When Artificial Intelligence comes to Town: Crowding-Out Effect of Data Centers through Electricity Markets

Undergraduate Senior Essay Prospectus

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1 Problem Statement

The promised benefits of artificial intelligence (AI) have led to a rapid surge of private and public investment in the past decade. A growing body of literature is investigating how advances in AI will reshape productivity growth, innovation, and the broader macroeconomy. However, the ramifications of diverting input resources toward AI development have been comparatively understudied. This paper will examine the economic impact of AI-driven data center development through electricity markets. I hypothesize that the rapid introduction of data centers will place intense demand pressure on regional electricity markets, crowding out local household consumption and energy-intensive industrial activity. I will capture these general equilibrium dynamics through a multi-region dynamic general equilibrium (DGE) framework featuring an AI-technology sector and electricity markets, estimating both the regional and aggregate national effects of the AI data center race on firms and households. I further intend to conduct counterfactual analyses under alternative scenarios of AI development and regional grid constraints.

2 Introduction

2.1 Background

In November of 2022, the field of AI leapt into the public and commercial spotlight with the release of OpenAI's ChatGPT. Though AI technology had been steadily gaining prominence since the 1950s, the potential of generative AI caught the attention of firms and investors, who have since poured hundreds of billions of dollars into AI development. According to private-sector estimates, AI-related spending has recently played a disproportionately large role in sustaining U.S. aggregate output, with one widely cited estimate placing its contribution at approximately 40% of recent real GDP growth.[1]

Such colossal spending on AI reflects strong investor confidence in the technology's potential contribution to future economic growth, yet emerging qualitative evidence suggests that this sector-specific investment is straining the rest of the real economy. The computational demands of training new AI models and running existing ones at scale are enormous, fueling a race among firms to build computing infrastructure across the nation and thereby secure a competitive edge. From Santa Clara County to Ashburn, Virginia, newly constructed data centers are reportedly driving soaring demand for electricity and water, raising utility costs for nearby residential communities and firms.[2] Households living near data centers are also reporting quality of life issues related to environmental, noise, and light pollution.[3] While the economic consequences of data centers through water and pollution channels warrant careful analysis in their own right, this essay will focus specifically on the electricity channel. Given the AI sector's rising economic footprint and early empirical accounts of data center-associated electricity price hikes, the study of the sector's potential spillover effects through electricity markets is an area of macroeconomic salience and policy relevance.

[1]The estimate comes from research firm Pantheon Economics, which found that AI-related spending accounted for a 0.5 percentage point difference in annualized GDP growth for the first half of 2025.

[2]A Bloomberg investigation in September 2025 found that wholesale electricity prices in areas near data centers have risen by as much as 267% over the past five years.

[3]Kay Richards provided an illustrative account in Business Insider on her experience living near a data center in Northern Virginia.

2.2 Relevant Literature

The growing body of literature on AI can generally be classified into three broad categories. The first branch of the literature is concerned with how AI may affect micro-level productivity and automation. Acemoglu and Restrepo (2018a) introduce a task-based framework in which automation reshapes labor demand through two counteracting forces: a displacement effect that reduces labor demand and wages in automated tasks, and a productivity effect that raises labor demand in the remaining, non-automated tasks. Empirical analysis investigating the displacement effects of AI suggests early signs of falling labor demand in occupations with tasks most exposed to the technology (Eloundou et al. 2024; Brynjolfsson et al. 2025; Hui et al. 2024), while randomized and quasi-experimental designs have revealed AI-driven productivity gains in specific environments (Brynjolfsson et al. 2023; Noy & Zhang 2023; Peng et al. 2023; Dell'Acqua 2023).

The second branch of the literature studies the role that AI is playing in reshaping the frontier of micro-level knowledge production. Cockburn et al. (2018) conceptualize AI as a general-purpose "method of invention" that can transform the process of innovation, while emerging empirical work documents how AI adoption complements product innovation and restructures the R&D process at the firm level (Babina et al. 2024; Arenas Díaz et al. 2025; Dell'Acqua et al. 2025). These findings remain preliminary, reflecting the early stage of AI diffusion in commercial innovation and the limited availability of comprehensive data.

The final branch of the literature seeks to aggregate the micro-level effects of AI to characterize the implications for long-run growth and structural macroeconomic change. Acemoglu and Restrepo both build on their task-based framework in a macro context, deriving insights on changes to total factor productivity, wage inequality, and factor income shares (Acemoglu & Restrepo 2018b, 2021; Acemoglu 2024, Restrepo 2025). Meanwhile, Aghion et al. (2017) incorporate both AI-driven productivity and idea production into its growth model, exploring conditions under which AI can generate explosive growth and the bottlenecks that would prevent such singularities.

By studying the crowding-out effects of AI that arise through its reallocation of constrained input resources, this paper introduces a line of inquiry that lies outside the three general branches of the existing AI economic literature. I will build on prior literature examining how systemically resource-hungry sectors shape macroeconomic outcomes. The government is the canonical sector of study within this crowding-out literature, with seminal work showing how public spending can crowd out private consumption and investment (Barro 1981; Baxter & King 1993; Aschauer 1989; Barro 1990; Donaldson & Hornbeck 2016; Ramey & Zubairy 2014; Galí et al. 2007; Ramey 2011; Leeper et al. 2012). Analogous mechanisms have been studied in the private sector, including the Dutch-disease models in which booming non-tradable industries crowd out tradable production (Corden & Neary 1982; Corden 1984; van Wijnbergen 1984; Sachs and Warner 2001) and the extensive DSGE literature showing how housing-market fluctuations propagate through collateral and wealth channels to influence aggregate activity (Kiyotaki & Moore 1997; Iacoviello 2005; Davis & Heathcote 2005; Iacoviello & Neri 2010).

While these models in the literature have demonstrated strong explanatory power, they are largely tailored to the idiosyncrasies of their respective sectors. To capture the microstructure of regional electricity markets, my DGE framework will build on canonical electricity market GE models (Borenstein et al. 2000; Joskow & Tirole 2000). I will also draw from prior work modeling energy as a final good for households and an intermediate input in production (Millard 2011; Amin & Marsiliani 2015). To my knowledge, no canonical approach currently exists for modeling an AI-technology sector within a DGE environment. I therefore will propose a novel method for embedding such a sector in the following section.

3 Methodology

I will adopt a three-stage approach that combines reduced-form empirical analysis with a structural multi-region DGE framework. In the first stage, I will conduct econometric analysis to document the causal impact of data center expansion on regional electricity prices, household consumption, and firm activity. In the second stage, I will build a multi-region DGE model featuring an AI-technology sector and regional electricity markets calibrated to the causal mechanisms identified in the reduced-form analysis. In the final stage, I will use the DGE model to conduct counterfactual simulations under alternative scenarios of AI development and regional electricity constraints.

3.1 Reduced-Form Empirical Analysis

I propose the following causal pathway as a framework for guiding my reduced-form analysis. In geographic region j at time t,

$$\begin{aligned}
\text{data center energy demand}_{jt} &\overset{\text{(A)}}{\Rightarrow} \text{wholesale electricity prices}_{jt} \\
&\overset{\text{(B)}}{\Rightarrow} \text{retail electricity prices}_{jt} \\
&\overset{\text{(C)}}{\Rightarrow} \begin{cases} \text{household responses}_{jt} \\ \text{firm responses}_{jt}, \end{cases}
\end{aligned}$$

where (A) represents the effect of regional data center load on wholesale prices paid by load serving entities (LSEs) such as utility companies, (B) the pass-through to retail rates paid by end-users, and (C) the economic responses of households and firms. I will walk through the regressions I intend to employ for each causal link.

3.1.1 (A) Data Center Demand Loads to Wholesale Prices

The electric grid can be conceptualized as a mosaic of separate regional markets linking energy users and generators. To reflect the value of electricity at different locations, the markets employ locational marginal prices (LMPs) that account for the demand load, generation, and the physical constraints of the transmission system at a particular node of the grid. LSEs purchase electricity wholesale from generators at the LMPs corresponding to their particular service area, then setting retail prices for end-users. The introduction of data centers creates large, localized, and inelastic demand shocks at specific locations in the grid, as the compute infrastructure housed in data centers requires a consistent source of electricity 24/7. Because the short-run elasticity of generation and transmission capacity is limited, the data center demand shocks should raise nearby LMPs. To measure this dynamic, I will employ a standard panel regression of the form

$$\mathrm{LMP}_{jt} = \beta_A \cdot D_{jt} + \alpha_j + \gamma_t + X_{jt}\delta + \varepsilon_{jt}, \tag{1}$$

where D_{jt} is the aggregate data center power demand load in region j, LMP_{jt} is the real-time wholesale prices of grid nodes averaged over region j and year t, and coefficient β_A captures the average effect of data center demand on wholesale prices. Across different specifications, j will be set at the county, utility service area, and state level to measure the geographic reach of crowding-out effects. Regional fixed effects α_j control for geography and baseline grid conditions, and year fixed effects γ_t absorb common nationwide shocks such as fuel prices, macro trends, and climate change. I will also control for regional-specific weather pattern changes and generation capacity expansions, as captured by the term X_{jt}.

For robustness, I will also estimate an alternative panel regression of the form

$$\mathrm{LMP}_{rit} = \beta_{A'}(r) \cdot D_{it} + \alpha_i + \gamma_t + \varepsilon_{it}, \tag{2}$$

where D_{it} is the power demand of an individual data center i at year t, and LMP_{rit} is the real-time average wholesale price of grid nodes over year t within an r-mile radius of data center i. By mapping the relationship between β'_A and r, I can recover a higher-resolution measure of the spatial extent of crowding-out effects. While the demand load of data centers may vary over time in reality, I will treat the demand load of data center i as $D_{it} = 0$ before its documented or estimated year of operation and $D_{it} = \bar{D}_i$ afterwards due to lack of such data.

Owing to data limitations on data centers, the pooled regressions described above can be implemented only at an annual frequency. To capture the effect of data center demand loads on wholesale prices with greater precision, I will exploit the public timelines of several high-profile AI data centers and employ an event-study specification. Denoting T_i as the operational month of data center i, my event-study regression takes the form

$$\mathrm{LMP}_{jt} = \sum_{\tau \neq -1} \beta_\tau \cdot \mathbb{1}\{\tau = t - T_i\} \cdot \bar{D}_i + \alpha_i + \gamma_t + \varepsilon_{it}, \tag{3}$$

where $\bar{D}_i$ is the constant operational demand load of data center i, and coefficient β_τ measures the average effect of data center i at time τ. As with regression (1), I estimate this regression under alternative definitions of the spatial unit j to assess the geographic reach of the results.

3.1.2 (B) Wholesale Prices to Retail Prices

Wholesale electricity price changes are passed through to retail prices faced by end-users, but the extent and speed of this pass-through depend on specific regulatory regimes that vary by state. In a regulated market, LSEs pass wholesale costs to retail customers gradually through a review and approval process by a public utility commission, while in a deregulated market, wholesale price fluctuations are more directly and often immediately reflected in retail utility bills. As an additional layer of complexity, attempts to isolate the causal effect of wholesale on retail prices are confounded by common shocks that affect both price types. For instance, extreme weather events can dramatically increase electricity demand for heating and cooling, driving up LMPs in the area. Simultaneously, such events can increase the transmission and distribution costs for LSEs due to outages or infrastructure damage, thereby affecting retail rates.

To address the issue of endogeneity between wholesale and retail prices, I will use data center demand load D_{jt} as an instrument. Large, inelastic data center demand shocks should raise local LMP prices by increasing marginal electricity generation and congestion costs as established in (1), yet such idiosyncratic changes to local demand are plausibly orthogonal to the environmental, political, and business-related factors that shape retail price-setting (more on this in 3.1.3). I will employ the following 2SLS setup:

$$\text{LMP}_{jt} = \beta_A \cdot D_{jt} + \alpha_j + \gamma_t + X_{jt}\delta + \varepsilon_{jt}, \tag{1}$$

$$p_{jt} = \beta_B \cdot \widehat{\text{LMP}}_{jt} + \alpha_j + \gamma_t + X_{jt}\theta + u_{jt}, \tag{4}$$

where p_{jt} is the average retail price over region j and time t, and $\widehat{\text{LMP}}_{jt}$ is the fitted value from the first stage driven only by exogenous variation in data center demand load. I can then interpret β_B as the causal pass-through effect from wholesale prices to retail rates for the component of wholesale variation driven by data centers. Due to data limitations, I will set j at the utility service area-level and t at the annual level.

As mentioned earlier, the regulatory regime of a utility service area may have a significant role in determining the pass-through effect from wholesale to retail prices. I will thus also employ an additional second-stage specification. Let R_j be an indicator equal to 1 if utility service area j operates under a deregulated (also called restructured) regulatory regime and 0 otherwise. My alternative second-stage specification becomes:

$$p_{jt} = \beta_{B0} \cdot \widehat{\text{LMP}}_{jt} + \beta_{B1} \cdot (\widehat{\text{LMP}}_{jt} \times R_j) + \alpha_j + \gamma_t + X_{jt}\theta + u_{jt}, \tag{5}$$

where β_{B0} can be interpreted as the causal pass-through effect under regulated regimes and $\beta_{B0} + \beta_{B1}$ as the effect in deregulated regimes.

3.1.3 (C) Retail Prices to Local Economic Responses

Finally, I would like to measure the causal effects of retail electricity prices on household and firm responses. Salient household variables include electricity use, spending, and debt burden, while relevant firm variables include electricity use, output, and employment. Retail electricity prices are, however, jointly determined with these local economic outcomes. Regions with growth in business activity, income, or population will exhibit positive economic response trends while demanding more electricity, thereby raising retail prices. Conversely, declining regions may exhibit negative response trends and weakening load demand. As a result, retail prices are endogenous to the economic outcomes I seek to study.

I will again use data center demand load D_{jt} as an instrument to address the endogeneity between retail electricity prices and local economic outcomes, employing the following 2SLS setup:

$$p_{jt} = \lambda \cdot D_{jt} + \alpha_j + \gamma_t + X_{jt}\psi + \omega_{jt} \tag{6}$$

$$y_{jt} = \beta_C \cdot \widehat{p}_{jt} + \alpha_j + \gamma_t + X_{jt}\mu + \nu_{jt} \tag{7}$$

where y_{jt} is the local economic outcome variable at utility service area j and year t and $\widehat{p}_{jt}$ is the fitted retail price driven by variation in data center demand load, which I interpret as operating through the wholesale price channel under the pass-through mechanism established in the previous section. Coefficient β_C can thus be interpreted as the average effect of data center-driven retail price shocks on local economic outcomes.

The validity of this IV design hinges on two conditions. Data center demand shocks must demonstrate relevance with respect to retail prices, a condition that depends on the strength of wholesale-retail pass-through as measured in the previous section. The condition whose validity is perhaps less obvious is the exclusion restriction: conditional on fixed effects and observed controls, data center demand shocks must only affect local economic outcomes through the electricity market channel. I recognize two plausible counterarguments to the validity of the exclusion restriction. The first is the presence of simultaneity: local economic outcomes may in turn shape the data center location decisions made by the AI-technology sector. However, data centers do not derive any advantage from proximity to growing economic centers and are instead documented to prioritize areas with reliable energy access, available land, and favorable tax incentives. I will assess this simultaneity concern using the following pre-trends test:

$$\Delta D_{jt} = \gamma \bar{g}_{jt5} + \alpha_j + \gamma_t + \varepsilon_{jt}, \tag{8}$$

where ΔD_{jt} is the change in data center demand load in year t, and $\bar{g}_{jt5}$ is the average GDP growth of state j over the previous five years (not including year t). If $\gamma = 0$, then past regional economic growth does not systematically predict future data center expansion once I control for state and time fixed effects. While this test cannot establish the exclusion restriction directly, the lack of differential pre-trends in regional economic conditions prior to data center entry substantially weakens the concern of simultaneity. Such a finding would also reduce the plausibility of a confounding variable channel in link (B), through which local economic outcomes could influence both retail electricity prices and data center expansion.

The second potential threat to the exclusion restriction is that data center expansion may generate direct economic spillovers into the local economy independently of electricity prices. Although data centers are highly capital-intensive, the compute facilities typically employ very few workers and rely minimally on local supply chains.[4] Labor-intensive construction activity may last a few years but is undertaken by specialized contractors who serve multiple regions, which makes persistent effects on local economic outcomes unlikely. However, I will take caution in interpreting the regression results in the 2SLS, noting that β_C may be biased by non-electricity channels.

Using the causal effects I have measured (β_A, β_B, β_C) across each link of the proposed causal pathway, I will build and calibrate a DGE model that reflects the mechanisms shown through reduced-form analysis.

[4]Synergy chief analyst John Dinsdale notes in the WSJ that data centers may employ more than a thousand workers for construction but rarely require more than one to two hundred employees for post-construction operation.

3.2 The Model

3.2.1 Baseline Model Setup

I will develop a baseline DGE model that offers a structural framework explaining the crowding-out effect of data center expansion through regional electricity markets. The baseline model will assume fixed electricity generation capacity and no AI-driven contribution to productivity, thereby capturing short-run crowding-out effects. The exact specifications of this model are subject to change based on my reduced-form analysis, but I intend to adhere to the following structure to balance explanatory power and tractability.

The model will follow a two-region economy $j \in \{0, 1\}$, identical in all respects except that region $j = 1$ is capable of hosting data center facilities. Each region will contain a representative household that maximizes CES utility over non-energy consumption C_{jt}, residential electricity use E^H_{jt} (expressed in units of energy), and leisure $1 - L_{it}$. Following Amin & Marsiliani (2015), household preferences are given by

$$U_j = \sum_{t=0}^{\infty} \beta^t u_{jt} \tag{H1}$$

$$u_{jt} = \phi \ln \left[\theta (C_{jt})^{\frac{\sigma_H - 1}{\sigma_H}} + (1-\theta)(E^H_{jt})^{\frac{\sigma_H - 1}{\sigma_H}} \right]^{\frac{\sigma_H}{\sigma_H - 1}} + (1-\phi) \ln (1 - L_{jt}), \tag{H2}$$

where the elasticity of substitution between C_{jt} and E^H_{jt}, σ_H, will be calibrated to match the estimated reduced-form household electricity demand elasticity.

Each region will also feature two competitive sectors $\mathcal{S}$ producing a single national final good: an energy-intensive industrial sector I and non-energy-intensive commercial sector C. Following earlier neoclassical growth literature that incorporates energy (Millard 2011; Schreiner & Madlener 2022), both sectors will operate a Cobb-Douglas production technology with electricity $E^{\mathcal{S}}_{jt}$ as a third input factor:

$$Y^{\mathcal{S}}_{jt} = A_t (K^{\mathcal{S}}_{jt})^{\alpha_{\mathcal{S}}} (L^{\mathcal{S}}_{jt})^{\beta_{\mathcal{S}}} (E^{\mathcal{S}}_{jt})^{\sigma_{\mathcal{S}}}, \tag{$\mathcal{S}$P}$$

where sectoral heterogeneity arises solely from differences in factor intensities rather than from technology shocks, placing the focus solely on the electricity channel. For simplicity under the baseline model, TFP A_t is consistent nationally and follows an exogenous growth trend at constant rate g.

Total output in the region j is given by $Y_{jt} = Y_{jt}^I + Y_{jt}^C$. A single national final good aggregates regional outputs in the linear form $Y_t = \omega_0 Y_{0t} + \omega_1 Y_{1t}$, where $\omega_0 + \omega_1 = 1$. The price of this national final good is normalized to one. The national resource constraint equates aggregated national output to the sum of regional household consumption, capital investment, and electricity generation costs:

$$Y_t = \sum_j [C_{jt} + I_{jt} + C_j(E_{jt})], \tag{RC}$$

where $C_j(E_{jt})$ captures the regional cost of generating electricity E_{jt}.

To prevent commercial and industrial activity from immediately re-allocating across regions, I will use a capital law of motion with a standard quadratic adjustment cost consistent with the framework established by Lucas & Prescott (1971):

$$K_{j,t+1} = (1-\delta)K_{jt} + I_{jt} - \frac{\psi}{2}\left(\frac{I_{jt}}{K_{jt}} - \delta\right)^2 K_{jt}, \tag{LOM}$$

where deviations of the investment rate I_{jt}/K_{jt} from the depreciation rate δ are costly, thereby smoothing investment dynamics.

Following Borenstein & Holland (2005), electricity in each region will be produced competitively by a representative generator with a quadratic cost function

$$C_j(E_{jt}) = \frac{a_{jt}}{2} E_{jt}^2, \tag{EC}$$

where a_j is the slope of the marginal cost curve $C_j'(E_{jt}) = a_j E_{jt}$ and can be interpreted as the capacity constraint in region j. In the short-run baseline model with fixed generation capacity, I will fix $a_{jt} = \bar{a}$ and calibrate the parameter using the reduced-form estimate of β_A. Because the LMP or wholesale price is equal to the marginal cost of the marginal generator under competitive electricity markets, it follows that

$$\text{LMP}_{jt} = a_j E_{jt}, \tag{WP}$$

Abstracting away the LSE profit maximization problem and regulatory regimes, retail electricity prices will follow a static pass-through rule

$$p_{jt} = \bar{p} + \varphi \cdot \text{LMP}_{jt}, \tag{RP}$$

where $\bar{p}$ captures the components of the retail cost that do not vary with wholesale prices, and φ governs the pass-through rate that I estimate with β_B.

I will include a simple AI-technology section in the baseline model. In region $j = 1$, electricity use by data centers E_t^{DC} will be determined exogenously. To model the short-run effects of AI, the AI-technology sector is purely a demand-side consumer of electricity and does not contribute to TFP. The regional electricity market clearing condition can then be specified as

$$E_{jt} = E_{jt}^H + E_{jt}^I + E_{jt}^C + \mathbb{1}\{j = 1\} \cdot E_t^{DC} \tag{EMC}$$

A competitive equilibrium for this baseline two-region economy will consist of household decisions, firm input allocations, and electricity quantities and prices such that all optimality conditions and market-clearing constraints are satisfied for a regional data center demand load E_t^{DC}. Because TFP A_t grows at constant rate g, all real economic variables such as consumption, output, electricity use, and capital should grow proportionally along a balanced growth path. Once detrending variables with A_t to find the equilibrium expressed in terms of a steady state, I will conduct comparative static analysis of data center demand shocks to isolate how exogenous changes in electricity demand from the AI-technology sector propagate through regional electricity prices, factor allocation, final good production, and household outcomes.

3.2.2 Potential Model Extensions

Dependent on feasibility, I will consider three potential extensions to the baseline model M0 that may yield greater insight into the long-run consequences of data center crowd-out. In the first proposed extension M1, I would allow data center computing power to contribute to national TFP with possible asymmetries between industrial and commercial productivity. While the long-run impact of AI is still an area of speculation, it would be interesting to examine what type and magnitude of AI-driven contribution would negate crowding-out effects in the long-run.

In the second proposed extension M2, I will construct a richer electric grid sector with an endogenous ability to relax generation constraints. In the real world, the main bottleneck to grid improvement is the lack of adequate transmission capacity. Private-sector development in power generation facilities is currently constrained by the amount of electrical power that current electric grids can reliably carry, a feature governed by the transmission-capacity constraints, interconnection procedures, and market-clearing rules administered by RTO/ISOs operating under FERC regulation.[5] In this model extension, I would allow the national final good to be invested by regional RTO/ISOs to lower the grid capacity constraint a_j. By solving the social planner problem to obtain the optimal grid investment rule, I can use this extension to draw qualitative insights on the extent to which grid development can ease crowding-out effects in the long-run.

In the final proposed extension M3, I will endogenize data center location decisions by the AI-technology sector. The extended model will house J regions with $N < J$ regions

[5]RTO: Regional Transmission Organization; ISO: Independent System Operator; FERC: Federal Energy Regulatory Commission; Both RTOs and ISOs are independent, non-profit organizations that manage transmission grids in the U.S. with minor differences in service pricing.

that are viable for data center construction, a model simplification for land availability and tax incentive differences in the real world. A representative AI-technology firm would select regions for data center development, facing new construction costs that exceed the renewal costs of existing facilities. This model extension can illustrate where long-run data center development and crowding-out effects will occur as electricity prices shift with demand loads.

3.3 Counterfactual Simulation

3.3.1 Alternative Scenarios of AI Development

Leveraging current forecasts on the future data center power demand, I will construct four alternative scenarios that map to the exogenous data center energy demand E_t^{DC} in the baseline model M0 and AI-productivity extension M1. The scenarios are as follows:

- **Continued Growth Scenario:** a benchmark trajectory in which E_t^{DC} grows at current industry-consensus forecasts, reflecting steady improvements in model scale and deployment consistent with present trends.

- **Bubble Scenario:** E_t^{DC} grows at current industry-consensus forecasts for the next several years but is driven by speculative overbuilding, followed by a sharp contraction once industry promises of AI are unrealized and investment boom unwinds.

- **Efficient Compute Scenario:** E_t^{DC} grows at current industry-consensus forecasts for the next several years but then gradually flattens, induced by rapid gains in model- and chip-level energy efficiency.

- **Explosive Compute Scenario:** E_t^{DC} accelerates beyond current forecasts due to breakthroughs in model scaling, autonomous agents, and user demand.

An assessment of regional and national economic responses to the following scenarios can shed useful insights into how macroeconomic development will be shaped by the AI-technology sector.

3.3.2 Alternative Scenarios of Regional Grid Constraints

Applying the model extension M2 with an enriched grid sector, I will use alternative projections of future transmission expansion to evaluate the extent to which grid development can mitigate data center crowding-out effects. The results from these counterfactual simulations may shed light into the necessity for RTO/ISOs to embark on immediate wide-scale grid improvements as immense data center demand loads come online in the next several years.

4 Concluding Notes

While this proposal is ambitious for an undergraduate essay, I hope that my work can speak to broader economic dynamics of how resource-hungry industries reshape the economy and growth paths of nations. The framework I aim to develop for AI could potentially be generalized to other emerging, energy-intensive industries (e.g., semiconductor fabrication, battery manufacturing, de-carbonization initiatives), providing lasting analytical value. Given the limited timeframe in which I have to finish this paper (April 2026), I may have to exclude some of the proposed model extensions (discussed in 3.2.2) in the final version. Dependent on the insights revealed by the reduced-form empirical analysis and baseline structural model, I intend to pursue subsequent research that enriches the model environment to capture further institutional and economic features.

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