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, yet standard models treat capacity as unlimited. 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 by mapping more than 650k U.S. plants to their local grids. 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. Further, firms with higher electricity intensity face greater exposure to these shocks.

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 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 empirical asset-pricing tests (Section 4.2) we show that the electricity-tightness factor (ELX) 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 both difference-in-differences and instrumental variables approaches, 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 shocks have 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.

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.

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; 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. The aggregate electricity supply process follows:[1]

$$\log \bar{E}_{t+1} = \rho_E \log \bar{E}_t + \epsilon^E_{t+1}, \quad \varepsilon^E_{t+1} \sim \mathcal{N}(0, \sigma^2_{\varepsilon^E}).$$

Similarly, the aggregate electricity demand process is:

$$\log E^D_{t+1} = \rho_D \log E^{exp}_t + \epsilon^D_{t+1}, \quad \varepsilon^D_{t+1} \sim \mathcal{N}(0, \sigma^2_{\varepsilon^D}).$$

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 $\alpha_1 + \alpha_2 < 1$. The parameter σ governs the elasticity of substitution between the capital-labor composite and electricity.[2]

When aggregate electricity demand $E^D_{t+1} = \sum_i E^d_{i,t+1}$ exceeds the available supply $\bar{E}_{t+1}$, a

[1] The assumption of AR(1) supply process is consistent with the logic of persistent outages due to disrupted technology or weather-related events. In standard electricity markets, the process is typically near unit root.

[2] 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 ...).

proportional rationing rule is applied[3]:

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

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.[4] 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

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

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

firm's capital and labor choices and arises endogenously from the production technology.

Given the nested CES production function

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

the firm's notional demand is:

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

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

$$\sum_i E_{i,t+1}^{d} = \chi \sum_i Z_{i,t}$$

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 $E_{i,t+1}^{rat}$:

$$E_{i,t+1}^{rat} = \kappa_{t+1} E_{i,t}^{d} = K_{i,t}^{\alpha_1} L_{i,t}^{\alpha_2} \cdot \chi \cdot \kappa_{t+1}$$

Then:

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

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:

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

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 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

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

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 $\frac{\mathrm{d}}{\mathrm{d}\kappa}\mathbb{E}_t\Big[\Pi_{i,t}\big(K_{i,t}^*, L_{i,t}^*; \kappa\big)\Big] > 0$ 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

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

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.

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

Proposition 3.

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

Proof in the Appendix.[5]

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*

[5]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.[6] 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.

[6] 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

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). SAIDI captures realized supply outages. Throughout this paper, we measure SAIDI as the number of days a unit of observation is without electricity supply. We measure SAIDI at the county level and use 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).

Second, 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).

Figure 1 displays the geographical distribution of the two measures of electricity tightness for the year 2021. Figure 1a documents outages throughout the U.S., with some notable scattering in Texas, the North West, and the North East. A primary driver of the outages in Texas in 2021 was the Uri Winter Storm (Brelsford et al., 2024). In 2021, some of the most exposed counties 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. The electricity regions Florida (FERC), Midwest (MISO), New York (NPCC) had the lowest values of AEC, at around 5%, while regions in the East, Southeast, and Southwest of the U.S. had the highest values, at around 20%.

We create firm-level exposures to electricity tightness by utilizing the locations of firms' establishments from the National Establishment Time Series (NETS) data. We first link public firms to their establishments. From the NETS data, we know the exact location of establishments and map

them to counties and electricity regions. We then 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 baseline sample for real outcomes begins in 2014. Local, realized tightness as measured by SAIDI is not available in earlier time periods. AEC is available for earlier periods. Hence, 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.[7]

Table 1 presents summary statistics for our main tests. Panel A exhibits substantial heterogeneity in both the infrastructure variables that underpin our identification strategy and the usual balance-sheet controls. *Anticipated Excess Capacity* (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 $e^{0.363} \approx 1.4$ k workers and holds roughly \$1.1 bn in assets ($\log \text{Assets} = 7.0$), but the upper decile reaches $e^{9.8} \approx 18$ bn. Investment intensity is modest (median *CAPEX/Assets* = 1.7%); profitability is thin (median *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 (P25 $= e^{1.609} \approx 5$; P75 $= e^{3.258} \approx 26$; 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 at the county level. Panel C1 reports grid tightness and local economic size for all industries. EMP and EST are total employment and establishments;

[7] 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.

the table shows means (with SD) and selected percentiles (p1, p10, p50, p90, p99). 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 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 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 anticipated excess capacity, 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. 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, 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. 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.

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 a one-standard-deviation improvement in AEC lifts q by roughly 1.7%, 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 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 stock returns of most-tight and least-tight companies based on AEC, is economically large and poorly spanned by the usual Fama–French factors (Tables 5–6). Second, ELX commands a statistically significant premium in sorted-portfolio regressions (Tables 7-8). Third, the factor earns a positive price of risk in the cross-section of individual stocks once conventional characteristics are controlled for (Table 9). Taken together, these results are fully consistent with the model's comparative statics in Section 2.

Table 5 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.[8] The monthly Sharpe ratio is 0.2.

Table 6 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 anticipated excess capacity 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) and ELX.

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

Table 7 (FF factors) and Table 8 (expanded factors) report the standard factor-time-series regressions.

Columns 1–10 show that γ_p rises monotonically from about -0.55 for the most constrained portfolio to 0.46 for the least constrained portfolio; the spread is highly significant ($t > 9$ in both samples). The five-factor alphas are economically modest and statistically insignificant once ELX is included, and the GRS statistics cannot reject the joint null of zero intercepts ($p = 0.60$). Adding three other auxiliary factors—momentum, BAB, and liquidity—leaves the pattern intact and ELX retains significance ($p < 0.01$), while the stricter GRS test still fails to reject.

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

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 betas at 0.5% to mitigate the impact of outliers.

Table 9 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 7.

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 9 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 Reform

Our identification approach combines quasi-experimental variation from the February 2021 Winter storm Uri blackout and subsequent market reforms in ERCOT, and an instrumental variables design for realized outages (SAIDI) and anticipated excess capacity (AEC) associated with these shocks.

In 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. We treat the reform as a second, positive shock, this time to expected tightness, κ_t—the looseness of expected capacity constraint.[9] 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

[9]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 SB3 has been one of the first if not the first significant shock in this regard.

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. 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.

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 11 considered as the first day of the storm and the first trading day after which widespread electricity outages followed in Texas. For our second shock, we consider May 31, 2021, the passage date 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 Uri shock, and -6 to +2 trading days for ERCOT shock. For each day, we show point estimates of the differences along with 90% confidence intervals.

Figure 2 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 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 May 31, 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 10, 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 do find that in response to both shocks AEC observed a long-term increase in value while SAIDI experienced a short-term jump in 2021. 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 only muted for the longer term. We further confirm the statistical significance of the results in Table 11 for the short-term effects. For the short-term effects, we restrict the post period to one year, 2021. In Table 12, we present the long-term results, in which we omit year 2021 and focus on the years 2022–2024 in the post period. We also test for the presence of pre-trends in both tests and report the results in Table 13. We find little evidence of significant pre-trends possibly invalidating the assumptions of the difference-in-differences approach.

Apart from using a difference-in-differences framework, we also use the two shocks as instruments to our baseline measures, AEC and SAIDI. Given the nature of the shock they are likely to satisfy the exclusion restriction.

$$\text{SAIDI}_{it} = \pi_1 \text{URI Shock } 1_{it} + \Pi Z_{it} + \eta_{it}, \tag{4.7}$$

where URI Shock_{it} is defined as before. In the same table, we report F-statistic of the first-stage regression. In all specifications, the F-statistics exceed the conventional critical values, supporting the relevance condition of our instrument. The results from the instrumental variable regressions confirm evidence from the reduced form: in the short-run, profitability is significantly negative; valuation is also lower, driven by increases in realized electricity capacity constraints. However, in the long-run, factor inputs and valuation increase significantly and exceed pre-shock levels.

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 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 14 implements these ideas using two complementary shifters of tightness—anticipated excess capacity (forward-looking slack) and SAIDI (realized outages).

Panel A of Table 14 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 log(EMP) and log(EST) 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).

Columns 3–5 of Panel A focus on NAICS 518210 (data processing/hosting), a power-intensive benchmark sector. We find effects on both the extensive and intensive margins. First, the probability that the industry is present in the county increases with anticipated slack (column 3), consistent with entry being more likely when expected rationing risk is low. Second, conditional on presence, county *employment* and the *number of establishments* in 518210 rise with the gap (columns 4–5), mirroring the sector's sensitivity to the expected availability of electricity. 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 B replaces expectations with realized *SAIDI* outages. 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). In the 518210 regressions, realized scarcity lowers the likelihood of industry presence and compresses both employment and establishment counts where present (columns 3–5). 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 14 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 two-way clustered 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 conditional on presence. 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 14 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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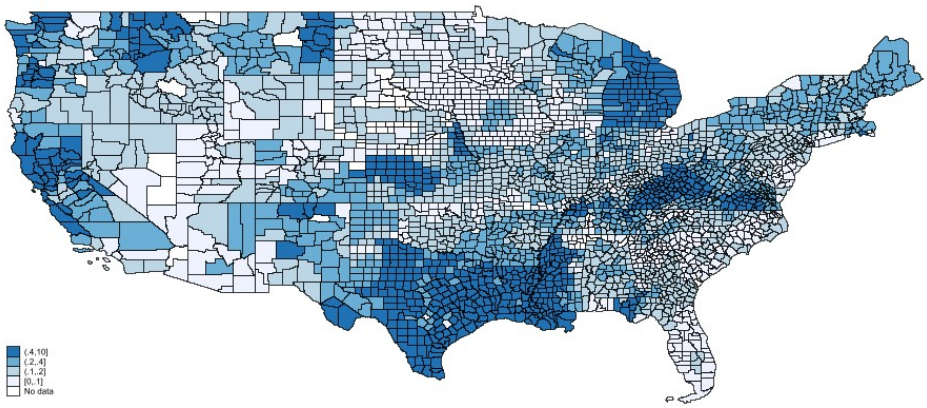
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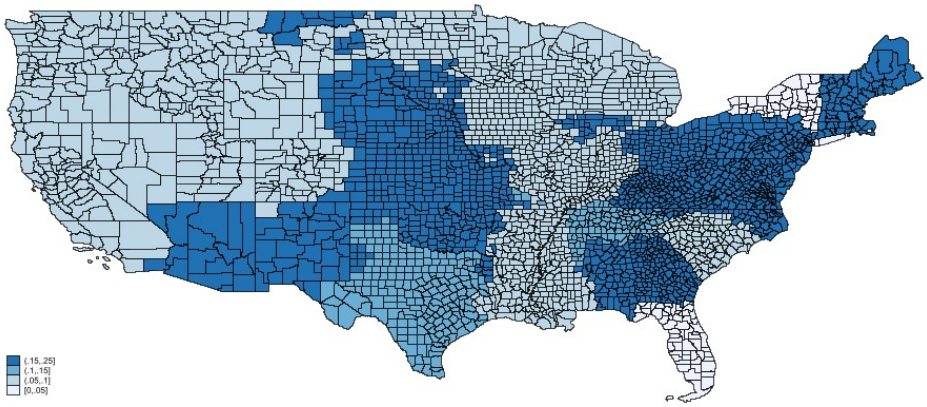
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Figures



(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.

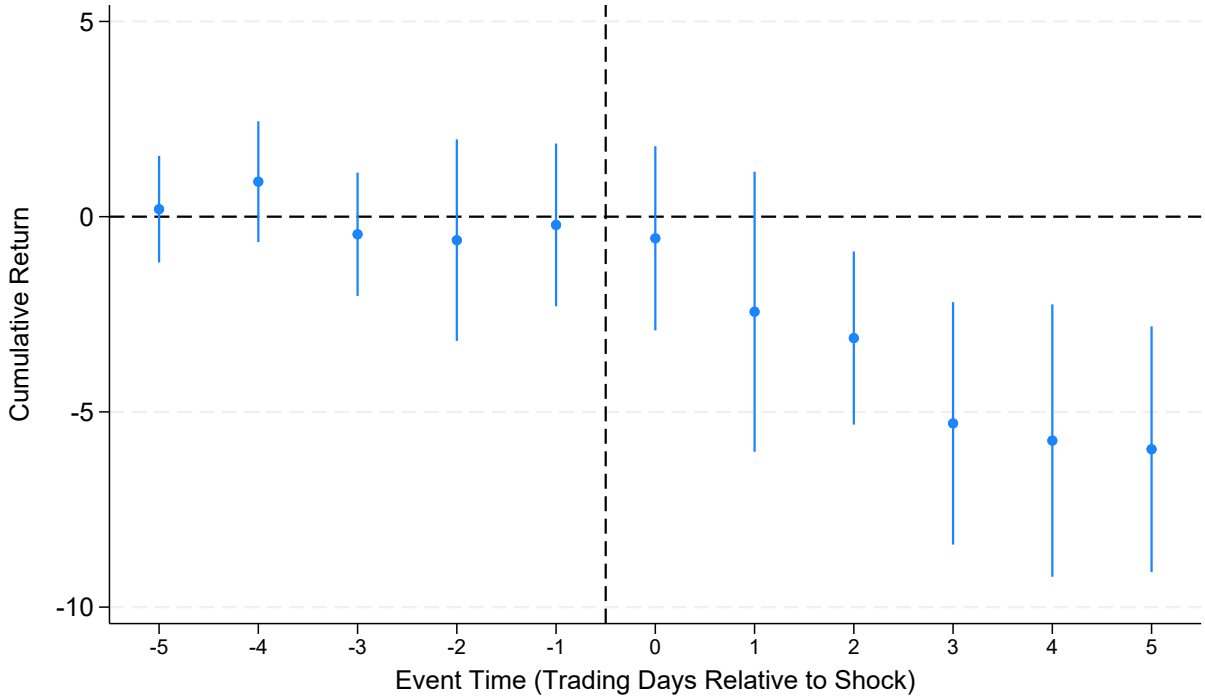


Figure 2: Cumulative Stock Returns around Uri Winter Storm Shock

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 rolling outages in the Texas ERCOT grid had started. The sample window starts 6 trading days before the shock and ends 6 trading days after the shock. Confidence intervals are at the 10% level.

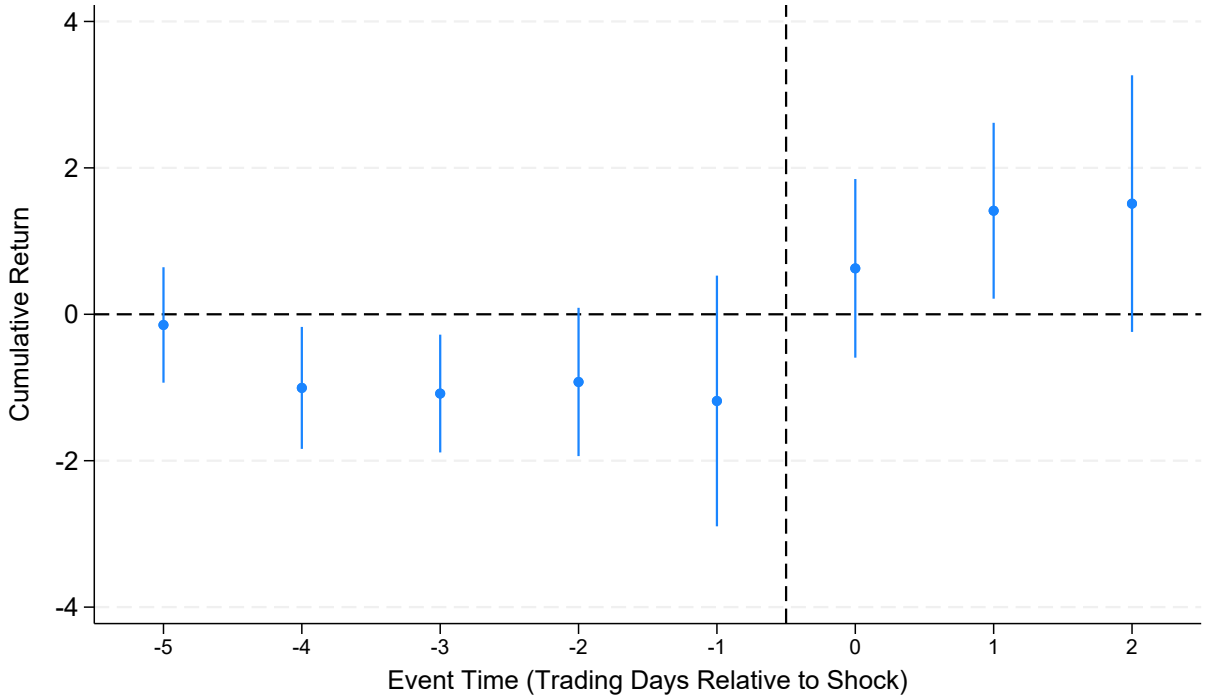
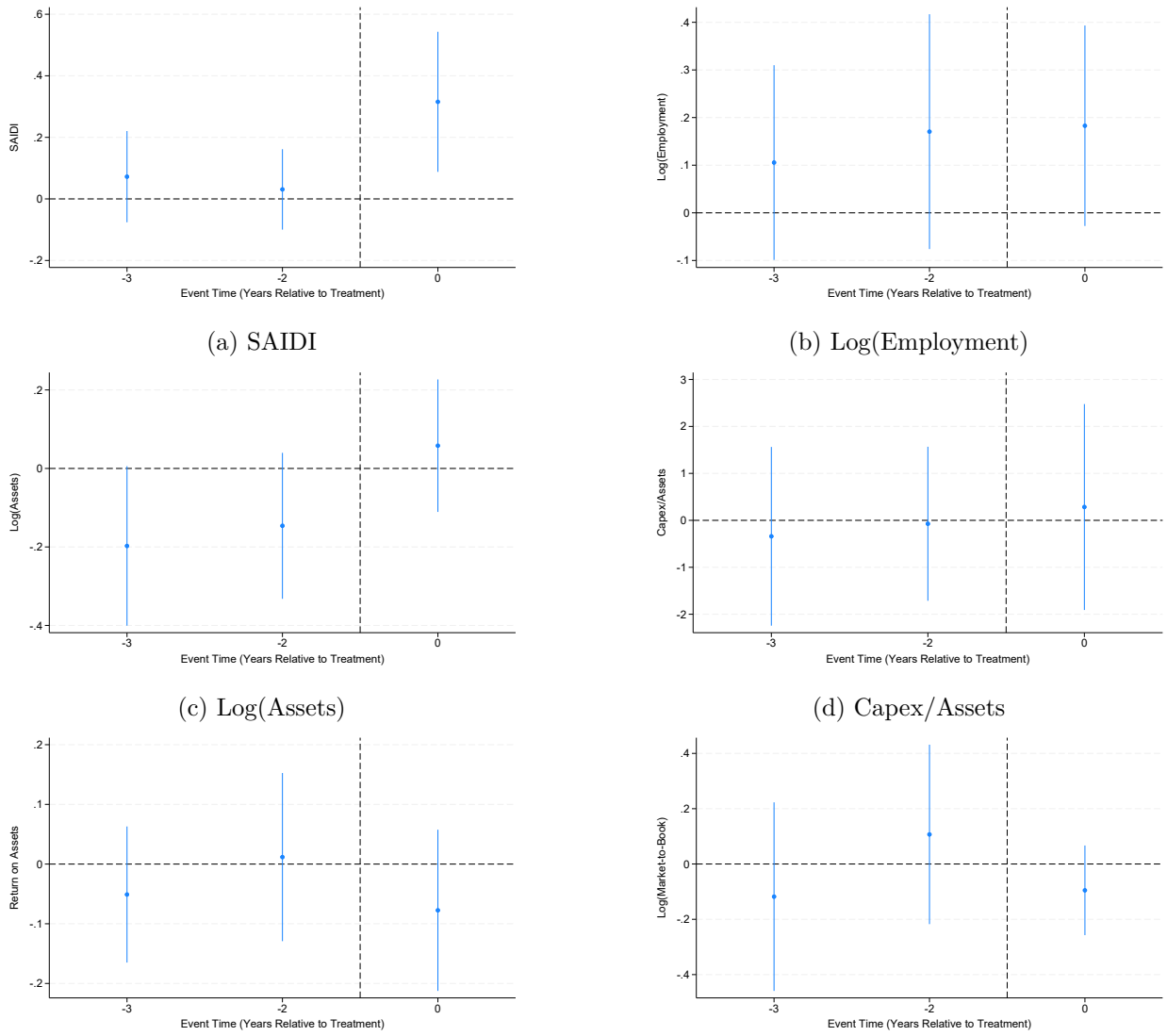


Figure 3: Cumulative Stock Returns around post-Uri Policy Adoption

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 6 trading days after the shock. Confidence intervals are at the 10% level.



(a) SAIDI

(b) Log(Employment)

(c) Log(Assets)

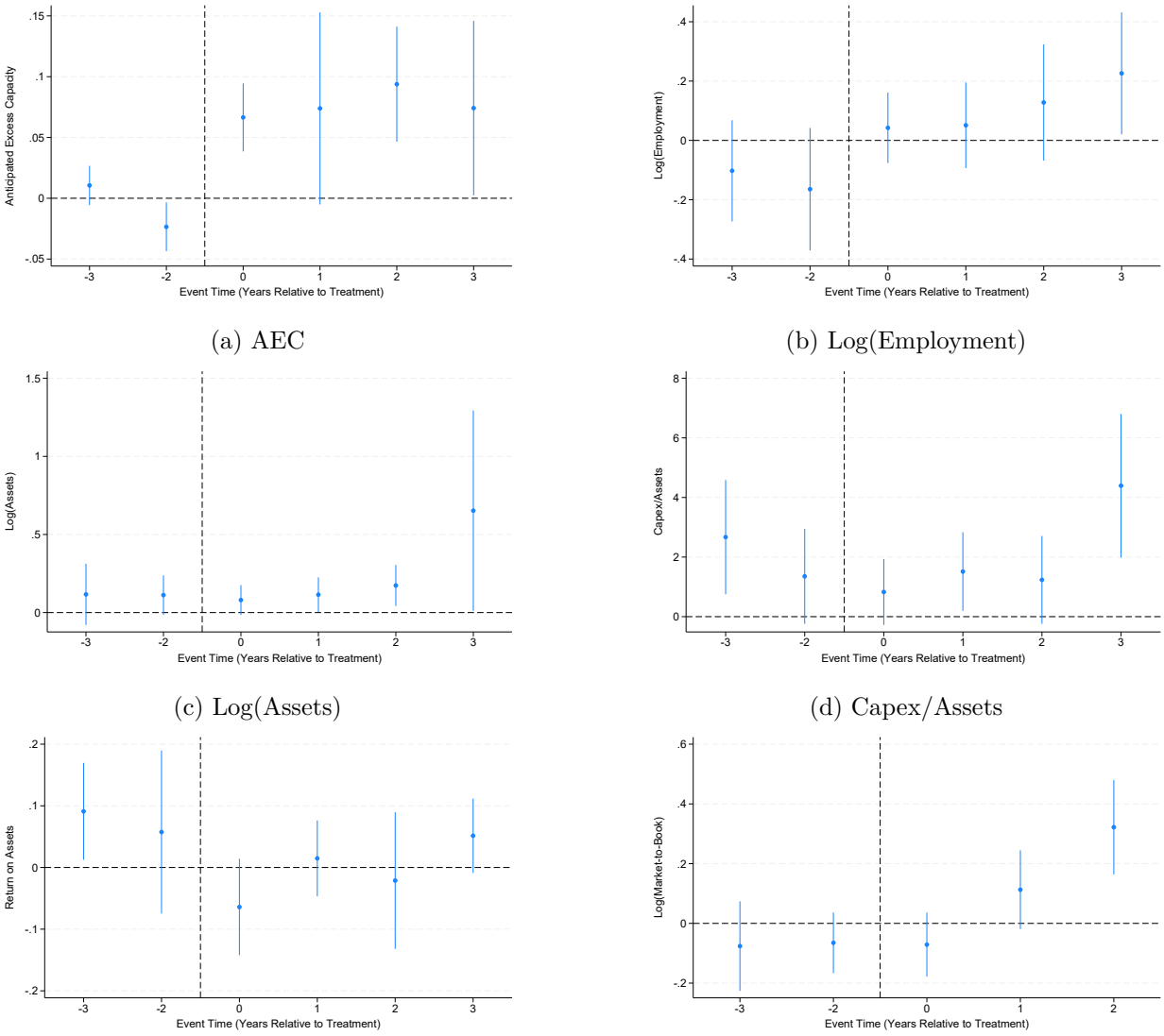
(d) Capex/Assets

(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 Texas 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 Texas ERCOT 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	STD DEV	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	STD DEV	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: County-Year

VARIABLE	MEAN	STD DEV	P10	P25	P50	P75	P90
Panel C1: *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 C2: *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 period begins in 2014 and ends in 2024. The sample consists of U.S. firms in Compustat. Panel B reports summary statistics for the firm-establishment-year sample. The sample period begins in 2014 and ends in 2020. The sample consists of Compustat firms matched with plants in the NETS data. Panel C reports summary statistics for the county-year sample. The sample period begins in 2014 and ends in 2023. The sample consists of all U.S. counties in the CBP data.

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	0.286**	
	(0.118)	
SAIDI		-0.035*
		(0.021)
L.SALES GROWTH	0.129***	0.129***
	(0.016)	(0.016)
SALES GROWTH	0.112***	0.112***
	(0.015)	(0.015)
F.SALES GROWTH	0.181***	0.180***
	(0.016)	(0.016)
L.ROE GROWTH	0.026***	0.026***
	(0.003)	(0.003)
ROE GROWTH	0.028***	0.028***
	(0.003)	(0.003)
F.ROE GROWTH	0.036***	0.036***
	(0.003)	(0.003)
L.ROA	-0.148***	-0.148***
	(0.042)	(0.042)
L.LOG(ASSETS)	0.039***	0.039***
	(0.005)	(0.005)
MOMENTUM	0.627***	0.626***
	(0.015)	(0.015)
VOLATILITY	-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 Returns: Summary Statistics

Estimation Sample: 2005–2024										
	ELX	ELXREL	MKT	SMB	HML	RMW	CMA	PS_VWF	MOM	BAB
Mean (%)	0.49	0.46	0.81	-0.02	-0.10	0.35	0.02	0.09	0.12	0.39
Median	0.55	0.61	1.26	-0.03	-0.32	0.34	-0.09	0.22	0.43	0.47
p_{25}	-0.77	-1.00	-1.85	-1.85	-1.82	-0.76	-1.15	-2.14	-1.74	-0.74
p_{75}	1.78	1.84	3.36	1.52	1.45	1.33	1.00	2.69	2.61	1.90
SD	2.52	2.37	4.47	2.67	3.20	1.85	1.90	3.90	4.40	2.69

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 6: 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 7: Portfolio Sorts (deciles) and ELX Factor Returns

	Dependent variable: value–weighted excess return of decile d										1–10 spread	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
ELX	−0.544***	−0.085*	−0.059	−0.070*	−0.037	0.091**	0.129***	0.212***	0.047	0.456***		
	(0.042)	(0.052)	(0.041)	(0.036)	(0.033)	(0.040)	(0.044)	(0.050)	(0.044)	(0.042)		
MKT-RF	0.941***	1.005***	1.041***	0.967***	1.066***	0.992***	0.919***	0.970***	0.889***	0.941***		−0.015
	(0.024)	(0.032)	(0.033)	(0.026)	(0.028)	(0.026)	(0.032)	(0.031)	(0.028)	(0.024)		(0.046)
SMB	0.262***	0.030	0.091	0.056	−0.100***	−0.047	0.098	−0.071	0.199***	0.262***		0.018
	(0.051)	(0.059)	(0.059)	(0.044)	(0.031)	(0.040)	(0.061)	(0.059)	(0.054)	(0.051)		(0.082)
HML	0.021	−0.044	−0.097*	0.028	0.015	0.083*	0.040	−0.115***	−0.109**	0.021		0.118
	(0.052)	(0.061)	(0.050)	(0.045)	(0.036)	(0.043)	(0.048)	(0.041)	(0.050)	(0.052)		(0.097)
RMW	−0.016	0.044	0.099	0.111*	0.063	−0.047	−0.098	−0.130*	−0.163**	−0.016		0.157
	(0.060)	(0.083)	(0.074)	(0.060)	(0.044)	(0.052)	(0.075)	(0.071)	(0.071)	(0.060)		(0.111)
CMA	0.002	0.164	0.055	−0.102	0.054	−0.119*	0.061	0.040	0.170*	0.002		−0.098
	(0.076)	(0.104)	(0.086)	(0.075)	(0.056)	(0.072)	(0.090)	(0.075)	(0.087)	(0.076)		(0.130)
Constant	−0.116	−0.071	−0.202*	0.009	−0.119	0.044	0.067	0.100	0.050	−0.116	0.490***	0.520***
	(0.102)	(0.125)	(0.110)	(0.092)	(0.083)	(0.086)	(0.124)	(0.124)	(0.117)	(0.102)	(0.166)	(0.174)
Observations	240	240	240	240	240	240	240	240	240	240	240	240
R^2	0.917	0.855	0.880	0.917	0.947	0.927	0.868	0.869	0.860	0.914		

This table presents estimations of monthly regressions of decile-portfolio excess returns on the market, size, value, profitability, investment, and the electricity-tightness factor (ELX). Robust standard errors (Newey–West, five lags) in parentheses. The sample starts in 2005 and ends in 2024. ***,** ,* denote significance at the 1%, 5%, and 10% levels, respectively.

Table 8: Portfolio Sorts (deciles) and ELX Factor Returns: Expanded Factors

	Value–weighted excess return of decile d										1–10 spread	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
ELX	−0.550***	−0.088*	−0.062	−0.065**	−0.040	0.089**	0.126***	0.210***	0.048	0.450***		
	(0.038)	(0.045)	(0.039)	(0.032)	(0.033)	(0.038)	(0.044)	(0.050)	(0.043)	(0.038)		
MKT-RF	0.927***	1.026***	1.043***	0.984***	1.047***	0.988***	0.917***	0.980***	0.888***	0.927***		−0.020
	(0.022)	(0.034)	(0.037)	(0.023)	(0.024)	(0.024)	(0.032)	(0.031)	(0.029)	(0.022)		(0.049)
SMB	0.259***	0.032	0.080	0.079*	−0.122***	−0.049	0.099	−0.065	0.210***	0.259***		0.016
	(0.056)	(0.057)	(0.060)	(0.047)	(0.033)	(0.041)	(0.062)	(0.062)	(0.056)	(0.056)		(0.078)
HML	0.039	0.023	−0.058	0.005	0.013	0.094**	0.061	−0.085*	−0.123**	0.039		0.123
	(0.044)	(0.064)	(0.051)	(0.042)	(0.041)	(0.043)	(0.048)	(0.045)	(0.053)	(0.044)		(0.103)
RMW	−0.018	0.051	0.105	0.106*	0.066	−0.047	−0.098	−0.128*	−0.168**	−0.018		0.157
	(0.058)	(0.078)	(0.073)	(0.059)	(0.045)	(0.052)	(0.074)	(0.072)	(0.071)	(0.058)		(0.111)
CMA	0.002	0.146	0.070	−0.140*	0.097	−0.117	0.054	0.021	0.152*	0.002		−0.095
	(0.070)	(0.102)	(0.083)	(0.073)	(0.059)	(0.073)	(0.093)	(0.079)	(0.091)	(0.070)		(0.137)
PS_VWF	0.038	0.057	0.072**	−0.092***	0.066***	0.023	0.023	0.012	−0.042	0.038		0.014
	(0.029)	(0.040)	(0.035)	(0.027)	(0.024)	(0.025)	(0.038)	(0.035)	(0.033)	(0.029)		(0.055)
MOM	−0.025	0.101***	0.036	0.022	−0.047**	−0.004	0.009	0.046	−0.014	−0.025		−0.007
	(0.027)	(0.039)	(0.031)	(0.025)	(0.022)	(0.034)	(0.033)	(0.035)	(0.028)	(0.027)		(0.072)
BAB	0.131**	−0.001	0.008	−0.057	0.031	0.045	0.065	0.022	0.028	0.131**		0.033
	(0.053)	(0.058)	(0.052)	(0.038)	(0.042)	(0.040)	(0.049)	(0.044)	(0.049)	(0.053)		(0.088)
Constant	−0.157*	−0.101	−0.218*	0.027	−0.120	0.028	0.040	0.079	0.045	−0.157*	0.490***	0.529***
	(0.095)	(0.127)	(0.112)	(0.087)	(0.084)	(0.091)	(0.126)	(0.124)	(0.120)	(0.095)	(0.166)	(0.183)
Observations	240	240	240	240	240	240	240	240	240	240	240	240
R^2	0.922	0.864	0.884	0.924	0.951	0.928	0.871	0.871	0.861	0.920	–	–

Robust (Newey–West, 5 lags) standard errors in parentheses. The sample starts in 2005 and ends in 2024. ***,** ,* denote significance at the 1%, 5%, and 10% levels, respectively. The final two columns regress the 1-10 return spread on the same factors; zeros indicate coefficients not reported in the original spreadsheet.

Table 9: Price of Risk in the Cross-section of Stocks

	Dependent variable: EXRET_{t+1} (%)			
	(1)	(2)	(3)	(4)
β_{t-1}^{ELX}	0.113**	0.107**		
	(0.055)	(0.054)		
$\beta_{t-1}^{\text{ELXREL}}$			0.087*	0.081*
			(0.047)	(0.046)
β_{t-1}^{MKT}	0.113	0.089	0.118	0.095
	(0.152)	(0.102)	(0.152)	(0.102)
β_{t-1}^{SMB}	0.003	0.036	0.003	0.037
	(0.082)	(0.058)	(0.082)	(0.057)
β_{t-1}^{HML}	0.066	0.068	0.066	0.067
	(0.087)	(0.067)	(0.087)	(0.067)
β_{t-1}^{RMW}	0.035	-0.003	0.033	-0.006
	(0.045)	(0.036)	(0.045)	(0.036)
β_{t-1}^{CMA}	−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)
$\text{Electricity Price}_{t-1}$		0.409		0.393
		(0.939)		(0.938)
$\text{Volatility}_{t-12:t-1}$		-0.356		-0.385
		(1.022)		(1.021)
$\ln(\text{Size})_{t-1}$		-0.046		-0.046
		(0.046)		(0.046)
$\ln(\text{BM})_{t-1}$		0.022		0.022
		(0.064)		(0.064)
$\ln(\text{PPE})_{t-1}$		0.085***		0.085***
		(0.029)		(0.029)
$\text{Momentum}_{t-12:t-1}$		-0.026		-0.025
		(0.118)		(0.118)
$\ln(\text{Turnover})_{t-1}$		-0.033		-0.034
		(0.062)		(0.062)
ROE_{t-1}		0.182**		0.183**
		(0.076)		(0.076)
$\text{HHI}_{\text{Emp},\,t-1}$		-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)
Time FE	Y	Y	Y	Y
Industry FE	N	Y	N	Y
Observations	530,416	530,416	530,416	530,416
R^2	0.193	0.193	0.193	0.193

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

Table 10: 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

TREAT URI is a dummy 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 from June 1, 2021. Standard errors are clustered at the firm headquarter county-level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 11: Short-Run Real Effects of the Texas Shocks

PANEL A: FIRST STAGE AND REDUCED FORM - SHORT-TERM EFFECTS OF THE TEXAS 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 × POST	0.298*	0.123	0.159	0.326	-0.095*	-0.172
	(0.155)	(0.091)	(0.101)	(1.342)	(0.057)	(0.111)
N	743	743	743	743	743	533
R2	0.714	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

PANEL B: SECOND STAGE - SHORT-TERM EFFECTS OF THE TEXAS SHOCK					
	LABOR	CAPITAL		PROFIT	VALUE
DEP VAR:	LOG(FIRM EMP)	LOG(ASSETS)	CAPEX/ASSETS	ROA	LOG(MB)
	(1)	(2)	(3)	(4)	(5)
SAIDI	0.413	0.534	1.080	-0.317	-0.431
	(0.380)	(0.498)	(4.587)	(0.258)	(0.441)
N	743	743	743	743	533
R2	0.023	-0.025	0.099	0.011	0.318
F (1st stage)	32.974	32.974	33.999	33.221	34.561
CONTROLS	X	X	X	X	X
YEAR FE	X	X	X	X	X
FIRM FE	X	X	X	X	X

This table reports coefficient estimates from difference-in-differences and instrumental variable regressions of the short-run (one period) effects of the Texas shocks based on equation 4.7. Panel A presents the first stage and reduced-form results. Panel B presents the second stage results, in which SAIDI is instrumented by the URI × POST variable. 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. 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. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 12: Long-Run Real Effects of the Texas Shocks

PANEL A: FIRST STAGE AND REDUCED FORM - LONG-TERM 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)
ERCOT × 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

PANEL B: SECOND STAGE - LONG-TERM EFFECTS OF THE TEXAS SHOCK					
	LABOR	CAPITAL		PROFIT	VALUE
DEP VAR:	LOG(FIRM EMP)	LOG(ASSETS)	CAPEX/ASSETS	ROA	LOG(MB)
	(1)	(2)	(3)	(4)	(5)
AEC	0.017*	0.007	0.033	-0.005	0.019***
	(0.010)	(0.006)	(0.054)	(0.006)	(0.005)
N	5,969	5,969	5,969	5,969	3,989
R2	0.004	0.055	0.037	0.054	0.236
F (1st stage)	476.537	476.537	476.788	476.104	287.792
CONTROLS	X	X	X	X	X
YEAR FE	X	X	X	X	X
FIRM FE	X	X	X	X	X

This table reports coefficient estimates from difference-in-differences and instrumental variable regressions of the long-run (one period) effects of the Texas shocks based on equation 4.7. Panel A presents the first stage and reduced form results. Panel B presents the second stage results, in which AEC is instrumented by the ERCOT × POST 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. 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. 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 2024, with the short-run effects in 2021 being omitted. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 13: 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)
$\text{POST}_{t-3} \times URI$	0.072	0.106	-0.197*	-0.340	-0.051	-0.118
	(0.090)	(0.124)	(0.103)	(1.152)	(0.069)	(0.206)
$\text{POST}_{t-2} \times URI$	0.031	0.170	-0.146	-0.073	0.012	0.107
	(0.079)	(0.149)	(0.094)	(0.993)	(0.085)	(0.196)
$\text{POST}_{t} \times URI$	0.315**	0.183	0.058	0.284	-0.077	-0.095
	(0.138)	(0.127)	(0.086)	(1.327)	(0.082)	(0.098)
N	743	743	743	743	743	533
R2	0.725	0.924	0.981	0.726	0.714	0.929
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 14: Excess Capacity and Real Outcomes: Aggregate Outcomes

PANEL A: ANTICIPATED EXCESS CAPACITY					
	COUNTY TOTAL		NAICS 518210		
DEP VAR:	LOG(EMP)	LOG(EST)	INDUSTRY PRESENT (0/1)	EMP	EST
	(1)	(2)	(3)	(4)	(5)
AEC	0.049***	0.029***	0.007	0.428*	-0.118
	(0.015)	(0.009)	(0.068)	(0.233)	(0.079)
N	30,157	30,157	30,157	12,002	12,002
R2	0.998	0.999	0.034		
PSEUDO R2				0.964	0.923
ESTIMATION	OLS	OLS	OLS	POISSON	POISSON
YEAR FE	X	X	X	X	X
COUNTY FE	X	X		X	X

PANEL B: SAIDI					
	COUNTY TOTAL		NAICS 518210		
DEP VAR:	LOG(EMP)	LOG(EST)	INDUSTRY PRESENT (0/1)	EMP	EST
	(1)	(2)	(3)	(4)	(5)
SAIDI	-0.005***	-0.003***	-0.023***	-0.034*	0.005
	(0.001)	(0.001)	(0.007)	(0.019)	(0.007)
N	30,157	30,157	30,157	12,002	12,002
R2	0.998	0.999	0.034		
PSEUDO R2				0.964	0.923
ESTIMATION	OLS	OLS	OLS	POISSON	POISSON
YEAR FE	X	X	X	X	X
COUNTY FE	X	X		X	X

This table reports coefficient estimates from panel regressions. EMP denotes employment. EST denotes establishment count. 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 hosting infrastructure, web hosting, streaming, application hosting, data processing, and automated data entry 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. Standard errors are clustered at the firm headquarter 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 logs 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

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

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

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

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

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

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.

□

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

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

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

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

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

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

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

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

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 $\kappa \leq 1 \Rightarrow \ln \kappa \leq 0$, 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

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

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

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

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

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

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, $RP_{i,t} = -\,\mathrm{Cov}_t(M_{t+1}, D_{i,t+1})/P_{i,t}$ 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.

OA.6.1 Market set-up

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).[10]

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.

OA.6.2 Optimal electricity demand

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 $\mathcal{L} = P_Y A F(K, L, E^D) - rK - wL - p_E(E^D)E^D + \lambda(\bar{E} - E^D)$. 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 $\lambda = P_Y\, A\, \partial F/\partial E\big|_{\bar{E}} - c$.

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

OA.6.3 Equivalence to quantity-rationing baseline

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.

[10] 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.

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

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

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, $\partial \operatorname{Var}[\Delta \log C]/\partial \kappa$ 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 $\bar{C} \equiv \mathbb{E}[C_t]$:

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

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 Uri Storm Timeline

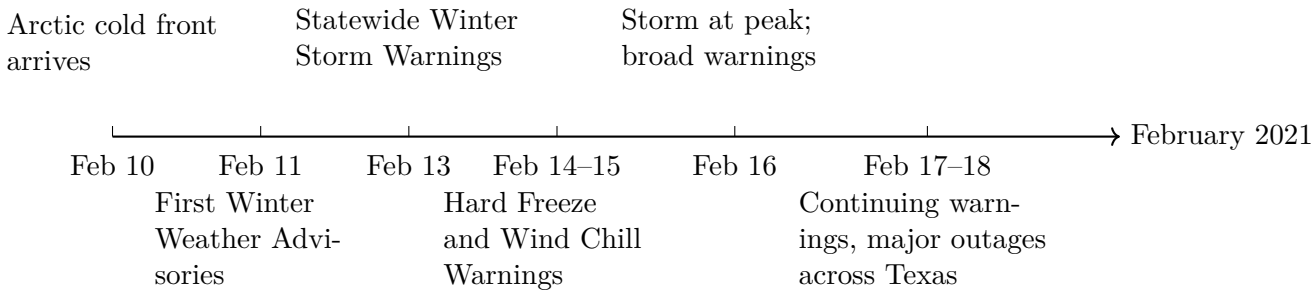


Figure 6: Warning timeline for Winter Storm Uri, February 2021