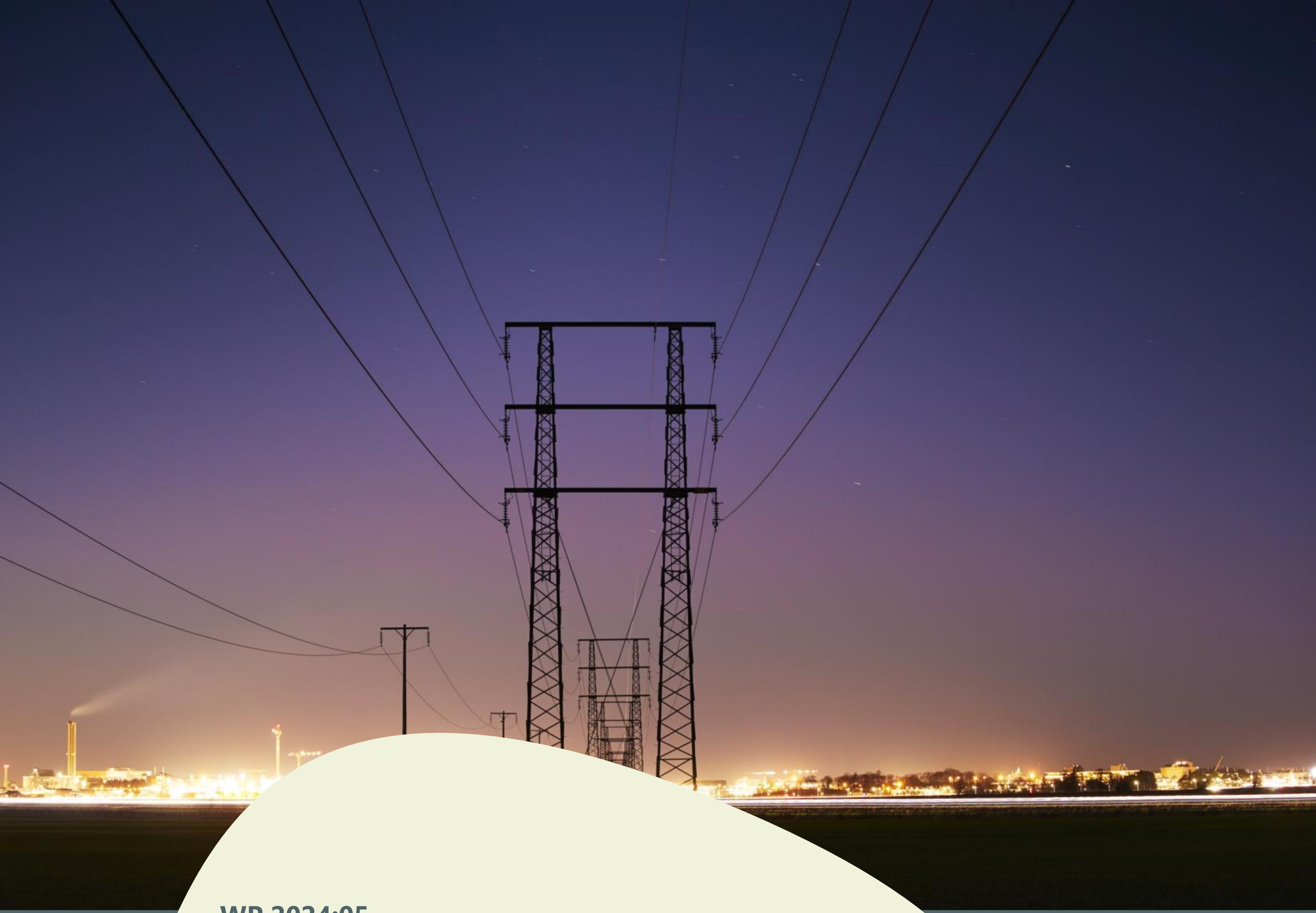

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The cost of electricity supply interruptions and value of lost load in Swedish electricity intensive industrial plants

Growth analysis
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The mission of Tillväxtanalys (the Swedish Agency for Growth Policy Analysis) is to evaluate and analyze the effects of government initiatives on sustainable national and regional growth. We also aim to provide input and recommenddations for the development, reassessment, and improvement of policies.

This study highlights the significant economic consequences of power outages for Sweden’s electricity-intensive industries and underscores the shortcomings of traditional metrics, such as value-added-based methods, in reliably estimating these costs. The study is part of Tillväxtanalys’s project "Economic Effects of Electricity-Intensive Industries" (ELIN), which aims to explore if and how the government can act to shift the economy toward a greater or lesser reliance on electricity-intensive activities.

The study was authored by Professor Tommy Lundgren of the Swedish University of Agricultural Sciences (SLU), Associate Professor Lars Persson, and Professor Emeritus Runar Brännlund, both from Umeå University. The authors are affiliated with the Centre for Environmental & Resource Economics in Umeå (CERE). The project leader was Simon Falck.

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Sverker Härd
Director General, Tillväxtanalys

Contents

Summary

The Value of Lost Load: A key metric for assessing economic impacts

The Value of Lost Load (VoLL) serves as a vital metric for assessing the economic consequences of electricity supply interruptions, particularly for electricity-intensive industries. VoLL quantifies the monetary cost of unsupplied energy (e.g., SEK/kWh or SEK/MWh), and helps assess the impact of outage across sectors and regions. While the concept is straightforward, accurately estimating VoLL remains a significant challenge.

Interruptions in electricity supply impose substantial financial burdens on industries, causing productivity losses, equipment damage, and operational delays. Policymakers, utility companies, and regulators rely on VoLL to guide infrastructure investments aimed at improving grid reliability and mitigating the effects of outages. By aligning reliability improvements with economic trade-offs, reliable estimates of VoLL can facilitate better resource allocation.

Challenges in Sweden's energy landscape

In Sweden, the rising electricity demand driven by industrial electrification and transportation, coupled with increasing reliance on non-schedulable generation sources, integration with European electricity markets, and higher electricity prices, has intensified concerns about supply security. Against this backdrop, uninterrupted electricity access is critical for operations, particularly for electricity-intensive sectors.

Survey approach and data Integration

This analysis is based on a survey targeting the 1,000 largest electricity-consuming plants in Sweden, as defined by the ISEN group managed by Statistics Sweden. Key details of the study include:

- Survey scope: A questionnaire was sent to the targeted plants, receiving 359 responses after two reminder rounds.
- Focus areas: The survey addressed power outages, their associated costs, and broader consequences.
- Data integration: Survey responses were combined with plant-level production data from Statistics Sweden, to enable comparisons and robust analysis.

Insights on economic impacts

The study reveals that traditional metrics, such as value-added (VA) or production function approach, underestimate the economic impact of power outages.

- Underestimated costs (value per hour)
  - ✓ Average lost VA per hour: 68,000 SEK (based on reported data).
  - ✓ Stated cost per hour: 968,000 SEK (as reported by industries in the survey).
- VoLL discrepancies (value per kWh)
  - ✓ VoLL derived from VA: 26 SEK/kWh.
  - ✓ VoLL based on stated costs: 1,500 SEK/kWh for an average outage, 221 SEK/kWh for a one-hour interruption.

These findings emphasize the importance of incorporating stated cost data into VoLL estimations to more accurately reflect the financial burdens on industries.

Impact of outage duration and severity

The economic impact of power outages depends significantly on their length.

- High fixed costs for shorter outages:
  - ✓ Short interruptions are disproportionately costly due to immediate production losses, equipment impairment, and response efforts.
  - ✓ Marginal costs decline as the duration increases, spreading fixed costs over time.
- Longer-terms effects:
  - ✓ Restarting production and repairing equipment after prolonged outage can take months.
  - ✓ Many businesses report lingering effects of even a one-hour outage, with some unable to fully recover even a year later.

Electricity use patterns and industry vulnerabilities

The costs of power interruptions are more closely linked to electricity consumption than to the type of industry.

- Consumption as the key factor:
  - ✓ High electricity consumption strongly correlates with higher outage costs, regardless of sector (in this case forestry, steel, chemical, or mining).
- Continuous operations and vulnerability:
  - ✓ Plants with 24/7 production schedules report higher costs due to their reliance on uninterrupted energy supply.
  - ✓ However, the marginal effect of additional production hours on costs diminishes as total hours increase.
- Comparison with broader sectors:
  - ✓ Swedish energy-intensive plants report lower VoLL estimates than other sectors, that could suggest unique coping mechanisms and/or adeptness.

Reflections on the study’s assumptions and approach

This study employs a comprehensive approach, integrating survey responses with detailed production data. Key considerations can be summarized as follows.

- Strengths:
  - ✓ The combined dataset enables a nuanced understanding of outage costs for electricity-intensive industries.
- Limitations:
  - ✓ Findings are specific to the surveyed group and may not generalize to less electricity-intensive industries.
  - ✓ Traditional VA metrics can potentially underestimate costs, underscoring the need for stated cost data to improve accuracy.

Key insights and future directions

This study underscores the significant economic impacts of power outages on Sweden’s electricity-intensive industries and the limitations of traditional metrics like the VA approach in capturing these costs. By integrating stated cost data and refining analytical tools, stakeholders can develop more effective resilience strategies, and make better-informed decisions about balancing reliability improvements with economic trade-offs.

Expanding research to include less electricity-intensive industries and regional contexts will further enhance understanding and guide policies to foster a more reliable and sustainable electricity system.

1. Introduction and background

The value of lost load (VoLL) is a key metric for understanding the economic impact of electricity supply interruptions, which is particular important for electricity-intensive sectors and industries. In the economics context, VoLL is a monetary measure reflecting the cost associated with an interruption in electricity supply. Importantly, the measure of cost is defined in terms of energy – typically kWh or MWh. A complementary view of VoLL is the monetary "value" of energy not supplied. VoLL is used to assess the economic impact of power supply interruptions across sectors and customer types in economies (countries, regions, etc.). Although well-defined in theory, the main challenge with VoLL is accurately measuring or estimating its cost component.. VoLL is also essential for policymakers, utility companies, and regulators. It helps plan infrastructure investments to enhance electricity reliability and reduce the effects of power interruptions (Sullivan et al., 2009). By understanding VoLL, stakeholders can make better-informed decisions about the trade-offs between reliability improvements and the economic costs of outages. From a societal perspective, there are potential efficiency gains from considering the so called equimarginal principle. In this context, this means allocating the marginal unit of electricity so that its benefits are distributed equally across plants. Of course, this is likely an over-simplification of any real-world power outage scenario, but still a social welfare reference point. More about this below.

Industries are especially sensitive to power interruptions due to their reliance on continuous electricity delivery for production, machinery operation.[1] Disruptions can cause significant financial losses, reduced productivity, and even damage to equipment (Sullivan et al., 2015). As electricity demand in Sweden rises—driven by the electrification of core industries and transport—there is an increasing need to address the risk of delivery disruptions. Changes in the composition of electricity generation towards non-schedulable sources, combined with the Europeanization of electricity markets and rising electricity prices, have further intensified concerns about security of supply (CEER, 2010). The primary focus of the current report is however not on the realized number of outages as such, but rather on the cost of a given outage.[2]

VoLL plays a crucial role in optimizing investment decisions for grid reliability. Accurate VoLL estimates provide a benchmark for comparing infrastructure investment costs with the economic benefits of avoiding outages. For example, industrial areas with high VoLL may justify more investments that are robust in

[1] Focus in this report is power interruptions including blackouts. Industries are also sensitive to variations in voltage and frequency (see e.g., Ekström and Brännlund (2022), this is however not within the scope of the current report.

[2] This means that common measures like SAIDI (System Average Interruption Duration Index) and SAIFI (System Average Interruption Frequency Index) are not covered in this report.

reliability compared to residential areas, where VoLL tends to be lower (Sullivan et al., 2009). By quantifying the cost of outages, VoLL enables planners to prioritize grid upgrades, maintenance, and generation capacity that yield the highest net benefits. Furthermore, VoLL estimates inform dynamic pricing strategies and demand response programs, which incentivize consumers to adjust their electricity use during peak times, reducing the need for costly peak generation capacity (Woo et al., 1992, 2011).

In Europe, methodologies for estimating VoLL vary by country, reflecting differences in economic conditions, industrial structures, and reliability standards. Some countries rely on customer surveys to estimate VoLL, while others use indirect methods, such as analyzing outage costs and historical data (CEER, 2010). The Nordic region, including Sweden, Norway, Finland, and Denmark, emphasizes VoLL in regulatory frameworks due to the critical importance of electricity reliability in their cold climates. Power outages during long winters can have severe consequences for both the economy and public safety, making reliable electricity supply essential (CEER, 2010).

In Sweden, the application of VoLL is central to both regulatory practices and market operations. The Swedish Energy Markets Inspectorate (EI) uses VoLL to establish standards for acceptable reliability levels and to design compensation schemes for customers affected by outages. Sweden’s energy policy focuses on maintaining high reliability while transitioning to renewable energy sources. The cost of power interruptions is particularly high in electricity-intensive industries like pulp, paper, and metal manufacturing, sectors that are vital to Sweden’s economy. Reliable electricity supply is critical to maintaining their productivity and competitiveness on the global stage (Energiforsk, 2021).

Several methodologies are used to estimate VoLL, including customer surveys, historical outage data analysis, and simulation models. The Council of European Energy Regulators (CEER) highlights the importance of a consistent methodology across Europe for assessing the economic impact of power outages, ensuring a harmonized approach to reliability and infrastructure investment (CEER, 2010). Different regions use VoLL estimates to guide decisions about investment in reliability and the design of performance-based regulation schemes, where utilities are rewarded or penalized based on their performance. These case studies emphasize the need for tailored VoLL estimates that reflect the unique economic conditions and reliability requirements of different sectors (Newell et al., 2014). For recent reviews of the value of lost load and a discussion of different metrics and related issues, see Schröder and Kuckshinrichs (2015), Gorman (2022), and Lebepe and Mathaba (2024).

VoLL estimates can also optimize decisions around reserve margins and grid capacity. For example, a study in ERCOT (Electric Reliability Council of Texas) demonstrated that using VoLL to optimize the reserve margin led to significant cost savings and improved reliability (Newell et al., 2014). Similarly, countries like Germany and the United Kingdom have implemented performance-based regulatory frameworks that reward utilities for achieving high reliability standards or penalize them for failing to meet these standards (CEER, 2010).

The Nordic electricity market is also a solid example of the use of VoLL in market design. The system operator, Nord Pool, uses VoLL to set scarcity prices during periods of high demand or supply shortages. These prices reflect the cost of outages, encouraging sufficient investment in generation and grid capacity. The industrial sector in the Nordic countries, including Sweden, is particularly sensitive to power interruptions due to the high electricity use in industries such as pulp and paper, metallurgy, and chemicals. The cost of power interruptions in these sectors is high, highlighting the critical importance of continuous power supply (CEER, 2010).

In Sweden, the estimation of VoLL is critical for both policy and industry. A report by Energiforsk (2021) reveals that VoLL in Swedish industry is particularly high for sectors like pulp, paper, and steel manufacturing. This highlighting the critical need for a reliable electricity supply to sustain industrial productivity. The report also notes that the increasing integration of renewable energy sources into the grid, combined with rising electricity demand, presents challenges for maintaining high levels of reliability. In light of these challenges, it is crucial for policymakers and industry leaders to understand and manage the economic impact of power outages through accurate VoLL estimates.

To sum up, studying VoLL is essential for improving electricity reliability, guiding infrastructure investments, and shaping regulatory policies. Accurate VoLL estimates allow stakeholders to make informed decisions that balance the costs of reliability improvements with the benefits of avoiding power interruptions. As the energy landscape evolves, with increasing integration of renewables and smart grid technologies, VoLL will continue to play a critical role in ensuring a resilient and efficient power system.

This study examines the costs and consequences of delivery disruptions and outages for electricity-intensive industries in Sweden. Using a targeted survey of major electricity users, it collects data on production losses, recovery capabilities, flexibility options, backup systems, and investments in on-site electricity generation. The findings are compared with microeconomic data to provide a comprehensive understanding of the extent and causes of outage-related costs. By combining quantitative consumption/use data with qualitative insights from plants, the study aims to illuminate the actual impact of outages on industrial operations.

Some of the most noteworthy findings of the analysis are:

- Traditional metrics based on reported value added (VA) significantly underestimate the financial impact of power outages, suggesting that relying solely on VA to evaluate outage costs fails to capture the true economic burden, especially on electricity-intensive industries. This indicates a substantial discrepancy between theoretical calculations and real-world impacts, underscoring the need to consider stated cost data in VoLL estimations.
- The duration of an outage significantly affects its cost, with shorter outages proving disproportionately expensive, reflecting high fixed costs associated with initial disruptions. However, the marginal cost decreases as the outage lengthens.
- Specific industry type does not notably impact the cost of power interruptions; instead, the amount of electricity consumed by a plant is a more critical determinant. Furthermore, industries operating 24/7 incur higher costs, although the marginal effect diminishes as production hours increase.
- Production losses often extend well beyond the outage duration, with many plants facing prolonged disruptions due to the complexities of restarting processes and/or repairing machinery damage. A significant number of businesses report not fully recovering from the losses caused by a one-hour outage even after 12 months, highlighting the extended impact of power interruptions.

The report is structured as follows. Section 2 presents a conceptual approach to the costs of power interruptions (outages) and an overview of current estimates together with methodological approaches in the literature. In section 3, focus turns to the survey approach and the questionnaire feeding the analysis with data. In this section, general descriptive results are also reported. In section 4, results from the questionnaire and micro-level data are presented and analyzed based on relevant metrics, the conceptual section and previous studies. Section 5 presents and reports a regression approach to analyze factors that effects the cost of electricity interruptions (outages). Finally, section 6 summarizes the main findings, implications, and outlines future research.

2. VoLL and current estimates

2.1 Understanding VoLL: A production theory perspective

To accurately assess the cost of power outages, it is essential to define what is being measured and how. The primary focus is on the cost of supply disruptions and electricity outages in terms of lost profits for firms due to interruptions in production activities. In general, the cost will vary across consumers and firms, depending on factors like: (1) substitution options (among inputs and across time); (2) the interruption's duration; (3) timing (season, day of the week, time of day); (4) impacts on stored inputs/outputs; (5) precautionary measures (backup); and (6) the prices of produced goods.

Broberg et al. (2021) conceptually outline how interruption costs can be measured and calculated, based on assumptions about substitution options and input flexibility. Flexibility here means that e.g., labor can still be productive during outage (maintenance, for example) or materials can be stored and used later. They show that different assumptions about input flexibility can lead to significantly different outage cost estimate, and provide benchmarks for empirical estimations using available firm level data on production revenues and input costs. Note that several factors affecting outage costs, such as time of day, season, and duration, are not explicitly accounted for in their model.

The outset is a firm that produces a product or a line of products. The firm uses the variable inputs electricity, labor, material, and capital (fixed in the short-run). Output and input markets are competitive.

Assume that a power outage occurs and electricity supply drops to zero, what happens?

- The difference in profit from before the outage will depend on the production technology, which decides to what extent the use of labor and material adjusts as a response to the outage.
- In general, the change in profit resulting from an outage equals the change in revenue plus the change in variable cost.
- The magnitude of the loss clearly depends on technology (substitutability) and the flexibility of labor and material inputs. If labor and material can easily substitute electricity, meaning electricity is non-essential, and both inputs are flexible, the loss is relatively small. Conversely, if labor and material cannot replace electricity or are poor substitutes, and both inputs are inflexible, the loss will be significantly higher.

It can then be shown that the **lower limit** on the lost value, when labor and materials are flexible[3] but electricity is a necessity, equals the variable **profit** before the outage (revenue minus variable cost).

An **upper limit** of the loss is when production ceases completely because of the outage (again, assuming electricity is a necessary input), the labor force becomes completely unproductive, and material cannot be stored. We can then conclude the following:

- The value lost as a result of the outage, given that labor (and capital) cannot be adjusted, and that material potentially get spoiled equals the **value added** (profits plus labor) **plus the value of spoiled material**.
- If material that is not used during the outage have an alternative value, e.g., in another point in time through storage, the economic value lost due to a outage equals the loss in the **value added** by the firm.

In most empirical studies using the production function approach (e.g., de Nooij et al., 2007; Leahy and Tol, 2011; Broberg et al., 2021), estimations assume electricity is essential, labor input is fixed, and material input is fully flexible over time. While valid for some industries, these assumptions do not apply universally. In addition, earlier studies implicitly assume that firms decide input levels (electricity, labor, materials) without considering the uncertainty of outages.

However, uncertainty about outages may alter how firms manage inputs. Tishler (1993) suggests a firm maximizes profit by choosing electricity and labor based on its belief about electricity reliability. If an outage is certain, losses align with profit loss. If uncertain, decisions on labor and electricity usage will consider the likelihood and duration of an outage, making the expected outage cost dependent on these probabilities.

Another way to quantify loss is through the cost of hedging against outages. The hedge cost or foregone profit depends on optimal electricity use, perceived outage risk, and risk preferences, similar to the concept of certainty equivalence, where a firm is willing to pay to eliminate the risk of an outage (like an insurance premium). We refer to the Appendix for a brief portrayal of the certainty equivalence concept, its relation to VoLL, and the willingness to accept to be insured against supply interruptions. This conceptual approach would be an appropriate framework or tool when thinking about backup investments and how the probability of power interruptions will affect the willingness to pay for insuring against them.

[3] When labor can have alternative use and materials can be stored.

2.2 Sectoral effects of power interruptions

In this study, we focus on electricity intensive industry and take a closer look at the industrial sectors forest, chemical, mining and steel/metal (the so called SKGS cluster, www.skgs.se). Power interruptions can significantly impact various sectors, each with unique technologies and operational characteristics (see e.g., Lebepe and Mathaba, 2024; Douglas and Fung, 2022).

Forest Industry: This sector utilizes both mechanical and chemical processes. Interruptions can cause production delays, lead to material damage and quality issues, and complicate the process of restarting machinery, which requires time and recalibration.

Chemical Industry: Relying on continuous processes that are sensitive to temperature and pressure, the chemical industry faces particular challenges. Safety risks are a major concern with abrupt power loss potentially leading to unsafe process fluctuations. Additionally, such interruptions can render chemical batches unusable if specific conditions are not maintained, and restarting processes can stress system integrity.

Mining Industry: Mining operations depend heavily on electrically powered machinery for drilling, blasting, and material handling. Power losses can halt essential operations such as ventilation and pumping, introducing severe safety hazards, especially in underground environments. Equipment may also be strained, implying maintenance issues and potential failures.

Basic iron and steel industry: Involving high-energy processes like melting, casting, and rolling, the steel industry requires a continuous and stable power supply. Interruptions can freeze production lines, especially during continuous casting, leading to high energy losses and increased operational costs. Processes halted midway may also result in significant material waste and increased scrap rates.

Across these industries, interruptions generally lead to direct production losses, economic strain from increased operational costs, and potential penalties for supply delays. Safety and environmental risks also rise due to abrupt shutdowns and startups, potentially leading to non-compliance with environmental regulations. Recovery from such interruptions often involves complex and costly restart procedures, especially in industries with intricate machinery and processes.

2.3 Literature and current estimates of VoLL

The literature in the field can be divided into basically two areas. One focuses on the methodological aspects of VoLL, while the other focuses on obtaining the actual values of VoLL. Importantly, most of the literature has an economy-wide approach covering individual households, the public sector, agriculture, small- and medium sized enterprises, large industries, etc. In the present report, the focus is solely on the Swedish electricity intensive plants. For the literature review, primary focus is on the industry, and if possible, the energy (or electricity) intensive sectors. In the case of duration specific VoLL estimates, these are reported separately in the table below.

In the first strand of literature we find, for example, the Council of European Energy Regulator's (CEER) report.[4] This is a hands-on document with recommendations and guidelines for national energy regulatory authorities to be applied on cost-estimation studies regarding interruptions and voltage disturbances. Although they cover all types of customers and the society, methodological recommendations are well in line with the approaches taken in this study. For the industry, CEER recommends the *direct worth method* where customers are asked to estimate their expenses due to hypothetical interruptions. They also recommend the *preventative cost method* measuring customers expenditures to prevent or counteract the consequences of interruptions. For example, our direct cost questions for hypothetical interruptions, as well as investments and backup capacity fits very well to their recommendations.

In the US context, Sullivan, et al. (2018) give guidance on the estimation of power system interruption costs. Also here, the population of interest is the society as a whole, and not in particular electricity intensive industries. For the methodological aspects, the scope matters and in general survey-based approaches are preferred. Once again, our study is well in line with the methodological recommendations. For large companies and industries, they emphasize asking personnel who are familiar with the facility, operations and cost structure. Given our ISEN population[5] with experienced respondents at each plant, our approach seems reasonable. Sullivan, et al. (2018) put forward the *direct cost method* for commercial and industrial customers. The method is based on asking questions about specific costs incurred and savings realized for a set of hypothetical power interruption scenarios – then summing them over all customers for the total cost. In principle, the direct cost is a function of the value of lost production (VLP), interruption-related costs (IRC), and interruption-related savings (IRS).[6] The VLP is summarized as a business' net loss in economic value - accounting for the ability to catch up on lost production. Examples of the IRC could be damage to equipment, labor to make up on lost production and

[4] Guidelines of Good Practice on Estimation of Costs due to Electricity Interruptions and Voltage Disturbances. Ref: C10-EQS-41-03. 7 December 2010. Council of European Energy Regulators. The report is based on (see executive summary) Hofmann, M., Seljeseth, H., Volden, G. H., & Kjølle, G. H. (2010). Study on Estimation of Costs due to Electricity interruptions and Voltage Disturbances. *SINTEF Energy Rearch*.

[5] ISEN is the Swedish survey of energy use in manufacturing industry: https://www.scb.se/en/finding-statistics/statistics-by-subject-area/energy/energy-supply-and-use/energy-use-in-manufacturing-industry/

[6] See section 3.1.1 in Sullivan 2018 for a more detailed description.

restarting processes, material for restarting, damage to input, re-processing, cost for operating backup generation. Lastly, examples of IRS could be unused input, raw materials, unused fuel, unpaid wages, etc. They also emphasize that although savings from outages are small in general, for enterprises where energy and feedstock costs are relatively high savings can be significant. Our approach and set of questions largely cover and allows for these aspects and VoLL components.

There are other recent reports, predominantly in the US context, like Brattle Group (2024), Midcontinent Independent System Operator (2024) and Sergici et al. (2023). These reports mainly contain further literature reviews on VoLL and updated estimates or summaries of existing estimates. See also Peter (2019) for a review of methodological aspects regarding VoLL in European electricity markets.

In the Norwegian context, Kjölle, et al. 2008 conducted a customer survey in 2001-2003 on consumer valuations of interruptions where they combined direct worth (DW) and willingness to pay approaches (WTP). For the DW approach, interruption scenarios were described, and respondents stated their expected costs for the respective interruption. In the WTP approach, respondents were instead asked about their WTP to avoid the respective interruption. Overall, the DW approach gave significantly larger cost estimates. For large industries, the DW approach gave costs of 23.8, 20.7 and 7.4 NOK/kWh for 1hr, 4hrs and 24hrs duration respectively. For the WTP approach, the corresponding costs were instead 9.8, 10.2 and 4.1 NOK/kWh for the respective duration. In the table below with estimates, their reported average VoLL is however presented.

In Table 1 below, we present some of the findings in the literature regarding VoLL, with a particular focus on the industry (or similar) when possible. There are more publications and reports estimating VoLL, but this is a selection of common references and over countries. If applicable, results are presented for duration specific VoLL estimates.

Table 1 VoLL estimates in the previous literature.

Country	Sector(s), year of data, etc.	Author & year	Duration	VoLL (per kWh)	VoLL (per kWh) in SEK[7]
Italy	Business. 2003	CEER 2010		€21.6	251
Portugal	Manufacturing	Castro et al 2016		€1.28	15
Portugal	Non-domestic	Castro et al 2016		€4,2	49
Norway	Industry	Kjölle et al 2008	1 hr	NOK14.4	14
			4 hrs	NOK10.8	10
			24 hrs	NOK8.8	9

[7] VoLL in SEK is calculated based on the following exchange rates: SEK/€=11.63, SEK/£=13.68, SEK/NOK=0.97 and SEK/$=10.67.

Country	Sector(s), year of data, etc.	Author & year	Duration	VoLL (per kWh)	VoLL (per kWh) in SEK[7]
Great Britain	Industrial & Commercial	London Economics 2013		£1.654	23
Italy	Business, Stated direct cost	Bertazzi et al 2005	1 hr	€118	1372
			2 hrs	€83	965
			4 hrs	€67	779
			8 hrs	€40	465
Italy	Business, (WTP+WTA)/2	Bertazzi et al 2005	1 hr	€45	523
			2 hrs	€32	372
			4 hrs	€28	326
			8 hrs	€16	186
	Non-domestic	Bliem 2009, (London Economics 2013)		£41	561
United states	Non-domestic	Sullivan et al 2009 (London Economics 2013)		£225	3078
	Non-domestic	CRA 2007 (London Economics 2013)		£63.14	864
United States, Meta study	Industrial & Commercial, >50MWh	Sullivan et al 2015	Momentary	$190.7	2035
			30min	$37.4	399
			1 hr	$21.8	233
			4 hrs	$12.1	129
			8 hrs	12.9	138
			16 hrs	12.7	136
United States, Meta study	Industrial & Commercial, >50MWh	Sullivan et al 2009	Momentary	$173.1	1847
			30min	$38.5	411
			1 hr	$25	267
			4 hrs	$18.2	194
			8 hrs	$14.4	154
Netherlands	Small and medium sized enterpr.	Report 2022		€20	233
Netherlands	Large-scale enterpr., Energy intensive	Report 2022		€62	721
Netherlands	Large-scale enterpr., Non-energy intensive	Report 2022		€73	849

Country	Sector(s), year of data, etc.	Author & year	Duration	VoLL (per kWh)	VoLL (per kWh) in SEK[7]
Ireland	Industry. 2007.	Leahy and Tol 2011		€4	47
	Industry. 2008.	Leahy and Tol 2011	1 hr	€7	81
Spain	Manufacturing	Linares and Rey 2013		€1.38	16
Sweden	Industry	Broberg et al 2021		SEK68.8	69
Sweden	Industry	Carlsson et al 2019		SEK160	160
Netherlands	Manufacturing. 2001.	De Nooij et al 2007		€1.87	22

To summarize, the current literature on VoLL is rather extensive but has not focused on the electricity intensive industry in particular. The reported estimates of VoLL vary substantially across countries and studies without any clear spatial trends or patterns. Over duration-specific VoLL, however, previous studies indicate a decreasing pattern in VoLL with duration. Overall, our conclusions from the literature are that methodological aspects matter and that VoLL reduces with electricity (energy) use. From the definition of VoLL, this is expected.

3. Data collection and the questionnaire

The main purpose with the survey approach was to gather detailed, both quantitative and qualitative, information related to electricity interruption costs and consequences in the Swedish electricity intensive industries. Much of the focus were on the link between electricity interruptions and the implications for production (processes), time to recover, etc. Other areas of great interest were experiences and expectations of interruptions, reliability, backup investment and capacity, and own electricity production. In close collaboration with Statistics Sweden, the questionnaire targeted major electricity consumers in the energy intensive industries through the so-called ISEN call.[8] Specifically, the population was the 1,000 plants with the highest electricity use and who had responded to the ISEN call in 2022. The questionnaire consisted of 33 main questions, with additional sub- and follow-up questions. The design of questions was based on a previous (pilot) study implemented in Broberg et al. (2021), and other similar surveys (including recommendations) like Sullivan, et al. (2018). The individual responses (plants) from the survey were matched with the plant-level microeconomic data obtained from Tillväxtanalys for parts of the analysis.

The survey was sent out to the population of 1,000 plants (see above) in November 2023 and responses were collected until January 2024 with three waves, one main- and two reminder waves. In total, 359 plants responded to the questionnaire. Statistics Sweden reported that no systematic patterns could be found based on number of employees or SNI-categories in their drop-out analysis.

The results sections report and analyze responses relevant to the main objective of this study. Nevertheless, it is important to characterize and illustrate the sample. The level of aggregation is plant (WP) and not firm or company. This does not, however, rule out a plant to also correspond to a single firm/company (when a firm has only one plant). The number of such cases is not known or analyzed.

In general, results are presented as totals for the full sample, for the sectors, and over electricity use with plants grouped in four quantiles. Plants are divided into different sectors based on the 3-digit SNI2007 classification. Most results, including tables, are based on the four main industrial sectors, namely “Forest” (Pulp&Paper and Wood), “Chemical” (Chemical), “MiningStone” (Mining and Stone&Mineral), “Basic IS” (Basic iron and steel), and “Other” (the rest). This grouping is based on the traditional Swedish core industries and that they are

[8] ISEN includes industrial energy use broken down by energy carriers and sectors. See https://www.scb.se/en/finding-statistics/statistics-by-subject-area/energy/energy-supply-and-use/energy-use-in-manufacturing-industry/

relatively energy intensive. The Swedish core or basic industry are traditionally grouped under SKGS (Skogen, Kemin, Gruvor och Stål), www.skgs.org. For the quartiles, plants are sorted according to reported electricity use and then in four equal sized groups.

In our sample, most plants (208) are not within the Swedish core sectors (SKGS). For the core sectors, Forest is the largest group with 69 plants, followed by 31 in Basic IS and Chemical, and 20 in MiningStone. Basic IS and MiningStone have the largest plants with a maximum of 2,279 and 1,796 employees, respectively. The median number of employees in the four sectors ranges from 53 in MiningStone to 128 in Forest.

Table 2 Annual electricity use, MWh, over sectors and quartiles.

	N	Mean	Median	Min	Max
Forest	69	140 598	15 870	2 818	1 652 552
Chemical	31	59 361	8 234	2 913	751 793
MiningStone	20	128 997	8 307	2 746	1 079 324
Basic IS	31	138 140	31 912	3 052	1 832 334
Other	208	11 686	5 995	2 703	256 420
Q1	90	3 434	3 410	2 703	4 297
Q2	90	5 656	5 641	4 319	7 444
Q3	90	11 300	10 445	7 577	19 846
Q4	89	213 476	60 852	19 853	1 832 334
Total sample	359	58 035	7 444	2 703	1 832 334

Concerning electricity use, Table 2 shows that the Swedish heavy and energy intensive industry, usually represented by the so called SKGS cluster (Forest, Chemical, MiningStone, Basic IS), use far more electricity than plants in other industrial sectors (other). Furthermore, Table 2 reveals that within the SKGS cluster plants in the Forest, MiningStone and Basic IS on average use considerably more electricity than Chemical. Table 2 also shows that there is a large difference between the mean and the median, especially for SKGS sectors, with very large values at the right end of the distribution. In other words, a few plants use a lot of electricity. Notably, the Chemical sector has the by far the lowest mean electricity use, and also a low median plant size. Looking at the min/max, Chemical has a somewhat less extreme distribution of plants. Moreover, although the “Other” has a significant number of plants, its share of total electricity use is low.

For the quantiles, Q1-Q4, in Table 2, the mean (and median) use increases significantly moving up the quartiles, indicating that the largest consumers of electricity are significantly larger, as expected. Notice the sharp increase in Q4, which confirms that the rather extreme electricity consumers in the respective sectors are found in the same quartile. By definition, Q1 consists of the smallest electricity users and therefore has a very small share of total electricity use in the sample.

Table 3 reports the reported annual working hours and number of employed over SKGS and electricity use quartiles. The working hours refers to "normal production" – hereafter *production hours*. The statistics reflect that although all plants are considered high electricity consumers, there is a lot of heterogeneity. Disregarding the zero employed, the numbers range from just a few to several thousands. Over quartiles plants have increasing number of employed, but not a clear pattern across the SKGS sectors. Also for production hours the numbers increase with quartiles, where more electricity follows with more production hours. For the production hours, the results also indicate that most plants are producing more than regular office hours, which would correspond to about 2,000 hours. Notice that 24/7 production would imply 8,760 hours, which is the maximum reported for all sectors in our sample. An interesting topic regarding production hours would be how it potentially relates to exposure and cost of electricity interruptions.

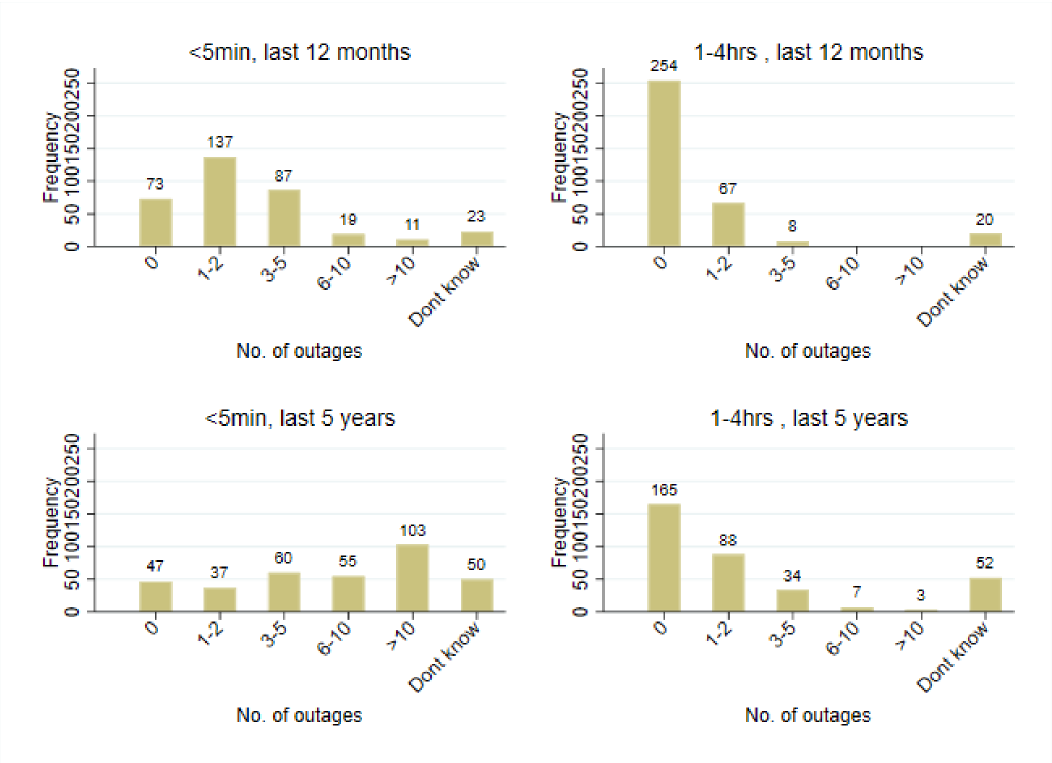
Table 3 Number of employed and production hours.

	Employed					**Production hours**			
	Mean	Median	Min	Max		Mean	Median	Min	Max
Forest	212	128	0	942		7 074	8 400	1 800	8 760
Chemical	230	110	14	1 739		7 383	8 217	2 340	8 760
MiningStone	262	53	10	1 796		5 848	7 238	2 000	8 760
Basic IS	350	114	34	2 279		7 136	8 000	3 300	8 760
Other	288	108	0	15 794		7 007	7 900	1 920	8 760
Q1	88	60	3	498		5 884	6 000	1 920	8 760
Q2	117	78	0	511		6 744	7 524	1 800	8 760
Q3	206	124	0	1 333		7 345	8 000	1 960	8 760
Q4	680	326	0	15 794		8 012	8 592	2 500	8 760
Total sample	272	109	0	15 794		6 997	8 000	1 800	8 760

An underlying assumption for the study is that plant representatives (the respondents) have knowledge about the consequences and costs that emerge from a power outage. This knowledge could be related to their experience of actual and historical interruptions. The respondents were asked about how many power outages the respective plant had experienced during the last 12 months, and the last 5 years respectively. In the questionnaire, the questions were on a rather detailed level asking about seven outage durations.[9] In Figure 1, results for one short duration (<5minutes) and one relatively long duration (1-4 hours) of historical outages are presented to give an overall view of outage experience.

For the last 12 months, 254 plants had experienced at least one power outage of up to 5 minutes, whereas 75 plants had experienced at least one outage with duration 1-4 hours. For the last 5 years, the corresponding number of plants with experience of outages were 255 and 132, respectively. It is of course expected that more plants have experienced outages during a longer time period, but perhaps we would have expected a larger difference. It is important to mention that, in retrospect, the formulation of the question regarding one and five years was likely not clear enough. Specifically, it was not made clear if the "within last five years" question should include the last 12 months. Based on the answers, most respondents likely interpreted the questions as referring to the last 2-5 years. Based on this, these questions should be analyzed with care and separately. In the figure below, the histograms show how the respondents chose among the alternative intervals with number of outages. For example, 87 plants had experienced 3-5 outages of less than 5 minutes during the last 12 months.

Figure 1 Experience of power outages



[9] The durations were specified as (1) less than 5 min, (2) 6-15 min, (3) 16-60 min, (4) 1-4 hrs, (5) 5-12 hrs, (6) 13-24 hrs and (7) more than 24 hrs.

A summary of all responses with any experience of interruptions the last 12 months and 5 years are shown in Table 4. Note that this does not reflect the frequency of interruptions experienced, since all chosen frequencies are aggregated for the respective duration. The last column on the right is the total "ticks" made over the varying durations. This is not to be understood as the total number of outages experienced. Recall from Figure 1 above that the question was designed with intervals regarding the frequency of outages, with total number of outages hence being much larger. A takeaway from these results is that most plants likely have experienced outages. Another takeaway is that just a few have experienced longer durations than 12 hours. This should be kept in mind when considering responses on survey questions related to costs for hypothetical outages of varying durations.

Table 4 Number of responses (ticks) aggregated over all frequencies

	Duration							
	<5min	6-15min	16-60min	1-4hrs	5-12hrs	13-24hrs	>24hrs	Total
Last year	254	104	127	75	16	5	1	582
Last 5 years	255	159	168	132	33	12	6	765

In Section 4, the main results of the survey are reported and discussed.

4. Survey results and calculation of cost metrics

Based on the data collected, we are able to calculate and report several important metrics related to the costs and consequences of power interruptions (outages). The first part of the results is based on the microeconomic data collected from national statistics sources and not the questionnaire per se. In line with the previous sections, the results are reported for the SKGS sectors as well as the four quantiles of electricity use, with a particular focus on outage duration.

4.1 Value added (VA) and VA-based VoLL

To approach the cost and consequences of power interruptions, it is reasonable to start from the values created in production as a baseline. Note also that these values can be extracted from national statistical sources. A common measure in this context is the “value added” (VA), which is defined as the value of produced goods- and services minus the costs for inputs in production including electricity. Since profit is total revenues minus total costs, VA is also defined as profit plus labor- and capital costs. In other words, VA can be understood as the additional value a company creates during its production process. During a power outage, and if production processes stall, values are lost but less electricity is also used. To compare across sectors and categories, VA is normalized in per hour and energy used. If lost VA of an interruption corresponds to the cost, the metric would be cost per hour. However, the information in this metric can be debated since the actual cost may (likely) differ from lost VA only. The normalization of VA in per unit energy is denoted the Value of Lost Load (VoLL) in the production function approach. In this report there is however a distinction between VA-based VoLL, and cost-based VoLL.

In Table 5, we report annual VA, VA per production hour, and VA per kWh electricity use for SKGS sectors and the four quantiles. The calculations are based on value added and the total kWh electricity used at the plant level in 2021 (reported in the production data). Results are reported for SKGS, quartiles and for the total sample. Plants with negative VA have been dropped (5 plants).

Table 5 VA, VA per production hour, and VA/KWh (VoLL).

	VA (tkr)			**VA/hr (tkr)**			**VA/kWh (kr)**	
	Mean	Median		Mean	Median		Mean	Median
Forest	427 961	234 258		59.79	38.85		13.74	11.21
Chemical	750 511	133 639		98.31	23.63		36.20	20.69
MiningStone	1 492 606	84 532		189.05	32.67		10.50	8.91
Basic IS	460 723	128 837		56.96	19.03		9.33	6.58
Other	405 591	92 388		55.80	14.21		32.45	13.52

	VA (tkr)			VA/hr (tkr)			VA/kWh (kr)	
Q1	102 715	52 111		18.56	8.86		29.41	14.55
Q2	169 184	81 627		29.81	13.25		31.16	14.12
Q3	341 876	145 235		46.18	25.10		31.23	15.09
Q4	1 416 411	513 668		177.54	64.42		12.23	5.26
Total sample	506 400	118 092		68.21	19.41		26.02	12.49

For plants belonging to SKGS, the VA is highest in MiningStone followed by Chemical, Forest, and Basic IS. Note that the VA columns are not normalized, these are absolute values in thousands of Swedish krona (SEK). The distribution of VA across plants is very skewed with significantly higher mean than median values. In MiningStone this is most remarkable with a rather extreme difference in mean and median.

Since quartiles are based on MWh electricity use, we are looking at VA values from the lowest quartile to the highest in terms of MWh consumed. The same pattern appears for value added as for electricity use when looking at quartiles, i.e., it rises sharply as we move from quartile 1 to quartile 4. This is to be expected as the quartiles are likely to say something about the size of the plant and that is likely to correlate with value added generation and electricity use. Although less remarkable, the skewed nature of the observations holds also over the quartiles.

For VA per hour, the number of plants (observations) is somewhat lower because 12 observations on production hours are missing. Also, one plant with annual production hours of 300 has been dropped in the calculation of VA per hour of production. Although such few hours could be correct, it is an outlier in this context where the second lowest production hours are 1 800. We first look at the "VoLL measurement" (VA) per hour motivated by a so-called production function approach (see, e.g., Broberg et al., 2021). This measure is value added per hour and is displayed by quartile (based on MWh electricity use) in Table 5. Operating hours per year is taken from the survey we conducted. We see that the largest consumers of electricity (Q4) have a significantly higher VoLL per hour (almost 180tkr) compared to smaller consumers. This reflects that large consumers of electricity also generate relatively high value added, which is to be expected.

If we instead break down VoLL (VA) per hour over the SKGS cluster, it is obvious that mining shows the highest value at 189tkr, followed by chemical at about half of that value, and forest and iron/steel at a significantly lower levels at par with non-SKGS plants (50-60tkr). Overall, the results still indicate heterogeneity both within and across sectors.

Now we turn to the conventionally used metric for VoLL using the production function approach, i.e., value added per kWh. This measurement will "penalize" high electricity use relative to the value added generated. That is, big consumers of electricity generally show relatively low VoLL, since value added per kWh used tends to be lower. This is obvious by examining the table above. As we move up the quartiles and plants become larger electricity users, we also see VoLL (per kWh) drop significantly. In essence, this means that a mechanical pulp plant with relatively high electricity use per unit of value added, will have a much lower VoLL metric than, e.g., a business establishment in a less energy intensive sector that use significantly less electricity per value added generated. This means that VoLL in terms of value added per kWh is heavily influenced by the technology of the firm. This also has implications in a rationing situation where it must be decided which consumer to disconnect. Using this metric would suggest disconnecting smaller value VoLL first to maximize the value added per kWh reserved in the system.

In the SKGS cluster, we find Basic IS, MiningStone and Forest to have relatively low VoLL in terms of VA per kWh. This basically confirms that these have relatively more electricity intensive production technologies. Chemical has the by far highest VA per kWh among the the SKGS sectors. This is driven by their relatively low electricity use (see Table 2) and still reasonably high VA. Note also that most plants in the SKGS cluster seem to have lower VA per kWh than the non-SKGS sectors (Other).

Overall, we would expect the values from our sample and this definition of VoLL to be lower than in studies like Broberg et al. (2021), which was based on similar official statistics. In the current sample the average use of electricity is probably higher than in Broberg, et al. (2021), implying a lower VoLL for a given level of value added. This general expectation is feasible also in comparison to other previous studies calculating VoLL.

4.2 Costs for given durations

In the questionnaire, respondents were faced with direct cost questions for six durations ranging from 1 minute to 12hrs. They were asked to state their total cost for an unexpected power outage of the respective duration. In total, 13 plants have been dropped from the dataset due to inability to answer, or no answer. We find several zero responses to the direct cost questions. Although less likely for longer durations, the cost of an interruption could be zero. Plants may, for example, have backup systems and are therefore unaffected by interruptions from external electricity sources. In the analysis, zero costs have been kept as a baseline. The total number of zeros ranges from 50 for the 1min interruption to 14 for the 60min duration and 11 for 3-hour and 12-hour durations. Stating a zero cost can be debated, but we have no way of knowing if it is a true or fake cost. It is, however, good to find that the number of zero cost declines over durations and thus that we have cleaned the data from obvious errors. Keeping zeros in the analysis is important and aligns with our decision to keep the very high stated costs (more about trimming data later in the paper).

4.2.1 Cost per interruption, all plants, over quartiles

To understand the magnitude of interruption costs more clearly, Table 6 presents the stated costs over durations, SKGS sectors and quartiles. The plants are grouped into quartiles based on electricity use.

Overall, the observation is that the cost increases with duration. Note that the value is what the respective plant has stated in the survey as their total cost of the outage. That said, it would correspond to the theoretically correct measure of cost, including not just the cost/value during the power outage. The median is consistently lower than the mean, indicating a sample distribution that is skewed to the right with some very high values. Given the heterogeneity in both electricity use and VA this is expected.

For the SKGS sectors, the pattern of distributional skewness and increasing costs as the duration becomes longer, appears in Table 6. Concerning the SKGS sectors, the highest stated cost for shorter durations can be observed in Chemical for which we see a doubling of the cost comparing a one-minute interruption to a 12-hours interruption. In Basic IS and MiningStone we see a more than tenfold increase in cost as we move from shortest to longest duration, which is an indication that longer interruptions are very costly for these sectors. The Forest sector shows a moderate increase in cost as duration becomes longer, except there seem to be a significant jump in cost for a 12-hour interruption, indicating that very long durations once again are more costly.

Furthermore, we observe that the cost per interruption increases with quartile (grouped again by size of use in MWh) and length of interruption, which is to be expected. More use of electricity is likely to be related to size of production and VA.

Table 6 Stated costs over durations in tSEK, mean (median).

	Cost per interruption, mean (median), tSEK					
	1 min	5 min	30 min	60 min	180 min	720 min
Forest	697	699	727	888	1114	2 248
	(50)	(50)	(80)	(100)	(200)	(504)
Chemical	2 778	3 073	3 276	3 463	4 482	5 726
	(30)	(50)	(100)	(100)	(300)	(450)
MiningStone	317	331	614	1 196	1 943	5 438
	(40)	(40)	(100)	(100)	(200)	(800)
Basic IS	569	590	704	815	1 162	7 540
	(45)	(50)	(100)	(150)	(340)	(1 000)

	Cost per interruption, mean (median), tSEK					
Other	403	441	513	625	957	2 795
	(25)	(35)	(60)	(100)	(181)	(500)
Q1	32	43	76	119	255	878
	(10)	(15)	(30)	(50)	(100)	(265)
Q2	84	102	115	150	291	817
	(45)	(48)	(65)	(100)	(150)	(400)
Q3	158	168	223	326	645	1 869
	(40)	(50)	(100)	(120)	(250)	(600)
Q4	2 431	2 588	2848	3 289	4 276	10 518
	(200)	(200)	(369)	(500)	(790)	(2 400)
Total sample	672	723	813	968	1 363	3 505
	(30)	(50)	(75)	(100)	(200)	(500)
N	330	329	329	329	329	330

Table 6 gives a good overall picture of how the cost of outages changes over duration and across sectors and quartiles. That said, it is hard to draw any final conclusions since the change in duration is not the same between the observations. For example, it is interesting to know if the duration plays a larger role for short outages, than for long, or the other way around. Given large "fixed" costs also for short outages, the importance of duration would be diminishing. In the regression approach in section 5, we are able to say more about this.

4.2.2 VoLL calculated from stated cost, over durations

The cost per interruption naturally reflects lost values from production, meaning that large plants are expected to experience larger costs. In line with the definition of VoLL, the stated costs can be normalized by lost energy (kWh) for the corresponding duration. That is, the cost per duration divided by the average energy use for the same duration (normalizing the production hours to minutes, etc.). This corresponds to a duration-specific VoLL metric and is reported in Table 7. Also here, the results are presented across SKGS and the quartiles of electricity users. For comparative reasons, we have also calculated VoLL for an "average hour" of duration.[10]

[10] This measure is calculated by first transforming all costs to be in "per hour", then summing over durations and calculating the average. This is then normalized by the energy use per hour to work like an "average" one-hour VoLL.

Table 7 Direct cost based VoLL.

	Duration specific VoLL, mean (median), in SEK/kWh						
	1 min	5 min	30 min	60 min	180 min	720 min	"Avg"
Forest	5 720	1 161	219	129	62	37	1 221
	(1 017)	(204)	(47)	(42)	(23)	(13)	(228)
Chemical	8 067	2 036	461	317	208	149	1 873
	(786)	(449)	(149)	(74)	(50)	(31)	(480)
MiningStone	1 938	538	114	92	44	38	461
	(708)	(142)	(59)	(46)	(31)	(21)	(154)
Basic IS	3 765	809	206	130	84	74	845
	(1 670)	(395)	(126)	(91)	(39)	(22)	(373)
Other	8 104	1 885	392	267	169	133	1 828
	(1 657)	(565)	(125)	(100)	(56)	(41)	(449)
Q1	2 835	787	247	195	153	129	720
	(907)	(233)	(98)	(67)	(50)	(35)	(229)
Q2	6 173	1 586	286	189	119	85	1 406
	(2 826)	(617)	(133)	(95)	(52)	(39)	(629)
Q3	4 885	1 072	257	202	150	115	1 114
	(1 395)	(335)	(102)	(76)	(45)	(38)	(347)
Q4	13 677	2 870	530	298	123	89	2 931
	(1 055)	(229)	(57)	(57)	(29)	(18)	(243)
Total sample	6 882	1 579	331	221	136	105	1 543
	(1 222)	(321)	(104)	(77)	(43)	(29)	(319)
N	319	318	318	318	318	319	318

For the SKGS sectors we see a clearly declining VoLL over durations. The big difference between mean and median values still indicates quite significant skewness in the data with a few very high observations. In the normalized VoLL however, both the total cost and energy use are important factors. A remark is that the duration does not increase linearly from left to right in the table. For example, recall there is a nine-hour difference between the two longest durations. Over quartiles, there is no clear pattern in VoLL, except that Q4 has a very high VoLL for short durations relative the other quartiles (and SKGS).

For the total sample and durations ranging from 1 minute to 12 hours, we see that cost, or value, per kWh is much higher for short durations. For a 1 min outage, VoLL is almost 6 900 SEK/kWh, while for a 12 hours outage it is about 100 SEK/kWh. This likely suggests that there is large fixed costs associated with interruptions. That is, even a very short outage will incur significant cost, as indicated by the table above. It is also noteworthy that even for long durations there are plants that report a minimum cost per kWh of zero. This would mean that, for example, a 3-hour outage can for some plants be recovered in terms of production losses, input spoilage, etc.

In the column "Avg", we have calculated the average cost per interruption translated to 1-hour, and then normalized by the average energy use per production hour. This is mainly as a point of reference but can be thought of as an "average" one-hour VoLL over the durations. For the total sample, this is calculated to about 1 500 SEK/kWh, with a median of 319 SEK/kWh.

For the average VoLL, no clear pattern can be found across quartiles. For the SKGS cluster, Chemical has by far the largest VoLL, followed by Forest. Both MiningStone and Basic IS have relatively low average VoLL. In this respect, with relatively low electricity use it is reasonable that Chemical reports lower VoLL's.

It is interesting to find the difference between the VA and total cost approach to be very large. The stated total cost per kWh for an average duration is about 60 times the VA per kWh (means) from production data (not the questionnaire). This indicates that the production interruption following a power outage is likely much longer, and is characterized by large additional costs.

4.3 Electricity interruption vs. production interruption and recovery

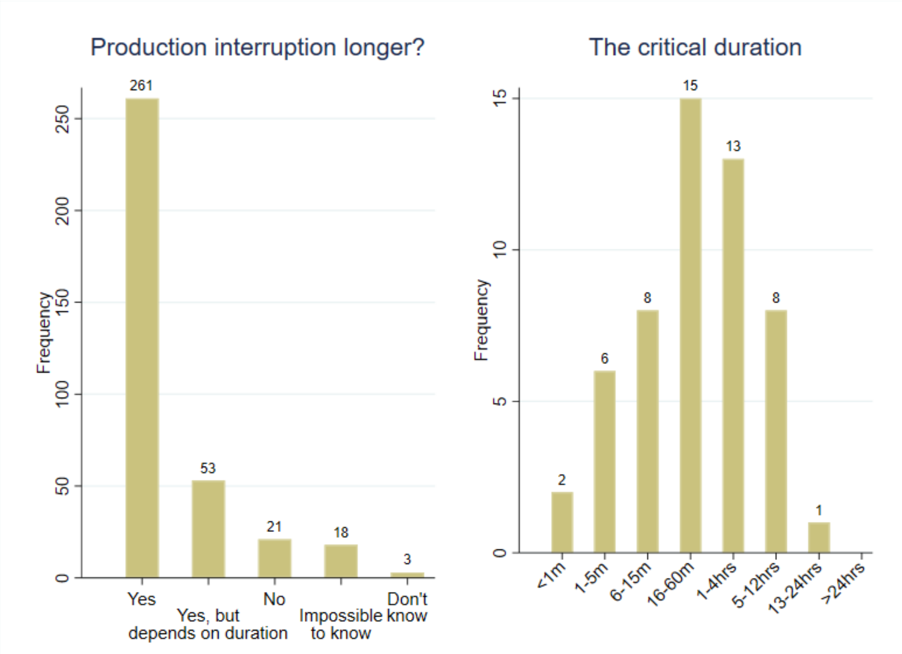
Given the results from the previous section, it is interesting to investigate the more "qualitative" aspects of power interruptions. For example, can we identify potential factors explaining the big difference in reported total cost of outages, and the lost value added. This section reports the results from analyzing additional and more qualitative questions in the questionnaire.

As a point of reference, it is found that 138 plants report that they need a heads-up at least 24 hours before the outage to limit the cost and consequences of any outage, and 43 report that a heads-up does not help at all. Interestingly, 60 plants respond that a heads-up only 1-hour before would help reduce costs and consequences. Moreover, 245 plants report that they have "action plans" for when an outage occurs.

One set of questions opened for a decomposition of reported costs for the 1-5 minutes, and 61-180 minutes outages. The alternatives were fixed, meaning that the sum of these costs is not equivalent to the total cost. The by far highest cost was stated for lost production, with an average of 781 tSEK and 1 565 tSEK for the two durations. Although most other costs were reported much smaller (below 100 to almost 500 tSEK over the alternatives and durations), "undefined" and cost for "destroyed materials, machines, etc." were both relatively high (about 300 to almost 500 tSEK). Notably, the lowest costs were reported for labor being "out of job".

Another set of questions was devoted to the interruption in production and the possibilities to recover (given an outage). Once again note that the duration of a power outage is not necessarily reflected by a corresponding production interruption. Figure 2 shows that the absolute majority of plants respond that the production interruption will be significantly longer than the power interruption, no matter what. This would essentially mean that production processes cannot just be restarted when power is on again. Specifically looking at the SKGS sectors (not shown in the figure), we find that very few tick anything else than "Yes". By inspecting responses, most of the other chosen alternatives are found to be from the group "Other". For the quartiles, we also find (not shown in the figure) that the likelihood to tick anything else than "Yes" sharply reduces with use of electricity.

Figure 2 Power interruption vs. production interruption.

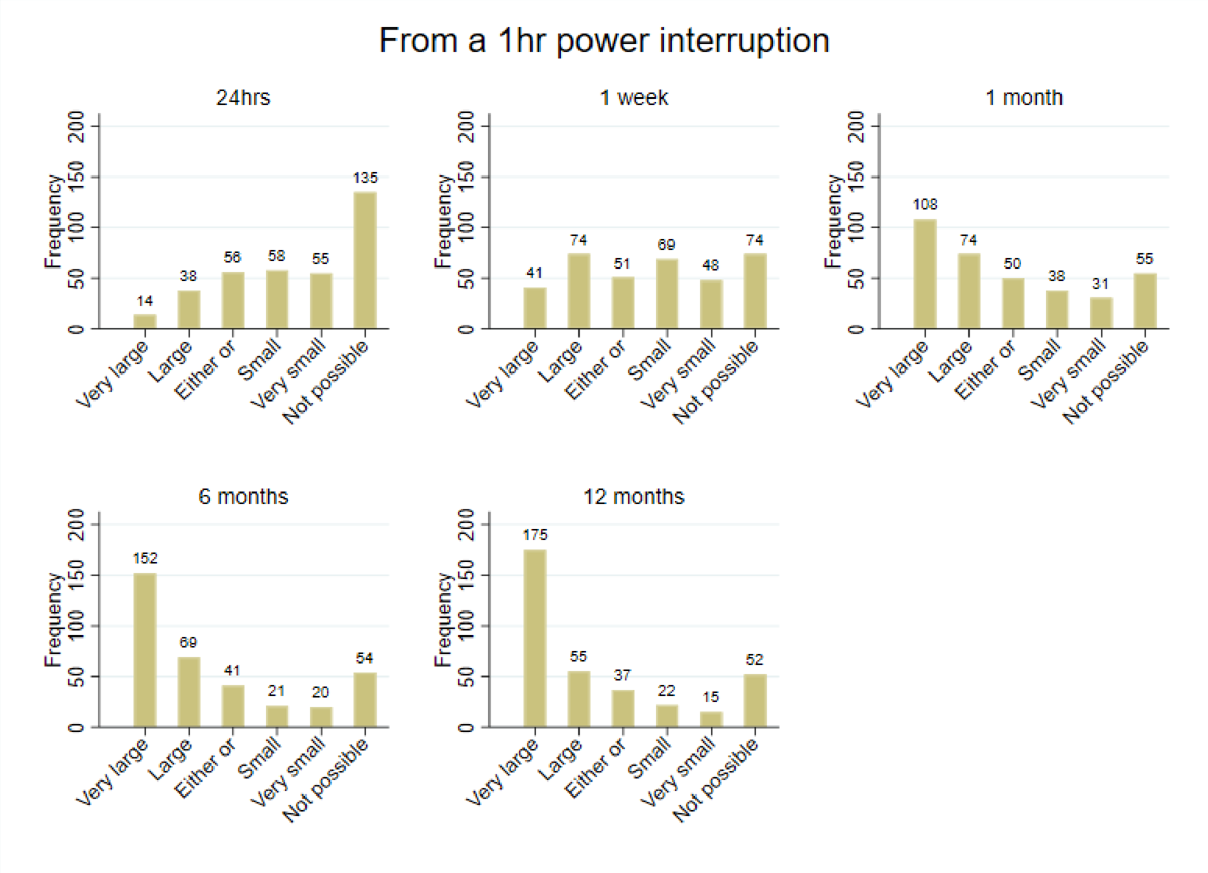


For the option "Yes, but it depends on the duration", a follow-up question addressed what duration would be critical for the production interruption being longer. The responses are shown in the right graph of Figure 2, and show that most plants report the critical duration to be within an hour and up to four. Given previously presented results regarding the distribution of costs across durations, this will indicate that there are large initial (fixed) costs with short duration that does not necessarily correlates with how long it takes to restart production.

Focusing on a one-hour power outage, we asked about the possibility to recover lost production. The options were in terms of the possibility to recover lost production within days, weeks, months, etc. In Figure 3 we report the outcome over time for "within 24 hours" to "within a year". Notice again that this is from a 1-hour power outage.

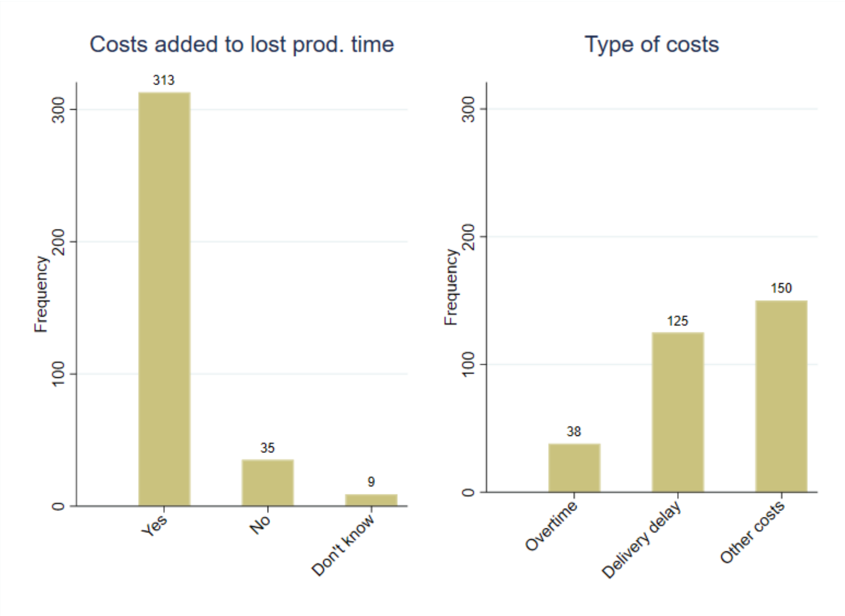
Interestingly, and still intuitive, the results show a clear pattern that the possibility to recover increases over time. For example, it is about 70% (248 plants) who state that the possibility to recover a one-hour outage within 24hrs is small, very small and not possible. Perhaps even more interestingly however, also within 12 months 52 plants state that it is not possible to recover the production losses from a one-hour power outage. It is of course hard to know the reasons for this, but likely these plants already produce at full capacity and cannot speed-up or produce more to recover.

Figure 3 The possibility to recover lost production within 24hrs to 12months.



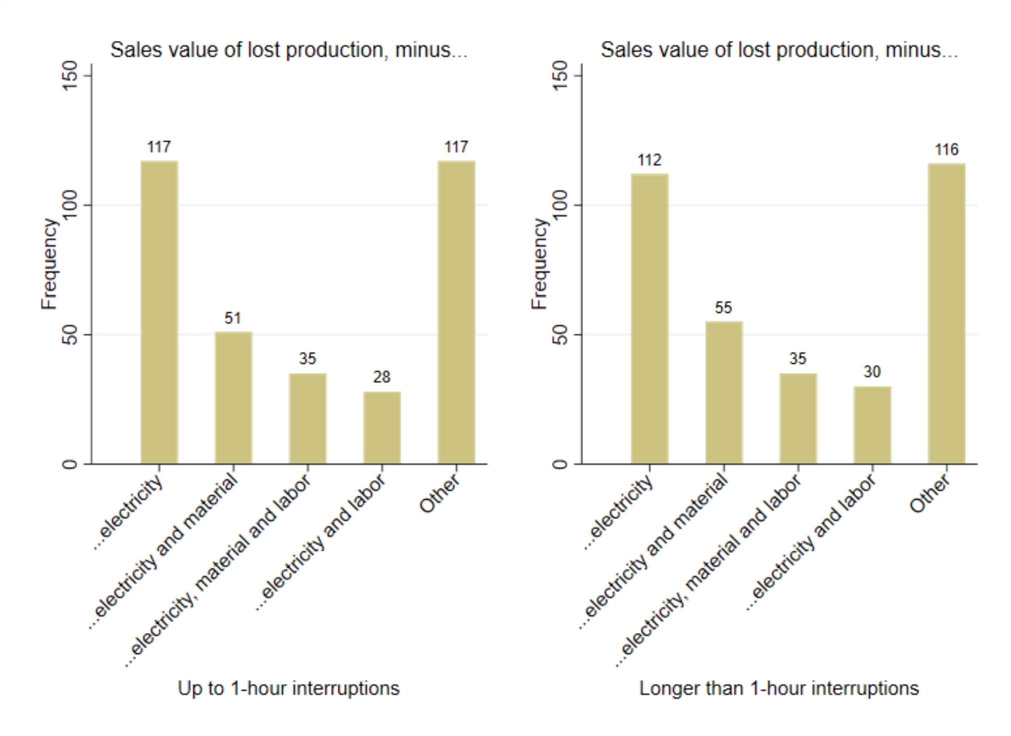
To further elaborate on the consequences, we asked about potential costs adding to the lost time of production. As is visible from Figure 3, about 88% (313 plants) have additional costs from an interruption – only 35 plants have no extra costs added to the lost time in production. For those with extra costs, 38 plants characterize those as "overtime costs", 125 as costs from "delays in delivery of goods". Only these three options were available, and 150 plants stated to have other types of additional costs.

Figure 4 Frequency of plants that state that they have additional costs.



In the analysis so far, we have presented the stated total costs of power outages for different durations. To follow-up on this part, we asked respondents what type of calculation that would be the best representation of their stated total costs, i.e., the composition of costs. Respondents were asked to choose between a prespecified set of alternatives. The alternatives were all based on the “sales value of lost production”, and then adjusted with (1) reduced cost for electricity, (2) cost for electricity and material, (3) cost for electricity, material and labor, and (4) cost for electricity and labor. These alternatives were designed to reflect the alternative cost calculations presented in the conceptual part of this report. The questions were separated in “up to one-hour interruptions” and “more than one-hour interruptions. Figure 5 shows the results of these questions.

Figure 5 Composition of costs, frequencies.



4.4 Investments in backup capacity

Given a cost of power outages, there are incentives to take actions to reduce this cost. These actions may take various forms, where one could be to invest in backup power generation. We address this by asking all plants about their existing investment in backup capacity, their planned investments, and the main purpose with the backup. For the total sample, 218 (61%) responded that they do not have any backup capacity, 102 (28%) reported that they have backup generators, while 70 (19%) reported to have backup in the form of batteries. Asking about the main purpose with backup, a vast majority ticked "Protecting machinery" and "Protect critical functions" – 85 (24%) and 135 (38%), respectively. Notably, 47 (13%) ticked that the purpose would be to maintain full- or part of the production. In total, 45 plants responded to "How much of production can be maintained by backup during an outage?". Over six categories from 100 to 10 percent, responses were allocated such that 6 responded 100%, while 36 responded 50% or less. Most responses (22) were on 10%.

We also investigated the issue of potential in-house electricity production in addition to backup. In total, 34 plants responded (357 responses) that they have such in-house electricity production. Across the SKGS sectors, most (11) were in the Forest sector. Over quartiles, 14 were found in the 4th quantile, and then the rest evenly distributed over quantiles 1-3. Finally, we also asked about "the purpose of the in-house electricity production". Most (28) ticked that it was for profitability reasons, whereas only 11 ticked that it was for handling current or future interruptions. For when they had invested in in-house electricity production, 15 responded “More than 10 years ago” and 18 responded “Within the last 5 years”.

To highlight the magnitude of investments in backup, Table 8 reports on the 118 plants who responded with a positive number on how much they had invested in backup. Table 7 shows the total investments in tSEK for the SKGS sectors and the quartiles, respectively.

Table 8 Backup investments.

		Backup investment, tSEK						
	N	Mean	Median			N	Mean	Median
Forest	26	6 892	1 000		Q1	16	888	200
Chemical	12	10 696	2 500		Q2	18	3 718	350
MiningStone	8	14 263	4 000		Q3	42	3 969	500
Basic IS	11	10 409	2 500		Q4	42	11 781	6 000
Other	61	3 385	500					
Total	118	6 293	1 000					

For the separate sectors in SKGS, it is shown that backup investments are significantly higher than for other plants (Other) in the sample, suggesting that these kinds of investments are more common in electricity intensive firms. For the means, Chemical, MiningStone and Basic IS are the largest investors in backup. Also, for the median values, Chemical, MiningStone and Basic IS have the highest backup investments, followed by Forest. The overall relatively low investments in Forest could reflect their own electricity production based on renewable residuals, which is substantial for some plants.

For the quartiles, and as expected, the larger the consumer of electricity, the more is invested in backup. Looking both at the mean and median we find a rather sharp increase in backup for the largest consumers of electricity (Q4). The exposure and vulnerability to interruptions is thus likely to increase with electricity use.

Finally, in another question we find that most backup investments were done within the last 10 years, for Chemical and MiningStone the median value is 100%. This indicates that backup investments have become more prevalent the last 10 years.

4.5 The perceived probability of and attitudes toward interruptions

It is reasonable to believe that the level and interest in backup (including actual investments) is related to the perceived risk of interruptions. In the questionnaire, a set of questions were focused on the perceived probability of electricity interruptions of more than 5 minutes. Respondents were asked to state the probability of plant level outages, out of seven alternative probabilities expressed both in words and percentages.

In the short run (week, month, 12months), it is found that the perceived risk (probability) of interruptions is low. The likelihood clearly increases with time (from week to month to year) but is still rather low with an "average" response of "Very unlikely (0-10 percent probability)". If anything, it is found (for an average response) that the perceived risk reduces with electricity usage, i.e., the most electricity consuming plants perceive the risk as lower. This is somewhat counterintuitive given that investment in backup will increase with electricity use in the sample.

For the coming year (12months), and across seasons (Dec-Feb, March-May, June-August, Sept-Nov), results show that it is still perceived rather unlikely having an interruption. The average response is "Unlikely (0-33 percent probability), and also here the more electricity consuming plants perceives the risk as lower. Interestingly, the perceived risk is similar across seasons, except for the summer (June-August) having a higher probability. The median response is "Unlikely" instead of "Very unlikely" for the summer in the full sample. This is an interesting finding and could be seen in light of that plants likely are "closed" during this period and the cost of summer outages are lower (see below).

Finally, the same question was also asked for the coming 5 years. As expected, the perceived probability of at least one 5-minute interruption or more is now higher. That said, the average response is still just "As likely as unlikely (33-66 percent probability)" or lower. Once again it is found that the perceived risk is lower in June-August. For the 5-year horizon however, there is no clear trend across the four electricity use quantiles.

To complement the picture of perceived risk with expectations about security of delivery, we asked about what would be acceptable regarding interruptions. The plant respondents were faced with four durations: up to 1-minute, 1-5min, 5-60min and 1-4hrs. The alternatives were "Acceptable", "Unacceptable" and "No opinion" and, overall, 338 plants responded.

For the 5-60 minutes duration, and perhaps surprisingly, 1 plant ticked "acceptable" with one interruption per week, 1 ticked one per month, 9 ticked one every three months, 24 one every 6th month, 93 once per year and 189 once every 5th year.

For an interruption of less than one-minute, a higher degree of acceptance would be expected. For this scenario, no plants ticked "acceptable" with one interruption per week, 4 ticked one per month, 22 ticked one every three months, 84 one every 6th month, 180 once per year and 252 once every 5th year.

Finally, for the longest duration we expect to find the lowest level of acceptance. That said, we still find that 1 plant ticked “acceptable” with one interruption per week, 1 ticked one per month, 2 ticked one every three months, 6 one every 6th month, 41 once per year and 115 once every 5th year.

The takeaway from this exercise is that the level of acceptance for interruptions is higher than one would expect. For example, it is surprising to find plants for which it is acceptable with 1-hour interruptions, or longer, once every week/month. That said, we also find several plants with zero stated costs of outages. This result is based on very few responses, and a misunderstanding of the questions is of course possible, but still this is what we find.

Turning to the issue of timing of an interruption, we do not explicitly model timing or season for our power outage scenarios. This is a limitation, but also a consequence of our population consisting of large industries in energy intensive sectors with rather continuous production processes. That said, we asked about the perceived importance of season and time of day, relative to an “average” outage. Looking at an average response, the results do not give any clear evidence of season being an important factor. If anything, it is relatively more costly in December-February, and less costly during the summer months. For the SKGS sectors, Forest and MiningStone have the biggest difference between winter and summer in terms of cost for an outage. An interpretation could be that they consider that production is reduced during summer for vacation.

For the question about time of day, the evidence of any difference is even weaker. As expected, the average response is slightly lower for nighttime than daytime or evening. Also here, the median response is the same over “daytime”, “evening” and “nighttime”, i.e. the cost is just as for an average interruption.

5. Estimating cost functions

Estimating cost functions with a regression approach will help to predict the cost of interruptions for other durations than asked about in the questionnaire, and to in more detail study drivers and factors underlying costs. Here, primary focus is on drivers and factors for the cost of interruptions.

The dependent variable (cost) in any of our specifications is continuous, non-negative, and its distribution is characterized by high density in low (zero) values. Therefore, the traditional OLS estimator is not the best alternative. A censored-type of model would be attractive, and we therefore apply a Tobit specification (see Wooldridge, 2002; Carlsson et al., 2019; Carlsson et al., 2021, and Moeltner and Layton, 2002 for similar applications).[11] Each response to a specific duration of a power outage will, in our context, constitute an observation of the dependent variable (cost). It is assumed that these observations are generated by an underlying latent variable and censored at zero. For the dependent variable y_{it}, this is modeled with a general Tobit specification:

$$y_{it}^{*} = f(x_{it}, \beta, \varepsilon_{it})$$
$$y_{it} = max(0, y_{it}^{*})$$

where y_{it}^{*} is the latent value of the dependent variable corresponding to the observation of plant i's stated cost (SEK) in situation t. The vector x_{it} represents the characteristics of the scenario and the plants, β is a vector of coefficients and ε_{it} a random error term. Each plant is faced with scenarios for all the six durations (1-minute to 12 hours), meaning that the data has a panel-like structure. To better reflect this, we model this in a random-effects Tobit setting.[12] This means that we allow for unobserved plant-specific effects, i.e., differences across plants that remain the same, but may affect the outcome (cost). These effects are modelled as so called "random effects".

The dependent variable (cost) is not normally distributed, but rather characterized by high density in low (zero) costs and a rather thick right-tail.[13] To adjust for the skewedness characteristic, we use the logarithm of the cost variable in the specifications.[14] Other variables in our specifications that have similar

[11] Skewed non-negative outcomes with rather many zero values are often handled with Tobit or two-part models. In this context, the dependent variable is such that it is possible to take on values close to zero which is in line with the Tobit. The outcome variable (cost) is not really a "true" truncated variable, but Wooldridge (2002, pp. 518-520 discusses and motivates the use of a Tobit model in "corner solution" outcome contexts like this. Moreover, it is reasonable that the determinants for zero observations are also valid for non-zero observations. This makes two-part specifications less attractive in our context.

[12] Throughout the estimation process, we have also tested OLS and the standard (non-panel) Tobit estimators.

[13] We have elaborated on trimming the most extreme observations (cost). In the appendix, model estimations with winsorized cost at the 2.5% level are shown. With trimmed data, the overall results still hold.

[14] Following the literature (e.g., Fishe, Maddala & Trost (1994) and Moeltner & Layton (2002)) we recode original zero cost values to 1 before log transformation. This gives log values of zero at the "truncation point", which is convenient for the censoring specification (Tobit).

characteristics are also modelled in logarithms. Modelling both cost and duration in log form is reasonable in outage cost contexts, with concave and monotonically increasing function properties. This implicitly suggests that incremental costs are largest in the beginning of an outage, and then decreases as the plant may take damage control measures.[15] In the analysis of coefficients, it is important to recall that coefficients in a log-log specification correspond to the elasticity. To predict any cost in their original scale, a log-transformation is necessary. To reduce any log-transformation bias, we use the estimated overall variance in residuals in the calculation of predicted values of cost.

5.1 The base model

As a point of reference, we specify a model with electricity use (ln(MWh)), duration and production hours as explanatory factors for the stated cost of an outage. Electricity use and duration are well documented factors in the literature, and we expand this to also include the production hours at the plant level. A novelty with our data is that we explicitly asked about the annual production hours in the survey, with the hypothesis that it is a driver for outage cost. For example, no matter the timing, a plant running 24/7 is definitely affected by an outage, while another plant could actually be not producing during the outage. Of course, the timing of the outage is not known but this would still play a role for the expected cost of a hypothetical outage. Also, it is reasonable that production hours reflect other unobservables that may affect the outage cost. For example, with 24/7 production (or similar) already in place, recovery and overtime work is likely harder to implement. For more details on the production hours, see Table 3 (above). To complement the basic specification, we also test specifications with controls for the SKGS groups, quartiles (MWh), electricity price areas, and current backup investment and planned backup investment. A selection of these estimations is found in Table 9.[16] For electricity price areas and backup investment, we were not able to find any significant effects (therefore not reported). Once again, recall that the dependent variable is the logarithm of cost in SEK throughout the specifications.

Model 1 allows for linear and interaction effects, which is to be seen as a baseline specification.[17] All coefficients in model 1 are statistically significant (except the intercept) and with the expected sign. Cost increases with electricity use (MWh),

[15] Regarding extreme values in variables, one option would be to trim the data and, for example, drop some given percentage of the most extreme observations. For this report however, all observations are kept.

[16] To consider within-cluster correlation we apply a bootstrap procedure for standard errors. For all specifications, the random effects Tobit regression is preferred over the standard Tobit regression at any relevant level of significance. Sigma_u is the panel-level variance, while sigma_e is the overall variance. Rho is the panel level variance share of total variance.

[17] Not in any specification, interactions with production hours were found statistically significant and are therefore left out of the models.

duration and production hours. The negative interaction term indicates that the effect from duration is weaker for higher levels of electricity use.

Model 2 is more flexible and allows for non-linear effects in the variables. The respective coefficients related to duration and production hours are now significant with the same sign. For electricity use (MWh), each separate coefficient is no longer significant, except for the interaction term with duration. That said, the overall importance of electricity use is still statistically significant.[18] For both models, we find the panel level variance to be statistically significant. For all models (also below), a likelihood ratio test comparing a "pooled" Tobit with the panel estimator consistently rejects the null hypothesis of no panel-level effects.

Model 3 and 4 extend Model 2 to allow for separate effects of the SKGS sector and the quantiles, respectively. With "Other" as the reference sector in Model 3, allowing for SKGS specific effects does not contribute to the understanding of cost determinants, although the other coefficients basically remain.[19] In model 4 we allow for quartile specific effects but this turns out as statistically non-significant at any reasonable level. Also here, the coefficients related to duration are robust for changing specifications.

Table 9 Modelling log-cost, Models 1-4.

	1		2		3		4	
ln_mwh	0.775	**	0.974		0.940		0.699	
	(0.145)		(1.428)		(1.579)		(3.018)	
Duration	0.008	**	0.022	**	0.022	**	0.022	**
	(0.001)		(0.001)		(0.002)		(0.002)	
Prod.hrs	0.000	**	0.002	*	0.002	*	0.002	*
	(0.000)		(0.001)		(0.001)		(0.001)	
Dur # ln_mwh	-0.000	**	-0.000	**	-0.000	*	-0.000	**
	(0.000)		(0.000)		(0.000)		(0.000)	
ln_mwh # ln_mwh			-0.006		-0.006		0.010	
			(0.066)		(0.077)		(0.126)	
Dur # Dur			-0.000	**	-0.000	**	-0.000	**
			(0.000)		(0.000)		(0.000)	
Prod.hrs # Prod.hrs			-0.000	*	-0.000	*	-0.000	*
			(0.000)		(0.000)		(0.000)	
SKGS (Base=Other)								
Forest					0.502			
					(0.406)			
Chemical					-1.184			
					(0.951)			

[18] A test for the total marginal effect shows statistical significance at the 1% level.
[19] This is also true if combining SKGS with any of the other variables – it is still not a significant factor.

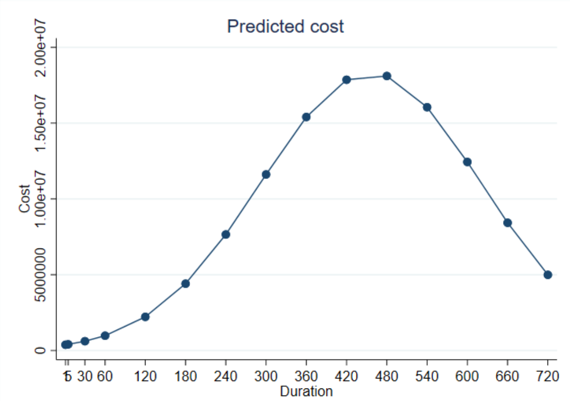
	1		2		3		4	
MiningStone					0.460			
					(0.785)			
Basic IS					-0.095			
					(0.630)			
Quartiles, MWh (Base=Q1)								
Q2							0.600	
							(0.771)	
Q3							0.253	
							(1.311)	
Q4							0.015	
							(1.866)	
Intercept	0.947		-5.151		-5.330		-4.166	
	(1.344)		(8.270)		(8.933)		(16.482)	
sigma_u	3.050	**	3.029	**	3.004	**	3.021	**
	(0.311)		(0.311)		(0.288)		(0.298)	
sigma_e	2.102	**	1.974	**	1.974	**	1.974	**
	(0.164)		(0.124)		(0.150)		(0.145)	
rho	0.678		0.702		0.698		0.701	
	(0.062)		(0.051)		(0.056)		(0.049)	
Log likelihood	-4387.25		-4289.70		-4286.87		-4288.87	
No. observations	1904		1904		1904		1904	
** p<.01, * p<.05								

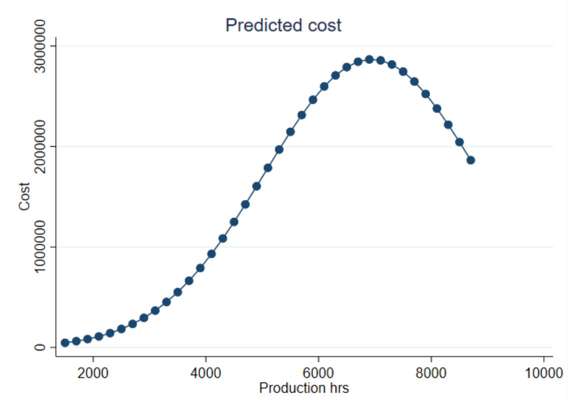
As an application and exercise to show how the cost varies over duration and production hours (keeping other variables fixed), Model 2 is used for predictions of outage costs. This is shown in Figure 6. Note that the predictions (vertical axis) are in the original scale (SEK), and to avoid a log-transformation bias, we use the estimated overall variance in residuals in the calculation of predicted values of cost.[20] The figure shows how the cost changes with duration in a non-linear pattern. The cost increases with an increasing rate until about 8 hours, and then decreases until 12 hours. Recall that these values are predictions from the estimated Model 2 and that the explicit cost questions referred to specific durations. Interestingly, this is in line with what is found in other studies, although not for the exact same population. For example, Sullivan et al. (2009) find a similar pattern in the American context for durations up to 8-hours. In their more recent report from 2015 however, they find a less pronounced pattern for durations longer than 8 hours. Carlsson et al. (2019) also find a similar, but not as clear, pattern for at least the public sector.

[20] To convert predicted values to the original scale, we used $\widehat{cost} = exp(ln(cost)) * exp(0.5\sigma_e^2)$.

Turning to the production hours, the function gives a similar pattern although now over hours. In the graph, predictions are extracted for every 200 hours from 1500 to 8 800. Recall that we have actual observations from 1 800 to 8 760, where the latter corresponds to 24/7 production. The cost sharply increases with production hours, but for more than about 7 000 hours, the marginal effect is negative. To our knowledge, this is not shown in previous literature.

Figure 6 Cost predictions based on model 2, over durations and production hours.





Before leaving this first set of specifications, we note that investment in backup systems does not significantly explain cost variations. It does not matter if we include actual investments or planned investments – none are statistically significant at any relevant level. Furthermore, simply controlling for the presence or absence of backup does not yield statistically significant results. These additional specifications are left out of the report.

5.2 Using value added and VoLL to predict cost

A novelty with our dataset is that we have information about reported values created in the production (value added) and matched to survey responses. Production data like VA is normally more accessible, and it would therefore give valuable insights to know how this relates to the reported cost of interruptions. Specifically, the production function approach in the literature typically relies on value added (gross value added). This will only capture the lost production values during the interruption, without accounting for additional costs such as restarting processes, recovering material losses, or labor expenses. Notably, this is also what we observe in the previous sections calculating VoLL metrics. Also recall that the reported cost would be the theoretically correct measure.

In Table 10 we have collected five specifications to highlight how VA and VA/kWh (VoLL) potentially contribute to the understanding of drivers for the cost of interruptions. In other aspects, the modelling strategy follows models 1-4 in the previous section. Again, the dependent variable is log reported cost.

Table 10 Modelling log-cost with an extended set of covariates (VA and VA/kWh).

	5		6		7		8		9	
ln_mwh	0.189		0.733							
	(1.475)		(1.238)							
Duration	0.019	***	0.021	***	0.018	***	0.017	***	0.017	***
	(0.002)		(0.002)		(0.001)		(0.001)		(0.002)	
Prod.hrs	0.002	**	0.002	**	0.001	*	0.002	**	0.002	***
	(0.001)		(0.001)		(0.001)		(0.001)		(0.001)	
Dur # Dur	-0.000	***	-0.000	***	-0.000	***	-0.000	***	-0.000	***
	(0.000)		(0.000)		(0.000)		(0.000)		(0.000)	
ln_mwh#ln_mwh	0.015		0.015							
	(0.067)		(0.058)							
Prod.hrs#Prod.hrs	-0.000	**	-0.000	**	-0.000		-0.000	*	-0.000	**
	(0.000)		(0.000)		(0.000)		(0.000)		(0.000)	
Dur # ln_mwh	-0.001	***	-0.000	***						
	(0.000)		(0.000)							
ln_va	0.524	***								
	(0.186))									
ln_va # Dur	0.000	*								
	(0.000)									
ln_voll_sek			0.588	***	0.226		0.383	**	0.340	*
			(0.153)		(0.189)		(0.162)		(0.178)	
Dur # ln_voll_sek							0.000	***	0.000	***
							(0.000)		(0.000)	
4 quantiles, MWH. (Base=Q1)										
2							0.959	*		
							(0.493)			
3							1.228	**		
							(0.590)			
4							3.069	***		
							(0.618)			

	5		6		7		8		9	
SKGS (Base=Other)										
Forest									1.722	***
									(0.425)	
Chemical									-0.738	
									(1.032)	
MiningStone									1.734	*
									(0.905)	
Basic IS									1.181	
									(0.849)	
Intercept	-6.023		-6.371		3.123		1.242		0.641	
	(8.534)		(7.590)		(2.757)		(2.994)		(2.677)	
sigma_u	2.962	***	2.963	***	3.197	***	3.029	***	3.099	***
	(0.279)		(0.275)		(0.268)		(0.317)		(0.281)	
sigma_e	1.965	***	1.969	***	1.976	***	1.968	***	1.969	***
	(0.153)		(0.159)		(0.149)		(0.140)		(0.151)	
rho	0.694		0.694		0.724		0.703		0.713	
	(0.050)		(0.043)		(0.049)		(0.050)		(0.044)	
Log likelihood	-4208.79		-4211.50		-4235.93		-4216.34		-4221.65	
No. observations	1874		1874		1874		1874		1874	
*** p<.01, ** p<.05, * p<.1										

Adding log value added linearly and interacted with duration shows statistical significance for the respective coefficient (Model 5). In this respect, value added is clearly a determinant for the cost of interruptions and seems to increase with duration (the interaction term).[21]

An alternative approach would be to normalize the values created in production with the electricity use, i.e., the logarithm of value added per kWh. Recall that value added per kWh is the production function approach version of VoLL (not based on the reported costs). The results from this specification are found in Model 6. Empirically, log VoLL shows statistical significance although log MWh is still not significant. Note that the electricity use is now part of the VoLL metrich. In model 7-9 we do not explicitly control for MWh, but instead keep the VoLL metric in the specifications. These specifications have somewhat less flexible functional forms not including any non-linear effects from VoLL, but still give good model fit.

In model 8 and 9, we allow for the categorical variables' quartile and SKGS, respectively. The results verify that electricity use (in terms of quartiles) is a

[21] A quadratic term was also tested but did not contribute to the model.

determinant for the cost. The VoLL coefficients are significant, as are the quartiles. It is also expected that the size of coefficients over quartiles is increasing. Controlling for the SKGS cluster, Model 9 shows that Forest and MiningStone have relatively higher costs compared to Other, while the other sectors continue to show no statistical significance. Note however that that the level of statistical significance is 10 percent for MiningStone.

6. Concluding discussion

This study has examined the costs and consequences of delivery disruptions for electricity-intensive industries in Sweden, based on a targeted survey of the 1,000 largest electricity-consuming plants, as identified by the ISEN group and managed by Statistics Sweden. A questionnaire was distributed to these plants, yielding 359 responses after two rounds of reminders. The survey addressed a wide range of topics, including the frequency and severity of power outages, their associated costs, and their broader consequences. The responses were analyzed in conjunction with plant-level production data, providing a robust foundation for evaluating the economic burden of electricity interruptions. This concluding section synthesizes the key insights from the study, presenting critical takeaways while offering broader reflections on its implications. By summarizing the findings, the study delivers a refined understanding of its contributions and underscores its relevance for decision-makers and future research initiatives.

Key observations on cost implications

The study demonstrates that traditional metrics, such as value added (VA) based measures, significantly underestimate the financial impact of power outages. While the average lost VA per hour is calculated to be around 68 thousand SEK (from officially reported data), the stated cost of a one-hour outage, as reported by the surveyed industries, is significantly higher, averaging 968 thousand SEK.

This stark difference indicates that relying solely on VA as a metric underestimates the true economic burden on electricity-intensive industries. The VA approach often overlooks indirect costs, such as restarting operations, material spoilage, and extended downtime impacts, which are better captured through stated cost data.

The study also compares the Value of Lost Load (VoLL) derived from two approaches. When calculated using reported VA, the VoLL is approximately 26 SEK/kWh, whereas VoLL based on stated costs is much higher, around 1500 SEK/kWh for an average outage. These findings reveal substantial discrepancy between theoretical, VA-based, calculations and the real-world financial impacts, particularly for electricity-intensive sectors like pulp and paper or steel manufacturing. This underscores the importance of incorporating stated cost data into VoLL estimations to achieve a more accurate understanding of outage costs.

Duration and intensity of outages

Power outage duration is a critical determinant of their economic impact. Shorter outages are disproportionately costly relative to their length, primarily due to high fixed costs associated with initial disruptions. These costs may include immediate production losses, damage to machinery, or the need for rapid response measures. As the duration of the outage extends, the marginal cost of each additional hour decreases, reflecting the fact that many fixed costs are already incurred in the initial hours of disruption.

However, the consequences of outages often extend well beyond their immediate duration. Restarting production processes, repairing equipment, and addressing other disruptions can require significantly more time and resources. Many businesses reported that the effects of a one-hour outage could linger for months, with some stating that they are unable to fully recover from the losses even 12 months after the event. These extended disruptions underscore the enduring consequences of power outages, particularly for electricity-intensive industries.

Industry and electricity consumption patterns

The cost of power interruptions is not significantly influenced by the type of industry. Whether a plant operates in forestry, steel, chemistry, or mining/mineral production, the economic impact of an outage is more closely tied to the volume of electricity consumed than to the specific sector. High electricity use, regardless of the industry, emerges as the primary driver of outage costs.

Plants with extensive production schedules, such as those running 24 hours a day, 7 days a week, tend to report higher stated costs of power outages. Their continuous operations make them particularly vulnerable to disruptions. However, increase in outage costs diminishes as total production hours rise, indicating a nonlinear relationship between production hours and stated costs.

When compared to broader economic sectors studied in previous research, Swedish energy-intensive plants report relatively lower VoLL estimates. This suggests that, despite their high electricity use, these industries may have developed specific coping mechanisms or adaptive strategies that mitigate some of the financial impacts of power outages.

Reflections on methodology and assumptions

This study integrates survey responses with plant-level production data. This approach provides comprehensive and detailed view of the cost implications of power outages for Sweden’s electricity-intensive industries. This ensures that the findings are well-supported by both qualitative and quantitative data.

It is important to note, however, that the findings are strictly valid for the surveyed population of large electricity users. While similar trends might be observed in less electricity-intensive industries, the specific conclusions drawn from this study should not be generalized beyond the target group without further investigation.

Considerations for future research

The findings of this study highlight several promising avenues for future research. One important area is a comprehensive cost-benefit analysis of investment strategies aimed at improving grid stability and backup power capabilities. This analysis could compare the benefits of investing in public grid infrastructure versus supporting private-sector backup power installations. By examining the balance between public and private investments, such research could help develop resilience strategies are both cost-effective and sustainable.

Another valuable area for exploring is the regional variation in the Value of Lost Load (VoLL) across Sweden's electricity markets. Different regions and electricity price zones may face unique challenges stemming from variations in grid reliability, industrial structures, and economic activities. A deeper understanding of these regional differences could inform tailored policy interventions, enabling region-specific solutions to strengthen resilience and address local vulnerabilities more effectively.

The potential of demand flexibility as a resilience strategy for electricity-intensive industries also merits further investigation. This research could focus on how businesses can adapt production processes to respond to dynamic pricing signals, reducing their dependence on backup power systems. Adaptive strategies like these could enable industries to support overall grid stability during periods of high demand, providing a complementary approach to traditional resilience measures.

Final reflections

This study underscores the substantial economic impacts of power outages on Sweden's electricity-intensive industries and highlights the limitations of traditional metrics like value added in capturing these costs. The findings emphasize the need for a comprehensive approach that integrates stated cost data to reflect for the real-world consequences of outages of outages more accurately.

While the results provide valuable insights for the surveyed population, their applicability to less electricity-intensive industries remains limited. Expanding the research to include other sectors and regional contexts could provide a more holistic understanding of outage costs across Sweden's economy, supporting tailored solutions for diverse industries.

Advancing research into energy resilience and refining methodologies for assessing the economic impact of outages will enable policymakers to make well-informed decisions. By fostering a more reliable, adaptive, and sustainable electricity system, such efforts can ensure greater economic stability and resilience in the face of future challenges.

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Appendix

A1. The value of hedging against lost load of electricity[22]

Being faced with the uncertainty of potential lost load will give the firm incentive to incur cost to try to hedge against this undesirable outcome. Here we explore the possibility to theoretically assess the value of hedging against lost load using the concept of certainty equivalence.

Assume a firm that uses, among other inputs (X), electricity (E) to produce output (Q). Write the production function as

$$Q = Q(X, E)$$

Profits can then be expressed as

$$\pi = \pi(Q(X, E)) = \pi(X, E)$$
$$\frac{\partial \pi}{\partial E} > 0, \frac{\partial \pi^2}{\partial^2 E} < 0$$

Assume that the probability of a business-as-usual (BAU) outcome in a specific period is p and the probability of lost load or outage is (1 - p). The value/cost of electricity used associated with the outcome p is E^*, and the value of electricity use associated with (1 - p) is 0. If lost load occurs production stops and the loss for that period is C (start-up costs, loss of profit/output, etc.)

Expected value/cost of electricity use in each period with the risk of lost load becomes

$$Exp[E] = pE^* + (1 - p) \cdot 0 = pE^*$$

Expected profits in each period with the risk of lost load becomes

$$Exp[\pi(X, E^*)] = p\pi(X, E^*) + (1 - p)\pi(X, 0) = p\pi(X, E^*) - (1 - p)C$$

What would be the amount or value of certain electricity delivery that the firm would accept if it could hedge away the uncertainty? This is the amount of electricity (E^{CE}) that equalizes expected profits to the certainty equivalent amount of profits:

$$Exp[\pi(X, E)] = \pi(X, E^{CE})$$

or

$$p\pi(X, E^*) - (1 - p)C = \pi(X, E^{CE})$$

Assuming $\pi(X, E) = \pi(E) = \sqrt{E}$ (suppressing X) for BAU, and $\pi(0) = -C$ for when an outage occurs, we can write

[22] This follows closely the exposition in Broberg et al. (2021).

$$p\sqrt{E^*} - (1-p)C = \sqrt{E^{CE}}$$

So that,

$$E^{CE} = p^2E^* - (1-p)^2C^2$$

Now observe figure below. The distance between the expected value of electricity pE^* and E^{CE} is the amount of electricity that the firm would willingly forego to achieve a certain amount of electricity instead of the expected or amount which is associated with the "gamble" that the positive probability of lost load introduces. The profit foregone, or willingness to accept for the no-risk outcome, is the difference between profits at the "gamble" electricity level pE^* and profits at the certainty equivalence use of electricity E^{CE}. That is, lost value of eliminating risk ($LVER$) is

$$LVER = \pi(pE^*) - \pi(E^{CE}) > 0,$$

if the profit function is concave in E. In other words, the loss in profits that the firm is willing to accept (WTA) to eliminate the risk of lost load. Using $\pi = \sqrt{E}$ we can write this expression as

$$LVER = \sqrt{pE^*} - \sqrt{p^2E^* - (1-p)^2C^2}$$

The effect of increasing the probability of the bad outcome (decreasing p) is that the cost of eliminating risk, LVER, increases (that is, $dLVER/dp < 0$, meaning $dLVER/d(1\text{-}p) > 0$.

In sum; the firm would be willing to incur costs (or lose profits) in order to avoid the risk of lost load and that cost is associated the probability of an unfavorable outcome, p, the level of the desired outcome electricity, E^*, and the cost of an outage, C. The more firms dislike risk, the larger the WTA a profit loss to achieve a certain outcome, as is represented by the curvature or concavity of the profit function, $\pi(E)$.

The figure below illustrates the argument. The concave curvature of the profit function signals risk-aversion. This risk-aversion induces a value of a certainty equivalence outcome, that is, the WTA a profit loss to avoid the gamble of potential lost load. The more concave the profit function, the more risk-avert the firm is, and consequently the higher the WTA value for a certain outcome.

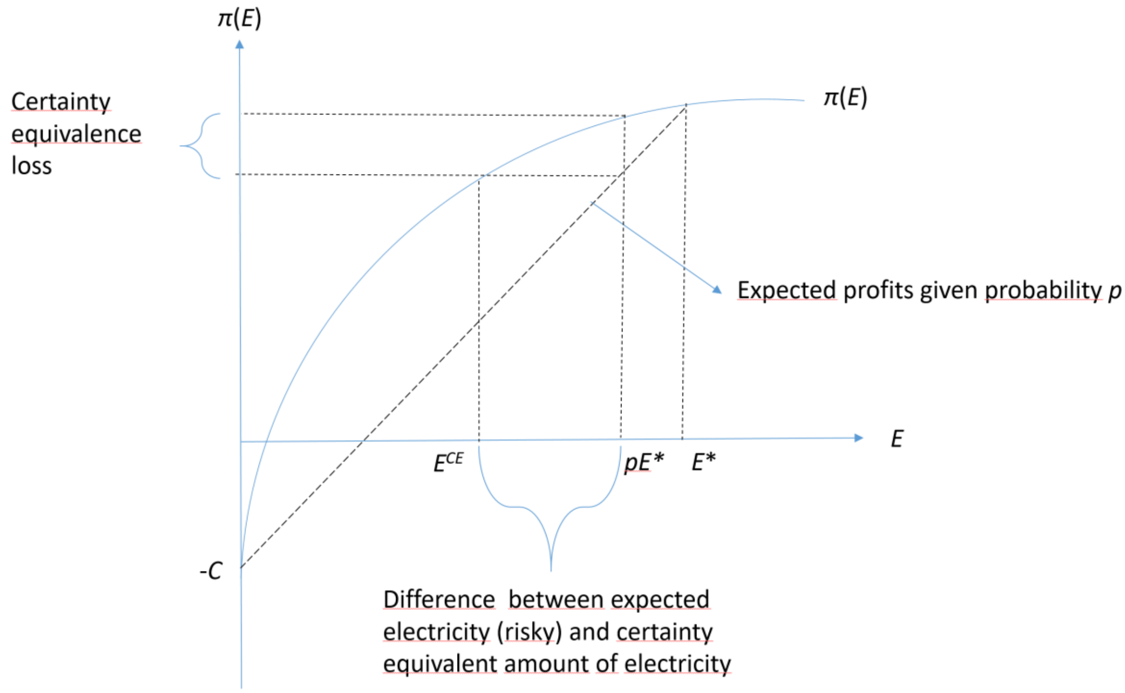

Illustration. Certainty equivalence loss when profit function is concave in electricity use. Own interpretation based on figure in Broberg et al. (2021).

A2. Model estimations with trimmed (winsorized) cost

The report has presented and discussed that the reported cost is skewed and characterized by some "extreme" plants. As one form of robustness check, we have trimmed the cost variable with a so-called winsorizing approach. Specifically, the 2.5% most extreme costs are transformed to the next less extreme observation. The model results based on this data is presented in Table A1 and A2.

Table A1 Model 1-4 with winsorized at P=0.025 cost.

	1		**2**		**3**		**4**	
ln_mwh	0.821	**	1.833		1.822		0.443	
	(0.169)		(1.609)		(1.599)		(3.702)	
dur	0.008	**	0.022	**	0.022	**	0.022	**
	(0.001)		(0.002)		(0.002)		(0.002)	
dur # ln_mwh	-0.000	**	-0.000	**	-0.000	**	-0.000	**
	(0.000)		(0.000)		(0.000)		(0.000)	
dur # dur			-0.000	**	-0.000	**	-0.000	**
			(0.000)		(0.000)		(0.000)	
ln_mwh # ln_mwh			-0.049		-0.047		0.015	
			(0.078)		(0.077)		(0.155)	
SKGS (Base=Other)								
Forest					-0.049			
					(0.489)			

	1		2		3		4	
Chemical					-1.117			
					(0.863)			
MiningStone					-0.353			
					(0.897)			
Basic IS					-0.148			
					(0.683)			
4 quantiles (Base=Q1)								
2							0.810	
							(0.614)	
3							0.668	
							(1.320)	
4							0.572	
							(2.011)	
Intercept	2.431		-3.235		-3.144		3.582	
	(1.572)		(8.184)		(8.025)		(20.015)	
sigma_u	3.162	**	3.174	**	3.161	**	3.163	**
	(0.347)		(0.365)		(0.321)		(0.356)	
sigma_e	2.122	**	1.993	**	1.993	**	1.993	**
	(0.156)		(0.139)		(0.161)		(0.145)	
rho	0.689		0.717		0.715		0.716	
	(0.054)		(0.049)		(0.053)		(0.053)	
Log likelihood	-4557.66		-4460.40		-4458.94		-4459.41	
Number of observations	1970		1970		1970		1970	
** p<.01, * p<.05								

Table 11 Model 5-9 with winsorized at P=0.025 cost.

	5		6		7		8		9	
ln_mwh	0.308		0.834							
	(1.249)		(1.401)							
Duration	0.020	***	0.022	***	0.018	***	0.017	***	0.017	***
	(0.002)		(0.002)		(0.002)		(0.002)		(0.001)	
Prod.hrs	0.002	**	0.002	***	0.001	*	0.002	**	0.002	**
	(0.001)		(0.001)		(0.001)		(0.001)		(0.001)	
Dur # Dur	-0.000	***	-0.000	***	-0.000	***	-0.000	***	-0.000	***
	(0.000)		(0.000)		(0.000)		(0.000)		(0.000)	
ln_mwh#ln_mwh	0.009		0.009							
	(0.057)		(0.068)							
Prod.hrs#Prod.hrs	-0.000	**	-0.000	***	-0.000		-0.000	**	-0.000	*
	(0.000)		(0.000)		(0.000)		(0.000)		(0.000)	

	5		6		7		8		9	
Dur # ln_mwh	-0.001	***	-0.000	***						
	(0.000)		(0.000)							
ln_va	0.510	***								
	(0.173)									
ln_va # Dur	0.000									
	(0.000)									
ln_voll_sek			0.564	***	0.216		0.367	**	0.334	
			(0.161)		(0.180)		(0.176)		(0.223)	
Dur # ln_voll_sek							0.000	**	0.000	**
							(0.000)		(0.000)	
4 quantiles, MWH. (Base=Q1)										
2							0.962	**		
							(0.447)			
3							1.232	**		
							(0.528)			
4							2.976	***		
							(0.481)			
SKGS (Base=Other)										
Forest									1.734	***
									(0.433)	
Chemical									-0.822	
									(1.117)	
MiningStone									1.713	**
									(0.749)	
Basic IS									1.167	*
									(0.674)	
Intercept	-6.452		-6.746		3.109		1.275		0.625	
	(6.064)		(7.490)		(2.848)		(2.521)		(3.188)	
sigma_u	2.940	***	2.941	***	3.159	***	3.001	***	3.057	***
	(0.295)		(0.297)		(0.233)		(0.256)		(0.251)	
sigma_e	1.967	***	1.970	***	1.979	***	1.972	***	1.972	***
	(0.114)		(0.150)		(0.179)		(0.170)		(0.123)	
rho	0.691		0.690		0.718		0.698		0.706	
	(0.044)		(0.046)		(0.036)		(0.044)		(0.038)	
Log likelihood	-4208.10		-4210.05		-4235.16		-4216.62		-4220.76	
No. observations	1874		1874		1874		1874		1874	
*** p<.01, ** p<.05, * p<.1										

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