Valuation of the impact of works disruptions and supply interruptions using the wellbeing valuation method

This work was produced using statistical data from ONS. The use of the ONS statistical data in this work does not imply the endorsement of the ONS in relation to the interpretation or analysis of the statistical data. This work uses research datasets which may not exactly reproduce National Statistics aggregates.

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1 Executive Summary

The aim of this study is to assess the impact of works disruption and supply interruptions on the subjective wellbeing of SGN customers and to derive an implied valuation for such impacts.

SGN operates within an Ofgem regulated environment with the next price control period, RIIO - GD2 (2018), commencing in March 2021. The results from this valuation research will be used to better inform decision making when investing, to avoid disruptions.

This approach makes use of the wellbeing valuation methodology. This methodology is innovative within the gas sector but has emerged from a growing academic literature and is now recognised by the UK government as being a rigorous approach to valuing non-market goods/outcomes. It has also been increasingly applied across the infrastructure and utility sector.

The research links SGN data on incidents relating to works disruptions and supply interruptions to Office for National Statistics' data from the Annual Population Survey on the subjective wellbeing of over 110,000 individuals within the SGN area of operation. The data are linked based upon the postcodes affected by the incident and the timing of the incident relative to the interview date in the survey.

Regression analysis of subjective wellbeing, measured by life satisfaction, on incidents and a range of control variables allows us to conclude that:

- Works disruptions have a negative association with subjective wellbeing that is statistically significant;
- That the implied impact of a works disruption incident is £54,494, aggregated across all of the households within 500m of the road affected;
- This equates to an average impact of £1.60 per day for the average household within 500m of the road affected;
- Supply interruptions appear to have a negative association with subjective wellbeing but the association is not significantly different from zero;
- We are not able, therefore, to derive a valuation for supply interruptions;
- This lack of evidence for an association for supply interruptions can be explained by a number of factors including the relatively short-lived nature of most of the interruptions and the relatively small number of matches that we can make between the two datasets and the imprecision in that matching process.

This research successfully applies a methodology not previously used in the gas sector to value works disruption incidents. This valuation reflects the impact of works disruptions on those living nearby. Although we cannot be sure of the mechanisms through which these impacts occur, they are likely to reflect the impact of noise, dust and traffic flow disruptions on those living nearby.

2 Study Context

SGN manages the network that distributes natural and green gas to homes and businesses across Scotland and the south of England. They are one of four Gas Distribution Network companies in Great Britain.

SGN operates within a regulatory environment under a licence issued by Ofgem. The next price control period, RIIO - GD2 (2018), will commence in March 2021. The objective of this research is to value the impact of certain aspects of SGN's activity on their customers. In particular, it looks to value the impact of works disruptions (i.e. maintaining and replacing infrastructure, generally on roadways) and supply interruptions (i.e. periods of time during which customers are without gas supplies, either due to planned or unplanned work on the network). These valuations will be used to better inform decision making when investing, to avoid disruption.

This research focuses on valuing the impact of these activities through their impact on the subjective wellbeing of those affected. Subjective wellbeing refers to self-assessment by individuals of their quality of life. By understanding this impact, we can infer an implied value/cost of the incident by considering the change in income that would bring about the equivalent change in subjective wellbeing.

The use of subjective wellbeing to value activities such as those covered here is relatively new and innovative. However, the approach is aligned with the increasingly important role of subjective wellbeing in policy and business decision making, examples of which include:

1. The establishment of the UK National Wellbeing Programme in 2010;
2. The use of wellbeing metrics in UK government guidance on policy evaluation (the HM Treasury Green Book, 2018) and valuation studies in the UK;
3. The centre stage role that subjective wellbeing has taken in guidelines produced by the Organisation for Economic Cooperation and Development on wellbeing metrics; and
4. International trends elsewhere such as the uptake of the wellbeing valuation method by governments in Australia and New Zealand.

3 Valuation Theory

3.1 Approaches to valuation

The works disruptions and service interruptions that we are looking to value in this study are not traded in a market, so no price/value can be derived directly from market prices. As such, we need to adopt an appropriate measure to estimate the non-market value (or shadow price) of the outcome in question.

There is an extensive body of research on approaches to valuing such outcomes or goods. This research has fed into best-practice approaches to valuation (HM Treasury, 2018; OECD, 2013). At the heart of valuation of outcomes is the concept of two welfare measures developed by Hicks & Allen (1934):

- **Compensating surplus (CS)** is the amount of money, paid or received, that will leave the individual in their initial welfare position following a change from the status quo. For example, the CS for experiencing an interruption to supply (which reduces an individual's overall welfare) is the minimum amount of money that the individual is willing to accept to experience that interruption.
- **Equivalent surplus (ES)** is the amount of money, to be paid or received, that will leave the individual in their subsequent welfare position in the absence of a change from the status quo. For example, the ES for experiencing an interruption to supply is the maximum amount of money that an individual would be willing to pay to avoid experiencing the interruption.

Three broad methods for assessing these values are highlighted in the various guidance documents that are relevant to this area: revealed preference, stated preference and wellbeing valuation.

Revealed preference approaches involve making inferences about the value people place on non-market goods through their actual choice behaviour in a closely related market. An example would be valuing greenspace through assessing the impact that proximity to greenspace has on house prices. While such an approach is effective, it can only pick up impacts to the extent that there is a relevant proxy market (such as the property market in this case) that is well-functioning, and which responds to the non-market good of interest. In many cases, it is difficult to identify such a market or, in the case of activities that have not yet happened, there may be no existing evidence from past market activity.

Stated preference approaches involve using surveys on hypothetical markets to elicit peoples' willingness to pay for a non-market good. An advantage of stated preference methods is that they are extremely flexible, allowing a wide range of goods, services and outcomes to be valued. They also allow us to estimate the value to both those who are directly affected (so-called 'use value') and those who are not affected but nevertheless see a value in the good, service or outcome. The latter is important when valuing something like heritage assets which people value even if they are not directly making use of them. It can also be effective for estimating the potential value of future or planned changes which have not yet been experienced. However, one disadvantage of stated preference approaches is that they rely on individuals' assessment of scenarios that they may not have experienced in practice. As a result, they can be subject to biases that reduce the accuracy of the values calculated. Stated preference methods, therefore, require carefully designed survey and sampling procedures.

This study makes use of the third potential valuation method, **wellbeing valuation.** While this approach is relatively new and innovative, it is based upon a growing academic literature. The wellbeing valuation approach involves measuring the impact of an outcome by estimating its effect on subjective wellbeing and then converting this to a monetary value by estimating the sum of money that would have an equivalent impact.

A key benefit of this approach is that it allows us to value the impact of a good without asking people to hypothetically consider how this affects them. This could be particularly useful in relation to works disruption and service interruptions as people may struggle to correctly envisage the impact these activities might have on their lives if asked to do so in a questionnaire context. Another key benefit of applying wellbeing valuation to these activities is that we can use large samples of data on SGN's customers (approximately 100,000 responses) that can potentially be matched to incident data, which is significantly larger than what would be possible in most stated preference studies.

3.2 Implementing the wellbeing valuation methodology

A potential challenge for the wellbeing valuation method is to find a suitable measure of subjective wellbeing which can be captured accurately and without bias. Subjective wellbeing measures are generally either considered to be evaluative or experiential. The former asks people to provide a holistic assessment of their lives overall. The latter explicitly asks how someone felt at a specific moment in time. The Office for National Statistics has four best practice measures of subjective wellbeing that are used across their datasets and have been adopted more widely. These include two evaluative measures and two experiential measures.

Table 1: ONS Subjective Wellbeing Measures

Measure	Question asked	Evaluative/Experiential
Life Satisfaction	Overall, how satisfied are you with your life nowadays?	Evaluative
Worthwhile	Overall, to what extent do you feel the things you do in your life are worthwhile?	Evaluative
Happiness (positive affect)	Overall, how happy did you feel yesterday?	Experiential
Anxiety (negative affect)	Overall, how anxious did you feel yesterday?	Experiential

In general, evaluative measures of wellbeing are preferred for understanding the impact of activities/outcomes that have some level of persistence over time. Within the pool of potential evaluative measures of wellbeing, life satisfaction is the main measure used in social science (Diener, 2000) and wellbeing valuation research.

There is a variety of evidence to suggest that, overall, life satisfaction is a good measure of wellbeing. As a single data point, it is relatively easy to collect as compared to multi-question indices such as some of those linked to mental health. Whilst some studies have suggested that contextual factors such as the weather can adversely influence and bias life satisfaction responses, Eid & Diener, (2003); Fujita & Diener, (2005); Pavot & Diener, (1993); Pavot et al., (1991) and Schimmack & Oishi, (2005) find mood, question order and contextual effects to be limited. Further, bias due to mood is likely to average out in large representative samples.

There is a range of evidence that demonstrates that there is a strong correlation between wellbeing ratings and a range of outcomes that we would intuitively relate to wellbeing such as emotions (smiling and frowning) and health (Kimball & Willis, 2006; Sales & House, 1971), while life satisfaction has a high level of retest reliability, i.e. it is generally stable when someone is re-asked in quick succession (Krueger & Schkade, 2008).

Overall, life satisfaction can be viewed as a reliable measure of wellbeing and as a consequence has been extensively used in the academic and government research literatures (Diener et al., 1999; Veenhoven, 2007). As such, it is the principle measure that we use in this analysis, in particular for deriving valuations. However, we do consider the impact of the activities on the experiential measures used by the ONS (i.e. happiness and anxiety) to corroborate and test our overall findings with regard to the impact of the activities on wellbeing.

4 Data and Methodology

4.1 Data Sources

This study draws on two main sources of data:

i) **The Annual Population Survey (APS)** is a UK-wide continuous household survey. We use it mainly for information on respondents' wellbeing, which is used as the outcome variable in our analysis, and important social and socio-economic variables at personal and local levels, which are used as control variables. We use a secured access version of the data, available in the ONS' Virtual Microdata Laboratory, as this provides the postcode of the respondents' home address, which is vital in ensuring we can identify who lives near to the incidents in question.

ii) **Data on incidents** provided by SGN covering both works disruptions and supply interruption incidents. For the former, the data provides details of the location for the works, the type of works and the start and end date of the works. Streets are also categorised as Type 0 to 4 on the basis of levels of average traffic flow. For supply interruptions, the data provides the postcode of the meter point affected, the start and end date/time of the interruption and certain information regarding the type of interruption, in particular if it is a planned or unplanned incident.

The APS provides data on the four ONS measures of subjective wellbeing. All responses are measured on a scale of 0-10[1]. As noted in section 3.2, the primary measure used in this study is life satisfaction. The measures relating to happiness and anxiety are also used to corroborate and support the life satisfaction results.

The APS also provides a wide range of variables relating to survey respondents, including demographic characteristics, and socioeconomic factors. In our models we use these to control for a wide range of factors known to be associated with subjective wellbeing. In particular we use the following, which are based on the control variables recommended in Fujiwara & Campbell (2011):

- Age
- Gender
- Marital status
- Ethnicity
- Educational status
- Employment status and earnings
- Number of children
- Geographic region (local authority)

[1] Where 0 is not at all satisfied, happy, anxious, or worthwhile and 10 is completely satisfied, happy, anxious, or worthwhile.

- Wave of survey
- Month of interview
- Population density

4.2 Data Matching Process

We merged these two data sources on the basis of a match in terms of both time and location of the incident and the time when the survey was conducted. The postcode address of the respondent in APS was matched to the postcodes deemed to be affected by the incidents and, at the same time, the respondent's interview date was matched to the dates over which that incident was ongoing. Only where there was a match both spatially and temporally did we deem an individual as being treated (i.e. affected by the incident).

The works disruptions data provided by SGN did not include postcode data; instead it generally provided the street name of the road affected and a reference town. In some cases, this town actually referred to a smaller location (village or other agglomeration). In a limited number of cases, the data did not provide street names, instead referring to road numbers (e.g. A30) or referencing non-street locations (e.g. footpaths).

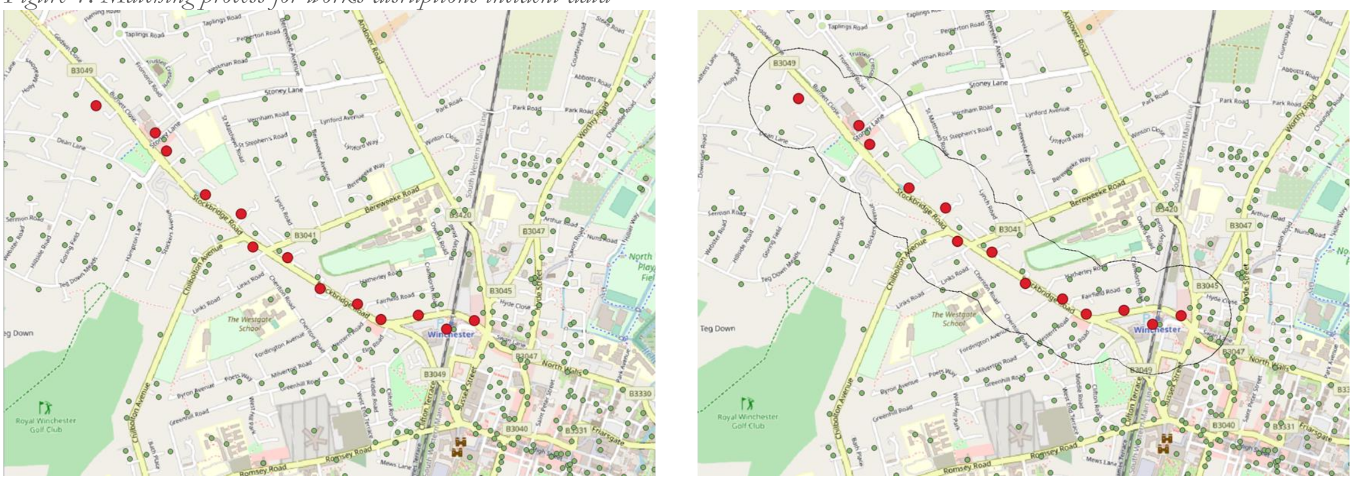
As the APS data only provides postcode data (rather than street), it was first necessary to look to match roadworks to postcodes affected. We used the Postal Address File® (PAF) from Royal Mail to match the road names to the list of all postcodes on the affected road. As the works disruption incident data did not necessarily include complete postal addresses, we matched incidents using three methods:

- Unique combined match on street name and town against street and town in PAF data within the SGN area;
- Unique combined match on street name and town against street and village in PAF data within the SGN area; and
- Unique match on street name within the SGN area (allowing for the town to not match e.g. where the town/village recorded in the SGN data did not correspond to a location used for postal addresses).

We were not able to match the data that did not have a street address. In addition, some of the sample had to be excluded because there was ambiguity when matching the street address to the postcode data for example when the town in SGN data had no match in town/village in PAF data and the street name was not unique within the SGN area. Overall 75% of the incident data was matched to single postcode or set of postcodes[2].

For each postcode identified on the road, we then generated a list of postcodes affected by placing a distance buffer around the postcode centroid and marking all other postcodes with centroids within that circle as affected. We used a range of sizes of buffers ranging from 100m to 1km in our analysis. This is illustrated in Figure 1. In this case the incident data shows a works disruption on Stockbridge Road. We initially identified all the postcodes that are on Stockbridge Road, then created a buffer around each (forming the contiguous shape shown on the right-hand side of the figure) and then recorded all of the postcode centroids that sit within that shape.

Figure 1: Matching process for works disruptions incident data



- Postcodes on Stockbridge Road
- All other postcodes
- Distance buffer around Stockbridge Road gives other postcodes defined as affected

For the supply interruptions, the dataset from SGN included postcodes, so we were able to match directly on the basis of the postcodes in APS and the postcodes affected.

With regard to the temporal linkage, we used buffers ranging from 7 days to 90 days, i.e. a person was deemed affected by the incident (whether roadworks disruption or supply interruption) if it had been ongoing at any point within the last 7, 30 or 90 days before their APS survey.

[2] It is not possible to be certain whether the data that was not matched had any systematic effect on our results. A proportion of the incidents excluded were on non-road locations (footpaths etc) so may still have been in residential areas. Others were on A-roads without a street name, which generally indicates that they are not in a residential area. The rest of the data that remained unmatched appeared to be relatively random in nature.

4.3 Econometric Specification

It is crucial that, in seeking to identify the impact of incidents on wellbeing, we adjust, where possible, for the impact of wider factors correlated with the occurrence of incidents (but not caused by them) which also drive wellbeing.

In econometric terms, this means ensuring that we adjust for any of the observable causes of endogeneity bias in our estimates of the impact of incidents on subjective wellbeing. For example, living in a densely populated urban area may make incidents more likely to occur (because of the increased density of pipework). However, it is also plausible that living in a densely populated urban area may also itself influence wellbeing due to better access to services (positive) or increased congestion (negative). It would not be appropriate in estimating the value of incidents to include the additional wellbeing impacts, if any, of living in a densely populated urban area per se.

To help control for these and similar factors we employ a set of statistical models which seek to compare wellbeing for individuals *with and without* incidents who are otherwise similar and live in similar areas.

Our models seek to test the relationship between subjective wellbeing and proximity to works disruptions and supply interruption incidents. In particular, we fit the econometric model below using multivariate ordinary least squares (OLS) regression analysis:

$$(1)\quad SWB_i = \alpha + \beta_1 \text{Incident}_\text{i} + \boldsymbol{X}_i \boldsymbol{\beta} + \varepsilon_i$$

where SWB_i denotes the subjective-wellbeing of individual i; $Incident_i$ is a variable which relates to whether the individual has been affected by a works disruption or supply interruption; and $\boldsymbol{X}_i$ is a list of the control variables.

The $Incident_i$ is defined slightly differently for the works disruptions and the service interruptions. For the former, the variable is defined as the number of works disruptions that affected the individual's postcode within the relevant time period. For the latter, the variable was a dummy which took the value of 1 if they were impacted by a service interruption within the relevant time period and 0 if not.

The coefficient β_1 is the key coefficient for our analysis. Our expectation is that it should be negative, meaning that being affected by an incident is associated with a reduction in an individual's wellbeing.

The models were run for a sample of respondents who reside in SGN's area of operations.[3]

4.4 Buffer selection

A key issue was to decide the time and distance thresholds within which individuals would be classified as having been affected by an incident. To do this we first ran econometric models for each combination of the following thresholds:

For works disruptions:

- Distance – Incident was associated with a road for which at least one postcode was within 100m, 500m and 1000m of the centre of the individual's home postcode

- Time period – Incident occurred at most 7, 30 and 90 days before the individual's APS interview

For supply interruption incidents, only the time period buffers were relevant.

For all specifications we maintain a fixed group of unaffected individuals. These represent the respondents in the APS sample within the SGN area of operations who have not been affected by a works disruption within 1000m of their home postcode in the last 90 days. It should be noted that, when using the smaller buffer areas, this approach means that a proportion of the sample is dropped to allow us to better evaluate where we should define the thresholds for the temporal and spatial buffers. This is shown in Figure 2 where the unaffected group are those in the orange cells and the affected group, in this case for 100m and 7 days, are those in the blue cell. Those in the cells in between are excluded from the regression.

Figure 2: Illustration of approach to buffer selection for works disruptions

		Distance to roadworks			
		< 100m	101m - 500m	501m - 1000m	Wider SGN Area
Period within which roadworks experienced	Within 7 days				
	8 to 30 days ago				
	31 to 90 days ago				
	More than 90 days ago				

In setting the thresholds, we are looking to balance the need for a material number of individuals to fall in both the treated and non-treated groups (ensuring good sample size to minimise estimation

[3] A list of postcode areas was provided by SGN.

error in the results) with the need for behaviourally plausible assumptions about the temporal and spatial range of the impact of incidents.

It is important to note that we should aim to ensure that all people affected by the incident are marked as treated but that it does not matter if we include some people who are not affected. This is because the regression coefficient for whichever buffer area represents the average impact of the average person affected. If we include some people who are not affected, this average will fall, but the overall valuation of the incident should remain the same as the population in the treated group rises. However, if we are too generous with our buffer, we risk diluting the average impact too much, hence making it harder to identify it within the noise of the sample. Our aim, therefore, is to ensure that all those affected are included but without setting the buffer (either in time or space) to be so large as to dilute the average impact.

4.5 Generating a per incident value

Once we have derived β_1, the impact of an incident on wellbeing, we can then estimate the equivalent amount of money that would have the same impact on wellbeing. To do this, we need to understand the causal effect of income on subjective wellbeing. We use the findings from a previous piece of research (Fujiwara and Dolan, 2016) which uses the British Household Panel Survey. The study looks at the impact of lottery wins on subjective wellbeing.

By using this aspect of income, the study is avoiding the issues that result from the expectation that the causal link between income more broadly and subjective wellbeing is likely to run in both directions. That is, higher incomes are likely to cause someone to have higher subjective wellbeing, but that higher subjective wellbeing is also likely to cause an individual to be able to obtain a higher income (e.g. due to a being more successful in the labour market). The study also controls for the other factors which are correlated with income and subjective wellbeing such employment that may be related to earning more income.

The values we derive from the coefficients represent the individual's willingness to accept an incident as if it were occurring for a full year. This is because they use a measure of annual income to derive the value. In order to derive a value that represents the entire welfare loss associated with each works disruptions and supply interruption incident, we need to adjust for both the length of time that the incident impacts on the individual and for the number of people affected. As such we follow the steps set out in Table 2 to calculate the value per incident.

Table 2: Summary of the steps to calculate a per incident value

Step	Adjustment	Reason for adjustment
1	Monetise the association between disruption and wellbeing based on the impact of income on wellbeing	This converts the impact to a monetary amount on the basis of the equivalent amount of income that would result in the same change in subjective wellbeing. The resulting value is on a *per year per individual* basis for the average person in the treatment threshold.
2	Multiply the result of step 1 by the average household size in the SGN region	This ensures that the impact is on a *per year per household* basis.
3	Multiply the result of step 2 by the average time affected by an incident (expressed in years)	The monetary valuation method provided by steps 1 and 2 is an annual value. The maximum time that someone was deemed to be affected by an incident was defined by the average length of the works disruption plus the relevant time buffer used. Assuming that the timing of APS is random with respect to the incident of works disruptions, the average time that people in the sample would be affected would, therefore, be half of this figure. This gives us a *per household per incident* figure.
4	Multiply the result of step 3 by the average number of households within the distance threshold	This aggregates the impact across all affected households. As noted in Section 4.4. it does not matter if we have some people within the buffer who are unaffected as this would lower the average impact per household that we derive and, as long we do have all the affected people within our buffer, we should derive the same *overall per incident value* when it is aggregated across the population.

4.6 Disaggregated Analysis

As well as our core analysis, we also considered whether there were differences in the impact of incidents on the basis of certain key characteristics.

In particular, for the works disruptions, we examined the variability in impact by limiting the sample to specific road types and work types and re-estimating model (1). Roads were classified in the data as Type 0 (busiest) through to Type 4 (least busy).

For supply interruption incidents, we also looked at the impacts of incidents across various sub-groups using the following interactive model specification:

$$(2) \qquad SWB_i = \alpha + \beta_1 \text{Incident}_\text{i} + \beta_2 \text{Subgroup}_\text{i} + \beta_3 \text{Incident}_\text{i} * \text{Subgroup}_\text{i} + \boldsymbol{X}_i \boldsymbol{\beta} + \varepsilon_i$$

We considered how the impact of incidents differed by the following factors:

- the **age** of the individual affected;
- whether the incident occurred in **winter**;
- whether the incident was an **unplanned** interruption; and
- whether the incident was classified as being **emergency** work.

5 Results and Interpretation

In total, there are 116,579 APS respondents across the five years of data who have data on all of the variables needed for the analysis and who live at a postcode that lies within the SGN operational area. This provides a significant sample to allow us to identify any impacts from gas-related incidents and is the base sample for the analysis across both works disruptions and supply interruptions.

5.1 Descriptive statistics – Works Disruptions

SGN data provided data on 251,354 incidents of works disruptions for the years 2012-2017. The number of people within the APS sample for the SGN area that were deemed to be affected by these incidents varied from just over 3,000 to over 76,000 depending on buffers that we use (in terms of area and time). 40,335 were unaffected by any incident within the last 90 days within 1km of their postcode. This was the control group against which we assessed any impact.

Table 3 sets out the number of people within the sample who were affected by at least one works disruption incident for each of the buffer areas/time periods and the proportion of the overall population within the APS survey for the SGN area that this represents.

Table 3: Distribution of APS sample across buffer areas/time period

Distance Buffer	**100m**			**500m**			**1000m**		
Time period buffer	**7 days**	**30 days**	**90 days**	**7 days**	**30 days**	**90 days**	**7 days**	**30 days**	**90 days**
Affected sample size	3,124	6,160	12,445	24,377	40,178	59,562	41,756	59,434	76,241
Proportion of population	2.7%	5.3%	10.7%	20.9%	34.5%	51.1%	35.8%	51.0%	65.4%

As well as the location and timing of the incidents, SGN provided data on the road type affected as well as the type of the work being carried out. Table 4 and 5 show the distribution of disruptions by these two characteristics. These highlight that works disruptions on Type 4 roads (the most minor roads) are by far the largest subset of activities.

Table 4: Distribution of all work disruptions by type of the road (2012-17)

Road Type	**Carriageway type 0**	**Carriageway type 1**	**Carriageway type 2**	**Carriageway type 3**	**Carriageway type 4**	**Other/Road type missing**
Number of Incidents	741	14,180	22,631	23,906	156,072	33,824
Proportion of incidents	0.3%	5.6%	9.0%	9.5%	62.1%	13.5%

Table 5: Distribution of all work disruptions by type of disruption (2012-17)

Disruption Type	Immediate	Standard	Major	Minor	Missing
Number of Incidents	110,771	34,268	25,629	80,654	32
Proportion of incidents	44.1%	13.6%	10.2%	32.1%	< 0.1%

5.2 Regression analysis - Works Disruptions

The regression analysis of the works disruptions data supports the conclusion that the wellbeing impact of experiencing a works disruption is negative. In other words, works disruptions have a cost to those living nearby in terms of their subjective wellbeing as measured by life satisfaction. It is important to stress here that our approach accounts for a range of factors that might be reasonably expected to affect life satisfaction, so our results imply that when comparing two people with similar circumstances, one of whom was recently affected by roadworks and another not, there is a negative impact for the former person's life satisfaction.

While the coefficients calculated for the impact under various models are not always statistically significant, there are enough robust results across the different models to reach the conclusion that works disruptions have a negative subjective wellbeing cost on those living nearby. Our preferred buffer is 500m and 30 days, which is broad enough to capture all those affected without diluting the effect to the extent that it is difficult to discern the impact effectively. With this buffer, we do have a significant result for incidents across all road types. The consistency of our results is illustrated by the fact that the size of the impact of works disruptions on life satisfaction generally decreases with increasing size and length of the buffer considered.

Using the coefficient for all works, based upon a buffer of 500m and 30 days, the implied value of the wellbeing cost per incident of a works disruption is £54,494 aggregated over all affected households. This equates to around £24 per incident per household within the 500m buffer. Given that the SGN works disruption data shows an average length of disruption of just over 15 days, this equates to around £1.61 per day of disruption per household within the 500m buffer. Alternatively, it can be viewed as implying a per incident, per day value of £3590.

To be clear, this is an average impact across all the households within the 500m buffer and it is certainly true that different households will experience different impacts. Indeed, the evidence suggests that those within 100m of the works are facing a higher cost, at around £2.40 a day, although this figure is subject to considerable uncertainty.

We separately considered the impacts for specific subgroups. There were some indications that the impact of disruptions taking place on road types 0 to 3 were greater than those on type 4 roads, in particular when considered across the smaller 100m buffer, but these findings are not conclusive.

All statistical estimations from regression models represent the most likely value for the number that we are estimating. However, there remains the possibility that our sample of individuals is not representative of those affected by works disruptions. The APS is designed to be representative of the population at a regional level but is not wholly representative at the very local level. There may also be factors that affect how much people are affected by works disruptions that are not accounted for in the sampling strategy for the survey (e.g. those with disabilities may face additional access problems as a result of work disruptions but the APS does not use disability as a sampling factor).

Given these factors, it is important to recognise that there is a possibility that there is error within our estimates. The potential extent of this error is illustrated by the confidence interval around our estimates of the coefficients in the regression model and, hence, around the values that we derive from the coefficients. We can choose different levels of confidence to determine the range. A 90% confidence interval is relatively standard and provides the range of values within which we can be confident that the true value most of the time. However, there remains a 10% chance that the true value still sits outside of this range.

The 90% confidence interval for a range of measures of the wellbeing cost of incidents are set out in Table 7. These confidence intervals are relatively wide. Crucially, however, the do not cross zero, hence our confidence in saying that there is a wellbeing cost associated with works disruptions. The width of the confidence interval reflects the variation within the sample as to how people appear to be affected by works disruptions.

Table 6: 90% confidence intervals for wellbeing cost of works disruptions

Measure	Lower bound of confidence interval	Central estimate	Upper bound of confidence interval
Per incident	£16,015	£54,494	£92,973
Per incident per household within 500m	£7.16	£24.37	£41.58
Per incident per day	£1,055	£3,590	£6,125
Per incident per day per household	£0.47	£1.61	£2.74

Fuller results from the regression analysis are presented in Annex A.

5.3 Descriptive Statistics – Service Interruptions

SGN data provides data on 67,190 incidents of supply interruptions. As these incidents generally only affect a single postcode, the number of people within the APS sample for the SGN area that are deemed to be affected is much smaller than for the works disruption. As shown in Table 7, even allowing for a 90-day buffer, the number of people that we deem as being affected within the data is only around 3,000.

Analysis of the length of the service interruptions shown in Table 8 highlighted that most of the incidents affecting people within the sample were relatively short in nature, with 85%-94% of the incidents linked to individuals within the sample being less than 24 hours long.

Table 7: Distribution of sample across buffer time period

Time period buffer	7 days	30 days	90 days
Affected sample size	477	1,233	2,977
Proportion of population	0.4%	1.1%	2.6%

Table 8: Distribution of sample across buffer time period

Length of interruptions	7-day time buffer	30-day time buffer	90-day time buffer
Less than 1 hour	130	396	1,085
1 hour – 3 hours	123	326	735
3 hours – 24 hours	157	401	977
Greater than 24 hours	67	110	180
% <24 hours	86%	91%	94%

5.4 Regression analysis - Service Interruptions

The regression analysis of the supply interruptions suggests that the wellbeing impact of experiencing a gas supply interruption is negative. As would be expected, the impact does appear to decline as the time buffer increases (i.e. as, on average, the incident under consideration happened longer ago). However, none of the coefficients are statistically significantly different from zero at the 10% level. As such, we are not able to report monetised wellbeing values per gas supply interruption. The core results of the regression analysis are presented in Annex A and the full regression results are available on request.

We explored whether the impact of incidents that might be expected to have a larger impact (e.g. occurring in winter or impacting the elderly) could be seen within the data. While the impact might be expected to be greater for such incidents, by taking a subset of those affected, the sample sizes were inevitably smaller, hence limiting our chances of identifying an impact. Analysis of impacts by the age of the individual, the season in which the incident occurred, whether the incident was unplanned and whether the incident was classified as an emergency all failed to yield any statistically significant impacts.

6 Discussion and Conclusions

The study has successfully calculated a per incident value for the works disruptions that result from SGN's activities to maintain its infrastructure network. It has not been able to identify an impact (and hence a value) for service interruptions.

6.1 Works Disruptions

The values that we derive for works disruption represent a measure of the impact of such disruptions on people's subjective wellbeing. Our analysis does not specifically identify the mechanisms through which this impact occurs, but we could reasonably assume that factors such as noise, dust and disruption to parking/traffic flow would be included. The values represent the impact of an average incident. Factors that may affect the value of a specific incident include length of disruption, the severity of disruption to traffic flows, the residential housing density around the location of the disruption and the level of noise associated with the specific work being carried out. We have shown that one proxy for one of these factors (disruption to traffic flows) does affect the estimated cost of an incident in line with expectations.

It is useful, however, to consider what is not included in such a value. The values do not account for any impacts on those outside the buffer zone. In general, this is because our assumption is that such impacts are limited. However, in certain cases, where works are occurring on routes that see a significant flow of traffic from further away (e.g. main commuter routes), we would expect there to be additional costs associated with the traffic disruption that would affect people living outside of the buffer, even when this is set at the 1km level. The values also do not account for the impacts on businesses where works disruptions affect the volume of trade except to the extent that these business owners are living within the buffer zones. Finally, they do not reflect environmental costs that may be associated with the incident such as carbon emissions linked to energy used or other pollutants generated.

The valuations derived in this report can be considered against similar metrics derived using alternative valuations methods, in particular stated preference surveys, to corroborate the findings. We understand that previous stated preference work conducted by SGN concluded that customers were willing to pay an additional £0.99 to reduce the duration of a roadwork incident by 15% and £1.91 to reduce it by 30%.

If we take account of our finding that the average works disruption is 15 days, these alternative estimates imply a per customer per day willingness to pay around £0.42. Although this is somewhat below our figure of £1.61 per affected household per day, it lies close to the lower bound of the confidence interval for our estimates. The stated preference figure will, itself, also be associated with a confidence interval, meaning that they may well overlap. More significantly, it should be noted that the stated preference and wellbeing values are not measuring the exact same impact. The stated preference is deriving a hypothetical willingness to pay across all customers to reduce roadworks impacts. The wellbeing values represent an experienced willingness to accept, i.e. the compensation that would be required to bring the person back to their initial state of wellbeing, for a specific incident that has affected an individual. There is no theoretical reason why they should be identical[4].

It is not possible to say that one method is necessarily superior to the other. Stated preference approaches can suffer from biases associated with how qudestions are framed or how people view hypothetical situations. Equally, the wellbeing valuation approach relies on the assumption that life satisfaction adequately measures people's quality of life as well as specific assumptions around which control variables are included and how the income coefficient is derived. We are confident that we have applied the methodologies in line with best practice literature.

Overall this comparison supports our view that our findings plausibly represent the impact of works disruptions as measured through the impact on people's subjective wellbeing.

6.2 Service Interruptions

There are a number of possible reasons for the lack of statistically significant findings with regards to service interruptions.

Firstly, the sample sizes are relatively small. Moreover, unlike with the works disruptions where it is reasonable to assume that everyone within a postcode may have broadly equal exposure to the incident, it is generally the case with supply interruptions that only one household within the postcode is actually affected. As we are not able to access data on the precise address of the APS respondent, we are only able to make a match on the basis of postcode. As there are on average around 17 households per postcode, this effectively means that we have a 1 in 17 chance of our match actually corresponding to the person affected by the supply interruption. This reduces the precision of our estimate.

Secondly, the short-term nature of most interruptions means that any impact on wellbeing is likely to be small and short-lived. A significant majority of incidents are resolved within 24 hours, with around 30% lasting less than one hour. It is not unreasonable that such short-lived incidents do not have an impact on an evaluative measure of subjective wellbeing such a life satisfaction, in particular if the incident has happened some time ago (up to 90 days ago in the most extreme situation).

Relatedly, it may be that an evaluative measure such as life satisfaction is not necessarily the optimal measure of wellbeing for capturing the impact of interruptions. It may be better to use an experiential measure of subjective wellbeing such as happiness or anxiety. However, the measures in this area are based upon a question which asks respondents to consider how happy/anxious they were the day prior to being interviewed. This would imply that we need to have a buffer period of just one day, which would effectively cut our sample of affected individuals to the extent that

[4] We understand that the stated preference study was based upon the average length of roadworks being 6 weeks, which conflicts with our finding from the data that the average duration is only 15 days. It is unclear whether respondents viewed the proposed reduction as 15% or specifically as a reduction by 1 week. If the latter, the implied willingness to pay per day would be lower.

regression analysis was no longer feasible. We did investigate using measures of anxiety/happiness with a 7-day buffer, but the results were not significant.

We are aware that previous stated preference studies have found values for customer's willingness to pay to reduce the impact of gas supply interruptions relating to improvements in the length of time to restore gas supply after an unplanned interruption. There may be various reasons for these differences. Firstly, wellbeing valuation methods estimate the wellbeing impact of individuals who actually experience the disruption and can better account for adaptation, in contrast to stated preference methods which ask people explicitly about the disruption in a hypothetical context. Secondly, in the stated preference survey, respondents may include in their WTP, both values relating to their own impact from the disruption (use values) as well as for the impact on others in the community (non-use values). Lastly, the lack of findings in this case may also reflect our inability to precisely identify those affected from within the data sample.

7 Annex A: Regression Analysis Results

Tables 9 to 12 provide the coefficients representing the impact of works disruptions/service interruptions on life satisfaction for a range of buffers (temporal and spatial). Full regression results including control variables are available on request.

Table 9 Association between works disruptions and life satisfaction by distance and time period buffers

Time period/distance buffer	7-day time buffer	30-day time buffer	90-day time buffer
100m	-0.0214	-0.0149	-0.0158
500m	-0.0155**	-0.0100**	-0.0068***
1km	-0.0008	0	-0.0002

Note: Coefficients marked with asterisks are significant at the 1% (***), 5% (**) and the 10% (*) level.

Table 10 Association between works disruptions and life satisfaction by distance and time period buffers (works affecting Type 0-3 roads)

Time period/distance buffer	7-day time buffer	30-day time buffer	90-day time buffer
100m	-0.1056**	-0.0591*	-0.0214
500m	-0.0448**	-0.0189	-0.0124
1km	-0.0094***	-0.0017	-0.0024

Note: Coefficients marked with asterisks are significant at the 1% (***), 5% (**) and the 10% (*) level.

Table 11 Association between works disruptions and life satisfaction by distance and time period buffers (works affecting Type 4 roads)

Time period/distance buffer	7-day time buffer	30-day time buffer	90-day time buffer
100m	-0.0274	-0.0346	-0.0316**
500m	-0.0217**	-0.0191**	-0.0083*
1km	-0.0075**	-0.0065***	-0.0013

Note: Coefficients marked with asterisks are significant at the 1% (***), 5% (**) and the 10% (*) level.

Table 12 Association between service interruptions and life satisfaction by time period buffers

Time period/distance buffer	7-day time buffer	30-day time buffer	90-day time buffer
No distance buffer used	-0.050	-0.033	-0.012

Note: All regressions coefficients are found to be statistically insignificant.

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