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Zero Energy Day: How Nationwide Blackouts Affect the Economy*

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Abstract

Electricity reliability is a central challenge for the energy transition, as growing energy demand, renewable energy integration, and natural disasters increase the risk of large-scale blackouts. However, the economic impacts of large-scale blackouts remain largely unknown. Combining electricity market data with high-frequency economic transaction data from Chile, we find that economic activity declined by 35 percent on the nationwide blackout day, but half of this loss was recovered on subsequent days, highlighting the importance of intertemporal substitution. Exploiting spatial variation in blackout severity, we show that accounting for endogenous recovery is critical when estimating the marginal value of lost load.

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1 Introduction

Electricity reliability has become a central challenge for the energy transition. The rapid expansion of renewable energy has increased power systems' exposure to intermittency and weather-driven supply fluctuations. At the same time, electrification of transportation, heating, and industry—coupled with the rapid growth of data centers—has increased both the level and volatility of electricity demand. These pressures are compounded by aging transmission and distribution infrastructure, delays in grid expansion, and intensifying climate-related shocks such as heat waves, droughts, and extreme storms (Warner, Callaway and Fowlie, 2025). Together, these forces complicate the real-time balancing of electricity supply and demand, increasing the risk of severe system-wide power outages[1].

In fact, large-scale blackouts have recently affected many parts of the world. In March 2026, Cuba experienced a nationwide blackout caused by fuel shortages, leaving about ten million people without power for approximately 29 hours. Chile—one of the frontier countries in renewable energy expansion—experienced a nationwide blackout in February 2025. Similarly, Portugal and Spain, both highly renewable-intensive power systems, were hit by the 2025 Iberian Peninsula blackout in April, leaving large portions of the two countries without electricity for more than ten hours. In North America, wildfire-driven power outages have become increasingly frequent in recent years, affecting millions of electricity customers in California and across the western United States and Canada. Finally, the 2021 winter power crisis in Texas left more than four million homes and businesses without electricity for several days.

Despite the growing importance, the economic impacts of large-scale blackouts remain largely unknown. One key challenge is that nationwide outages are rare events—particularly in developed economies—and tend to occur under exceptional technical or environmental conditions. As a result, much of the existing empirical literature relies on survey-based measures, partial outages, or settings characterized by chronic electricity shortages. Consequently, empirical estimates of the

[1] Borenstein, Bushnell and Mansur (2023) provides a comprehensive review of the economics of electricity reliability.

Value of Lost Load (VoLL) in markets where outages are infrequent remain limited, despite the central role VoLL plays in electricity market design and reliability planning.[2]

A second challenge is conceptual. The economic losses generated by blackouts unfold over time rather than occurring instantaneously. Economic activity disrupted during an outage may be permanently lost, partially reallocated to other locations, or postponed to subsequent periods. Ignoring these dynamic responses risks mismeasuring the true economic costs of outages. Yet, most empirical studies rely on static comparisons that do not explicitly account for intertemporal substitution or endogenous recovery.

In this paper, we study the economic effects of a rare and unexpected nationwide blackout in Chile that occurred on February 25, 2025, leaving more than 90 percent of the population without electricity for several hours. The event provides a unique opportunity to examine the real-time economic consequences of a large-scale supply failure in a middle-income country with a modern electricity system, high rates of electronic payments, and rich administrative data. We combine hourly substation-level electricity demand and supply data from the Chilean electricity market with high-frequency economic transaction data provided by the Central Bank of Chile. Our data cover both retail and business-to-business activity, to quantify immediate losses, recovery dynamics, and the marginal effect of unserved electricity on economic activity.

We begin by estimating the aggregate impact of the blackout using an event-study design. Economic transactions declined by approximately 35 percent on the blackout day. However, nearly half of this loss was recovered in the four days following the outage, highlighting the importance of accounting for dynamic intertemporal substitution when evaluating blackout costs. We find that sectors selling durable or postponable goods exhibit large contemporaneous losses followed by strong recovery, while sectors providing time-sensitive or perishable goods experience more persistent declines. Taking the universe of credit and debit card transactions, we estimate total economic losses between $36 and $70 million for approximately 32.2 GWh of lost load. These es-

[2]The Value of Lost Load (VoLL) measures the economic cost of electricity outages, typically expressed as dollars per unit of unserved electricity (e.g., $/MWh). Existing estimates often rely on stated-preference methods or simulations based on engineering models.

timates imply an average Value of Lost Load (VoLL) ranging from \$1,118/MWh when accounting for dynamic recovery to \$2,170/MWh when based solely on static, day-of losses.

We then exploit spatial variation in blackout severity to estimate the marginal effect of lost load on economic activity. A key identification challenge is that outage duration and recovery are not randomly assigned across space. For example, system operators may prioritize restoration in areas with higher expected economic losses, in which case naïve comparisons across locations would substantially understate the true marginal cost of unserved electricity.

We address this concern using instrumental variables that exploit exogenous variation in the topology of the transmission network and supply-side recovery constraints. Our estimates imply that ordinary least squares substantially underestimate the economic cost of unserved electricity. We find that a one–percentage-point increase in lost load leads to an additional 1.9 percent decline in economic activity on the blackout day. We translate these losses to VoLL estimates at the province level and find that the VoLL is relatively stable as a function of the percentage of lost load and in line with the aggregate estimates. Although the results are noisy, the relationship tends to be negative: areas with longer blackouts have a smaller (marginal) VoLL, consistent with prioritization by regulators.

The empirical findings of our analysis underscore the economic importance of reliability in electricity markets and provide new estimates of the impacts of zero-energy events. Our key findings—including the static and dynamic effects of large-scale blackouts, their implications for VoLL, the potential endogeneity of spatial variation in blackout duration, and econometric methods to address this challenge—are policy-relevant for many countries as they are increasingly facing electricity reliability challenges in the energy transition.

Contributions and related literature Our study makes three primary contributions to the economics literature. First, we fill an important gap by providing among the first empirical evidence on the economic costs of severe, system-wide electricity failures—events that are central to reliability planning and infrastructure investment for the energy transition. As highlighted in a recent review by Borenstein, Bushnell and Mansur (2023), most of the relevant economic research has focused on the impacts of blackouts in developing countries, where blackouts are characterized by chronic and frequent electricity shortages, such as anticipated and regular load shedding.[3] While this literature provides valuable insights into firm behavior and adaptation under persistent electricity constraints—conditions commonly observed in developing countries—it offers limited guidance for quantifying the economic costs of severe system-wide failures.

Second, we quantify the economic costs of nationwide blackouts using administrative records from both the electricity market and the Central Bank of Chile. A key challenge in assessing large-scale, unanticipated blackouts—as opposed to chronic and frequent electricity shortages—is that such analysis requires high-frequency and granular data on both electricity loads and economic transactions. Most existing studies therefore rely on surveys or engineering models, because standard economic data—such as monthly or annual measures of economic activity—lack the temporal resolution needed to identify both the immediate impacts of outages and the subsequent dynamics of recovery. To our knowledge, our analysis is the first to overcome this challenge by integrating hourly, substation-level electricity data from electricity markets with confidential microdata on daily economic transactions obtained from a central bank.

Third, our approach—based on high-frequency administrative records during a system-wide blackout—complements with other revealed-preference methods for estimating VoLL. For example, several recent studies use a defensive investment method that examines residential electricity customers' purchases of batteries or generators in relation to blackout risks to infer their willingness to pay (WTP) to avoid electricity shortages at home (Harris, 2023; Brehm, Johnston and Milton, 2024; Brown and Muehlenbachs, 2024; Adelowo, 2025). A key advantage of this method is that it could capture a broad range of VoLL components, including utility losses from inconvenience and discomfort that are not directly reflected in the economic transaction data we analyze.

[3] Key studies in this strand of the literature include Alby, Dethier and Straub (2013); Andersen and Dalgaard (2013); Goldberg (2015); Fisher-Vanden, Mansur and Wang (2015); Allcott, Collard-Wexler and O'Connell (2016); Abeberese (2017); Makhdoom, Nawaz and Narejo (2017); Hardy and McCasland (2021); Jha, Preonas and Burlig (2022); Meeks, Omuraliev, Isaev and Wang (2023); Berkouwer, Biscaye, Mikdash, Puller and Wolfram (2024); Moreblessing, Wadesango and Sitsha (2024).

A key challenge, however, is that the defensive investment method requires consumers to form accurate beliefs about future outage risk and to respond to that risk in a rational and forward-looking manner. By contrast, our approach directly estimates VoLL from realized economic damages rather than inferring it from preventive behavior, and it captures impacts across a broad set of sectors in the economy rather than focusing solely on residential customers. Taken together, each method has distinct strengths and limitations and is therefore complementary for quantifying the economic costs of large-scale blackouts.

2 Background and Data

To investigate the economic impact of this nationwide blackout, we integrate electricity market data with economic data from the Central Bank of Chile. In this section, we also provide more context for the event itself.

2.1 The Nationwide Blackout on February 25, 2025

At 3:16 PM on February 25, 2025, Chile experienced a widespread power failure across the nation, leaving more than 90 percent of the population without electricity for prolonged hours. The immediate cause of the outage was traced to a malfunction in the protection and control systems of a high-voltage transmission line in Coquimbo region. The long-distance transmission line plays a critical role in linking electricity generation in northern Chile with demand centers in central and southern regions (Gonzales, Ito and Reguant, 2023).

In response, the Chilean government declared a state of emergency and implemented temporary security measures, including curfews in some regions, to maintain public order during the blackout. Power restoration progressed gradually over the evening and overnight, and by the following day electricity had been restored to the vast majority of affected households and businesses.

Figure 1 shows hourly electricity consumption (GWh) for regulated customers (*clientes regu-*

lados), which include residential and commercial users.[4] Panel A shows the raw data, and Panel B presents the recovery ratio, defined as total hourly electricity consumption divided by consumption in the same hour on the day prior to the blackout (February 24, 2025). It shows that most customers lost electricity immediately following the blackout at 3:16 pm and did not regain power until around midnight.

2.2 Electricity Market Data from the System Operator

Our electricity market data consist of (i) hourly electricity demand at the substation level and (ii) hourly power generation at the power plant level. Both datasets are publicly available from the Coordinador Eléctrico Nacional, the system operator of the Chilean electricity market.[5]

Electricity demand—Our hourly electricity demand data are available at the substation level. Chile has a three-tiered administrative structure with 16 regions, 56 provinces, and 346 communes. Typically, there are multiple substations in a commune, totaling 1252 substations nationwide. We aggregate substation-level demand data to the national level in Section 3 and to the commune level in Section 4.

Electricity generation—We also gather power plant–level hourly generation data, which we link to commune-level transaction data in Section 4. Because not all communes have power plants, we aggregate hourly generation data to the province level using the longitude and latitude of each plant.

2.3 Economic Data from the Central Bank of Chile

To identify both the immediate impacts of the blackout and the potential intertemporal recovery, we require high-frequency data. Standard economic data, such as census data or surveys, are not suitable because they are recorded at annual or monthly frequencies. We therefore entered into a

[4] Another customer segment consists of free customers (*clientes libres*), primarily mining and large industrial users, who procure electricity through direct contracts with suppliers. We focus on regulated customers in this figure because our economic outcome data primarily capture activity among commercial customers.

[5] The website is https://www.coordinador.cl (last accessed on December 28, 2025).

data use agreement with the Central Bank of Chile to access two proprietary datasets that record high-frequency economic transactions.

Administrative tax records—Our first economic dataset consists of the universe of administrative tax records on retail transactions, known as *boletas electrónicas*. In Chile, retail sellers are required to record all sales transactions and report them in real time to the Servicio de Impuestos Internos (SII), Chile's tax authority.

The dataset contains transaction-level information on the date and time of each transaction, the seller's tax identifier, the transaction amount, and the value-added tax (VAT). A key advantage of this dataset is that, due to mandatory reporting, it captures high-frequency consumer spending for the universe of formal retail transactions. Importantly, it includes transactions with all payment methods, including cards, cash, and checks. The dataset also classifies transactions by economic sector, which allows us to study heterogeneous effects across sectors in Section 3.2.

This dataset has two main limitations. First, it does not capture business-to-business transactions. Second, although it records establishment locations, these locations typically correspond to firm headquarters rather than points of sale. This limitation does not affect our analysis of national-level impacts in Section 3.1, but it makes the data unsuitable for regional-level analysis in Section 4.

Credit, Debit, and Prepaid Card Transactions—Our second economic dataset consists of the near-universe of real-time transactions made with credit, debit, and prepaid cards. The Central Bank of Chile obtains these data from the two leading transaction processors, Transbank and Getnet, which together account for 93% of card transactions in Chile (Feller, 2024; Diario Financiero, 2024).

Chile is a leading country in cashless payments, with over 80% of transactions made using debit, credit, or prepaid cards (Central Bank of Chile, 2025). Nevertheless, a limitation of this dataset relative to our administrative tax records is the absence of cash payments.

This dataset has several important advantages. First, each transaction includes the actual location of the transaction, which allows us to exploit spatial variation in Section 4. Second, it covers both business-to-business and business-to-consumer transactions, capturing a broader range of economic activity than retail-only data.

2.4 Potential Threats to Data Collection During Blackouts

An advantage of our two datasets is that they are high-frequency administrative records collected in real time. A potential concern, however, is that the blackout itself may have disrupted data collection, which could confound our analysis.

Although this is an important threat, it is unlikely to materially affect our results for several reasons. First, retailers in Chile typically use mobile, portable payment terminals to process transactions. The batteries of these devices last for several days, making them unlikely to be directly affected by the blackout (La Tercera, 2025; BioBioChile, 2025), allowing retailers to continue processing card transactions over mobile networks.[6]

Nevertheless, this issue remains an important consideration for our data, and more generally for any data collected during blackouts. For example, if a customer attempts to make a purchase but the transaction cannot be completed due to a power outage, our data record this as an absence of transactions. Accordingly, our empirical estimates should be interpreted as capturing the total economic impact of the blackout, including both the loss of transactions due to payment disruptions and other channels, such as reduced customer access to retail locations.

3 Economic Impacts of Blackouts and Intertemporal Recovery

In this section, we use event-study regressions to estimate the economic impact of blackouts and intertemporal recovery. We present results for the aggregate economy in Section 3.1 and sectoral

[6] Specifically, infrastructure classified as critical level 1—such as core network switching centers, primary data centers, network operation centers, and backbone nodes essential for system-wide functionality—must ensure a minimum of 48 hours of autonomous operation. Moreover, critical level 2 infrastructure—including mobile radio base stations, access network antennas, and local aggregation nodes serving end users—must provide at least 4 hours of autonomy (Ministerio de Transportes y Telecomunicaciones, 2012).

heterogeneity in Section 3.2.

3.1 Aggregate Impact on the Economic Activity

We use x_{dy} to denote the natural log of total economic transactions (in billions of Chilean pesos) on day d in year y. Using daily data from 2022–2025, we estimate the event-study regression by OLS:

$$x_{dy} = \alpha_y + \gamma_d + \theta_j + \sum_{j=-s}^{s} \phi_j D_{j,dy} + \epsilon_{yd}, \tag{1}$$

where α_y is the year fixed effects and γ_d is the calendar day fixed effects (e.g. February 25). We use j to denote the event-time relative to the blackout day. For 2025, $j = 0$ on the blackout day, February 25 (Tuesday), 2025, and we include daily data between $j = -14$ and $j = 14$. For other years, we define $j = 0$ to be the last Tuesday of February. That is, our event-time j is the day relative to the last Tuesday of February in each year. In this way, our event-time fixed effects (θ_j) controls for both seasonality and day-of-the week effects. In addition, our calendar-day fixed effects (γ_d) absorb unobserved effects systematic to each calendar date. $D_{j,dy}$ equals one if the day d in year y corresponds to event-time j and zero otherwise. The estimates of interest are θ_j, which are event-time coefficients for days in 2025, controlling for the set of fixed effects in equation (1). We use heteroskedasticity- and autocorrelation-consistent standard errors.

Figure 2 presents the estimated event-study coefficients $\hat{\theta}_j$ based on the card transaction data that cover both retail and business-to-business transactions.[7] It shows that the economic transactions declined by approximately 0.4 log points (33 percent) on the black-out day relative to the day before the blackout. The figure also suggests that there were intertemporal recovery effects after the blackout day.

To identify the blackout-day impact and intertemporal recovery effect, we estimate the follow-

[7] The corresponding event-study figure based on the administrative tax records is reported in A.1. As we show in Table 1, the estimated impacts are quantitatively similar across the two datasets.

ing regression by OLS:

$$x_{dy} = \alpha_d + \gamma_y + \theta_j + \beta B_{dy} + \rho R_{dy} + \epsilon_{yd}, \tag{2}$$

where B_{dy} is an indicator variable for the blackout-day, which equals one on February 25, 2025 and zero otherwise. R_{dy} is an indicator variable for the potential intertemporal recovery effects, which equals one for the four days after the blackout day.[8] We use heteroskedasticity- and autocorrelation-consistent standard errors.

In Table 1, we show the estimation results of equation (2). The first column shows the blackout-day impact on the economic activity in percentage effects.[9] Our estimate indicates that the nationwide economic transactions declined by 34.7% on the blackout day based on the card transactions data. The result based on the tax records show a 32.6% decline, implying that we find quantitatively similar results between the two datasets.

The second column of Table 1 suggests that it can be misleading to conclude the impact only based on the blackout-day impact. This is because some of the lost transactions can be substituted by an increase in transaction after the recovery. We find that the total recovery during the four days after the blackout day was 16.9%, implying that the net impact is a 17.8% decline in transaction based on the card transaction data—similarly, the total recovery during the four days after the blackout day was 17.2%, implying that the net impact is a 15.4% decline in transaction based on the tax records.[10]

3.2 Heterogeneity by Economic Sector

Blackout impacts could vary across sectors due to differences in electricity dependence, the scope for intertemporal substitution, reliance on electronic payments and information technologies, and

[8]The blackout-day was Tuesday. We include the four days after that date (Wednesday, Thursday, Friday, and Saturday) to capture the potential intertemporal recovery throughout the week.

[9]$\hat{\beta}$ in equation (2) provides an effect in log points. We convert it to the exact percentage effect by $100 \cdot (\exp(\hat{\beta}) - 1)$ and calculate the standard errors by the delta method.

[10]Recall that R_{dy} in equation (2) is an indicator variable for the four days after the blackout day. Thus, we calculate the total recovery effect in percent by $4 \cdot 100 \cdot (\exp(\hat{\rho}) - 1)$ and calculate the standard errors by the delta method.

the degree of customer substitution across locations. Sectors producing time-sensitive or non-storable services are expected to experience larger and more persistent losses, whereas sectors selling durable or postponable goods may exhibit faster recovery following the restoration of power.

In Figure 3 and the bottom part of Table 2, we use administrative tax records to estimate the blackout-day impact and intertemporal recovery of economic activity by sector. The sectoral analysis yields several key findings.

First, sectors selling durable goods—such as automobiles, hardware, and agricultural materials—experience large negative effects on the blackout day, much of which is subsequently recovered through intertemporal substitution. For example, car sales declined by 60% on the blackout day but increased by 52% during the recovery period, resulting in a net decline of 8.5%. Similarly, sales of agricultural raw materials fell by 33% on the blackout day, with most of the loss recovered in subsequent days.

Second, sectors selling perishable goods—such as supermarkets, food stores, and pharmacies—also experience negative effects on the blackout day, but exhibit only partial intertemporal recovery. For instance, supermarket sales declined by 25% on the blackout day and increased by only 9.8% during the recovery period, yielding a net decline of 15.5%.

Third, we observe a similar pattern of limited recovery in sectors selling discretionary goods, including department stores and textile retailers. Department store and textile sales declined by 45% and 52%, respectively, on the blackout day, with only modest recovery thereafter.[11]

3.3 Implied Value of Lost Load

The aggregate and sectoral patterns provide a direct mapping from lost electricity supply to realized economic losses, which can be used to construct empirical measures of the Value of Lost Load (VoLL). VoLL measures the economic cost of electricity outages. Conceptually, the VoLL captures the welfare loss experienced by consumers and firms when electricity supply is interrupted. The

[11] Point estimates for online sales and intermediate goods suggest recovery effects that exceed the blackout-day impact; however, these estimates are imprecise and have large standard errors, as shown in Table 1.

VoLL plays a central role in electricity market design and reliability planning, as system operators and regulators use it to evaluate trade-offs between investments in generation capacity, transmission, and other reliability measures and the expected costs of outages and blackout risk.

To obtain an average VoLL, we can convert the implied loss in economic volume and compare it to the lost energy. Our average estimates suggest that the blackout led to a net loss of 17.8% of one-day economic activity, accounting for the dynamic inter-temporal substation effects on the subsequent days. The static effect, which does not incorporate this dynamic effect, is a loss of 34.7% of economic activity (see Table 1). Taking the universe of credit card transactions, this is a loss between $36 to 70 million over a lost load of about 32.2 GWh during the blackout (see Figure 1), leading to an average VoLL between $1,118/MWh (if we take into account for the dynamic substitution effects) to $2,170/MWh (if we focus on the static losses). We interpret this as an average realized VoLL for a rare, large-scale system-wide outage.

In addition to the nationwide VoLL, we can use our data to compute regional VoLLs. First, we use hourly electricity demand data to calculate counterfactual lost load at the commune level. Second, we estimate commune-level impacts on economic activity by estimating Equation (2) separately for each commune. VoLL may differ across regions for several reasons, e.g., due to underlying differences in economic activity per unit of electricity, which imply differences in VoLL. In addition, the cost of a blackout depends on its nature and duration. While total losses increase with outage length, the VoLL is typically modeled as declining with outage length. Consistent with this approach, Figure A.2 shows that regional VoLL ($/MWh) declines as lost load increases.

We can compare our estimated VoLL to existing estimates for Chile. Recently, Comisión Nacional de Energía (2025) employ a direct survey-based method and report a short-duration value of approximately $6,430/MWh for commercial interruptions lasting four hours or more (and about $8,600/MWh for interruptions shorter than four hours), consistent with a declining VoLL in stated-preference surveys as duration increases. The same study also presents substantially higher estimates under an aggregate value-added approach based on sectoral GDP and electricity consumption, with commercial VoLL exceeding $14,000/MWh. These magnitudes are broadly consistent with the national short-duration values reported in the earlier CNE study (Comisión Nacional de Energía, 2021), which imply figures on the order of $14,000/MWh.

Relative to these figures, our estimate is substantially lower, but it is derived from the universe of realized retail transactions rather than from surveys or value-added ratios. It therefore measures revealed, preference-based losses in the form of foregone transactions in retail and services. At the same time, it does not capture the full social cost of outages, which includes production losses beyond the retail margin, consumer surplus effects, inconvenience, safety risks, and broader disruptions to daily life. Our estimate should thus be interpreted as a conservative lower bound for policy evaluation, providing a high-precision benchmark for direct transactional losses that complements broader, structurally derived VoLL measures.

4 Using Spatial Variation to Estimate the Marginal Effect of Lost Load

While informative for benchmarking reliability costs, the average VoLL in the previous section does not capture how losses scale with outage severity, which is the relevant object for many reliability and restoration decisions. In this section, we try to go further and estimate the VoLL at the margin. For this purpose, we exploit spatial variation in unserved electricity across communes to test its impact on economic activity.

One major identification concern is that spatial variation in lost load may be endogenous in practice. For example, regulators may anticipate heterogeneous economic impacts of outages and prioritize power restoration in regions where losses are expected to be larger, e.g., in densely populated or highly commercial areas. This behavior can make outage duration non-random across space, requiring careful treatment in empirical analysis. We discuss this challenge in Section 4.1 and describe our approach to addressing it in Section 4.2.

4.1 Challenges in Exploiting Spatial Variation in Lost Load

To measure the marginal impact of lost load on economic activity we use daily commune-level sales data. In our regression, we will focus on the percent of power that was lost in a given region.

As a benchmark, consider the regression in which we regress the estimated impact of the black-out on its severity

$$\hat{\beta}_i = \alpha + \gamma L_i + \epsilon_i, \tag{3}$$

where $\hat{\beta}_i$ is the black-out day impact on the log of economic activity in commune i, obtained by estimating equation (2) separately by commune. L_i is the percentage of lost demand in area i. The coefficient γ captures the average percentage change in sales associated with an additional percent loss in demand.

One concern with this specification is that it might be too parsimonious. If the timing of blackouts is exogenous but their effects vary with duration, e.g., longer blackouts are marginally more or less costly, one can allow for non-linear impacts by estimating duration-specific effects or a quadratic or flexible specification for the impact of the blackouts as a function of the severity of losses, $\gamma(L)$.

A more general concern is that the impacts of blackouts are heterogeneous across areas and potentially correlated with the duration of the blackout. For example, it is plausible that blackout recovery depends on local economic characteristics such as economic activity and population density, making it endogenous. If restoration is prioritized toward areas with higher expected losses, then locations experiencing longer outages will tend to have lower marginal impacts, mechanically attenuating OLS estimates of the effect of lost load.

To illustrate this endogeneity concern, suppose that power restoration follows a priority rule,

$$L_i = \eta + \phi Z_i + \rho V_i + u_i, \tag{4}$$

where V_i captures the economic importance of area i, and Z_i includes other determinants of restoration. A negative ρ would reflect prioritization of economically valuable areas. If V_i is correlated with expected blackout impacts $E[\beta_i]$, then longer blackouts will tend to occur in locations with smaller marginal losses. In this case, estimated duration effects β_q need not increase with q, and may appear concave even when the underlying causal effect is linear or increasing in duration.

Panel A of Figure 4 presents a numerical illustration of how OLS estimates of γ can behave in the presence of heterogeneous impacts and endogenous blackout duration. The dashed black line shows a benchmark case with constant marginal effects and random recovery, where each additional hour of outage reduces sales by 5%. The solid red line represents a setting with selection or genuinely declining marginal effects, in which the incremental impact of an additional blackout hour diminishes. The dotted red line illustrates a case in which prioritization dominates and areas with small impacts are recovered more slowly on average. In this case, the OLS impact of blackout length can be substantially attenuated.

4.2 Estimating the Marginal Effect of Lost Load

There are several potential approaches to estimating the conditional effect of blackouts while addressing selection in outage duration. One strategy is to exploit variation in outage exposure conditional on the economic value of an area, V_i, and other observable characteristics that are likely to be correlated with the impact β_i, for example through rich fixed effects and controls. A second approach is to design empirical strategies around thresholds or prioritization rules that govern restoration, such as preferential treatment of critical infrastructure like hospitals, if sufficiently granular data are available. A third option is to use instruments Z_{it} that shift the magnitude of the blackout shock exogenously, for instance through variation driven by network topology or technical constraints. In our context, we address selection concerns by exploiting plausibly exogenous variation in the restoration rollout.

We first obtain an estimate of the impact of the blackout for each commune. Recall that Equation (2) estimates the blackout-day effect, β, on economic activity using an event-study regression that controls for calendar-day fixed effects, event-time fixed effects, and year fixed effects. To obtain commune-level economic impacts β_i for each commune i, we estimate this specification separately for each commune. We then convert it into percentage effects using $1 - \exp(\beta_i)$.

Panel B of Figure 4 presents a binscatter plot of the commune-level blackout-day effects (percentage changes in economic transactions) against lost load, measured as the percentage of electricity load lost during the 24 hours following the blackout relative to the same 24-hour window on the previous day.[12] The empirical pattern in Panel B is consistent with the theoretical prediction illustrated in Panel A, with a U-shaped relationship between blackout-day impacts and blackout severity.

Regressing the commune-level blackout-day impact on lost load using OLS yields a slope estimate of -0.105 with a standard error of 0.091. However, as discussed in Section 4.1, this OLS estimate may be biased if lost load is endogenously determined based on anticipated heterogeneous economic impacts β_i. To address this endogeneity concern, we construct two instrumental variables.

Our first instrument is the distance from each commune to the Coquimbo region, the origin of the grid failure. As described in Online Appendix C, power restoration began in regions farther from the origin and gradually propagated toward other regions. Because this restoration pattern was largely driven by technical characteristics of the transmission network, distance to the origin provides plausibly exogenous variation in recovery speed.

Our second instrument exploits supply-side variation in electricity generation. Following the outage, different generation technologies required different ramp-up processes to resume production, which resulted in heterogeneous supply-side lost load at the power-plant level. We aggregate this measure to the province level to construct a province-level supply-side lost load variable, defined analogously to the demand-side lost load.[13] Because this variation is driven by technical constraints of generation technologies, it also provides plausibly exogenous variation in recovery dynamics.

[12] Using commune-level hourly electricity consumption data, we calculate total electricity consumption between 3:00 p.m. on February 25, 2025 and 3:00 p.m. on February 26, and divide it by the same measure for the previous day to quantify the fraction of load lost.

[13] Using plant-level hourly generation data, we calculate total electricity generation between 3:00 p.m. on February 25, 2025 and 3:00 p.m. on February 26, and divide it by the same measure for the previous day. Aggregation is performed at the province level because not all communes host power plants.

Both of our instruments rely on quasi-experimental variation and therefore have limitations. A potential concern with the distance-based instrument is that distance to Coquimbo may be correlated with unobserved regional characteristics that affected recovery speed. The second instrument—the timing of power plant recovery—is plausibly more exogenous, as recovery timing is primarily determined by plants' technical characteristics. Nevertheless, we cannot fully rule out the possibility that the timing or sequence of power plant recoveries was endogenously determined or correlated with unobserved factors. Given the emergency conditions on the blackout day, system operators likely had strong incentives to restore any available power plants as quickly as possible, subject to technical constraints. However, because plant recoveries occur sequentially, restoration may not have been fully random across space. We emphasize these limitations of each instrument and therefore report results based on each instrument separately, as well as results using both instruments jointly, in Table A.1.

Figure 4 reports our main result with the two IVs (IV-GMM). We use a linear two-step Generalized Method of Moments with instrumental variables (IV-GMM) with both instruments. The IV-GMM estimate is -1.889 with a standard error of (0.62), indicating that the OLS estimate is substantially attenuated due to endogeneity. Our estimate implies that a one-percentage-point increase in lost load leads to an approximately 1.9-percent additional decline in economic activity on the blackout day.

Table A.1 reports the full set of estimation results: (i) OLS, (ii) IV using the first instrument, (iii) IV using the second instrument, and (iv) IV-GMM using both instruments. Both instruments exhibit strong first-stage relationships. The IV estimates based on each instrument separately are similar to the IV-GMM estimate, with the latter providing greater efficiency and a smaller standard error.

5 Conclusion

This paper studies the economic effects of a severe nationwide blackout using high-frequency administrative data from Chile. We document that economic activity declined sharply on the blackout day, by 35%, but half of this loss was shifted to subsequent days, highlighting the importance of accounting for intertemporal substitution. These recovery dynamics vary systematically across sectors. Activity in sectors selling durable or postponable goods rebounds quickly, while losses in sectors providing time-sensitive or perishable goods are more persistent. Depending on whether static or dynamic effects are accounted for, estimates of the value of lost load are $1,118/MWh and $2,170/MWh, respectively. Taken together, these findings highlight that blackout costs are inherently dynamic and that static, same-day measures can substantially overstate the economic impact of large-scale electricity outages.

We also use spatial variation in outage severity to estimate the marginal effect of unserved electricity on economic activity. Accounting for endogenous recovery patterns substantially increases the estimated cost of lost load relative to naïve comparisons. Our estimates imply that even small increases in outage severity lead to economically meaningful additional losses.

While our analysis captures only economic transaction losses, and therefore represents a lower bound on the full welfare cost of blackouts, it contributes to our understanding of the impacts of blackouts with very detailed high-frequency data. As electricity systems become more complex and more central to economic activity, understanding both the immediate and dynamic consequences of rare but severe outages will be critical for the design of efficient and resilient electricity markets.

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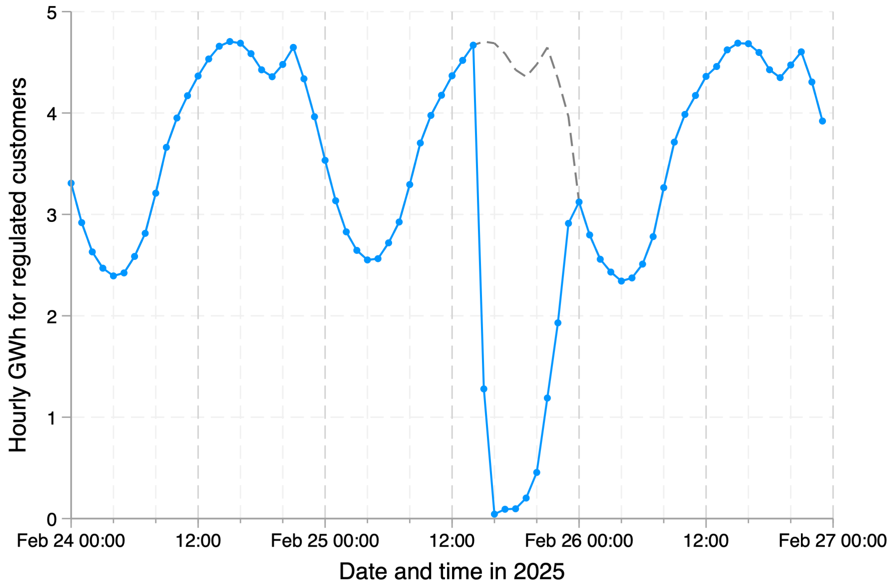
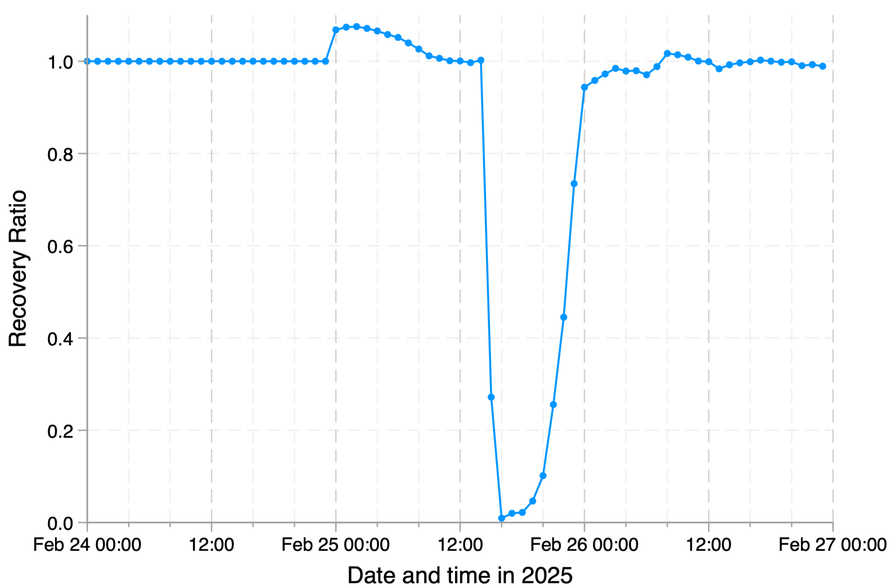
Figures and Tables

Figure 1: Hourly Electricity Consumption During the 2025 Chile Blackout

Panel A: Hourly Electricity Consumption (GWh)

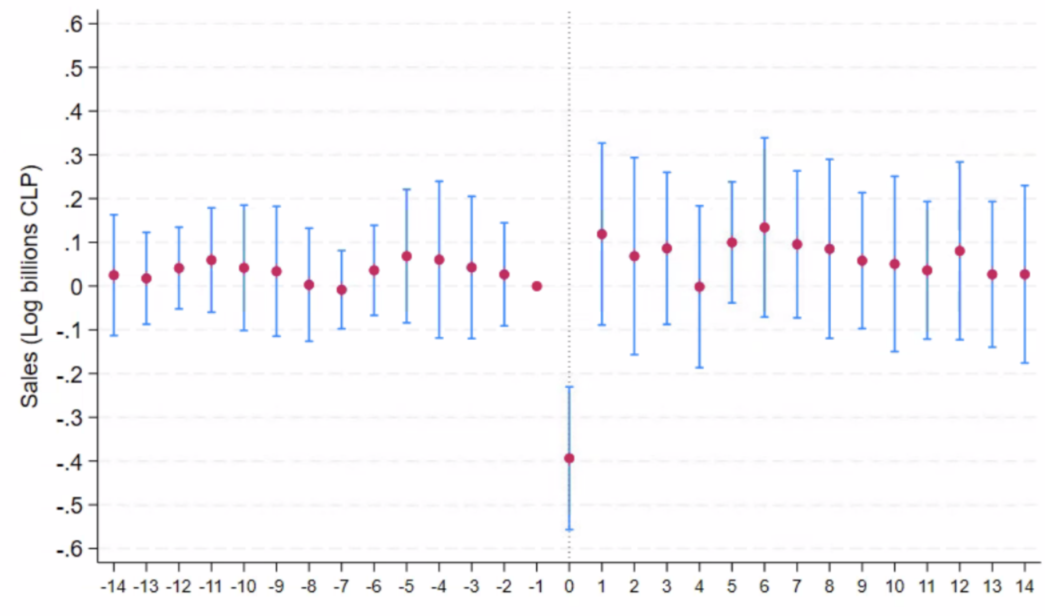


Panel B: Lost Load Relative to February 24



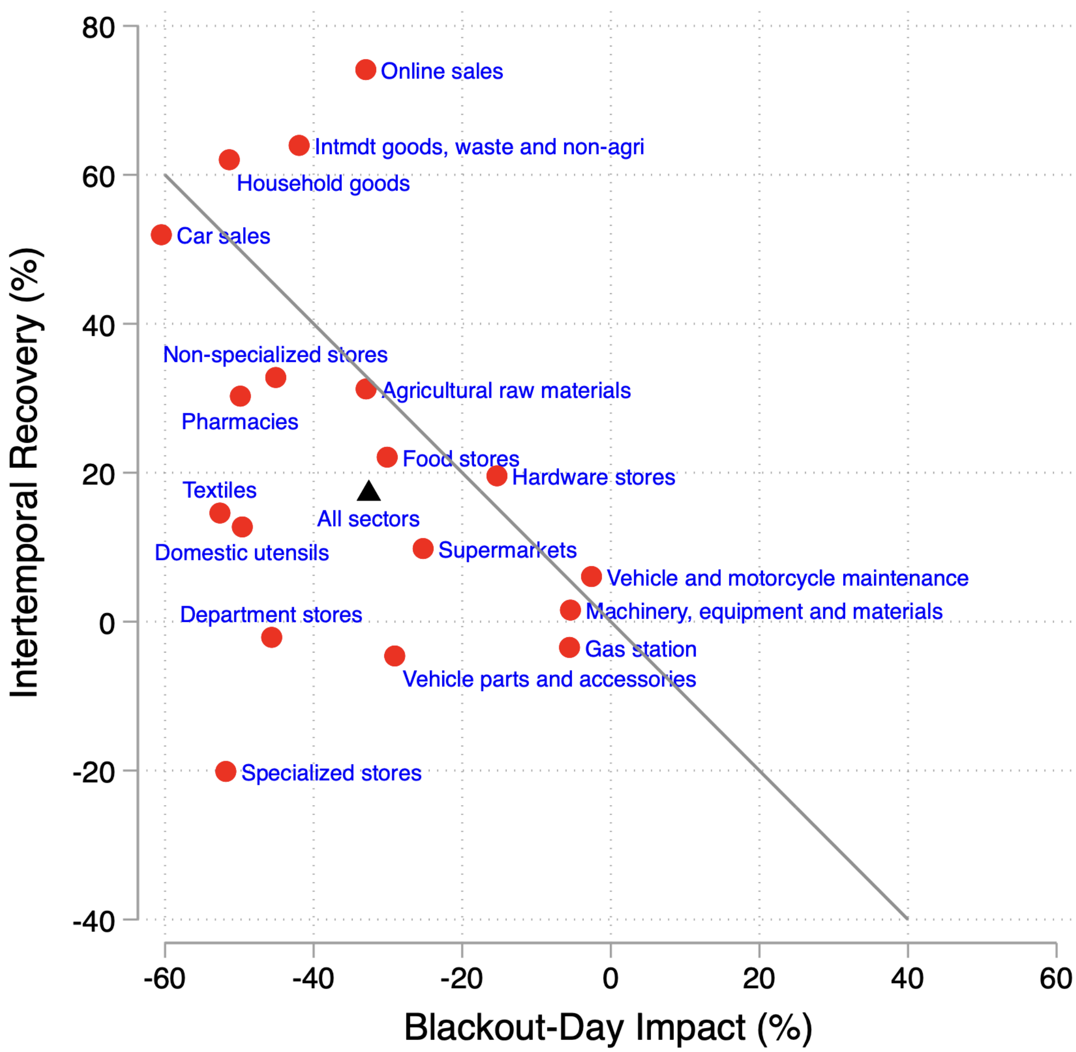
Note: Panel A shows total hourly electricity consumption (in GWh) for regulated customers. Panel B displays the recovery ratio, defined as total hourly electricity consumption divided by consumption in the same hour on the day before the blackout (February 24, 2025).

Figure 2: Event-Study Regression Coefficients



Note: This figure presents the event-study coefficients estimated from equation (1) based on the card transaction data that cover both retail and business-to-business transactions. The outcome variable is aggregate retail sales, measured in the natural log of billions of Chilean pesos. The bars indicate 95 percent confidence intervals based on heteroskedasticity- and autocorrelation-consistent standard errors.

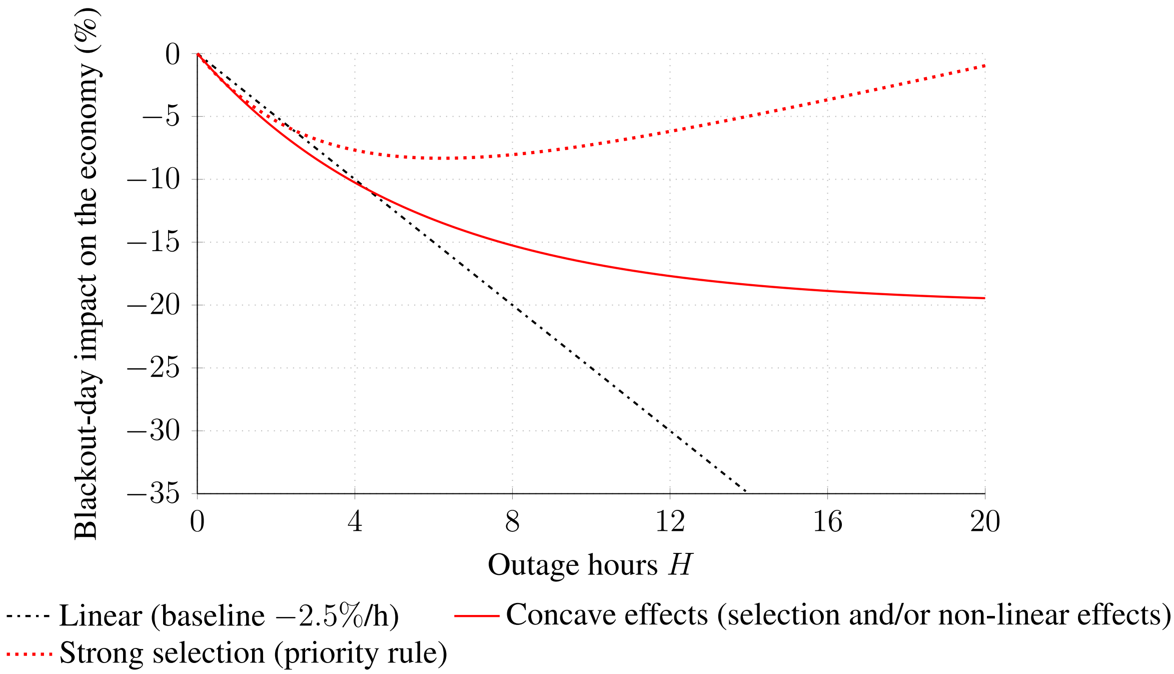
Figure 3: Blackout-Day Impacts vs. Intertemporal Recovery



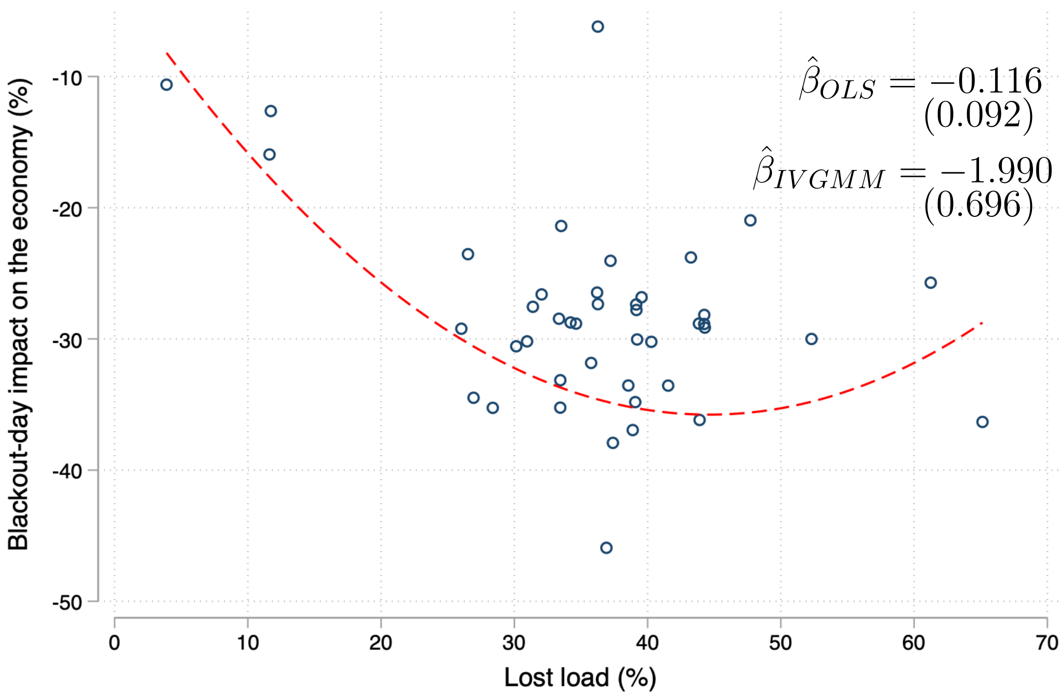
Note: This figure presents the estimated impact on the day of the blackout (x-axis) against the effect during the four days after the blackout (y-axis) estimated in Section 3.2 and reported in Table 1. Observations near the inverse 45-degree line imply greater recovery.

Figure 4: Marginal Effect of Lost Load on the Economy

Panel A: Theoretical Predictions



Panel B: Empirical Results



Note: This figure presents the theoretical (Panel a) and empirical (Panel b) impacts of the impacts of the blackout over different regions. The theoretical model emphasizes that priority in recovery areas that are more impacted by the blackout (e.g., high economic activity areas), can lead to a U-shape pattern (dotted red line). This conjecture is consistent with the evidence in Panel b. We report the full estimation results of OLS and IV-GMM in Table A.1.

Table 1: Economic Impacts of Nationwide Blackouts and Intertemporal Recovery

Sector	Percentage Effects on Economic Activity: Blackout-Day Impact	Intertemporal Recovery	Net Impact	Ave. Transactions (million CLP/day)
All sectors				
Card transactions (retail & business)	-34.7 (3.0)	16.9 (11.1)	-17.8 (10.5)	201690
Tax records (retail)	-32.6 (2.7)	17.2 (9.3)	-15.4 (9.1)	58205
By sector (tax records)				
Supermarkets	-25.3 (4.1)	9.8 (14.3)	-15.5 (13.7)	17341
Gas station	-5.6 (4.3)	-3.5 (9.4)	-9.0 (9.0)	7980
Pharmacies	-49.9 (1.8)	30.3 (12.2)	-19.6 (12.1)	6160
Hardware stores	-15.3 (1.8)	19.6 (6.4)	4.2 (6.5)	5263
Department stores	-45.7 (3.1)	-2.1 (14.0)	-47.8 (13.3)	4402
Textiles	-52.6 (2.9)	14.6 (13.6)	-38.0 (13.1)	3991
Intmdt goods, waste and non-agri	-42.0 (7.5)	64.0 (23.1)	22.0 (22.5)	2550
Domestic utensils	-49.6 (3.6)	12.7 (16.1)	-36.9 (15.9)	1744
Specialized stores	-51.8 (2.0)	-20.1 (12.5)	-71.9 (12.3)	1732
Agricultural raw materials	-32.9 (4.3)	31.2 (15.2)	-1.7 (15.0)	1374
Food stores	-30.1 (3.3)	22.1 (11.8)	-8.0 (11.9)	1163
Vehicle parts and accessories	-29.1 (2.8)	-4.6 (15.4)	-33.7 (15.4)	1042
Household goods	-51.4 (3.6)	62.0 (17.9)	10.7 (17.6)	912
Online sales	-33.0 (17.9)	74.1 (96.5)	41.1 (95.4)	896
Car sales	-60.5 (6.0)	52.0 (53.2)	-8.5 (51.7)	501
Vehicle and motorcycle maintenance	-2.6 (4.6)	6.1 (13.9)	3.5 (14.7)	487
Non-specialized stores	-45.1 (5.3)	32.8 (29.2)	-12.3 (29.0)	387
Machinery, equipment and materials	-5.4 (15.4)	1.5 (38.0)	-3.9 (37.5)	172

Note: This table shows the estimation results of Equation (2) with heteroskedasticity- and autocorrelation-consistent standard errors in parentheses.

Online Appendix A Appendix Tables

Table A.1: Marginal Effect of Lost Load on the Economy

Dependent variable: Commune-level blackout-day impact on economic activity (%)				
	(1)	(2)	(3)	(4)
Lost load (%)	-0.116	-1.982	-1.999	-1.990
	(0.092)	(0.917)	(0.991)	(0.696)
Constant	-29.834	39.125	39.738	39.408
	(3.480)	(34.382)	(37.113)	(26.411)
Estimation	OLS	IV	IV	IV-GMM
Instruments		Distance	Supply loss	Both
First stage F-stat		22.082	18.488	13.775
Mean of dep. var.	-27.42	-27.42	-27.42	-27.42
Observations	306	306	306	306

Note: The instrumental variable in Column 2 is the distance from each commune to the Coquimbo region, the origin of the grid failure. The instrumental variable in Column 3 is supply-side lost load variable—we use plant-level hourly generation data to calculate total electricity generation at the province level between 3:00 p.m. on February 25, 2025 and 3:00 p.m. on February 26, and divide it by the same measure for the previous day. Column 4 uses both instruments with the two-step Generalized Method of Moments. We report heteroskedasticity- and autocorrelation-consistent standard errors in parentheses. The observations are weighted by each commune's average sales.

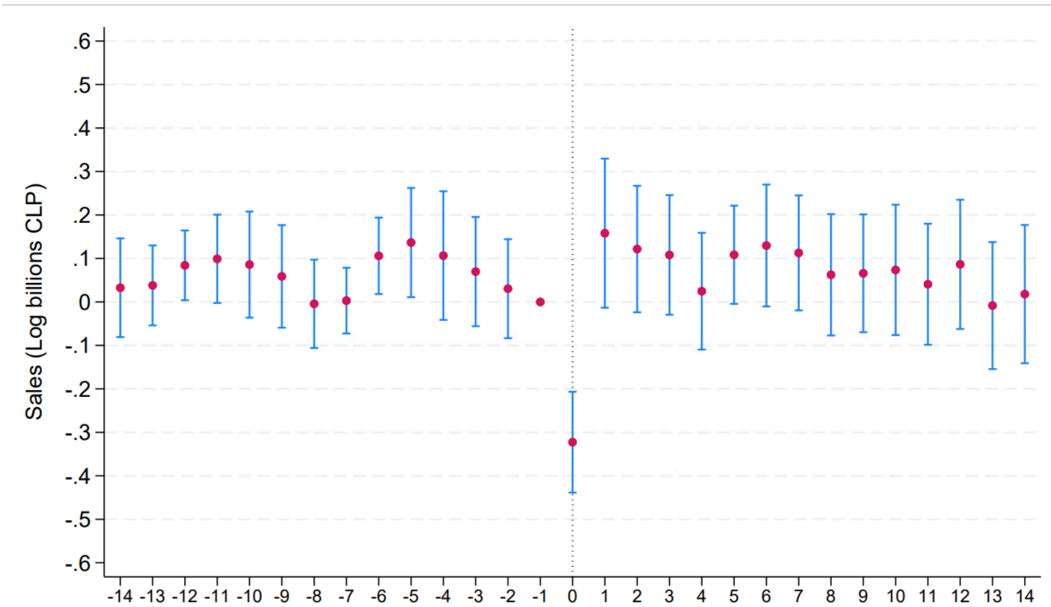
Table A.2: First-stage Results

Dependent variable: Lost load (%)		
	(1)	(2)
Distance (1,000km)	-4.268	
	(2.035)	
Supply loss (%)		0.045
		(0.020)
Constant	39.785	34.009
	(1.092)	(1.670)
Observations	306	306

Note: This table shows the first stage estimation results for our two instrumental variables. The instrumental variable in Column 1 is the distance from each commune to the Coquimbo region, the origin of the grid failure. The instrumental variable in Column 2 is supply-side lost load variable—we use plant-level hourly generation data to calculate total electricity generation at the province level between 3:00 p.m. on February 25, 2025 and 3:00 p.m. on February 26, and divide it by the same measure for the previous day. We report heteroskedasticity- and autocorrelation-consistent standard errors in parentheses.

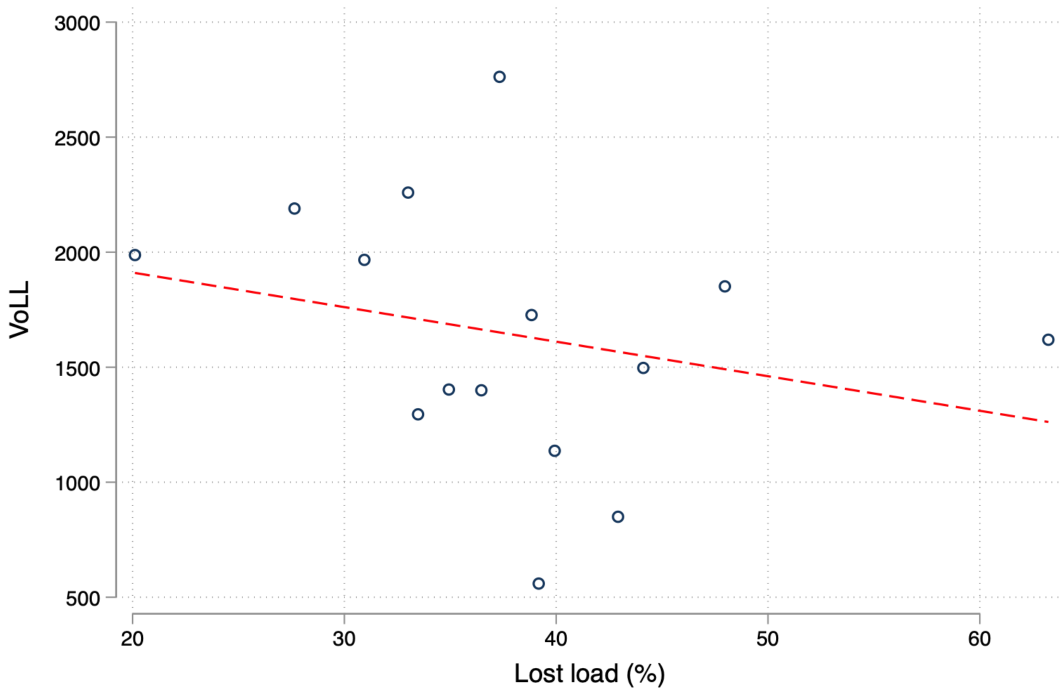
Online Appendix B Appendix Figures

Figure A.1: Event-Study Regression Coefficients (Based on Tax Records)



Note: This figure presents the event-study coefficients estimated from equation (2) based on the administrative tax records. The outcome variable is the log of aggregate retail sales from boletas, measured in billions of Chilean pesos. The bars indicate 95 percent confidence intervals.

Figure A.2: VoLL v.s. Percentage Lost Load



Note: This figure presents the relationship between the (marginal) VoLL (USD/MWh) and the severity of the blackouts, as described in Section 3.3.

Online Appendix C   Details of 2025 Chile Blackout

Chile's *Sistema Eléctrico Nacional* (SEN) is one of the most extensive and integrated power networks in Latin America, coordinating 833 companies across the generation, transmission, and distribution segments. The system spans approximately 39,340 km of transmission lines, interlinked through 1,239 substations and 1,187 circuits, forming a long, narrow north–south corridor that mirrors the country's geography. As of 2025, the SEN possessed a total installed capacity of 36,780MW, supplied by 1,105 generation plants, with a growing contribution from renewable sources connected under the *Pequeños Medios de Generación Distribuida (PMGD)* regime—772 PMGD units providing 3,402MW of installed capacity. In the hours preceding the 25 February 2025 blackout, the SEN operated in a stable, interconnected state, maintaining synchronized power flows between the northern and southern subsystems. Total national generation reached approximately 11,657MW, of which the north supplied a dominant share—mainly solar and wind energy—through the 2×500kV Nueva Maitencillo–Nueva Pan de Azúcar line, transporting around 1,800MW, or 90% of its rated capacity. This corridor served as the backbone for renewable-energy transfers from the Atacama and Antofagasta regions toward central Chile, where demand and industrial activity are concentrated. Nationally, renewables accounted for 73% of generation, led by solar (4,632MW, 49.4%) and wind (1,548MW, 16.5%), complemented by hydroelectric (1,635MW) and thermoelectric (1,306MW) sources. The SEN was operating under N-1 security criteria, meaning that the system was designed to remain operational even if one critical element—such as a line, transformer, or generator—were suddenly lost. In theory, this standard ensures continuity of supply under single-component failure conditions.

The chain of events leading to the blackout began within this corridor. At 13:35 hours, the transmission operator Interchile notified the *Coordinador Eléctrico Nacional* that it had disabled the communication module of one of the line's main protection functions. Although the line remained fully operational with backup protections active, no risk report or request for intervention authorization was submitted. At 15:13 hours, *Interchile*, a transmission firm, restarted the communication controller at the Nueva Maitencillo substation to re-establish the signal, without prior coordination or approval. Two minutes later, at 15:15 hours, the protection system re-synchronized improperly, triggering an automatic disconnection of both circuits of the 500kV line. According to manufacturer protocols, the equipment should have been physically isolated prior to reconnection, a step that was omitted. The disconnection instantly split the national grid into two electrical islands —the northern subsystem ($\approx$ 30% of total demand) and the central-southern subsystem ($\approx$ 70%)—initiating the cascading instability that culminated in one of the most extensive blackouts in Chile's history.

The immediate loss of both circuits caused the system to fragment within 1.5 seconds, generating rapid frequency and voltage deviations in both islands. The *Estudio de Análisis de Falla (EAF)* requested by the authority, indicates that automatic generation-tripping and load-shedding schemes activated sequentially to restore the supply–demand balance. In the north, the island remained operational for roughly four minutes, but escalating instability in voltage and frequency ultimately led to a complete generation collapse. In the central–southern subsystem, instability developed within four seconds of the fault: the interruption of 1,800MW from the north caused an estimated 25% supply deficit, which rapidly propagated through the interconnected network. While defense mechanisms and contingency controls operated, they did so without the speed or magnitude necessary to halt the progression of the event. Consequently, the cascading tripping of generation units and exhaustion of frequency-containment reserves led to a complete national loss of energy supply, effectively reducing the SEN's output to zero.

Following the nationwide collapse, the *Coordinador Eléctrico Nacional* activated the *Plan de Recuperación del Servicio (PRS)* within two minutes of the event. The plan relied on the Supervisory Control and Data Acquisition (SCADA) system and direct voice communication lines (Hotline)linking the National Control Center (Centro de Despacho y Control, CDC) with the regional *Centros de Operación para la Recuperación del Servicio* (COR) managed by coordinated companies. The SCADA system—receiving approximately 70,000 measurement and status signals every three seconds —enabled real-time monitoring of grid conditions, while the Hotline facilitated continuous voice coordination to issue instructions and exchange operational information. The PRS operates under a modular islanding approach, where the system is first stabilized in isolated electrical zones and then progressively reconnected to re-establish national synchrony. Each COR was responsible for executing recovery procedures in predefined geographical areas, re-energizing autonomous generation units and implementing *Esquemas de Recuperación de Servicio* (ERS) to reestablish supply in stages.

Despite the prompt activation of the PRS, the restoration process faced significant technical constraints that delayed normalization. Several generation units across different companies encountered communication and synchronization difficulties when attempting to reconnect to the grid. The principal causes of these delays were the lack of visibility within SCADA systems of certain coordinated companies, unavailability of remote control (telecontrol) and point-to-point communication channels, and partial failure of telemetry systems . These issues prevented the establishment of the operational conditions necessary for the effective execution of black-start procedures. The transmission operator Transelec, acting as COR in multiple regions, experienced a SCADA and telecontrol outage lasting nearly three hours, which notably slowed the overall recovery timeline. As a result, the restoration of service was conducted sequentially by areas— Arica, Tarapacá, Centro, O'Higgins, Cordillera, Biobío, and Araucanía —with autonomous generation capacities ranging from 15MW to more than 1.7GW , progressively reconnecting the national system until full stability was achieved.