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Valuing electricity-dependent infrastructure: An essential-input approach

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ABSTRACT

Electricity is an essential input to both the production of household commodities, and the provision of public infrastructure services. The latter, in turn, are essential to the generation of additional household goods. Thus, customers' willingness to pay to avoid power interruptions will reflect both aspects of foregone household production. We recognize this as an opportunity to value infrastructure services via stated preference methods based on power outage scenarios. We motivate our model using household production theory, and implement it empirically within a Random Utility framework to derive European households' willingness-to-pay to avoid disruption of electricity provision to the "front door," as well as the loss of important public services. We find that a considerable portion of total willingness-to-pay, to the order of 20–80%, relates to the public service component. This stresses the importance of explicitly specifying the scale of outages and their effect on public services in stated preference elicitation. Failure to do so will produce welfare estimates that are unfit to inform policy, and normalized outage cost estimates that are biased - potentially by a very large margin.

1. Introduction

Severe weather events, which are expected to become more frequent due to climate change, pose increasing risks to the reliable provision of electricity around the globe. On the supply side, increasing temperatures and more frequent heat waves decrease the efficiency of thermal and nuclear power plants by hampering thermal conversion, and by reducing the availability and ability of water for cooling. Hydropower plants, in turn, are vulnerable to extreme precipitation and flood events, as well as inter-annual variation in inflows (Arent et al., 2014). All types of supply installations in low-lying areas are at an increased risk of flooding (Davis and Clemmer, 2014). On the transmission and distribution side, more frequent violent storms damage transmission lines and other elements of the electric grid year-round. Wildfires, which are increasing in frequency and ferocity, directly destroy electric infrastructure, and interfere with the conductivity of transmission lines (Davis and Clemmer, 2014). On the demand side, rising temperatures and intense heat waves increase the demand for cooling in many regions, further taxing the capacity of the electricity system (Davis and Clemmer, 2014). All these risks lead to more frequent and prolonged power interruptions. For the example, in the U.S. the average annual number of weather-related power outages has doubled between 2003 and 2012, affecting an average of 15 million customers each year (Kenward and Raja, 2013).

Extreme weather and a changing climate also affects other elements of the public infrastructure, such as water supply, sanitation services, and transportation. Water supply is affected both in terms of quantity due to reduced renewable surface and groundwater resources in many regions, and in terms of quality due to increased sedimentation and runoffs, as well as disruption of treatment facilities during floods (IPCC, 2014). More frequent heavy rainfall events can also overload the capacity of sewer systems and wastewater treatment plants, causing disruptions in sanitation

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services (Arent et al., 2014). Transportation services, in turn, are vulnerable to flooding, will require higher maintenance due to larger temperature swings, and face cooling challenges in many parts of the world (Arent et al., 2014). Naturally, disruptions in any of these primary services can, in turn, affect the provision of health and emergency services (IPCC, 2014).

Importantly for our study, all of these public services rely to a large extent on the provision of electricity. Therefore, climate change is expected to exacerbate disruptions of basic infrastructure services *directly*, via the factors mentioned above, and *indirectly*, by increasing the risk of power outages. In consequence, the economic value of electric service reliability is intrinsically linked to the societal value of other segments of the public infrastructure. Our analysis exploits this linkage to elicit values for both power provision and power-dependent infrastructure services (ISs).

This study adds to the outage cost literature by dis-aggregating total willingness-to-pay (WTP) to avoid a power interruption into values lost due to electricity not delivered directly to the household (i.e. the "front door"), and values lost due to interrupted ISs in the households' neighborhood or region. This informs decisions regarding the optimal provision of these services, which are often largely funded by taxpayers, as well as the prioritization of infrastructure protection from power interruptions.

We find that a sizable portion of average hourly outage costs, to the order of 20–80 %, can be attributed to lost ISs for our sample of residents from eight European countries. Customers are especially sensitive to losing medical, communication, transportation, and sanitation services. Our findings raise serious concerns about using the common "WTP/kilowatt hour (kwh) unserved" metric to express outage impacts to residents, since kwh unserved are traditionally computed at the "front door," whereas, as shown in this study, household WTP relates to a much broader set of impacts and thus a much larger volume of lost electric load.

1.1. Power outages and infrastructure services

It is well documented that large-scale power outages can severely affect critical elements of the public infrastructure. For example, as summarized by Public Safety and Emergency Preparedness Canada (2006), the Northeastern Interconnection power outage of 2003, attributed to an overloaded grid, affected 50 million people in the U.S. and Canada, and impacted "virtually all ten critical infrastructure sectors," such as banking services, food distribution, waste water treatment, traffic lights, highway signs, gas pumps, and even internet services and firewalls, which exposed customers to multiple cyber threats.

A 2003 storm-related outage that affected most of Italy brought trains to a standstill and disrupted communication and telephone services (BBC News, 2003). An overload in Germany's power network triggered widespread outages in five European countries in late fall of 2006, leaving people stuck in elevators and delaying numerous trains (BBC News, 2006). A 2007 winter storm that hit the U.S. Midwest caused large-scale outages that left people without electric heat or lights, halted airport operations, and disrupted water supply to thousands of residents due to the failure of electric pumps (NBC News, 2007). In 2012, a series of thunder storms caused power outages affecting nearly four million customers in the mid-Atlantic and South-Eastern region of the U.S., cutting out traffic lights, halting train services, and even knocking out Amazon's cloud (data storage) services, with the cascading effect of interrupting popular internet sites and services such as Netflix and Instagram (CNN News, 2012).

It is therefore well conceivable that respondents have these IS interruptions in mind when asked to think about their WTP to avoid a specific outage scenario. However, with the exception of Reichl et al. (2013), none of the published outage cost studies based on survey methods elaborate on the *spatial scale* of a stipulated interruption.[1] Households are either told that, for additional payments, front-door delivery of power will remain uninterrupted (Layton and Moeltner, 2005; Carlsson and Martinsson, 2007), or asked to choose from a set of outage bundles that vary in timing, length and / or frequency, and are each linked to a specific fee added to the electricity bill (Beenstock et al., 1998; Carlsson and Martinsson, 2008; Baarsma and Hop, 2009; Blass et al., 2010).

In the first case, elicited WTP can only be interpreted as values for household commodities produced exclusively with front-door electricity (refrigeration, meals, hair drying, etc.) and provides no guidance as to the broader societal value of protecting or maintaining ISs. The second approach raises even bigger issues, as it is not clear which outage scale, and thus the extent of impact on ISs, respondents have in mind when they select from a given outage choice menu. This makes it impossible to clearly assign derived WTP estimates to front-door losses versus ISs-related damages, and, in turn, makes it difficult to use resulting estimates for policy purposes.

1.2. Valuing infrastructure services

The ISs considered in this study are best described as quasi-public goods, as they are all associated with fees, and are - at least to some extent - provided by commercial entities. However, most of them are typically subsidized by the government (medical care, water and sanitation services, public transit) or require publicly financed infrastructure (gas pipelines, road maintenance, traffic lights and signage, land and access roads for cell phone towers, etc.). In addition, some of them are overseen by public utility commissions that have considerable control over service scope, quality, and pricing (e.g water and sanitation).

Thus, to the extent that taxpayer moneys are involved in the provision and maintenance of these services, it is economically meaningful to think of an optimal level of provision. This, in turn, requires information on costs and benefits. In many cases, the latter will be difficult to gauge based on observed behavior alone, given muddled price signals due to subsidies, regulation, or lack of temporal or spatial variability. As in many other such cases, this suggests elicitation approaches based on Stated Preferences (SP) methods.

We are aware of only a handful of studies that have attempted to value essential public services in developed countries. For example, Hensher et al. (2005) and Willis et al. (2005) use a Choice Experiment (CE) approach to estimate households' WTP for uninterrupted water and sanitation services in Australia and England, respectively. Hackl and Pruckner (2006), using contingent valuation (CV) methods, elicit Austrian households' values for publicly funded emergency medical services, using a scenario of "possible future privatization." Schwarzlose et al. (2014) implement a CE in three Texan counties to elicit stakeholders' values of various public transportation attributes, with focus on expanded services for the elderly and using private car registration fees as payment vehicle. Savage and Waldman (2009), also employing a CE, estimate customers' WTP for various attributes of home internet service, such as reliability, speed, and independence of phone connections.

While all these studies find that people care about these services, such direct SP approaches also carry with them a set of empirical risks. As discussed in Hensher et al. (2005) and Willis et al. (2005), given the critical nature of some of these services to cover basic human needs, and a lack of historic problems with service provision, respondents may question the realism of stipulated interruption

1 Using a repeated discrete choice format similar to that employed in this study, Reichl et al. (2013) stipulate outages that differ in scale between "street-only" and "province-level" to their sample of Austrian households. However, they do not report scale-specific WTP estimates.

scenarios. Furthermore, any suggestions of taking away services traditionally provided by local governments will undoubtedly trigger protest responses, and may introduce sample selection problems into the empirical analysis.

However, as discussed above and as is evident from our empirical data, most households, even in developed countries, will have experienced power outages in recent history. Furthermore, large scale outages are highly publicized in the media, reaching a population well beyond actually affected residents. Therefore, the notion of losing ISs that are reliant on electric power should not appear foreign and inconceivable to survey respondents. This should mitigate any realism problems that may arise with more direct cessation-of-service scenarios. In our application, we have a second built-in safeguard against a lack of buy-in for stipulated scenarios. Specifically, as described below in more detail, we let respondents decide themselves if they *believe* specific ISs will be affected in their neighborhood or region by a prolonged outage. We find pronounced WTP premia for households that hold such beliefs.

2. Modeling framework

2.1. Conceptual model

Given our main objective to value services to the household that depend on electricity, the best-suited theoretical approach is through a household production framework. As discussed in detail in upper-level textbooks (e.g. Bockstael and McConnell, 2007; Phaneuf and Requate, 2017), the household production approach to the valuation of some quasi-fixed public good, say q, rests on the notion that both q and observed market goods x enter a household technology function that combines these inputs to generate useful services, say H. Importantly, aside from its contribution to the provision of these services, q does not otherwise enter the consumer's utility function. Bockstael and McConnell (1983) show that utility-theoretic welfare measures for *non-marginal changes in* q can be obtained in the special case where x is an essential input in the production of H. That is, if x is zero, no H can be produced, regardless of the level of q.

In this study, electricity is the essential input for household production of electricity-dependent goods and services, while elements of the public infrastructure (water and sanitation, public transportation, communication and internet, etc.) take the role of the (semi-) public good q. In this section we show that, due to electricity's essential good characteristic, welfare measures related to the provision of electricity can be unambiguously interpreted as values for electricity-dependent household production. Furthermore, using a survey-based identification strategy, we show that a good portion of these values can be attributed to lost ISs.

A given household depends on electricity provision in two ways to produce household goods and services, such as warm meals, ironed shirts, online shopping, and entertainment: (i) It uses electricity directly delivered to the "front door," and (ii) it uses quasi-public ISs such as the internet, ATM machines, and cell phone communication that themselves depend on electricity.

Let $\mathbf{H}_1$ be a vector of k_1 household-produced, infrastructure-*in*dependent goods and services, each of which uses electricity e_{1k} (e.g. operating a stove), household labor l_{1k} (e.g. cooking a meal), and other market inputs x_{1k} (e.g. groceries). The production technology for the entire bundle can then be expressed as

$$\mathbf{H}_1 = \mathbf{f}_1\left(\mathbf{e}_1, \mathbf{l}_1, \mathbf{x}_1\right), \tag{1}$$

where vectors $\mathbf{e}_1$, $\mathbf{l}_1$, and $\mathbf{x}_1$ comprise the inputs for the k_1 services.

Analogously, let $\mathbf{H}_2$ be a vector of k_2 household-produced, infrastructure-dependent services, each of which uses elements of the public infrastructure G_k (e.g. internet service), household labor l_{2k} (e.g. time spent on the computer), and other market inputs x_{2k} (e.g. PC, high-speed modem, etc.). The production technology for the entire bundle can then be expressed as

$$\mathbf{H}_2 = \mathbf{f}_2\left(\mathbf{G}\left(\mathbf{e}_2, \mathbf{g}\right), \mathbf{l}_2, \mathbf{x}_2\right), \tag{2}$$

where the vector notation is as before. Importantly, as denoted in Eq. (2), the infrastructure services depend themselves on electricity $\mathbf{e}_2$, in addition to other inputs $\mathbf{g}$ that are exogenous to the household. Moreover, electricity is an *essential input* for the production of $\mathbf{H}_1$, and - via its pivotal role in the provision of $\mathbf{G}$, also the production of $\mathbf{H}_2$. We therefore have the essential input restrictions

$$\begin{aligned} &\mathbf{H}_1 | \left(\mathbf{e}_1 = 0\right) = \mathbf{f}_1\left(\mathbf{0}, \mathbf{l}_1, \mathbf{x}_1\right) = \mathbf{0}, \quad \text{and} \\ &\mathbf{H}_2 | \left(\mathbf{e}_2 = 0\right) = \mathbf{f}_2\left(\mathbf{G}\left(\mathbf{0}, \mathbf{g}\right), \mathbf{l}_2, \mathbf{x}_2\right) = \mathbf{f}_2\left(\mathbf{0}, \mathbf{l}_2, \mathbf{x}_2\right) = \mathbf{0} \end{aligned} \tag{3}$$

Given our focus on power outages that last for a relatively short time horizon, we will treat the household's market inputs related to the use of infrastructure services ($\mathbf{x}_2$), which will primarily be durable goods such as communication or computing devices, as fixed in the following derivation.

Following standard reasoning for household production models (e.g. Bockstael and McConnell, 2007; Phaneuf and Requate, 2017) the household's optimization problem can be conceptually described as a two-step process: First, the household chooses home-used electricity $\mathbf{e}_1$, market inputs $\mathbf{x}_1$, labor allocations $\mathbf{l}_1$ and $\mathbf{l}_2$, and public services $\mathbf{G}$ to achieve a certain level of household services $\mathbf{H}_1$ and $\mathbf{H}_2$ at the lowest possible cost. This produces the cost function

$$\begin{aligned} C\left(p_e, \mathbf{p}_1, \mathbf{p}_G, \mathbf{H}_1, \mathbf{H}_2\right) = \min_{\mathbf{e}_1, \mathbf{x}_1, \mathbf{l}_1, \mathbf{l}_2, \mathbf{G}} &\left\{ p_e \mathbf{e}_1 + \mathbf{p}_1' \mathbf{x}_1 + \mathbf{p}_G' \mathbf{G}(.) \right. \\ &+ \boldsymbol{\lambda}_1' \left(\mathbf{H}_1 - \mathbf{f}_1(.)\right) + \boldsymbol{\lambda}_2' \left(\mathbf{H}_2 - \mathbf{f}_2(.)\right) \\ &\left. + \lambda_3 \left(L - \sum_{k=1}^{k_1} l_{1k} - \sum_{k=1}^{k_2} l_{2k} \right) \right\}, \end{aligned} \tag{4}$$

where p_e is the price of electricity, and $\mathbf{p}_1$ and $\mathbf{p}_G$ are, respectively, the price vectors for $\mathbf{x}_1$ and $\mathbf{G}$, L is the total available amount of at-home labor, and the λ terms are multipliers.

This cost function then feeds into the second conceptual step, in which the household maximizes utility over $\mathbf{H}_1, \mathbf{H}_2$, and a numeraire commodity z, subject to constraints for budget, technology, and labor, that is:[2]

$$\begin{aligned} &\max_{\mathbf{e}_1, \mathbf{x}_1, \mathbf{l}_1, \mathbf{l}_2, \mathbf{G}, z} \quad U\left(\mathbf{H}_1, \mathbf{H}_2, z\right) \quad \text{s.t.} \\ &m = C\left(p_e, \mathbf{p}_1, \mathbf{p}_G, \mathbf{H}_1, \mathbf{H}_2\right) + z \\ &\mathbf{H}_1 = \mathbf{f}_1\left(\mathbf{e}_1, \mathbf{l}_1, \mathbf{x}_1\right) \\ &\mathbf{H}_2 = \mathbf{f}_2\left(\mathbf{G}\left(\mathbf{e}_2, \mathbf{g}\right), \mathbf{l}_2, \mathbf{x}_2\right) \\ &L = \sum_{k=1}^{k_1} l_{1k} + \sum_{k=1}^{k_2} l_{2k} \end{aligned} \tag{5}$$

[2] In the interest of parsimony but without loss in generality we abstract from any labor-leisure decisions in our model.

where m is the total available household budget. Assuming interior solutions for all choice variables, this yields the indirect utility function

$$\begin{aligned} & V\left(\mathbf{H}_1^*, \mathbf{H}_2^*, z^*\right), \quad \text{with} \\ & \mathbf{H}_1^* = \mathbf{f}_1\left(p_e, \mathbf{p}_1, \mathbf{p}_G, m, L\right) \\ & \mathbf{H}_2^* = \mathbf{f}_2\left(p_e, \mathbf{p}_1, \mathbf{p}_G, m, L\right) \quad \text{and} \\ & z^* = z\left(p_e, \mathbf{p}_1, \mathbf{p}_G, m, L\right) \end{aligned} \tag{6}$$

where we continue to implicitly condition on $\mathbf{x}_2$. In a standard household production framework the next step would be to invoke the essential input condition and express compensating variation (CV) for a change in $\mathbf{G}$ (potentially down to zero) as the area between two shifted Hicksian demands for $\mathbf{e}_2$, and use observed demand for $\mathbf{e}_2$ to approximate this amount. In our case, this is problematic since electricity $\mathbf{e}_2$ needed to run $\mathbf{G}$ is beyond the control of an individual household, so there are no choke prices or observed demands for this input at the household level.

Instead, we now switch to a stated preference framework to estimate welfare associated with lost ISs, asking respondents to choose between payment to avoid a specific (widespread) outage, or tolerate the interruption at no loss of income. We exploit the essential input condition in the sense that if the interruption takes place, all of $\mathbf{e}_1, \mathbf{e}_2, \mathbf{G}, \mathbf{H}_1$, and $\mathbf{H}_2$ are driven to zero. Therefore, the estimated WTP to avoid the outage can be directly interpreted as the welfare losses associated with foregone production and consumption of household goods and services. Furthermore, since $\mathbf{G}$ is itself an essential input in the production of $\mathbf{H}_2$, as is evident from the second line in Eq. (3), welfare losses associated with ceased production of $\mathbf{H}_2$ can be unambiguously interpreted as the CV for the availability of $\mathbf{G}$. As mentioned above, we use a survey-based identification strategy to extract this latter component of WTP.

Approximating indirect utility in Eq. (6) with a standard linear form and adding a random error term allows us to cast the household problem in a Random Utility Modeling (RUM) framework. Specifically, let indirect utility for household i under uninterrupted electricity service during a specific time frame s (e.g.: summer weekday, 6 am–10 am) be given as

$$\tilde{V}_{si}^* = d_s\left\{\mathbf{H}_{1i}^{*\prime}\boldsymbol{\beta}_{1s}^* + \mathbf{H}_{2i}^{*\prime}\boldsymbol{\beta}_{2s}^*\right\} + \tau m_i - d_s\left\{\tau\left(p_e\mathbf{e}_{1i}^* + \mathbf{p}_1'\mathbf{x}_{1i}^* + \mathbf{p}_G'\mathbf{G}_i^*(.)\right)\right\} + \tilde{\epsilon}_{si} \tag{7}$$

where d_s measures the number of time periods (hours), the $\boldsymbol{\beta}^*$ terms denote the marginal utility, per hour, of household goods and services $\mathbf{H}_{1i}^*$ and $\mathbf{H}_{2i}^*$, respectively, τ is the marginal utility of income, $\tilde{\epsilon}_{si}$ is a time-sensitive, idiosyncratic error term, and we have used the relationship $z_i^* = m_i - d_s\left(p_e\mathbf{e}_{1i}^* + \mathbf{p}_1'\mathbf{x}_{1i}^* + \mathbf{p}_G'\mathbf{G}_i^*\right)$.

Now consider a blackout during the exact same time frame. This implies that neither home-used electricity $\mathbf{e}_1$ nor any of the quasi-public services $\mathbf{G}$ will be available, driving the home production of $\mathbf{H}_1$ and $\mathbf{H}_2$ to zero. At the same time, the household will not incur any expenses for electricity $\mathbf{e}_1$ and public infrastructure $\mathbf{G}$. However, a perishable share of private inputs, say $\alpha\mathbf{x}_{1i}$, with $0 \leq \alpha \leq 1$, will be lost in case of an outage.

The indirect utility function thus reduces to

$$\tilde{V}_{s,i0}^* = \tau m_i - d_s\tau\alpha\mathbf{p}_1'\mathbf{x}_{i1}^* + \tilde{\epsilon}_{s,i0} \tag{8}$$

where we specify a different idiosyncratic error $\tilde{\epsilon}_{s,i0}$ to accommodate additional or different unobservables that may enter indirect utility in case of a power outage compared to the case of power provision.

The compensating variation (willingness-to-pay) CV_{si} to avoid this outage scenario "s" is then implicitly defined as

$$\tilde{V}_{si}^*\left(m_i - CV_{si}\right) = \tilde{U}_{s,i0}^*, \tag{9}$$

which, using Eqs. (7) and (8) yields

$$\begin{aligned} & CV_{si} = d_s\left\{\mathbf{H}_{1i}^{*\prime}\boldsymbol{\beta}_{1s} + \mathbf{H}_{2i}^{*\prime}\boldsymbol{\beta}_{2s}\right\} - d_s\left\{p_e\mathbf{e}_{1i}^* + (1-\alpha)\,\mathbf{p}_1'\mathbf{x}_{i1}^* + \mathbf{p}_G'\mathbf{G}_i^*(.)\right\} + \epsilon_{si} \\ & \text{where} \quad \boldsymbol{\beta}_{rs} = \frac{\boldsymbol{\beta}_{rs}^*}{\tau}, \quad r = 1, 2 \quad \text{and} \quad \epsilon_{si} = \frac{\tilde{\epsilon}_{si} - \tilde{\epsilon}_{s,i0}}{\tau} \end{aligned} \tag{10}$$

As is clear from this derivation CV_{si} includes components related to both infrastructure-independent and infrastructure-dependent household services. It represents the lost value of both types of home production, minus foregone expenditures from not using electricity or public infrastructure services, and the value of non-perishable inputs that can be used at a later point in time.

If the household is offered some arbitrary bid P_{si} to avoid an outage of type s, it will take the contract if its willingness to pay exceeds the bid, that is if

$$\begin{aligned} V_{si}^* = & CV_{si} - P_{si} = d_s\left\{\mathbf{H}_{1i}^{*\prime}\boldsymbol{\beta}_{1s} + \mathbf{H}_{2i}^{*\prime}\boldsymbol{\beta}_{2s}\right\} \\ & - d_s\left\{p_e\mathbf{e}_{1i}^* + (1-\alpha)\,\mathbf{p}_1'\mathbf{x}_{i1}^* + \mathbf{p}_G'\mathbf{G}_i^*(.)\right\} - P_{si} + \epsilon_{si} > 0 \end{aligned} \tag{11}$$

where V_{si}^* is the economic surplus left to the household after paying to avoid the outage. In essence, Eq. (11) represents the increasingly popular "surplus" version of the random utility model, aka "estimation in willingness-to-pay (WTP) space" (e.g. Train and Weeks, 2005; Sonnier et al., 2007; Scarpa et al., 2008).[3]

Empirically, this conceptual framework can be made operational by letting

$$V_{si}^* = d_s\left(\mathbf{h}_i'\boldsymbol{\beta}_{hs} + \mathbf{r}_{si}'\boldsymbol{\beta}_{rs}\right) - P_{si} + \epsilon_{si}, \tag{12}$$

where $\mathbf{h}_i$ is a vector of household characteristics, $\mathbf{r}_{si}$ is a vector of binary indicators for infrastructure services, and the $\boldsymbol{\beta}$ terms are corresponding coefficients. Specifically, in our empirical application the elements $\mathbf{r}_{si}$ take on a value of one if household i believes the corresponding infrastructure service will be affected by outage scenario s, and a value of zero otherwise.

The interaction $\mathbf{h}_i'\boldsymbol{\beta}_{hs}$ captures the *net value* of lost infrastructure-independent production per hour of interruption, that is the term $\mathbf{H}_{1i}^{*\prime}\boldsymbol{\beta}_{1s} - p_e\mathbf{e}_{1i}^* - (1-\alpha)\mathbf{p}_1'\mathbf{x}_{i1}^*$ in Eq. (11). This leaves $\mathbf{r}_{si}'\boldsymbol{\beta}_{rs}$ to measure the net value of lost household production per hour of outage that is dependent on infrastructure services, i.e. the term $\mathbf{H}_{2i}^{*\prime}\boldsymbol{\beta}_{2s} - \mathbf{p}_G'\mathbf{G}_i^*(.)$ in Eq. (11).

2.2. Econometric model

Our survey elicits households' WTP a specified bid P_{si} to avoid outage scenario s, for a set of S different interruptions, each distinguished by duration, time of occurrence, and season, as described in more detail in the next section. Allowing for unrestricted error

[3] As described in these references, the surplus model can equivalently be derived by dividing indirect utility by the marginal utility of income, which in a linear-in-income model, amounts to the coefficient of the price term.

correlations, the full system of S surplus equations can thus be written as

$$\begin{aligned}
V_{1i}^{*} &= d_1\left(\mathbf{h}_i'\boldsymbol{\beta}_{h1} + \mathbf{r}_{1i}'\boldsymbol{\beta}_{r1}\right) - P_{1i} + \epsilon_{1i} \\
V_{2i}^{*} &= d_2\left(\mathbf{h}_i'\boldsymbol{\beta}_{h2} + \mathbf{r}_{2i}'\boldsymbol{\beta}_{r2}\right) - P_{2i} + \epsilon_{2i} \\
&\vdots \\
V_{Si}^{*} &= d_S\left(\mathbf{h}_i'\boldsymbol{\beta}_{hS} + \mathbf{r}_{Si}'\boldsymbol{\beta}_{rS}\right) - P_{Si} + \epsilon_{Si}, \quad \text{with} \\
\epsilon_i &= \left[\epsilon_{1i} \quad \epsilon_{2i} \quad \dots \quad \epsilon_{Si}\right]' \sim n\left(\mathbf{0}, \boldsymbol{\Sigma}\right)
\end{aligned} \tag{13}$$

Thus, our combined error vector follows a multivariate normal distribution with zero mean and a full variance-covariance matrix $\boldsymbol{\Sigma}$.[4] Furthermore, we allow all surplus variances to be scenario-specific. Since our stipulated outages differ in duration this allows ex ante for more uncertainty from unobservables (i.e. a larger error variance) for longer interruptions. This is confirmed in our empirical application.

Individual i's contribution to the likelihood function is the joint probability of observing the S-fold vector of outage responses $\mathbf{y}_i$. Expressing latent WTP (that is surplus V_{si}^{*} minus bid P_{si}) as y_{si}^{*} and collecting all S bids offered to respondent i in $\mathbf{P}_i$, and all IS-responses in $\mathbf{r}_i$ this term can be written as:

$$\begin{aligned}
\text{prob}\left(\mathbf{y}_i|\mathbf{h}_i, \mathbf{r}_i, \mathbf{P}_i; \boldsymbol{\beta}, \boldsymbol{\Sigma}\right) &= \text{prob}\begin{bmatrix} b_{1i,l} < y_{1i}^{*} < b_{1i,u} \\ b_{2i,l} < y_{2i}^{*} < b_{2i,u} \\ \vdots \\ b_{Si,l} < y_{Si}^{*} < b_{Si,u} \end{bmatrix} \\
&= \Phi_i\left(\mathbf{h}_i, \mathbf{r}_i, \mathbf{P}_i; \boldsymbol{\beta}, \boldsymbol{\Sigma}; T_i\right),
\end{aligned} \tag{14}$$

where $\boldsymbol{\beta} = \left[\boldsymbol{\beta}_1' \quad \boldsymbol{\beta}_2' \quad \dots \quad \boldsymbol{\beta}_S'\right]'$, and $b_{si,l}$ and $b_{si,u}$ designate, respectively, the lower and upper threshold for latent WTP, as implied by the observed response y_{si}. Specifically, $b_{si,l} = P_{si}$ and $b_{si,u} = \infty$ if $y_{si} = 1$ ("yes").[5] If a negative response is observed, i.e. $y_{si} = 0$, we have $b_{si,l} = -\infty$ and $b_{si,u} = P_{si}$. As indicated by the last line of Eq. (14) this joint probability can be concisely expressed as an S-fold cumulative normal density Φ_i, truncated to the S-dimensional region T_i.

For the sample at large the likelihood function is thus given by

$$\text{prob}\left(\mathbf{y}|\mathbf{H}, \mathbf{R}, \mathbf{P}; \boldsymbol{\beta}, \boldsymbol{\Sigma}\right) = \prod_{i=1}^{N} \Phi_i(.), \tag{15}$$

where vector $\mathbf{y}$ comprises all individuals' outage responses and $\mathbf{P}$ collects all individual bid vectors. Analogously, matrices $\mathbf{H}$ and $\mathbf{R}$ collect all $\mathbf{h}_i$ and $\mathbf{r}_i$, respectively.

Maximum likelihood estimation of this model would be cumbersome for this high-dimensional equation system with individual-specific truncation restrictions. We therefore opt for a Bayesian estimation framework. The resulting Gibbs Sampler (GS) is straightforward to implement and converges after a reasonable number of burn-ins. The GS draws consecutively and repeatedly from the conditional posterior distributions $p\left(\boldsymbol{\beta}|\left\{\mathbf{y}_i^{*}\right\}_{i=1}^{N}, \mathbf{H}, \mathbf{R}, \mathbf{P}; \boldsymbol{\Sigma}\right)$, $p\left(\boldsymbol{\Sigma}|\left\{\mathbf{y}_i^{*}\right\}_{i=1}^{N}, \mathbf{H}, \mathbf{R}, \mathbf{P}; \boldsymbol{\beta}\right)$ and $p\left(\left\{\mathbf{y}_i^{*}\right\}_{i=1}^{N} |\mathbf{y}, \mathbf{H}, \mathbf{R}, \mathbf{P}; \boldsymbol{\beta}, \boldsymbol{\Sigma}\right)$, where vector $\mathbf{y}_i^{*}$ combines latent WTP for all S outage equations for household i. Posterior inference is based on the marginals of the joint posterior distribution $p\left(\boldsymbol{\beta}, \boldsymbol{\Sigma}|\mathbf{y}, \mathbf{H}, \mathbf{R}, \mathbf{P}\right)$. Further details for this GS and its implementation are given in a separate online appendix.[6]

Collecting primary parameters $\boldsymbol{\beta}$ and $\boldsymbol{\Sigma}$ in vector $\boldsymbol{\theta}$, the GS yields draws of $\boldsymbol{\theta}$ from the joint posterior distribution $p\left(\boldsymbol{\theta}|\mathbf{y}, \mathbf{H}, \mathbf{R}, \mathbf{P}\right)$. Posterior predictive distributions (PPDs) of the expected hourly WTP for the typical household in each country, for each of the four outage scenarios, can be obtained in straightforward manner. For each draw of $\boldsymbol{\beta}_s$ from the GS we compute $\hat{wtp}_{sc}|\boldsymbol{\beta}_s = \frac{1}{n_c}\sum_{i\in c}\left(\mathbf{h}_i'\boldsymbol{\beta}_{hs} + \mathbf{r}_{si}'\boldsymbol{\beta}_{rs}\right)$, that is the sample average of observation-specific estimates of expected hourly WTP for country c. Repeating this computation for all draws of $\boldsymbol{\beta}_s$ from the original sampler yields the desired PPD, which can then be examined for its statistical properties.

As discussed below in more detail, setting all elements of $\boldsymbol{\beta}_{rs}$ to one (zero) produces WTP predictions for an otherwise typical household that believes that all (none) of the public services are affected.

3. Empirical application

3.1. Data

Our data are based on survey of residential electricity customers conducted between fall 2012 and spring 2013 in all 27 EU nations at that time. The survey team contacted over 176,000 households and recruited between 260 and 300 respondents in each member state, taking efforts to assure representativeness for the respective underlying population along key demographic dimensions, such as geographic location, gender and age of the head of household, employment status, and income. Households had the choice to complete the questionnaire by phone or online. Details of the sampling process and survey implementation are given in Garcia Gutierrez et al. (2013), appendices A–D.[7]

Importantly, a few weeks prior to the actual telephone or online survey, each participant was sent a confirmation letter that reminded them "*to be conscious of their surroundings and activities and think about all the ways they use electricity in their daily life*," to get them to start thinking of the potentially widespread effects of a power outage.

Three parts of the questionnaire are relevant for this study. Part one collected background information on respondents' experience with power outages. In addition, households were asked to indicate on an ordinal scale to what extent they believed each of eight essential ISs would be affected by a prolonged outage. Part two elicited their WTP to avoid each of a set of eight unplanned power interruptions. Part three then collected standard information on household demographics.

For this study we focus on four of the stipulated interruptions that were described as occurring at the country-level, as opposed to being

[4] It should be noted that despite the binary nature of the observed dependent variables (yes/no responses) all terms in $\boldsymbol{\Sigma}$ are identified, since responses are given with respect to a known numerical threshold (the stipulated bid).

[5] Strictly speaking, as noted by a reviewer, the upper threshold for WTP is household income, not ∞. However, we only capture income in general intervals in our survey, and thus do not have precise point measures. Also, given that bids are in the €0.25–70 range, and annual income is in the € tens of thousands, this distinction will have no statistical impact when characterizing the area under the cumulative WTP distribution to the right of the bid (in other words, probability mass to the right of annual income will be zero by definition).

[6] The Matlab code to implement the model is available from the authors upon request.

[7] Given budget constraints, the survey team aimed for an initial target of 250 participating households per country. This level was exceeded in all cases. Households were initially contacted by telephone or e-mail and asked about their willingness to participate in a subsequent telephone or online survey. This first contact also served as a screening tool to eliminate households that did not fit within the demographic target quotas. The recruiting/screening procedure was carried out until about 125–150 participants per country agreed to participate in a phone interview and 100–125 agreed to participate in the online survey. Those who did fit the target quotas and agreed to participate were sent a confirmation letter that contained the survey booklet or a web link to the booklet. A second phone call was then made to walk the respondent through the survey. Online participants were sent a survey link instead.

Table 1
Power provision statistics by country (2012).

Country	Year joined EU	Sample size (HHs)	Annual kwh/p.c.	Price/kwh (euros)	Num. of out. last yr.			Longest outage last 5 yrs.		Satisfied w. utility (%)
					% zero	Mean	Std.	<1 h	>4 h	
Austria	1995	230	2093	0.20	48.3%	1.4	1.9	18.3%	13.0%	100%
Belgium	1958	214	1789	0.23	55.1%	1.4	2.9	20.1%	10.7%	94%
Denmark	1973	213	1790	0.30	59.2%	1.1	1.9	16.4%	11.7%	98%
Ireland	1973	235	1772	0.22	61.7%	0.9	1.5	6.0%	17.0%	97%
Luxembourg	1958	206	1746	0.17	57.8%	0.9	1.6	26.7%	8.3%	99%
Netherlands	1958	230	1496	0.19	61.7%	0.8	1.4	15.2%	16.5%	97%
Sweden	1995	234	4100	0.20	60.3%	1.2	2.4	17.1%	21.8%	96%
UK	1973	245	1807	0.17	56.3%	1.2	2.0	9.8%	19.2%	98%

kwh = kilowatt hour / Std. = standard deviation / p.c. = per capita / num. = number / yr. = year.

highly localized ("street level"). This assures that respondents could reasonably assume that ISs were affected by such widespread events.

Furthermore, we narrow our sample to a subset of eight countries that share a similar outage history and, on average, hold similar beliefs regarding affected ISs. This choice is largely driven by data limitations given our modest sample sizes at the country level. Specifically, preliminary analyses indicated clearly that the marginal effects of covariates differ significantly across outage scenarios, i.e. coefficient vectors $\boldsymbol{\beta}_{hs}$ and $\boldsymbol{\beta}_{rs}$ in Eq. (12) are truly scenario specific, as presumed in our conceptual notation in the previous section. This preempts any pooling of parameters across outages. The resulting large parameter space (close to 90 estimable model coefficients, plus six variance-covariance terms) does not leave enough degrees of freedom to estimate *country-specific* coefficients with any reasonable degree of precision. We therefore opt to pool our data across a subset of countries that are homogeneous in key aspects of this study, especially in beliefs regarding IS interruptions. However, our model still allows for *country-specific* predictions of WTP, as shown below.[8]

The resulting set of countries, listed in alphabetical order and comprising a total of 1807 households, is given in Table 1. As is evident from the first column, most of these nations have been EU members for at least 40 years, with Austria and Sweden (1995) constituting more recent additions. Sample sizes, after dropping observations with missing key information, are comparable across countries (column two), and so are measures of historic outage frequency (columns five through seven), and satisfaction levels with the local utility (last column). The survey also elicited information on the longest outage respondents had experienced in the preceding five-year period. As can be seen from columns eight and nine, the resulting implicit distribution of maximum outage length differs somewhat across countries, with Belgium and Luxembourg exhibiting the largest share of relatively short "longest outages" (< 1 h), and Sweden and the UK showing the highest percentage of respondents that experienced an outage exceeding 4 h in duration.

The eight nations also differ markedly in annual per capita electricity consumption (column three), with Sweden (4100 kwh) taking the lead and the Netherlands showing up as the thriftiest member (1496 kwh). The Danish pay by far the highest price for electricity (€0.30/kwh, column four), while the remaining countries face similar prices, in the €0.17–0.23 range.[9]

Table 2 shows aggregate respondent and household characteristics for our sample. Overall, our data display a good representation of female respondents (41–53 %), a comparable age structure across countries, and expected average household sizes in the range of 2–3 persons. The degree of urbanization (column 4) differs markedly across nations, from less than 50% in Austria to close to 80% in Denmark. The majority of respondents in each country hold an A-level diploma (a requirement for university entry), with Ireland and the Netherlands falling slightly below the 50% mark. Households in Luxembourg have the highest average income (close to €50,000/year), while the other nations show similar averages in the mid-€20,000s to low €30,000s range.[10]

The survey template with the IS perception questions is given in the online appendix. It shows a table for which each row corresponds to one of eight essential services: medical care (including emergency response, henceforth abbreviated as "medical"), fuel and gas supply (for private and public transportation, as well as heating, "fuel/gas"), electronic payment options (ATM use, credit card transactions, electronic banking, "payments"), communication (land and mobile telephone network, "phone"), heating systems (reliant on electric pumps, "heating"), internet and network connections ("internet"), electrically operated traffic (public transport, metro, "transport"), and sanitation and sewage services (including water supply, "sanitation"). For each IS respondents were asked to mark the degree to which they thought it would be affected during an outage that started 4 h ago, from "not at all affected," "moderately affected," "strongly affected," to "very strongly affected."

To keep our analysis tractable, we convert the four-tiered opinion scale into a binary indicator of "affected" (combining responses of "strongly affected" and "very strongly affected"), and "not affected" (combining responses of "not at all affected" and "moderately affected"). For consistency with the all-or-nothing extrapolation for a change in public services in our conceptual framework, and in absence of any further information on respondents' interpretation of "affected," we treat a stated belief of "affected" as commensurate with the *complete loss* of a given service. To the extent that respondents thought that a residual degree of the IS would still be provided,

[8] To determine such homogeneity, we computed the percentage of households that believed that a given IS would be affected for each country and IS. We then examined the deviations of these shares across all eight ISs and all 27 countries. The final set of eight nations exhibits a deviation in average shares over all ISs of no larger than 8%, and a deviation in IS-specific shares of 20% or less across all public services. In conjunction with similar income levels in most of these countries and a comparable degree of (high) historic power reliability, we take this as an indication that citizens of these nations are also likely to share similar preferences for infrastructure services. We thus pool these data and estimate a single set of coefficients per outage scenario for all eight nations. This strikes us as a reasonable compromise between allowing marginal effects - and thus average hourly WTP - to remain scenario-specific, while preserving a full set of explanatory variables and a large enough sample size to assure identification.

[9] Statistics on electricity consumptions in 2012 were obtained from European Commission (2016a). Electricity prices for 2012 are given by European Commission (2016b).

[10] Income was computed based on the midpoints of ten interval bins. We approximate the upper bound of the highest category as the lower bound of that category plus the bandwidth of the preceding bin. Household demographics for all 27 EU nations are given in Cohen et al. (2016).

Table 2
Sample statistics by country.

Country	Female	Age		% urban	Education	HH size	Income (€000s)	
		Mean	Std.		(A level)		Mean	Std.
Austria	49%	47.3	14.4	46%	53%	2.67	26.75	12.13
Belgium	49%	47.3	14.3	67%	68%	2.40	25.73	10.19
Denmark	41%	49.9	15.7	76%	53%	2.08	31.99	13.00
Ireland	46%	48.6	14.5	69%	47%	2.88	29.26	14.58
Luxembourg	45%	48.1	13.5	59%	60%	2.78	48.24	18.03
Netherlands	52%	49.0	14.4	65%	40%	2.17	24.11	10.12
Sweden	44%	47.4	15.4	72%	74%	2.00	24.22	11.15
UK	53%	47.3	14.4	68%	56%	2.67	23.51	12.63

Std. = standard deviation.

Table 3
Infrastructure failure perceptions by country (%).

	Medical	Fuel/Gas	Payments	Phone	Heating	Internet	Transport	Sanitation
Austria	55	57	79	69	74	82	89	50
Belgium	55	50	70	63	71	72	82	45
Denmark	60	53	81	62	73	79	88	57
Ireland	60	56	77	54	80	82	83	40
Luxembourg	55	59	69	66	79	76	75	50
Netherlands	63	55	77	73	74	67	85	50
Sweden	56	48	80	59	64	79	85	55
UK	72	57	77	62	77	78	85	46

Entries show the percentage of respondents that believed that a given infrastructure service would be strongly or very strongly affected after 4 h of power interruption.

our WTP estimates can be interpreted as a lower bound for welfare losses associated with a complete cessation of service.

Table 3 summarizes these beliefs of IS failure for our set of eight EU members. We see that the vast majority of households (70–90 %) believe that payments, heating, internet, and transport would be affected. These percentages are slightly lower (50–70 %) for medical fuel/gas, and phone, while only 40–50 % of respondents worry about impacted sanitation services. Overall, therefore, our data exhibits sufficient variability in beliefs to identify an IS effect, that is to disentangle total WTP to avoid a given outage into WTP to preserve household production related to front-door electric service, and WTP to avoid a loss of services related to the public infrastructure.

Each country-level outage scenario presented to the respondents is unplanned, and defined by *duration* (1, 4, 12, 24 h), and *season* (summer, winter). Respondents were given the option to pay a specified bid (in form of an add-on to their next electricity bill) and avoid the outage or to decline payment and experience the interruption. Importantly, we stressed that the extra payment would leave the household completely unaffected, including "all important services discussed in the last section." To provide some technical realism linking payment to protection, respondents were told that "*These days there are technical solutions that can prevent critical events from leading to power outages, such as weather-resistant underground cables and smarter switchgear equipment. These measures improve service reliability significantly, especially during critical events, but their cost is also significant*." This was followed by the actual elicitation question: "*For each scenario … I will read out a sum of money and ask you to tell me whether you think you would prefer to pay this sum and therefore not be affected by this power outage, or whether you would prefer not to pay but instead experience this outage.*"[11]

Our preference elicitation format thus corresponds to a repeated contingent valuation question, each framed in a single-bounded discrete-choice format as employed in Layton and Moeltner (2005), Carlsson and Martinsson (2007), and Reichl et al. (2013). The settings for duration generally reflect the spectrum found in the existing literature (e.g. Layton and Moeltner, 2005; Carlsson and Martinsson, 2007; Carlsson and Martinsson, 2008; Baarsma and Hop, 2009; Reichl et al., 2013). All of our stipulated outages occur on a weekday and include a time span of likely high activity in the household, i.e. either early morning or early evening. Table 4 depicts the outage attributes for the four country-level scenarios. The online appendix shows an example of an outage scenario, as it was presented to the respondent.

We stipulated between three and four country-specific bid values per outage scenario. The bid design was informed by a recent study on energy reliability in Austria (Reichl et al., 2013). Specifically, we adopt the four bids administered in that survey for outages of equal length to those in our scenarios, with an adjustment for income differences between Austria and the other seven countries in our set. The survey team examined the share of "yes" responses for all bids and countries for the first 25 observations to assure adequate coverage. This screening process did not prompt any ex-post adjustments to the bid ladders.[12]

[11] While we did not ask about backup technologies in our survey, we believe that it is highly unlikely that a household in our sample of eight developed western nations, many of them living in highly urbanized settings, have access to backup power generation, based on discussions with utilities and public advocacy groups during the survey design and implementation stage. Furthermore, such technologies would not help with the provision of semi-public infrastructure services, leaving that portion of WTP unaffected at any rate.

[12] Originally, a total set of four bids were selected for each country across all eight outage scenarios. Since we only consider the national-scale interruptions for this analysis, the number of effective bids is reduced to three for some country/scenario combinations, and - in the case of Luxembourg - to two for the first scenario. While this is less than ideal from an efficiency perspective, the lowest and highest bids are identical (up to income adjustments) for all countries and scenarios (see online appendix Table 1). Thus, we at least bound implicit underlying WTP distributions in equal fashion across nations. The bids in the Austrian study were derived based on a D-optimality criterion with balanced utilities (Huber and Zwerina, 1996; Burgess and Street, 2003; Burgess and Street, 2005; Ferrini and Scarpa, 2007). The full set of bid amounts and share of "yes" responses for each scenario and country are given in the online appendix. As is evident from the table, with few exceptions the percentage of "yes" responses decreases monotonically over increasing bids, as expected. Other than for differences in these bid amounts, the survey instrument including the outage scenarios and actual contingent valuation questions were identical across all eight nations.

3.2. Estimation results

We implement our correlated binary choice model with fixed effects for each country to capture unobserved differences in relevant aspects of power provision. Household vector $\mathbf{h}_i$ in Eq. (13) includes three age categories (35–45 years, 46–60 years, over 60 years, with omitted baseline of 20–35 years), an indicator for an "urban" residential location (as opposed to suburban or rural), an indicator for gender (with "female" the omitted baseline), household size, and educational attainment (an indicator equal to one if the respondent holds an A-level diploma). Household characteristics also include the historic 12-month outage frequency, indicator categories for the longest outage experienced in the preceding five years (1–4 h, 4–8 h, 8–24 h, and over 24 h, with < 1 h the implicit baseline category), and a binary indicator variable for the household's declared satisfaction with the local power utility (1 = "very" or "fairly" satisfied, 0 = "not very" or "not at all" satisfied).

This is followed by the eight IS indicators (vector $\mathbf{r}_{si}$ in Eq. (13)), each taking value of one if a given respondent believed the service in question would be affected, and a value of zero otherwise. As discussed above, and as explicitly shown in Eqs. (12) and (13), the marginal effects for all variables in $\mathbf{h}_i$ and $\mathbf{r}_{si}$ are allowed to vary over the four scenarios.

Our specification is completed by a binary indicator "scenario ordering," taking a value of one if the respondent received a survey version that showed the local outages first, followed by the country-wide scenarios, and zero for the reversed case, to test for (undesirable) formatting effects.

Ideally, we would collect separate IS beliefs for each outage scenario, as indicated by the "s" subscript in $\mathbf{r}_{si}$. In reality we only observe respondents' opinion on IS impacts for a generic "4 h +" interruption, as shown in top left cell of the survey template in Appendix A. Our empirical model thus rests on the assumption that whichever beliefs a given respondent held for an outage lasting 4 h also applies to our other three outage scenarios, with respective durations of one, 12, and 24 h(see Table 4 above). Fortunately, for most unobserved cases this assumption is rather mild - those who answered "affected" for the 4 h interruption would most likely also hold the same belief for outages of 12 and 24 h. Conversely, those who believed that ISs would not be affected after 4 h can be safely assumed to feel that way as well for a shorter outage of 1 h.

This leaves only three of six unobserved counterfactuals for which our common-belief assumption is somewhat more tenuous: beliefs for 12 and 24 h if they voted "unaffected" for 4 h, and beliefs for 1 h if they voted "affected" for 4 h. Fortunately, in both situations a wrong assumption would bias our IS coefficients, and thus our WTP estimates for IS services, in the same direction, that is downwards. Thus, any potential bias due to carrying 4-h beliefs through all other scenarios goes in the same direction as making wrong assumptions on respondents' interpretation of "affected," as discussed above. This simply reinforces that our WTP estimates are best interpreted as lower bounds of the true welfare effect of a scenario-specific full cessation of a given IS.[13]

A third reason for this lower-bound interpretation is presented by the fact that we do not observe any savings that non-use of ISs would bring - that is the term $\mathbf{p}_G'\mathbf{G}_i^*$ in Eq. (11). However, in most cases these savings will be relatively small (foregone public transportation fees, not using heat for a few hours, etc.), such that we would not expect full WTP and WTP net of savings to deviate much from one another.

[13] It should be noted that we cannot run our system of equations with different counterfactual imputations of beliefs for the less clear-cut cases, perhaps followed by Bayesian model averaging. This is because each equation has its own separate set of coefficients, so that any imputation other than the one we employ would automatically result in a column of all ones or all zeros for the entire sample, and thus preempt any identification of IS effects.

Table 4
Attribute settings for outage scenarios.

Scenario	Duration (hours)	Season	Time span
1	1	Winter	8 pm–9 pm
2	4	Summer	6 am–10 am
3	12	Summer	8 am–8 pm
4	24	Winter	10 am–10 am

Full estimation results for model coefficients are given in Table 5, while estimates for error variances, covariances, and resulting correlations (i.e. the elements of $\mathbf{\Sigma}$ in Eq. (13)) are depicted in Table 6. For each coefficient the table captures the posterior mean, the posterior standard deviation, and the proportion of the posterior distribution that exceeds zero. The latter metric provides an at-a-glance assessment if a given variable has a predominantly positive effect ("prop > 0" is close to one), a predominately negative effect ("prop > 0" is close to zero) or an ambivalent effect ("prop>0" approaches 0.5). In the following we will focus our discussion on regressors for which at least 90% of the posterior distribution lies to the left or to the right of zero, and refer to them as "significant", in slight abuse of Classical terminology.

As is clear from Table 6, error variances increase markedly with outage duration (i.e. $var(\epsilon_2) > var(\epsilon_4) > var(\epsilon_3) > var(\epsilon_1)$), as expected. In addition, all six correlation terms are strongly positive, ranging from 0.318 for the first two equations to 0.642 for equations two and four. Together, these findings support our choice of a fully correlated system with equation-specific variances.

As discussed previously, the coefficient estimates captured in Table 5 are to be interpreted as the marginal effects of each regressor on the *average hourly* WTP for a given scenario. We can see from the table that household size is the only demographic variable that has a consistent positive effect on WTP across all scenarios, with WTP increasing by €0.3–0.5 per additional household member. This is as expected, as larger households comprise more individuals that could feasibly be inconvenienced by an outage. Higher age also increases WTP in most cases. For example, a person in the 60+ age category is willing to pay €1.7 more to avoid a 1-h winter outage compared to the baseline category (under 35), and approximately €0.5 more to prevent either one of the two summer interruptions. This is, again, not surprising as elderly individuals face larger health risks in case of lost heating or cooling, and might otherwise feel more helpless and vulnerable when power is lost. Having an A-level education also adds €0.3–0.4 to hourly WTP compared to less-educated households. This is likely due to the higher need by this segment to use the internet and other electronic services that would be lost during an outage. Similarly, urban residents pay a premium of €1.4 to avoid the 1-h winter outage, and an increment of €0.3 to prevent the 12-h summer outage compared to rural customers. Presumably, this points at the higher degree of dependence of urban households on infrastructure services, such as local transportation, as many of them may not own a personal vehicle.

Of our outage history variables, the strongest signal comes from the "longest outage >24 h" indicator, which significantly boosts WTP for scenario one by close to €3.5 over the baseline group (with the longest outage experienced in the recent past not exceeding 1 h). This mirrors the finding in Layton and Moeltner (2005), who also report a positive relationship between WTP to avoid a future outage, and the combined duration of all recently experienced interruptions. We concur with these authors that while households may have learned to cope with shorter outages, it appears that extremely long interruptions evoke decidedly unpleasant memories and thus lead to higher WTP.

Scenario ordering (last row of the table) has a moderate, but significant effect for the summer scenarios three and four. This could suggest undesirable anchoring effects for these two interruptions,

Table 5
Full estimation results for coefficients.

	Winter, 1 h			Winter, 24 h			Summer, 4 h			Summer, 12 h		
Variable	Mean	Std.	prop.> 0	Mean	Std.	prop.> 0	Mean	Std.	prop.> 0	Mean	Std.	prop.> 0
Austria	−1.993	1.648	0.106	−0.175	0.740	0.409	−1.670	0.649	0.003	−2.313	0.858	0.003
Belgium	−3.05	1.64	0.03	−0.236	0.714	0.369	−1.543	0.640	0.005	−2.399	0.839	0.001
Denmark	−0.468	1.64	0.39	0.731	0.730	0.842	−1.174	0.643	0.030	−1.488	0.843	0.033
Ireland	−0.757	1.66	0.32	−0.383	0.743	0.304	−1.544	0.653	0.007	−2.723	0.865	0.000
Luxembourg	−1.681	1.66	0.15	0.920	0.742	0.892	−1.271	0.656	0.023	−1.351	0.861	0.051
Netherlands	−2.296	1.61	0.08	−0.536	0.720	0.229	−1.814	0.641	0.001	−2.761	0.850	0.000
Sweden	−2.871	1.633	0.037	−0.253	0.723	0.367	−1.835	0.645	0.001	−2.405	0.853	0.001
UK	−3.106	1.667	0.030	−0.552	0.742	0.229	−1.789	0.661	0.003	−3.264	0.892	0.000
Urban	1.371	0.461	0.999	0.229	0.190	0.887	0.056	0.160	0.642	0.293	0.205	0.925
Male	1.227	0.434	0.998	−0.020	0.175	0.462	0.020	0.148	0.547	−0.177	0.189	0.171
Age 35 to 45	0.422	0.652	0.745	0.167	0.273	0.731	0.314	0.234	0.908	0.043	0.292	0.567
Age 46 to 60	0.737	0.599	0.896	−0.231	0.254	0.179	−0.003	0.212	0.491	−0.032	0.269	0.454
Age 60 plus	1.675	0.665	0.995	0.131	0.270	0.685	0.486	0.235	0.980	0.451	0.285	0.945
Longest out. 1–4 h	0.190	0.480	0.650	−0.057	0.199	0.393	−0.085	0.171	0.310	−0.122	0.216	0.286
Longest out. 4–8 h	0.722	0.758	0.836	−0.462	0.313	0.067	0.123	0.269	0.674	0.036	0.340	0.538
Longest out. 8–24 h	−0.193	1.207	0.441	−0.557	0.523	0.142	−0.467	0.454	0.150	−0.358	0.556	0.263
Longest out. > 24 h	3.458	1.504	0.993	−0.263	0.577	0.323	0.456	0.503	0.816	−0.091	0.662	0.445
Num out. 12 months	−0.048	0.120	0.344	−0.014	0.049	0.393	−0.006	0.042	0.449	−0.024	0.053	0.324
HH size	0.448	0.189	0.993	0.143	0.076	0.971	0.218	0.066	1.000	0.229	0.085	0.998
A-level educ.	0.454	0.441	0.851	0.400	0.183	0.987	0.333	0.157	0.984	0.377	0.197	0.975
Satisfied	0.835	1.266	0.741	0.379	0.544	0.759	0.317	0.473	0.749	1.457	0.638	0.991
Medical affected	0.446	0.446	0.841	0.076	0.189	0.660	0.279	0.164	0.959	0.496	0.203	0.994
Fuel/gas affected	0.037	0.456	0.534	0.085	0.189	0.672	−0.240	0.161	0.067	0.005	0.203	0.514
Payments affected	0.328	0.543	0.733	−0.234	0.230	0.153	0.358	0.199	0.965	−0.115	0.242	0.312
Phone affected	0.978	0.477	0.983	0.373	0.197	0.974	0.391	0.170	0.991	0.266	0.208	0.901
Heating affected	−1.005	0.521	0.025	0.397	0.211	0.973	−0.087	0.183	0.315	0.003	0.227	0.506
Internet affected	0.551	0.561	0.835	−0.082	0.235	0.361	−0.112	0.202	0.289	−0.154	0.254	0.271
Transport affected	−1.396	0.624	0.010	0.450	0.257	0.962	0.143	0.221	0.748	0.582	0.287	0.981
Sanitation affected	0.890	0.469	0.976	0.870	0.199	1.000	0.340	0.165	0.981	0.395	0.210	0.973
Scenario ordering	−0.244	0.416	0.278	−0.083	0.172	0.320	0.213	0.149	0.924	0.261	0.187	0.919

Mean = posterior mean, Std. = posterior standard deviation.
prob.(> 0) = share of posterior density to the right of zero.

Table 6
Estimation results for error covariance matrix.

	Variances, covariances			Correlations		
	Mean	Std.	prop.>0	Mean	Std.	prop.>0
ϵ_1	45.25	10.25	1.00			
ϵ_1, ϵ_2	140.03	23.97	1.00	0.318	0.040	1.000
ϵ_2	4373.13	671.15	1.00			
ϵ_1, ϵ_3	39.59	6.15	1.00	0.625	0.029	1.000
ϵ_2, ϵ_3	325.78	40.45	1.00	0.470	0.034	1.000
ϵ_3	90.00	14.52	1.00			
ϵ_1, ϵ_4	112.70	19.56	1.00	0.523	0.035	1.000
ϵ_2, ϵ_4	1512.33	183.12	1.00	0.642	0.031	1.000
ϵ_3, ϵ_4	209.05	25.29	1.00	0.619	0.031	1.000
ϵ_4	1287.07	219.12	1.00			

Mean = posterior mean, Std. = posterior standard deviation.
prob.(> 0) = share of posterior density to the right of zero.

warranting some caution in interpreting the results related to these equations. Fortunately, scenario effects emerge as irrelevant for the two winter equations.[14]

Our main focus, however, rests with the IS indicators, captured in the second-to-last block of rows of the table. Most noteworthy, concerns about failure in communication ("phone") and water and sanitation ("sanitation") services increase WTP in all four cases. These are also the only significant IS effects for the shorter winter outage. Not surprisingly, the three longer outages all produce additional IS effects with the bulk of posterior mass above zero. Specifically, for the winter, 24 h case heating and transportation are of primary concern, while a possible disruption of medical services produces significant results for both summer scenarios. In addition, "payments" emerge as significant for the shorter summer outage, while "transport" plays an important role for the summer, 12 h interruption. [15]

Figs. 1 and 2 depict these IS results in graphic form. Fig. 1 shows the posterior distribution of the marginal IS effects on average hourly WTP for the two winter scenarios, while Fig. 2 provides the analog for the summer interruptions. A dotted vertical zero-line is superimposed on each sub-figure. As can be seen from these graphs, the marginal IS effects identified as significant in the above discussion all have posterior distributions that lie almost exclusively to the right of zero.

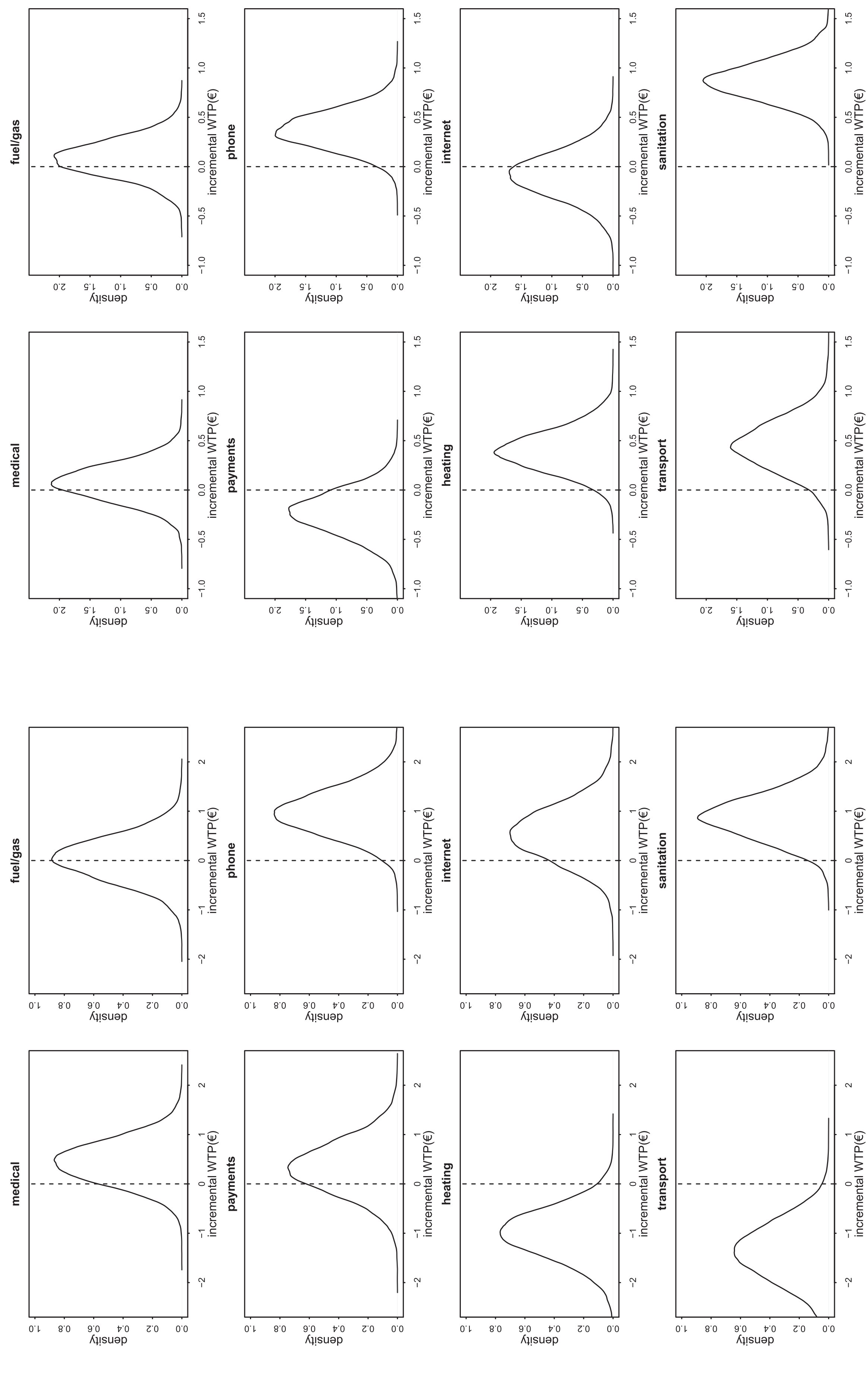
Thus, as the main result of our study, we conclude that there exist indeed separate IS effects within households' overall WTP to avoid a power outage. Furthermore, these effects are non-trivial in magnitude, with posterior expectations ranging from €0.3/h to close to €1/h. Recall that these figures are best interpreted as lower bounds given our data limitations. In order to put these estimates in perspective to overall WTP, we now proceed to our predictive welfare analysis.

3.3. Predicted WTP

We derive posterior predictive distributions for each scenario and country for the following three settings of IS indicators: (i) as

[14] We re-estimated our model for the two sub-samples associated with a given scenario ordering. While model coefficients change somewhat with the loss of 50% of our sample, the IS effects, which are the central focus of our analysis, remain qualitatively similar for both groups and compared to the full sample. That is, essentially the same ISs emerge as important for a given outage scenario in all three specifications.

[15] In contrast, transportation has a counter-intuitive significant negative effect on WTP for the 1 h winter outage. This is likely due to the fact that some respondents that believed transportation services would be affected for a longer interruption did not hold this concern for this short outage. As mentioned above, this would bias the corresponding coefficient downwards.



(a) Scenario 1 (total outage length = 1 hour)

(b) Scenario 2 (total outage length = 24 hours)

Fig. 1. Incremental hourly WTP, winter.

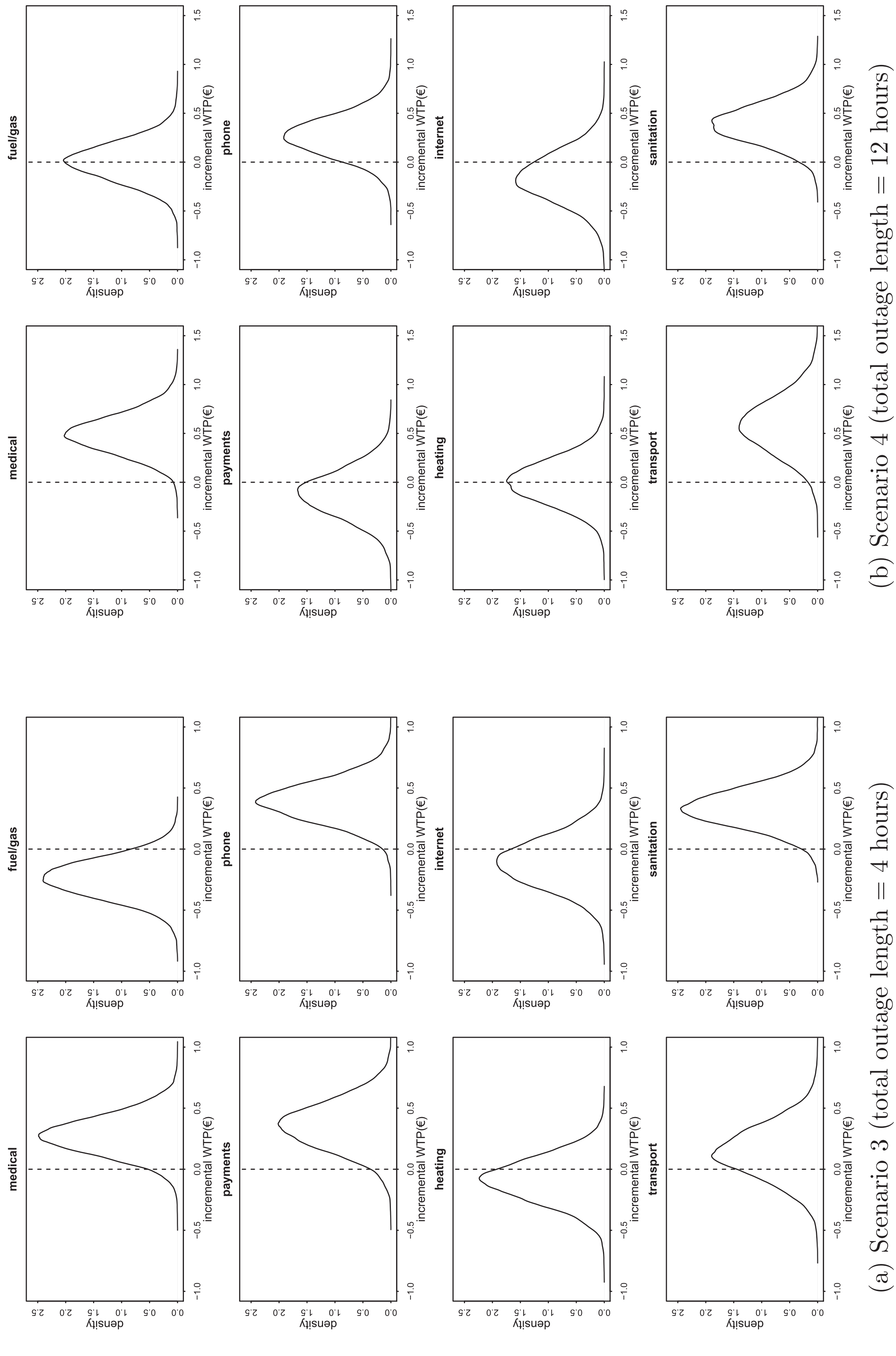


Fig. 2. Incremental hourly WTP, summer.

Table 7
Predicted hourly WTP.

Country	Winter, 1 h			Winter, 24 h			Summer, 4 h			Summer, 12 h		
	Mean	Std.	prob.>0	Mean	Std.	prob.>0	Mean	Std.	prob.>0	Mean	Std.	prob.>0
Actual beliefs												
Austria	2.425	0.567	1.000	1.948	0.241	1.000	0.402	0.209	0.970	1.087	0.257	1.000
Belgium	1.452	0.604	0.991	1.881	0.245	1.000	0.466	0.219	0.979	0.944	0.271	1.000
Denmark	4.243	0.635	1.000	2.894	0.279	1.000	0.858	0.217	1.000	1.934	0.267	1.000
Ireland	3.932	0.606	1.000	1.671	0.234	1.000	0.498	0.206	0.990	0.682	0.265	0.991
Luxembourg	2.986	0.604	1.000	3.116	0.274	1.000	0.783	0.222	0.999	2.075	0.273	1.000
Netherlands	2.115	0.567	1.000	1.547	0.233	1.000	0.175	0.217	0.794	0.589	0.273	0.981
Sweden	1.923	0.570	0.999	1.843	0.235	1.000	0.198	0.214	0.826	0.939	0.269	0.999
UK	1.554	0.565	0.995	1.571	0.235	1.000	0.326	0.214	0.934	0.263	0.283	0.829
All services affected												
Austria	3.140	0.645	1.000	2.664	0.278	1.000	0.765	0.231	0.999	1.610	0.281	1.000
Belgium	2.228	0.680	0.999	2.678	0.292	1.000	0.882	0.245	1.000	1.515	0.301	1.000
Denmark	4.931	0.721	1.000	3.580	0.321	1.000	1.188	0.237	1.000	2.423	0.296	1.000
Ireland	4.852	0.713	1.000	2.524	0.281	1.000	0.962	0.232	1.000	1.290	0.291	1.000
Luxembourg	3.665	0.680	1.000	3.850	0.318	1.000	1.217	0.243	1.000	2.662	0.299	1.000
Netherlands	2.786	0.642	1.000	2.233	0.269	1.000	0.486	0.237	0.977	1.050	0.293	1.000
Sweden	2.548	0.643	1.000	2.612	0.279	1.000	0.546	0.237	0.989	1.478	0.293	1.000
UK	2.300	0.635	1.000	2.329	0.271	1.000	0.693	0.230	0.998	0.748	0.296	0.988
No services affected												
Austria	2.311	0.866	0.996	0.729	0.366	0.977	−0.307	0.327	0.172	0.132	0.417	0.636
Belgium	1.399	0.855	0.949	0.743	0.351	0.982	−0.191	0.322	0.280	0.037	0.413	0.551
Denmark	4.101	0.909	1.000	1.645	0.377	1.000	0.116	0.334	0.641	0.945	0.421	0.985
Ireland	4.022	0.892	1.000	0.589	0.362	0.948	−0.111	0.324	0.374	−0.188	0.424	0.337
Luxembourg	2.835	0.857	0.999	1.915	0.363	1.000	0.145	0.322	0.678	1.183	0.414	0.997
Netherlands	1.956	0.856	0.988	0.298	0.360	0.798	−0.587	0.333	0.034	−0.428	0.433	0.158
Sweden	1.718	0.848	0.977	0.678	0.357	0.970	−0.527	0.325	0.050	0.000	0.422	0.516
UK	1.470	0.872	0.955	0.394	0.369	0.865	−0.380	0.337	0.122	−0.730	0.452	0.042
IS component	0.829	0.864	0.835	1.935	0.384	1.000	1.072	0.325	1.000	1.478	0.416	1.000

Mean = posterior mean, Std. = posterior standard deviation.
prob.(> 0) = share of posterior density to the right of zero.

observed in the actual sample ("actual"), (ii) all indicators set to one (counterfactual belief that all of the services are impacted, "all affected"), and all to set to zero (counterfactual belief that none of the services are impacted, "none affected"). The last metric thus produces benchmark estimates for WTP related exclusively to the loss of front-door electricity, net of (likely minor) savings due to non-use of appliances. In all three cases predicted WTP estimates are averaged over all individuals within a given country.

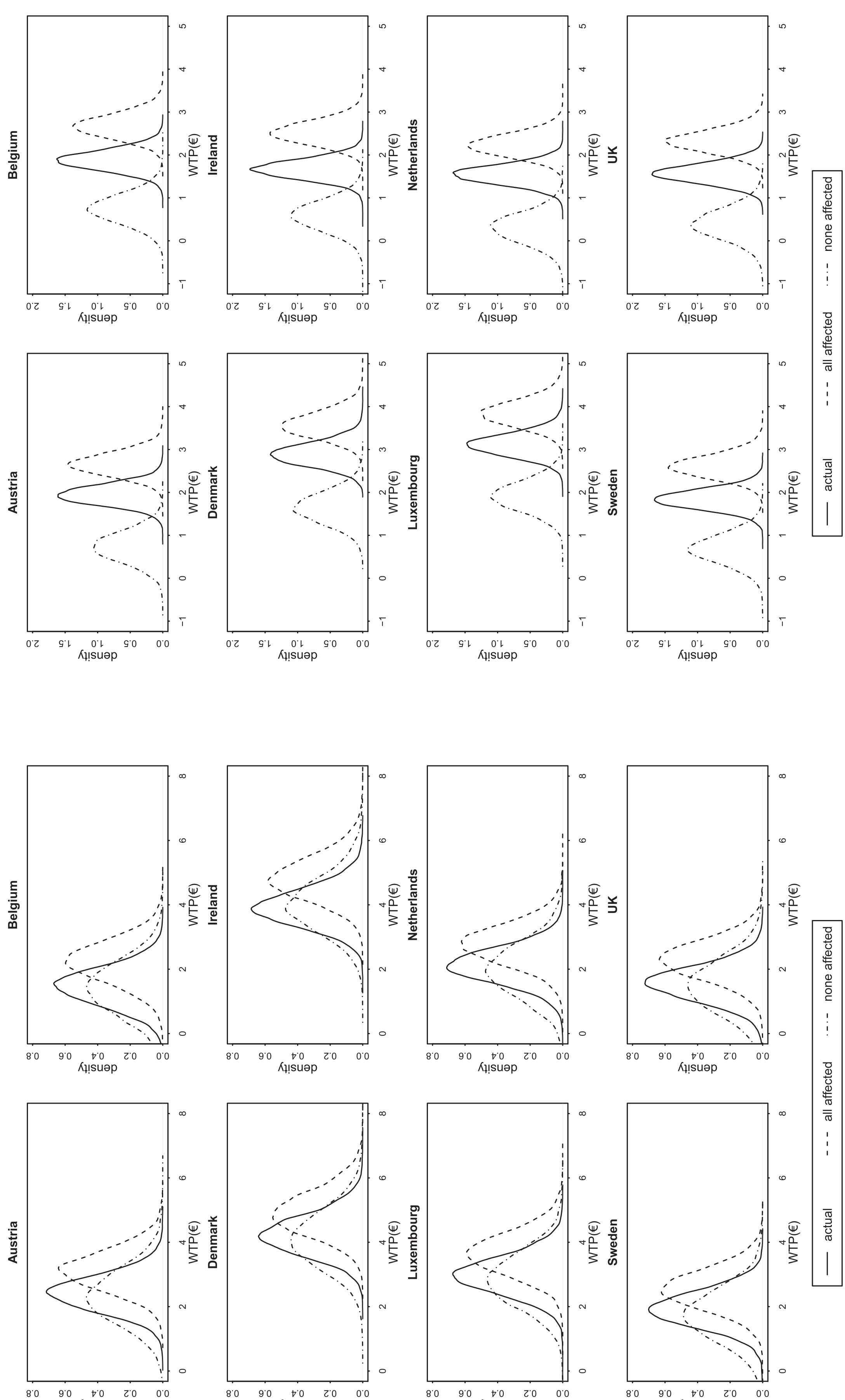
Numerical results are given in Table 7. The first block of rows shows within-sample predictions based on actually observed beliefs about IS impact. Thus, these estimates combine front-door and IS-related values, as one would obtain without explicitly distinguishing between the two components in the first place. As is evident from the table, average hourly WTP is clearly positive for all country-scenario combinations, and generally larger in winter than in summer. Interestingly, average hourly WTP is generally lower for the longer winter outage compared to the shorter winter scenario, but higher for the longer summer outage compared to the shorter summer interruption. This suggests decreasing marginal costs over duration in winter (perhaps due to gradual adaptation), and increasing marginal costs in summer (perhaps due increasing food losses due to spoilage). Overall, hourly WTP in winter lies in the €1.50– €4.2 range, compared to a range of €0.20– €2.1 for the summer.

The second block of rows shows posterior results for predicted WTP, with all IS indicators set to one. This leads to an unambiguous increase in values for all scenario-country combinations, with hourly estimates now lying in the €2.2– €5.0 range for winter, and in the €0.5– €2.7 range for summer. Conversely, WTP bare any IS effects, as captured in the last block of rows is markedly reduced compared to the within-sample, especially for the three outages lasting longer than 1 h. In fact, with few exceptions (Denmark, Luxembourg) WTP becomes statistically indistinguishable from zero for the two summer outages once we abstract from IS impacts.[16]

Figs. 3, for winter, and 4 for summer present a graphical representation of these posterior predictive distributions (PPDs). Each subplot shows the PPD of the within-sample ("actual") predictions, with the PPDs for "none affected" and "all affected" super-imposed for each case. As is evident from Fig. 3, there is considerable overlap of the three distributions for the 1-h interruption for all eight countries. This is not surprising, as IS impacts will likely be a relatively minor concern for such short interruptions for the typical resident. In contrast, the "none affected" and "all affected" densities are clearly pulled apart for the 24 h winter outage. The same holds for both summer interruptions (Fig. 4). Thus, our predictive analysis lends additional evidence to the fact that total WTP to avoid a residential outage includes a sizable, and potentially dominating IS component.

Reassuringly, our WTP estimate for the 1-h winter outage for Sweden for the "none affected" counterfactual (€1.72) lies within 30% of the estimate produced by Carlsson and Martinsson (2007) based on their Swedish 2004 data for a winter scenario of equal length, but occurring earlier in the evening (6 pm compared to 8 pm in our case). When converted to euros and adjusted for inflation their estimate

16 Our linear model leaves the support of predicted WTP unrestricted, which produces negative entries for several posterior means for the summer interruptions. We also estimated our model with latent WTP in log form to restrict predictions to the positive domain. However, with only three to four bids per scenario, the tails of the implicit log-normal distributions are poorly characterized. This leads to excessive posterior means for predicted WTP. We therefore opt to use the linear model for inference.



(a) Scenario 1 (total outage length = 1 hour)

(b) Scenario 2 (total outage length = 24 hours)

Fig. 3. Total hourly WTP by perceptions, winter.

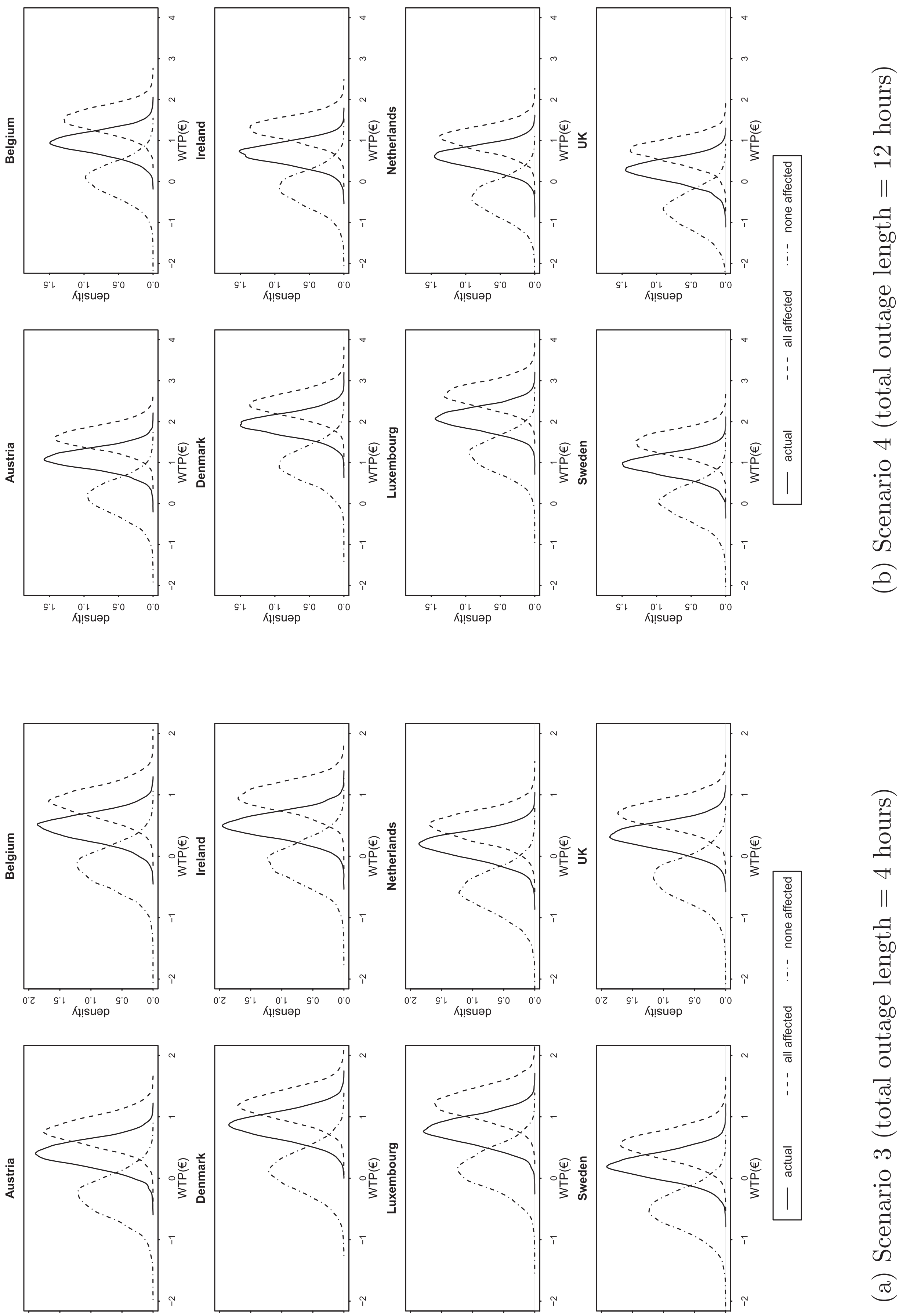


Fig. 4. Total hourly WTP by perceptions, summer.

Table 8
Share of WTP attributable to infrastructure services.

	Winter		Summer	
Service	1 h	24 h	4 h	12 h
Percent of total WTP				
Medical			65.9%	48.8%
Payments			83.8%	
Phone	38.4%	18.4%	91.2%	26.1%
Heating		19.5%		
Transport		22.1%		57.4%
Sanitation	34.9%	42.8%	79.6%	38.9%
Percent of within-HH WTP				
Phone	44.2%	50.8%		
Heating		57.1%		
Transport		66.3%		
Sanitation	39.1%	117.2%		

All entries are posterior means based on the full sample of 1807 households.
All entries are significant (have at least 90% of their posterior distribution >0).
Empty or missing cells reflect cases for which either incremental WTP for a given infrastructure service and/or within-HH baseline WTP are either negative or not significantly different from zero.

amounts to €2.42. In that study, the authors took great care to stress to respondents that payment of the proposed bid would only guard against front-door losses, so our "none affected" result is the appropriate measure stick for comparison. The residual gap between the two estimates is likely due to the difference in the stipulated time of onset for the interruption and potential shifts in preferences of power provision over the decade that separates their data from ours. Reichl et al. (2013) report an average hourly WTP of €1.9 across all of their outage scenarios for their 2009 sample of Austrian households, which varied in season and duration in similar fashion to our design. In their analysis, respondents were directly instructed to expect IS failures when making a payment decision. Thus, the most relevant measure for comparison are our hourly predictions from the "all affected" counterfactual, which, for Austria, range from €0.8 (summer, 4 h) to €3.1 (winter, 1 h), and thus bracket Reichl et al.'s aggregate result, as expected.

To gain a sense of the relative proportions of WTP related to front-door losses and values related to disrupted IS services we compute IS values as percentage of total WTP and as percentage of front-door WTP for all IS services that emerged as significant for a given scenario for the full sample of households. For the comparison relative to front-door WTP can only use winter scenarios since, as discussed above, the benchmark WTP for front-door effects is essentially zero for summer interruptions and the typical household.

The resulting percentages are captured in Table 8. In terms of overall hourly WTP, the share of IS-related values ranges from close to 20% to over 40% for winter interruptions, and from 26% to over 90% for our summer scenarios. If we use front-door losses as benchmark, WTP to secure IS services ranges from close to 40% to over 100% of the amount associated with front-door losses alone.

In summary, we conclude that IS-related values play an important role in outage cost estimation. This makes it crucially important to either explicitly abstract from them or explicitly include them in SP approaches to the valuation of the reliability of power provision. If IS effects are ignored, but considered by respondents during value elicitation, resulting WTP estimates will likely by substantially inflated if they are interpreted as pure values for front-door service.

4. Conclusion

This study shows how the essential-input property of electricity in the provision of household commodities can be exploited to dis-entangle welfare effects related to power delivered to the "front door" from values related to the disruption of vital infrastructure services. Specifically, we illustrate how the popular surplus model based on Random Utility Theory combines naturally with a household production framework with electricity playing the central role of an essential input. Using a survey-based identification strategy, we partition total WTP to avoid a specific power interruption into front-door and IS effects.

Though our welfare estimates for ISs can only be interpreted as lower bounds given the limitations of our empirical data, our findings provide strong evidence that a considerable portion of total WTP to avoid an outage relates to the loss of public services. We find our sample of households from eight EU nations to be especially sensitive to a disruption of medical, communication, transportation, and sanitation services. This stresses the importance of explicitly specifying the scale of outages and their expected impact on IS components in SP elicitation. Either a convincing statement needs to be made to respondents that stipulated outages are highly localized, leaving ISs unaffected, or survey participants should be prompted to think about IS impacts (or given information on potential IS effects) when confronted with interruption scenarios that cover a larger spatial scale. Failure to do so will produce welfare estimates that are unfit to inform policy.

From a public policy perspective, our findings are perhaps best interpreted as strong evidence that a widespread loss of power harms residential customers through more than just the interruption of front-door service. Protecting vital elements of the public infrastructure may be just as important, if not more so, than assuring adequate power flow to the neighborhood grid. From a EU standpoint our findings stress the importance of the planned expansion of the electric transmission network to improve inter-regional connectivity and grid reliability, since large-scale, IS-impacting outages are frequently caused by transmission failures (Buldyrev et al., 2010; European Commission, 2012; ENTSO-E, 2012). Taking our results as a first indication, the welfare gains from increased reliability of power provision due to a strengthening of the transmission grid could be potentially much larger than one would conclude from past valuation studies that only focused on front-door effects, especially in light of increasing threats to the grid due to climate change.

Our findings also raise concerns surrounding the use of normalized outage costs based on "WTP/kwh unserved" to facilitate inter-study comparison (e.g. Doane et al., 1988a; Doane et al., 1988b; Woo et al., 1991; Beenstock et al., 1998; Layton and Moeltner, 2005; Carlsson and Martinsson, 2007). For this common metric "unserved" refers to the front-door load that would have been normally consumed by the household in absence of a given interruption. However, in cases where the scale of a hypothetical interruption is left to the guess of the respondent, such WTP/kwh estimates will be misleading, since WTP may refer to much broader damages than those that could be fixed by leaving front-door service intact. Specifically, if WTP comprises IS components but WTP/kwh is meant to apply exclusively to front-door losses and consumption, the numerator and thus the entire fraction will be inflated. If WTP/kwh is meant to hold for all losses (front-door plus IS) the denominator would have to be computed as the sum of front-door consumption plus per-capita electricity consumption that would have fed into IS's for the metric to have any meaningful interpretation.

Naturally, our study is best thought of as a starting point for a more in-depth analysis of infrastructure values, using hypothetical scenarios on power outages and stated preference methods as identification vehicle. Our modest sample sizes and lack of hierarchical depth in our data layers preempts any examination of individual or even country-level heterogeneity in IS-related preferences. Furthermore, it would be desirable in subsequent research to ask the IS-perception question for each stipulated outage, perhaps with more detailed probing of how exactly loss-of-service would affect the household. A more surgical approach could also be taken by focusing exclusively on a single IS, for example public transportation, and assuring respondents that other ISs would remain unaffected. This could be further developed to allow for quality changes in service, instead of or in addition to the all-or-nothing condition implicit in our scenarios.

At a more general level, our study provides insights on the broader economic values at stake if the electricity sector is not protected against the increasing threats related to climate change. It also offers a glimpse into the direct values-at-risk related to other infrastructure services, thus adding to the "limited set of published studies" that have examined the potential impacts of climate change on public services using a quantitative approach (Arent et al., 2014). While adaptive measures will need to be taken to increase the resilience of all of these elements of the public infrastructure, the power grid clearly deserves special attention due to the essential input property of electricity.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eneco.2018.05.018.

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