment may be required.

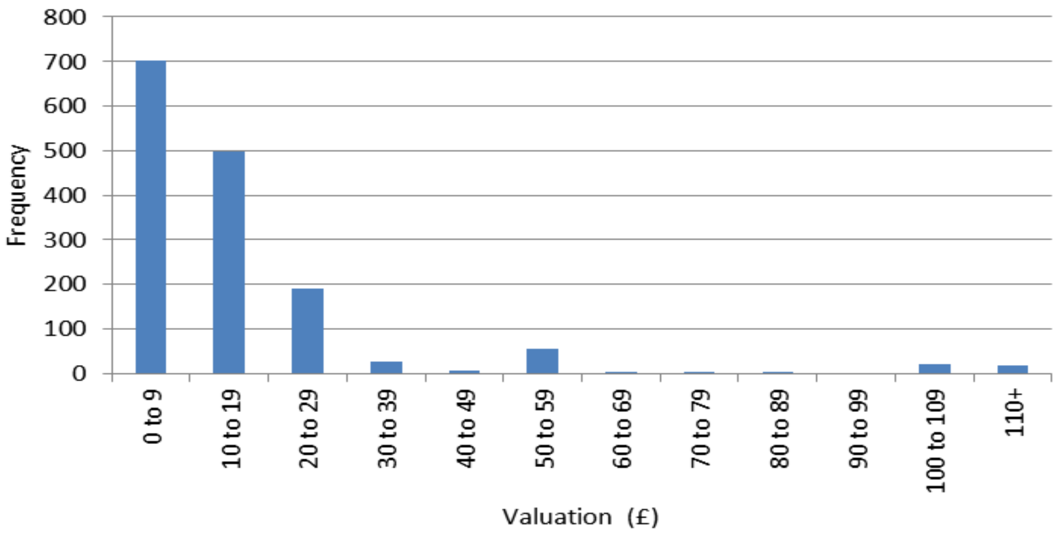
Figure 31:Fair payment to experiencea one hour outage at peak times on a weekday during Winter- domestic consumers



Note: Only responses in the range £0-£80 are shown. This is to show the clustering of responses.
Source: London Economics analysis of online survey data.

Visually, it is also useful to display the contingent valuation results in bands. This is done in Figure 32 and shows the clustering of responses between £0-to-£20. The next largest spike in responses is in the £20-to-£29 band. There is also a much smaller spike in the £50to-£59 band which indicates that these respondents believe that they should receive a payment of around £55 due to a one hour outage of electricity. We can also see that a small percentage of respondents believe that they should receive a payment of over £100 to experience this one hour outage.

Figure 32:Fair payment to experience a one hour outage at peak times on a weekday during Winter- domestic consumers (bands)



Source: London Economics analysis of online survey data.

Table 13 displays the results shown graphically in terms of standard statistical indicators such as mean, median and standard deviation. This table shows the importance of removing observations that are substantially higher than the average.

On average, consumers think that a fair payment would be £19.55 for experiencing a one-hour outage[140] at peak times on a weekday in the winter based on the CV. This is significantly higher than the estimate for WTA derived using the choice experiment (around £6.16-£6.84 for this type of outage). However, the average includes all observations including some very high stated values such as £2,000. It is unclear if these were so-called 'non-engagement' choices, or similar, but excluding outliers and the impact of reducing the variation is shown below. The median, however, is more in line with the CE estimate.

[140] All averages calculated based on contingent valuation responses include both zero value responses and non-zero responses unless otherwise stated.

Table 74: Average valuation of fair payment to experience a 1 hour outage during peak times on a weekday during Winter - domestic consumers

Sample	Average (£)	Median (£)	Max. (£)	Min. (£)	Std. Dev.	Sample %[1]
Full sample	19.55	10	2000	0	100.49	100%
Limited sample: Mean +/-2 std. dev.	12.91	10	201	0	20.66	99%
Limited sample: Mean +/-1 std. dev.	11.84	10	100	0	15.39	99%
Limited sample: Mean +/-0.5 std. dev.	10.50	10	65	0	11.06	97%
Excluding zero responses	23.13	10	2000	1	108.93	85%

Note: 1. Refers to the number of observations in the sample as a share of the full sample.
Source: London Economics analysis of online survey data

To adjust for these large possible outliers, we limited our sample by removing observations that were varying numbers of standard deviations above the mean. This method essentially removes a different number of the highest (and typically the lowest, but in this case, the low values are always zero) values in the sample and changes the maximum value of the sample. We can see that this reduces the average payment level required to between £10.50 and £12.91 which is closer to the results derived using the choice experiment. Dropping these larger payment observations does not reduce the sample size significantly and in the smallest sample, the sample size is still 97% of the full sample.

The final point that needs to be made about the table above is with regard to zero responses. Around 15% of the sample who answered this question believed that the fair level of payment for an electricity outage of this type was zero. This is quite high and there may be justification for removing some of these 'low' observations. However, our assumption in the table above is that zero is a fair response and simply indicates that a respondent is indifferent to a one hour electricity outage at peak times on a weekday during the winter.

These estimates of WTA derived using a contingent valuation approach can be converted into VoLL estimates using information on electricity bills compiled in the survey. A similar analysis as conducted previously to remove possible large outliers is undertaken and the results are shown in Table 75. According to the latest information from DECC, the average electricity bill in the UK corresponds to average annual domestic electricity consumption of 3.934 MWh.[141] Again, there appear to be a few very large electricity users who bring up the level of the average electricity bill. Removing some of these gives us an estimate that is relatively close to the official estimate published by DECC.

141 DECC (2009) "DECC: Energy Trends: March 2009" http://www.decc.gov.uk/en/content/cms/statistics/publications/trends/trends

Table 75: Analysis of annual average electricity bill						
Sample	**Mean**	**Std. Dev.**	**Med.**	**Max**	**Min**	**%**
Full sample	721.82	537.15	600	5000	52	100%
Limited sample: Mean +/-3 std. dev.	661.92	360.21	600	2288	52	98%
Limited sample: Mean +/-2 std. dev.	641.33	321.49	600	1680	52	96%
Limited sample: Mean +/-1 std. dev.	594.94	261.67	540	1248	52	91%
Limited sample: Mean +/-0.5 std. dev.	530.52	197.11	520	960	52	81%

Note: Excludes any respondent who claimed to have a zero electricity bill.
Source: London Economics analysis of online survey data

Similar to our previous discussion, conversion to VoLL requires a per MWh figure on usage to convert the raw £WTP figures to VoLL/MWh. VoLL is not estimated base on electricity bills and thus these monetary values have to be converted into annual electricity use values. The implied electricity consumption of the electricity bill levels are shown in Table 76. We have assumed that the average price of electricity paid by consumers is £0.16 per kWh.

Table 76: Analysis of annual average electricity consumption (MWh)						
Sample	**Mean**	**Std. Dev.**	**Med.**	**Max**	**Min**	**%**
Full sample	4.49	3.34	3.73	31.08	0.32	100%
Limited sample: Mean +/-3 std. dev.	4.11	2.24	3.73	14.22	0.32	98%
Limited sample: Mean +/-2 std. dev.	3.99	2.00	3.73	10.44	0.32	96%
Limited sample: Mean +/-1 std. dev.	3.70	1.63	3.36	7.76	0.32	91%
Limited sample: Mean +/-0.5 std. dev.	3.30	1.23	3.23	5.97	0.32	81%

Note: Excludes any respondent who claimed to have a zero electricity bill and is estimated based on an assumed price of 0.16p/kWh.
Source: London Economics analysis of online survey data

We derive the implied levels of VoLL from the CV approach. This is done by using the monetary value that respondents provided in response to the CV question and estimating their annual electricity consumption.[142] The result of this analysis is shown in Table 77 and these estimates show average values that range from £20,548/MWh-£34,926/MWh. There is much less variation in the median estimates of VoLL using this method. This estimate ranges from £15,873/MWh-£18,793/MWh. Our comparable WTA estimates[143] (for this type of electricity outage) of VoLL using the choice experiment range from £13,719 - £15,235 so the CV method appears relatively consistent when the median value is used.

[142] This annual electricity consumption is converted into hourly demand in order for estimations of VoLL.

[143] Using a constant electricity demand profile for all choice scenarios.

Table 77: Estimates of VoLL based on fair compenstaion (WTA) (£/MWh)						
Sample	**Mean**	**Std. Dev.**	**Med.**	**Max**	**Min**	**%**
Full sample	34,926	90,641	18,793	2,710,546	0	100%
Limited sample: Mean +/-3 std. dev.	29,575	38,496	18,070	293,643	0	99%
Limited sample: Mean +/-2 std. dev.	27,553	32,018	17,737	201,355	0	98%
Limited sample: Mean +/-1 std. dev.	25,153	26,401	17,619	121,090	0	97%
Limited sample: Mean +/-0.5 std. dev.	20,548	18,515	15,873	78,305	0	91%

Note: Excludes any respondent who claimed to have a zero electricity bill and is estimated based on an assumed price of 0.16p/kWh.
Source: London Economics analysis of online survey data

It can be argued that using the CV method to elicit a WTA estimate may overstate the true value of WTA for the good under consideration.[144] We believe that implementing a carefully designed choice experiment is one way to reduce this possible overestimation. Our results indicate that our VoLL estimates are indeed lower using the choice experiment. The CV analysis is used as a sense check to examine consumer's responses to more direct questions.

Willingness to pay

In general, previous research has shown that consumers may not respond with their true valuation when being asked how much they would be willing to pay to support a public good.[145] A public good is one that is typically non-excludable and non-rivalrous. In relation to electricity network reliability, this means that we cannot exclude someone from gaining the benefits of a reliable electricity network. Non-rivalrous refers to ones consumption of the good not having any impact on other people's consumption of the same good.[146]

A common response to the contingent valuation question about, what consumers' would be willing to pay extra for most public goods is zero. This suggests that there is a general unwillingness to pay more, especially in the context of a good to which respondents may believe that they have some entitlement. Alternatively, consumers may realise that in reality their consumption potential of the good is not conditioned on their payments (in spite of how the question is phrased). This is a known disadvantage of contingent valuation methodologies. This description is appropriate when discussing possible electricity outages.

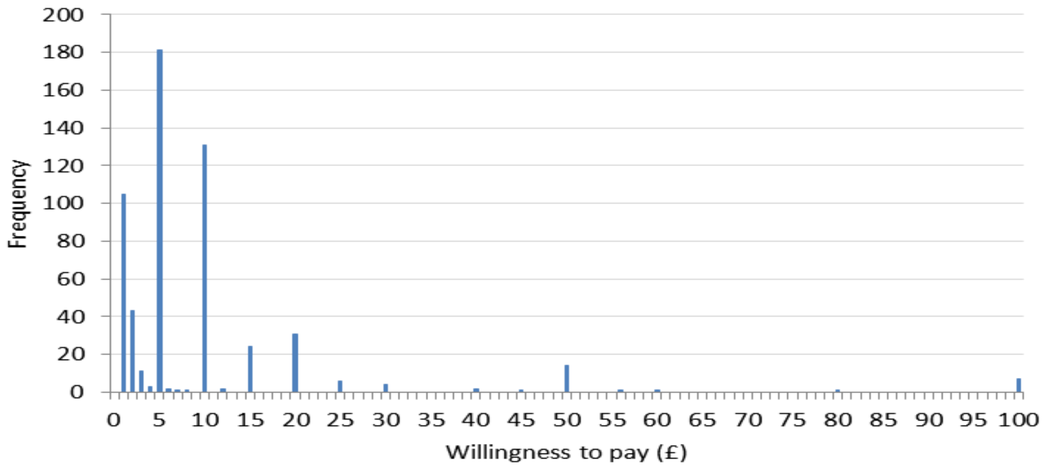
[144] Competition Commission, 2010, "Review of Stated Preference and Willingness to Pay Methods." http://webarchive.nationalarchives.gov.uk/+/http://www.competition-commission.org.uk/our_role/analysis/summary_and_report_combined.pdf

[145] Varian, H. (1996) Microeconomic Analysis, Fourth edition.

[146] See Kiesling and Giberson (2004) for a discussion of network reliability as a public good. Available at http://faculty.wcas.northwestern.edu/~lki851/LK_MG_rel_pubgood_Jan05.pdf

Focusing on positive value responses in the range from £1 to £100, we observe clustering in the responses as we did for WTA (Figure 33). The clustering is again around multiples of £5. The payment levels are the same for the WTP choice experiment as per the WTA experiment. In the analysis of positive values, £5 is the amount that the most respondents have chosen as the level they would pay to avoid an electricity outage.

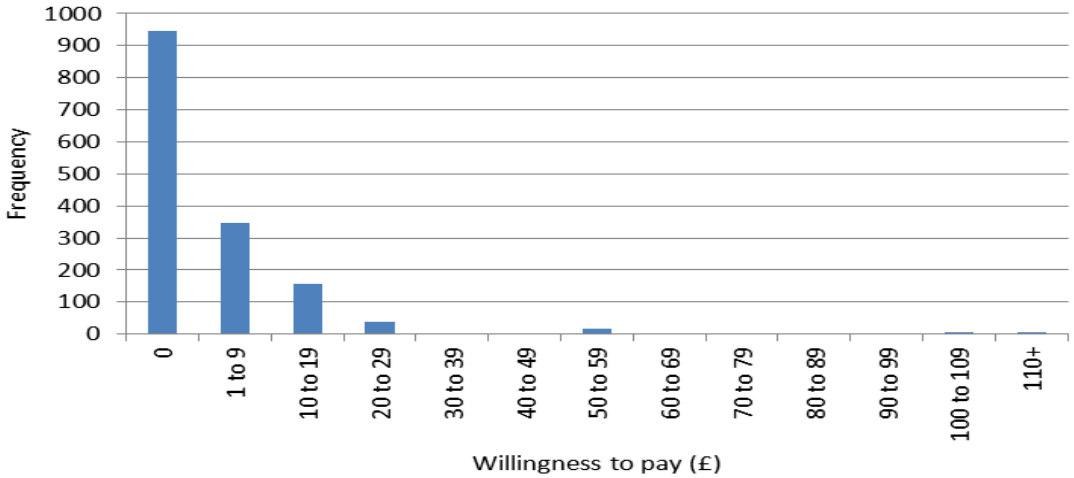
Figure 33:Fair payment of a one hour outage at peak times on a weekday during Winter- domestic consumers



Note: Only responses in the range £1-£100 are shown.
Source: London Economics analysis of survey data

The graph above does not include zero responses and these represent a large portion of overall responses (about 62%). Figure 34 includes these zero responses and groups the various fair payments into different bands. The largest bands (aside from zero) are between £1 and £20 with very few observations above this level. As with the WTA CV analysis, there is a small spike at the £50 mark.

Figure 34:Fair payment of a one hour outage at peak times on a weekday during Winter- domestic consumers (bands)



Source: London Economics analysis of survey data

The average amount that consumers would be willing to pay to avoid a one hour electricity outage occurring at peak time on a weekday during the winter is £6.35. It should be noted that the question has specified that this is a 'once-off' payment to avoid an electricity outage of this type. As with our analysis of WTA, this average WTP is somewhat biased upwards by some large stated WTP estimates. We show the impact of omitting some of these large values in Table 14.

This brings down the average WTP and the standard deviation significantly. Dropping the one observation of 1,000 brings down the average value to £3.61. Limiting the sample further by dropping high observations (that fall outside various standard deviation criteria) leads to a range of £2.52 to £3.04. It must be noted that this is higher than our choice experiment results which indicated a WTP of around £1 for an outage of this type.

As well over 50% of the respondents indicated that they would not be willing to pay extra to avoid this specified electricity outage; the median value is £0. Finally, excluding the zero responses increased the average WTP to £16.74 which appears to be far too high given our previous analysis. Thus, we believe that the estimate of WTP using the contingent approach should include zero observations.

Table 78: Average willingness to pay for a one hour outage at peak times on a weekday during Winter- domestic consumers (bands)

Sample	Average (£)	Median (£)	Max. (£)	Min. (£)	Std. Dev.	Sample %[1]
Full sample	6.35	0	1,000	0	48.93	100%
Limited sample: Mean +/-2 std. dev.	3.61	0	100	0	9.85	100%
Limited sample: Mean +/-1 std. dev.	3.04	0	50	0	6.82	99%
Limited sample: Mean +/-0.5 std. dev.	2.52	0	30	0	4.79	98%
Excluding zero responses	16.74	5	1000	1	78.38	38%

Note: 1. Refers to the number of observations in the sample as a share of the full sample.

Source: London Economics analysis of survey data

As per our CV WTA analysis, we convert the derived monetary willingness to pay estimate into VoLL figures. The same procedure and assumptions are used as previously. As expected, the VoLL results for WTP are significantly lower (Table 79) than the WTA estimates. However, they are higher than the comparable values of VoLL derived using a choice experiment approach.

Table 79: Estimates of VoLL based on fair payment (WTP) (£/MWh)

Sample	Mean	Std. Dev.	Med.	Max	Min	%
Full sample	9,972	34,845	0	629,234	0	100%
Limited sample: Mean +/-3 std. dev.	6,774	14,103	0	112,759	0	99%
Limited sample: Mean +/-2 std. dev.	6,279	12,438	0	78,305	0	98%
Limited sample: Mean +/-1 std. dev.	4,944	9,401	0	43,503	0	97%
Limited sample: Mean +/-0.5 std. dev.	3,277	6,430	0	27,316	0	91%

Note: Excludes any respondent who claimed to have a zero electricity bill and is estimated based on an assumed price of 0.16p/kWh.
Source: London Economics analysis of online survey data

Comparison of face-to-face contingent valuation results with the online sample

We use our online sample as the primary data source to estimate WTA and WTP estimates. This sample is representative of the GB population. The face-to-face sample is deliberately skewed to include only 'vulnerable' consumers. The exact definition of this has been outlined previously. Thus, the results of the online survey and the face-to-face survey are not directly comparable.

For WTA, the overall average is £9.75[147] which is significantly less than the estimate for the online sample. It is noticeable that the face-to-face interviews have much lower maximum values and much lower standard deviations. There may be many different reasons for this. Overall, the face-to-face sample appears to require about half of what the representative online survey in terms of fair payment. However, the online survey appears to have significantly higher possible outliers and this skews up the mean of the sample.

[147] The confidence interval of this variable indicated that the lower bound was £7.52 and the upper bound was £11.97. For WTP, the respective figures were £1.69 and £3.64

Table 80: Fair payment and willingness to pay valuations based on contingent valuation responses from the face-to-face sample vs. online sample

	Mean(£)	Med. (£)	Max. (£)	Min. (£)	Std. Dev.
			Face-to-face		
Fair payment	9.75	5	100	0	13.80
Willingness to pay	2.67	0	40	0	6.04
			Online		
Fair payment	19.55	10	2,000	0	100.49
Willingness to pay	6.35	0	1,000	0	48.93

Source: London Economics analysis of face-to-face survey data

For willingness to pay, the most common response is zero (105 out of 150 respondents), and the average is only £2.67. This is significantly less than for the representative online sample. Again, the face-to-face sample has a much lower standard deviation from the mean.

A8.2 SME Contingent valuation results

This section presents the results of the contingent valuation questions for SME electricity users and compares the results to those of the choice experiment. This is used as somewhat of a sense check on the results derived using the choice experiment approach. The analysis undertaken in this section is very similar to the contingent valuation consumer analysis shown previously.

For the SME survey, the CVM questions were phrased as follows:

- WTA contingent valuation question: If your electricity supply were to be interrupted for **one hour** during **these critical hours** that you just mentioned, on a **typical business day** in the **winter**, how much do you think would be a fair amount of compensation?
- WTP contingent valuation question: Thinking about the same **one hour** electricity interruption during **these critical hours** on a **typical business day** in the **winter**, how much extra would you be willing to pay as a one-off payment to avoid this?

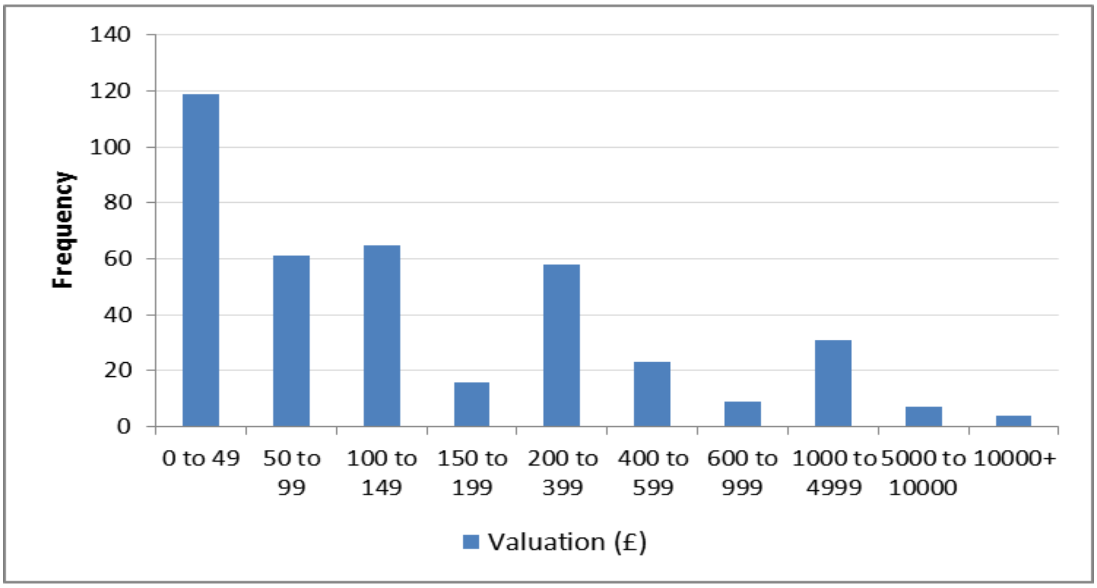
It must be remembered that the once-off payments in the choice experiments were described as various percentages of the firm's annual electricity bill. In the CV question, the SMEs were also able to choose their own peak usage time.

WTA estimates

We would expect significantly more variation in the payment levels that SMEs would require to experience a one hour electricity outage of this type. An important distinction between the consumer survey and the SME survey is that SMEs are told that the outage occurs on a typical working day. For the WTA CV question, 28% of respondents chose 'don't know' or refused to answer. This answer was not an option in the online survey. These responses are removed from our analysis.

We have grouped the observations into larger bands for ease of comparison purposes (Figure 35). Around 12% of the sample felt that they were not entitled to any payment as a result of this particular electricity outage and thus chose zero. Around 18% of SME respondents felt that a payment of less than £50 was appropriate. There is a noticeable spike in the £1000-£4999 range where about 8% of respondents feel the fair payment should be in this band.

Figure 35:Fair payment to experience an outage lasting one hour at peak times on a working day in the Winter- SMEs



Source: London Economics analysis of SME survey data

The maximum response in the CV analysis was a payment level of 65,000 for the one hour outage. As before, we analysed the sample in terms of different numbers of standard deviations above the mean. The full sample average payment level required is found to be around £612. However, this appears to be upwardly biased due to some large observations. By removing the top 4% of the sample, the average payment required drops to around £205. These results are shown in Table 19 and show the importance of some large observations. However, these large responses are not necessarily outliers and may reflect the type of business that an SME is doing. If an electricity outage leads to a complete cessation of production, then the disruption value might be quite large. For these types of SMEs where electricity is so vital, they may already have alternative ways of coping with an electricity outage and thus the level of payment required should be lower. This provides some justification for removing these respondents who appear to have very large annual electricity consumption. Finally, around 8% felt that no payment was appropriate. Removing these observations increases the mean payment level to around £693.

It is worthwhile to compare these estimates with the estimates derived previously using the choice experiment. Comparable estimates from the choice experiment indicate that typical SMEs require a payment of £165 to experience a one hour outage of this type. This result is as broadly as expected we believe that the appropriate range of estimates from the contingent valuation approach is between £205 and £328. It must also be noted that the contingent valuation approach allows respondents to choose their own peak usage period. In terms of WTA estimates, using the contingent valuation method may result in higher estimates than using the choice experiment approach. This is because when asked direct about levels of payment they expect to receive respondents may be more inclined to overstate their actual acceptable level. Using the choice experiment approach asks respondents more indirect questions with the intention of obtaining a payment level that is closer to the actual level of payment that they would really accept.

Table 81: Fair payment to experience an outage lasting one hour at peak times on a working day in the Winter- SMEs

Sample	Mean (£)	Med. (£)	Max. (£)	Min. (£)	Std. Dev.	Sample %[1]
Full sample	612.13	100	65,000	0	3637.69	100%
Limited sample: Mean +/-3 std. dev.	328.49	100	5,400	0	800.18	99%
Limited sample: Mean +/-2 std. dev.	328.49	100	5,400	0	800.18	99%
Limited sample: Mean +/-1 std. dev.	241.62	100	4,000	0	481.94	97%
Limited sample: Mean +/-0.5 std. dev.	205.45	100	2,000	0	328.72	96%
Excluding zero responses	693.51	100	65,000	1	3,865.30	88%

Note: 1. Refers to the number of observations in the sample as a share of the full sample. There are around 28% of respondents who answered this question as 'don't know'.
Source: London Economics analysis of survey data

We also convert these monetary values into levels of VoLL. This is done in a similar fashion to the consumer contingent valuation analysis. There is very large variation in the reported electricity bills for SMEs in our sample of 550 SMEs. The average electricity consumption is estimated based on dividing the annual bill by a price of £0.0852 per kWh.[148] It is clear that SMEs pay different amounts for their electricity but it is not possible to identify the exact amount they pay. The full sample average electricity consumption is around 58 MWh per annum. However, as previously, this includes a number of very large electricity users. Thus, we believe it is appropriate to remove some of these very large users. This gives us an annual electricity consumption of around 28-30 MWh which is roughly around seven times the official figure for domestic users. Around 20% of SMEs surveyed did not know or refused to estimate their annual electricity bill. There does not appear to be any official source on SME electricity consumption and thus we have used estimates derived from our sample. We acknowledge that this relies on a number of assumptions.

[148] DECC (2012) https://www.gov.uk/government/statistical-data-sets/prices-of-fuels-purchased-by-manufacturing-industry. There does not appear to any one specific accepted price of electricity for SMEs. Thus, we have taken a conservative approach and adopted an official estimate but this estimate may not be directly applicable for SMEs.

Table 82: Estimated electricity use (MWh) per annum – SMEs						
Sample	**Mean**	**Med.**	**Max.**	**Min.**	**Std. Dev.**	**Sample %**[1]
Full sample	58.41	14.08	5,868.55	1.17	364.15	100%
Limited sample: Mean +/-3 std. dev.	29.30	14.08	469.48	1.17	49.68	99%
Limited sample: Mean +/-2 std. dev.	29.30	14.08	469.48	1.17	49.68	99%
Limited sample: Mean +/-1 std. dev.	28.42	14.08	375.59	1.17	45.64	99%
Limited sample: Mean +/-0.5 std. dev.	23.72	13.40	211.27	1.17	28.93	97%

Note: This is based on the reported annual electricity bill. It is assumed that a price of 8.52 pence per Kwh is paid by all SMEs and all the bill is translated into MWh.
Source: London Economics analysis of survey data

The estimates of fair payment to experience a one-hour outage (Table 82) are converted into VoLL estimates by dividing by hourly electricity consumption as shown in Table 19. These estimates range from £75,886/MWh to £91,806/MWh. As expected, these results are significantly larger than our estimates from the choice experiment approach. For comparison, our largest WTA-based VoLL estimate for SMEs using the choice experiment was around £39,000/MWh.

Table 83: Estimates of WTA VoLL using a contingent valuation approach			
	WTA (£)	**Elec. Use (MWh)**	**VoLL (£/MWh)**
Full sample	612.13	58.41	91,806
Mean +/- 3 s.d.	328.49	29.30	98,216
Mean +/- 2 s.d.	328.49	29.30	98,216
Mean +/- 1 s.d.	241.62	28.42	74,483
Mean +/- 0.5 s.d.	205.45	23.72	75,886

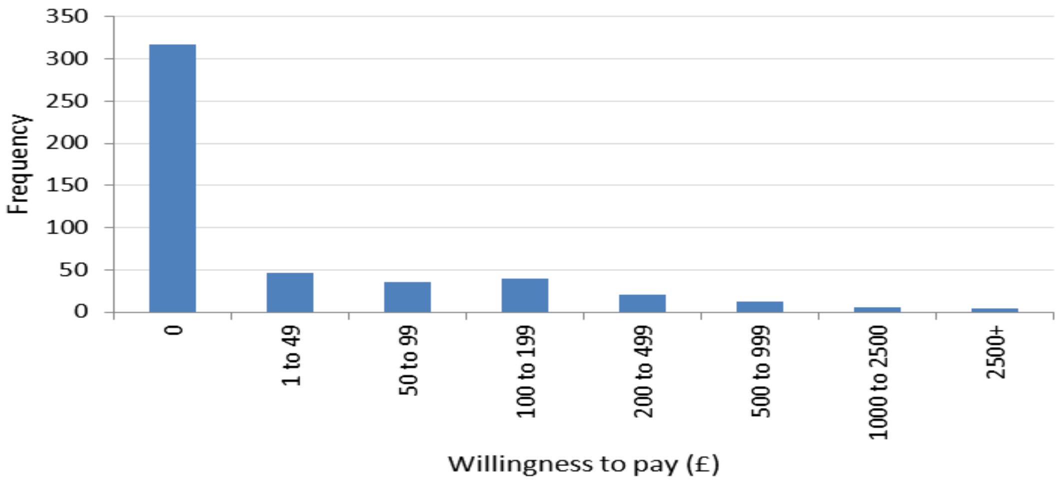
Note: Electricity use is shown in annual consumption. For conversion to VoLL, the hourly electricity consumption of this figure is used.
Source: London Economics analysis

In this section, we have shown the monetary valuation of the fair payment that SMEs would require in the event of a one hour outage on a typical working day at peak times in the winter. It was found that this varied significantly due to a number of large observations. This value exceeded the value derived in the choice experiment by around 53%. These estimates were then converted into VoLLs using summary statistics on average payment and average electricity use.

Willingness to pay

As observed for domestic respondents, most SMEs have no willingness to pay to avoid a one hour outage on a working day at peak times in the winter. Out of the 550 SMEs providing a specific figure, 317 (around 58%) stated they are not willing to pay anything at all. There was also about 12% of the SME sample who either didn't know what they would pay or refused to answer. The results of the 'fair payment' question are presented in different bands in Figure 36. For our subsequent analysis we have dropped all respondents who did not provide a number that they would be willing to pay to avoid the one-hour electricity outage.

Figure 36:Fair payment for an outage lasting one hour at peak times on a working day in the Winter- SMEs



Source: London Economics analysis of survey data

The maximum fair payment to avoid the electricity outage is a once-off payment of £10,000 and for the full sample of respondents who provided a number the average is £104.75. Removing the highest 1% and 2% of observations reduces this mean to £46.81 and £36.04.

Thirty-four per cent of SME respondents provided a non-zero response. Including only non-zero responses increases the average WTP to £307 and the median to £75. As over 50% of the sample chose zero as their fair payment, the median value is zero for the other reduced samples.

Table 84: Fair payment for an outage lasting one hour at peak times on a working day in the Winter- SMEs

Sample	Mean (£)	Med. (£)	Max. (£)	Min. (£)	Std. Dev.	Sample %[1]
Full sample	104.75	0	10,000	0	687.88	100%
Limited sample: Mean +/-3 std. dev.	50.91	0	2,000	0	158.49	99%
Limited sample: Mean +/-2 std. dev.	46.81	0	1,000	0	130.99	99%
Limited sample: Mean +/-1 std. dev.	38.74	0	792	0	97.58	98%
Limited sample: Mean +/-0.5 std. dev.	36.04	0	500	0	88.26	98%
Excluding zero responses	307.21	75	10,000	1	1,153.62	34%

Note: 1. Refers to the number of observations in the sample as a share of the full sample. There are around 12% of respondents who answered this question as 'don't know'.
Source: London Economics analysis of survey data

Both the payments in the contingent valuation and choice experiment have been phrased as 'once-off' payments so they are somewhat comparable. The appropriate estimates of WTP using the contingent valuation method range from around £36 to £51. This compares with an estimate of around £100 for a similar type of outage using the choice experiment. This is as expected as asking more direct questions about additional payments may lead to a lower estimate than the actual additional payment that the respondent would be willing to pay to avoid this outage. As well as this, respondents may typically choose zero as their WTP estimate. In the choice experiment, respondents are faced with different trade-offs that are aimed at indirectly obtaining a WTP measure. This measure may reflect a truer estimate of WTP than when using the direct approach (contingent valuation).

Finally, the WTP are converted into VoLL estimates using summary information on the fair payment to avoid the electricity outage and the hourly electricity consumption. These estimates are shown in Table 85. These estimates are broadly consistent with VoLL estimates derived using the choice experiment approach. However, it must be noted that the electricity consumption is different between the two estimates. There is no clear estimate of annual electricity for SMEs in the UK and thus, we believe it is prudent to provide a range of estimates and show how different assumptions impact on the VoLL results.

Table 85: Estimates of WTP VoLL using a contingent valuation approach

	WTP (£)	Elec. Use (MWh)	VoLL (£/MWh)
Full sample	104.75	58.41	15,710
Mean +/- 3 s.d.	50.91	29.30	15,221
Mean +/- 2 s.d.	46.81	29.30	13,997
Mean +/- 1 s.d.	38.74	28.42	11,941
Mean +/- 0.5 s.d.	36.04	23.72	13,313

Note: Electricity use is shown in annual consumption. For conversion to VoLL, the hourly electricity consumption of this figure is used.
Source: London Economics analysis

Annex 9 Validity and quality of responses to choice experiments

This Annex provides statistics on responses to the choice experiment which can be used to assess the validity and quality of the responses. In particular, we analyse for both WTP and WTA:

- What percentage of respondents responds 'don't know' to all six choices?
- What percentage of respondents responds 'Option A' to all six choices?
- What percentage of respondents responds 'Option B' to all six choices?

If respondents are engaging with the experiment and understand the basic concept of the experiment, we would expect these percentages to be small. Some issues arose in the analysis of the household survey with regard to the level of respondent who answered 'don't know' for all choice cards. This was particularly true for the WTP choice cards where around 11% of respondents chose 'don't know' for all choice cards. We believe that this represents a type of 'non-engagement' and these respondents have been removed from the sample. However, choosing the 'don't know' option is not necessarily a bad thing as respondents may not be able to choose between alternatives. For this reason, respondents who chose 'don't know' for some choice cards are included and a dummy variable is used to model this impact.

Table 86: Choice experiment answering patterns (% of total) - WTA

Sample	Always chose 'don't know'[1]	Always chose Option A[1]	Always chose Option B[1]
Household online	5.64%	0.92%	2.03%
Household face-to-face	3.33%	5.33%	2.67%
SME	0.4%	3.2%	1.1%

Note: 1. Percentage of total respondents.

Source: London Economics analysis

Table 87: Choice experiment answering patterns (% of total) – WTP			
Sample	**Always chose 'don't know'[1]**	**Always chose Option A[1]**	**Always chose Option B[1]**
Household online	10.76%	1.90%	1.18%
Household face-to-face	16.00%	0.67%	0.67%
SME	2.5%	1.1%	2.9%

Note: 1. Percentage of total respondents.
Source: London Economics analysis

In the tables below (Table 88-Table 91), we show the percentage of respondents who chose different options. For example, in Table 88, 81.33% of the sample never chose a 'don't know' option. Furthermore, 10.67% of the sample never chose 'Option A' for any of the six choice scenarios. The importance of this analysis is evident for the WTP choice experiments where a significant portion of the sample chose 'don't know' for each choice scenario.

Table 88: WTA distribution of f2f choices (%)			
Number of times option chosen	**Option Don't know**	**Option A**	**Option B**
0	81.33	10.67	10
1	5.33	13.33	9.33
2	2	16.67	24.67
3	3.33	27.33	28.67
4	3.33	22.67	14.67
5	1.33	4	10
6	3.33	5.33	2.67

Note: 0 indicates that the respondent never chose a 'Don't know' option for any of the 6 WTA choice cards.
Source: London Economics

Table 89: WTA distribution of online choices (%)			
Number of times option chosen	**Option Don't know**	**Option A**	**Option B**
0	82.81	8.79	7.74
1	6.1	10.3	8.53
2	2.49	20.21	27.17
3	1.25	28.87	29.33
4	1.05	25.46	17.13
5	0.66	5.45	8.07
6	5.64	0.92	2.03

Note: 0 indicates that the respondent never chose a 'Don't know' option for any of the 6 WTA choice cards.
Source: London Economics

Table 90: WTP distribution of f2f choices (%)			
Number of times option chosen	**Option Don't know**	**Option A**	**Option B**
0	68.67	20	16.67
1	4	11.33	10
2	5.33	22	16
3	4	26.67	32
4	2	14	18
5	0	5.33	6.67
6	16	0.67	0.67

Note: 0 indicates that the respondent never chose a 'Don't know' option for any of the 6 WTP choice cards.
Source: London Economics

Table 91: WTP distribution of online choices (%)			
Number of times option chosen	**Option Don't know**	**Option A**	**Option B**
0	66.73	15.42	16.01
1	7.22	10.96	11.02
2	5.64	25.59	22.64
3	4.07	23.62	24.41
4	2.95	17.91	19.55
5	2.62	4.59	5.18
6	10.76	1.9	1.18

Note: 0 indicates that the respondent never chose a 'Don't know' option for any of the 6 WTP choice cards.
Source: London Economics

Impact of question order on level of 'don't knows'

Table 92: Impact of question order on level of 'Don't knows' for WTP		
	WTP questions asked first	**WTP questions asked second**
Option A	38.34	41.36
Option B	37.82	42.46
Don't know	23.85	16.18

Source: London Economics

Table 93: Impact of question order on level of 'Don't knows' for WTA		
	WTA first asked first	**WTA asked second**
Option A	46.53	44.13
Option B	48	42.67
Don't know	5.47	13.21

Source: London Economics

- Order appears to have an influence in the level of 'don't' knows' that are recorded for both the WTP and WTA estimates.
    - When WTP questions are asked second, there appear to be fewer 'Don't know' responses.
    - However, when WTP questions are asked first, the level of 'don't knows' for the WTA choices increases (from 6% to 13%).
- Respondents answer 12 choices so there may be some element of survey fatigue which would lead to higher levels of 'don't knows' for the choice cards that were asked second.
    - This does not appear to be the case for the WTP where fewer 'don't knows' are recorded for the choice cards that were asked second.
- This may be indicative of non-engagement behaviour where consumers believe that they should not have to pay for something for which they have already paid (and paid significantly).

Annex 10 VoLL estimates by domestic consumers' characteristics

This Annex presents further details of the WTP and WTA analysis for domestic consumers. The details presented in this Annex are for an outage lasting one hour and occurring on a weekend at peak times in the winter. It also provides additional analysis on the likely reasons for the differences in the various estimates.

A10.1 WTA and WTP for different domestic consumer groups

This section analyses to what extent the WTA and WTP of domestic consumers vary according to their different personal/household characteristics. In this section, we will examine whether certain characteristics lead to higher or lower VoLLs. Some of the relationships should be expected or intuitive, *a priori*. For example, we would expect respondents who stated that an outage would have a 'high impact' on them to pay (accept) higher amounts to avoid (accept) an electricity outage. However, some of relationships are not so clear and we will examine these in this section.

We present the results focusing on WTA and WTP for electricity outages lasting one hour in the winter time at peak times on a weekend day. Section A10.2 includes the exact definitions and sizes of the sub-samples being considered.

WTA estimates

Figure 37 provides a graphical representation of the WTA estimates for an outage lasting one hour and occurring at peak times at the weekend in the winter for different sub-samples compared to the baseline estimates presented in the main report.

The results are largely as expected with the following respondents having a WTA significantly larger than the baseline:[149]

- Respondents associated with a 'high impact' of an electricity outage;
- Off gas network; and
- Home owner.

As discussed, respondents with a 'high impact' should be expected to accept a higher monetary value if indeed an electricity outage has a 'high' impact on them. Similarly being off the gas network may make households more reliant on electricity for heating, and thus the electricity outage may have a higher impact. The rationale why homeowners (as opposed to renters) appear to have a higher WTA is less obvious, but perhaps intuitive. This sub-group may have other common factors (e.g., higher income) that are driving the WTA estimate, or it might be that homeowners are more likely to be at home or perform tasks and enjoy activities dependent on electricity at home than renters.

[149] The baseline refers to the average result of all respondents to the online survey. This online survey is representative of GB and the baseline is the average VoLL.

Another factor that may be driving different VoLL estimates is income. *A priori*, we expect to see a positive relationship between VoLL and income. Thus, we would expect respondents with 'high income' to require a larger payment compared with someone on 'low income'. The rationale is that 'high income' respondents may be valuing an electricity outage against a loss in earnings or consumption that they would have made if at home. The value of these earnings or consumption would likely be higher for 'high income' respondents. The graph indicates that these 'high income' respondents do require a slightly higher level of payment in £ than 'low income' respondents. However, the difference is not substantial and it does not appear that income is a key driver in determining different levels of VoLL.

There are no clear groups that should have a significantly lower WTA except respondents who have indicated that an outage would have a 'low impact'. As discussed before, respondents with 'low income' typically require slightly lower levels of payment. Income may be correlated with other groups such as the 'vulnerable' group. If income was a key driver of WTA, then these groups may all have estimates that are below the average. However, this is not the case. Respondents classified as 'vulnerable' would accept payment that is roughly around the average.

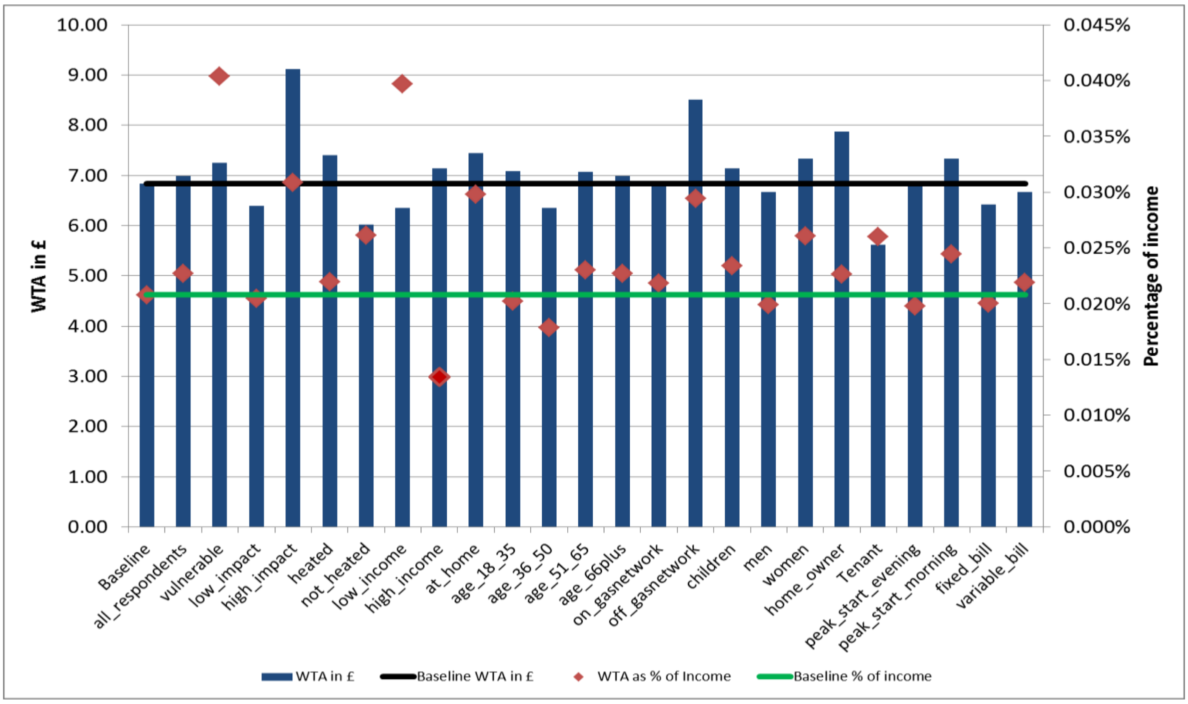
The final group to discuss is those who indicated that they could not keep their home 'adequately heated'. As shown in the graph below, this group would require a smaller payment than the average. This group may typically be associated with lower than average incomes. However, the differences may be driven by other factors such as the type of heating system used. This system may be neither gas nor electric and thus an electricity outage may have a relatively lower impact. These results indicate that income is important but does not appear to be the key driver in differences in the various levels of payment required by different groups.

As part of this analysis, we also examine the percentage of annual income[150] that this payment represents. We have calculated the average gross household income for each of these sub-groups based on the results of the survey. The average gross household income of our sample was £32,914. Applying this to our baseline WTA estimate implies that the average respondent would be willing to accept a payment equal to 0.02% of their annual gross household income. The results of this analysis indicate that vulnerable and 'low income' respondents would be willing to accept a higher percentage of their annual incomes than the baseline, but a lower absolute £ figure.

In the graph below, percentage of income is displayed on the secondary axis and show that 'vulnerable' and 'low income' respondents would accept the highest percentage of their income. This is as expected as it is a fairly general aspect of 'necessity' goods that the percentage of the income spent on the good decreases with income.

[150] Twenty-one percent of the sample did not provide information on gross household income.

Figure 37:WTA a one hour outage once in at peak times at the weekend in the winter – various groupings of domestic consumers



Source: London Economics

It may also be true that there is a link between the payment required and the size of the electricity bill. A high electricity bill is associated with high usage and the impact of an outage tends to be greater for consumers that use a larger amount of electricity. It must be noted that 71% of the sample are classified as 'low impact' respondents. Thus the average electricity bill will be driven by 'low impact' respondents.

Table 94: Impact of electricity outages and average annual electricity bill

Impact of electricity outage	Average annual electricity bill
Low impact	£688
High impact	£803
Average	£722

Note: Respondents are defined as low impact if an outage would have 'no impact' or 'a small impact' on their household, and are defined as high impact if an outage would have 'a large impact' or 'a very large impact' on their household.
Source: London Economics analysis of online survey data

Another possible scenario put forward is that an electricity outage may impact more on individuals who are classified as 'at home' (i.e., do not work). This would be consistent with our finding that individuals place a higher value on outages that occur at the weekend when more people are at home. Figure 33 indicates that respondents 'at home' have a slightly higher WTA than the baseline. The results of this cross-tabulation of respondents 'at home' by impact level is shown in

Table 95. However, there may be two countervailing impacts that are driving 'at home' respondents. These respondents may be more likely to be 'at home' when an electricity outage occurs which may mean a higher disruption value. This higher disruption value may indicate higher VoLLs. However, respondents who are described as 'at home' may have lower levels of income which may indicate that they place a lower value on lost leisure time.

However, the difference to the baseline is larger when taken as a percentage of income because people who stay at home generally have a lower income and Figure 33 shows that they require around 0.03% of their annual income in payment for a one-hour outage.

Table 95: Share with 'low' and 'high' impact of electricity outages by whether they stay at home

	Low impact	High impact
Staying at home	74%	24%
Working	70%	27%
Average	72%	26%

Note: Respondents defined as 'staying at home' if their employment status is 'unemployed', 'retired' or 'looking after home/family'. Respondents defined as 'not staying at home' if their employment status is 'employed', 'student or 'other'. Totals may not add up to 100% as some respondents answered 'don't know' to the impact question.
Source: London Economics analysis of online survey data

WTP estimates

Figure 38 provides a graphical representation of the WTP estimates for an outage lasting one hour and occurring in the winter at peak times on a weekend day for different sub-samples compared to the baseline estimates. The same sub-samples as per the WTA estimates are analysed in this section. It must be noted that the WTP figures are significantly lower than the WTA estimates. Both models have been estimated based on a 'once-off' payment. This makes the estimates somewhat comparable. We would expect the relationships between WTP and different characteristics to be broadly consistent with our WTA results, albeit at a lower level.

The largest WTP estimate is derived from the 'high impact' sample where it is estimated that these respondents would be willing to pay around £2.86 for a one hour outage of this type. The other main sub-group that shows a larger than average WTP estimate is the group with a 'fixed' bill. As discussed previously, we would expect to get such a result for 'high impact' respondents. There does not appear to be any obvious reason why respondents with a 'fixed' bill[151] would be willing to pay more.

As with WTA, we also examine the percentage of annual income that this payment represents. This is a much smaller amount to the WTA amount. The average gross household income of our sample was £32,914. Applying this to our baseline WTP estimate implies that the average respondent would be willing to pay around 0.0029% of their annual income. As a percentage of

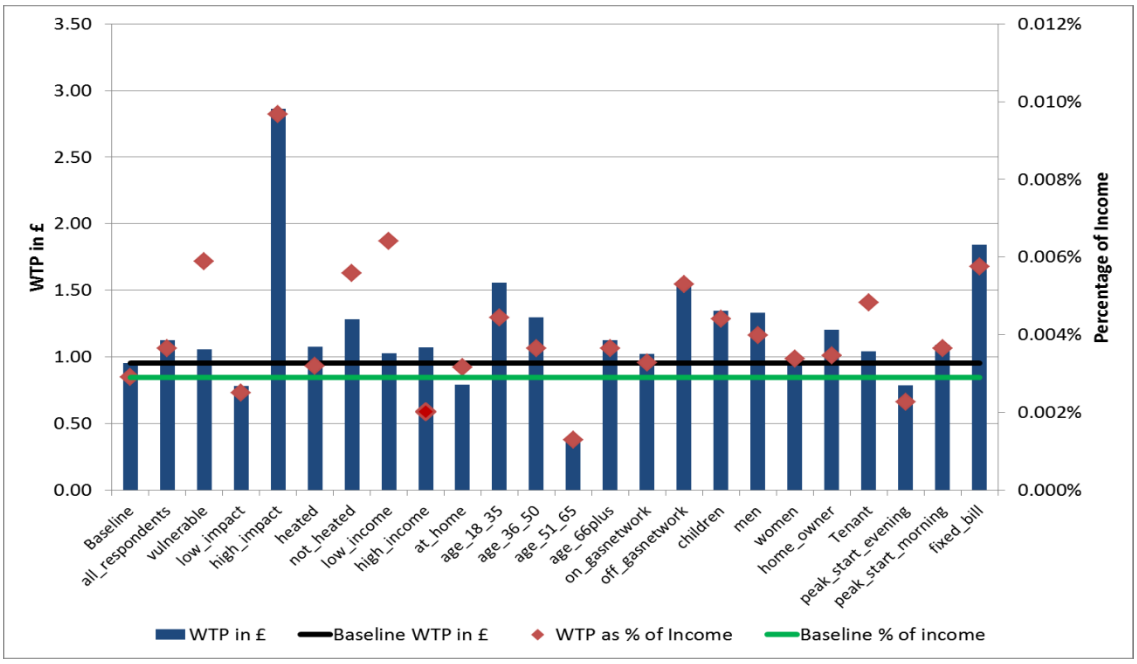
[151] A 'fixed' rate tariff is a tariff where the supplier guarantees that the price per unit of electricity will stay the same for a set period.

annual income, 'high impact' respondents and 'low income' have the highest percentage of income in terms of WTP. However, it must be noted that the differences in monetary amounts are very small and often not statistically significant.

As shown with the WTA estimates, respondents who are 'off' the gas network place higher value on an electricity outage.

A number of the broad results are common between the WTA and WTP models. However, there are a number of noticeable differences between the two sets of results. The most obvious is with regard to the 'not heated' group. This group consists of respondents who feel they are not able to adequately heat their home. This group would be willing to pay more than the average amount to avoid a one hour electricity outage of this type. There is also a clear distinction for the 'non-professional lower income'[152] group. The graph shows that this group would be willing to pay significantly less than the average amount.

Figure 38:WTP for a one hour outage at peak times on a weekend day in the winter – domestic consumers



Source: London Economics

The confidence intervals for each of these groups and the size of the groups are shown in A10.2. It must be noted that splitting up the sample in this way leads to having groups that have relatively few observations. This influences statistical significance.

152 This is defined as per the ONS classifications. Work-type and income-group based on Occupation and approximated Socio-economic-income Group.

A10.2 Number of observations in sub-analyses

Table 96 and Table 97 give an overview of the number of respondents and observations used in each of the WTA and WTP sub-analyses.

We note that each domestic respondent was presented with 12 choice cards (six for both WTA and WTP) implying that, in the baseline, a total of 9,300 choices were made (6 X 1550) and each choice consisted of three alternatives for the total number of observations 27,900 (3 X 9,300). As stated previously, there was a strong 'non-engagement' vote in the WTP with around 11% of respondents answering 'don't know' for all observations. These have been removed from the estimation.

We also note that the baseline is based on the GB representative sample which only includes observations from the online survey.[153] The face-to-face estimates are based on the data from the face-to-face interviews only, and all other estimates are based on sub-sets of the combined online and face-to-face sample, i.e., the estimates for vulnerable consumers include observations for vulnerable consumer in the online sample *and* in the face-to-face sample.

Table 96: Number of respondents in WTA sub-analyses

	Observations	Respondents
Baseline	25,254	1,403
All respondents	27,666	1,537
Vulnerable	12,006	667
Low impact	20,106	1,117
High impact	7,092	394
heated	20,538	1,141
Not heated	6,768	376
Low income	13,302	739
High income	8,964	498
At home	9,216	512
Age 18-35	6,408	356
Age 36-50	6,930	385
Age 51-65	7,974	443
Age 66plus	27,666	1,537
On gas network	22,752	1,264
Off gas network	4,464	248
With Children	18,522	1,029
Men	12,978	721
Women	14,688	816
Home owner	19,566	1,087
Tenant	7,920	440
Peak start evening	8,982	499
Peak start morning	14,706	817
Fixed bill	8,586	477
Variable bill	9,432	524

Source: London Economics

[153] This is to ensure that vulnerable groups are not overrepresented.

Table 97: Number of respondents in WTP sub-analyses		
	Observations	Respondents
Baseline	22,320	1,240
All respondents	24,444	1,358
Vulnerable	10,476	582
Low impact	17,910	995
High impact	6,084	338
Heated	18,144	1,008
Not heated	6,012	334
Low income	11,682	649
High income	8,028	446
At home	8,172	454
Age 18-35	6,084	338
Age 36-50	5,940	330
Age 51-65	6,822	379
Age 66plus	24,444	1,358
On gas network	20,142	1,119
Off gas network	3,942	219
With Children	16,362	909
Men	11,502	639
Women	12,942	719
Home owner	17,280	960
Tenant	6,984	388
Peak start evening	8,082	449
Peak start morning	13,194	733
Fixed bill	7,686	427
Variable bill	8,208	456

Source: London Economics

A10.3 Confidence intervals for results

This section provides two tables with confidence intervals for the WTA and WTP estimates for the different subsamples.

Table 98: WTA to avoid a one hour outage at peak times on a weekend day in the winter – domestic consumers						
	WTA in £	WTA as % of income	No. of observation	R-squared	Confidence interval	
					LB	UB
Baseline	6.84	0.0208%	25,254	0.34	5.92	7.77
All respondents	6.99	0.0227%	27,666	0.34	5.97	7.91
vulnerable	7.25	0.0404%	12,006	0.32	5.37	8.71
Low impact	6.39	0.0205%	20,106	0.35	5.48	7.31
High impact	9.12	0.0309%	7,092	0.32	6.04	12.21
Heated	7.41	0.0220%	20,538	0.34	6.16	8.65
Not heated	6.01	0.0261%	6,768	0.34	4.65	7.37
Low income	6.35	0.0397%	13,302	0.33	5.12	7.59
High income	7.14	0.0134%	8,964	0.36	5.60	8.69
At home	7.45	0.0298%	9,216	0.32	5.50	9.39

Age 18-35	7.08	0.0202%	6,408	0.37	5.44	8.73
Age 36-50	6.35	0.0179%	6,930	0.34	4.93	7.76
Age 51-65	7.08	0.0230%	7,974	0.32	5.25	8.90
Age 66plus	6.99	0.0227%	27,666	0.34	6.05	7.93
On gas network	6.83	0.0218%	22,752	0.34	5.85	7.81
Off gas network	8.51	0.0294%	4,464	0.33	4.88	12.13
With Children	7.15	0.0234%	18,522	0.34	6.00	8.29
Men	6.66	0.0199%	12,978	0.34	5.34	7.99
Women	7.33	0.0260%	14,688	0.34	5.98	8.68
Home owner	7.87	0.0226%	19,566	0.34	6.49	9.25
Tenant	5.62	0.0260%	7,920	0.34	4.43	6.81
Peak start evening	6.86	0.0198%	8,982	0.35	5.36	8.35
Peak start morning	7.33	0.0244%	14,706	0.34	5.93	8.73
Fixed bill	6.42	0.0200%	8,586	0.34	4.88	7.97

Note: Confidence intervals are calculated based on the Delta method. WTA as a percentage of income is calculated as WTA in pounds divided by the average income for consumers in each subgroup where the income is calculated based on the midpoint of the ranges.
Source: London Economics

Table 99: WTP to avoid a one hour outage at peak times on a weekend day in the winter – domestic consumers

	WTP in £	WTP as % of income	No. of obs.	R-squared	Confidence interval	
					LB	UB
Baseline	0.96	0.0029%	22,320	0.25	0.51	1.40
All respondents	1.12	0.0037%	24,444	0.25	0.69	1.56
vulnerable	1.06	0.0059%	10,476	0.24	-0.48	1.07
Low impact	0.78	0.0025%	17,910	0.26	0.30	1.26
High impact	2.86	0.0097%	6,084	0.24	1.76	3.96
Heated	1.08	0.0032%	18,144	0.26	0.61	1.55
Not heated	1.28	0.0056%	6,012	0.24	0.21	2.36
Low income	1.03	0.0064%	11,682	0.26	0.36	1.70
High income	1.07	0.0020%	8,028	0.26	0.36	1.79
At home	0.79	0.0032%	8,172	0.24	-0.11	1.69
Age 18-35	1.55	0.0044%	6,084	0.28	0.93	2.18
Age 36-50	1.30	0.0037%	5,940	0.26	0.42	2.17
Age 51-65	0.40	0.0013%	6,822	0.25	-0.38	1.18
Age 66plus	1.12	0.0037%	24,444	0.25	0.69	1.56
On gas network	1.02	0.0033%	20,142	0.25	0.55	1.49
Off gas network	1.53	0.0053%	3,942	0.25	0.38	2.68
With Children	1.35	0.0044%	16,362	0.26	0.84	1.86
Men	1.33	0.0040%	11,502	0.24	0.65	2.01
Women	0.95	0.0034%	12,942	0.26	0.40	1.50
Home owner	1.20	0.0035%	17,280	0.24	0.67	1.74
Tenant	1.04	0.0048%	6,984	0.27	0.32	1.76
Peak start evening	0.78	0.0023%	8,082	0.27	0.07	1.50
Peak start morning	1.09	0.0036%	13,194	0.25	0.49	1.70
Fixed bill	1.84	0.0058%	7,686	0.26	1.13	2.56
Variable bill	0.03	0.0001%	8,208	0.27	-0.75	0.81

Note: Confidence intervals are calculated based on the Delta method. WTP as a percentage of income is calculated as WTP in pounds divided by the average income for consumers in each subgroup where the income is calculated based on the midpoint of the ranges.
Source: London Economics

Annex 11 VoLL estimates by SME of different characteristics

This Annex presents further details of the WTP and WTA analysis for SMEs. The details presented in this Annex are for an outage, lasting one hour and occurring during a working day in the winter.

A11.1 VoLL for different SME groups

This section analyses to what extent the WTA and WTP of SME electricity users vary depending on the characteristics of the firm. As our sample collected has various SME characteristics data, it will be interesting to see to what extent firm characteristics are driving VoLL estimates.

We present the results focusing on WTA and WTP for electricity outages lasting one hour, and occurring at peak times on a workday in the winter time. In our choice experiment, this scenario was typically found to be associated with the largest WTA and WTP estimate. Details of the size of the various sub-samples along with confidence intervals are shown in A11.2.

WTA estimates

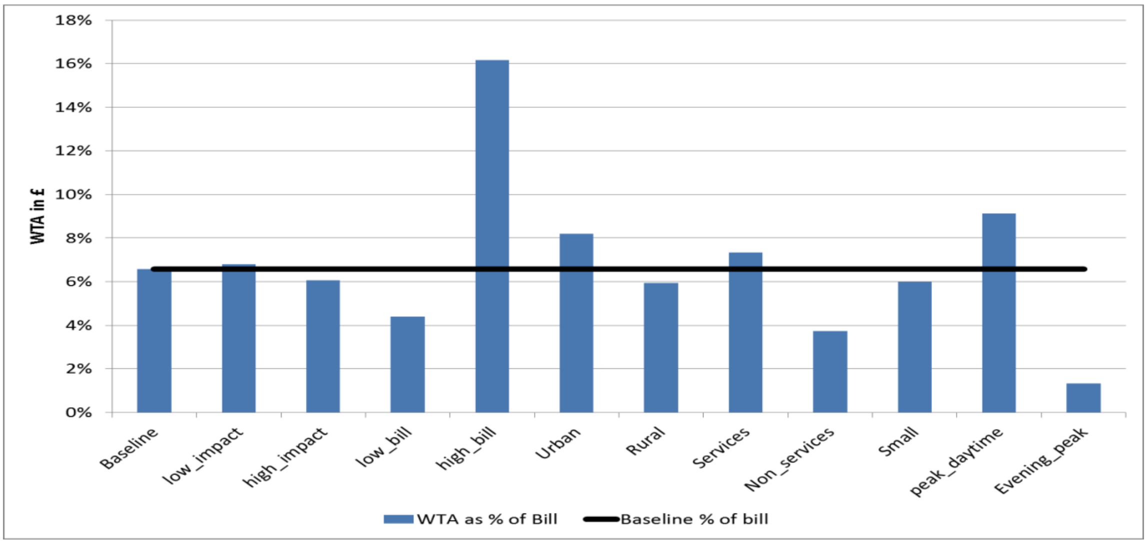
Figure 39 provides WTA estimates for different types of SMEs. These graph shows that the baseline WTA value is around 6% of the annual electricity bill and this represents about £165. The figures presented below are in percentage terms and do not take into account the fact that different groups have different electricity bills.

The standout group is that who are deemed to have 'high' electricity bills. It is estimated that this group would need to receive a much higher payment in order to accept this particular one hour outage. In contrast, SMEs who typically have 'low' electricity bills require a lower payment. This impact may also be magnified in monetary terms as 'low' electricity bill SMEs will have much lower average bills. The other notable deviations away from the baseline are for 'urban' SMEs and SMEs who are classified as 'non-services'. SMEs that are classified as a 'services' SME may be typically involved in some form of retail business. SMEs engaged in 'non-services' may be in construction or primary production which may require less electricity inputs.

Finally, SMEs with a peak electricity demand during typical business hours (9am-5pm) require larger payments to experience an outage that occurs during peak hours (3pm-9pm). For a similar outage, SMEs with an evening peak demand require much lower payments.[154]

[154] This is as one would expect.

Figure 39:WTA for a one hour outage at peak times on a working day in the Winter



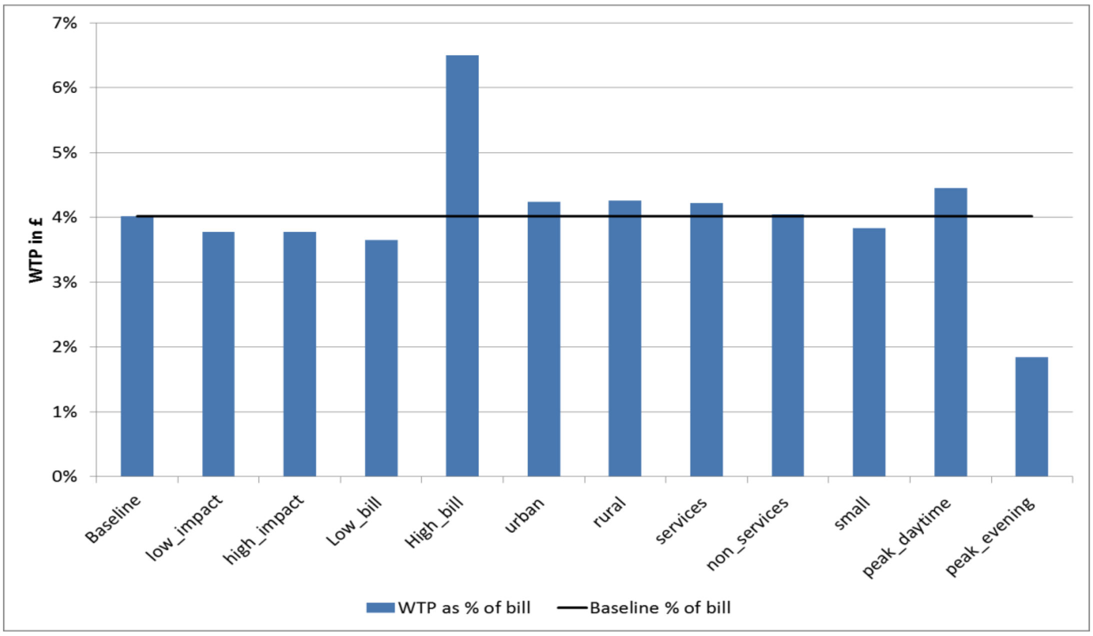
Source: London Economics analysis of SME survey

WTP estimates

Figure 40 provides a graphical representation of the WTP estimates for an outage lasting one hour occurring on a typical working day at peak times in the winter for different sub-samples compared to the baseline estimates presented in the previous subsections. The baseline monetary value of the outage is about £100 which represents around 4% of the annual electricity bill.

It must be noted that our SME sample is much smaller than the household sample and dividing the sample into further groups may lead to unrealistic or insignificant results. Again, the most obvious deviation away from the baseline is SMEs with a 'high' electricity bill.

Figure 40:WTP for a one hour outage at peak times on a working day in the Winter



Source: London Economics

A11.2 Number of observations in sub-analyses

Table 100 and Table 101 give an overview of the number of respondents and observations used in each of the WTA and WTP sub-analyses presented in this Annex.

We note that each respondent was presented with six choice cards implying that in the baseline a total of 1,656 choices were made (6 X 276) and each choice consisted of three alternatives making the total number of observations 4,968 (3 X 1,656). Certain observations were dropped due to either the respondent making irrational choices or answering 'don't know' for all choice cards. In the WTP sample, there was also some element of 'non-engagement' where respondents appeared to choose dominated choices. These observations were removed.

Table 100: Number of respondents in WTA sub-analyses

	Observations	Respondents
Baseline	4,821	268
Low impact	2,004	111
High impact	2,784	155
Low bill	1,539	86
High bill	1,812	101
Urban	2,904	161
Rural	1,452	81
Services	3,273	182
Non services	1,548	86
Small	4,557	253
Medium	264	15
Peak daytime	4,470	248
Evening peak	1,305	73

Source: London Economics

Table 101: Number of respondents in WTP sub-analyses		
	Observations	Respondents
Baseline	4,281	238
Low impact	1,731	96
High impact	2,520	140
Low bill	1,323	74
High bill	1,746	97
Urban	2,859	159
Rural	1,038	58
Services	2,991	166
Non services	1,290	72
Small	4,098	228
Medium	183	10
Peak daytime	4,005	223
Evening peak	942	52

Source: London Economics

A11.3 Confidence intervals for SME results

This section provides two tables with confidence intervals for the WTA and WTP estimates for the different subsamples.

Table 102: WTA for a one hour outage on a working day in the winter - SMEs				
	WTA in £	WTA as % of bill	Confidence interval	
			LB	UB
Baseline	164.33	6.6%	0.4%	12.8%
Low impact	169.62	6.1%	-0.7%	14.3%
High impact	151.71	6.8%	-4.1%	16.2%
Low bill	109.54	4.4%	-3.6%	12.4%
High bill	403.93	16.2%	-2.3%	34.6%
Urban	205.08	8.2%	-1.8%	18.2%
Rural	148.31	5.9%	-4.2%	16.0%
Services	183.62	7.3%	-0.5%	15.1%
Non services	93.01	3.7%	-5.1%	12.6%
Small	149.92	6.0%	0.1%	11.9%
Peak daytime	228.08	9.1%	0.5%	17.7%
Evening peak	33.34	1.3%	-4.4%	7.1%

Note: Confidence intervals are calculated based on the Delta method.
Source: London Economics

Table 103: WTP for a one hour outage on a working day in the winter – SMEs

	WTP in £	WTP as % of bill	Confidence interval	
			LB	UB
Baseline	100.41	4.0%	1.4%	6.6%
Low impact	94.48	3.8%	0.6%	7.0%
High impact	94.47	3.8%	0.0%	7.6%
Low bill	91.13	3.6%	0.0%	7.3%
High bill	162.55	6.5%	-2.8%	15.8%
Urban	106.07	4.2%	0.9%	7.6%
Rural	106.35	4.3%	-1.6%	10.1%
Services	105.59	4.2%	1.0%	7.4%
Non services	101.26	4.1%	-1.0%	9.1%
Small	95.93	3.8%	1.3%	6.4%
Medium	111.22	6.3%	1.4%	7.5%
Peak daytime	45.99	4.4%	-1.8%	5.4%
Evening peak	100.41	1.8%	1.4%	6.6%

Note: Confidence intervals are calculated based on the Delta method.

Source: London Economics

Annex 12 Electricity demand profile for domestic and SME electricity users

In this Annex, we will describe how we have converted annual electricity consumption into electricity consumption that reflects the eight different choice scenarios for both domestic and SME electricity users. These eight choice scenarios were estimated using the choice experiment and highlight that domestic and SME consumers are willing to accept/pay significantly different amounts depending on the timing of the electricity outage. These differences may be somewhat explained by differences in electricity consumption in these periods.

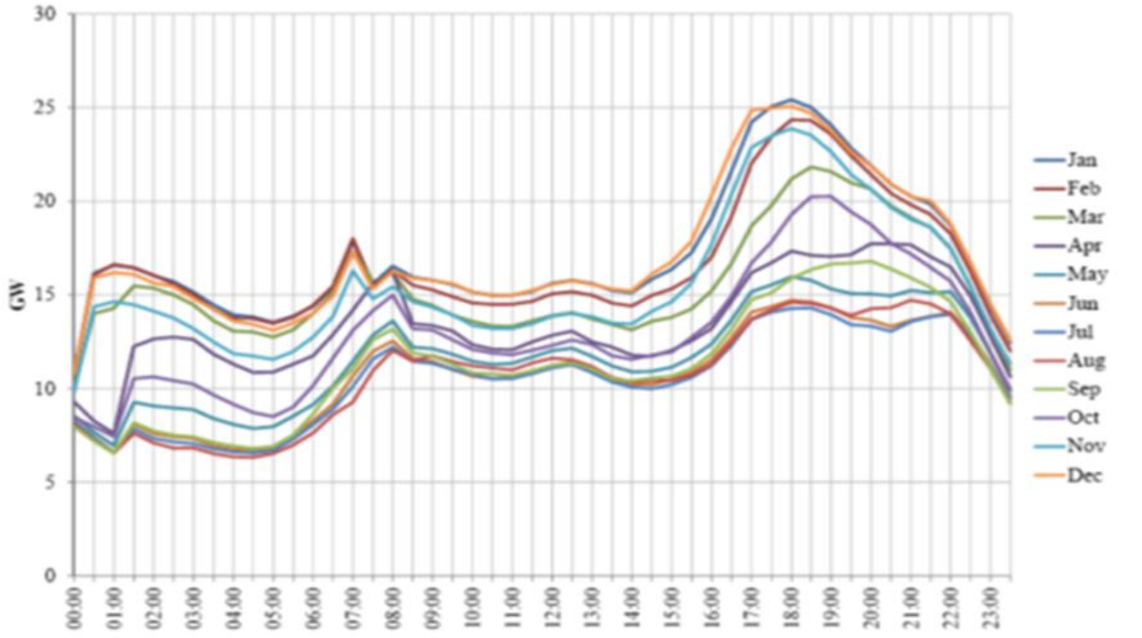
A12.1 Domestic electricity users

We base the electricity demand in each of these choice scenarios on the annual total electricity consumption (3.934 MWh[155]).This is a mean annual electricity consumption figure. For weekdays, we have based our conversion on the average daily electricity consumption patterns as shown in Figure 41. This chart gives a very detailed breakdown of electricity consumption broken down by time of the day (thirty-minute intervals) and month of the year. This chart represents typical weekday electricity consumption. The choice scenarios have been described previously in section 2.2.1. These scenarios are quite broad and thus estimating the exact electricity consumption from the graphs below is not feasible or likely to yield any improvements in the results.

We have assumed that the average consumption per thirty minute interval is 15 GW. This average is converted using the total annual electricity consumption. The choice of 15 GW as the base does not impact on the estimated electricity consumption. The key driver is the difference between the consumption in the various choices against the base demand of 15 GW. For example, the choice scenario with the lowest electricity consumption is one that occurs not in winter, not at peak and at the weekend. This is about half the demand of highest electricity consumption which occurs during winter at peak times (3pm-9pm). The graph below indicates that electricity demand is more 'peaky' than what we used. However, our choice scenarios cover quite long time periods, we believe using a less 'peaky' demand profile is prudent. For example, an outage occurring at 3pm on a winter day would typically have a very different electricity demand than an outage occurring at 6pm on the same winter day. However, these outages would be the same in terms of our choice scenarios. We also make an adjustment for differences in consumption at weekends. The consumption is very similar but is slightly lower at weekends. We have estimated that weekend consumption is 97% of weekday consumption (See Figure 32 and 33).

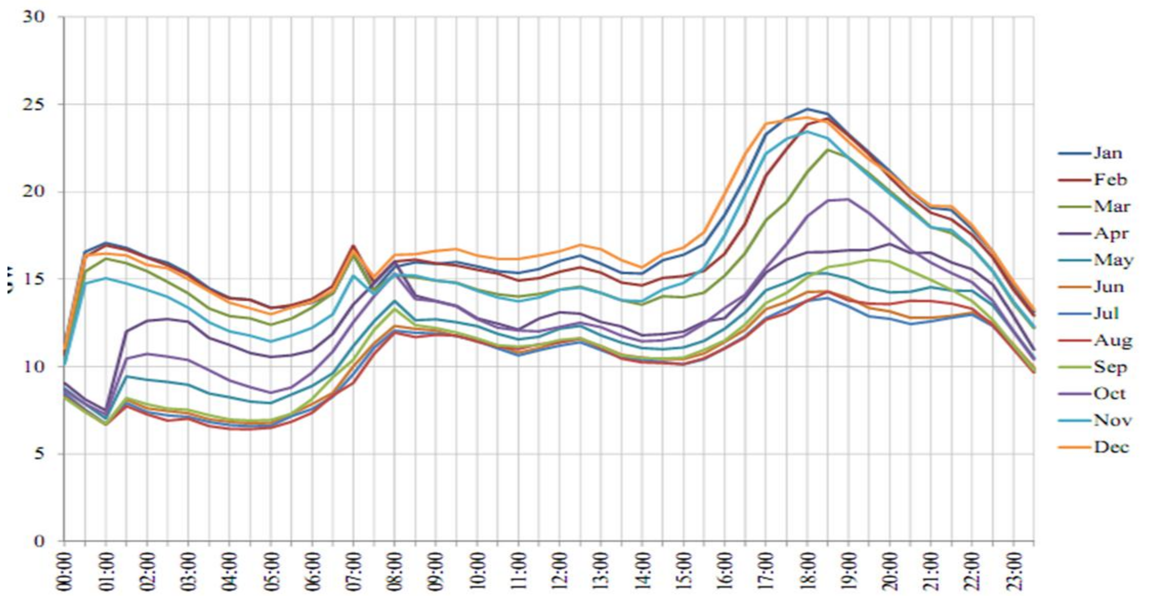
[155] DECC (2009) "DECC: Energy Trends: March 2009" http://www.decc.gov.uk/en/content/cms/statistics/publications/trends/trends

Figure 41:Electricity demand profile – UK – average domestic demand on weekdays



Note: These electricity consumption values are in 30 minute intervals for every 30 minute interval of the day.
Source: Sustainability First

Figure 42:Electricity demand profile – UK – average domestic demand on weekend days



Note: These electricity consumption values are in 30 minute intervals for every 30 minute interval of the day.
Source: Sustainability First

A12.2 SME electricity users

We base the electricity demand in each of these choice scenarios on the annual total electricity consumption (29.35 MWh). This is a mean annual electricity consumption figure. The method to convert the average electricity demand into annual demand that accounts for the demand profile is very similar to the method applied to the domestic sector.

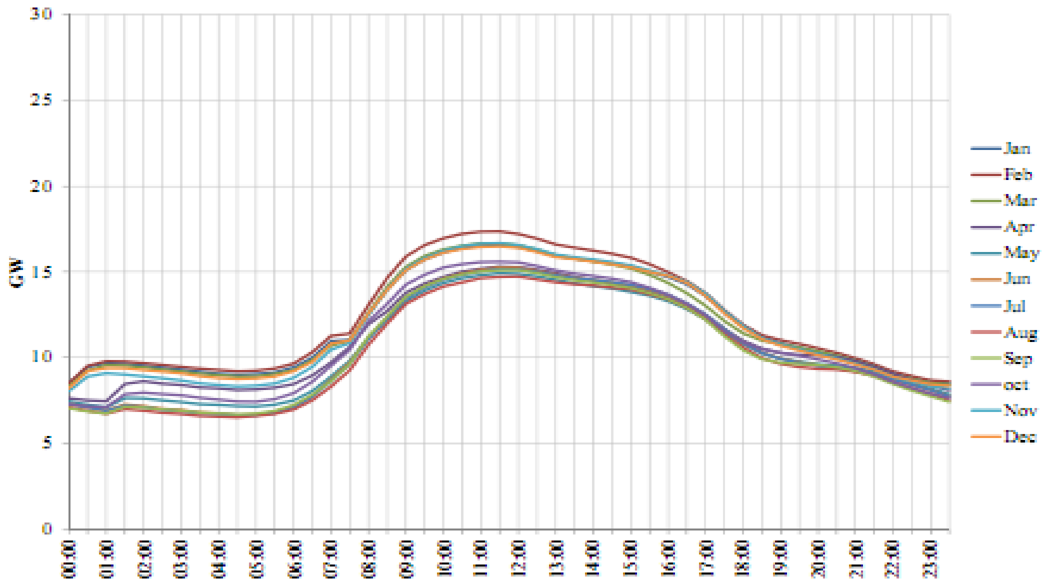
We use the demand profile of 'commercial' electricity users to represent SMEs. This demand profile is shown in Figure 43. We acknowledge that this commercial sector may not entirely represent the level of SME demand. However, for the purposes of this conversion, the shape of the demand profile is the important element and not the overall level of electricity demand.

There are a number of important distinctions that should be regarding the demand profile for commercial electricity users including:

- Our choice scenarios distinguish between workday and non-workday. The demand profile chart below does not directly account for this. However, we examine the electricity demand outside of typical working hours (9pm-5am). From this analysis, we estimate that electricity demand is 1.7 times higher on a typical working day.
- The overall electricity demand profile is much less 'peaky'
    - There appears to be little difference between peak demand (3pm-9pm) and off-peak (10pm-2pm)
    - Based on our analysis on the chart below, we have estimated that peak demand is 10% higher than off-peak demand.
- There is much less seasonal variety in the commercial demand profile. In the research that accompanies the chart below, it is estimated that winter demand is only 10% higher than summer demand. We use this assumption to account for the seasonal difference in our choice scenarios.

These assumptions allow us to convert the annual electricity consumption figure into figures that somewhat account for the different electricity demands in the various choice scenarios. These estimates should be qualified somewhat as they are based on a number of assumptions. Overall, the demand profile for SMEs appears to be much less 'peaky' than for domestic users. SMEs appear to have longer flatter peak during typical business hours (9pm – 5pm). Also, there does not appear to be much seasonal variety.

Figure 43:Electricity demand profile – UK – average 'Commercial'demand on weekdays



Note: These electricity consumption values are in 30 minute intervals for every 30 minute interval of the day.
Source: Sustainability First

Annex 13 Background to Value-at-risk method to calculate VoLL

This Annex provides further background information regarding using the GVA/VAR method to estimate VoLL for I&C customers. These are typically much larger customers in terms of electricity consumption. This Annex also shows the regression results that were used to explain and estimate VoLL in the main report. In the main report, we outlined the various methods used to estimate VoLL for I&C customers. We only presented our headline figures for I&C customers and did not present the sectoral breakdown of this analysis. This sectoral analysis is important and highlights some of the major concerns of the GVA/VAR methodology.

A13.1.1 Energy and Electricity Usage in Industry

The following table (see Table 104) shows the structure of energy consumption by industrial sector. Gas is the largest contributor to final energy use in the UK industrial sector with a 38% share in total energy use (when excluding refineries and feedstocks), closely followed by electricity and heat with 34%. It is important to note the significantly different share that electricity accounts for across the different industrial sectors. For example, electricity use constitutes around 71% of energy use for the "Non-ferrous metals" sector yet only 23% for the "Mineral products" sector.

Table 104: Energy Use in Industry % of industry total, UK 2011

Sector	Coal	Oil	Gas	Other	Electricity and Heat
Unclassified	0%	78%	0%	22%	0%
Iron and steel	3%	0%	36%	35%	26%
Non-ferrous metals	2%	3%	25%	0%	71%
Mineral products	25%	5%	47%	0%	23%
Chemicals	1%	2%	50%	10%	36%
Mechanical engineering etc.	1%	5%	42%	0%	52%
Electrical engineering etc.	0%	4%	32%	0%	65%
Vehicles	3%	6%	52%	0%	39%
Food, beverages etc.	1%	6%	60%	0%	33%
Textiles, leather etc.	5%	9%	53%	0%	33%
Paper, printing etc.	3%	2%	53%	0%	42%
Other industries	2%	28%	16%	10%	43%
Construction	1%	25%	42%	0%	32%
Total	**4%**	**17%**	**38%**	**17%**	**34%**

Source: Digest of UK Energy Statistics (DUKES, 2012)

This would indicate that an electricity interruption would have more severe consequences for the sectors with high electricity shares. Electricity consumption in industry is summarised in Table 105 for the period 2006 to 2011. Industrial electricity use declined significantly by over 10% between 2008 and 2011 mainly due to the effect of the recession. There may also be some structural issues which influence energy use declines but this is unlikely given this short time period under consideration. The chemicals sector is the largest industrial electricity user.

Table 105: Electricity Use in UK Industry 2006 to 2011 (MWh 000s)						
Sector	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**
Iron and steel	5,860	4,937	4,657	3,615	3,842	3,842
Non-ferrous metals	7,524	7,386	7,391	6,075	6,726	6,972
Mineral products	7,869	7,811	7,931	7,010	7,266	7,008
Chemicals	20,391	20,197	20,287	17,702	18,454	17,504
Mechanical engineering etc.	8,490	8,458	8,614	7,688	7,653	7,368
Electrical engineering	7,341	7,290	7,397	6,455	6,657	6,396
Vehicles	5,748	5,723	5,812	5,012	5,284	5,189
Food, beverages etc.	12,117	12,082	12,257	10,741	11,520	11,352
Textiles, leather etc.	3,360	3,349	3,395	3,013	3,050	2,991
Paper, printing etc.	12,906	12,741	12,865	11,069	10,954	10,912
Other industries	21,449	21,028	21,729	19,771	21,494	21,325
Construction	1,840	1,798	1,817	1,586	1,621	1,539
Total	**114,896**	**112,799**	**114,151**	**99,738**	**104,520**	**102,396**

Source: DUKES 2012

A13.1.2 GVA/VAR estimates of VoLL

Table 106: Estimate of electricity VoLL, 2011			
	Total GVA £/yr (millions)	**Total Elec. use (MWh 000s)**	**Unadjusted VoLL (£/MWh)**
Other mining and quarrying	1,092	1,545	707
Food products	19,476	9,048	2,153
Beverages	6,920	2,170	3,189
Tobacco products	1,654	134	12,336
Textiles	1,910	1,937	986
Wearing apparel	985	847	1,163
Leather and related products	401	207	1,940
Wood and of products of wood and cork, except furniture; articles of straw and plaiting materials	2,461	2,579	954
Paper and paper products	3,853	7,026	548
Printing and publishing of recorded media and other publishing activities	5,361	3,886	1,380
Coke and refined petroleum products	2,735	4,831	566
Chemicals and chemical products	9,438	15,852	595
Basic pharmaceutical products and pharmaceutical preparations	9,431	1,651	5,711
Rubber and plastic products	7,873	10,534	747
Other non-metallic mineral products	4,472	5,463	819
Basic metals	4,571	10,814	423
Fabricated metal products, except machinery and equipment	13,280	4,404	3,015
Computer, electronic and optical products	8,626	3,919	2,201
Electrical equipment	4,439	2,477	1,792
Machinery and equipment n.e.c.	13,380	2,964	4,515
Motor vehicles, trailers and semi-trailers	10,777	3,283	3,282

Other transport equipment	9,398	1,906	4,931
Furniture	2,537	985	2,575
Other manufacturing	4,050	1,331	3,042
Water collection, treatment and supply	10,262	5,289	1,940
Waste collection, treatment and disposal activities; materials recovery	6,042	606	9,978
Civil Engineering	11,971	1,539	7,779
Total	177,395	107,228	1,654
Total (manufacturing - 10-32)	148,028	98,248	1,507

Source: London Economics analysis

At the sectoral level, it is useful to consider how our VoLL estimates based on the unadjusted VAR/GVA method are sensitive to the largest and smallest values in the sample. As can be seen above, there are a number of industrial sectors that have significantly higher estimates of VoLL. Therefore a simple statistical analysis of the various VoLL estimates by industry is shown in Table 107. The average figure (£2,936/MWh) is the average of all the different VoLL estimates by sector.

In the table below we limit the sample by standard deviations above the mean. The table shows the impact of removing some of these possible outliers on the average level of VoLL.

For example, removing VoLL estimates that are greater than one-half of the standard deviation from the mean reduces the sample by 22% and reduces the mean VoLL from 2,936 £/MWh to 1,620 £/MWh.

Table 107: Analysis of Unadjusted VoLL estiamtes by sector (£/MWh)

Sample	Average	Median	Max.	Min.	Std. Dev.	Sample %[1]
Full sample	2,936	2,981	12,336	423	2,981	100%
Limited sample: Mean +/-2 std. dev.	2,278	1,851	7,779	423	1,851	93%
Limited sample: Mean +/-1 std. dev.	2,049	1,485	5,711	423	1,485	89%
Limited sample: Mean +/-0.5 std. dev.	1,620	976	3,282	423	976	78%

Note: 1. Refers to the number of observations in the sample as a share of the full sample (27 sectors).

Source: London Economics analysis

As we have discussed previously, assuming that all output will be lost as a result of an electricity disruption will typically lead to VoLL estimates that are appear to overestimate the VoLL.

Relationship between GVA and electricity use

The table below gives a summary of the relationship between GVA and electricity use for industrial sectors in the UK. As we can see, sectors with the largest levels of GVA do not necessarily have the largest levels of electricity consumption.

Table 108: Relationship between GVA and electricity use, 2011

	Total GVA £/yr (millions)	Rank of GVA	Total Elec. use (MWh 000s)	Rank of Elec. use
Other mining and quarrying	1,092	25	1,545	20
Food products	**19,476**	**1**	9,048	**4**

Beverages	6,920	12	2,170	16
Tobacco products	1,654	24	134	27
Textiles	1,910	23	1,937	17
Wearing apparel	985	26	847	24
Leather and related products	401	27	207	26
Wood and wood products	2,461	22	2,579	14
Paper and paper products	3,853	19	7,026	5
Printing and publishing	5,361	14	3,886	11
Coke and refined petroleum products	2,735	20	4,831	8
Chemicals and chemical products	**9,438**	**7**	15,852	**1**
Basic pharmaceutical products	**9,431**	**8**	1,651	**19**
Rubber and plastic products	7,873	11	10,534	3
Other non-metallic mineral products	4,472	16	5,463	6
Basic metals	4,571	15	10,814	2
Fabricated metal products, except machinery and equipment	13,280	3	4,404	9
Computer, electronic and optical products	8,626	10	3,919	10
Electrical equipment	4,439	17	2,477	15
Machinery and equipment n.e.c.	**13,380**	**2**	2,964	**13**
Motor vehicles, trailers and semi-trailers	10,777	5	3,283	12
Other transport equipment	9,398	9	1,906	18
Furniture	2,537	21	985	23
Other manufacturing	4,050	18	1,331	22
Water collection, treatment and supply	10,262	6	5,289	7
Waste collection, treatment and disposal activities; materials recovery	6,042	13	606	25
Construction/Civil Engineering	**11,971**	**4**	1,539	**21**

Source: London Economics analysis

The typical sector that tends to be associated with significant overestimates of VoLL using the production function method is the construction sector. The recent Reckon study using UK data again highlighted this point. The table above gives the primary reason for this overestimate. The construction/civil engineering sector has high levels of GVA (ranked 4th of sectors listed above) yet has very low electricity consumption (ranked 21st). It must be noted that the "construction" sector analysed above is the manufacturing component (i.e. civil engineering) component which is significantly smaller than the overall construction sector. However, the features of this sector are similar to the overall construction sector. This is true with relation to the ratio of GVA to electricity use.

Table 109: Ranking of VoLL estimates by sector, 2011

	VoLL (£/MWh)	Rank (VoLL)
Other mining and quarrying	707	23
Food products	2,153	13
Beverages	3,189	8
Tobacco products	12,336	1
Textiles	986	19
Wearing apparel	1,163	18
Leather and related products	1,940	14
Wood and of products of wood and cork, except furniture; articles of straw and plaiting materials	954	20
Paper and paper products	548	26
Printing and publishing of recorded media and other publishing activities	1,380	17
Coke and refined petroleum products	566	25
Chemicals and chemical products	595	24
Basic pharmaceutical products and pharmaceutical preparations	5,711	4
Rubber and plastic products	747	22
Other non-metallic mineral products	819	21
Basic metals	423	27
Fabricated metal products, except machinery and equipment	3,015	10
Computer, electronic and optical products	2,201	12
Electrical equipment	1,792	16
Machinery and equipment n.e.c.	4,515	6
Motor vehicles, trailers and semi-trailers	3,282	7
Other transport equipment	4,931	5
Furniture	2,575	11
Other manufacturing	3,042	9
Water collection, treatment and supply	1,940	15
Waste collection, treatment and disposal activities; materials recovery	9,978	2
Civil Engineering/Construction	7,779	3

Source: London Economics analysis

The basic metals sector appears to have the lowest value of VoLL. This is based on the production function approach and may be somewhat counterintuitive. As shown in Table 108, this sector has the second highest electricity consumption which may indicate that electricity is an important production input. As this has relatively low GVA, the production function approach will suggest that this sector has low VoLL. In reality, electricity may be significantly more important for this sector than other sectors.

The same logic may be applied to sectors with high electricity consumption yet comparatively low GVA. Such sectors may include chemicals and chemical products, basic metals and rubber and rubber products. However, it must be noted that the production function method will still lead to overestimates of VoLL for these sectors unless an electricity outage leads to a 100% loss of GVA. However, firms may be able to store stock or ramp-up production after the outage which mitigates against the cost of an electricity outage.

A13.1.3 Estimating VoLL using 'critical' electricity consumption

It is also important to consider the final purpose of this electricity consumption. This is an important consideration of relevance to calculation of VoLL because electricity used for non-process purposes is much less likely to impact production and therefore value added than electricity used in actual processes critical to manufacturing output.

Table 110: Breakdown of electricity consumption by industrial process and sector, 2011

	High temperature process	Low Temperature Process	Drying / Separation	Motors	Compressed Air	Lighting	Refrigeration	Space Heating	Other
Other mining and quarrying	50%	4%	4%	36%	0%	0%	0%	1%	5%
Food products	0%	35%	4%	26%	0%	0%	27%	0%	8%
Beverages	0%	35%	4%	26%	0%	0%	27%	0%	8%
Tobacco products	0%	36%	0%	27%	0%	0%	28%	0%	8%
Textiles	0%	21%	6%	50%	0%	0%	0%	23%	0%
Wearing apparel	0%	21%	6%	50%	0%	0%	0%	23%	0%
Leather and related products	0%	21%	6%	50%	0%	0%	0%	23%	0%
Wood and wood products	0%	11%	6%	63%	14%	0%	0%	3%	3%
Paper and paper products	0%	19%	30%	17%	21%	0%	0%	5%	7%
Printing and publishing	0%	19%	30%	17%	21%	0%	0%	5%	7%
Coke and refined petroleum products	0%	12%	6%	60%	15%	0%	0%	5%	3%
Chemicals and chemical products	3%	8%	4%	53%	14%	0%	15%	1%	3%
Basic pharmaceutical products	3%	8%	4%	53%	14%	0%	15%	1%	3%
Rubber and plastic products	0%	11%	6%	63%	14%	0%	0%	3%	3%

Other non-metallic mineral products	50%	4%	4%	36%	0%	0%	0%	1%	5%
Basic metals	78%	0%	0%	12%	0%	0%	0%	0%	10%
Fabricated metal products,	5%	46%	0%	3%	8%	10%	0%	26%	2%
Computer, electronic and optical products	3%	25%	0%	2%	7%	24%	0%	34%	5%
Electrical equipment	3%	25%	0%	2%	7%	24%	0%	34%	5%
Machinery and equipment	5%	46%	0%	3%	8%	10%	0%	26%	2%
Motor vehicles, trailers and semi-trailers	3%	26%	0%	3%	10%	20%	0%	33%	4%
Other transport equipment	0%	37%	0%	6%	16%	0%	0%	34%	7%
Furniture	0%	11%	6%	63%	14%	0%	0%	3%	3%
Other manufacturing	0%	11%	6%	63%	14%	0%	0%	3%	3%
Water	0%	11%	6%	63%	14%	0%	0%	3%	3%
Waste collection	0%	11%	6%	63%	14%	0%	0%	3%	3%

Source: ECUK, London Economics analysis

All electricity processes may not be critical to the production process.

In the main report, we quantitatively examine the 'critical' production of individual sectors making reference to the different industrial processes. We examine two different scenarios and how these impact on the estimate of 'critical' electricity consumption. The scenarios that we analysed were:

- Scenario (1) critical: All electricity consumed for space heating, lighting and 'other' purposes is assumed to be non-critical to the production process; and
- Scenario (2) critical: As per scenario 1 except we assume that 50% of electricity consumed for motors is non-critical.

Table 111: Scenario analysis to estimate 'critical' electricity inputs

	Scenario (1) critical	Scenario (2) critical
Other mining and quarrying	94%	76%
Food products	92%	79%
Beverages	92%	79%
Tobacco products	92%	78%
Textiles	77%	52%
Wearing apparel	77%	52%
Leather products	77%	52%
Wood and wood products	94%	63%
Paper and paper products	88%	79%
Printing and publishing	88%	79%
Coke and refined petroleum products	92%	62%
Chemicals and chemical products	96%	70%
Basic pharmaceutical products	96%	70%

Rubber and plastic products	94%	63%
Other non-metallic mineral products	94%	76%
Basic metals	90%	84%
Fabricated metal products	62%	60%
Computer, electronic and optical products	37%	36%
Electrical equipment	37%	36%
Machinery and equipment n.e.c.	62%	60%
Motor vehicles, trailers and semi-trailers	42%	41%
Other transport equipment	59%	56%
Furniture	94%	63%
Other manufacturing	94%	63%
Water collection, treatment and supply	94%	63%
Waste collection, treatment and disposal activities;	94%	63%

Source: London Economics analysis, ECUK data

The results of this analysis at the sectoral level are shown in Table 112. The results highlight that applying these conditions regarding ‘critical’ electricity consumption has significantly different implications for different sectors.

Table 112: VoLL Estimates range £/MWh			
Sector	**Unadjusted VoLL (£/MWh)**	**Scenario (1) - VoLL (£/MWh)**	**Scenario (2) - VoLL (£/MWh)**
Other mining and quarrying	707	662	534
Food products	2,153	1,982	1,703
Beverages	3,189	2,937	2,523
Tobacco products	12,336	11,320	9,650
Textiles	986	756	511
Wearing apparel	1,163	892	603
Leather and related products	1,940	1,488	1,006
Wood and of wood products	954	896	597
Paper and paper products	548	480	432
Printing and publishing	1,380	1,208	1,088
Coke and refined petroleum products	566	521	352
Chemicals and chemical products	595	574	416
Basic pharmaceutical products	5,711	5,506	3,989
Rubber and plastic products	747	702	468
Other non-metallic mineral products	819	767	618
Basic metals	423	382	356
Fabricated metal products, except machinery and equipment	3,015	1,858	1,819
Computer, electronic and optical products	2,201	821	796
Electrical equipment	1,792	668	649
Machinery and equipment n.e.c.	4,515	2,782	2,723
Motor vehicles, trailers and semi-trailers	3,282	1,395	1,342
Other transport equipment	4,931	2,913	2,776
Furniture	2,575	2,418	1,612
Other manufacturing	3,042	2,857	1,904
Water collection, treatment and supply	1,940	1,822	1,214
Waste collection, treatment and disposal activities; materials recovery	9,978	9,371	6,246
Average	2,750	2,230	1,766

Note: The average refers to the sum of VoLLs for each sector divided by the number of sectors.
Source: London Economics analysis

A13.1.4 Low capacity utilisation

We also considered the issue of capacity utilisation which may have a significant impact on estimates of VoLL using the GVA/VAR methodology. The sectoral results of applying our method to account for possible capacity underutilisation (described in section 3.1.2) are shown in Table 113.

As noted previously, this differs by sector. For the purposes of estimating an aggregate number, we take the average capacity utilisation figures across all sectors. In the table below (Table 114), we apply individual capacity utilisation estimates to the unadjusted VoLL estimates.

Table 113: Analysis of the Ratio of output to inputs for various Industrial sectors (2011)

sic2007	Min(Ratio)	Max(Ratio)	Inputs	Output	Max Output	Capacity Utilisation
Food products	1.36	1.43	53,075	72,062	75,816	95%
Tobacco products	7.52	11.43	1,013	10,366	11,582	90%
Textiles	1.50	1.63	3,692	5,530	6,023	92%
Wearing apparel	1.38	1.60	2,207	3,164	3,525	90%
Wood and wood products	1.49	1.66	4,369	6,832	7,248	94%
Coke and refined petroleum products	1.30	1.91	33,947	44,287	65,001	68%
Chemicals and chemical products	1.27	1.42	31,368	40,497	44,501	91%
Rubber and plastic products	1.52	1.63	14,013	21,715	22,790	95%
Basic metals	1.24	1.35	15,574	19,982	21,058	95%
Fabricated metal products	1.65	1.86	18,552	31,629	34,443	92%
Computer, electronic and optical products	1.31	1.78	11,318	19,690	20,160	98%
Electrical equipment	1.46	1.57	9,590	14,026	15,021	93%
Machinery and equipment n.e.c.	1.51	1.61	24,445	37,288	39,336	95%
Other transport equipment	1.43	1.79	18,256	27,793	32,757	85%
Construction	1.44	1.61	26,650	38,246	42,932	89%

Note: Min (Ratio) refers to the minimum ratio of inputs to outputs that each sector used over the period 2001-2011.
Source: London Economics analysis

Table 114: Estimate of electricity VoLL, 2011 (applying a capacity utilisation factor)			
	Unadjusted VoLL (£/MWh)	Capacity Utilisation	Adjusted VoLL (£/MWh)
Other mining and quarrying	707	95%	672
Food products	2,153	90%	1938
Textiles	986	92%	907
Wearing apparel	1,163	90%	1047
Wood and wood products	954	94%	897
Coke and refined petroleum products	566	68%	385
Chemicals and chemical products	595	91%	541
Rubber and plastic products	747	95%	710
Basic metals	423	95%	402
Fabricated metal products, except machinery and equipment	3,015	92%	2774
Computer, electronic and optical products	2,201	98%	2157
Electrical equipment	1,792	93%	1667
Machinery and equipment n.e.c.	4,515	95%	4289
Motor vehicles, trailers and semi-trailers	3,282	85%	2790

Source: London Economics analysis

A13.1.5 Possible Aggregation bias

Another type of potential bias from the GVA method arises if there is unobserved heterogeneity in the underlying industries that are aggregated to get the higher level GVA estimates. This becomes especially evident when statistical re-classifications occur in order to better represent the changing structure of the economy.

For our analysis, we have used concordance tables to match sectors from the classification SIC (2003) to SIC (2007). These have been aggregated at the two-digit level. At the two-digit level, there does not appear to be any difference between SIC (1992) and SIC (2003).

Table 115: Concordance table to convert SIC (2003) and SIC (2007) classifications		
SIC2003	Sector	SIC2007
14	Other mining and quarrying	8
15	Manufacture of food products and beverages	10
15.9	Manufacture of beverages	11
16	Manufacture of tobacco products	12
17	Manufacture of textiles	13
18	Manufacture of wearing apparel; dressing and dyeing of fur	14
19	Manufacture of leather and leather products	15
20	Manufacture of wood and wood products	16
21	Manufacture of pulp, paper and paper	17
22	Publishing, printing and reproduction of recorded media	18
23	Manufacture of coke, refined petroleum products and nuclear fuel	19
24	Manufacture of chemicals, chemical products and man-made	20

	fibres	
24.4	Manufacture of pharmaceuticals, medicinal chemicals and botanical products	21
25	Manufacture of rubber and plastic products	22
26	Manufacture of other non-metallic mineral products	23
27	Manufacture of basic metals	24
28	Manufacture of fabricated metal products, except machinery and equipment	25
30	Manufacture of office machinery and computers	26
31	Manufacture of electrical machinery and	27
32	Manufacture of other electronic equipment	26
33	Manufacture of medical devices	26
29	Manufacture of machinery and equipment not elsewhere classified	28
34	Manufacture of motor vehicles, trailers and semi-trailers	29
35	Manufacture of other transport equipment	30
36	Manufacture of furniture; manufacturing not elsewhere classified	31
36	Manufacture of furniture; manufacturing not elsewhere classified	32
40	Electricity, gas, steam and hot water supply	35
41	Collection, purification and distribution of water	36
90	Sewage and refuse disposal, sanitation and similar activities	38
45	Construction/Civil Engineering	42

Source: London Economics analysis

This table is then used for both the GVA figures and the energy consumption data. It is important that these data are as directly comparable as possible.

When the analysis is done at the two-digit level, a number of key changes have occurred in the latest statistical classification (SIC (2007)). These include:

- Beverages have been removed from the overall food sector and are now a separate two-digit sector;
- Pharmaceuticals have been removed from the basic chemicals sector and are now a separate two-digit sector; and
- The two-digit sectors 30, 32 and 33 have been aggregated into one two-digit sector (26) in SIC (2007); this new sector focuses on the manufacture on different types of equipment and medical devices.

Typically, some level of aggregation is necessarily in compiling government statistics, particularly Gross Value Added (GVA) and energy consumption. However, this aggregation may cause bias in terms of estimating lost load under a number of circumstances:

- If there are aggregated sectors that have very different energy consumption profiles; or
- If there are aggregated sectors with different GVA profiles.

For purposes of our analysis, we have disaggregated historical data (pre-2007) for some sectors based on the current industrial sector classifications (SIC (2007)). This creates additional industrial sectors for beverages and pharmaceuticals. Historical data is constructed using shares as per the 2007 data. The benefit of this approach can be seen in Table 108 as the energy consumption profile is very different for the “chemical and chemical products” sector and the “basic pharmaceutical products. Both sectors had similar levels of GVA in 2011 but the pharmaceutical sector consumed around ten times less electricity. When these sectors are aggregated together, the estimate of VoLL would be severely biased.

A key conclusion of this analysis is the importance of examining VoLL at as disaggregated a level as possible. Taking the VoLL of aggregated groupings (e.g. manufacturing) will not show the very large heterogeneity that exists within individual sectors of manufacturing. There may also be large variation within these sectors as discussed in this section. The GVA/VAR method has a number of useful features but its application and interpretation should be viewed with a degree of caution.

Relationship between VoLL and other variables

Using a relatively long time-series, we attempt to establish what the main predictors of electricity VoLL are. We also econometrically examine the production function and show its relationship with electricity inputs. We make use of the ‘Energy Consumption in the United Kingdom (ECUK)’ database which splits energy (electricity) use into sectors and processes. We also undertake analysis based on estimates of electricity use taken from the DUKES database. These energy data are supplemented with data on GVA from the Office of National Statistics (ONS).

We have also constructed a dataset of energy consumption and GVA from 1995-2011. This is a panel as this information is available by year and at the sectoral level. Combining with national accounts statistics, we have data on the following economic and energy variables:

- Turnover (Output);
- Employment;
- Cost of employment;
- Capital expenditure;
- Capital accumulation;
- Intermediate inputs;
- Energy prices;
- Energy consumption by fuel type; and
- Energy expenditure.

Table 116 shows the correlations between the various variables in our dataset. As expected, many of the variables that drive the GVA estimates are highly correlated. It appears that electricity consumption is negatively correlated with VoLL. This indicates that industrial sectors with lower levels of electricity consumption tend to have higher levels of VoLL. Although this seems somewhat counterintuitive, this is consistent with our prior analysis of electricity VoLL. For example, the manufacture of basic metals had a high level of electricity consumption but a low level of VoLL. In contrast, the manufacture of tobacco products had a relatively low level of electricity consumption but a high estimate of VoLL. The electricity share appears to have a very weak correlation with the VoLL.

Table 116: Correlations between various variables, 1995-2011						
	VoLL	gva	tot_employment	cap_exp	elec_share	elec_cons_~h
voll	1					
gva	0.75	1				
tot_employment	0.73	0.95	1			
capital_exp.	0.49	0.77	0.70	1		
Elec. share	0.01	-0.03	-0.09	0.04	1	
Elec._consumption	-0.32	0.06	0.02	0.23	-0.03	1

Source: London Economics analysis

A13.1.6 Regression analysis

As discussed previously, there are a number of potential biases in the estimation of electricity VoLL using the production function approach. However, this production function approach has been used in many different countries and gives estimates based on comparable industrial classifications. A brief overview of these results is included in the literature review section (Annex 1). As discussed previously, these results tend to differ significantly by sector. Also, typically these results are presented at more aggregated sector level than presented in this report.

A potentially interesting empirical question is 'what are the key variables that drive electricity VoLLs?' Using the dataset described previously, we can analyse the statistical relationships between VoLL and other economic and energy variables using regression analysis.

Our regression approach starts with a simple investigation of the correlations between the VoLL, electricity usage, and single explanatory variables, such as employment. We use these to analyse which variables typically have the largest impact on the calculation of the electricity VoLL using the VAR method.

Finally, we consider more sophisticated models of production where electricity is included as an explanatory variable in the production function. The interpretation of this is that VoLL is really the impact of electricity outages on output. Thus, we can include electricity as an input into the production function. When this input to the production function becomes zero, we are also estimating a type of VoLL.

Employment

The first model that we will analyse is the relationship between the levels of employment in the sector and the electricity VoLL. The computation of GVA is based on the cost of employment rather than the actual number in employment. If all sectors pay the exact same wage rate, then these variables will be perfectly correlated and regression estimation may be invalid. However, there may be significant differences between sectors in terms of average wage levels. This may be due to a number of factors.

A priori, we believe that there will be a positive relationship between electricity VoLL and employment levels. This is based on our earlier analysis of VoLL and sectoral composition. We use panel data estimates which allow us to control for time and space characteristics. A log-log specification is chosen.

The results of the estimate are found in the table overleaf. We present the results using three different estimation techniques. We use both pooled OLS and fixed effects panel data estimators. Typically, the fixed effects estimator is considered superior as it takes into account factors that may be influencing the explanatory variable (i.e. VoLL) that time invariant. For example, the location of a firm may never change and the remoteness of this location means a large dependence on electricity for production. This location may be an important explanatory variable but our pooled OLS model would not be able to control for such a variable unless we included an explicit variable. However, it may not be feasible or practical to include an explanatory variable for every possible time invariant impact. This is a key advantage of using a fixed effects estimator. As this 'location' does not change over the sample period, the 'fixed effect' allows us to account for this effect. Although we may not know the size of this impact, we know that the model accounts for it and the model no longer has 'omitted variable bias' problems.

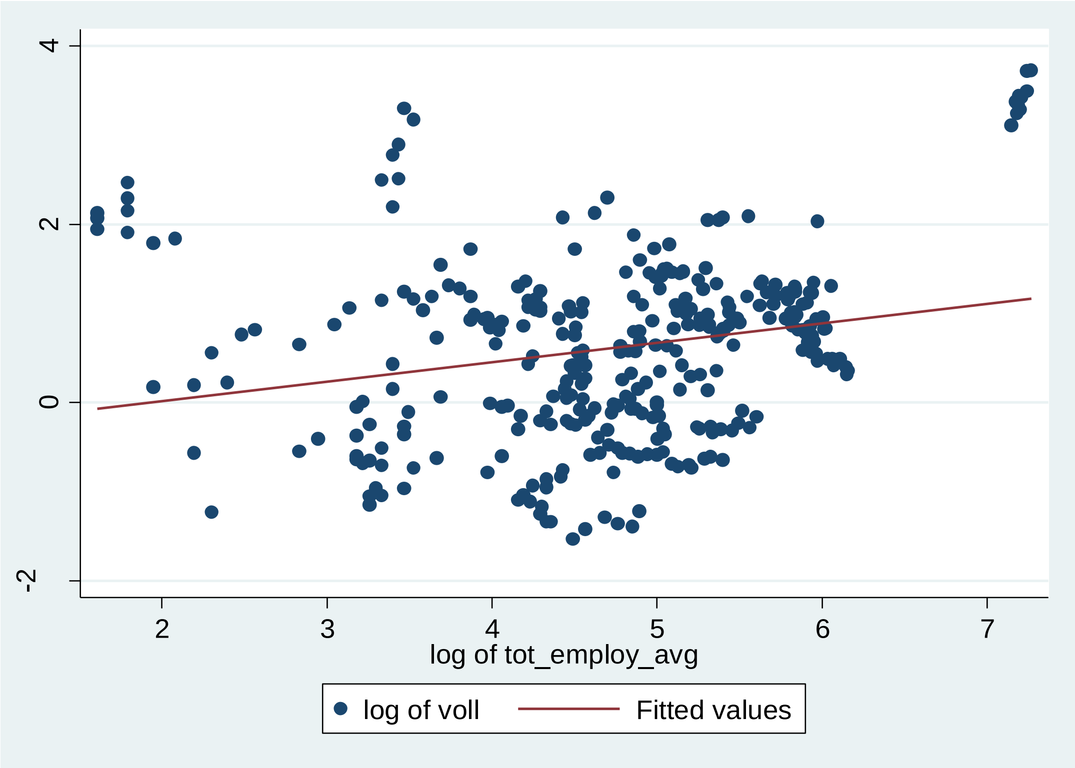
Table 117: Impact of employment on VoLL

	Employment Pooled OLS	Fixed effects	Multivariate Fixed effects
ln_tot_employ_avg	0.297*** (4.45)	0.579*** (6.19)	0.139 (1.40)
ln_cap_exp	-0.1207** (-1.97)	0.06* (0.91)	0.014 (0.36)
ln_intermediate_exp_less_elec			0.785*** (5.46)
ln_elec_exp			-1.12*** (-11.11)
energy_sh			6866.9*** (2001.06)
_cons	13.724 (44.86)	11.27*** (39.28)	11.92 (15.50)
N	325	325	107
R-sq.	0.06	0.05	0.70
t statistics in parentheses			
* p<0.10	** p<0.05	*** p<0.01"	

Note: data from DUKES and ONS, VoLL is the dependent variable.

Source: London Economics analysis

Figure 44:log_VoLL_GVA vs log_employment



Source: London Economics analysis

The regression results indicate a clear positive relationship between VoLL and employment numbers. This somewhat explains previous published results which indicate that a sector like construction appears to have a very large (and often unrealistic) levels of VoLL. Under a range of different econometric models, the coefficient on employment ranges from 0.30 to 0.58. We believe that the 0.58 estimate is superior as it is based on a fixed panel data estimator. The reasons why this estimate may be a superior estimate were discussed previously. As both variables are in logs, this coefficient can be directly interpreted as an elasticity. Thus, a 1% increase in the levels of employment will lead to a 0.58% increase in the estimate of VoLL. In reality, this type of result does not appear to make sense in terms of the impact of an electricity outage on production (value added).

As this section uses single variate models, it is also useful to use a graphical approach. Figure 44 above shows the graphical relationship estimated for VoLL against employment from the fixed effects model. The graph clearly shows the positive relationship between the two variables. This indicates that sectors with higher levels of employment tend to have higher levels of electricity VoLL.

Gas/Other Energy consumption

Sectors with large gas consumption (or non-electricity energy consumption) may or may not be largely unaffected by an electricity disruption. In some cases, critical energy processes will be driven by other energy sources. Critical processes will continue and the impact of this outage on production will be minimal. Alternatively, some processes, while primarily needing non-electricity energy inputs, may still require electricity. The degree to which electricity is substitutable with other sources is an empirical question. We test this hypothesis using the same method as per levels of employment. We will run simple bivariate regressions initially followed by multivariate regressions which allow us to account for other time varying factors.

The first bivariate regression that we estimate is the impact of the consumption of non-electrical energy on the VoLL. The results of this regression are shown in Table 118 which shows a statistically significant negative relationship between VoLL and the consumption of non-electrical energy. *A priori*, such a relationship was expected. A number of reasons for this may be put forward but the most obvious one might be that the key production processes entail a certain degree of substitution among energy inputs. The key production processes will also typically constitute a large share of energy consumption.

Table 118: Impact of electricity consumption on VoLL

	Non Elec. Consump	Elec. Share	Non Elec. consump & Employment	Full Fixed effects model
ln_non_elec_consump	-0.476*** (-14.61)		-0.582*** (-23.32)	-0.580*** (-25.42)
sh_elec		1.306*** (4.18)		
ln_tot_employ_avg			0.756*** (19.06)	0.532*** (8.76)
ln_cap_exp				0.0347 (0.80)
ln_intermediate_exp				0.401*** (7.48)
_cons	1.397*** (25.35)	0.156 (1.34)	4.92*** (26.98)	-2.06*** (5.06)
N	419	419	330	325
R-sq.	0.353	0.043	0.58	0.58
t statistics in parentheses				
="* p<0.10	** p<0.05	*** p<0.01"		

Note: All regressions are based on a fixed effects model. The log of VoLL is the dependent variable.
Source: London Economics analysis

We also run a similar bivariate regression where the explanatory variable is the electricity share of total energy consumption. This indicates a positive relationship between the share of electricity and the VoLL. This would suggest that industrial sectors where electricity represents a large share of energy inputs typically have a higher VoLL. However, this finding has a number of caveats. Firstly, this share doesn't take into account the total consumption and the importance of this consumption. For example, a 100% electricity share may be due to simply lighting and space heating. It can easily be argued that these industrial processes may have little impact on GVA (a key component of the VoLL value).

We also add in some additional explanatory variables and test the various statistical relationships among the variables' estimated relationships to VoLL. The coefficient on the log of non-electricity energy consumptions remains quite consistent across a number of different specifications.

The final model that we estimate is a more formal production function approach where the explanatory variables constitute the different variables of a typical production function with VoLL being the dependent variable instead of GVA.

The key purpose of the table above is to examine the relationship between non-electricity energy consumption and electricity VoLL. The various econometric models indicate a statistically significant and negative relationship between non-electrical energy consumption and electricity VoLL. The result is as expected. Sectors with large consumption of energy (less electricity) typically have lower estimates of electricity VoLL. This indicates that these types of sectors will be less affected in terms of production as a result of an electricity outage.

A13.1.7 Modelling of VoLL in the production function context

The final analysis that we undertake is to examine VoLL in the context of a formalised production function. The results of this have been shown in the main report. In this section, we show this analysis at the sectoral level.

Econometric predictions of VoLL

Table 119: 'Predicted' levels of VoLL, using a Cobb-Douglas production funciton approach

	VoLL (predicted) (£/MWh)	Unadjusted VoLL (£/MWh)	% predicted
Other mining and quarrying	18,699	15,821	118%
Food products	1,039	1,683	62%
Beverages	3,154	2,451	129%
Tobacco products	9,642	9,541	101%
Textiles	1,402	1,073	131%
Wearing apparel	5,136	4,058	127%
Leather and related products	5,885	2,268	260%
Wood and wood products	2,122	1,370	155%
Paper and paper products	826	564	146%
Printing and publishing	1,550	2,935	53%
Coke and refined petroleum products	878	418	210%
Chemicals and chemical products	505	554	91%
Basic pharmaceutical products	2,361	3,043	78%

Rubber and plastic products	715	772	93%
Other non-metallic mineral products	1,124	882	127%
Basic metals	456	317	144%
Fabricated metal products, except machinery and equipment	1,496	2,556	59%
Computer, electronic and optical products	1,538	2,750	56%
Electrical equipment	1,937	2,265	86%
Machinery and equipment n.e.c.	1,656	3,516	47%
Motor vehicles, trailers and semi-trailers	2,236	2,500	89%
Other transport equipment	2,556	3,879	66%
Furniture	2,126	2,210	96%
Other manufacturing	2,973	2,918	102%
Civil Engineering	5,189	23,752	22%
Total (average)	2,846	3,602	79%

Source: London Economics analysis

Table 120: Estimates of 'predicted' VoLL using 'translog' production function model with constraints

	VoLL (predicted) (£/MWh)	Unadjusted VoLL (£/MWh)	% predicted
Other mining and quarrying	8,455	15,821	53%
Food products	1,604	1,683	95%
Beverages	2,396	2,451	98%
Tobacco products	8,871	9,541	93%
Textiles	947	1,073	88%
Wearing apparel	3,250	4,058	80%
Leather and related products	2,320	2,268	102%
Wood and of products of wood and cork, except furniture; articles of straw and plaiting materials	1,363	1,370	99%
Paper and paper products	528	564	94%
Printing and publishing of recorded media and other publishing activities	2,545	2,935	87%
Coke and refined petroleum products	464	418	111%
Chemicals and chemical products	524	554	95%
Basic pharmaceutical products and pharmaceutical preparations	2,846	3,043	94%
Rubber and plastic products	737	772	95%
Other non-metallic mineral products	873	882	99%
Basic metals	302	317	95%
Fabricated metal products, except	2,585	2,556	101%

machinery and equipment			
Computer, electronic and optical products	2,214	2,750	80%
Electrical equipment	2,088	2,265	92%
Machinery and equipment n.e.c.	3,439	3,516	98%
Motor vehicles, trailers and semi-trailers	2,411	2,500	96%
Other transport equipment	4,219	3,879	109%
Furniture	2,242	2,210	101%
Other manufacturing	2,543	2,918	87%
Civil Engineering	22,637	23,752	95%
Total (Average)	**3,207**	**3,602**	**89%**

Source: London Economics analysis

Annex 14 VoLL for larger electricity users - real options approach

In this Annex, we apply the real options approach to estimating VoLL to two selected industries: crude oil refining and aluminium smelting. This is a secondary method for estimating VoLLs in the I&C sector. This Annex provides some background information behind the rationale and implementation of the real options approach that is also used to estimate VoLL for large electricity users. It also presents the results of this analysis.

A14.1 Introduction: Crude oil refining

Crude oil refining is an interesting case to examine VoLL estimates for I&C electricity users. The primary inputs (crude oil and electricity) can be measured in the same unit of energy (MWh) as the outputs (gas oil, gasoline and light fuel oil) and daily market prices are available for gas oil, crude oil, gasoline, light fuel oil and electricity. Therefore, we can estimate the VoLL using publically available market prices.

A particularly interesting, but nonetheless surmountable, challenge is due to the interaction of volatile fuel and electricity prices. Our approach to this is to use the so-called real options approach, with some additional modifications to adjust for timing, time horizon, and potential empirical factors in the time-series such as mean reversion versus random walks.[156]

We start by examining the recent historical averages of the value of the crack spread. The crack spread here represents the gross profit made without an option value or any volatility driven adjustments. This gives a per unit (1 MWh) of input value of production for crude oil refining.

We then use a real options approach that includes a plant shutdown option to evaluate the VoLL for electricity users of this kind. In addition to looking at crude oil refining we will also examine the VoLL to aluminium smelting as this industrial process requires large amounts of electricity.

A14.2 Intrinsic value of crack spread for VoLL

A14.2.1 Description of method

The starting point for estimating VoLL for an industrial electricity user is the price per unit of inputs (electricity, crude oil, bauxite) less the price per unit of outputs (gas oil;, aluminium etc.) – the so-called crack spread.

Equation 1: $$\boldsymbol{\pi_t = \{p_t - VC_t\} = VoLL_t}$$

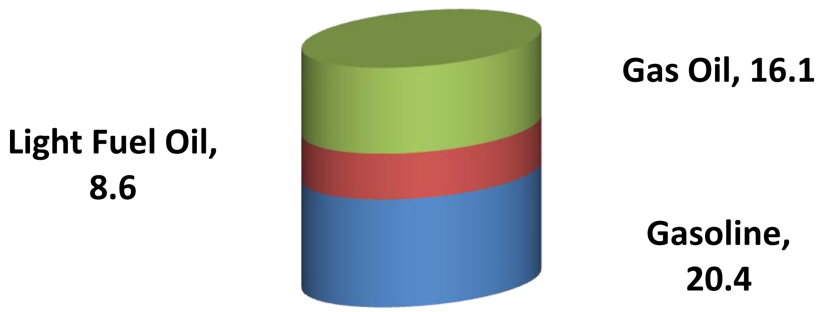
[156] The standard approach to the value of an option, developed for financial products, assumes a random walk process for the price series of the underlying asset. This assumption is not likely to be valid for electricity prices, oil prices or crack/smelt spreads over the long run.

The VoLL is simply the value of production gross profit, π_t (price of outputs produced, p_t), in the time period t (t-subscript), less the variable cost VC_t (price of inputs used in production). In the case of crude oil refinery p_t represents the total price of production inputs (crude oil and electricity) per MWh of crude oil used. Therefore, VC_t is made up of the total price of outputs produced (gas oil, light fuel oil, gasoline) per MWh of crude oil refined.

A14.2.2 Petroleum refining

Crude oil refining will produce several oil products, each of different heating values. Therefore, it is important to ensure that the appropriate quantities of inputs and outputs, involved in the refining process, are used in our analysis. Through the process of refinery 42 US gallons (one barrel) of crude oil will yield 45 US gallons of refined petroleum products.[157] For the purpose of this analysis we have assumed that a refined barrel of crude oil will produce three petroleum products; gasoline, light fuel oil and gas oil. In reality there are more than three petroleum products produced in the refining process but many of these have very similar heat values and some of these do not have daily traded prices.

Figure 45:Products made from barrel of crude oil through refining – US Gallons



	Products made form barrel of crude oil (Gallons) - Total output of 45 gallons
Gas Oil	16.1
Light Fuel Oil	8.6
Gasoline	20.4

Note: Bloomberg data.
Source: EIA & LE assumptions

Using the above proportions together with the individual heating values for each petroleum product we can estimate how much of each petroleum product, measured in MWh, will be produced for each MWh of crude oil refined. To estimate the amount of electricity used in the refining of one barrel of crude oil we divided the total number of barrels of crude oil refined in the

[157] http://www.eia.gov/energyexplained/index.cfm?page=oil_refining

UK in 2005 (the most recent year with relevant data available) 573,007,143[158] by the total amount of electricity consumed by petroleum refineries in the UK in the same year, which was 5,624,000[159] MWh. Therefore, the average electricity used per barrel of crude oil by petroleum refineries was 0.0098 MWh and as crude oil contains 1.7MWh per barrel the average electricity used per MWh of crude oil refined is taken as 0.0058 MWh.

A14.2.3 Aluminium smelting

The second industry we consider is aluminium smelting. Aluminium smelting involves the extraction of aluminium from alumina using an electrolytic process that involves the passing of low voltages at high amperages through the material to produce aluminium. The alumina used in this smelting process is extracted originally from the principle ore, bauxite. Significant bauxite deposits are found throughout Australia, the Caribbean, Africa, China and South America. Bauxite is purified using a chemical process known as the Bayer process. Therefore, aluminium smelting has two primary inputs of production; electricity and bauxite. In order to produce 1 MT (metric tonne) of aluminium, 4.2 MT of bauxite and 14 MWh of electrical power is required.[160] Aluminium smelting in contrast to crude oil refinery represents a very electricity intensive industrial production process.

A14.2.4 Empirical estimates

We present our empirical estimates of the crack spread value in this section.

Data

We obtained daily price data from 01/01/2008 until 11/01/2013, using Bloomberg Professional for the following commodities:

1. Electricity (peak)
2. Crude Oil (Brent)
3. Gas Oil
4. Gasoline
5. Light Fuel Oil (jet fuel)
6. Aluminium

Bauxite prices were available only at an annual level. For the purpose of our analysis all commodities prices were converted to £/MWh with the exception of aluminium and bauxite which were measured in £/MT (metric tonne). Each refined oil product has different energy contents to that of crude oil and when converting price per bbl (barrel) to price per MWh these energy or heat contents must be taken into account.

[158] United Nations Statistics Division.

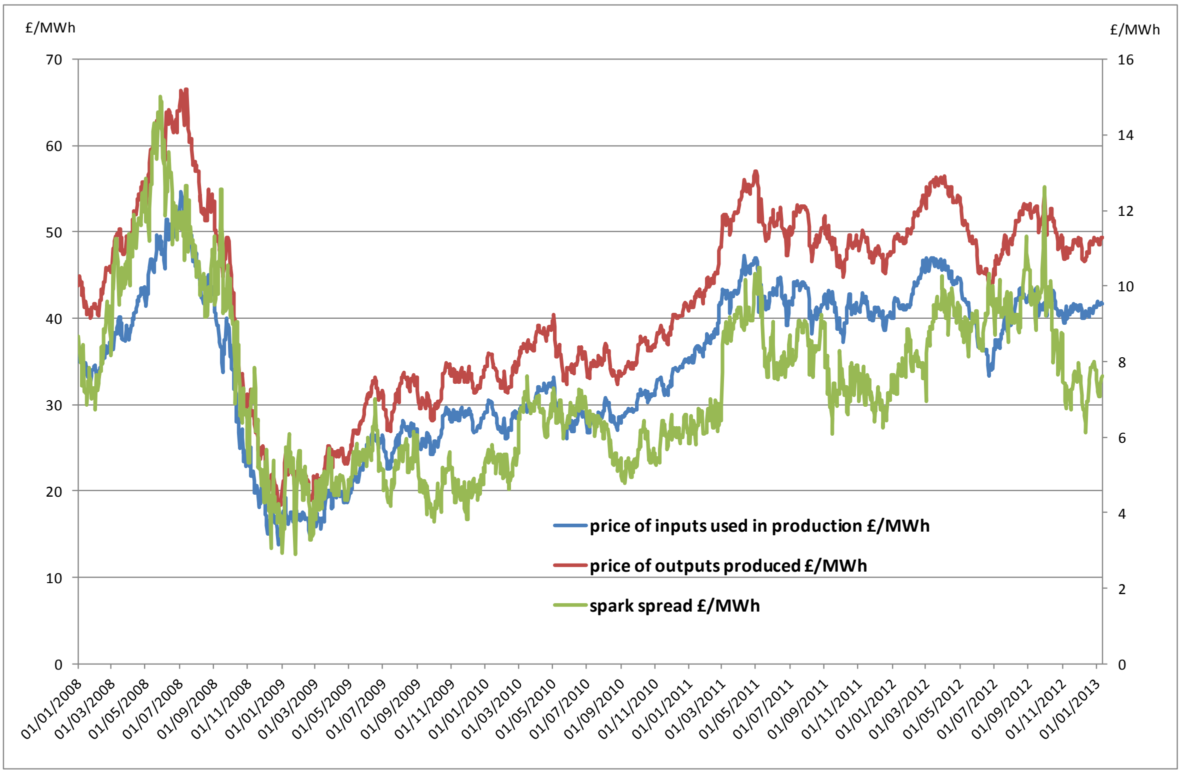
[159] United Nations Statistics Division.

[160] http://www.aalco.co.uk/datasheets/Aluminium-Alloy_Introduction-to-Aluminium-and-its-alloys_9.ashx
http://www.clarence.nsw.gov.au/cp_themes/metro/page.asp?p=DOC-TCC-15-16-18

Crude oil crack spread prices

We first present the data graphically which will be informative as to the nature of the data. The full dataset time series for the crude oil refining crack spread is presented below. The units are all in pounds per mega-watt hour. The data are the historical data on daily closing spot prices. Note that the price of production inputs and price of production outputs are measured on the primary axis while the crack spread is measured on the secondary axis.

Figure 46:Time series of UK crack spread for crude oil refining – £/MWH of crude oil



Note: Bloomberg data.
Source: London Economics

It is an empirical question whether the spike that is evident from autumn 2008 should be included in the data. For now, we argue that it should be in the sense that if there is an electricity outage when gasoline prices or prices of other refined petroleum products are high, then this is exactly what we are interested in when estimating VoLL. Even though spikes tend to be one-off events, the probability of a once-off event of any number of types perhaps would be best included in our VoLL estimates, if we are perhaps more worried about underestimating VoLL than overestimating it.

The table below presents the average crack spread data across the full period and the most recent time periods. Overall the spread is about £7.39 per MWh of crude oil refined or £1280 per MWh of electricity used. Spreads have risen from the average for 2010 in each year.

Another point of note is to consider the flexibility of plant to shut down and avoid low price periods. To test this we estimated the average spread when taking the maximum over (spread, 0).

Empirically, there is no difference (the graphical analysis also confirms this). The third column is the average excluding negative spreads, i.e., using the formula:

$$\pi_t = E(\mathrm{Max}\{p_t - VC_t, 0\})$$

The option of shutting production down, not producing when there is a negative spread, appears to offer no value to crude petroleum producers as the option is always in the money.

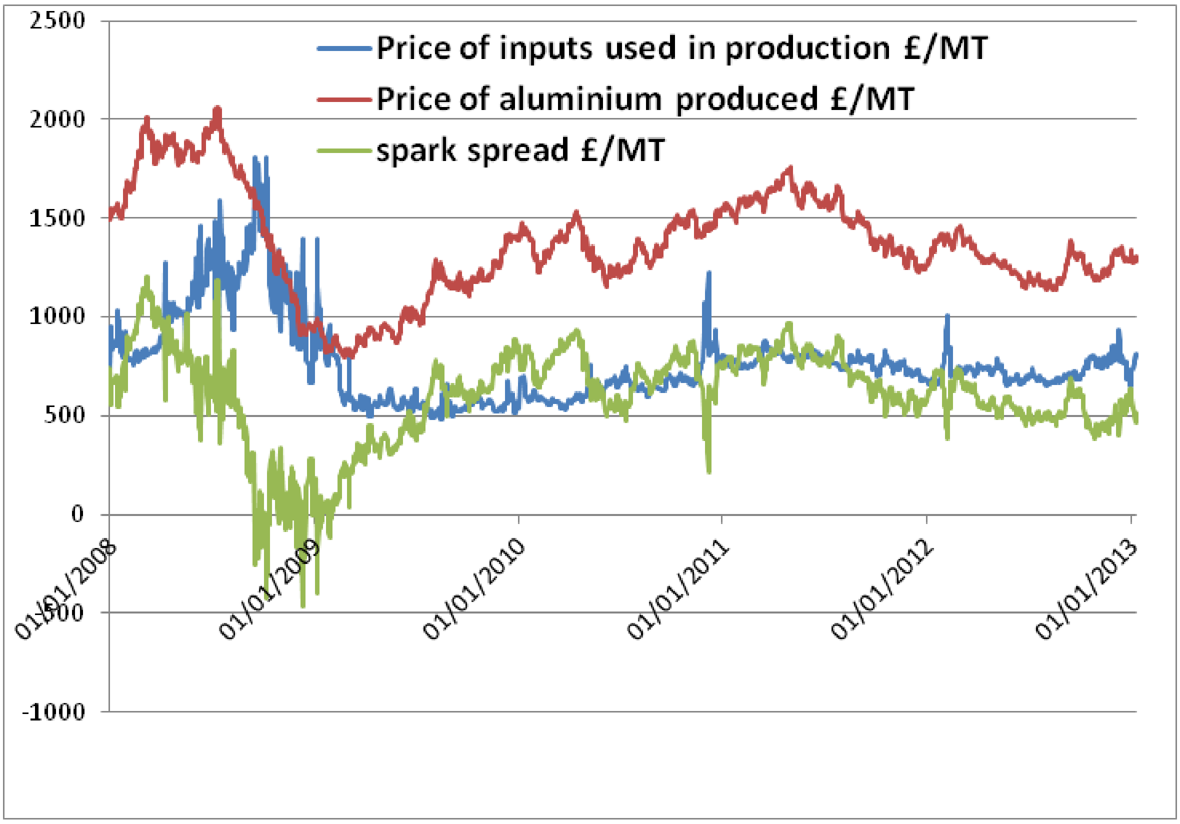
Table 121: Average UK crack spread- Crude oil Refining

Time period	£/MWh of crude oil	£/MWh of electricity	£/MWh of electricity max[sprd,0]
2008/2013 m1	7.39	1280.01	1280.01
2010	6.07	1050.98	1050.98
2011	7.82	1353.99	1353.99
2012	8.72	1510.90	1510.90

Note: Bloomberg data.
Source: London Economics

Aluminium

Figure 47:Time series of UK smelt spread for aluminium smelting – £/MT of aluminium



Note: Bloomberg data.
Source: London Economics

The third column is the average excluding negative spreads, i.e., using the formula:

$$\pi_t = E(\mathrm{Max}\{p_t - VC_t, 0\})$$

Table 122: Average UK smelt spread- Aluminium smelting

Time period	£/MT of aluminium	£/MWh of electricity	£/MWh of electricity max[sprd,0]
2008/2013 m1	604.09	43.15	43.39
2010	715.94	51.14	51.14
2011	739.28	52.81	52.81
2012	552.37	39.45	39.45

Note: Bloomberg data.
Source: London Economics

The choice of which time period is "correct" for our VoLL estimate is difficult. The answer depends in part on what one's view is of the smelt spread time series drivers. If one believed the smelt spread time series has some kind of long run equilibrium value, then we might take the long run average as the best estimate. If there are elements of "permanence" in shocks to the spread, then the spread average over the most recent and a shorter time period might be more representative of our best estimate. We discuss these and additional issues in the following sections.

A14.3 Real options approach

Estimating VoLL for large electricity consumers, such as crude oil refiners, should take account of the probability that refined petroleum prices are likely to be high when crude oil prices are high. Further, when producers can shut down when prices are low, the average crack spread will be too low an estimate of VoLL. In terms of aluminium smelting, we would expect a weaker relationship between electricity prices and aluminium prices. However, a real options-based approach is appropriate method for estimating VoLL for a small subset of large industry and the contrast in the intensity of electricity use on the productions processes makes these two industries interesting examples to examine. For this approach, we rely on market data on the UK spot prices for all production inputs and outputs where available (bauxite prices are only prices used in analysis that were not available daily). The value of production gross profit in any given hour in the future is given by the following formula:

Equation 2: $$\pi_t = E(\mathrm{Max}\{p_t - VC_t, 0\})e^{-rt}$$

Where *E* is the expectations operator, p(t) is the spot price of production inputs and VC(t) is the spot price of production outputs (all in £/MWh for petroleum refinery or £/MT for aluminium smelting), *e* is the exponential function and r is the risk free rate, and t is the time period.

The formula above illustrates that the production of refined petroleum products or aluminium is like a European call option on the so-called "crack-spread", the difference between the value of the production inputs and the value of the production outputs in equivalent units. This methodology has been applied to the valuation of gas contracts and peaking power plants (See Swinand, Rufin, and Sharma 2005).[161] Additional details can be found in Deng (1999).[162]

As a European call option, the crack spread option value can be estimated as an option value using standard techniques, such as the well-known Black-Scholes-Merton (BSM) formula. The BSM formula requires estimates of underlying parameters, such as market prices of the power and gas, volatilities, and risk free rates, which all can be estimated from the available data.

As discussed in Deng et al (1999), some adjustments to the BSM formula are made to accommodate the crack spread option. The valuation formula is altered to change the variable of the underlying from the price (Log price) of a single security to the log of the ratio of prices {ln(p1/p2)}. The general intuition is the same, however, as the formula measures the probability that the option will be "in the money" (i.e., that the price of electricity exceeds its gas and carbon price of production) at some point in the future.

It is necessary, however, to review the parameters and assumptions of the model and make appropriate adjustments so as to make our VoLL estimate as realistic as possible. These are discussed in further detail in the section below.

It is necessary, however, to review the parameters and assumptions of the model and make appropriate adjustments so as to make our VoLL estimate as realistic as possible. These are discussed in further detail below.

A14.4 Mathematical formula and discussion of parameters

Adjusted BSM formula for VoLL as crack/smelt spread call value

$$V = e^{-rt}\left[P_o^{t,T} N(d_1) - ((VC_i^{t,T})/N(d_2)\right]$$

Where:

$$d_1 = \frac{\ln\left[P_o^{t,T}/VC_i^{t,T}\right] + v^2(T-t)/2}{v\sqrt{T-t}}$$

$$d_2 = d_{1\_}v\sqrt{T-t}$$

[161] Gregory P. Swinand, Carlos Rufin, Chetan Sharma, "Valuing Assets Using Real Options: An Application to Deregulated Electricity Markets," Journal of Applied Corporate Finance Volume 17, Issue 2, pages 55–67, Spring 2005.

[162] Deng, Johnson, and Sogomonian (1999), "Spark Spread Options and the Valuation of Electricity Generation Assets" Proceedings of the 32nd Hawaii International Conference on System Sciences – 1999.

$$v^2 = \frac{\int_t^T \left[\sigma_o^2(s) - 2\rho\sigma_o(s)\sigma_i(s) + \sigma_i^2(s)\right] ds}{T - t}$$

Note that subscript o represents output, which in the case of crude oil refinery means gas oil, gasoline and light fuel oil. In the case of aluminium smelting the output represents aluminium. Similarly subscript i, as in($VC_i^{t,T}$) represents the variable cost of the production inputs, be it crude oil and electricity or bauxite and electricity.

A14.4.1 Volatility estimates

A key input to the crack spread option value estimating formula is the volatility. We estimated the volatility using the all years include in our analysis, which is from January 2008 until January 2013.

We estimated the volatility for each of the crude oil refinery and aluminium smelting crack/smelt spread data. This was done by taking the standard deviation of the log of the spread. We then tested empirically to see if volatility was growing with time. This test was structured to assess if the log spread was displaying properties of a random walk function. We would expect a random walk function to exhibit increasing volatility if assessed monthly or annually as opposed to daily. As the crack spread analysis was all completed on a daily basis there may have been a need to annualize the volatility figure. To do this you would need to adjust the volatility of the log spread by a factor of $\sqrt{365}$. However when tested we found that volatility was not increasing if we estimated it on a monthly basis as opposed to our base case of estimating it on a daily basis. Therefore a time volatility adjustment was not considered necessary in this instance.

A14.4.2 Risk-free rate and risk neutrality

One of the key assumptions of the BSM formula is that there is a replicating portfolio for an option and the underlying commodity. It can be argued how much such assets might be constructed to create any replicating portfolio, but in the case of commodity prices in the UK, liquidity is already an issue with the underlying commodities, and trading is in some cases illiquid. To argue that a crack/smelt spread could be risk-neutralized/hedged could be somewhat tenuous. While there is little doubt that some traders do perform such hedging, the question at hand is whether such an assumption is appropriate for an estimate of VoLL. The risk-free rate, or non-risk free rate used, will impact on the option value based on the discounting. Thus, the value of the option will fall as the value of the discount rate rises. Thus, for estimating the value of the VoLL as a crack/smelt spread option further into the future, we might consider discounting by a risk-adjusted cost of capital rather than the risk free rate, or alternatively using an option pricing model specifically designed to incorporate the market price of risk. For our purposes, we will estimate the VoLL based on the year-ahead forward curve, and so discounting will have very little impact on our results. We discuss the rationale for this below.

We used a risk free rate of 0.18%. This is based on UK Gilt rates for the BOE and as reported in www.FT.com. The rate is the most recent one-year borrowing rate taken on 19/03/2013.

A14.4.3 Time, expiry and discounting

Another issue that needs to be addressed is the timing and time period assumed. We must choose a particular time-period into the future for the option. Financial option contracts typically have a "time of expiry", in other words a fixed time when the option expires.

In general, we cannot make a particular choice about the time period, the time of expiry and the discounting as this needs particular inputs from Ofgem on how they are implementing the VoLL estimates. For example, if Ofgem is considering how much I&C electricity consumers might be willing to pay to avoid an outage of one day, continuously over a five-year period, then this would imply the time period of the outage and the option value, and the appropriate discount rate and discounting formula would then apply.

The choice of which time period is "correct" for our VoLL estimate is difficult. The answer depends in part on what one's view is of the smelt spread time series drivers. If one believed the smelt spread time series has some kind of long run equilibrium value, then we might take the long run average as the best estimate. If there are elements of "permanence" in shocks to the spread, then the spread average over the most recent and a shorter time period might be more representative of our best estimate. We discuss these and additional issues in the following sections.

Our solution is to choose a "near-term period" – call it next year, and this would then avoid the issues created by discounting and by the risk-free assumptions, the lack of a time of expiry, etc.

A14.5 Results of crack/smelt spread estimates

A14.5.1 Crude oil refining

The table below presents our estimates of VoLL and some of the underlying building blocks for the refining of crude oil into petroleum products. Note that Pgo refers to price of gasoil produced; Plfo refers to the price of light fuel oil produced and Pgasol the price of gasoline produced.

Table 123: Crude oil refining crack spread VoLL estimates £/MWh

Price/item	£/MWh of electricity
Electricity price (Pe)	48.59
Crude Oil price (Pco)	5,963.27
Revenue from outputs sold (Pgo+Plfo+Pgasol)	7,291.86
Variable cost (Pe+Pco)	6,011.85
Crack spread ((Pgo+Plfo+Pgasol) - (Pe+Pco))	1,280.01
Option value VoLL	1,280.01

Note: prices from January 2008 – January 2013.
Source: London Economics

The table above shows the results of our estimates of the VoLL for industrial and commercial users of electricity, specifically those engaged in the process of petroleum refinery. The gas oil, light fuel oil and gasoline prices in the table refer to the price of each produced in crude oil refining when 1 MWh of electricity is used in production. Therefore, the value of each output is made up of each products price per MWh multiplied by the quantity of each produced. When 1 MWh of electricity is used by a crude oil refinery the following quantities, measured in MWh, of each of these three outputs are produced; 70 MWh of Gasoline, 62 MWh of Gas oil and 33 MWh of light fuel oil. The quantities of gasoil, gasoline and light fuel oil produced, come from 173 MWh of crude oil (roughly 100 barrels).

As each barrel of crude oil requires only 5.8 KWh (0.0058 MWh) the value of the outputs per MWh of electricity used in production is significantly bigger than the total value of electricity used per barrel of crude. The table shows that the two production inputs, crude oil and electricity, have hugely different shares in the production cost with the price of crude oil used per MWh of electricity costing over ten times what the electricity used itself costs. On average our analysis shows that electricity makes up less than 1% (0.81%) of the variable costs of crude oil refining. The option-value adjustment decreases the estimate of VoLL £2.30/Mwh more over the intrinsic value or average spread value. The crack spread value is made up of the revenue from outputs less the variable cost of the production inputs, this values the VoLL at £1,280.01/MWh. The Option value of VoLL using the BSM formula as discussed previously is £1,280.01

A14.5.2 Aluminium Smelting

The table below presents our estimates of VoLL and some of the underlying building blocks for the refining of crude oil into petroleum products.

Table 124: Aluminium smelting smelt spread VoLL estimates £/MWh

Price/item	£/MWh of electricity
Aluminium price (Pal)	97.81
Electricity price (Pe)	48.59
Bauxite price (Pbx)	6.07
Variable cost (Pe+Pbx)	54.66
Smelt spread (Pal - (Pe+Pbx))	43.15
Option value VoLL (per MWh of electricity)	43.16

Note: prices from January 2008 – January 2013.
Source: London Economics

The aluminium price represents the total value of the output of production in aluminium smelting. The prices presented above are for each input/output per MWh of electricity used in production. As producing a metric tonne of aluminium required on average 4.2 tonnes of bauxite and 14 MWh of electrical power the smelt spread per MT of aluminium produced is £603.12. However, unlike crude oil refining electrical power makes up a significantly higher proportion of the variable cost of production in aluminium smelting than the other production input, bauxite. According to our analysis, during the time period examined, electrical power made up over 88% of the variable cost of aluminium production with the raw material bauxite making up the remainder. Therefore, this industry is using electricity much more intensely than crude oil refining. The smelt spread per MWh of electricity £43.15 is therefore much lower than that of crude oil refinery. It is important to note that this figure amounts to the production of 0.07 MT of aluminium. Additionally, the results in the table above show that the option-value adjustment VoLL of £43.16 for aluminium smelters is an increase of £0.01 from the average smelt spread value.

A14.6 Conclusions of estimation of VoLL for I&C users

We conclude that, when using the real options approach, the value of lost load for typical I&C electricity users when measured on a £/MWh will vary according to how electricity intensive the industrial process is. One of the two examples used, uses electricity very intensively (per MT of aluminium produced) with 14MWh of electrical power required for the production on 1 MT of aluminium. The other industry examined, crude oil refinery, uses electricity much less intensively per unit of production. For one barrel of crude oil to be refined, only 5.8KWh of electrical power is needed. The VoLL value is estimated £1,280.01/MWh for crude oil refinery but only £43.16 for aluminium smelting. While these values may differ from those when using the GVA approach the results here suggest that the greater the share electricity has in the producers cost function the less the VoLL will be per MWh. One obvious reason for the large difference in these two commodities is in terms of value added. Typically, VoLL is analysed in terms of value added. As electricity constitutes such a large portion of aluminium smelting, there is actually very little value added (labour or capital) aside from electricity.

While this result is interesting it is worth examining the production processes used for the analysis. It was assumed daily that 1 MT of aluminium was being produced and that 1 barrel of crude oil was being refined. If you took the VoLL for one day of production the numbers would look quite different. For aluminium smelting the VoLL was valued per MT of production at £604.20 while per barrel of crude oil refined the VoLL was £7.39. These numbers are only useful however to plants which follow this exact production schedule and would potentially only ever experience a power outage that would stop production for exactly one day. In reality these figures are useful to assess the £/MWh figure that has been the focus of this Annex. This gives a value for a standardized production plant, which may in reality not be the case with all I&C customers, but will give a very good indication at the standard level of efficiency.

In discussing our conclusions, caveats and cautions to our analysis are important to recognize. While our analysis has made every effort to give precise estimates of the VoLL, there are reasons to view the results carefully.

A first issue with our results is they are based on market commodity data from financial markets. An implicit assumption is that, because of liquid trading, the market daily closing price is the best estimate of the value of the commodity on the day for the given delivery period. Changes in the price from day to day are also typically assumed to be driven by changes in information about supply and demand, financial conditions, and other market fundamentals. If market trading is not liquid then other factors such as risk-aversion of traders, who is trading (and possibly their size and bargaining power) could drive prices too.

The options methodology is known to be sensitive to a number of factors, but most significantly is the estimated volatility. Furthermore, the ‘correct’ volatility estimate would depend on the exact nature of the stochastic process driving the crack/smelt spread (or its underlying components, crude oil prices, electricity prices, refined petroleum prices, aluminium prices in GBP). In principle, one would need to undertake rigorous statistical testing of the series to test for unit roots or jumps, and then testing of models to see how well they fit the data. Such modelling and testing would have added rapidly to the complexity and length of this report, and is beyond the scope of this project.

On the whole, our judgment is that our estimates are conservative, in the sense of not being too large. We note that the values differ somewhat from those calculated using the GVA method, some of this may be due to the simplicity of the analysis done using the real options approach. Cost elements such as chemicals, overheads and labour have been ignored and therefore may cause our figures to be slightly over/underestimated. Sensitivity analysis could have been carried out on more of the parameters, but we do not think this would have altered our estimates or central expectations for the VoLL.

Annex 15 Further details regarding the potential cost of voltage reduction

This Annex provides indicative cost estimates of number products that may be impacted by SO-directed actions. As discussed in the main report, there is very little evidence of a quantified cost of voltage reduction. While the evidence analysed suggests little or no cost of voltage reduction, it is worth noting that if there was in fact no cost to voltage reduction then it would already be widely used tool to target both energy balancing and energy saving[163]. As this is not the case we have included in this Annex indicative estimates of what the cost of this may be.

Two cost-estimation methods put forward by the Council of European Energy Regulators,[164] survey based and case based were not considered for this report. Survey based estimation was considered unsuitable due to the difficulty for households to observe voltage quality disturbances and case based cost-estimation was outside the scope of this project. These techniques have been utilised[165] in power quality studies before but appear more suitable when only looked at industrial users.

For the purpose of analysing the costs of potential voltage sags to consumers in Great Britain we define a worst case, plausible, scenario in terms of voltage sag. That is the maximum reduction in voltage deemed possible, by Ofgem,[166] in a power emergency. Taking the midpoint of the statutory limit at +2% and applying a scenario where the voltage must be reduced to 6% below the minimum statutory level (-6%), then the total reduction would be 14%. Any costs associated with this scenario can be presumed to be less in the case of voltage sag of lower magnitude. Additionally we will use the most likely voltage reduction scenario which, according to discussions with Ofgem and their engineering team, is a reduction of 6%.

A15.1 Cost of protective equipment

To structure an estimate on the value of protective power quality equipment to households in Great Britain there are a number of steps we have covered. First we analyzed prices of surge protection equipment for households and got an average price across several popular domestic surge protection products. Using price data from several of Great Britain's largest electronic

[163] However it is noteworthy that Voltage Reduction service providers business cases are currently investigating this, and according to DECC, some innovation projects are looking at how this can be developed as a SO tool.

[164] Council of European Energy Regulators ASBL (2010). 'GGP on Estimation of Costs due to Electricity Interruptions and Voltage Disturbances'.

[165] "Toward Voltage-Quality Regulation in Italy", M. Delfanti, E. Fumagalli, P. Garrone, L. Grilli, L. Lo Schiavo, April 2010, IEEE Transactions on Power Delivery, Vol. 25, No. 2, pp. 1124-1132.

[166] Originally a voltage sag scenario of sag 22% was included as the worst case scenario. Taking the statutory limit of the nominal voltage supply at +10% we assessed a scenario where voltage supplied at this level would have to be reduced to 6% below the lower statutory limit of -6%, meaning a total reduction of 22%. Ofgem advised that this was extremely unlikely and suggested taking the midpoint of the statutory range as a sensible starting point.So the calculation is (10 + 6)/2 = 8 is the range.

retailers[167] we estimated an average price of £172.33 per household using surge protectors in Great Britain.

The next step we took on this value of £172.33 is to amortize it over the lifetime of the protection, taken at 12 years, with a consumer rate of 10%. Finally, given the National Grid figure of 3.9MWh per year average household electricity usage, we divided our annual cost by this figure to calculate a cost per MWh of protection at £5.84. All figures are contained in the table below.

Table 125: Value of surge protection per household – (£/MWh)

	Various units
Average Cost (£)	172.33
Annual Cost - amortized (£)	22.99
Household usage per year (MWh)	3.9
Household value (£/KWh)	0.01
Household value of surge protection (£/MWh)	5.84

Note: Average cost amortized over 12 years with interest rate of 10%, Household value in £/KWh rounded up.
Source: National Grid, LE

A15.2 Induced shutdown costs

To estimate the cost of such time spent resetting/starting household equipment we must discuss the idea of opportunity cost. If a person has to spend ten minutes on a task such as resetting a computer that is time that otherwise would have been spent on either work or leisure time. Therefore, that time has some value to this consumer. Having to spend such time on an activity made necessary by SO directed actions is a cost incurred by consumers. To estimate the value of such time to a typical consumer in Great Britain we use the median gross weekly average wage as given by the ONS to estimate an opportunity cost per minute of a typical consumer's time.

Table 126: Indicative analysis of resetting costs from voltage sag induced shutdown.

Device	Resetting time (minutes)	Number of devices in household	Cost per minute (£)	Total cost per shutdown per household (£)
PC	4.07	1	0.24	0.98
Clock	0.87	3	0.24	0.63
			Total	**1.61**

Source: LE analysis, ONS

The table above contains the indicative analysis of potential restart costs to household occurring from a voltage sag induced shutdown. We tested the restart time on several PCs and clocks to estimate average restart times. Additionally, we assume the average household would have one PC and 3 clocks. The cost per minute is calculated using ONS[168] data on median full-time gross

[167] www.criticalpowersupplies.co.uk www.argos.co.uk www.currys.co.uk

[168] Annual Survey of Hours and Earnings - Office for National Statistics.

weekly earnings from April 2012. Assuming an average of 35 hours in a working week the cost per minute of someone's time to spend on restarting household appliances is £0.24. Taking our assumptions about this typical household the total costs of a shutdown if all the appliances listed were to need restarting would be £1.61.

A15.3 Cost from reduced useful life of appliances

As is clear from the discussion in Section 4.3 there is a lot of uncertainty surrounding the damage caused to electrical equipment from voltage sags and brown-outs and whether there is a cost of any significance to consumers coming from having to replace domestic equipment sooner having experienced a voltage sag. There is, however, literature from Siemens[169] that suggests a 4.3% consistent voltage differential throughout the life of a standard appliance would reduce the useful lifetime of that appliance to 55% of its rated life.[170][171]

Therefore, in spite of the uncertainty surrounding the topic considered, we have included an indicative analysis based on the assumption that for one hour of voltage surge with magnitude 4% a typical appliance would lose 0.81 hours of its useful lifetime, based on a proportional allocation of the reduction estimated by the Siemens document. The table below contains the calculations involved in arriving at this assumption. It is important to note that no substantial information was available concerning effects of a voltage sag, so voltage surge impacts are detailed here in the absence of quantitative data concerning voltage sag induced damage. We take voltage sags and surges to have proportionally similar effects on household equipment for the purpose of our indicative analysis.

The lifetime reduction figure comes from the assumption that appliances are losing 45% of its rated lifetime during 55% of its lifetime. For example if a device has a 10-year rated lifetime and it is subjected to a 4% voltage surge constantly it will take 5.5 years to burn out, therefore losing 4.5 of its expected lifetime. Therefore the cost of the lifetime reduction due to a voltage surge will be proportional to an appliances useful lifetime and initial cost.

Table 127: Indicative analysis of cost of reduced useful lifetime of household applainces due to SO directed voltage reductions (£)

Device	Average cost[172]	lifetime (years)	Annual cost	Cost to household of 5 hour voltage sag of depth 86%
Washer	£427.99	4.5	£111.56	£0.18
Fridge	£640.12	4.5	£166.85	£0.27
Tumble dyer	£361.39	4.5	£94.20	£0.15
Cooker	£429.16	7.5	£76.39	£0.12

[169] http://www.siemens.co.uk/pool/about_us/businesses/industry/t34_power_management_solutions_steve_barker.pdf

[170] Institution of Electrical Engineers (IEE).

[171] It is difficult to ascertain the full validity of these results as, it has been suggested by DECC's internal review team, that if this indeed were the case that appliances would be wearing out more rapidly than is the current norm. We note again therefore that our anal=ysis should be viewed with caution and as merely scenarios.

[172] These costs (prices) are taken from a variety of sources including retra.co.uk, Argos and Amazon.

Dishwasher	£404.24	4.5	£105.37	£0.17
Computer	£831.66	3	£304.02	£0.50
TV	£968.56	5	£232.28	£0.38
Radio	£58.67	3.5	£18.80	£0.03

Note: annual cost is amortized cost over useful lifetime, r=0.1.

Source: LE analysis, Institution of Electrical Engineers (IEE), retra.co.uk (prices), Argos (prices), amazon (prices)

The table above shows results of our estimation of the present cost of future depreciation of a list of household appliances after experiencing a five hour voltage sag at depth 86%. As the costs are proportional to average lifetime and cost of each appliance, those devices that cost most will incur greater costs as will those devices with shorter expected lifetime (rated). Computers will incur the most damage per unit of such a voltage quality event and radios will incur the least damage in £ terms. We have tested one scenario in terms of depth and duration of voltage sag, but as the damage is assumed to be linear any change in voltage sag depth or duration would give proportionally adjusted estimates.

The table below presents this cost in a per MWh format. We have assumed a typical household which has one of each of the appliances listed above. Therefore the total cost of this five hour voltage sag is £1.81, meaning the per hour of voltage sag cost is £0.36. Taking the National Grid figure of annual household average electricity use of 3.934 MWh we can estimate the average hourly use per household. We combine the average hourly electricity usage with the cost of an hour long voltage sag at depth 86% to give a result of £807.60 per MWh as the indicative cost estimate per household, in equipment damage, due to a voltage sag of 86%.

Table 128: Indicative analysis of cost of reduced useful lifetime of household applainces due to SO directed power quality reductions

Cost to household of 5 hour voltage sag of depth 86%	Cost to household of 1 hour voltage sag of depth 86%	Average household annual electricity usage (MWh)	Average hourly household electricity usage (MWh)	Cost to household of 1 hour voltage sag of depth 86% (£/MWh)
£ 1.81	£ 0.36	3.934	0.0004	807.60

Source: LE analysis, National Grid

Annex 16 Possible uses of VoLL and how this impacts which VoLLs to use

This short Annex considers some of the uses of the value of lost load. Its purpose is to help give guidance as to how to use the various VoLL estimates.

A16.1 Definition of VoLL in consumer economics

A first step is to consider our basic model of supply and demand, and what that means for heterogeneous consumer types in a standard economics framework, and then see how VoLL impacts this.

A first point to recall from the fundamental supply and demand market model is the marginal consumer and producer.

As energy economists, we often think of the electricity supply curve in terms of the "merit order" or "marginal cost stack" of plant available on the system. In this model, the least cost plant are "despatched first" via the cost-minimisation rule. The supply curve is just the sum over all available plant, stacked in the merit order.

The consumer-side, demand, is the exact mirror image of this (at least in theory). The demand curve is the merit order 'stack' of consumers, and the sum over all consumers who are willing to participate in the market is the demand curve. Each consumer, and their marginal willingness to pay for X MWhs in any given hour in the demand curve. Consumers with higher willingness to pay are "despatched" first, and likewise, on down until the marginal consumer is just willing to pay the marginal cost.

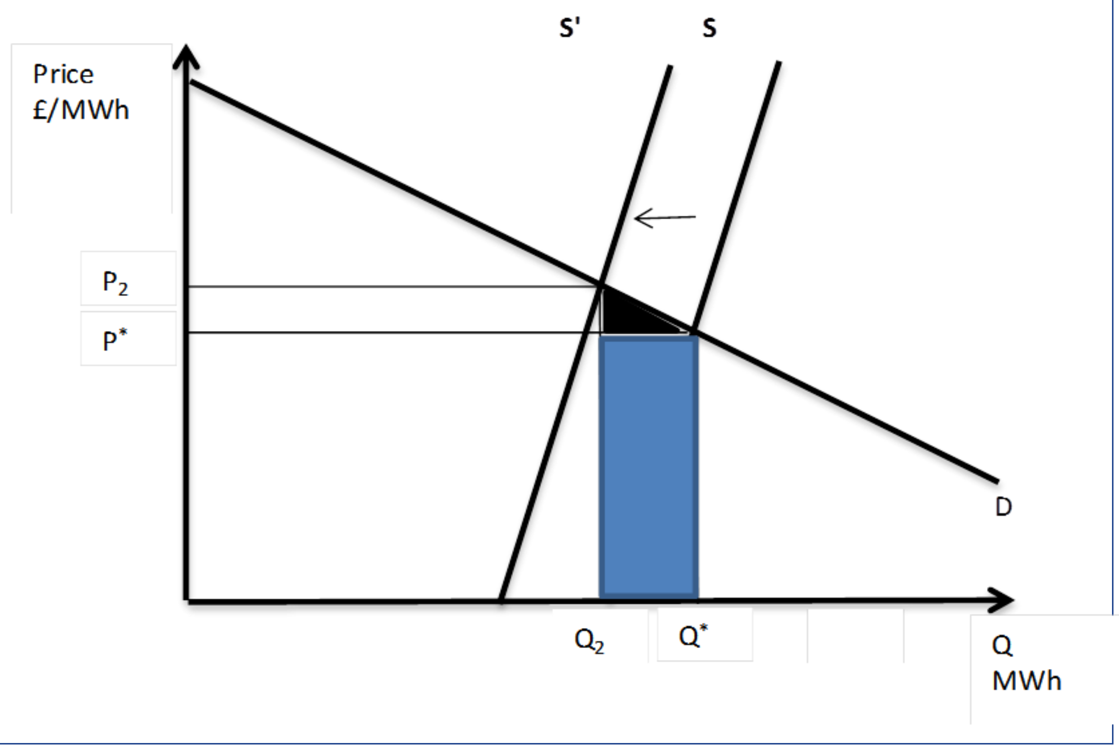
We thus have our standard supply and demand framework.

The first issue to make the standard framework useful for VoLL is to consider what actually happens when a power emergency occurs. In essence, the System Operator (SO) determines that there is a shortfall of a certain number of MW capacity, and that it will take a certain amount of time to bring new capacity online or that demand might reduce given the available forecasts of demand patterns. If voltage reduction is not available, and similarly any available flexible demand response, or has already been exhausted, the SO will be required to ask DNOs to conduct demand disconnections, probably via rolling blackouts.

This immediately then gives some insight to VoLL, because it in fact starts to illustrate that VoLL can be either marginal or semi-marginal, and the reason for this is that it depends on the 'discrete size' of demand (in MWh) not served.

We see that if only a single MW were turned off for an hour, and we could have a 'stack' of consumers, then the least cost/lowest willingness to pay consumer(s) and their VoLL per MWh would indeed be the VoLL to use. Likewise, if we turned off a small number of consumers, then this would be the sum over the lowest value consumers.

Figure 48:Supply and demand curve when supply is reduced



Source: London Economics

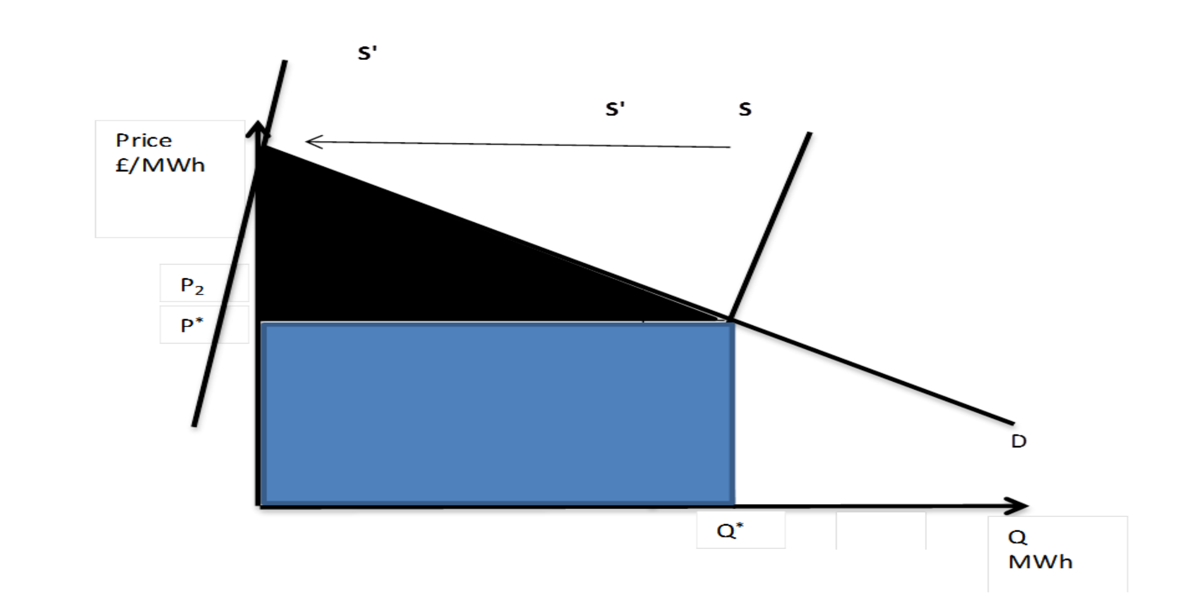
In Figure 48, with the supply reduction (from S to S') the supply curve shifts back. The lost surplus is the black shaded triangle, but the lost total value is the black triangle, plus the blue shaded area.

However, we see that since the demand disconnections should be for some time period, and we cannot identify the consumers who will receive the blackout, then this is not possible.

Another important point is to realize that it is indeed the consumers surplus, plus the value of the energy at the equilibrium price that is being lost.

Consider if indeed the whole of GB were to experience a blackout for one hour. The cost to society would be the sum of consumer surplus plus revenue.

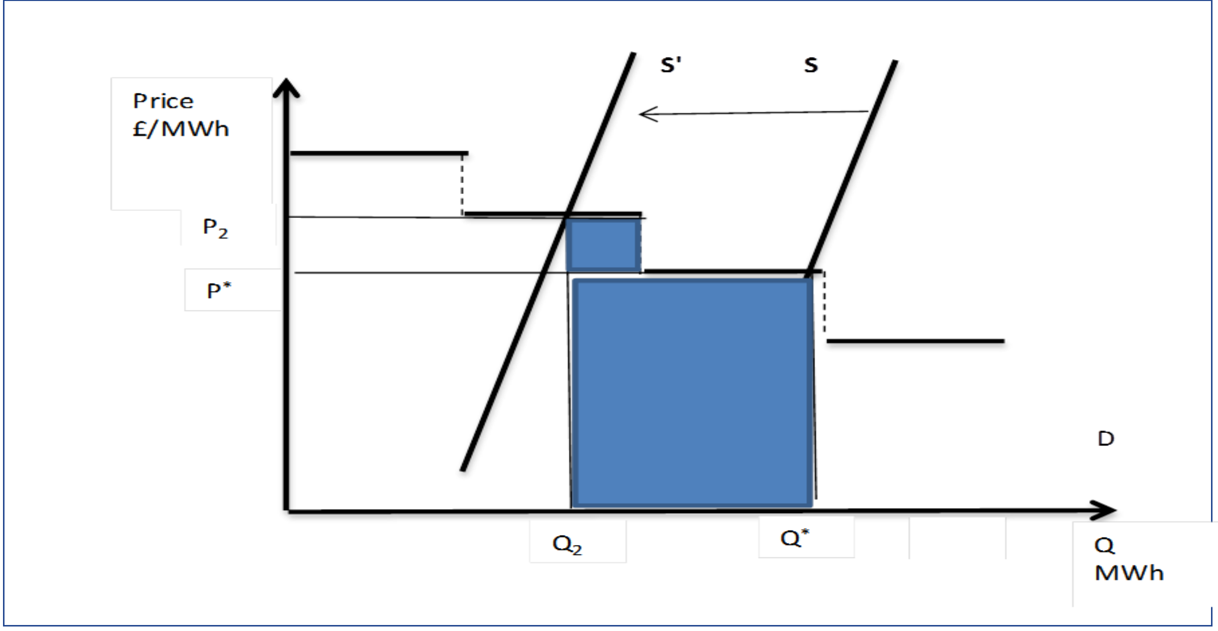
Figure 49: Impact of electricity supply going to zero (i.e. a blackout)



Source: London Economics

Now consider our rolling blackouts where we have some distinct 'groups' of consumers, Households, I&C, and SMEs. We don't have empirical estimates of the willingness to accept or pay for individual units within these groups (save a few large customers, and GVA VAR estimates for I&C); however, we do have VoLL estimates for the individual groups, so we can show these as the average VoLLs for different groups.

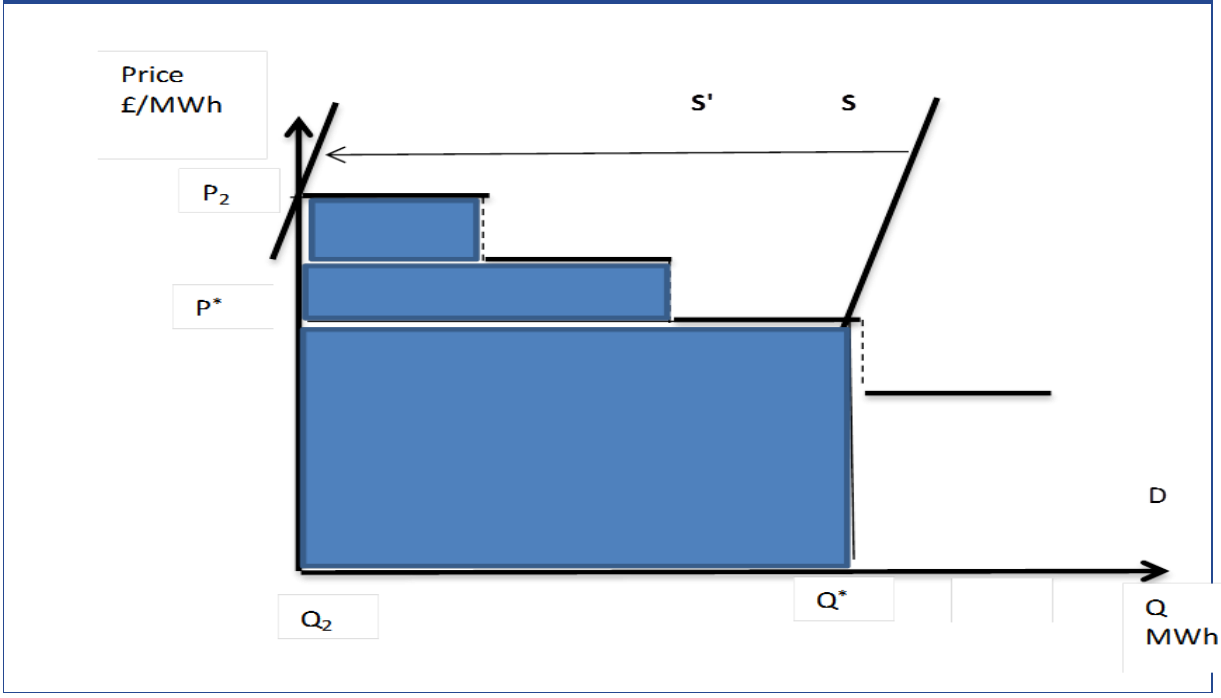
Figure 50: Impact of supply reduction on demand



Source: London Economics

Now the above framework can be applied to *any* slice of the demand curve. So we can think of a small randomly chosen slice of demand, and this will likely be the demand that is disconnected in a power emergency. In other words, we do not know exactly who will be disconnected, but we might assume that a random slice of demand is selected. This random slice will thus likely contain households, SMEs, I&C customers that do not have their own back-up generation, etc. Thus, we can consider that the last graphic could be depicted *as if all of the demand within this random slice was not served.* So the VoLL is then the combination of the situation where all of demand is not served, and the previous graph, where we have a selection of different consumer "types".

Figure 51:Total impact of a supply loss on demand



Source: London Economics

So the area under the curves is the total amount consumers would be willing to pay to avoid the outage. The distance, Q* to Q2 is the size of the outage. (e.g., 2000MW for one hour). We also see that if the price each group, i=1,2,3, was willing to accept given the outage, call this $VoLL_i$, then the *sum over load x* $VoLL_i$ would give us the total value to avoid the outage on the system.

A16.2 Relating to the reliability standard

In general, the parameters that describe reliability of the system are estimated via economic-engineering grid security simulation models. The model takes forecasts of supply and demand, and all facets of the system to add as much reality as possible. It is also usual that random 'shocks' are added to the system, such as supply outages or unexpected increases in demand.

If the distributions of the past random events can be estimated, and if the simulation is a reasonable representation of the system, then the model will usually generate a loss of load probability (LOLP) and a loss of load expectation (LOLE). In general, the probability in any given hour (or half hour), depending on the model and system and the size of the outage, is then predicted on the system for all hours.

Reliability standards are generally set such that, given some security of supply model, the predicted number of hours of lost load does not exceed a certain number, such as three hours in one year. To find the reliability in terms of LOLE in any given year, the sum over all hours for the year times the LOLE[173] in each hour is found;

$$\overline{\mathrm{LOLE}} = \sum_{t=1}^{8760} \mathrm{LOLE_t}\left(\mathrm{Q_t^D}, \mathrm{Q_t^S}, \mathbf{A}, \mathbf{t}\right)$$

The above simply says that the sum over the loss of load expectations in the hours in the year gives the planning standard (LOLE bar) for the system. LOLE is a function of supply and demand in the system, system attributes, A, and time and technology t.

Notice then that the above is instructive as to the marginal cost of security of supply improvements. To reduce the LOLE, added capacity or resources must be added to the system.

$$\overline{\Delta\mathrm{LOLE}} = \sum_{t=1}^{8760} \mathrm{LOLE_t}\left(\mathrm{Q_t^D}, \Delta\mathrm{Q_t^S}, \mathbf{A}, \mathbf{t}\right)$$

$$\Delta\mathrm{Cost} = \mathrm{C}\left(\Delta\mathrm{Q_t^S}\right)$$

So the change in capacity is the marginal cost of reducing the LOLE by one hour over the relevant time period, 10 years.

We note that there should be a ‘typical’ size of outage, given that disconnections might occur. Let us set this to 1000MW, and a typical duration, for example, one hour.

So if we were to lose 1000MW for one hour, and then households, SMEs, and I&C customers were disconnected (randomly) then we would expect the distributional make-up of the customers’ disconnected would reflect the distribution of the customer profile at large. Let us say that in any given hour, in any given DNO, on average, 2/5 of demand is made up by HH, 2/5 by I&C, and 1/5 by SMEs. Then the VoLL for that typical outage would be:

$$\mathrm{VoLL}_\tau = 1000\mathrm{MWh}\left[\left(\frac{2}{5}\right)\frac{£10{,}289}{\mathrm{MWh}} + \left(\frac{2}{5}\right)\frac{£1{,}472}{\mathrm{MWh}} + \left(\frac{1}{5}\right)\frac{£49{,}046}{\mathrm{MWh}}\right] = £14.5m$$

173 The LOLE may vary depending on the exact expected supply margins over expected demand, and this will depend on the model being used.

So in essence, the VoLL total (τ) is the load-share-weighted average £VoLL/MWh across customer types for the peak hour in question, times the expected size of the outage in MWh.

The above values for VoLL for the customer groups are from the VoLL estimates, and are from the winter-peak-workday estimates. So the value to the system of saving one hour of expected lost load in the winter, for the typical outage of 1000MW of one hour, would be £18.8m.

A16.3 Time-varying VoLL

The above framework is suggestive of how to use the various time-specific VoLL's estimated in the LE study. For example, off peak and summer. The weights on the user-values should be reflective of the demand distribution across customer types. Let us assume the typical distribution of total demand for summer weekday peak is made up by 1/6 HH, 3/6 I&C, and 2/6 by SMEs, then the total value of lost load would be for the typical summer hour:

$$\mathrm{VoLL}_{\tau} = 1000\mathrm{MWh}\left[\left(\frac{1}{6}\right)\frac{£9{,}257}{\mathrm{MWh}} + \left(\frac{3}{6}\right)\frac{£1{,}472}{\mathrm{MWh}} + \left(\frac{2}{6}\right)\frac{£49{,}267}{\mathrm{MWh}}\right] = £12.7m$$

These illustrative estimates include an estimate for I&C. As discussed in the main report, there may be a case for dropping I&C users. It may be that the typical outage changes too (e.g., 500 MW in summer), in which case the total would be:

$$\mathrm{VoLL}_{\tau} = 500\mathrm{MWh}\left[\left(\frac{1}{6}\right)\frac{£9{,}257}{\mathrm{MWh}} + \left(\frac{3}{6}\right)\frac{£1{,}472}{\mathrm{MWh}} + \left(\frac{2}{6}\right)\frac{£49{,}267}{\mathrm{MWh}}\right] = £6.3m$$

If alternatively, the VoLL(τ) was to be used for a system of availability payments, such that availability in each hour were remunerated, then the LOLE would be input as the MWh figure, in other words, the expected lost load in each hour would be the relevant quantity, if available, and the sum over all the VoLLs during the year would be the value of the VoLL(τ) for the year.

$$\mathrm{VoLL}_{\tau} = \sum_{t=1}^{8760} \mathrm{LOLE}_{\mathrm{t}}\left(\mathrm{Q}_{\mathrm{t}}^{\mathrm{D}}, \mathrm{Q}_{\mathrm{t}}^{\mathrm{S}}, \mathbf{A}, \mathbf{t}\right)\left[\left(\mathrm{w}_{\mathrm{t}}^{\mathrm{hh}}\right)\frac{£\mathrm{VoLL}_{\mathrm{t}}^{\mathrm{hh}}}{\mathrm{MWh}} + \left(\mathrm{w}_{\mathrm{t}}^{\mathrm{IC}}\right)\frac{£\mathrm{VoLL}_{\mathrm{t}}^{\mathrm{IC}}}{\mathrm{MWh}} + \left(\mathrm{w}_{\mathrm{t}}^{\mathrm{SME}}\right)\frac{£\mathrm{VoLL}_{\mathrm{t}}^{\mathrm{SME}}}{\mathrm{MWh}}\right] = £Xm$$

Where the w^{i}_{t}, are the load-share weights for a given time period (t) on the different customer classes (i=1,2,3 {HH, I&C, SME}).

These illustrative estimates (above) include an estimate for I&C electricity users. As discussed in the main report, there may be a case for dropping I&C users.

A16.4 Balancing energy and VoLL

The above framework can easily be modified to apply to the situation of balancing. Suppose, as an example, that a 400MW generator trips and so is scheduled to run, but within a few hours of gate closure (one hour ahead of real time) suffers an unplanned outage.

At one level, we could assume that the SO has the choice between procuring added balancing energy of 400MW, for example using offers in the balancing mechanism, or alternatively not serving load.

A16.5 Calculating weighted average VoLL

As discussed previously, the weighted average VoLL may be estimated excluding the I&C electricity users. The implications of this are shown below.

Table 129: Inputs into calculating load-share weighted average VoLL

Number of SMEs	1,542,373
Number of Households	26,400,000

Note: These data are the latest available.
Source: ONS, datamonitor.com

As noted previously, there is less seasonal variation in electricity demand for SMEs. In our analysis, we found that SME electricity demand was roughly seven times higher than domestic demand[174]. When this seasonal variation is accounted for, SME demand is about six times higher than domestic demand. This is the figure we use to create the load share-weightings. We multiply this electricity demand by the number of households to get the total electricity demand for households. For SMEs, we multiply the number of SMEs by the average electricity consumption at winter, peak, weekday to get the total SME electricity consumption. The weight for SMEs is then simply the electricity demand for SMEs divided by the total demand (households plus SMEs). This method gives us a weighting of 74:26[175] for domestic: SMEs. We use this figure to estimate load-share weighted average.[176]

[174] See Table 41 and Table 82 for further analysis of the differences between electricity consumption of households and SMEs

[175] The weight for the domestic (74%) is (total households*annual electricity consumption at winter, peak, weekday)/(total electricity consumption of SMEs and households at winter, peak, weekday). The ratio is calculated as: (total households*average annual domestic electricity consumption at winter, peak, weekday)/(total electricity consumption of SMEs and households at winter, peak, weekday). Data for total households is sourced from ONS and average electricity consumption from DECC. Data for total SME consumption is sourced from SME survey. The number of SMEs is sourced from Datamonitor's Buyer Segment Market Share Monitor (Q4 2012).

[176] We use the relevant estimates from our WTA models. Thus, for domestic, we use £10,289/MWh and for SMEs we use £35,488 /MWh.

$$\mathrm{VoLL}_{\tau} = \left[\left(\frac{74}{100}\right)\frac{£10{,}289}{\mathrm{MWh}} + \left(\frac{26}{100}\right)\frac{£35{,}488}{\mathrm{MWh}}\right] = £16{,}940/MWh$$

Table 130: Load-share weighted average across domestic and SME users for winter, peak, weekday

VoLL (£/MWh)
16,940

Note: We have derived this weighted average using a 74:26 weighting for domestic: SME.
Source: London Economics analysis

Annex 17 Frequency Choice Experiment

A17.1 Introduction

This section will detail a simplified choice experiment using frequency, duration and price as variables. As discussed in A4.1.1, frequency was kept constant in our primary choice experiment. Choice experiments become more complicated and confusing for respondents as more variables are included. As the primary choice experiment kept frequency constant it is useful to examine how consumers would behave as frequency of output changes. Therefore, this experiment is used to examine the impact of frequency and act as a sense check to our primary choice experiment results.

A17.2 Survey design

The survey design followed the same methodological framework as the primary choice experiment. Details of this design and the benefits brought by such a design can be found in Section 2.1 of the main report.

In this choice experiment we have only undertaken a willingness to accept (WTA) model. Therefore, respondents are told that they will receive the compensation for each outage.

The key differences between the choice experiment examined in this section and the primary choice experiment are the attributes included. Details of the attribute selection and levels are included in the sub-section below.

A17.2.1 Attribute selection & levels

The selected attribute levels for non-price attributes are shown in Table 131. The attributes chosen for the CE were: duration, frequency and compensation. The design of this additional experiment is very similar to the main choice experiment with the duration and compensation attributes taking the same levels as per the main CE.

The selection of attribute levels was also based on recent evidence of an electricity outage of this type along with discussion between LE and the Ofgem project team. It is important to note that time of day, day of the week and season were set as constant and defined in advance by informing consumers of the timing of the outage. For this choice experiment the timing was set at peak time of day (3pm-9pm), on a day that you are typically at home during winter. It must also be noted that respondents are informed that they will receive the compensation amount on each occasion that the outage occurs.

Table 131: Selected attributes and attribute levels	
Attribute	**Attribute levels**
Duration of interruption	20 minutes
	1 hour
	4 hours
Frequency of interruption	Once every 2 years
	Once every 12 years[177]
	Once every 20 years
Price : Once-off payment (WTA)	£1
	£5
	£10
	£15

Source: London Economics

A17.2.2 Choice card structure

An actual example of the choice cards as would be seen by a respondent in the online survey is shown in Figure 53 below. The cards present a consumer with the attributes down the left and the levels of the attributes vary across the choices: Option A and Option B. Therefore, the example is a WTA, so the previous screen would have explained that a hypothetical choice would be presented, and the person should respond with their best choice based on their preferences. Before the choice card appeared the respondent would be informed that 'the outage occurs in the winter during the day between 3pm and 9pm, at a time when you would typically be at home'. This is how we framed the condition of the experiment. Figure 52 below shows the information that the respondents are given prior to answering the choice cards. It must also be noted that, as in our main CE, respondents initially answered some background questions on different aspects of their electricity usage.

[177] This "1 in 12" frequency estimate is based on Ofgem's 2012 capacity assessment which found that in 2015/16 the expectation of customer disconnections to be 1 in 12 years. See Ofgem (2012) "Electricity Capacity Assessment".

Figure 52:Experiment condition given in survey (WTA) - Frequency choice experiment

YouGov What the world thinks 36%

For the next six questions you will be presented with a choice between two alternative electricity outages and associated compensation you receive for it. Each alternative includes:

- How long the outage lasts for, e.g. 20 minutes;
- How frequently the outage is likely to occur; and
- How much compensation you receive for the outage

Assume the outage occurs in the winter during the day between 3pm and 9pm, a time when you would typically be at home.

These are hypothetical scenarios, but simply pick the one option you prefer based on the differences between them.

The next button will appear in 10 seconds.

Source: YouGov

Figure 53:Example of choice card (WTA) - Frequency choice experiment

YouGov What the world thinks 41%

	Option A	Option B
The frequency with which this will occur is …	Once every 20 years	Once every 2 years
It lasts for …	1 hour	20 minutes
You receive this much in compensation each time an outage occurs …	£5	£10

Please choose the option you prefer

- Option A
- Option B
- Don't know

Source: YouGov

It should be noted that the choice experiment includes a 'don't know' option in addition to the two alternative scenarios presented on the choice cards. It is generally recommended that choice experiments include a no-choice option.

Some respondents chose the 'don't know' option for some choice scenarios and this may mean that the respondents couldn't decide between the two choices presented to them. Excluding these types of responses would bias the results and would force respondents to choose between choices where neither is preferred. We thus assumed that only those respondents that answered 'don't know' for all of the choice cards were displaying 'non-engagement', and all others we assumed 'don't know' responses resulted from not being able to choose between the different alternatives. This approach is the same as per the main choice experiment.

A17.2.3 Choice experiment sample

The survey for the frequency choice experiment consisted of an online survey with 511 respondents.

The sample for the online survey was drawn at random from YouGov's 400,000 strong online panel of adults.[178] Quotas were set to ensure that the resulting sample was representative of the GB population in terms of age, gender and socio-economic characteristics. It should be noted that since the online sample is a random sample and is broadly representative of the GB population.

A17.3 Methodological approach

In this subsection, we give a brief overview of how the results from the choice experiment are converted into estimates of WTA for domestic customers. Additional details are available in the Section 2.5 of the main report and Annex 4. This involves a number of steps as follows:

- Choice of estimation method;
- Description of model and explanatory variables; and
- Calculation of WTA from estimation results.

The estimation method used was the same as detailed in the primary choice experiment. Further details can be found in Section 2.5.1.

A17.3.1 Description of model and explanatory variables

The model is set up as the primary choice experiment detailed in the main report. In the model, duration is specified as a continuous variable while frequency is set up with dummies and then interacted with duration to form our explanatory variables. This allows us to account for possible interactions between the variables. This is due to respondents' preferences on duration of outage potentially changing depending on how frequently they will occur.

A key feature of the model is the interpretation of the reference category. We use a scenario of an outage occurring once every two years as the reference category for this estimation.

The WTA model is shown in the equation below.

[178] It also ensured that no respondents who answered this experiment had previously answered the main choice experiment.

Pr (Choice)$_i$ = α + β_1*Duration$_i$ + β_2*(Duration$_i$*Frequency12$_i$) + β_3*(Duration$_i$*Frequency20$_i$) + δ*Monetary Value$_i$ + η*Don't know dummy + ε_i

Where for the domestic survey:

- Pr(Choice) is the probability any choice is made;
- "Duration" is a variable taking the values twenty minutes, one hour and four hours.
- "Frequency12" is a variable taking the value of 1, if in the choice scenario, the outage was specified to occur once in every 12 years.
- "Frequency20" is a variable taking the value of 1, if in the choice scenario, the outage was specified to occur once in every 20 years.
- "Don't know dummy" is equal to 1 if the respondent answered 'Don't know'.

We also tested a non-linear specification for this model but it did not appear appropriate based on statistical testing.

A17.3.2 Calculating WTP and WTA from the estimation results: transformation of parameter estimates

Once the conditional logit model is estimated, the marginal WTA estimates are computed directly from the model specified. For example, the ratio of the following two coefficients yields the WTA for the attribute 'i' (if there are no squared terms or interaction terms):

$$WTA_{attribute\ i} = \frac{\beta_i}{\delta}$$

where β_i indicates the parameter of the 'ith' attribute variable. In the chosen estimated model we have interaction terms. To estimate the WTA payment for the reference category (frequency of outage at once every two years), we apply the formula below (ratio of duration and payment coefficients).

$$WTA_{once\ every\ 2\ years, winter, peak} = \frac{\beta_1}{\delta}$$

A17.4 VoLL estimation results

The summary econometric results for the linear model are displayed in Figure 54 below. The sign of the parameter indicates whether an attribute increases or decreases the likelihood (probability) that an alternative scenario is chosen by the respondent. Thus, a negative sign indicates that this variable is less likely to lead to the choice being chosen.

In WTA regression it is the case that a longer duration of the outage reduces the likelihood that a 'choice scenario' is chosen (hence resulting in a negative sign on the "duration" variable).

It is also clear that respondents prefer outages to be less frequent although there does seem to be some indifference on whether they are once in 12 years or once in 20 years, as long as they are not once every two years.

Finally, the estimation results are as expected with regard to the payment to be paid (WTA) variables. The results show that respondents are more likely ("positive sign on the compensation variable") to choose an alternative if there is a higher payment associated with that alternative.

Figure 54:Estimation results of the model – Frequency choice experiment

	Coef.	Std. Err.	z	P>|z|	Lower	Upper
duration	-0.148	0.016	-9.03	0.00	-0.18	-0.12
duration_12	0.068	0.015	4.63	0.00	0.04	0.10
duration_20	0.074	0.017	4.48	0.00	0.04	0.11
comp	0.042	0.008	5.56	0.00	0.03	0.06
dont_know	-3.503	0.179	-19.53	0.00	-3.85	-3.15

Source: London Economics analysis of the online household survey results

A17.4.1 WTA estimates

Table 132 shows the WTA figures for each of the possible choice scenarios. The figures in the table provide estimates of how much total payment in pounds consumers would be willing to accept if a specified outage occurs. For example, for a one-hour outage occurring once every 12 years, consumers would require on average payment of £5.74. This result is in line with our WTA results in the primary choice experiment described in the main report. Table 9 of the main report shows comparable figures of £6.16 for a one-hour outage occurring during winter at peak times during the week and £6.84 for an outage occurring in winter during the weekend at peak times. Both of these WTA estimates were for outages occurring at a frequency of once every twelve years.

The regression results above also show that consumers would prefer outages occurring once every twelve years over once every two years. Thus, the WTA estimate for a one-hour outage occurring once every two years is £10.62. Therefore, these figures offer both a good indication on how frequency will change a consumer's WTA levels and a sense check for the results from the report's primary choice experiment.

Table 132: Estimates of WTA in £ for various outage duration occuring at different frequencies

	Frequency of outage		
Duration of outage	**1 in 2**	**1 in 12**	**1 in 20**
20 mins	**3.54**	**1.91**	**1.77**
1 hour	**10.62**	**5.74**	**5.30**
4 hours	**42.46**	**22.95**	**21.22**

Note: All values in bold indicate statistical significance at the 95% confidence interval.
Source: London Economics analysis of online household survey

A17.4.2 VoLL per MWh estimates

The next step is to convert the monetary values per outage estimates into VoLLs in £/MWh. Conversion of the WTA estimates into VoLLs in £/MWh requires:

- A monetary value for a one hour outage (e.g., £5.74 for a one-hour outage occurring once every twelve years (the value shown previously));
- Hourly electricity consumption for the consumer type and outage scenario[179] (MWh); and
- The VoLL, in £/MWh, will simply be the ratio of these two variables.

We obtained estimates of domestic electricity usage from data provided by DECC. DECC estimates that the average (mean) domestic household uses 3.934 MWh of electricity per year.[180] This is converted into an hourly demand figure for purposes of conversion. The demand profile which is derived in the main body of the report corresponds to usage patterns for peak times during winter.

Table 133: Estimates of VoLL in £/MWh under different frequency scenarios – Domestic consumers – Frequency choice experiment

	Frequency of outage		
Duration of outage	**1 in 2**	**1 in 12**	**1 in 20**
1 hour	**10.62**	**5.74**	**5.30**
VoLL (£/MWh)	**18,029**	**9,745**	**9,008**

Note: All values in bold indicate statistical significance at the 95% confidence interval.
Source: London Economics analysis of online household survey

A17.4.3 VoLL estimates using a contingent valuation methodology

This subsection presents a short description of the results of the contingent valuation (CV) section of the frequency targeted survey. The CV survey asked respondents directly their valuation of outages. The contingent valuation method was used as a sense check for the results of our frequency choice experiment. The CV questions were also asked after the CE as the CE was the primary method of deriving the WTA/WTP estimates.

WTA estimates

As part of our study, respondents were asked directly what payment they would require to accept a one-hour outage in the winter on weekday at peak times.[181]

[179] Outage scenario for each choice was during winter at peak time.

[180] DECC (2009) "DECC: Energy Trends: March 2009" http://www.decc.gov.uk/en/content/cms/statistics/publications/trends/trends

[181] 'Peak times' are those selected by respondents as their own peak times earlier in the survey.

Table 13 shows the results of the WTA CV question in terms of standard statistical indicators such as mean, median and standard deviation. This table also shows the importance of removing observations that are substantially higher than the average.

On average, consumers think that a fair payment would be £25.04 to experience a one-hour outage[182] at peak times on a weekday in the winter based on the CV survey. This is significantly higher than the estimate for WTA derived using the choice experiment (values ranged from £5.30 to £10.62). However, the average includes all observations including some very high stated values such as £2,000. It is unclear if these were so-called 'non-engagement' choices, or similar, but excluding possible high values and the impact of reducing the variation is shown below. The median is more in line with our primary contingent valuation experiment and the CE estimate and therefore may be a better measure of CV than mean. It is also important to note that the CV mean value for the frequency choice experiment of £25.04 is not statistically different to the mean CV WTA value for our primary choice experiment (£19.55).

Table 134: Results for fair payment to experience a one hour outage during peak times on a weekday during Winter - domestic consumers – frequency experiment sample

Sample	Average (£)	Median (£)	Max. (£)	Min. (£)	Std. Dev.	Sample %[1]
Full sample	25.04	10	1500	0	108.49	100%
Limited sample: Mean +/-2 std. dev.	13.96	10	120	0	18.46	99%
Limited sample: Mean +/-1 std. dev.	13.96	10	120	0	18.46	99%
Limited sample: Mean +/-0.5 std. dev.	11.69	10	75	0	12.20	96%
Excluding zero responses	29.17	10	1500	1	116.58	86%

Note: 1. Refers to the number of observations in the sample as a share of the full sample.
Source: London Economics analysis of online survey data.

Willingness to pay

The frequency survey also included a WTP CV question to all respondents similar to the WTA question. According to the WTP CV survey results, the average amount that consumers would be willing to pay to avoid a one hour electricity outage occurring at peak time on a weekday during the winter is £4.85.

As with our analysis of WTA, the arithmetic mean CV WTP may be somewhat unduly skewed upwards by some very large stated CV WTP estimates. We show the impact of omitting some of these large values in Table 135. This brings down the arithmetic mean CV WTP and the standard deviation significantly. Well over 50% of the respondents indicated that they would not be willing to pay extra to avoid this specified electricity outage; the median value is £0. As was the case with the WTA estimates when compared to the primary CV estimation on the main report the means of the two samples of £4.85 and £6.35 are not statistically different.

[182] All averages calculated based on contingent valuation responses include both zero value responses and non-zero responses unless otherwise stated.

Table 135: Results for willingness to pay for a one hour outage at peak times on a weekday during Winter- domestic consumers

Sample	Average (£)	Median (£)	Max. (£)	Min. (£)	Std. Dev.	Sample %[1]
Full sample	4.85	0	700	0	33.68	100%
Limited sample: Mean +/-2 std. dev.	2.24	0	50	0	5.93	99%
Limited sample: Mean +/-1 std. dev.	2.07	0	35	0	5.29	98%
Limited sample: Mean +/-0.5 std. dev.	1.62	0	20	0	4.12	96%
Excluding zero responses	22.91	10	700	1	70.32	21%

Note: 1. Refers to the number of observations in the sample as a share of the full sample.
Source: London Economics analysis of survey data.

A17.5 Impact of discounting on WTA estimates

Table 136 below contains VoLL figures when the timing of payments is taken into account. The table contains the average of the present value of WTA payoffs, for one-hour outages, taken for each frequency scenario over a 20-year horizon. For this analysis it is assumed that the payoff will occur at the same time as an outage. It is also assumed that outages will occur in the first year of each frequency scenario. For example, for outages occurring once every two years there will be outages in year 1, 3, 5, 7, 9, etc. . Similarly, for outages occurring every 12 years there will be outages in year 1 and year 13.

Table 136: Estimates of VoLL with discounting – 20 year horizon – Outage occuring in first year

	Frequency of outage		
	1 in 2	1 in 12	1 in 20
Average of PV payoffs (£)	7.94	4.77	5.30
VoLL (£/MWh)	13,488	8,097	9,008

Note: r=3.5%[183].
Source: London Economics analysis of online household survey, HMT Green Book

The results show that the average VoLL figure of £12,991/MWh for a one hour outage occurring once every two years, over a 20-year horizon is roughly 33% lower than the corresponding figure of £18,029/MWh. For an outage occurring once every 12 years the VoLL figure is almost 20% less when discounting is included over the 20-year horizon. These figures illustrate the complicated nature of frequency at which outages occur, as the varied timing of outages would only further contrast the figures with and without discounting. The results suggest that the survey respondents may have overvalued, especially for outages with frequency once every two years, their WTA due to not considering a long enough horizon of payments. It is important to note that the VoLL is greater for outages occurring once every 20 years over outages once every 12 years. This is a

[183] HMT Green Book

result of selecting a twenty year horizon for this analysis, therefore only one payoff occurs for outages occurring with frequency one in 20 while there are two payoffs for outages with frequency one in 12. The second of the two payoffs in the latter scenario will be heavily discounted resulting in a lower average VoLL.

A17.6 Conclusions

This section has presented the results of our added CE focused on frequency. The added CE on frequency was undertaken in part as a validation of the main CE results—in which frequency of outage was held fixed (respondents were given up-front information about current frequency of outages). It should be recalled that important reasons for not including frequency in the main CE were that it was believed that the CE was becoming too complicated, and that the most difficult attribute for respondents to interpret was frequency.

The section offered several important results:

- The VoLL estimates indicated a preference of consumers for outages that occurred less frequently. Outages that occur once every twelve years were significantly preferred over outages that occurred once every two years;
- However there appears to be a threshold level of frequency as preference for outages once every 20 years over once every 12 years was not as strong;
- The frequency choice experiment gave a VoLL of £9,745/MWH which acted as a good sense check for the comparable VoLL figures (range from £10,289/MWh - £11,820/MWh from the primary choice experiment in the main body of the report);
- The CV evaluation results were similarly in line with those from the primary CV experiment; and
- Discounting of payoffs changed the VoLL figures when a significant time horizon is examined. The effects of discounting were more significant for outages occurring more frequently.

The key conclusion is that consumers' VoLLs do not seem to be sensitive to outage frequency if frequency is in the range of one in 12 to one in 20 years, however, if frequency increases significantly, such as to one in two years, then VoLL is likely to increase. Overall, the frequency CE results suggest if real-world frequency of outage does not deteriorate below one in 12, then the VoLL estimates in the main report should remain robust (all else equal). However, if frequency of outage was to reach one in two years then the main VoLL figures would not be reliable and should most likely be re-estimated.