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Infrastructure Capacity, Risk, and Firm Value: Evidence from U.S. Electricity Tightness

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Abstract

Real-time bottlenecks in non-storable infrastructure—most visibly electricity—can throttle modern production. We embed proportional rationing of grid supply into multi-sector economy, showing that unexpected scarcity cuts output, employment, and consumption, while the prospect of future capacity expansions mitigates those losses. To test the model's predictions, we measure U.S. public firms' exposure to realized electric capacity constraints and future expected capacity tightness. We confirm the model's predictions using panel regressions with fixed effects and establish causality by exploiting two quasi-natural experiments: the 2021 Texas blackout (a 34 GW supply shock) and subsequent state reforms that raised future expected capacity. Difference-in-differences estimates indicate a drop in short-term profitability and firm value in affected firms. Higher future anticipated capacity leads to higher longer-term employment, capital, and firm value. Investors demand higher expected returns for firms with greater exposure to electric capacity constraints, confirming that infrastructure tightness, either due to excess demand or limited supply, is a priced, macro-critical risk.

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1 Introduction

Infrastructure constraints are emerging as a central source of economic fragility. In an era of electrification, digitization, and climate stress, modern production depends on systems—like electricity grids—that are essential but often non-storable, non-tradable, and capacity-constrained in real time. When these systems become stressed, the consequences are not just technical or localized: they ripple through output, consumption, and asset markets. Yet, macroeconomics and finance largely lack models that capture how real-time infrastructure scarcity affects production and risk. We build and empirically test a framework in which electricity, a physically rationed and economically essential input, acts as a state-contingent constraint that propagates into volatility in firm-level cash flows and expected returns. The goal is to rethink infrastructure not just as a background condition for growth, but as a priced economic risk in its own right.

The model introduces a non-tradable, non-storable production input—electricity—that is subject to stochastic supply and demand constraints. Firms differ in their reliance on this input, and when total demand exceeds capacity, electricity is rationed through proportional allocation. This creates a tightness ratio that varies over time and acts as an endogenous aggregate shock. Because output, dividends, and aggregate consumption fall in tight states, electricity shortages co-move with marginal utility, leading to priced risk. The model predicts: (i) on the real side, factor inputs and firm profits are reduced in periods of electricity tightness; (ii) on the financial side, risk premia are increasing in the degree of electricity tightness.

Although we anchor the model in electricity markets for expositional clarity, the economic logic hinges on three generic features–not on anything idiosyncratic to power grids. First, the constrained input must be non-storable in real time, so short-run supply/demand shocks translate one-for-one into quantity rationing rather than deferred inventory draw-downs; this applies equally to data-center processing slots, last-mile broadband bandwidth, port berths, pipeline capacity, and airport take-off slots. Second, the input must exhibit low short-horizon substitutability, that is, firms cannot instantly switch to close substitutes without incurring large efficiency losses–precisely the situation faced by manufacturers during water-use bans, retailers during logistics bottlenecks, or cloud-native companies when CPU/GPU quotas are hit. Third, the constraint must be systemically shared, so rationing shocks co-move with aggregate consumption and feed into equilibrium discount rates; data-center congestion during peak AI-training cycles, drought-driven canal closures, or semiconductor-foundry capacity limits all satisfy this criterion because they simultaneously affect many firms' cash flows and consumers' welfare. Hence, the tightness-premium mechanism we derive generalizes naturally beyond U.S. electricity grids to any economy where a real-time, capacity-capped infrastructure service enters firm production technologies with limited short-run substitutability.

To test the model's predictions, we construct a panel of U.S. publicly traded firms based on a unique match between individual plants and their corresponding regional electricity tightness constraints. We proxy electricity supply tightness using two administrative data sources that are commonly used in electric reliability and capacity analysis: (i) the System Average Interruption Duration Index (SAIDI), which captures realized supply outages at the county level and is supplied by the U.S. Energy Information Administration (EIA); and (ii) anticipated reserve margins published in grid reliability assessments at the regional level by the North American Electric Reliability Corporation (NERC), which measures whether a region will have sufficient capacity to meet forecasted peak demand. We further saturate the model with firm-level observables and firm and year fixed effects. Finally, in the regressions with employment we also absorb firm-year and establishment fixed effects, which allows us to control for any firm-level time-varying shocks and time-invariant unobserved plant characteristics.

We show that firms facing greater exposure to tight periods–whether those periods reflect realized scarcity or forward-looking constraints–have lower employment at the plant level. Such firms have also lower profits and invest less. Further, in the cross-section, they also have lower equity valuations and earn systematically higher future returns; this premium is not explained by firm characteristics, sector effects, or energy input prices. In our asset-pricing tests, we show that the electricity-tightness factor (ELX), a portfolio that takes a long position in companies with tight electricity and a short position in companies with little tightness, is economically large and virtually unspanned by the Fama–French factors. Portfolios sorted on ELX exposure earn a monotonic return spread of roughly 5–6 percent per year that survives the full six-factor model, and cross-sectional regressions confirm a significantly negative price of risk for ELX betas after conditioning on size, value, investment, profitability, momentum, liquidity, and betting-against-beta. These results align closely with the model's prediction that real-time infrastructure scarcity co-moves with marginal utility and is therefore a distinct, priced source of systematic risk. The results support the core mechanism of the model: when electricity is scarce or is expected to become scarce, firms with greater physical exposure to supply constraints face more shocks that covary with consumption and command a return premium as compensation.

For identification, we pivot to a two–pronged strategy built around the Texas Winter-Storm Uri episode, which delivers both a realized and a forward-looking shock to grid tightness. First, the February 2021 blackout itself functions as an exogenous, weather-driven collapse in available capacity: overnight, 34 GW of generation went offline without any connection to firms' pre-existing fundamentals, giving us a clean realized-scarcity experiment. Second, the post-Uri policy package—ERCOT's mandated reserve-margin uplift, the shift to firming-obligation contracts, improved weatherization of power plants, and the $\$9k/MWh$ scarcity-price cap—provides an anticipated-capacity shock: it sharply revised expectations of future tightness while leaving contemporaneous output unaffected. We apply these two shocks in cross-sectional, panel, and event-study designs using difference-in-differences approach, and show that both precipitate the same patterns in inputs, profits, and returns. We further document that our estimates of risk premia are unchanged when the headline 2021 months are excluded. Taken together, the realized-plus-expected Uri tests assuage concerns that our results reflect endogenous demand swings or time-series confounds.

In our final tests, we show that electricity tightness has aggregate consequences that adversely affect employment and capital allocation in the entire regions more exposed to infrastructure constraints suggesting the general-equilibrium implications of the constraints. As a special example, firms offering data services, which are known to be electricity intensive, avoid locations with known electricity disruptions and adjust their production inputs accordingly.

Our paper relates to four strands of literature. First, it contributes to production-based asset pricing by introducing a novel friction: a non-storable, non-tradable production input that generates time-varying, state-contingent constraints. Although prior work emphasizes capital adjustment costs (see, e.g., Zhang, 2005) or labor frictions (e.g., Belo et al., 2014), this paper shows that real-time infrastructure scarcity can also be a priced source of aggregate risk. Second, it connects to rare disaster and tail risk models (e.g., Gabaix, 2012; Gourio, 2012) by microfounding aggregate consumption volatility through bottlenecks in physical production rather than exogenous shocks to preferences or endowments. Third, it complements the growing literature on climate risk and macrofinancial fragility (e.g., Bansal et al., 2019; Colacito and Croce, 2011) by focusing on infrastructure capacity as an economically essential input subject to short-run constraints. Finally, the article builds on theoretical and empirical studies showing that electricity shortages reduce firm production, employment and investment (e.g., Colmer et al., 2024; Fried and Lagakos, 2023; Allcott et al., 2016; Rud, 2012). Our paper adds to the existing literature by linking supply-side constraints with systematic variation in asset prices. In doing so, the paper bridges macrofinance and infrastructure economics, showing how physical bottlenecks can propagate into financial markets through firm-level exposure and consumption risk. In addition, the empirical literature documenting the importance of electricity access, reliability, and cost for firm-level performance focuses on developing countries (e.g., Abeberese, 2017; Fisher-Vanden et al., 2015; Dinkelman, 2011). This paper documents the relevance of electricity constraints in the context of a developed country, the United States. The empirical literature shows that energy endowments and access shape location decisions and industry specialization (e.g., Greenspon and Hanson, 2025; Manderson and Kneller, 2020; Gilje et al., 2016). These results nicely align with the macro implications of our paper, which indicate that electricity constraints matter for local production decisions and are particularly relevant in industries such as data centers that are large consumers of electricity. Our study highlights the increasing importance of electricity constraints, given the general trends in increasing electricity demand, tightening transmission restrictions, imperfect market integration, deregulation, and integration of renewables (e.g., Hausman, 2025; Borenstein et al., 2023). Finally, the remaining finance literature on electricity has focused primarily on issues around the governance utilities, generators' investment and financing decisions, and whether electricity consumption can predict stock returns, and not on the pricing of electric constraints (e.g., Ambec et al., 2025; Hong et al., 2025; Demirer and Karaduman, 2024; Andonov and Rauh, 2024; Lin et al., 2023; Garrett and Shive, 2022; Iyke et al., 2021; Lin et al., 2021; Bolton and Rosenthal, 2019; Da et al., 2017; Aïd et al., 2011; Joskow and Tirole, 2007)

The rest of the paper proceeds as follows. Section 2 lays out the model; Section 3 describes the data and identification strategy; Section 4 presents results and discusses further extensions. Section 5 shows macro implications of the infrastructure constraint and provides welfare calibration. Section 6 concludes. An online appendix shows robustness to priority contracts, price-clearing markets, capital dynamics, and correlated productivity-grid shocks.

2 Model

In many economies, electricity is a non-storable, centrally allocated input that becomes binding during capacity stress. Firms anticipate these constraints and adjust production and factor demand accordingly. This section develops a production-based asset pricing model in which electricity enters as a non-tradable input subject to stochastic rationing. Firms operate a nested CES production technology and choose capital and labor ex ante, while electricity is allocated ex post. A representative household has CRRA preferences, and asset prices reflect general equilibrium responses to electricity shocks. The model delivers closed-form predictions for how expected tightness affects firm input choices, profits, risk premia, and valuations.

2.1 Economic Environment

The representative diversified household supplies capital competitively and has CRRA preferences over aggregate consumption C_t:

$$U = \mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t \frac{C_t^{1-\theta}}{1-\theta}, \quad \theta > 0$$

There are a large number N of small firms indexed by i, each operating a decreasing returns-to-scale technology using capital $K_{i,t}$, labor $L_{i,t}$, and electricity $E_{i,t+1}$ as inputs. Capital and labor are chosen at time t; factor rentals r_t and w_t are set at time t; whereas electricity is allocated at $t+1$ after uncertainty resolves. Electricity is supplied inelastically by a system operator and is non-tradable and non-storable.

2.2 Firm Technology and Electricity Rationing

Firms produce output according to a nested CES production function:

$$Y_{i,t+1} = A_{i,t+1} \left[\delta_{KL} Z_{i,t}^{\frac{\sigma-1}{\sigma}} + \delta_E (E_{i,t+1})^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}}, \quad Z_{i,t} \equiv K_{i,t}^{\alpha_1} L_{i,t}^{\alpha_2}$$

where $A_{i,t+1}$ is firm-specific productivity, δ_{KL} and δ_E, both positive numbers, represent capital/labor (electricity) intensity with $\delta_{KL} + \delta_E = 1$. The choice between capital and labor follows DRS Cobb-Douglas technology with $\alpha_1 + \alpha_2 < 1$. We normalize to 1 the relative prices of Z and E. The parameter σ governs the elasticity of substitution between the capital-labor composite and electricity.[1]

When aggregate electricity demand $E_{t+1}^D = \sum_i E_{i,t+1}^d$ exceeds the available supply $\bar{E}_{t+1}$, a proportional rationing rule is applied[2]:

$$E_{i,t+1}^{\text{rat}} = \kappa_{t+1} E_{i,t+1}^d, \quad \text{where} \quad \kappa_{t+1} = \min\left(1, \frac{\bar{E}_{t+1}}{E_{t+1}^D}\right)$$

[1]We abstract from capital accumulation to keep the exposure channel transparent; adding convex adjustment costs does not change the qualitative predictions of our model (see Appendix OA.4).

[2]Proportional rationing mimics ISO practice where bids are pro-rated. The qualitative predictions of this model remain unchanged assuming instead priority contracts.

Because firms lock in K and L before rationing, the shock is a quantity share κ rather than a price. Even if firms were willing to pay an arbitrarily high price, extra megawatt-hours do not exist ex post. Hence, rationing operates like a multiplicative productivity shock that cannot be hedged in energy futures markets and that scales revenues one-for-one when $\kappa_t < 1$. Treating it as a simple input-price fluctuation would miss this commitment and non-tradability channel. In our model, firms take κ_{t+1} as exogenous and anticipate its distribution when choosing $K_{i,t}$ and $L_{i,t}$. It is stochastic and determined at $t+1$ as a function of $\bar{E}_{t+1}$ and E^D_{t+1}.

We assume the tightness process has expected value κ and is driven by a single mean-zero innovation, ε_{t+1}

$$\log \kappa_{t+1} = \log \kappa + \varepsilon_{t+1}, \qquad \varepsilon_{t+1} \sim \mathcal{N}(0, \sigma^2_\varepsilon),\ |\varepsilon_{t+1}| \ll 1.$$

Empirically, ϵ_{t+1} is the one-step forecast error in κ, also nesting errors from supply and demand processes.[3] We also assume idiosyncratic productivity, $\log A_{i,t+1}$, is independent of both ε_{t+1} and the aggregate productivity shock driving C_{t+1}.

2.3 Firm Problem

At time t, each firm chooses $K_{i,t}, L_{i,t}$ to maximize expected profits at time $t+1$:

$$\max_{K_{i,t}, L_{i,t}} \mathbb{E}_t \left[A_{i,t+1} \cdot F(K_{i,t}, L_{i,t}; \kappa_{t+1}) - r_t K_{i,t} - w_t L_{i,t} \right]$$

where $F(\cdot)$ is the nested CES function described above, and input prices r_t, w_t are competitively determined. Firms do not choose electricity input; rather, their notional demand $E^d_{i,t+1}$ determines their allocation via the exogenous rationing rule.

We define a firm's *notional electricity demand* $E^d_{i,t+1}$ as the amount of electricity the firm would wish to use in period $t+1$ if electricity were unconstrained. This demand is determined by the firm's capital and labor choices and arises endogenously from the production technology.

Given the nested CES production function

$$Y_{i,t+1} = A_{i,t+1} \left[\delta_{KL} Z^\rho_{i,t} + \delta_E (E^{rat}_{i,t+1})^\rho \right]^{\frac{1}{\rho}},$$

[3] One can show that $\kappa_{t+1} = \kappa e^{\varepsilon_{t+1}} = \kappa\big(1 + \varepsilon_{t+1} + O(\varepsilon^2_{t+1})\big) \approx \kappa\big(1 + \varepsilon_{t+1}\big)$.

the firm's notional demand is:

$$E^d_{i,t+1} = Z_{i,t} \cdot \chi \qquad \text{where } \chi \equiv \left(\frac{\delta_E}{\delta_{KL}}\right)^{\sigma} \text{ and } \rho \equiv \frac{\sigma - 1}{\sigma}.$$

Substituting the closed-form notional demand and aggregating across firms we obtain:

$$\sum_i E^d_{i,t+1} = \chi \sum_i Z_{i,t}$$

Thus, the tightness ratio becomes:

$$\kappa_{t+1} = \min\left(1, \frac{\bar{E}_{t+1}}{\chi \sum_i Z_{i,t}}\right)$$

The demand increases in the firm's production scale and in electricity intensity δ_E, and decreases in the elasticity of substitution σ. As the aggregate scale of production increases, the total notional demand rises, reducing κ_{t+1}. This amplifies the impact of electricity supply shocks and tightens the economy-wide constraint.

2.4 Optimal Capital and Labor Choices

Given that electricity is not a choice variable, and firms take its rationed level κ_{t+1} as given, we substitute the notional electricity demand into $E^{rat}_{i,t+1}$:

$$E^{rat}_{i,t+1} = \kappa_{t+1} E^d_{i,t} = K^{\alpha_1}_{i,t} L^{\alpha_2}_{i,t} \cdot \chi \cdot \kappa_{t+1}$$

Then:

$$Y_{i,t+1} = A_{i,t+1}\left[\delta_{KL} Z^{\rho}_{i,t} + \delta_E(\kappa_{t+1}\chi Z_{i,t})^{\rho}\right]^{\frac{1}{\rho}} = A_{i,t+1} Z_{i,t} \cdot \left[\delta_{KL} + \delta_E(\kappa_{t+1}\chi)^{\rho}\right]^{\frac{1}{\rho}}$$

Let:

$$\Phi(\kappa_{t+1}) \equiv \left[\delta_{KL} + \delta_E(\kappa_{t+1}\chi)^{\rho}\right]^{1/\rho} \text{and } \bar{A}_{i,t} \equiv \mathbb{E}_t\left[A_{i,t+1} \cdot \Phi(\kappa_{t+1})\right]$$

Then the firm's problem reduces to:

$$\max_{K_{i,t}, L_{i,t}} \; \bar{A}_{i,t} \cdot K^{\alpha_1}_{i,t} L^{\alpha_2}_{i,t} - r_t K_{i,t} - w_t L_{i,t}$$

Using first-order conditions for K and L we obtain their optimal choices:

$$K^*_{i,t} = \left(\frac{\alpha_1 \cdot \bar{A}_{i,t}(\kappa) \cdot \mu^{\alpha_2}}{r_t} \right)^{\frac{1}{1-\alpha_1-\alpha_2}}, \quad L^*_{i,t}(\kappa) = \mu K^*_{i,t}(\kappa)$$

where

$$\mu = \frac{\alpha_2}{\alpha_1} \cdot \frac{r_t}{w_t}.$$

We analyze the impact of electricity constraints on production factors via the following:

Proposition 1. *Consider the firm's optimal capital and labor choices when the mean electricity-tightness parameter equals $\kappa \in (0, 1]$. Then*

$$\frac{dK^*}{d\kappa} > 0, \qquad \frac{dL^*}{d\kappa} > 0 \quad \textit{for every } \kappa \in (0, 1].$$

Proof in the Appendix.

Intuitively, as electricity tightness relaxes (κ increases), firms anticipate higher effective productivity and scale up production by increasing both capital and labor inputs. Because $\partial^2\Phi/(\partial\kappa\,\partial\delta_E)$ is positive, the model also predicts that the employment- and CAPEX-responses to κ are stronger for plants with higher electricity intensity. Proposition OA.1 formalizes this result.

2.5 Profitability, Dividends, and Aggregate Consumption

We next analyze the role of electricity tightness for real outcomes, such as firm profits, dividends, and aggregate consumption. Using our notation, expected one-period firm-level operating profit is

$$\mathbb{E}_t\Big[\Pi_{i,t}(K, L; \kappa)\Big] = \mathbb{E}_t\Big[A_{i,t+1}\Phi(\kappa_{t+1})Z_{i,t}\Big] - r_tK - w_tL = \bar{A}_{i,t}(\kappa)Z_{i,t} - r_tK - w_tL.$$

We can then establish the following effect of expected tightness:

Proposition 2. *Let $(K^*_{i,t}(\kappa), L^*_{i,t}(\kappa))$ denote the unique FOCs solution. Then $\frac{\mathrm{d}}{\mathrm{d}\kappa}\mathbb{E}_t\Big[\Pi_{i,t}(K^*_{i,t}, L^*_{i,t}; \kappa)\Big] > 0$ for every $\kappa \in (0, 1]$.*

Proof in the Appendix.

We next show the effects for dividends. At time t, the firm commits to $K^*_{i,t}, L^*_{i,t}$ and pays rentals $r_t K^*_{i,t} + w_t L^*_{i,t}$. Next period's *realized* dividend therefore is

$$D_{i,t+1} = A_{i,t+1}\,\Phi(\kappa_{t+1}) Z_{i,t} - \left[r_t K^*_{i,t} + w_t L^*_{i,t}\right].$$

Because the second term of the equation is fixed at time t, the sign of $\partial D_{i,t+1}/\partial \kappa_{t+1} = A_{i,t+1} Z_{i,t} \Phi'(\kappa_{t+1})$ is positive. Taking expectations yields

$$\frac{\mathrm{d}}{\mathrm{d}\kappa}\mathbb{E}_t[D_{i,t+1}] = Z_{i,t}\,\frac{\mathrm{d}\bar{A}_{i,t}}{\mathrm{d}\kappa}.$$

Using the result from the previous section, the last identity has a strictly positive value. Next, we analyze the link to aggregate consumption. Competitive factor markets imply $C_{t+1} = w_{t+1}\bar{L} + r_{t+1}\bar{K} + \sum_i D_{i,t+1}$. Using $w_{t+1}\bar{L} + r_{t+1}\bar{K} = \sum_i r_t K^*_{i,t} + \sum_i w_t L^*_{i,t}$ (known at t), we obtain

$$C_{t+1} = A_{t+1}\,\Phi(\kappa_{t+1}) \sum_i Z_{i,t}, \qquad A_{t+1} \equiv \frac{1}{\sum_i Z_{i,t}} \sum_i A_{i,t+1} Z_{i,t}.$$

We take the first-order (log-linear) expansion of aggregate consumption around the mean value of the electricity-tightness parameter κ to obtain the expression for conditional variance of consumption. The lemma below summarizes the result:

Lemma 1.

$$\Delta \log C_{t+1} = \lambda(\kappa_{t+1})\,\varepsilon_{t+1}, \qquad \varepsilon_{t+1} \sim \mathcal{N}(0, \sigma^2_\varepsilon), \qquad \lambda(\kappa_{t+1}) = \kappa \frac{\Phi'(\kappa_{t+1})}{\Phi(\kappa_{t+1})}$$

Proof in the Appendix.

In summary, looser expected electricity tightness (higher κ) *simultaneously* (i) raises expected dividends through a level effect ($\bar{A}_{i,t}$ goes up) and (ii) weakens the transmission of supply shocks ($\lambda(\kappa)$ goes down).

2.6 Risk Premium

Building on the results, we study the implications of electricity constraints for individual firm risk premia. With CRRA preferences, the stochastic discount factor (SDF) is:

$$M_{t+1} = \beta \left(\frac{C_{t+1}}{C_t} \right)^{-\theta}$$

The return of asset i is:

$$R_{i,t+1} = \frac{D_{i,t+1}}{P_{i,t}}, \quad \text{with } P_{i,t} = \mathbb{E}_t[M_{t+1} D_{i,t+1}].$$

As before, the dividend process is of the form:

$$D_{i,t+1} = Z_{i,t}\, A_{i,t+1}\, \Phi(\kappa_{t+1}) - r_t K^*_{i,t} - w_t L^*_{i,t},$$

where $Z_{i,t}$ is fixed at t once inputs are chosen. The term $r_t K^*_{i,t} + w_t L^*_{i,t}$ is known at t, so it drops out of all conditional covariances. The factor prices affect the level of $D_{i,t+1}$ but not its state-contingent part that covaries with M_{t+1}. Hence, GE feedback drops out of the covariance.

Following our assumptions, the only covariance between the firm's cash flow and the SDF comes from ε_{t+1} via the common factor $\Phi(\kappa_{t+1})$. For any asset with return $R_{i,t+1}$, we can represent the related risk premium as:

$$\mathrm{RP}_{i,t+1}(\kappa) = \mathbb{E}_t[R_{i,t+1}] - R_{f,t} = -\operatorname{Cov}_t(M_{t+1}, R_{i,t+1}).$$

Because $P_{i,t}$ is time-t measurable,

$$\operatorname{Cov}_t(M_{t+1}, R_{i,t+1}) = \frac{1}{P_{i,t}} \operatorname{Cov}_t(M_{t+1}, D_{i,t+1}).$$

Let

$$g_{t+1} \equiv \Delta \log C_{t+1} = \log \frac{C_{t+1}}{C_t}, \qquad r_{i,t+1} \equiv \log R_{i,t+1}.$$

For a Lucas-tree asset whose payoff is proportional to C_{t+1} and consumption growth is iid, we have $r_{i,t+1} = g_{t+1}$. The log SDF is

$$m_{t+1} \equiv \log M_{t+1} = \log \beta - \theta g_{t+1}.$$

Using the standard log-normal covariance formula (Cochrane, 2005), jointly log-normal $(m_{t+1}, r_{i,t+1})$ and small shocks imply

$$\mathrm{Cov}_t(M_{t+1}, R_{i,t+1}) = \exp\Big(\tfrac{1}{2}\sigma_{mm}^2 + \tfrac{1}{2}\sigma_{rr}^2\Big)(e^{\sigma_{mr}^2} - 1) \approx \sigma_{mr}^2,$$

so with CRRA preferences we obtain

$$RP_{i,t+1} = -\,\mathrm{Cov}_t(m_{t+1}, r_{i,t+1}) = \theta\,\mathrm{Var}_t(g_{t+1}) = \theta\,\mathrm{Var}_t(\Delta \log C_{t+1}).$$

Using Lemma 1, we can rewrite firm-level risk premium and determine the sign of its total derivative with respect to expected electricity tightness.

$$\mathrm{RP}_{i,t+1}(\kappa) = \theta\sigma_\varepsilon^2\,\lambda(\kappa_{t+1})^2$$

Proposition 3.

$$\frac{dRP_{i,t+1}}{d\kappa} = -2\theta\,\sigma_\varepsilon^2\,\lambda(\kappa_{t+1})^2\left[\frac{1-\rho}{\kappa} + \rho\,\lambda(\kappa_{t+1})\right] < 0, \qquad 0 < \rho < 1.$$

Proof in the Appendix.[4]

To summarize, relaxing the electricity constraint (κ goes up) makes consumption growth less sensitive to supply shocks (λ goes down), shrinking the covariance between the firm's dividend and the SDF. The equity premium for the individual firm therefore falls. Firms with higher electricity weight δ_E or lower substitution elasticity σ have a larger $\lambda(\kappa)$ and therefore a bigger absolute drop in their premium when κ rises.

In our data, we study equilibrium responses to both expected and unexpected electricity tightness. To this end, we show that unexpected deviations in tightness, ε_{t+1}, also generate systematic cash-flow and return shocks. Corollaries 1–2 formalize these results.

Corollary 1. *For a small, mean-zero shock $\varepsilon_{t+1} = \log \kappa_{t+1} - \log \kappa$, $|\varepsilon_{t+1}| \ll 1$ the first-order effect*

[4]Similar comparative static result extends to a model with convex capital-adjustment costs of Section OA.4; detailed derivations are available upon request.

on next-period operating profit is

$$\Delta\Pi_{i,t+1} = A_{i,t+1} Z_{i,t} \Phi'(\kappa)\varepsilon_{t+1}$$

Given that $\Phi'(\kappa)$ is a positive number, a negative shock (unexpected tightening) lowers profits; the magnitude scales with electricity intensity δ_E and low substitutability σ.

Linearizing the SDF and dividend around κ yields an equivalent result for the abnormal return:

Corollary 2.

$$r_{i,t+1} - \mathbb{E}_t[r_{i,t+1}] = -\theta\lambda(\kappa)\varepsilon_{t+1} + \eta_{i,t+1},$$

where η is idiosyncratic noise.

Thus, unexpected tightness (negative ε) produces a negative abnormal return, stronger for firms with high $\lambda(\kappa)$, that is, high δ_E and low σ.

2.7 Firm Value

Next, we study implications of tightness for firm value. For a single firm i that pays next-period dividend $D_{i,t+1}$,

$$P_{i,t} = \frac{\mathbb{E}_t[D_{i,t+1}]}{R_{f,t} + RP_{i,t}(\kappa)} \equiv \frac{\mathbb{E}_t[D_{i,t+1}]}{R_{i,t}},$$

using the usual log-linear approximation that the dividend–price ratio is near its steady state value and one-period risk captures the relevant discount rate.[5] We establish the following result for the total derivative of firm value with respect to expected electricity tightness.

Proposition 4.

$$\frac{dP_{i,t}}{d\kappa} > 0.$$

The valuation effect naturally combines two previously established effects: the cash-flow channel, in which looser electricity tightness raises effective productivity, so expected dividends rise; and the discount-rate channel, in which the same change reduces both volatility and covariance of dividends with the SDF, so the required return falls. With higher cash flows and a lower discount rate, the equity price must increase.

[5]We assume that volatility is small.

2.8 Extensions

In this section, we discuss a number of extensions to our basic model, which underscore the robustness of our baseline model and generate additional testable implications. First, we discuss the amplification effects driven by differences in electricity intensity and input substitutability. We further discuss basic intuition for the versions of the model with priority weights, capital adjustment, correlated shocks, and electricity price adjustment. Finally, we summarize the main welfare results.

The Online Appendix establishes that the baseline tightness–premium mechanism is remarkably robust. *(i) Heterogeneous technologies.* Cross–partial derivatives in Section OA.2 show that relaxing expected tightness κ lowers risk premia more for firms that are (a) *electricity–intensive* (δ_E large) and (b) have *low short-run substitutability* (σ small). *(ii) Priority-weighted rationing.* Granting firm-specific weights ω_i preserves all monotone comparative statics—high–priority firms simply face a stochastically larger $\kappa_{i,t}$ and generates testable dispersion in size, profits, and premia (Section OA.3). *(iii) Capital dynamics.* Introducing quadratic adjustment costs turns rationing shocks into persistent investment wedges; nonetheless Propositions 1-3, the risk-premium formula, and valuation results survive with attenuated magnitudes (Section OA.4). *(iv) Correlated productivity–grid shocks.* Allowing arbitrary covariance between technology and supply shocks only alters the intercept of premia; the slope $d\,\mathrm{RP}/d\kappa < 0$ flips sign only under implausibly large negative correlation (Section OA.5). *(v) Price-clearing markets.* A competitive spot price with a hard capacity cap yields the *same* allocation and risk as quantity rationing (Section OA.6). *(vi) Welfare.* Because higher κ raises average consumption and dampens its volatility, lifetime utility is strictly increasing in κ; with convex grid-upgrade costs this delivers a unique optimal target κ^* (Section OA.7). Taken together, these extensions confirm that our empirical tests identify a general infrastructure-tightness channel rather than a knife-edge special case.

3 Data

In this section, we provide the sources and definitions of our main variables. First, we describe information related to electricity tightness, followed up by plant-level, corporate and stock market, and county data. Next, we provide summary statistics of the variables utilized in our regression models. For reference, Table A.1 of the Appendix provides the list of all the variables we use in our empirical tests.

We use two sources of U.S. administrative data to measure realized and expected electricity tightness. First, for realized tightness, we use the System Average Interruption Duration Index (SAIDI), which captures realized supply outages and is measured as the number of days a particular entity is without electricity supply. We measure SAIDI at the county level based on the data from the U.S. Energy Information Administration (EIA) via Form 861, the Annual Electric Power Industry Report. EIA Form 861 is a federally required annual survey that collects utility-level data on customer counts, electricity sales, revenues, service territories, and reliability for all electric utilities and power marketers in the United States. These entities report reliability metrics for each state in which they operate, as well as the exact counties and number of customers they serve locally. We compute the county-level SAIDI as a customer-weighted average of the state-level SAIDI values reported by all utilities serving that county. That is, we assign each utility's state-level SAIDI to every county it serves within that state, and then weight these values by the number of customers the utility serves in the county to arrive at the county-level measure (similar to e.g., Borenstein et al., 2023). Moreover, to calculate exposure to outages during the Uri Winter Storm, we use county-level outage data from the U.S. Department of Energy's EAGLE-I historic dataset, which includes power outage information at the county level at 15-minute intervals.

For expected tightness, we rely on anticipated reserve margins published in Long-Term Reliability Assessments at the regional level by the North American Electric Reliability Corporation (NERC), which measures whether a region will have sufficient capacity to meet forecasted peak demand. The anticipated reserve margin is expressed as a percentage over the expected peak electricity demand. This means it shows how much extra electricity capacity there will be compared to the highest amount of electricity people are expected to use at once (the peak demand). NERC's Long-Term Reliability Assessment is the federally recognized benchmark for evaluating future capacity and reserve margins in the United States, drawing on standardized, region-specific data from planning authorities to assess long-term resource adequacy. It is published annually at year end and forecasts reserve margins for up to 10 years ahead. We focus on the short-term, one-year ahead forecasts made by NERC. This data provides us a measure of Anticipated Excess Capacity (AEC).

For illustration, Figure 1 displays geographical distribution of the two measures of electricity tightness for the year 2021. Panel 1a presents the geographic distribution of SAIDI. We note a significant presence of scattered outages in Texas, North West, and North East, with a primary driver of the outages in Texas being the Uri Winter Storm (Brelsford et al., 2024). In fact, some of the most exposed counties in that year experienced outages lasting close to 10 days. Figure 1b shows the geographic distribution of AEC. AEC is regionally more clustered as electricity regions span larger areas than counties. Florida (FERC), Midwest (MISO), New York (NPCC) had the lowest values of AEC, at around 5%, while East, Southeast, and Southwest recorded the highest values, at around 20%.

We create firm-level exposures to electricity tightness by utilizing the locations of firms' establishment data. We first determine establishments of public firms and their locations. We then map establishments to counties and electricity regions. Afterwards, we calculate establishment-level exposure to realized and forecasted electricity tightness. To arrive at firm-level measures, we aggregate the exposure of firms' establishments and weigh them by the employment shares of the establishments.

Our data on firm-level fundamentals (annual) and stock returns (monthly and daily) come from Capital IQ. Our data on factor returns come from WRDS. We define the book value of common equity as a difference between the book value of stockholder's equity, adjusted for tax effects, and the book value of preferred stock. To construct the book value per share, we follow Asness and Frazzini (2013), and adjust book value for corporate actions between fiscal year-end and the date of portfolio formation. To construct price-to-book ratio, we divide current price by book value per share. The measure is updated monthly. *LOG(MARKET/BOOK)* is the natural logarithm of the price-to-book ratio. Market capitalization is a product of number of shares outstanding and stock prices (*prccm*). We use the last reported shares outstanding on the last trading day of the month (*cshom*). *LOG(SIZE)* is the natural logarithm of firm's market capitalization; *LEVERAGE* is the ratio of debt to book value of assets; momentum, *MOMENTUM*, is the average of the most recent 12 months' returns on stock i, leading up to and including month $t-1$; capital expenditures, *CAPEX/ASSETS*, is the firm's capital expenditures divided by the book value of its assets; *CASH/ASSETS*, is the firm's net cash divided by the book value of its assets; *PPE/ASSETS* is the firm's property, plant, and equipment over assets; the firm's assets' performance, *ROA*, is the ratio of a firm's net yearly income divided by the value of its assets; *VOLATILITY*, is the standard deviation of returns using the past 12-month observations; *SALES GROWTH* is the annual growth rate in firm sales. To mitigate the impact of outliers, we winsorize *LEVERAGE*, *CAPEX/ASSETS*, *ROA*, *MOMENTUM*, *VOLATILITY*, and *SALES GROWTH* at the 2.5% level. To arrive at our final sample of stock returns, we focus on primary issues of ordinary shares and exclude observations with stock prices below $1.

Constrained by the availability of SAIDI, our baseline sample for real outcomes covers the period 2014–2024. However, since AEC is available for earlier periods, our sample for stock return regressions, which relies on AEC, begins in January 2005, the first year in which reserve-margin forecasts, and plant-level ISO assignments are systematically reported under the current NERC taxonomy.[6] Table 1 presents summary statistics of key variables we use in our main tests.

Panel A reports information at firm level. We observe substantial heterogeneity in both the infrastructure variables that underpin our identification strategy and the usual balance-sheet controls. AEC, the forward-looking measure of grid slack, averages 0.11 with an inter-decile range of 0.04–0.20, whereas realized outages, *SAIDI*, are markedly more right-skewed, climbing from 0.07 at the 10^{th} percentile to 0.37 at the 90^{th}. Firm scale varies sharply: the median company employs $e^{0.363} \approx 1.4\,\text{k}$ workers and holds roughly \$1.1 bn in assets ($\log \text{Assets} = 7.0$), but the upper decile reaches $e^{9.8} \approx 18\,\text{bn}$. Investment intensity is modest (median $\textit{CAPEX/Assets} = 1.7\%$); profitability is thin (median $\textit{ROA} = 1.3\%$ with a left-tailed mean), and financial leverage centers around 23% of assets. Market valuations are equally dispersed, with *Market-to-Book* spanning 0.25–2.11 across the inter-decile range. Collectively, this breadth of variation along infrastructure, operating, and financial dimensions furnishes ample cross-sectional and time-series power for the regression analysis that follows.

Panel B shows that the establishment panel is both granular and dispersed. *Anticipated Excess Capacity* averages 0.10 (s.d. 0.07), with a wider spread than in Panel A (P10–P90: 0.02–0.20). Realized outages (*SAIDI*) are more right–skewed at the plant level: the median is just 0.13, while the mean rises to 0.23 and the 90^{th} percentile reaches 0.44. Establishment size varies sharply: the median unit has about $e^{2.303} \approx 10$ employees ($\text{P10} = e^{0.693} \approx 2$; $\text{P25} = e^{1.609} \approx 5$; $\text{P75} = e^{3.258} \approx 26$; $\text{P90} = e^{4.522} \approx 92$). Relative to the firm-year summary, these statistics indicate slightly lower average slack but greater cross-sectional dispersion in both infrastructure exposure and operating scale, providing useful within–and across-firm variation for the analyses that follow.

Panel C reports the summary statistics for stock returns at the firm-day level. Mean daily returns are 0.33%, with a standard deviation of 3.61%. Daily returns are calculated as log returns.

Panel D reports the summary statistics at the county level. Panel C1 reports grid tightness and local economic size for all industries. EMP and EST are total employment and establishments; the table shows means (with SD) and selected percentiles (p10, p25, p50, p75, p90). Panel C2 restricts to NAICS 518210 (data processing/hosting). Industry Presence indicates whether the county has any establishments in this industry; *EMP* and *EST* are the corresponding employment

[6] Using the full 1991-2024 window for AEC yields qualitatively similar results, but the earlier period is noisier because of reporting changes and structural breaks in electricity markets.

and establishments. Log variables are computed on the positive support (zeros excluded), so they summarize the size distribution conditional on the industry being present.

4 Empirical Results

In this section, we present empirical results testing the main predictions of our model. We first show that measures of capacity constraints, both expected and realized, correlate with real firm-level outcomes—factor inputs, profitability, and valuations. Next, we study the effect of the constraints on stock returns and risk premia and show that expected tightness significantly increases risk premia. Third, we provide robustness of our results to potential endogeneity concerns using evidence from Uri Winter storm and subsequent policy intervention in the Texas (ERCOT) market. Finally, we show that firm-level constraints affect aggregate macro outcomes at the county level thereby suggesting strong welfare implications.

4.1 From Capacity Tightness to the Real Economy

The model in Section 2 delivers sharp comparative-static predictions along two distinct margins. (i) When firms *expect* future reserve margins to widen (higher AEC), the shadow cost of infrastructure falls and they scale up hiring, investment, and production. (ii) Conversely, *realized* distribution shortfalls (higher SAIDI) destroy effective labor hours and idle capital in real time, eroding cash flows and valuations.

The empirical strategy below is designed to take these implications to the data: first on real outcomes under anticipated excess capacity (Table 2); next on the same outcomes under realized outages (Table 3); and finally on market valuation (Table 4). All specifications are annual, include the full set of controls listed in the tables, and rely on clustering by firm headquarter county (or establishment county).

We estimate:

$$y_{it} = \alpha + \beta AEC_{it} + \delta X_{it-1} + \mu_i + \gamma_t + \varepsilon_{it}, \tag{4.1}$$

where y_{it} is log-employment, log-capital, investment rate, or ROA for firm i in year t; AEC_{it} is the anticipated reserve-margin gap of firm i based on its employee-weighted aggregated plant-level exposures at region r; X_{it-1} is a vector of firm-level controls observed at year $t-1$; and μ_i and γ_t are firm and year fixed effects. Standard errors are double clustered by firm and year.

Columns 1–5 of Table 2 document that a one-standard-deviation increase in AEC is associated with a 2.5% rise in firm-level employment and a parallel, if muted, uptick at the establishment level. Notably, the latter specification absorbs firm-year fixed effects, thus controls for any time-varying firm-level unobservables, such as firm-specific demand shocks. Further, the rise in capacity also predicts a 2.1% expansion of the capital stock and a 6 basis point boost in the investment rate. Finally, we observe a 90 basis point improvement in ROA. These elasticities match the model's prediction that looser expected constraints operate through both intensive-margin productivity and extensive-margin scale channels (Proposition 2). As an auxiliary result, in column 2, we find that firms anticipating electricity constraints reallocate their labor from plants facing tighter constraints to those facing weaker constraints.

Next, we estimate similar regression model for realized outages. Formally:

$$y_{it} = \alpha + \beta SAIDI_{it} + \delta X_{it-1} + \mu_i + \gamma_t + \varepsilon_{it}, \tag{4.2}$$

where $SAIDI_{it}$ is the plant-weighted distribution-outage index for firm i based on the county-level variation. The controls mimic those in equation 4.1. Table 3 shows that outages shave statistically significant fractions off establishment employment (column 2), investment (column 4), and profitability (column 5). The firm-level employment effect in column 1 is close to zero, indicating intra-firm reallocation that partly cushions the blow—again in line with the model's short-run adjustment frictions. Similarly, the effect for assets is negative but estimated with noise.

Finally, we estimate the model alternately relating AEC and SAIDI to firm-level valuation:

$$q_{it} = \beta_1 AEC_{it} + \beta_2 SAIDI_{it} + \delta X_i + \mu_i + \gamma_t + \varepsilon_{it}, \tag{4.3}$$

where q_{it} is log market-to-book. Table 4 shows that firms with a one-standard-deviation higher AEC are associated with roughly 1.7% higher q, whereas a comparable increase in SAIDI depresses valuations by about 90 basis points. Both results obtain after conditioning on lagged, current, and forward sales and profitability growth, momentum, volatility, and a host of fixed effects.

Overall, three facts emerge. First, signs align with theory: expected slack stimulates, realized scarcity constrains. Second, the magnitudes are economically meaningful–comparable to canonical technology or demand shocks. Third, the results survive an exhaustive set of controls, alleviating the concern that tightness is merely a re-labeled firm-characteristic premium. Together, Tables 2–4 provide the real-side foundation for the risk premia estimated in Section 4.2.

4.2 Infrastructure Tightness as a Priced Risk Factor

This section establishes three facts. First, the electricity-tightness factor (ELX), defined as a difference in monthly stock returns of most-tight minus least-tight companies based on AEC, is economically large and poorly spanned by the usual Fama–French factors (Panels E of Table 1 and Table 5). Second, ELX commands a statistically significant premium in sorted-portfolio regressions (Tables 6-7). Third, the factor earns a positive price of risk in the cross-section of individual stocks once conventional characteristics are controlled for (Table 8). Taken together, these results are fully consistent with the model's comparative statics in Section 2.

Panel E of Table 1 reports moments of asset pricing factors we use in our analysis. ELX is highly volatile (monthly $\sigma \approx 2.5\%$) and its inter-quartile range exceeds 2.5 percent, comparable to the BAB factor and lower than most other factors. Importantly, the mean return equals 0.49 percent per month, implying an annualized premium of 5.9 percent.[7] The monthly Sharpe ratio is 0.2.

Table 5 shows that ELX is only weakly correlated with the six benchmark factors (maximum absolute correlation ≤ 0.20). Both the canonical market factor and investment (CMA) loadings are near zero. This low collinearity anticipates the incremental explanatory power documented below.

We next study time-series properties of the tightness factor using portfolio sorts. Following Fama and French (1993), each period, we sort all stocks into decile portfolios using the previous-month AEC measures and compute their value-weighted returns, R_t^p. Next, we regress the time series of each portfolio returns, net of the risk-free rate, on the asset-pricing factors (F). We further regress ELX on the same set of factors.

$$R_t^p - R_t^f - = \alpha_p + \beta_p^\top \mathbf{F}_t + \varepsilon_{pt}, \quad p = 1:10. \tag{4.4}$$

Table 6 reports the results. In Panel A, the five-factor alphas turn from positive (Decile 1) to negative (Decile 10). The return spread between Decile 1(most constrained) and Decile 10 (least constrained) portfolios is highly significant ($t > 9$). In the FF regression, alpha on Decile 10 is highly significant and p-value of GRS test is significant. Once we include ELX, in deciles 2-9, the alpha values become modest, and the GRS statistics cannot reject the joint null of zero intercepts ($p = 0.60$). Columns 1–10 of Panel B show that the coefficients from the regression of the decile portfolios on ELX decline monotonically from about 0.55 for the most constrained portfolio to -0.46 for the least constrained portfolio. Adding three other auxiliary factors—momentum, BAB,

[7] The sign is economically intuitive: investors require compensation to hold capacity-constrained firms that suffer in tight grids.

and liquidity—in Table 7 leaves the patterns intact, while the stricter GRS test still fails to reject.

Next, we examine the pricing of risk due to electricity following Fama-MacBeth approach. For each firm, we calculate a 60-month rolling-window electricity betas, as well as other risk-factor betas coming from the FF framework. We require a minimum of 36 monthly observations to estimate betas. We further winsorize all betas at 0.5% to mitigate the impact of outliers.

Table 8 implements a panel regression of individual excess stock returns on betas using ∼530,000 firm–month observations:

$$R^e_{i,t+1} = \lambda_{0t} + \lambda_{ELX,t}\,\hat{\beta}^{ELX}_{i,t} + \sum_{j=1}^{5} \lambda_{j,t}\,\hat{\beta}^{FF_j}_{i,t} + \mathbf{X}_{i,t}\boldsymbol{\delta}_t + \varepsilon_{i,t+1}. \tag{4.5}$$

We double cluster standard errors at firm and month dimensions to allay concerns of cross-sectional and autocorrelation across observations. Our coefficient of interest is λ, the price of electricity risk.

The slope of the ELX beta is 11 bp per unit of beta (8 bp for the relative capacity specification) and significant at the 5% level (columns 1–4). Economic magnitude is meaningful: moving from the 10th to 90th percentile of the beta distribution ($\Delta\hat{\beta} = 1.49$) predicts an expected-return differential of about 18 bp per month, that is, 2.1 % annually, closely matching the realized spread in Table 6.

In columns 2 and 4, we further present the results that additionally include stock characteristics as potential risk confounders, following the approach of Daniel and Titman (1997). In particular, we include measures of excess capacity and electricity price as well industry-fixed effects at 2-digit NAICS level. The results from this more comprehensive tests leave our main coefficient λ almost unchanged, which provides additional support that stock returns reflect differences in covariances rather than idiosyncratic characteristics, consistent with the predictions of our model.

Three further checks (unreported, available upon request) confirm robustness: (i) the time-series and cross-sectional price of tightness risk is not driven by the February 2021 Texas event. Re-estimating the specification in Table 8 on the 2005–2024 sample excluding the year 2021 yields $\lambda = 0.124$ (t = 2.2), slightly larger in magnitude than the baseline 0.113. All other factor prices remain virtually unchanged. Hence the ELX premium reflects pervasive covariation with the SDF rather than a single disaster episode. Similarly, the pricing results are unchanged if we restrict our sample to pre-2020 period reflecting potential effects due to Covid or the war in Ukraine. The coefficient λ remains virtually unchanged for the restricted sample. (ii) not winsorizing the top/bottom 0.5 % of extreme betas leaves λ_{ELX} unchanged; (iii) excluding utilities and energy stocks from both factor construction and regressions does not affect the sign or significance of any estimate.

Overall, the evidence supports the model's core prediction that electricity-network tightness is a priced aggregate shock. The factor materially improves both time-series and cross-sectional pricing relative to state-of-the-art factor models, while requiring no additional risk exposures once capacity improves.

4.3 Empirical Identification: Winter Storm Uri and ERCOT Reforms

For our identification, we utilize two shocks. Our first shock is the abrupt and severe generation shortfall in the Texas grid during February 2021, which we treat as a negative realization of κ. Winter Storm Uri was first flagged by U.S. forecasters as a dangerous event on February 10, 2021, when the National Weather Service (NWS) began issuing winter storm watches and warnings for large parts of the central United States, including Texas. By February 13, 2021, the NWS and local emergency agencies were explicitly warning of life-threatening cold, widespread power outages, and dangerous travel conditions, as the storm approached Texas. The peak electricity crisis, when ERCOT initiated rolling blackouts, was February 15–18, 2021. We present the specific time resolution of the weather news in Figure 3 of the Online Appendix.

In response to the shock and realization of network fragility, in the second quarter of 2021, the state of Texas implemented reserve margin uplifts, firming obligations, and adjustments to scarcity pricing caps. These policy changes altered forward capacity expectations without contemporaneously shifting demand. One of the most salient legislation was Texas Senate Bill 3 whose purpose was to reform the state's electricity system to improve reliability and resilience after the widespread power outages during Uri. The Texas Legislature enacted post-Uri reforms on May 31, 2021; the Public Utility Commission of Texas (PUCT) subsequently implemented these through rule makings and financing orders that introduced the ERCOT uplift securitization charges and initiated market redesign. We treat the reform as a second, positive shock, this time to expected tightness, κ_t—the looseness of expected capacity constraint.[8] In our analyses, we consider the ex-post consequences of the two shocks for our variables of interest, along the predictions of Corollary 1 and 2.

To illustrate the role of the two shocks we begin with an event-study difference-in-differences

[8]Unlike it is for the Uri shock where the timing and resolution of the weather shock has been very clear, the Texas anticipated upgrade has been made of a number of initiatives taking place in 2021 and 2022. For our purpose, the important fact is that SB 3 has been one of the first if not the first significant shock in this regard. Also, to many observers it was the first shock that removed any uncertainty related to the ERCOT uplift plans.

for cumulative stock returns:

$$cumret_{it} = \sum_{k \neq -1} \beta_k \mathbf{1}_{t=k} \times \text{ Shock}_c + \delta X_{it-1} + \mu_i + \gamma_t + \varepsilon_{it}, \tag{4.6}$$

where $cumret_{it}$ is the cumulative stock return for firm i up to and including day t, μ_i are firm fixed effects, γ_t are day fixed effects, and X_{it-1} includes a vector of firm controls. *Shock* is a generic variable for the two shocks we study. We cluster standard errors at the firm headquarter county.

For the first shock, our treatment sample, $Uri = 1$, includes companies in the top 10% empirical distribution of outage exposure to Uri. Our control sample, $Uri = 0$, includes companies in the bottom 90% in terms of the outage exposure to Uri. Both groups also require a minimum 50% of their total employment to be located in a Texas plant. The last choice allows for the possibility of geographical spillovers outside Texas border. For the second shock, our treatment sample, $ERCOT = 1$, includes companies with minimum 90% of employment exposure to ERCOT system. Our control sample, $ERCOT = 0$, includes companies with no exposure to ERCOT. Note that treatment definitions differ across events by design. The Uri shock was a meteorological disruption with spillovers beyond Texas; we therefore define treatment using exposure to the storm/outages, not ERCOT per se. In contrast, the post-Uri legislation affected market design within the Texas ERCOT footprint; to minimize contamination from multi-state operations we require a very high ERCOT footprint ($\geq$ 90%) for treated firms and 0% for controls. Results are robust to alternative cutoffs and to continuous exposure specifications.

We begin by validating the unexpected nature of our shocks using daily stock returns. For our first shock, we set as zero event date February 16, which is the first trading day after which widespread electricity outages followed in Texas. For our second shock, we consider June 1, 2021, the first trading day after the passage of the Texas Senate Bill 3. For each shock, we present the daily differences in cumulative stock returns between the samples of treatment and control groups in the event window of -6 to +5 trading days for the Uri shock, and -6 to +2 trading days for the ERCOT policy shock. For each day, we show point estimates of the differences along with 90% confidence intervals.[9]

Figure 6 presents the results for the Uri shock. We can observe no visible pre-trend in the period running up to the onset of the storm. Upon arrival of forecasts and the storm itself we

[9]We use a longer, 5-day post-period for Uri shock because different locations were affected within a few days of February 15, the first peak day. Given the overlapping nature of these events it is difficult to consider them as independent events. Hence, we set the first and the last day of the peak storm as our event window.

can see a visible decrease in stock prices progressively deepening as the storm intensified. Figure 3 presents the results for the ERCOT policy shock. Again, prior to the shock we observe no significant difference in cumulative returns between treatment and control groups, consistent with the idea of parallel trends and the unexpected nature of the shock. We can then see a positive 2-day response after June 1, 2021 when the Texas House and Senate agreed on the final version of the Bill.

To provide a statistical assessment of the return patterns, in Table 9, we present return responses to the shock using the difference-in-differences regression framework with day and firm fixed effects. We use daily returns as the outcome and a sample of 6 days before and 5 days after the respective shocks. For the Uri shock, we find a strong negative response of stock returns of treated stocks, relative to the control group. The difference is 120 basis points in daily returns. Conversely, for the policy shock and the loosening of electricity constraints, we find a strong positive response of 106 basis points in daily returns. Both results support the direction of the expected economic change and are statistically significant at 10% and 5% significance levels, respectively.

Subsequently, we trace down the short-term and long-term consequences of the shocks for real outcomes using annual frequency data. We first document the effect of the shock for AEC and SAIDI. Subsequently, we study the response for employment, assets, CapEx, ROA, and Tobin's q. Like before, we first report the graphical illustration of the difference-in-differences effects. Figures 4 and 5 present the results. Consistent with our hypotheses, we find that in response to both shocks SAIDI experienced a short-term jump in 2021 while AEC observed a longer-term increase in value. We also observe an increase in employment, firm assets, CapEx, and Tobin's q. The values for ROA, in turn, are lower for the year of the shock but muted for the longer term. We further confirm the statistical significance of the results in Table 10 for the short-term effects. For the short-term effects, we restrict the post period to one year, 2021. In Table 11, we present the longer-term effects, in which we omit year 2021 and focus on the years 2022–2024 of the post period.[10]

5 Aggregate and Welfare Implications

In this section, we take an aggregate perspective on our results. In particular, we examine the general equilibrium implications of electricity constraints. To the extent that firms may be differentially exposed to such constraint, the aggregate implications may simply be a wash. We assess this possibility empirically by relating county-level aggregates to our measures of constraints, AEC

[10] We also test for the presence of pre-trends in both tests and report the results in Table 12. We find little evidence of significant pre-trends possibly invalidating the assumptions of the difference-in-differences approach.

and SAIDI.

County-level aggregates provide a necessary complement to the firm- and establishment-level tests. First, they capture general-equilibrium spillovers that micro units cannot internalize—for example, reallocation of activity across firms within a county, migration of workers, or entry and exit along the extensive margin. Second, aggregate responses are the relevant objects for welfare and risk: in the model, electricity tightness scales aggregate consumption volatility and thus the stochastic discount factor. If grid scarcity is macro-critical, it must register in county employment and business formation. Third, aggregation guards against micro measurement error (e.g., plant-level reporting noise in employment) by exploiting a high signal-to-noise ratio in county totals. Table 13 implements these ideas using two complementary shifters of tightness—anticipated excess capacity (forward-looking slack) and SAIDI (realized outages).

Panel A of Table 13 links *anticipated excess capacity* to county real activity. Columns 1–2 show that higher expected slack is associated with larger county-scale economic activity: both *employment* and *establishment* counts rise with the forecast gap. The estimates are statistically precise and economically meaningful, indicating that when the grid is expected to be farther from its capacity constraint, local labor demand expands and the business base deepens. The model maps this directly to a lower shadow cost of the non-storable input, which raises effective productivity and scale (Proposition 1). Column 3 indicates that expected capacity constraints in the electricity system have implications for average *establishment sizes*: greater expected slack in the grid is associated with lager average establishment sizes. Columns 4–5 demonstrates implications for firm dynamics: while the anticipated excess capacity does not significantly affect *firm entry*, there is a strong negative association with *firm exit*. Higher expected capacity correlates with firm survival.

Panel B replaces expectations with realized *SAIDI* outages. The signs flip as the framework predicts for quantity rationing that arrives after inputs are chosen: higher outage duration is associated with lower county *employment* and fewer *establishments* (columns 1–2). Moreover, realized electricity constraints have significant implications for average *establishment sizes*. Based on the estimation in column 3, higher outages are associated with smaller establishment sizes. In addition, higher realized outages are negatively associated with *firm entry* (column 4), but have no effect on *firm exit* (column 5).

Panel C links *anticipated excess capacity* to county outcomes in industry NAICS 518210 (data processing/hosting), a power-intensive benchmark sector that includes data centers. County *employment* and *establishment sizes* in the data processing/hosting sector rise with the AEC (columns 1 and 3), mirroring the sector's sensitivity to the expected availability of electricity. *Establishment* counts are not affected by variation in AEC (column 2). Additionally, the probability that the industry is present in the county increases with anticipated slack (column 4) but not in a significant way. Effects on firm entry and exit are not estimated due to lack of public Census data at this level of granularity. Overall, these patterns line up with the model's cross-partials: sectors with higher electricity intensity (δ_E) should display stronger scale responses to κ.

Panel D connects realized *SAIDI* outages to activity in the NAICS 518210 sector. We find effects on both the extensive and intensive margins. Realized outages compress *employment* (column 1). There are no significant effects on *establishment* counts and average *establishment sizes*. Furthermore, column 4 displays that realized scarcity lowers the likelihood of industry presence, consistent with entry being less likely when realized rationing is high. Intuitively, outages destroy effective labor hours and idle installed capital in real time, so realized tightness operates as a negative productivity shock that scales down output one-for-one when $\kappa_t < 1$.

Two features deserve emphasis. First, the *extensive margin* reacts strongly in the power-intensive industry: expected slack predicts entry and scale, while realized outages discourage both. This is precisely the mechanism by which κ shifts the distribution of future rationing states that firms face; when the distribution stochastically improves, entry thresholds fall. Second, the *aggregate* results mirror the micro findings without being mechanically driven by them: the county totals incorporate within-county reallocation and net migration, which validates that electricity tightness bites at the macro level rather than merely reshuffling activity across incumbent plants.

All specifications in Table 13 are annual and use the covariates and fixed effects reported in the table notes (including time fixed effects and location/industry structure as applicable); standard errors are clustered by county as indicated. Outcomes are in logs where appropriate to accommodate heavy right tails in county size (see summary statistics). The 518210 "presence" regression is binary, while *EMP* and *EST* in that panel measure levels. Results are unchanged when we scale outcomes by county population or use alternative exposure definitions; these robustness checks are reported in the Online Appendix.

The county-level evidence in Table 13 substantiates the paper's central mechanism at macro scale: (i) forward-looking slack expands local employment and the business base, with pronounced effects in electricity-reliant industries; (ii) realized outages compress the same margins. These aggregate responses are the sufficient statistics that link infrastructure tightness to consumption growth and, ultimately, to the priced risk documented in Section 4.2.

6 Concluding Remarks

Infrastructure that cannot be stored or easily traded in real time reshapes both the real economy and financial markets. By embedding proportional grid rationing into a general-equilibrium production model, we have shown that unexpected scarcity compresses output, employment, and consumption, while the anticipation of future capacity reverses those losses and shrinks risk premia. Empirically, the 2021 Texas blackout and the ensuing reserve-margin reforms provide two clean, opposite shocks. Our plant–grid matches confirm the model's predictions: scarcity wipes out roughly 4 percentage points of local employment and 2 percent of Tobin's q; both margins recover once capacity is credibly secured. Equity investors price this risk, demanding higher expected returns from electricity-intensive firms.

Because tightness shocks are macro-critical, the welfare gains from even small improvements in reserve margins or demand response can be substantial. The results therefore lend support to recent proposals for firming-obligation contracts and dynamic scarcity pricing in wholesale markets.

Three directions for future research seem particularly promising. First, extending the framework to multi-node networks would allow for spatial spillovers and congestion rents. Second, incorporating endogenous investment in both generation and storage would shed light on transition dynamics and the pace of electrification. Third, the logic of real-time tightness applies equally to other non-storable infrastructures such as data-center cycles, pipeline capacity, or port berths; quantifying their macro–financial footprints is an open agenda.

Taken together, our findings reframe infrastructure not as a silent background condition but as a priced state variable that links engineering constraints to business cycles and asset markets.

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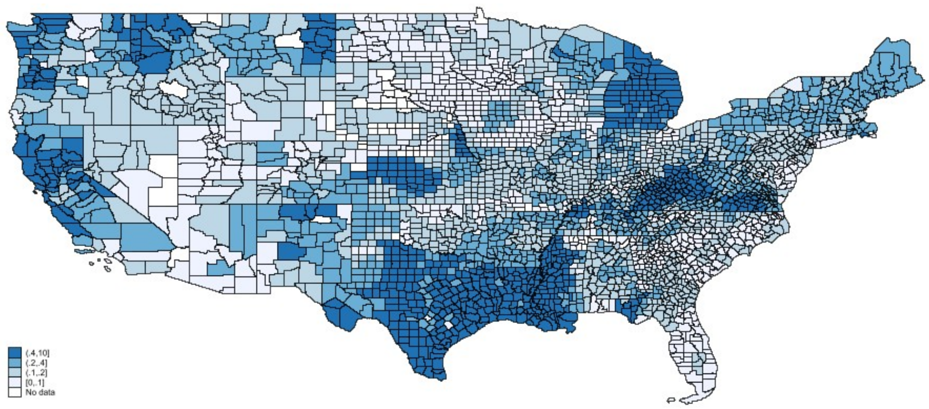
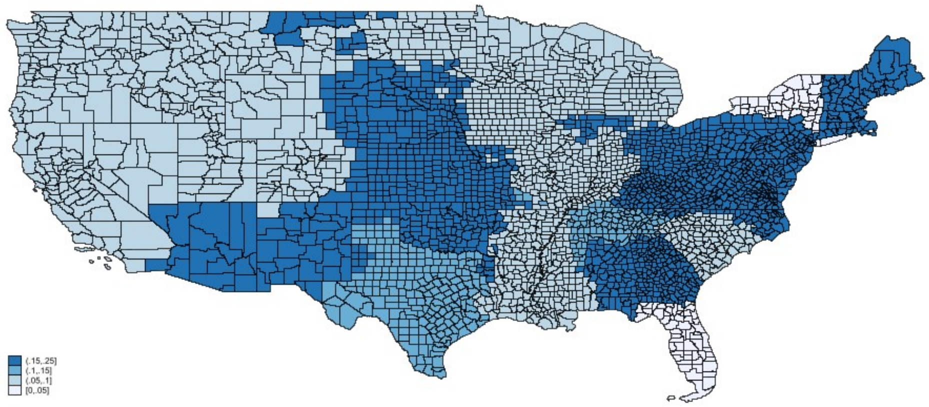
Figures



(a) SAIDI



(b) AEC

Figure 1: Geographical Distribution of Realized and Expected Electricity Constraints in 2021

These figures plot the county-level distributions of electricity constraints in the U.S. in 2021. Figure 1a displays the results for SAIDI. Figure 1b displays the results for AEC. AEC measures future excess capacity relative to the NERC reference capacity in percent. SAIDI measures total annual outages in days.

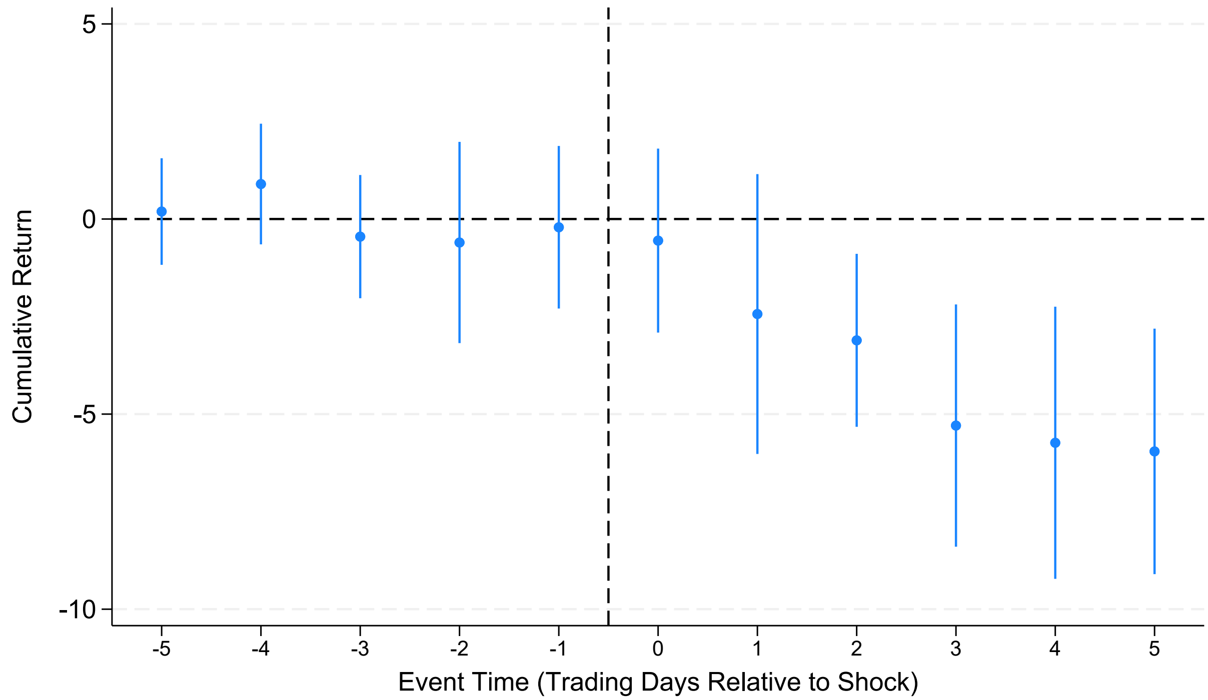


Figure 2: Cumulative Stock Returns around Uri Winter Storm Shock

This figure plots the cumulative stock market responses for treatment versus control firms to the Uri Winter storm shock. The sample consists of firms with at least 50% employment footprint in areas belonging to the Texas ERCOT grid. Treatment firms are firms in the top 10% of the empirical distribution in terms of outage exposure to Uri, and control firms are those in the bottom 90% of the same distribution. Event date t=0 is February 16, 2021, which is the first trading day after the widespread outages due to Uri storm. The sample window starts 6 trading days before the shock and ends 5 trading days after the shock. Confidence intervals are at the 10% level.

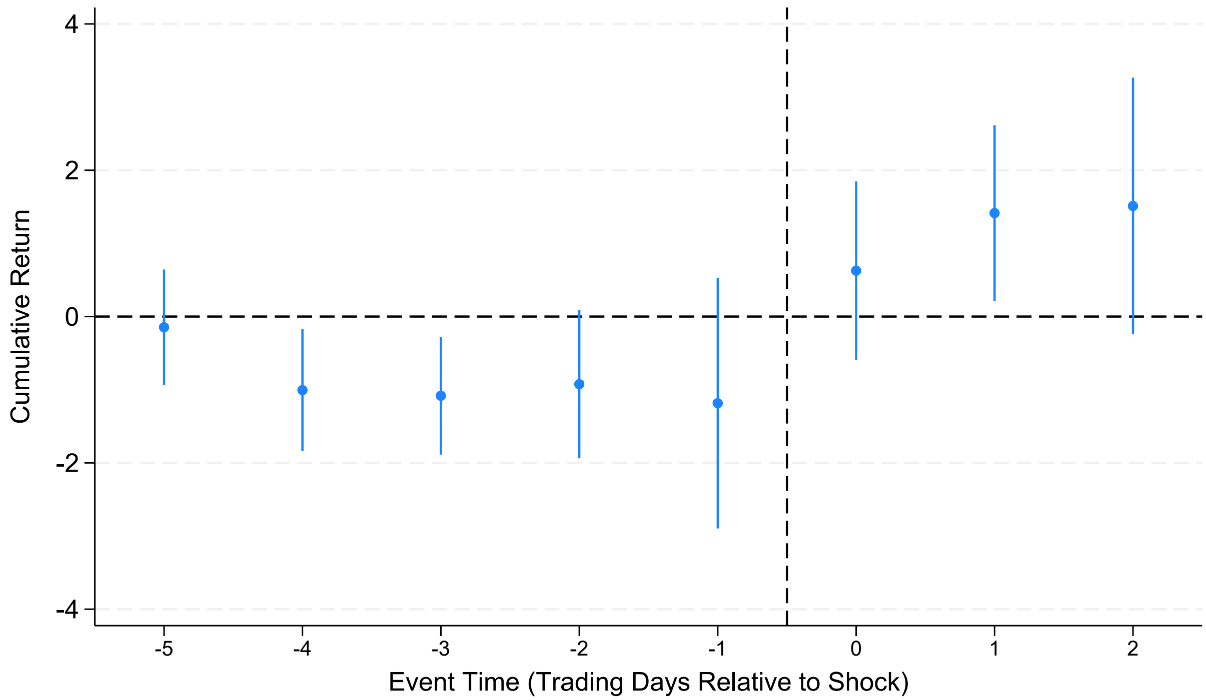
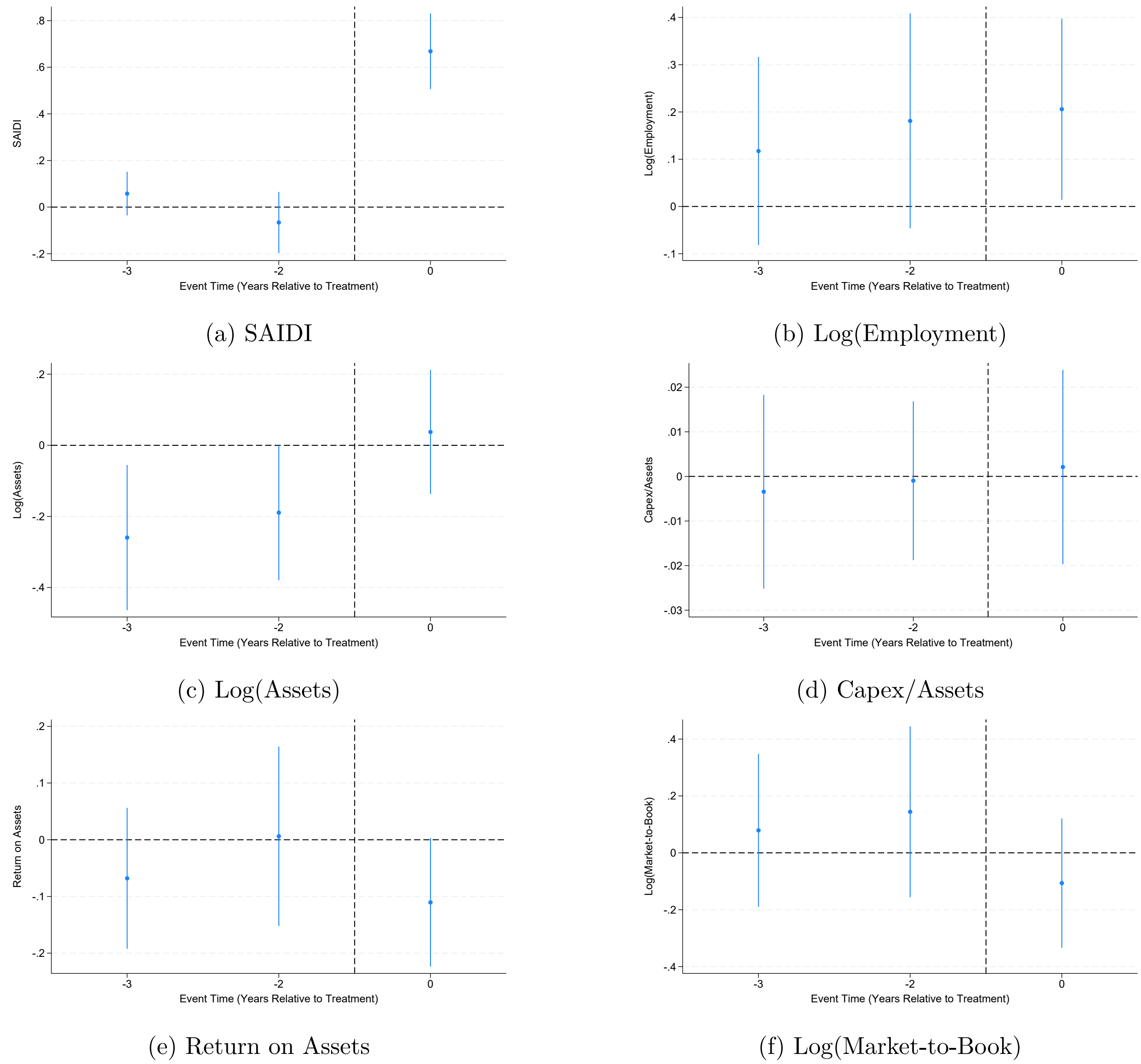


Figure 3: Cumulative Stock Returns around ERCOT Policy Adoption

This figure plots the cumulative stock market responses for treatment versus control firms to the signing of post-Uri legislations in the Texas Senate and House. Treatment firms are firms with at least 90% employment footprint in locations belonging to the Texas ERCOT grid, and control firms have no exposure to the Texas ERCOT grid. The figure displays the response to the policy adoption in the aftermath of the Uri shock. Event date t=0 is June 1, 2021, which is the first trading day after the signing of the post-Uri legislations in the Texas Senate and House. The sample window starts 6 trading days before the shock and ends 2 trading days after the shock. Confidence intervals are at the 10% level.



(a) SAIDI

(b) Log(Employment)

(c) Log(Assets)

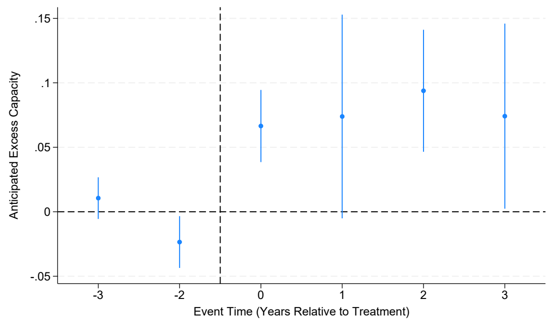
(d) Capex/Assets

(e) Return on Assets

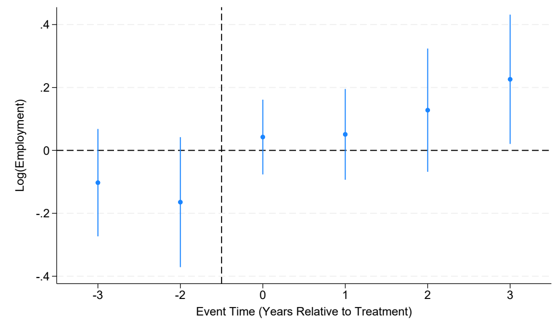
(f) Log(Market-to-Book)

Figure 4: Firm Electricity Constraints and Outcomes around Uri Outage Shock

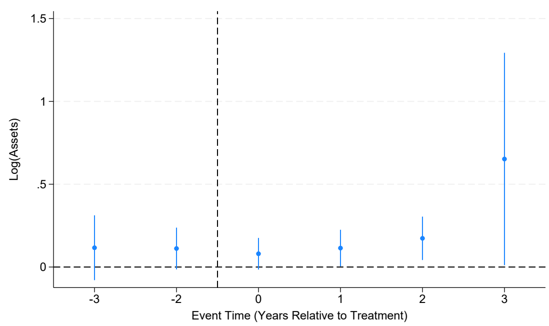
These figures plots the short-term firm responses for treatment versus control firms to the Uri shock using equation 4.6. The sample consists of firms with at least 50% employment footprint in areas belonging to the Texas ERCOT grid. Treatment firms are firms in the top 10% of the empirical distribution in terms of outage exposure to Uri, and control firms are those in the bottom 90% of the same distribution. The sample starts in 2018 and ends in 2021. Confidence intervals are at the 10% level.



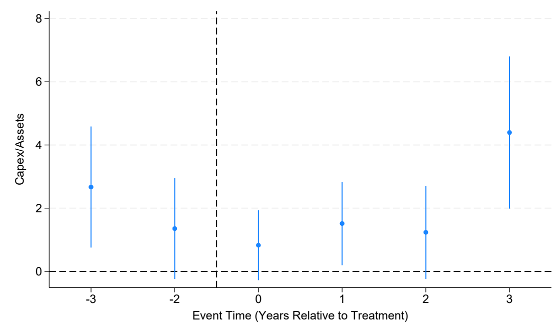
(a) AEC



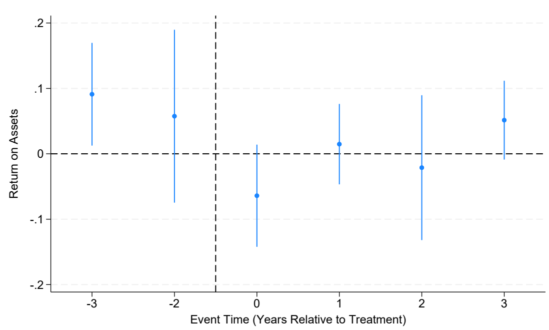
(b) Log(Employment)



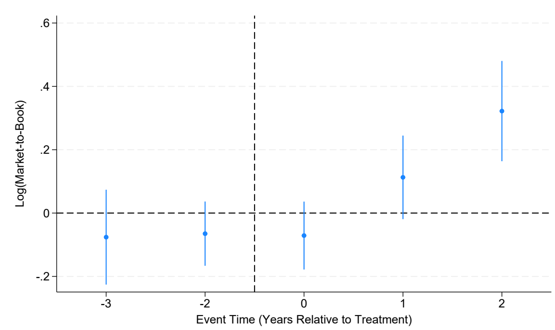
(c) Log(Assets)



(d) Capex/Assets



(e) Return on Assets



(f) Log(Market-to-Book)

Figure 5: Firm Electricity Constraints and Outcomes around ERCOT Capacity Shock

These figures plot the firm responses for treatment versus control firms to the Texas shocks using equation 4.6. Treatment firms are firms with at least 90% employment footprint in locations belonging to the Texas ERCOT grid, and control firms have no exposure to the grid. The sample starts in 2018 and ends in 2024. Confidence intervals are at the 10% level.

Tables

Table 1: Summary Statistics

			Panel A: Firm-Year				
VARIABLE	MEAN	SD	P10	P25	P50	P75	P90
ANTICIPATED EXC CAP (AEC)	0.113	0.058	0.040	0.074	0.104	0.152	0.195
SAIDI	0.208	0.251	0.065	0.097	0.154	0.238	0.371
LOG(EMP 1000s)	0.196	2.417	-2.996	-1.514	0.363	1.946	3.178
LOG(ASSETS)	6.703	2.646	3.161	5.138	7.002	8.482	9.800
CAPEX/ASSETS	0.032	0.041	0.001	0.004	0.017	0.044	0.082
ROA	-0.146	0.666	-0.433	-0.068	0.013	0.058	0.119
LOG(MARKET/BOOK)	0.807	1.046	-0.246	0.126	0.649	1.354	2.112
PPE/ASSETS	0.218	0.251	0.009	0.026	0.109	0.321	0.678
LEVERAGE	0.300	0.346	0.002	0.060	0.227	0.411	0.632
SALES GROWTH	0.128	0.452	-0.206	-0.037	0.060	0.189	0.453
CASH/ASSETS	0.194	0.232	0.010	0.032	0.095	0.261	0.569
HHI NAICS-3	0.074	0.070	0.021	0.023	0.048	0.093	0.187
ROE GROWTH	-0.046	2.158	-1.545	-0.586	-0.063	0.346	1.464
MOMENTUM	0.055	0.466	-0.510	-0.225	0.024	0.265	0.600
VOLATILITY	0.139	0.104	0.050	0.071	0.107	0.169	0.265
			Panel B: Firm-Establishment-Year				
VARIABLE	MEAN	SD	P10	P25	P50	P75	P90
AEC	0.102	0.070	0.023	0.042	0.094	0.158	0.204
SAIDI	0.228	0.354	0.055	0.081	0.131	0.231	0.440
LOG(EMP)	2.507	1.378	0.693	1.609	2.303	3.258	4.522
			Panel C: Firm-Day				
VARIABLE	MEAN	SD	P10	P25	P50	P75	P90
DAILY RETURN	0.326	3.612	-2.252	-0.795	0.054	1.333	2.980
			Panel D: County-Year				
VARIABLE	MEAN	SD	P10	P25	P50	P75	P90
Panel D1: *All Industries*							
AEC	0.114	0.077	0.022	0.052	0.102	0.170	0.226
SAIDI	0.280	0.438	0.073	0.105	0.166	0.281	0.540
EMP	40634.8	148288.6	936	2252	6806	21443	78565
EST	2585.5	9049.3	114	231	564	1583	5189
LOG(EMP)	8.933	1.741	6.842	7.720	8.826	9.973	11.272
LOG(EST)	6.485	1.503	4.736	5.442	6.335	7.367	8.554
Panel D2: *NAICS 518210*							
INDUSTRY PRESENCE (0/1)	0.232	0.422	0	0	0	0	1
EMP	435.6	1710.9	0	0	10	139	882
EST	12.04	38	0	0	1	7	29
LOG(EMP)	4.604	2.052	2.251	2.398	4.317	6.148	7.474
LOG(EST)	1.890	1.405	0	1.099	1.609	2.773	3.912

Panel A reports summary statistics for the firm-year sample. The sample consists of U.S. firms in Compustat. Panel B reports summary statistics for the firm-establishment-year sample. Panel C reports summary statistics for the county-year sample and consists of all U.S. counties in the CBP data. The sample period begins in 2014 and ends in 2024.

Table 1: Summary Statistics (continued)

Panel E: Firm-Month Factors					
VARIABLE	MEAN	SD	P25	P50	P75
ELX	0.49	0.55	-0.77	1.78	2.52
ELXREL	0.46	0.61	-1.00	1.84	2.37
MKT	0.81	1.26	-1.85	3.36	4.47
SMB	-0.02	-0.03	-1.85	1.52	2.67
HML	-0.10	-0.32	-1.82	1.45	3.20
RMW	0.35	0.34	-0.76	1.33	1.85
CMA	0.02	-0.09	-1.15	1.00	1.90
PS_VWF	0.09	0.22	-2.14	2.69	3.90
MOM	0.12	0.43	-1.74	2.61	4.40
BAB	0.39	0.47	-0.74	1.90	2.69

Panel E reports factor summary statistics. Returns are monthly in percent. ELX is *most-tight minus least-tight* decile portfolio return. ELXREL scales absolute excess capacity by reference margin. The sample starts in 2005 and ends in 2024.

Table 2: Anticipated Excess Capacity and Real Outcomes

	LABOR		CAPITAL		PROFIT
DEP VAR:	LOG(FIRM EMP)	LOG(EST EMP)	LOG(ASSETS)	CAPEX/ASSETS	ROA
	(1)	(2)	(3)	(4)	(5)
AEC	0.439^{***}	0.008^{*}	0.358^{***}	0.010^{*}	0.155^{*}
	(0.155)	(0.004)	(0.107)	(0.006)	(0.089)
PPE/ASSETS	0.136		-0.136	0.002	0.205^{**}
	(0.141)		(0.085)	(0.007)	(0.088)
LEVERAGE	-0.039		-0.279^{***}	-0.012^{***}	-0.490^{***}
	(0.041)		(0.036)	(0.002)	(0.054)
SALES GROWTH	0.089^{***}		0.114^{***}	0.006^{***}	0.051^{***}
	(0.017)		(0.012)	(0.001)	(0.010)
CASH/ASSETS	-0.072		-0.292^{***}	0.003	0.138^{***}
	(0.070)		(0.055)	(0.002)	(0.053)
HHI NAICS-3	0.706^{**}		-0.134	-0.009	-0.283
	(0.319)		(0.222)	(0.012)	(0.193)
CAPEX/ASSETS	0.799^{***}		0.461^{**}		-0.669^{***}
	(0.261)		(0.187)		(0.169)
ROA	0.083^{***}		0.088^{***}	-0.001^{*}	
	(0.022)		(0.017)	(0.001)	
LOG(ASSETS)				-0.011^{***}	
				(0.001)	
N	37,528	3,691,660	37,528	37,528	37,528
R2	0.934	0.987	0.976	0.692	0.759
YEAR FE	X		X	X	X
FIRM FE	X		X	X	X
FIRM-YEAR FE		X			
ESTABLISHMENT FE		X			

The table reports coefficient estimates from panel regressions (equation 4.1). FIRM EMP denotes firm employment. EST EMP denotes establishment employment. ASSETS denotes total assets. CAPEX/ASSETS denotes capital expenditure over lagged assets. ROA denotes return on assets. AEC measures firm exposure to anticipated electricity capacity, which measures future excess capacity relative to the NERC reference capacity in percent. The firm measure is an employment-weighted mean of the firms' establishment exposures. Columns 1, 3, 4, and 5 report results at the firm level. Column 2 is at the establishment level. Standard errors are clustered at the firm headquarter county level in firm-level regressions, and establishment county level in establishment-level regressions. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 3: SAIDI and Real Outcomes

	LABOR		CAPITAL		PROFIT
DEP VAR:	LOG(FIRM EMP)	LOG(EST EMP)	LOG(ASSETS)	CAPEX/ASSETS	ROA
	(1)	(2)	(3)	(4)	(5)
SAIDI	-0.005	-0.002***	-0.011	-0.002**	-0.032***
	(0.018)	(0.001)	(0.013)	(0.001)	(0.011)
PPE/ASSETS	0.134		-0.138	0.002	0.204**
	(0.141)		(0.086)	(0.007)	(0.088)
LEVERAGE	-0.038		-0.278***	-0.012***	-0.490***
	(0.041)		(0.036)	(0.002)	(0.055)
SALES GROWTH	0.089***		0.114***	0.006***	0.051***
	(0.017)		(0.012)	(0.001)	(0.010)
CASH/ASSETS	-0.075		-0.295***	0.003	0.137**
	(0.070)		(0.055)	(0.002)	(0.053)
HHI NAICS-3	0.731**		-0.113	-0.008	-0.274
	(0.320)		(0.224)	(0.012)	(0.194)
CAPEX/ASSETS	0.799***		0.461**		-0.669***
	(0.261)		(0.187)		(0.169)
ROA	0.084***		0.089***	-0.001*	
	(0.022)		(0.017)	(0.001)	
LOG(ASSETS)				-0.011***	
				(0.001)	
N	37,528	3,691,660	37,528	37,528	37,528
R2	0.934	0.987	0.976	0.692	0.759
YEAR FE	X		X	X	X
FIRM FE	X		X	X	X
FIRM-YEAR FE		X			
ESTABLISHMENT FE		X			

This table reports coefficient estimates from panel regressions (equation 4.2). FIRM EMP denotes firm employment. EST EMP denotes establishment employment. ASSETS denotes total assets. CAPEX/ASSETS denotes capital expenditure over lagged assets. ROA denotes return on assets. The independent variable SAIDI measures firm exposure to realized electricity capacity constraints, which measures total annual outages in days. The firm measure is an employment-weighted mean of the firms' establishment exposures. Columns 1, 3, 4, and 5 report results at the firm-level. Column 2 is at the establishment level. Standard errors are clustered at the firm headquarter county-level in firm level regressions, and establishment county level in establishment-level regressions. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 4: Electricity Constraints and Firm-Level Valuation

DEP VAR:	LOG(MB)	LOG(MB)
	(1)	(2)
AEC_t	0.286^{**}	
	(0.118)	
SAIDI_t		-0.035^{*}
		(0.021)
$\text{SALES GROWTH}_{t-1}$	0.129^{***}	0.129^{***}
	(0.016)	(0.016)
SALES GROWTH_t	0.112^{***}	0.112^{***}
	(0.015)	(0.015)
$\text{SALES GROWTH}_{t+1}$	0.181^{***}	0.180^{***}
	(0.016)	(0.016)
ROE GROWTH_{t-1}	0.026^{***}	0.026^{***}
	(0.003)	(0.003)
ROE GROWTH_t	0.028^{***}	0.028^{***}
	(0.003)	(0.003)
ROE GROWTH_{t+1}	0.036^{***}	0.036^{***}
	(0.003)	(0.003)
ROA_{t-1}	-0.148^{***}	-0.148^{***}
	(0.042)	(0.042)
LOG(ASSETS)_{t-1}	0.039^{***}	0.039^{***}
	(0.005)	(0.005)
$\text{MOMENTUM}_{t-12:t-1}$	0.627^{***}	0.626^{***}
	(0.015)	(0.015)
$\text{VOLATILITY}_{t-12:t-1}$	-1.289^{***}	-1.291^{***}
	(0.124)	(0.125)
N	26,766	26,766
R2	0.365	0.365
YEAR FE	X	X
NAICS-3 FE	X	X
HQ-COUNTY FE	X	X

This table reports coefficient estimates from panel regressions (equation 4.3). MB is market-to-book ratio. The independent variable AEC measures firm exposure to anticipated electricity capacity, which measures future excess capacity relative to the NERC reference capacity in percent. The firm measure is an employment-weighted mean of the firms' establishment exposures. The independent variable SAIDI measures firm exposure to realized electricity capacity constraints, which measures total annual outages in days. The firm measure is an employment-weighted mean of the firms' establishment exposures. Standard errors are clustered at the firm headquarter county-level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 5: Factor Correlation Matrix (2005–2024)

	ELX	ELXREL	MKTRF	SMB	HML	RMW	CMA	PS_VWF	MOM	BAB
ELX	1.0000									
ELXREL	0.9169	1.0000								
MKTRF	-0.0102	-0.0257	1.0000							
SMB	0.0108	-0.0183	0.3703	1.0000						
HML	0.1059	0.0846	0.1467	0.3246	1.0000					
RMW	0.1045	0.0874	-0.1915	-0.3758	0.0038	1.0000				
CMA	0.0299	0.0324	-0.1351	0.0449	0.5932	0.0971	1.0000			
PS_VWF	-0.0102	0.0069	0.1788	0.1464	-0.2750	-0.1412	-0.3576	1.0000		
MOM	-0.0301	-0.0281	-0.3748	-0.3033	-0.3320	0.0916	-0.0054	0.1430	1.0000	
BAB	0.0217	-0.0122	-0.0323	-0.1214	-0.1077	0.0566	0.0324	0.1801	0.3141	1.0000

This table presents correlations for variables in the firm-month sample. Complete matrices are reported for both samples; Panel B can be relegated to the Online Appendix without loss of continuity. The sample starts in 2005 and ends in 2024.

Table 6: Portfolio Sorts (deciles) and ELX Factor Returns

PANEL A: REGRESSIONS OF DECILE PORTFOLIOS ON FIVE FACTORS	DEP VAR: VALUE-WEIGHTED EXCESS RETURN OF DECILE d										1–10 SPREAD	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
MKT-RF	0.950***	1.007***	1.042***	0.969***	1.067***	0.991***	0.917***	0.967***	0.888***	0.934***		0.015
	(0.037)	(0.033)	(0.033)	(0.025)	(0.029)	(0.026)	(0.032)	(0.030)	(0.028)	(0.030)		(0.046)
SMB	0.252***	0.028	0.090	0.055	−0.101***	−0.045	0.100	−0.067	0.200***	0.270***		−0.018
	(0.069)	(0.058)	(0.058)	(0.044)	(0.032)	(0.040)	(0.061)	(0.063)	(0.054)	(0.063)		(0.082)
HML	−0.042	−0.054	−0.104**	0.019	0.011	0.094**	0.055	−0.090**	−0.103**	0.075		−0.118
	(0.054)	(0.060)	(0.049)	(0.048)	(0.037)	(0.045)	(0.053)	(0.044)	(0.052)	(0.082)		(0.097)
RMW	−0.102	0.031	0.090	0.100*	0.057	−0.033	−0.078	−0.097	−0.156**	0.055		−0.157
	(0.087)	(0.084)	(0.074)	(0.060)	(0.044)	(0.056)	(0.079)	(0.076)	(0.071)	(0.078)		(0.111)
CMA	0.055	0.173*	0.061	−0.095	0.057	−0.128*	0.048	0.019	0.166*	−0.043		0.098
	(0.085)	(0.104)	(0.085)	(0.076)	(0.057)	(0.073)	(0.094)	(0.079)	(0.087)	(0.111)		(0.130)
CONSTANT	0.167	−0.027	−0.171	0.045	−0.100	−0.004	0.000	−0.010	0.026	−0.353***	0.490***	0.520***
	(0.134)	(0.121)	(0.113)	(0.087)	(0.080)	(0.087)	(0.118)	(0.118)	(0.118)	(0.128)	(0.166)	(0.174)
N	240	240	240	240	240	240	240	240	240	240	240	240
R2	0.839	0.853	0.879	0.916	0.947	0.925	0.863	0.855	0.859	0.858		
PANEL B: REGRESSIONS OF DECILE PORTFOLIOS ON ELX												
ELX	0.556***	0.101	0.081	0.077	0.049	−0.078	−0.113	−0.170	−0.011	−0.444***		
	(0.168)	(0.152)	(0.161)	(0.148)	(0.157)	(0.157)	(0.161)	(0.150)	(0.140)	(0.168)		

This table presents estimations of monthly regressions of decile-portfolio excess returns on factors. Panel A shows regressions on five factors market, size, value, profitability, and investment. Panel B displays regressions on the electricity tightness factor. Deciles are formed based on *AEC*, with decile 1 having lowest AEC and decile 10 having highest AEC. Columns 11 and 12 show the results with the decile 1-decile 10 return spread as a dependent variable. Robust standard errors (Newey–West, five lags) are reported in parentheses. The sample covers the period 2005–2024. ***,** ,* denote significance at the 1%, 5%, and 10% levels, respectively.

Table 7: Portfolio Sorts (deciles) and ELX Factor Returns: Expanded Factors

	DEP VAR: VALUE-WEIGHTED EXCESS RETURN OF DECILE d										1–10 SPREAD	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
MKT-RF	0.938***	1.028***	1.044***	0.985***	1.048***	0.986***	0.915***	0.976***	0.887***	0.919***		0.020
	(0.035)	(0.034)	(0.037)	(0.023)	(0.024)	(0.025)	(0.032)	(0.032)	(0.029)	(0.032)		(0.049)
SMB	0.250***	0.030	0.079	0.077*	−0.123***	−0.048	0.101	−0.061	0.210***	0.267***		−0.016
	(0.072)	(0.057)	(0.060)	(0.047)	(0.033)	(0.040)	(0.063)	(0.064)	(0.056)	(0.064)		(0.078)
HML	−0.029	0.012	−0.066	−0.003	0.009	0.104**	0.077	−0.059	−0.117**	0.094		−0.123
	(0.060)	(0.063)	(0.049)	(0.043)	(0.043)	(0.046)	(0.051)	(0.046)	(0.055)	(0.072)		(0.103)
RMW	−0.104	0.037	0.096	0.096	0.059	−0.033	−0.078	−0.095	−0.160**	0.053		−0.157
	(0.087)	(0.080)	(0.074)	(0.058)	(0.046)	(0.055)	(0.077)	(0.076)	(0.072)	(0.074)		(0.111)
CMA	0.055	0.155	0.076	−0.134*	0.100*	−0.125*	0.042	0.001	0.147	−0.041		0.095
	(0.091)	(0.103)	(0.083)	(0.073)	(0.060)	(0.073)	(0.096)	(0.083)	(0.092)	(0.102)		(0.137)
PS_VWF	0.030	0.056	0.071**	−0.093***	0.065***	0.024	0.025	0.015	−0.041	0.044		−0.014
	(0.043)	(0.040)	(0.035)	(0.027)	(0.025)	(0.026)	(0.038)	(0.036)	(0.034)	(0.038)		(0.055)
MOM	−0.021	0.102***	0.036	0.022	−0.046**	−0.005	0.009	0.045	−0.014	−0.028		0.007
	(0.047)	(0.037)	(0.031)	(0.026)	(0.022)	(0.038)	(0.034)	(0.031)	(0.027)	(0.043)		(0.072)
BAB	0.113*	−0.004	0.006	−0.059	0.030	0.048	0.070	0.029	0.030	0.146**		−0.033
	(0.066)	(0.058)	(0.052)	(0.039)	(0.043)	(0.042)	(0.050)	(0.043)	(0.051)	(0.070)		(0.088)
CONSTANT	0.134	−0.055	−0.185	0.061	−0.098	−0.019	−0.026	−0.033	0.020	−0.395***	0.490***	0.529***
	(0.134)	(0.124)	(0.113)	(0.083)	(0.083)	(0.093)	(0.119)	(0.117)	(0.120)	(0.125)	(0.166)	(0.183)
N	240	240	240	240	240	240	240	240	240	240	240	240
R^2	0.843	0.862	0.883	0.922	0.950	0.926	0.866	0.858	0.861	0.865		

Deciles are formed based on *AEC*, with decile 1 having lowest AEC and decile 10 having highest AEC. The final two columns regress the 1-10 return spread on the same factors. Robust standard errors (Newey–West, five lags) are reported in parentheses. The sample covers the period 2005–2024. ***,** ,* denote significance at the 1%, 5%, and 10% levels, respectively.

Table 8: Price of Risk in the Cross-section of Stocks

	DEP VAR: EXRET_{t+1} (%)			
	(1)	(2)	(3)	(4)
β^{ELX}_{t-1}	0.113**	0.107**		
	(0.055)	(0.054)		
$\beta^{\text{ELXREL}}_{t-1}$			0.087*	0.081*
			(0.047)	(0.046)
β^{MKT}_{t-1}	0.113	0.089	0.118	0.095
	(0.152)	(0.102)	(0.152)	(0.102)
β^{SMB}_{t-1}	0.003	0.036	0.003	0.037
	(0.082)	(0.058)	(0.082)	(0.057)
β^{HML}_{t-1}	0.066	0.068	0.066	0.067
	(0.087)	(0.067)	(0.087)	(0.067)
β^{RMW}_{t-1}	0.035	-0.003	0.033	-0.006
	(0.045)	(0.036)	(0.045)	(0.036)
β^{CMA}_{t-1}	-0.061	-0.067*	-0.063	-0.068*
	(0.044)	(0.039)	(0.043)	(0.039)
AEC_{t-1}		-0.011*		-0.011*
		(0.006)		(0.006)
ELECTRICITY PRICE_{t-1}		0.409		0.393
		(0.939)		(0.938)
$\text{VOLATILITY}_{t-12:t-1}$		-0.356		-0.385
		(1.022)		(1.021)
LOG(SIZE)_{t-1}		-0.046		-0.046
		(0.046)		(0.046)
LOG(BM)_{t-1}		0.022		0.022
		(0.064)		(0.064)
LOG(PPE)_{t-1}		0.085***		0.085***
		(0.029)		(0.029)
$\text{MOMENTUM}_{t-12:t-1}$		-0.026		-0.025
		(0.118)		(0.118)
$\text{LOG(TURNOVER)}_{t-1}$		-0.033		-0.034
		(0.062)		(0.062)
ROE_{t-1}		0.182**		0.183**
		(0.076)		(0.076)
HHI EMP_{t-1}		-0.158		-0.158
		(0.105)		(0.105)
LEVERAGE_{t-1}		-0.174		-0.175
		(0.236)		(0.236)
CONSTANT	0.502***	0.942	0.498***	0.947
	(0.188)	(0.720)	(0.188)	(0.720)
N	530,416	530,416	530,416	530,416
R2	0.193	0.193	0.193	0.193
YEAR-MONTH FE	Y	Y	Y	Y
NAICS-3 FE	N	Y	N	Y

Robust standard errors (double–clustered by firm and month) in parentheses. The sample covers the period 2005–2024. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 9: Uri-related Shocks and Stock Returns

	URI SHOCK		POST-URI POLICY ADOPTION	
DEP VAR: DAILY RETURN	(1)	(2)	(3)	(4)
POST URI × TREAT URI	-1.197*			
	(0.682)			
POST URI$_{t-5}$× TREAT URI		-0.489		
		(1.081)		
POST URI$_{t-4}$× TREAT URI		-0.908		
		(0.928)		
POST URI$_{t-3}$× TREAT URI		-2.742***		
		(0.841)		
POST URI$_{t-2}$× TREAT URI		-1.373		
		(1.919)		
POST URI$_{t-1}$× TREAT URI		-0.789		
		(0.864)		
POST URI$_{t}$× TREAT URI		-1.798*		
		(0.994)		
POST URI$_{t+1}$× TREAT URI		-2.802*		
		(1.607)		
POST URI$_{t+2}$× TREAT URI		-2.579		
		(2.040)		
POST URI$_{t+3}$× TREAT URI		-3.154**		
		(1.409)		
POST URI$_{t+4}$× TREAT URI		-1.598		
		(1.095)		
POST URI$_{t+5}$× TREAT URI		-1.652		
		(1.716)		
POST ERCOT × TREAT ERCOT			1.060**	
			(0.416)	
POST ERCOT$_{t-5}$× TREAT ERCOT				-0.619
				(0.866)
POST ERCOT$_{t-4}$× TREAT ERCOT				-1.315
				(0.973)
POST ERCOT$_{t-3}$× TREAT ERCOT				-0.627
				(0.913)
POST ERCOT$_{t-2}$× TREAT ERCOT				-0.332
				(0.761)
POST ERCOT$_{t-1}$× TREAT ERCOT				-0.750
				(1.834)
POST ERCOT$_{t}$× TREAT ERCOT				1.329*
				(0.689)
POST ERCOT$_{t+1}$× TREAT ERCOT				0.247
				(0.988)
POST ERCOT$_{t+2}$× TREAT ERCOT				-0.210
				(1.368)
N	1,982	1,982	9,311	9,311
R2	0.186	0.189	0.065	0.066
WINDOW	[-6,5]	[-6,5]	[-6,2]	[-6,2]
DAY FE	X	X	X	X
FIRM FE	X	X	X	X

Sample widow is measured in trading days. TREAT URI is an indicator variable that equals one for firms in the top 10% of the empirical distribution in terms of outage exposure to Uri, and zero for those in the bottom 90% of the same distribution. POST URI equals one from February 16, 2021. TREAT ERCOT equals one for firms with at least 90% employment footprint in locations belonging to the Texas ERCOT grid, zero for firms have no exposure to the Texas ERCOT grid. POST ERCOT equals one from June 1, 2021, and zero otherwise. Standard errors are clustered at the firm headquarter county-level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 10: Short-Run Real Effects of SAIDI: Uri Winter Storm Shock

	ELECTRICITY	LABOR	CAPITAL		PROFIT	VALUE
DEP VAR:	SAIDI	LOG(FIRM EMP)	LOG(ASSETS)	CAPEX/ASSETS	ROA	LOG(MB)
	(1)	(2)	(3)	(4)	(5)	(6)
URI $\times POST$	0.673***	0.123	0.159	0.003	-0.095*	-0.172
	(0.085)	(0.091)	(0.101)	(0.013)	(0.057)	(0.111)
N	743	743	743	743	743	533
R2	0.698	0.926	0.981	0.729	0.739	0.903
CONTROLS	X	X	X	X	X	X
YEAR FE	X	X	X	X	X	X
FIRM FE	X	X	X	X	X	X

This table reports coefficient estimates from difference-in-differences regressions of the short-run (one period) effects of the Texas shocks. The sample covers the period 2018–2021. The variable SAIDI measures firm exposure to realized electricity capacity constraints, which measures total annual outages in days. The firm measure is an employment-weighted mean of the firms' establishment exposures. The sample consists of firms with at least 50% employment footprint in areas belonging to the Texas ERCOT grid. URI is a binary variable that equals one for firms in the top 10% of the empirical distribution in terms of outage exposure to Uri, and zero for firms in the bottom 90% of the same distribution. POST is a binary variable that equals one if it is the first period after the Uri shock, and zero otherwise. FIRM EMP denotes firm employment. ASSETS denotes total assets. CAPEX/ASSETS denotes capital expenditure over lagged assets. ROA denotes return on assets. MB denotes market-to-book ratio. Standard errors are clustered at the firm headquarter county-level. Controls include the same variables reported in the cross-sectional real outcome tests. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 11: Long-Run Real Effects of AEC: ERCOT Shock

	ELECTRICITY	LABOR	CAPITAL		PROFIT	VALUE
DEP VAR:	AEC	LOG(FIRM EMP)	LOG(ASSETS)	CAPEX/ASSETS	ROA	LOG(MB)
	(1)	(2)	(3)	(4)	(5)	(6)
ERCOT $\times$ POST	0.097***	0.168***	0.072	0.317	-0.048	0.177***
	(0.037)	(0.056)	(0.044)	(0.531)	(0.058)	(0.067)
N	5,969	5,969	5,969	5,969	5,969	3,989
R2	0.774	0.896	0.981	0.716	0.758	0.850
CONTROLS	X	X	X	X	X	X
YEAR FE	X	X	X	X	X	X
FIRM FE	X	X	X	X	X	X

This table reports coefficient estimates from difference-in-differences regressions of the long-run effects of the Texas shocks. AEC measures firm exposure to anticipated electricity capacity, which measures future excess capacity relative to the NERC reference capacity in percent. The firm measure is an employment-weighted mean of the firms' establishment exposures. ERCOT is a binary variable that equals one for firms with at least 90% employment footprint in locations belonging to the Texas ERCOT grid, and zero for firms with no exposure to the Texas ERCOT grid. POST is a binary variable that equals one for periods from 2021 onwards, and zero otherwise. FIRM EMP denotes firm employment. ASSETS denotes total assets. CAPEX/ASSETS denotes capital expenditure over lagged assets. ROA denotes return on assets. MB denotes market-to-book ratio. Standard errors are clustered at the firm headquarter county-level. Controls include the same variables reported in the cross-sectional real outcome tests. The sample starts in 2018 and ends in 2024, with the short-run effects in 2021 being omitted. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 12: Dynamic Effects of the Shocks

PANEL A: DYNAMIC EFFECTS OF THE URI SHOCK	ELECTRICITY	LABOR	CAPITAL		PROFIT	VALUE
DEP VAR:	SAIDI	LOG(FIRM EMP)	LOG(ASSETS)	CAPEX/ASSETS	ROA	LOG(MB)
	(1)	(2)	(3)	(4)	(5)	(6)
$\text{POST}_{t-3} \times URI$	0.058	0.117	-0.260**	-0.003	-0.068	0.079
	(0.057)	(0.120)	(0.104)	(0.013)	(0.075)	(0.162)
$\text{POST}_{t-2} \times URI$	-0.066	0.181	-0.189*	-0.001	0.006	0.144
	(0.079)	(0.138)	(0.096)	(0.011)	(0.096)	(0.182)
$\text{POST}_{t} \times URI$	0.669***	0.206*	0.037	0.002	-0.110	-0.106
	(0.098)	(0.116)	(0.089)	(0.013)	(0.069)	(0.137)
N	743	743	743	743	743	533
R2	0.699	0.926	0.981	0.729	0.740	0.904
CONTROLS	X	X	X	X	X	X
YEAR FE	X	X	X	X	X	X
FIRM FE	X	X	X	X	X	X

PANEL B: DYNAMIC EFFECTS OF THE TEXAS SHOCK	ELECTRICITY	LABOR	CAPITAL		PROFIT	VALUE
DEP VAR:	AEC	LOG(FIRM EMP)	LOG(ASSETS)	CAPEX/ASSETS	ROA	LOG(MB)
	(1)	(2)	(3)	(4)	(5)	(6)
$\text{POST}_{t-3} \times ERCOT$	1.057	-0.103	0.116	2.669**	0.091*	-0.076
	(0.979)	(0.104)	(0.100)	(1.164)	(0.048)	(0.091)
$\text{POST}_{t-2} \times ERCOT$	-2.349*	-0.164	0.112*	1.354	0.058	-0.065
	(1.219)	(0.125)	(0.064)	(0.969)	(0.080)	(0.061)
$\text{POST}_{t} \times ERCOT$	6.651***	0.042	0.080*	0.828	-0.064	-0.071
	(1.697)	(0.072)	(0.049)	(0.672)	(0.047)	(0.065)
$\text{POST}_{t+1} \times ERCOT$	7.389	0.051	0.114**	1.515*	0.015	0.113
	(4.793)	(0.088)	(0.056)	(0.801)	(0.037)	(0.080)
$\text{POST}_{t+2} \times ERCOT$	9.384***	0.128	0.173***	1.235	-0.021	0.322***
	(2.870)	(0.119)	(0.067)	(0.895)	(0.067)	(0.096)
$\text{POST}_{t+3} \times ERCOT$	7.416*	0.226*	0.652**	4.395***	0.051	
	(4.354)	(0.125)	(0.327)	(1.463)	(0.037)	
N	7,669	7,669	7,669	7,669	7,669	5,551
R2	0.738	0.892	0.980	0.705	0.732	0.865
CONTROLS	X	X	X	X	X	X
YEAR FE	X	X	X	X	X	X
FIRM FE	X	X	X	X	X	X

This table reports coefficient estimates from (dynamic) difference-in-differences estimations of the effects of the Texas shocks. Panel A presents the one-period results for the Uri shock. Panel B presents the long-term results. URI is a binary variable that equals one for firms in the top 10% of the empirical distribution in terms of outage exposure to Uri, and zero for firms in the bottom 90% of the same distribution. ERCOT is a binary variable that equals one for firms with at least 90% employment footprint in locations belonging to the Texas ERCOT grid, and zero for firms with no exposure to the Texas ERCOT grid. POST are dummy variables for the respective time periods. The omitted (reference) category is t-1 (the year before the shocks, i.e. 2020). FIRM EMP denotes firm employment. EST EMP denotes establishment employment. ASSETS denotes total assets. CAPEX/ASSETS denotes capital expenditure over lagged assets. ROA denotes return on assets. MB denotes market-to-book ratio. Standard errors are clustered at the firm headquarter county-level. Controls include the same variables reported in the cross-sectional real outcome tests. Cragg-Donald Wald F statistics are reported. The sample starts in 2018 and ends in 2021 (Panel A) and 2024 (Panel B). ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 13: Capacity Tightness and Real Effects: Aggregate Outcomes

PANEL A: COUNTY TOTALS - ANTICIPATED EXCESS CAPACITY					
	ESTABLISHMENTS			FIRMS	
DEP VAR:	LOG(EMP)	LOG(EST)	LOG(EMP/EST)	LOG(START-UPS)	LOG(EXITS)
	(1)	(2)	(3)	(4)	(5)
AEC	0.049***	0.029***	0.020*	-0.006	-0.097**
	(0.015)	(0.009)	(0.012)	(0.041)	(0.038)
N	30,157	30,157	30,157	25,352	25,352
R2	0.998	0.999	0.963	0.975	0.976
YEAR FE	X	X	X	X	X
COUNTY FE	X	X	X	X	X

PANEL B: COUNTY TOTALS - SAIDI					
	ESTABLISHMENTS			FIRMS	
DEP VAR:	LOG(EMP)	LOG(EST)	LOG(EMP/EST)	LOG(START-UPS)	LOG(EXITS)
	(1)	(2)	(3)	(4)	(5)
SAIDI	-0.005***	-0.003***	-0.002**	-0.011***	0.004
	(0.001)	(0.001)	(0.001)	(0.004)	(0.004)
N	30,157	30,157	30,157	25,352	25,352
R2	0.998	0.999	0.963	0.975	0.976
YEAR FE	X	X	X	X	X
COUNTY FE	X	X	X	X	X

PANEL C: COUNTY NAICS 518210 - ANTICIPATED EXCESS CAPACITY				
	ESTABLISHMENTS			
DEP VAR:	EMP	EST	LOG(EMP/EST)	INDUSTRY PRESENT (1/0)
	(1)	(2)	(3)	(4)
AEC	0.428*	-0.118	0.420*	0.007
	(0.233)	(0.079)	(0.234)	(0.068)
N	12,002	12,002	6,886	30,157
(PSEUDO-)R2	0.964	0.925	0.789	0.034
YEAR FE	X	X	X	X
COUNTY FE	X	X	X	

PANEL D: COUNTY NAICS 518210 - SAIDI				
	ESTABLISHMENTS			
DEP VAR:	EMP	EST	LOG(EMP/EST)	INDUSTRY PRESENT (1/0)
	(1)	(2)	(3)	(4)
SAIDI	-0.034*	0.005	-0.003	-0.023***
	(0.019)	(0.007)	(0.022)	(0.007)
N	12,002	12,002	6,886	30,157
(PSEUDO-)R2	0.966	0.925	0.788	0.034
YEAR FE	X	X	X	X
COUNTY FE	X	X	X	

This table reports coefficient estimates from panel regressions. EMP denotes employment. EST denotes establishment count. START-UPS stands for start-up count. EXITS denotes the number of firm exits. INDUSTRY PRESENT is binary variable that equals one if the industry is present in a county, and zero otherwise. NAICS 518210 is an industry code for data processing, hosting, and related services. AEC measures county exposure to anticipated electricity capacity, which measures future excess capacity relative to the NERC reference capacity in percent. The independent variable SAIDI measures county exposure to realized electricity capacity constraints, which measures total annual outages in days. Estimations in columns (1) and (2) of panels C and D are Poisson regressions. Standard errors are clustered at the county-level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Appendix

A.1 Proofs and derivations

Proof of Proposition 1. In our framework, the CES aggregator $\Phi(\kappa_{t+1})$ converts the rationed electricity input into effective productivity.

$$\Phi'(\kappa_{t+1}) \;=\; \delta_E \rho\, \chi^\rho\, \kappa^{\rho-1} \left[\delta_{KL} + \delta_E(\kappa\chi)^\rho\right]^{\frac{1-\rho}{\rho}} > 0.$$

Taking the logarithm of K^* we obtain

$$\log K^*(\kappa) = \frac{1}{1-\alpha_1-\alpha_2}\Big[\log \bar{A}_{i,t}(\kappa) + \log \alpha_1 + \alpha_2 \log \mu - \log r_t\Big].$$

Differentiation yields

$$\frac{dK^*}{d\kappa} = \frac{K^*(\kappa)}{1-\alpha_1-\alpha_2}\,\frac{1}{\bar{A}_{i,t}(\kappa)}\,\frac{d\bar{A}_{i,t}}{d\kappa},$$

We next obtain the derivative of $\bar{A}_t(\kappa)$. By definition

$$\bar{A}_t(\kappa) = \mathbb{E}_t\Big[A_{t+1}\Phi\big(\kappa_{t+1}\big)\Big], \qquad \mathbb{E}_t[\kappa_{t+1}] = \kappa.$$

Because Φ is increasing and κ_{t+1} shifts up with κ, the envelope theorem for expectations implies

$$\frac{d\bar{A}_t}{d\kappa} = \mathbb{E}_t\Big[A_{t+1}\Phi'\big(\kappa_{t+1}\big)\Big] > 0.$$

which is strictly positive because every factor on the right is positive.
Since $L^*(\kappa) = \mu\, K^*(\kappa)$ with $\mu > 0$ constant at time t,

$$\frac{dL^*}{d\kappa} \;=\; \mu\,\frac{dK^*}{d\kappa}$$

is positive. Hence, both optimal inputs are strictly increasing in the expected electricity-tightness parameter κ. □

Proof of Proposition 2. Because (K^*, L^*) maximizes Π for a given κ, the envelope theorem yields

$$\frac{d}{d\kappa}\,\Pi\big(K^*(\kappa), L^*(\kappa); \kappa\big) = \frac{\partial \Pi}{\partial \kappa} = Z_{i,t}\,\frac{d\bar{A}_{i,t}}{d\kappa}, \qquad Z_{i,t} = K_{i,t}^{*\alpha_1} L_{i,t}^{*\alpha_2} > 0.$$

It remains to sign $d\bar{A}_{i,t}/d\kappa$, which we already showed is positive, establishing the result. □

Proof of Lemma 1. From the production, for next-period aggregate consumption

$$C_{t+1} = \Lambda_t\, A_{t+1}\, \Phi\big(\kappa_{t+1}\big).$$

$\Lambda_t = \sum_i Z_{i,t}$ is already known at time t. κ_{t+1} is the only object in that product that carries the electricity-supply shock.

Taking a first-order Taylor expansion, we write consumption growth as

$$\Delta \log C_{t+1} \equiv \log \frac{C_{t+1}}{C_t} = [\log \Lambda_t - \log \Lambda_{t-1}] + [\log A_{t+1} - \log A_t] + [\log \Phi(\kappa_{t+1}) - \log \Phi(\kappa)].$$

The only random piece that depends on ε_{t+1} is the last bracket. Linearizing that term around the mean value κ we obtain:

$$\log \Phi(\kappa_{t+1}) \;\approx\; \log \Phi(\kappa) + \frac{\partial \log \Phi}{\partial \kappa}\Big|_{\kappa} (\kappa_{t+1} - \kappa).$$

Because $\kappa_{t+1} - \kappa = \kappa(\mathrm{e}^{\varepsilon_{t+1}} - 1) \approx \kappa\varepsilon_{t+1}$,

$$\log \Phi(\kappa_{t+1}) - \log \Phi(\kappa) \;\approx\; \underbrace{\left[\kappa \frac{\Phi'(\kappa)}{\Phi(\kappa)}\right]}_{\lambda(\kappa)} \varepsilon_{t+1}.$$

The last approximation follows from:

$$\frac{\partial}{\partial \varepsilon} \log \Phi\big(\kappa e^{\varepsilon}\big) \;=\; \frac{\Phi'\big(\kappa e^{\varepsilon}\big)}{\Phi\big(\kappa e^{\varepsilon}\big)} \cdot \frac{\partial(\kappa e^{\varepsilon})}{\partial \varepsilon}, \quad \text{and at } \varepsilon = 0, \text{ we have } \frac{\partial(\kappa e^{\varepsilon})}{\partial \varepsilon} = \kappa.$$

Hence the coefficient in front of ε_{t+1} is exactly $\kappa\Phi'(\kappa)/\Phi(\kappa)$.

To isolate the part of consumption growth that co-moves with the electricity shock, we can simply write

$$\Delta \log C_{t+1} = \lambda(\kappa)\, \varepsilon_{t+1} \;+\; (\text{terms independent of } \varepsilon_{t+1}).$$

For the covariance calculations used to price risk, those other terms drop out because they are uncorrelated with ε_{t+1}. Hence,

$$\Delta \log C_{t+1} = \lambda(\kappa)\, \varepsilon_{t+1}, \qquad \varepsilon_{t+1} \sim \mathcal{N}(0, \sigma_\varepsilon^2),$$

and

$$\mathrm{Var}_t(\Delta \log C_{t+1}) = \lambda(\kappa)^2 \sigma_\varepsilon^2$$

.

□

Proof of Proposition 3. To sign the risk premium, let

$$v(\kappa) \;=\; \sigma_\varepsilon^2\, \lambda(\kappa)^2, \qquad \lambda(\kappa) \;\equiv\; \frac{\Phi'(\kappa)}{\Phi(\kappa)}.$$

Then $\mathrm{RP}_i(\kappa) = \theta\, v(\kappa)$.

We differentiate $v(\kappa)$. Because $v = \sigma_\varepsilon^2 \lambda^2$,

$$\frac{dv}{d\kappa} = 2\, \sigma_\varepsilon^2\, \lambda(\kappa)\, \lambda'(\kappa).$$

Using the quotient rule

$$\lambda'(\kappa) = \frac{d}{d\kappa}\Big(\tfrac{\Phi'}{\Phi}\Big) = \frac{\Phi''}{\Phi} - \Big(\tfrac{\Phi'}{\Phi}\Big)^2.$$

Computing $\lambda'(\kappa)$ for the specific CES form of Φ, we can write

$$\lambda(\kappa) = \frac{\Phi'(\kappa)}{\Phi(\kappa)} = \frac{\delta_E \chi (\kappa\chi)^{\rho-1}}{\delta_{KL} + \delta_E (\kappa\chi)^{\rho}}.$$

We define $\lambda \equiv A(\kappa)/D(\kappa)$ with

$$A(\kappa) = \delta_E \chi (\kappa\chi)^{\rho-1}, \qquad D(\kappa) = \delta_{KL} + \delta_E (\kappa\chi)^{\rho},$$

and

$$A' = (\rho - 1)\,\frac{A}{\kappa}, \qquad D' = \rho\,\kappa\,\frac{A}{\kappa} = \rho A.$$

Quotient rule implies:

$$\lambda' = \frac{A'D - AD'}{D^2} = \frac{(\rho-1)A}{\kappa D} - \rho\frac{A^2}{D^2} = (\rho-1)\frac{\lambda}{\kappa} - \rho\lambda^2.$$

Substituting λ'

$$\frac{dv}{d\kappa} = 2\sigma_\varepsilon^2\,\lambda^2\Big[\frac{\rho-1}{\kappa} - \rho\,\lambda\Big],$$

which is a strictly negative number.

Plugging this expression back into the risk premium formula and $\frac{\mathrm{dRP}_{i,t}}{d\kappa} = \theta\frac{dv}{d\kappa}$ we obtain the final result.

$\square$

A.2 Variable definitions

Table A.1: Variable definitions

Variable	Definition
	Panel A: Firm-Year
ANTICIPATED EXCESS CAPACITY	One-year ahead forecasts of anticipated reserve margins, supplied by NERC. We use the exact location of establishments and map them to electricity regions of NERC's Long-Term Reliability Assessment. We aggregate the exposure of a firm's establishments and weigh them by the employment shares of the establishments.
SAIDI	System Average Interruption Duration Index, supplied by the EIA via Form 861, the Annual Electric Power Industry Report. We compute the county-level SAIDI as a customer-weighted average of the state-level SAIDI values reported by all utilities serving that county. That is, we assign each utility's state-level SAIDI to every county it serves within that state, and then weight these values by the number of customers the utility serves in the county to arrive at the county-level measure (similar to e.g., Borenstein et al., 2023). We use the location of establishments and map them to counties. We aggregate the exposure of firms' establishments and weigh them by the employment shares of the establishments.
LOG(EMP)	Log of firm employment. Compustat: log(emp).
LOG(ASSETS)	Log of firm assets. Compustat: log(at).
CAPEX/ASSETS	Capital expenditure scaled by lagged total assets. Compustat: capx/L.at.
ROA	Return on assets. Compustat: ib/L.at.
LOG(MARKET/BOOK)	Log of market-to-book ratio. Compustat: Depending on data availability, we calculate book equity as (i) seq - pstk + txditc, (ii) seq, (iii) ceq + pstk, or (iv) at - lt. Book equity is replaced as missing if negative. Market value of equity is defined as csho*prcc_f.
PPE/ASSETS	Property, plant and equipment scaled by total assets. Compustat: ppent/at.
LEVERAGE	Book leverage scaled by total assets. Compustat: (dlc+dltt)/at.
SALES GROWTH	Sales growth. Compustat: (sale-L.sale)/L.sale
CASH/ASSETS	Cash scaled by assets. Compustat: che/at.
HHI NAICS-3	Herfindahl–Hirschman Index (industry concentration) based on sales and three-digit NAICS code industry definition.
ROE GROWTH	Return on equity growth. Compustat: Return on equity is defined as ib over lagged book equity, with book equity being calculated as defined above.
MOMENTUM	Cumulative return over the last 12 months, excluding the most recent month.
VOLATILITY	Standard deviation of the last 12 monthly returns.
URI	Binary variable that equals one if a firm is in the top 10% of outage exposure during Uri outages, and zero otherwise. This variable is restricted to firms with at least 50% employment exposure to the ERCOT grid.
ERCOT	Binary variable that equals one if a firm has at least 90% employment exposure to the ERCOT grid, and zero if it has no exposure to the ERCOT grid.
POST	Binary variable that equals one for fiscal years after the Uri shock, and zero otherwise.
	Panel B: Firm-Establishment-Year
ANTICIPATED EXCESS CAPACITY	One-year ahead forecast of anticipated reserve margin calculated at electricity region-level to which establishment belongs.
SAIDI	System Average Interruption Duration Index calculated at county-level of the establishment.
LOG(EMP)	Log of establishment employment.
	Panel C: Firm-Month
ELX	Electricity capacity factor (absolute). Firm-level exposure to one-year ahead anticipated tightness based on establishment exposure to NERC's anticipated reserve margin forecast (absolute gap to reference margin in percentage points). ELX is most-tight minus least-tight decile portfolio return.
ELXREL	Electricity capacity factor (relative). Firm-level exposure to one-year ahead anticipated tightness based on establishment exposure to NERC's anticipated reserve margin forecast (relative gap to reference margin in percent). ELXREL is most-tight minus least-tight decile portfolio return.
MKT	Market factor, obtained from Ken French's website/WRDS.
SMB	Small-minus-big factor, obtained from Ken French's website/WRDS.
HML	High-minus-low factor, obtained from Ken French's website/WRDS.
RMW	Robust-minus-weak factor, obtained from Ken French's website/WRDS.
CMA	Conservative-minus-aggressive factor, obtained from Ken French's website/WRDS.
MOM	Momentum factor, obtained from Ken French's website/WRDS.
BAB	Betting against beta factor from Frazzini and Pedersen (2014).
ELECTRICITY PRICE	Average annual electricity price supplied by the EIA via Form 861, the Annual Electric Power Industry Report.
VOLATILITY	Standard deviation of the last 12 monthly returns.
LOG(SIZE)	Log of market capitalization. Compustat: Log(cshom*prccm/1000000).
LOG(BOOK/MARKET)	Log of book-to-market ratio as defined above.
LOG(TURNOVER)	Log of monthly turnover. Compustat: log(cshtrm/cshom).
LOG(PPE)	Log of property, plant, and equipment. Compustat: Log(ppent).
MOMENTUM	Cumulative return over the last 12 months, excluding the most recent month.
ROE	Return on equity. Compustat: Return on equity is defined as ib over lagged book equity, with book equity being calculated as defined above.
HHI EMP	Herfindahl–Hirschman Index (firm employment concentration) based on a firm's establishment employment.
LEVERAGE	Book leverage scaled by total assets. Compustat: (dlc+dltt)/at.

Table A.1: Variable definitions (Continued)

Variable	Definition
	Panel D: Firm-Day
DAILY RETURN	Daily log return. Compustat: log(((prccd/ajexdi)*trfd)/((L.prccd/L.ajexdi)*L.trfd)) * 100.
TREAT URI	Binary variable that equals one if a firm is in the top 10% of outage exposure during Uri outages, and zero otherwise. This variable is restricted to firms with at least 50% employment exposure to the ERCOT grid.
TREAT ERCOT	Binary variable that equals one if a firm has at least 90% employment exposure to the ERCOT grid, and zero if it has no exposure to the ERCOT grid.
POST URI	Binary variables that equals one for trading days from February 16, 2021, which is the first trading day after Uri-induced rolling outages in the ERCOT grid.
POST ERCOT	Binary variables that equals one for trading days from June 1, 2021, which is the first trading day after the Texas Senate and House approved ERCOT-related policy changes.
	Panel E: County-Year
ANTICIPATED EXCESS CAPACITY	One-year ahead forecast of anticipated reserve margin calculated at electricity region-level to which county belongs.
SAIDI	System Average Interruption Duration Index calculated at county-level.
EMP	Level of employment. Census County Business Patterns: EMP.
EST	Level of establishments. Census County Business Patterns: EST.
LOG(EMP)	Log of employment.
LOG(EST)	Log of establishments.
LOG(EMP/EST)	Log of employment/establishments.
LOG(START-UPS)	Log of number of new firms. Census Business Dynamics Statistics: Number of firms with age 0.
LOG(EXITS)	Log of number of exiting firms. Census Business Dynamics Statistics: Number of firms exiting.
INDUSTRY PRESENCE	Binary variable that equals one if a county has at least one establishment belonging to the NAICS code 518210 Data Processing, Hosting, and Related Services, and zero otherwise.

Online Appendix

In this Online Appendix, we present additional results related to our main model. In Section OA.1, we present additional propositions and proofs; in Section OA.2, we examine comparative statics in the world with heterogeneous firm dependence on electricity; in Section OA.3, we consider electricity rationing with firm-specific priority weights; in Section OA.4, we extend the model to account for capital accumulation with quadratic adjustment costs; Section OA.5 examines robustness for the case with correlated productivity and supply shocks; in Section OA.6, we present the model in which price of electricity can adjust to accommodate shortage shocks; in Section OA.7, we discuss welfare implications of our setting.

OA.1 Additional Proofs

Proposition OA.1 (Cross-partials for production inputs)**.** *The firm's effective-productivity shifter is*

$$\Phi(\kappa, \delta_E) = \left[\delta_{KL} + \delta_E(\kappa\chi)^\rho\right]^{\frac{1}{\rho}}, \qquad 0 < \rho < 1.$$

All real choices scale with

$$\bar{A}_{i,t}(\kappa, \delta_E) = \mathbb{E}_t[A_{i,t+1}\,\Phi(\kappa_{t+1}, \delta_E)]\,.$$

Because $\dfrac{\partial^2\Phi}{\partial\kappa\partial\delta_E} = (\rho-1)\,(\kappa\chi)^{\rho-1}\chi^\rho\left[\delta_{KL} + \delta_E(\kappa\chi)^\rho\right]^{\frac{1-\rho}{\rho}}$ is positive, the cross-partial of $\bar{A}_{i,t}$ is also positive. From the first-order conditions,

$$K^*_{i,t} \propto \bar{A}_{i,t}(\kappa, \delta_E)^{\frac{1}{1-\alpha}} \Longrightarrow \frac{\partial^2 K^*_i}{\partial\kappa\partial\delta_E} > 0,$$

and the same holds for L^*_i and $Z_{i,t}$.

OA.2 Heterogeneity in Electricity-related Production Parameters

We focus on two parameters electricity intensity (δ_E) and input substitutability between electricity and other inputs (σ). We show the following two results:

Proposition OA.2 (**Proposition (Cross effect with** δ_E**))**. *Under the regularity conditions ($\rho \in (0,1)$, $\kappa \in (0,1]$, $\delta_E \in (0,1)$, $\delta_{KL} = 1-\delta_E$).*

$$\frac{\partial^2 RP(\kappa, \delta_E)}{\partial\kappa\partial\delta_E} < 0$$

for all $\kappa \in (0,1]$, $\delta_E \in (0,1)$.

Proof of Proposition OA.2. Slope of log-consumption with respect to the electricity shock

$$\lambda(\kappa, \delta_E) \equiv \kappa\frac{\partial \log\Phi}{\partial\kappa} = \frac{\delta_E\chi(\kappa\chi)^{\rho-1}\kappa}{\delta_{KL} + \delta_E(\kappa\chi)^\rho} = \frac{M}{S+M}, \qquad S \equiv \delta_{KL},\ M \equiv \delta_E(\kappa\chi)^\rho.$$

Firm-level conditional variance of consumption growth

$$v(\kappa, \delta_E) = \sigma_\varepsilon^2\,\lambda^2.$$

Risk premium

$$(\kappa, \delta_E) = \theta v(\kappa, \delta_E).$$

For the cross derivative it suffices to work with v since θ is the positive constant.

We can write $M = M(\kappa, \delta_E) = \delta_E(\kappa\chi)^\rho$ and note

$$M_\kappa = \rho\frac{M}{\kappa}, \qquad M_\delta = \sigma\frac{M}{\delta_E}, \qquad M_{\kappa\delta} = \rho\sigma\frac{M}{\kappa\delta_E}.$$

Because $\lambda = M/(S+M)$,

$$\lambda_\kappa = \frac{M_\kappa S}{(S+M)^2} = \frac{\rho SM}{\kappa(S+M)^2} < 0,$$

$$\lambda_\delta = \frac{M_\delta S}{(S+M)^2} = \frac{\sigma SM}{\delta_E(S+M)^2} > 0,$$

$$\lambda_{\kappa\delta} = \frac{S\big[M_{\kappa\delta}(S+M) - 2M_\kappa M_\delta\big]}{(S+M)^3} = \frac{\rho\sigma SM}{\kappa\delta_E(S+M)^3}\big[S-M\big] < 0,$$

where the signs use $S = \delta_{KL} > 0$ and $M > 0$. $M > S$ almost always holds once electricity is an important input (empirically δ_E is at least 0.2–0.3 in power-intensive sectors).

Because $v = \sigma_\varepsilon^2\lambda^2$,

$$\frac{\partial v}{\partial \kappa} = 2\sigma_\varepsilon^2\lambda\,\lambda_\kappa, \qquad \frac{\partial^2 v}{\partial\kappa\partial\delta_E} = 2\sigma_\varepsilon^2\Big[\lambda_\delta\lambda_\kappa + \lambda\lambda_{\kappa\delta}\Big].$$

Plugging in the previous expressions:

$$\lambda_\delta\lambda_\kappa = \frac{\rho\sigma S^2M^2}{\kappa\delta_E(S+M)^4} < 0,$$

$$\lambda\,\lambda_{\kappa\delta} = \frac{\rho\sigma SM^2(S-M)}{\kappa\delta_E(S+M)^4} < 0,$$

so their sum is strictly negative. Hence

$$\frac{\partial^2 v}{\partial\kappa\,\partial\delta_E} \;<\; 0 \quad\Longrightarrow\quad \frac{\partial^2 RP}{\partial\kappa\,\partial\delta_E} = \theta\frac{\partial^2 v}{\partial\kappa\partial\delta_E} < 0.$$

□

Negative cross partial means that the risk-reducing effect of increasing κ is stronger for firms whose technology is heavily tilted toward electricity (large δ_E). Intuitively, a kilowatt-hour shortage hurts such firms twice—directly through lower current output and indirectly by amplifying covariance with the SDF—so giving them an extra unit of expected availability (κ goes up) trims their premia by more.

Proposition OA.3 (**Proposition (Cross effect with** σ**)**).

$$\frac{\partial^2(\kappa,\sigma)}{\partial\kappa\,\partial\sigma} > 0 \quad \textit{whenever } \delta_E < \delta_{KL}.$$

Proof of Proposition OA.3. Throughout we keep the intensity parameters δ_{KL}, δ_E fixed, so that only $\sigma > 1$ is varied. The key object is again

$$RP(\kappa,\sigma) = \theta\sigma_\varepsilon^2\, \lambda(\kappa,\sigma)^2, \qquad \lambda(\kappa,\sigma) = \frac{P}{Q+P},$$

with

$$Q \equiv \delta_{KL}, \qquad P(\kappa,\sigma) \equiv \delta_E\big(\kappa\,\chi(\sigma)\big)^{\rho(\sigma)}.$$

From $P = \delta_E\,\kappa^\rho q^{\sigma-1}$ where $q \equiv \delta_E/\delta_{KL}$:

$$\begin{aligned}
P_\kappa &= \frac{\partial P}{\partial \kappa} = \rho\,\frac{P}{\kappa}, \\
P_\sigma &= \frac{\partial P}{\partial \sigma} = P\Big[\ln q + \frac{\ln \kappa}{\sigma^2}\Big], \\
P_{\kappa\sigma} &= \frac{\partial^2 P}{\partial \kappa\,\partial \sigma} = \rho\sigma^{-1}\,\frac{P}{\kappa}\Big[\ln q + \frac{\ln \kappa}{\sigma^2}\Big].
\end{aligned}$$

Because $\lambda = P/(Q+P)$,

$$\begin{aligned}
\lambda_\kappa &= \frac{P_\kappa Q}{(Q+P)^2} = \frac{\rho Q\,P}{\kappa(Q+P)^2} < 0, \\
\lambda_\sigma &= \frac{P_\sigma Q}{(Q+P)^2} = \frac{Q\,P}{(Q+P)^2}\Big[\ln q + \tfrac{\ln \kappa}{\sigma^2}\Big], \\
\lambda_{\kappa\sigma} &= \frac{Q}{(Q+P)^3}\Big[P_{\kappa\sigma}(Q+P) - 2P_\kappa P_\sigma\Big].
\end{aligned}$$

Using $v = \sigma_\varepsilon^2\lambda^2$ we have

$$\frac{\partial^2 v}{\partial \kappa\,\partial \sigma} = 2\sigma_\varepsilon^2\Big[\,\lambda_\sigma\lambda_\kappa + \lambda\,\lambda_{\kappa\sigma}\Big].$$

Substituting the partials from above:

$$\frac{\partial^2 v}{\partial \kappa\,\partial \sigma} = \frac{2\sigma_\varepsilon^2\,Q\,P^2}{\kappa(Q+P)^4}\Big\{\rho\big[\ln q + \tfrac{\ln \kappa}{\sigma^2}\big]\;[Q-P] + \tfrac{\rho}{\sigma}(Q+P)\Big\}.$$

Let

$$\Xi(\kappa,\sigma) \equiv \big[\ln q + \tfrac{\ln \kappa}{\sigma^2}\big][Q-P] + \tfrac{Q+P}{\sigma},$$

so that $\dfrac{\partial^2 RP}{\partial\kappa\partial\sigma} = \theta\dfrac{2\sigma_\varepsilon^2\,\rho Q P^2}{\kappa(Q+P)^4}\,\Xi(\kappa,\sigma)$.

Empirically, the capital–labor share dominates the electricity share in gross output, that is, $\delta_E < \delta_{KL} \Rightarrow q < 1 \Rightarrow \ln q < 0$. Because $\kappa \le 1 \Rightarrow \ln \kappa \le 0$, both logarithms are non-positive. Moreover $Q - P > 0$ whenever q is not too large (again typical in the data).

The first product in Ξ is therefore non-negative (negative×negative). The second term $\frac{Q+P}{\sigma}$ is strictly positive. Hence

$$\Xi(\kappa,\sigma) > 0, \qquad 0 < \kappa \le 1,\ 1 < \sigma < \infty,\ q < 1.$$

Because every other multiplicative factor is positive, we conclude

$$\frac{\partial^2 RP(\kappa,\sigma)}{\partial\kappa\partial\sigma} > 0 \quad \text{whenever } \delta_E < \delta_{KL}.$$

□

When firms can substitute away from electricity more easily, the risk-saving effect of relaxing the average constraint is muted. Put differently, technologies with low substitution elasticity suffer most from expected shortages, so they benefit most (in terms of premium reduction) from higher κ.

OA.3 Electricity Rationing with Firm-specific Priority Weights

We discuss the alternative model of assigning electricity to firms in which the system operator assigns to every firm i a permanent, exogenously given priority weight

$$\omega_i > 0, \qquad \frac{1}{N}\sum_{i=1}^{N}\omega_i = 1,$$

reflecting, e.g., critical-infrastructure status or bilateral reliability contracts.

Let $\Omega \equiv \sum_j E^d_{j,t+1}\,\omega_j$ be the priority-weighted aggregate notional demand. If available supply $\bar{E}_{t+1}$ is insufficient, the operator satisfies firms in descending order of ω_i until supply is exhausted; ties are broken proportionally. The resulting allocation is

$$E^{\text{pri}}_{i,t+1} = \begin{cases} E^d_{i,t+1}, & \text{if } \omega_i \le \dfrac{\bar{E}_{t+1}}{\Omega}, \\ \dfrac{\bar{E}_{t+1}}{\Omega}\,\omega_i\,E^d_{i,t+1}, & \text{otherwise.} \end{cases}$$

Define the random tightness factor for firm i

$$\kappa_{i,t+1} \equiv \frac{E^{\text{pri}}_{i,t+1}}{E^d_{i,t+1}} = \min\Big(1,\ \frac{\bar{E}_{t+1}}{\Omega}\,\omega_i\Big) \in (0,1].$$

Unlike the proportional case, $\kappa_{i,t+1}$ is firm-specific–high-priority firms (large ω_i) face a truncated risk distribution that first-order-stochastically dominates that of low-priority firms.

Under priority rationing output becomes

$$Y_{i,t+1} = A_{i,t+1}\Big[\delta_{KL}Z^\rho_{i,t} + \delta_E\big(\kappa_{i,t+1}\chi Z_{i,t}\big)^\rho\Big]^{\frac{1}{\rho}} = A_{i,t+1}Z_{i,t}\,\Phi(\kappa_{i,t+1}), \quad \Phi(\kappa) \equiv \big[\delta_{KL} + \delta_E(\kappa\chi)^\rho\big]^{\frac{1}{\rho}}.$$

Let the mean effective-productivity shifter for firm i be

$$\bar{A}_{i,t}(\kappa,\omega_i) \equiv \mathbb{E}_t\big[A_{i,t+1}\Phi(\kappa_{i,t+1})\big].$$

Because $\kappa_{i,t+1}$ inherits the two-point support of rule (P-rule), we can write this explicitly as

$$\bar{A}_{i,t} = \Pr_t\Big(\omega_i \le \frac{\bar{E}_{t+1}}{\Omega}\Big)\, A_{i,t+1}\Phi(1) + \mathbb{E}_t\Big[A_{i,t+1}\Phi\Big(\tfrac{\bar{E}_{t+1}}{\Omega}\,\omega_i\Big) \;\Big|\; \omega_i > \tfrac{\bar{E}_{t+1}}{\Omega}\Big]\ \Pr_t\Big(\omega_i > \tfrac{\bar{E}_{t+1}}{\Omega}\Big).$$

With DRS Cobb-Douglas, the static profit maximization is unchanged except that $\bar{A}_{i,t}$ now depends on the priority weight:

$$\max_{K,L}\ \bar{A}_{i,t}(\kappa,\omega_i)\ K^{\alpha_1}L^{\alpha_2} - r_t K - w_t L.$$

First-order conditions yield

$$K^*_{i,t}(\kappa,\omega_i) = \Big[\tfrac{\alpha_1\,[\bar{A}_{i,t}(\kappa,\omega_i)]\,\mu^{\alpha_2}}{r_t}\Big]^{\frac{1}{1-\alpha_1-\alpha_2}}, \qquad L^*_{i,t} = \mu\, K^*_{i,t},$$

where $\mu \equiv (\alpha_2/\alpha_1)\,(r_t/w_t)$ as before.

Because $\kappa_{i,t+1}$ is weakly increasing in expected tightness κ for every ω_i, the proofs of Proposition 1 (inputs) and Proposition 2 (profits) go through verbatim once expectations are taken conditional on ω_i. The monotone-comparative-statics result therefore strengthens.

In particular, for any two firms i, j with $\omega_i > \omega_j$ and for every $\kappa \in (0,1]$,

$$K^*_{i,t}(\kappa,\omega_i) > K^*_{j,t}(\kappa,\omega_j), \qquad L^*_{i,t}(\kappa,\omega_i) > L^*_{j,t}(\kappa,\omega_j).$$

Priority access strictly increases optimal scale.

Asset-pricing moments All subsequent derivations (dividends, consumption, SDF, and risk premia) hold after replacing the common κ_{t+1} with the firm-specific $\kappa_{i,t+1}$. Expected return differentials now load on two observables:

$$\frac{d\mathrm{RP}_{i,t}}{d\kappa} < 0, \qquad \frac{d\mathrm{RP}_{i,t}}{d\omega_i} < 0,$$

implying that high-priority stocks command lower premia–an empirical prediction one can test by interacting firm-level electricity contracts with system-wide tightness shocks.

Overall, priority weights convert a purely aggregate shock into a partly idiosyncratic one. This destroys the knife-edge result of identical firms in the proportional model and naturally generates cross-sectional dispersion in size, profitability, and risk premia even when $A_{i,t+1}$ is i.i.d.

OA.4 Capital Accumulation with Quadratic Adjustment Costs

We can also extend our model by exploring the dynamic propagation of *proportionally* rationed electricity shocks. We endogenize the capital stock and introduce standard quadratic installation costs. Each firm i chooses $(I_{i,t}, L_{i,t})$ and evolves its capital according to

$$K_{i,t+1} \;=\; (1-\delta)\,K_{i,t} \;+\; I_{i,t}, \qquad 0 < \delta < 1.$$

Besides the purchase outlay $r_t I_{i,t}$, the firm pays adjustment costs of

$$AC(I_{i,t}, K_{i,t}) \;=\; \frac{\varphi}{2}\Big(\frac{I_{i,t}}{K_{i,t}} - \delta\Big)^2 K_{i,t}, \qquad \varphi > 0,$$

so the period-t dividend generalizes to

$$D_{i,t} = Y_{i,t} - w_t L_{i,t} - r_t I_{i,t} - AC(I_{i,t}, K_{i,t}),$$

where output with *proportional* rationing is $Y_{i,t} = A_{i,t}\Phi(\kappa_t)\, K_{i,t}^{\alpha_1} L_{i,t}^{\alpha_2}$ and $\Phi(\kappa_t) \equiv [\delta_{KL} + \delta_E(\kappa_t \chi)^\rho]^{1/\rho}$.

Let $q_{i,t}$ be Tobin's q (shadow value of capital in consumption units), and write $M_{t,t+1}$ for the stochastic discount factor. The current-value Hamiltonian is

$$\mathcal{H}_{i,t} = D_{i,t} + q_{i,t}\big[(1-\delta)K_{i,t} + I_{i,t} - K_{i,t+1}\big].$$

Taking first-order conditions, we obtain

$$\text{Labor:} \quad w_t = \alpha_2\, \bar{A}_{i,t}(\kappa)\, K_{i,t}^{\alpha_1} L_{i,t}^{\alpha_2 - 1}, \tag{OA.4.1}$$

$$\text{Investment:} \quad q_{i,t} = \; r_t + \varphi\Big(\frac{I_{i,t}}{K_{i,t}} - \delta\Big), \tag{OA.4.2}$$

$$\text{Capital Euler:} \quad q_{i,t} = \; \beta\, \mathbb{E}_t\Big[M_{t,t+1}^{-1}\big(\alpha_1\, \bar{A}_{i,t+1}(\kappa)\, K_{i,t+1}^{\alpha_1 - 1} L_{i,t+1}^{\alpha_2} + (1-\delta) q_{i,t+1}\big)\Big], \tag{OA.4.3}$$

where $\bar{A}_{i,t}(\kappa) \equiv \mathbb{E}_t\big[A_{i,t+1}\Phi(\kappa_{t+1})\big]$ is exactly the tightness-adjusted productivity already used in the main text.

From (OA.4.1) we recover the familiar capital–labor ratio $L_{i,t}^* = \mu_t K_{i,t}$. Hence Proposition 1 remains valid.

Solving (OA.4.2) for investment gives

$$\frac{I_{i,t}}{K_{i,t}} = \delta + \frac{q_{i,t} - r_t}{\varphi}, \tag{OA.4.2$'$}$$

so the adjustment-cost wedge $(q_{i,t} - r_t)$ drives investment. Combining this with (OA.4.3) and the labor rule yields the capital policy

$$K_{i,t+1}^* = \Big[\frac{\alpha_1\, \mathbb{E}_t\big[A_{i,t+1}\Phi(\kappa_{t+1})\big]}{r_t\, q_{i,t}^{1-\alpha_1} \mu_t^{-\alpha_2}}\Big]^{\frac{1}{1-\alpha_1-\alpha_2}},$$

which collapses to the static optimum when $\varphi \to 0$.

With $\varphi > 0$, proportional-rationing shocks affect output gradually via investment, moderating the instantaneous volatility relative to the baseline. Dividends now include the capital-gain term $q_{i,t+1}$, but Propositions 3–4 still hold; the magnitudes are dampened by φ and δ. Equation (OA.4.2$'$) predicts that $\Delta(I_{i,t}/K_{i,t})$ covaries negatively with electricity tightness κ_t, offering an additional empirical validation.

OA.5 Correlated Productivity and Supply Shocks

In the baseline model we assumed that the firm–specific (or aggregate) productivity shock $A_{i,t+1}$ is independent of the tightness shock $\varepsilon_{t+1} := \log \kappa_{t+1} - \log \kappa$. To gauge the importance of this assumption, let

$$\Delta \log A_{t+1} = \zeta_{t+1}, \qquad (\zeta_{t+1}, \varepsilon_{t+1}) \sim \text{i.i.d. log-normal}(0, \Sigma), \quad \Sigma = \begin{pmatrix} \sigma_\zeta^2 & \sigma_{\zeta\varepsilon} \\ \sigma_{\zeta\varepsilon} & \sigma_\varepsilon^2 \end{pmatrix}.$$

Hence $\sigma_{\zeta\varepsilon} \neq 0$ allows productivity to co-move with electricity supply.

Aggregate consumption growth. With decreasing returns to scale and proportional rationing,

$$\Delta \log C_{t+1} = \underbrace{\zeta_{t+1}}_{\text{productivity}} + \underbrace{\lambda(\kappa)\varepsilon_{t+1}}_{\text{rationing}}, \qquad \lambda(\kappa) := \kappa \frac{\Phi'(\kappa)}{\Phi(\kappa)}.$$

Because $\lambda(\kappa)$ is time-t measurable, the conditional variance that prices risk is now

$$\mathrm{Var}_t[\Delta \log C_{t+1}] = \sigma_\zeta^2 + 2\,\lambda(\kappa)\sigma_{\zeta\varepsilon} + \lambda(\kappa)^2\sigma_\varepsilon^2.$$

Proposition OA.4 (Risk premium with correlated shocks)**.** *Under CRRA utility with risk-aversion $\theta > 0$ the one-period equity premium for any firm satisfies*

$$RP_{i,t}(\kappa) = \theta\Big[\sigma_\zeta^2 + 2\,\lambda(\kappa)\,\sigma_{\zeta\varepsilon} + \lambda(\kappa)^2\,\sigma_\varepsilon^2\Big].$$

Its sensitivity to the expected tightness parameter is

$$\frac{dRP_{i,t}}{d\kappa} = 2\theta\,\frac{d\lambda}{d\kappa}\Big[\lambda(\kappa)\,\sigma_\varepsilon^2 + \sigma_{\zeta\varepsilon}\Big], \qquad \frac{d\lambda}{d\kappa} = \Big[\frac{\rho-1}{\kappa} - \rho\,\lambda(\kappa)\Big]\lambda(\kappa) < 0.$$

Proof. Because prices are known at time t, $RP_{i,t} = -\operatorname{Cov}_t(M_{t+1}, D_{i,t+1})/P_{i,t}$ as in the baseline. With $\log M_{t+1} = -\theta\Delta\log C_{t+1}$ and jointly log-normal shocks, the log-normal covariance formula (Cochrane 2005, App. B) gives $RP_{i,t} = \theta\ \mathrm{Var}_t(\Delta\log C_{t+1})$, delivering the first equality.

Only $\lambda(\kappa)$ depends on κ, so $dRP_{i,t}/d\kappa = \theta\,(2\sigma_{\zeta\varepsilon} + 2\lambda\sigma_\varepsilon^2)\,(d\lambda/d\kappa)$, and $d\lambda/d\kappa$ is obtained by differentiating $\lambda(\kappa) = \Phi'(\kappa)/\Phi(\kappa)$ for the CES aggregator $\Phi(\cdot)$. The sign of $d\lambda/d\kappa$ is negative (cf. Proposition 3); substituting yields the second claim. □

Interpretation. Setting $\sigma_{\zeta\varepsilon} = 0$ collapses to the formula in Proposition 3.

Positive correlation ($\sigma_{\zeta\varepsilon} > 0$). Productivity booms coincide with slack grids. The bracket $[\lambda\sigma_\varepsilon^2 + \sigma_{\zeta\varepsilon}]$ is larger than in the baseline, so the slope $dRP/d\kappa$ is more negative: easing expected tightness cuts risk premia even more strongly.

Negative correlation ($\sigma_{\zeta\varepsilon} < 0$). If electricity shortages arrive together with positive productivity surprises, the cross term can dominate. A necessary and sufficient condition for the sign reversal $dRP/d\kappa > 0$ is

$$\sigma_{\zeta\varepsilon} \;<\; -\lambda(\kappa)\,\sigma_\varepsilon^2.$$

Empirically, this would require an implausibly large negative covariance (e.g., massive hydropower losses when non-energy TFP soars), but the inequality provides a transparent falsifiable bound.

Robust qualitative prediction. For moderate $|\sigma_{\zeta\varepsilon}|$—in particular whenever $|\sigma_{\zeta\varepsilon}| < \lambda(\kappa)\sigma_\varepsilon^2$–the sign remains negative, and all comparative-statics in the main text carry through verbatim.

OA.6 Price– vs. Quantity–Clearing Electricity Markets

We now show that allowing a competitive spot price to clear the market yields the same real allocations and risk premia as quantity rationing, provided the grid faces a hard capacity cap. The result reconciles our proportional-rationing shortcut with the empirical reality that U.S. markets clear via price spikes rather than administrative pro-rationing.

Let the aggregate electricity supply curve be

$$p_E(E^D) \;=\; \begin{cases} c, & \text{if } E^D \le \bar{E}, \\ c + \gamma\,(E^D - \bar{E}) + \Pi, & \text{if } E^D > \bar{E}, \end{cases} \tag{OA.6.1}$$

where c is marginal cost, $\gamma > 0$ captures a steep upward slope near the cap, and $\Pi > 0$ is a scarcity adder (possibly hitting a regulatory ceiling).[11]

Each firm solves, *taking the spot price as given*,

$$\max_{K,L,E^D} P_Y\, A\, F(K, L, E^D) - rK - wL - p_E(E^D)\, E^D \quad \text{s.t.} \quad 0 \le E^D \le \bar{E},$$

with $F(\cdot)$ the CES technology from Section 2.

Let $\tilde{E}(K, L)$ denote the *notional* electricity demand that maximizes the objective when the constraint is slack ($p_E = c$).

Proposition OA.5. *For any K, L chosen in stage t, the firm's optimal electricity purchase under (OA.6.1) is*

$$E^{D*}(K, L) \;=\; \min\{\tilde{E}(K, L),\, \bar{E}\}.$$

When the capacity constraint binds, the Lagrange multiplier on $E^D \le \bar{E}$ is $\lambda = P_Y\, A\, \partial F/\partial E - c$ and the realized input equals $\kappa\, \tilde{E}$ with $\kappa = \bar{E}/\tilde{E}$ exactly as in the main text.

Proof. Set up the Lagrangian $\mathcal{L} = P_Y AF(K, L, E^D) - rK - wL - p_E(E^D)E^D + \lambda(\bar{E} - E^D)$. With p_E continuous and strictly increasing once $E^D > \bar{E}$, the first-order condition for E^D is $P_Y A \partial F/\partial E^D = p_E(E^D) + \lambda$.

(i) Slack constraint. If $\tilde{E}(K, L) \le \bar{E}$, the optimum satisfies the FOC at $\lambda = 0$ with $p_E = c$, hence $E^{D*} = \tilde{E}$.

(ii) Binding constraint. If $\tilde{E}(K, L) > \bar{E}$, any $E^D > \bar{E}$ raises cost at the steep slope $c + \gamma(\cdot)$ without increasing output (diminishing marginal product), so the optimum is at the corner $E^{D*} = \bar{E}$. Here $\lambda > 0$ absorbs the gap between marginal product and marginal cost c, yielding $\lambda = P_Y\, A\, \partial F/\partial E|_{\bar{E}} - c$.

Thus $E^{D*} = \min\{\tilde{E}, \bar{E}\}$, equivalently $E^{D*} = \kappa\, \tilde{E}$ with tightness $\kappa = \bar{E}/\tilde{E} \in (0, 1]$. □

Because the optimal realized electricity input is $E^{\text{rat}} = \kappa\tilde{E}$, output collapses to $Y = A\Phi(\kappa)K^{\alpha_1}L^{\alpha_2}$, exactly as in the baseline model. The firm's profit and every derivative $\partial\Pi/\partial\kappa$ are therefore identical to those under pure quantity rationing. Price spikes enter profits only through $p_E E^{D*} = c\bar{E} + \lambda\bar{E}$, that is, a constant plus the multiplier term already embedded in κ. Consequently all comparative-static signs in Propositions 1–3 and the asset-pricing results carry over unchanged.

Intuitively, when supply is perfectly (or near-perfectly) inelastic at $\bar{E}$, the spot price redistributes surplus but cannot relax the physical cap; the firm perceives a quantity shock, which drives both real outcomes and risk premia.

OA.7 Welfare Implications

We further study welfare implications of electricity constraints. The representative household's lifetime utility is

$$U(\kappa) = \sum_{t=0}^{\infty} \beta^t\, \frac{C_t(\kappa)^{1-\theta}}{1-\theta}, \qquad \theta > 0,$$

where $\kappa \in (0, 1]$ is chosen by the system operator (or the policy maker). Aggregate consumption in period t equals

$$C_t(\kappa) = A_t\, \Phi(\kappa_t)\, \Lambda_{t-1}(\kappa), \tag{OA.7.1}$$

[11] In many wholesale markets γ is effectively infinite once the security-constrained dispatch exhausts physical capacity; then p_E jumps to the price cap and additional quantity cannot be procured.

with $\Lambda_{t-1}(\kappa) \equiv \sum_i Z_{i,t-1}(\kappa)$, the aggregate scale of inputs decided in the previous period.

Firms solve exactly the problem in Section 2.5. Under decreasing returns to scale ($\alpha \equiv \alpha_1 + \alpha_2 < 1$), their optimal choices imply

$$\Lambda_{t-1}(\kappa) \propto \bar{A}_{t-1}(\kappa)^{\frac{1}{1-\alpha}}, \qquad \bar{A}_{t-1}(\kappa) := \mathbb{E}_{t-1}\big[A_t \Phi(\kappa_t)\big].$$

Proposition 2 already established that both Φ and $\bar{A}$ are increasing in κ; hence

$$\frac{\partial \Lambda_{t-1}}{\partial \kappa} \ > \ 0.$$

Differentiating (OA.7.1) yields

$$\frac{\partial C_t}{\partial \kappa} = A_t \Big[\, \Phi'(\kappa_t)\Lambda_{t-1} + \Phi(\kappa_t)\Lambda'_{t-1}\Big].$$

Taking expectations conditional on $t-1$:

$$\mathbb{E}_{t-1}\Big[\tfrac{\partial C_t}{\partial \kappa}\Big] = \bar{A}_{t-1}(\kappa)\Big[\, \Phi'(\kappa)\, \Lambda_{t-1}(\kappa) + \Phi(\kappa)\, \Lambda'_{t-1}(\kappa)\Big].$$

The derivative is positive. Its first term represents the *direct* effect of lower tightness on period-t productivity; the second term is the *general-equilibrium scale effect* stemming from larger input choices at $t-1$.

Differentiating $U(\kappa)$ term-by-term:

$$\frac{\partial U}{\partial \kappa} = \sum_{t=0}^{\infty} \beta^t\, C_t(\kappa)^{-\theta}\, \mathbb{E}_{t-1}\big[\tfrac{\partial C_t}{\partial \kappa}\big].$$

which is a positive number. Hence any marginal increase in expected electricity availability raises lifetime welfare. Intuitively, a higher κ lifts average productivity through (positive) $\Phi'(\kappa)$ and encourages firms to install more inputs (the Λ'_{t-1} term). As shown earlier, $\partial\,\mathrm{Var}[\Delta \log C]/\partial\kappa$ is a negative number; the representative risk-averse household values this risk reduction.

We obtain the decomposition of the welfare into a level and risk components by taking a second-order Taylor expansion around the steady state $\bar{C} \equiv \mathbb{E}[C_t]$:

$$dU \ \approx \ \frac{\beta\, \bar{C}^{-\theta}}{1-\theta}\Big[d\ln \bar{C} - \frac{\theta}{2}\, d\,\mathrm{Var}\big[\Delta \ln C\big]\Big],$$

with

$$d\ln \bar{C} = d\ln \Phi(\kappa) + \frac{1}{1-\alpha}\, d\ln \bar{A}(\kappa).$$

Overall, grid-reliability investments or market-design reforms that raise the average tightness ratio κ deliver *dual dividends*–higher average consumption and lower macro-risk–and the former is magnified by endogenous scale adjustment.

We further derive optimal target for expected tightness κ^* assuming a resource cost. Formally, the planner chooses $\kappa \in (0, 1]$ to maximize lifetime utility

$$W(\kappa) \ = \ U(\kappa) \ - \ \mathcal{G}(\kappa), \qquad U(\kappa) = \sum_{t=0}^{\infty} \beta^t\, \frac{C_t(\kappa)^{1-\theta}}{1-\theta},$$

where $\mathcal{G}$ captures the resource cost of lifting the grid's average availability (e.g., reliability investments, emergency-reserve contracts). We assume

$$\mathcal{G}(0) = 0, \qquad \mathcal{G}'(\kappa) > 0, \qquad \mathcal{G}''(\kappa) \geq 0 \quad \text{for all } \kappa \in (0, 1].$$

We study the effects for marginal utility. From (OA.7.1) in the main text $C_t(\kappa) = A_t\, \Phi(\kappa_t)\, \Lambda_{t-1}(\kappa)$ with $\Phi'(\kappa) > 0$ and $\Lambda'_{t-1}(\kappa) > 0$. Differentiating term-by-term yields

$$\frac{\partial U}{\partial \kappa} = \sum_{t=0}^{\infty} \beta^t\, C_t(\kappa)^{-\theta}\, A_t \Big[\Phi'(\kappa_t)\Lambda_{t-1}(\kappa) + \Phi(\kappa_t)\Lambda'_{t-1}(\kappa)\Big] \equiv \mathcal{M}(\kappa) > 0,$$

so marginal utility from relaxing the constraint is strictly positive.

The planner's optimal target κ^* solves

$$\mathcal{M}(\kappa^*) = \mathcal{G}'(\kappa^*) \tag{OA.7.2}$$

with the sufficient second-order condition $\frac{\partial^2 U}{\partial \kappa^2} - \mathcal{G}''(\kappa) < 0$.

Assuming a stationary environment ($A_t \equiv \bar{A}$, $\kappa_t \equiv \kappa$) and using decreasing returns $\alpha \equiv \alpha_1 + \alpha_2 < 1$, we obtain $C_t \equiv \bar{C}(\kappa)$, and

$$\bar{C}(\kappa) = \Phi(\kappa)^{\frac{1}{1-\alpha}}\, \bar{A}^{\frac{1}{1-\alpha}}, \qquad \frac{\partial \bar{C}}{\partial \kappa} = \bar{C}(\kappa) \Big[\frac{\Phi'(\kappa)}{\Phi(\kappa)} + \frac{1}{1-\alpha}\, \frac{\bar{A}'(\kappa)}{\bar{A}(\kappa)} \Big].$$

Plugging into equation OA.7.2 and discounting the geometric series ($\sum_{t=0}^{\infty} \beta^t = \frac{1}{1-\beta}$) gives

$$\frac{\beta}{(1-\beta)\,(1-\theta)}\, \bar{C}(\kappa^*)^{-\theta+1} \Big[\frac{\Phi'(\kappa^*)}{\Phi(\kappa^*)} + \frac{1}{1-\alpha}\, \frac{\bar{A}'(\kappa^*)}{\bar{A}(\kappa^*)} \Big] = \mathcal{G}'(\kappa^*). \tag{OA.7.3}$$

The choices of κ depend on the functional form of costs. For any strictly increasing convex $\mathcal{G}$, equation OA.7.3 has a unique interior solution because the LHS is positive and strictly decreasing in κ, while the RHS is increasing. Comparative statics follow directly:

$$\frac{\partial \kappa^*}{\partial \theta} \;<\; 0, \qquad \frac{\partial \kappa^*}{\partial \varphi} \;<\; 0 \quad \text{if } \mathcal{G}(\kappa) = \tfrac{\varphi}{2}\kappa^2,$$

so higher risk aversion or a steeper cost curve lowers the optimal target.

OA.8 Quarterly firm response to Uri Winter Storm

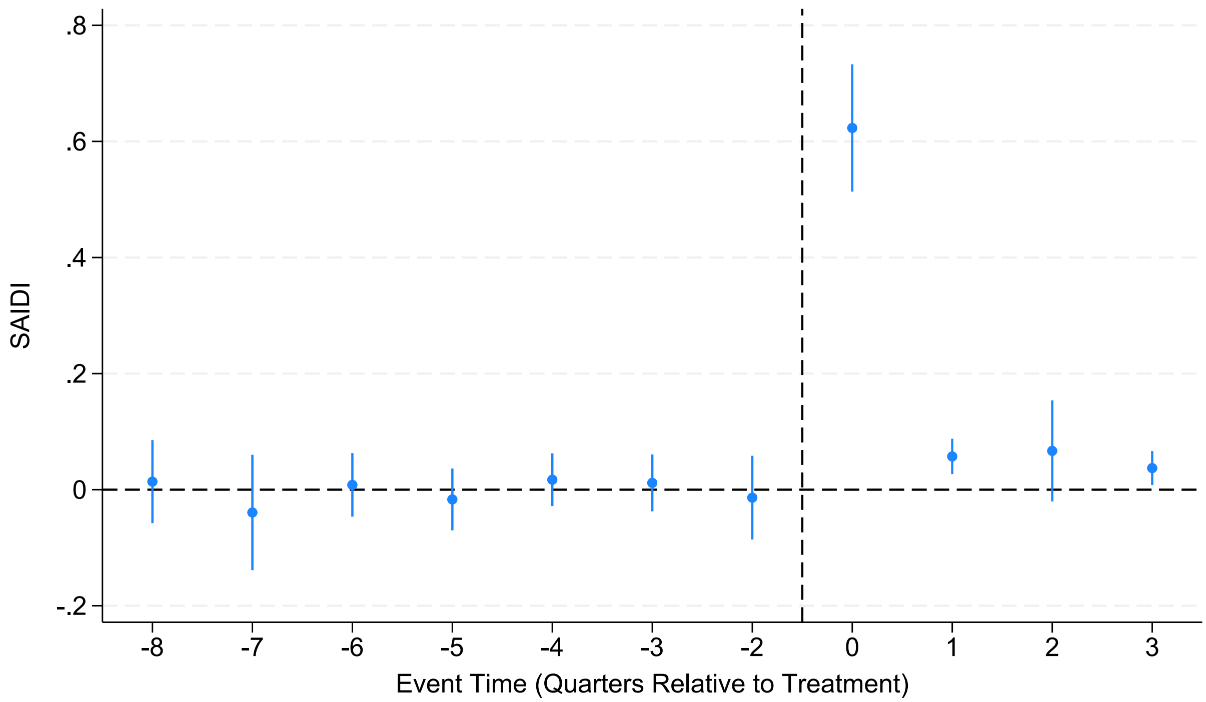


Figure 6: SAIDI

This figure plots SAIDI for treatment versus control firms around the Uri Winter storm shock. The sample consists of firms with at least 50% employment footprint in areas belonging to the Texas ERCOT grid. Treatment firms are firms in the top 10% of the empirical distribution in terms of outage exposure to Uri, and control firms are those in the bottom 90% of the same distribution. Event quarter t=0 is the quarter in which firms were exposed to the Uri shock. Confidence intervals are at the 10% level.

OA.9 Uri Storm Timeline

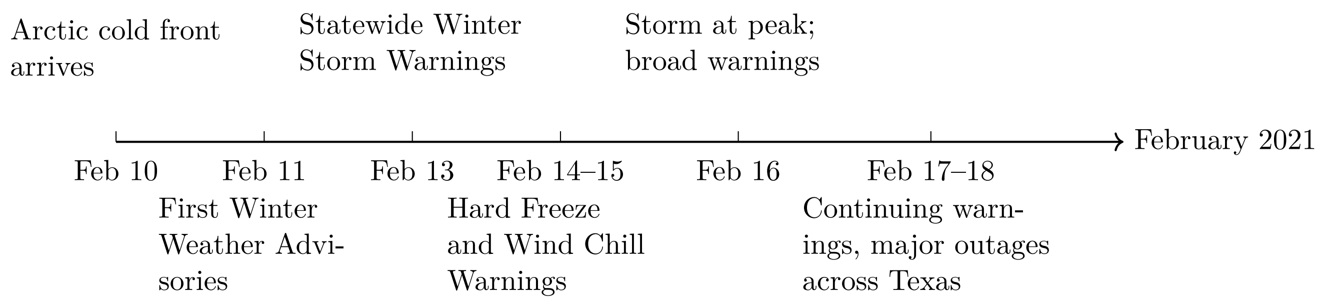


Figure 7: Warning timeline for Winter Storm Uri, February 2021

OA.10 Policy Timeline