Estimating regulatory distortions of natural gas pipeline investment incentives

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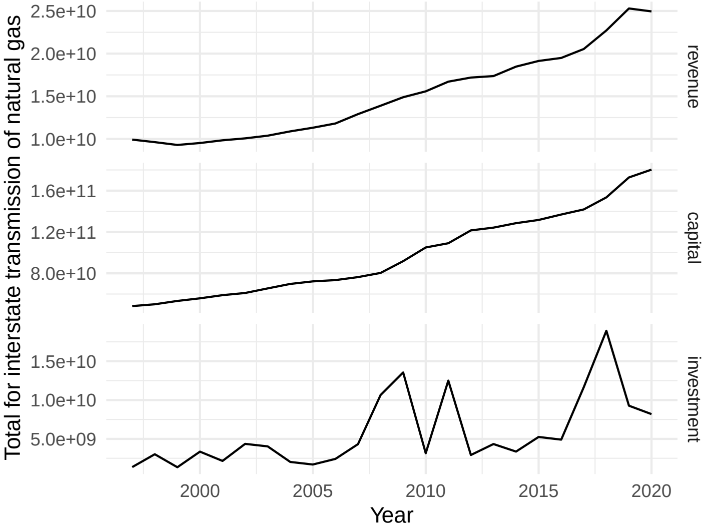
Introduction

- Interstate natural gas pipelines in US
  - Regulated price of transmission set by rate-of-return
  - Investment must be approved by regulator (FERC)
- How do the investment incentives faced by pipelines compare to the marginal value of investment?
- Estimate pipelines' perceived marginal value of investment from Euler equations
- Use differences in prices between trading hubs on pipeline network to measure marginal social value of investment

Natural gas is large and growing



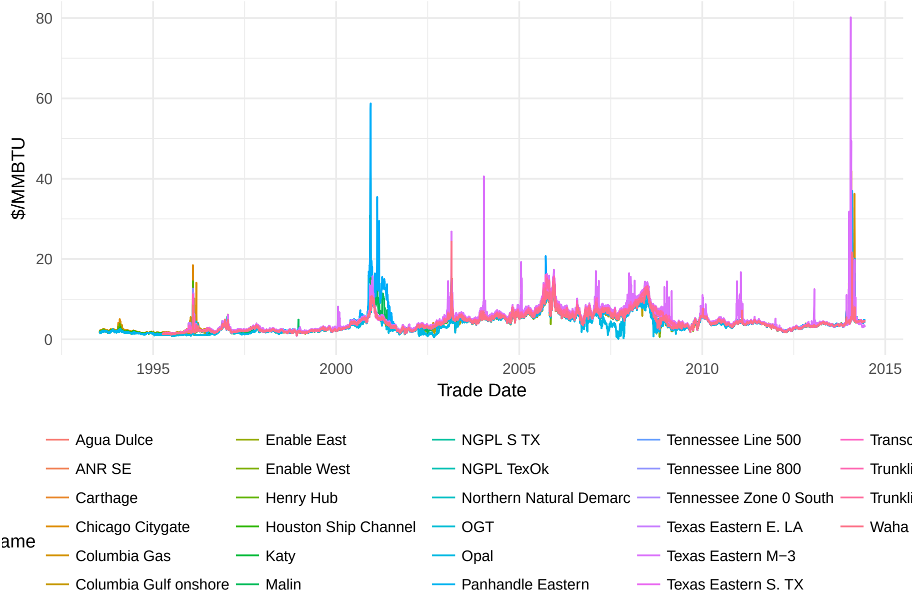
Suggestive evidence of over-investment

- Rate-of-return regulation – Averch-Johnson effect
  - Pipeline owners can raise their prices by increasing capital costs
- Rate of return allowed by FERC is high
  - von Hirschhausen (2008) : regulated rates of return average 11.6% for projects between 1996 and 2003
- FERC approves nearly all pipeline expansion projects – only two rejected application between 1996 and 2016
- Some empirical evidence supporting overcapitalization (Oliver, Mason, and Finnoff, 2014; Hausman and Muehlenbachs, 2019)

Suggestive evidence of under-investment

- Prices of natural gas at different locations sometime diverge
  - Cuddington and Wang (2006), Marmer, Shapiro, and MacAvoy (2007), Brown and Yücel (2008), Park, Mjelde, and Bessler (2008)
- Gas marketers, not pipeline owners, earn profits from arbitrage

Daily natural gas prices



Contributions

- Construct a detailed pipeline dataset from FERC and EIA filings
- Estimate pipelines' investment costs (including regulatory costs) from Euler Equations
  - Nonparametrically identified
  - Simple to estimate
  - Key assumption : information set of pipeline is observed or estimable
- Examine relationship between investment cost and pipeline network bottlenecks
- Areas of pipeline congestion have:
  - Lower regulatory marginal investment cost
  - Lower expected marginal product of capital

Natural gas from production to consumption

1. Production at well-head
2. Gas purchased at well-head by marketer
3. Marketer pays pipeline to transport gas
4. Gas sold to :
   - Other marketer at hub
   - Local distribution company
   - Power plant or large industrial user
5. Local distribution company delivers gas to industrial and residential consumers

Contracts between pipelines and marketers

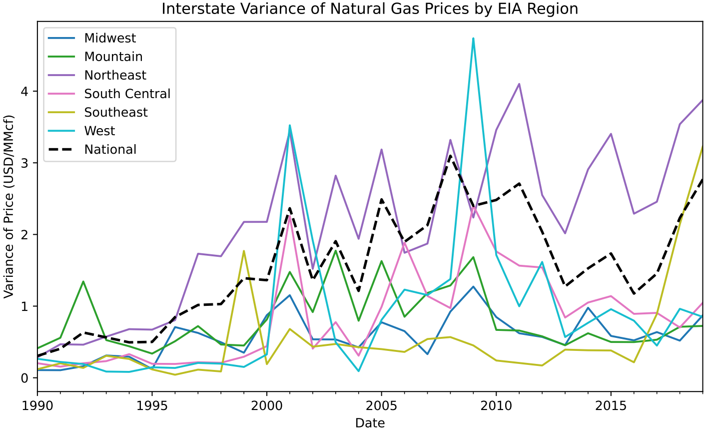
- Long term (average 9.1 years) contracts for firm transportation service
  - Guaranteed right to transport a specified volume of gas along a pipeline per day
  - Large reservation charge
    - Set by FERC using rate of return to cover capital costs
  - Small additional charge per unit used
    - Set by FERC to cover marginal operating cost
- Unused capacity sold as interruptible transportation service
  - Price $\leq$ reservation $+$ utilization price of FTS
  - Open access short term auctions through online bulletin boards

Building or expanding a pipeline

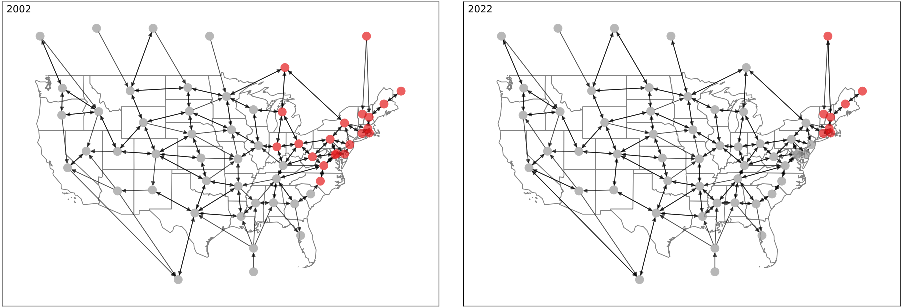
1. Obtain binding agreements from gas marketers to purchase 5-10 year FTS contracts for 80+% of planned capacity
2. File application with FERC
3. Public hearings, environmental assesments, etc
4. FERC approves 99% of applications

- Takes 1-3 years for new pipelines, much less for smaller projects
- Decommissioning and sales also need to be approved
- Streamlined for small projects
  - Automatic (<$11,400,000) notify landowners 45 days in advance
  - Prior notice (<$32,400,000) file plan with FERC, automatically approved after 60 days if no objection

Pipeline network has failed to integrate regional markets



Northeast is the primary physical bottleneck



Investment model

- Pipeline j choosing investment at time t
- Bellman equation:

$$V(k_t, s_t) = \max_{i_t} \pi(k_t, s_t) - c(i_t, k_t, s_t) + \beta \, \mathrm{E}\left[V(k_t + i_t, s_{t+1}) \mid s_t, k_t + i_t\right]$$
$$\text{s.t. } R(i_t, k_t, s_t) \leq 0.$$

Gross operating profit

Investment cost

Expectation over future state, given current state and capital

Regulatory constraint

where

- k_{jt} = capital
- i_{jt} = dollars of investment
- s_{jt} = vector of observed and unobserved variables affecting profits, e.g. k_{-jt}, details of pipeline network, gas prices
- β = discount factor

Investment model: Euler Equation

- Euler equation:

$$\frac{\partial c}{\partial i}(i_t, k_t, s_t) + \lambda_t \frac{\partial R}{\partial i}(i_t, k_t, s_t) = \beta \mathrm{E}\left[\begin{array}{c} \frac{\partial \pi}{\partial k}(k_{t+1}, s_{t+1}) + \frac{\partial c}{\partial i}(i_{t+1}, k_{t+1}, s_{t+1}) + \\ + \lambda_{t+1} \frac{\partial R}{\partial i}(i_{t+1}, k_{t+1}, s_{t+1}) + \\ - \frac{\partial c}{\partial k}(i_{t+1}, k_{t+1}, s_{t+1}) - \lambda_{t+1} \frac{\partial R}{\partial k}(i_{t+1}, k_{t+1}, s_{t+1}) \end{array} \middle| s_t, k_{t+1} \right].$$

- Define $c_r(i, k, s) \equiv c(i, k, s) + \lambda R(i, k, s)$

$$\frac{\partial c_r}{\partial i}(i_t, k_t, s_t) = \beta \mathrm{E}\left[\begin{array}{c} \frac{\partial \pi}{\partial k}(k_{t+1}, s_{t+1}) + \frac{\partial c_r}{\partial i}(i_{t+1}, k_{t+1}, s_{t+1}) + \\ - \frac{\partial c_r}{\partial k}(i_{t+1}, k_{t+1}, s_{t+1}) \end{array} \middle| s_t, k_{t+1} \right].$$

Identification of $\frac{\partial c_r}{\partial i}$

- s_t, k_{t+1} observed, so $\mathrm{E}[\cdot|k_{it+1}, s_t]$ is identified
  - Substantitive assumption: econometrician observes all information used by firms to form expectations
- Observe $\pi_{jt} = \pi(k_{jt}, x_{jt}) + \epsilon_{jt}$ so

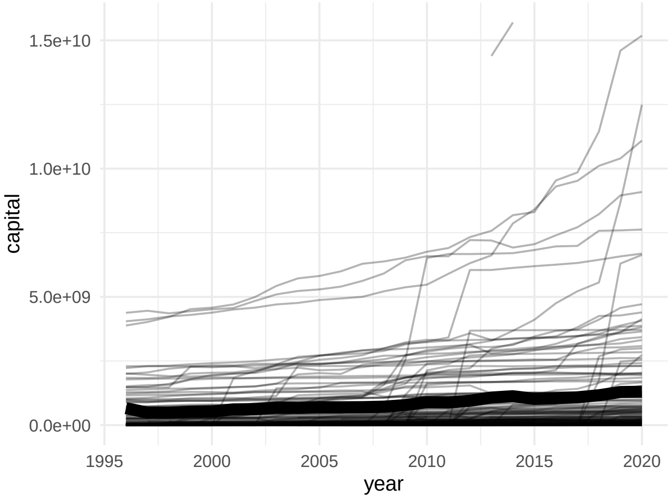
$$\mathrm{E}[\pi_{jt}|k_{jt}, x_{jt}] = \pi(k_{jt}, x_{jt}$$

- Only remaining unknown in Euler equation is marginal cost

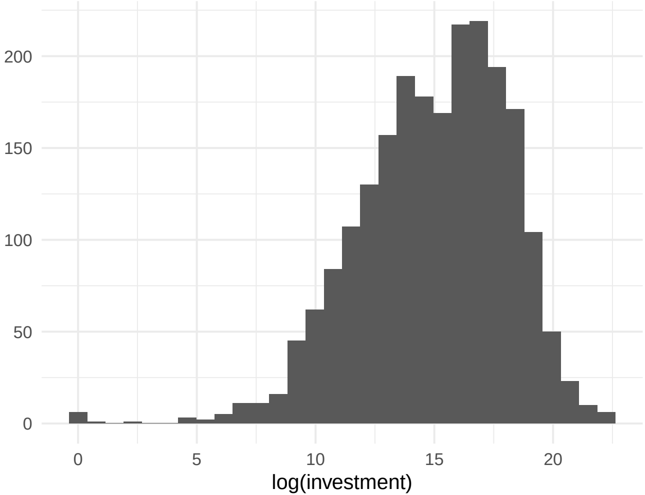
Pipeline data

- FERC Form 2/2a annual data on pipeline companies
  - 1996-2019
  - 96-123 companies each year
  - detailed information about evenue, expenses, capital, transmission volume, etc
  - limited information about pipeline locations and connections
- EIA form 176 has information on each pipelines' mileage and flow within each state and capacities between states
  - 1997-2019
  - merged with FERC data by company name — 3% of pipeline mileage unmatched

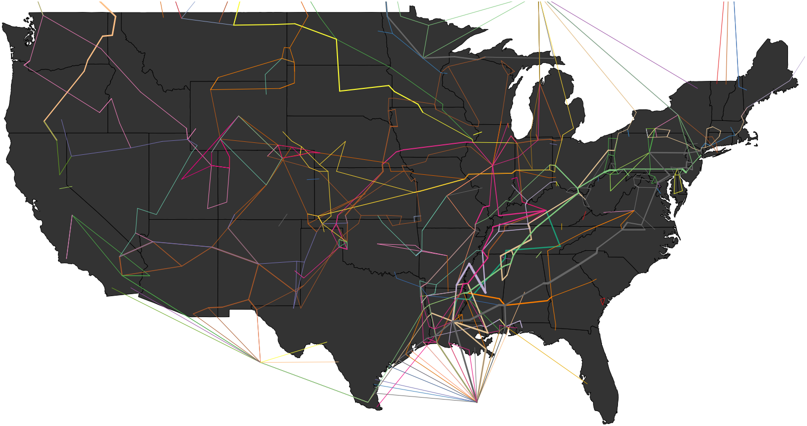
Evolution of capital



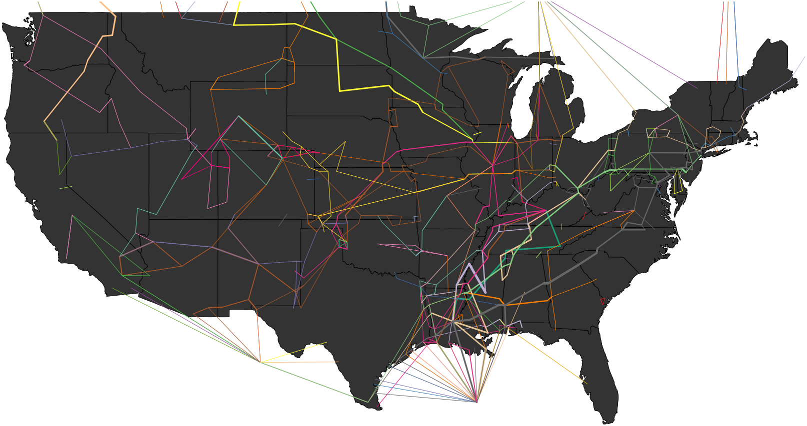
Distribution of investment



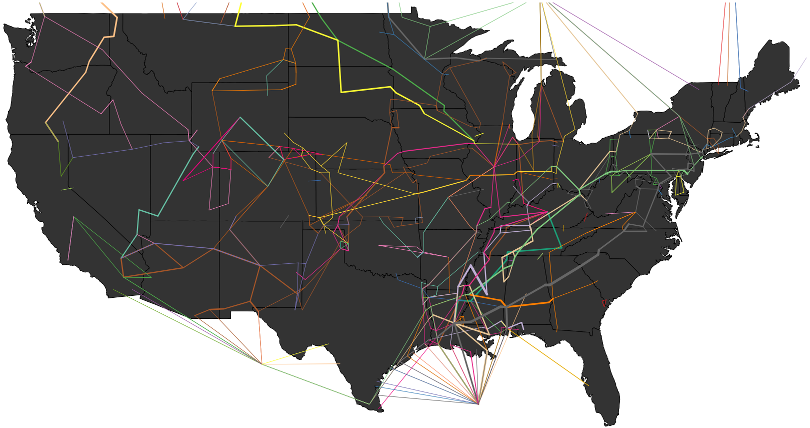
Schematic pipeline network in 1996



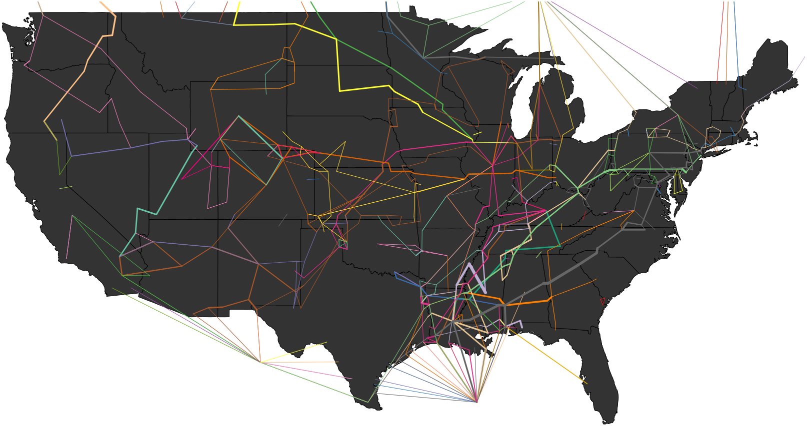
Schematic pipeline network in 2001



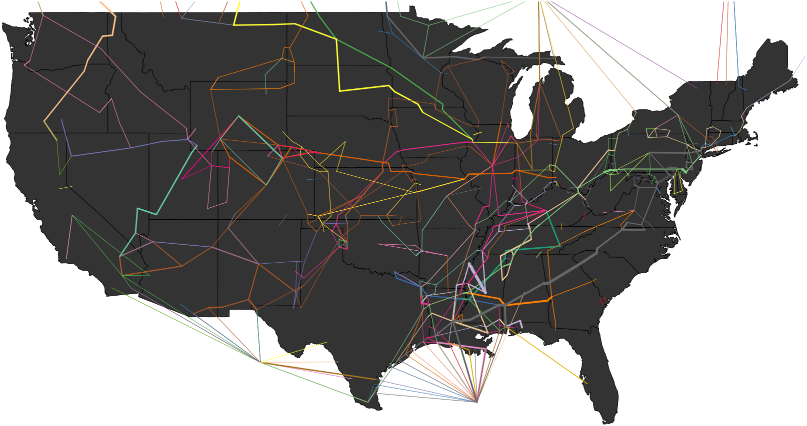
Schematic pipeline network in 2006



Schematic pipeline network in 2011



Schematic pipeline network in 2016



Estimation from Euler equation

- First order condition and envelope theorem, and the boundary condition, give the Euler equation:

$$\frac{\partial c}{\partial i}(i_t, k_t, s_t) - \beta \operatorname{E}\left[\frac{\partial c}{\partial i}(i_{t+1}, k_{t+1}, s_{t+1}) \,\middle|\, s_t, k_{t+1}\right] = \beta \operatorname{E}\left[\frac{\partial \pi}{\partial k}(k_{t+1}, s$$

- Estimation procedure:
  1. Estimate $\operatorname{E}[\frac{\partial}{\partial k}\pi_{t+1}|k_{t+1}, s_t]$ using an average derivative estimator based on Auto-DML details

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- Estimation procedure:
  1. Estimate $\mathrm{E}[\frac{\partial}{\partial k}\pi_{t+1} | k_{t+1}, s_t]$ using an average derivative estimator based on Auto-DML details
  2. Estimate $\mathrm{E}\left[\cdot \middle| s_t, k_{t+1}\right]$ with a Reproducing Kernel Hilbert Space (RKHS) embedding
  3. Invert the conditional expectation onto the profit function to estimate $\frac{\partial c}{\partial i}$

Auto-DML problem statement

- The problem of predicting future profits is very high dimensional
- Modern machine learning methods are really good at this type of prediction. Deep learning in particular for dynamic economic problems (Kahou et al. 2025). Especially when paired with regularization.
- Regularization creates bias in the estimator. It fits the profit function better, but would bias our estimates of the derivative $\theta_0 = \mathrm{E}[\frac{\partial}{\partial k}\pi_{t+1}|k_{t+1}, s_t]$.
- Goal, estimate θ_0 in such a way that it is robust to small perturbations of the nuisance parameters (ζ) of the ML estimator
  - Neyman orthogonality: $\partial_\zeta \mathrm{E}\left[\frac{\partial}{\partial k}\hat{\pi}^{\zeta}_{t+1}|k_{t+1}, s_t\right]\big|_\zeta = 0$

Auto-DML for profit estimation

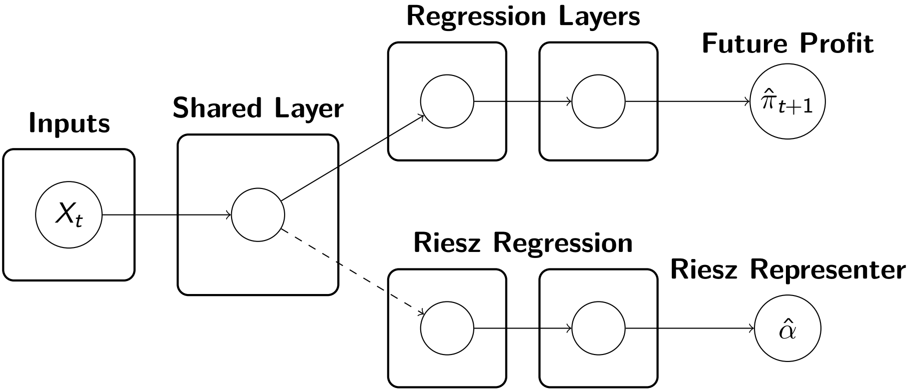

Figure: Graphical description of the Auto-DML architecture used to recover and debias the profit function.

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Auto-DML for profit estimation

- Goal is to estimate
  $\theta_0 = \mathrm{E}[m(k_{t+1}, s_t; \pi(\cdot), k_{t+1}, s_t)] = \mathrm{E}[\frac{\partial}{\partial k}\pi_{t+1}|k_{t+1}, s_t]$

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- First stage: estimate $\hat{\pi} = \arg\min_{\pi} \mathrm{E}[(\pi_{t+1} - \pi_0)^2 \mid k_{t+1}, s_t]$ using deep neural net

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- Use a hidden layer of the deep network as inputs to another deep network to estimate $\hat{\alpha} = \arg\min_{\alpha} \mathrm{E}[(\alpha - \alpha_0)^2 \mid k_{t+1}, s_t]$
  - α_0 is the Riesz representer of the moment function. Exists by linearity of m
  - e.g. a function such that $\mathrm{E}[m(k_{t+1}, s_t, \pi_{t+1}; g(\cdot)) \mid k_{t+1}, s_t] = \mathrm{E}[\alpha_0(k_{t+1}, s_t) g(k_{t+1}, s_t) \mid k_{t+1}, s_t]$
  - substitute the above into the loss function for $\hat{\alpha}$, gives $\hat{\alpha} = \arg\min_{\alpha} \mathrm{E}[\alpha(X)^2 - 2m(W, \alpha)]$, new objective does not depend on α_0.
  - Add some elastic net regularization

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  - Add some elastic net regularization
- Doubly robust estimator $\hat{\theta} = \mathrm{E}[\frac{\partial}{\partial k}\hat{\pi}(k_{t+1}, s_t) + \hat{\alpha}(k_{t+1}, s_t)(\pi_{t+1} - \hat{\pi}(k_{t+1}, s_t)) \mid k_{t+1}, s_t]$
- 5-fold cross-fitting: split data into 5 folds. Repeat: train $\hat{\pi}$ and $\hat{\alpha}$ on

Estimation of regulatory cost

- Suppose that $\frac{\partial c_r}{\partial i} \in \mathcal{H}$, a reproducing kernel Hilbert space
  - with kernel $k : S \times S \to \mathbb{R}$
  - inner product $\langle \cdot, \cdot \rangle$
  - elements of $\mathcal{H}$ are functions from state space S to $\mathbb{R}$
  - $\langle f, k(s, \cdot) \rangle = f(s)$
- Goal is to estimate a Riesz representer $\mu(x, \cdot)$ such that $\mathrm{E}[f(s') \mid s = x] = \langle f, \mu(x, \cdot) \rangle$
- Note that

$$\mathrm{E}\left[\left(f(s') - \langle f, \mu(s, \cdot) \rangle\right)^2\right] = \mathrm{E}\left[\langle f, k(s', \cdot) - \mu(s, \cdot) \rangle^2\right]$$
$$\leq \|f\|^2 \mathrm{E}[\|k(s', \cdot) - \mu(s, \cdot)\|^2].$$

- Estimate μ by solving

$$\min_{\mu} \frac{1}{N(T-1)} \sum_{i=1}^{N} \sum_{t=1}^{T-1} \|k(s_{it+1}, \cdot) - \mu(s_{it}, \cdot)\|^2 + \lambda \|\mu^2\|$$

Estimation of regulatory cost

- The minimizer is

$$\hat{\mu}(s,s') = k(s,\mathbf{s}_t)\,(K+\lambda I)^{-1}\,k(\mathbf{s}_{t+1},s')$$

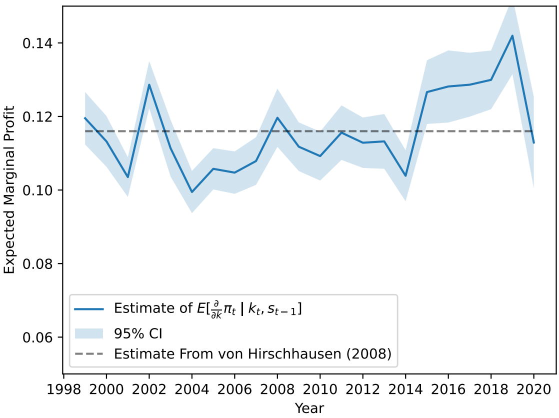
  - K is an $N(T-1)\times N(T-1)$ matrix with entries $k(s_{it},s_{jr})$
  - $k(s,\mathbf{s}_{t+1})$ is a $1\times N(T-1)$ vector with elements $k(s,s_{it+1})$
  - $k(\mathbf{s}_t,s')$ is a $N(T-1)\times 1$ vector with elements $k(s_{it},s')$.
- With this $\hat{\mu}$, the estimate of the conditional expectation is then

$$\begin{aligned}\widehat{\mathrm{E}[f(s')|s]} =& \langle f,\hat{\mu}(s,\cdot)\rangle \\ =& k(s,\mathbf{s}_t)\,(K+\lambda I)^{-1}\,f(\mathbf{s}_{t+1}).\end{aligned}$$

  - Standardize each component of s to have zero mean and unit variance
  - Gaussian kernel, $k(s,s') = e^{-\|s-s'\|^2}$, and set $\lambda = 1$.
- Represent $\frac{\partial c_r}{\partial i}$ by a neural network, minimize Euler residuals

$$\min_{\frac{\partial c_r}{\partial i}} \frac{1}{N(T-1)} \sum_{i,t}^{N,T-1} \left(\frac{\partial c_r}{\partial i}(s_{it}) - \beta k(s_{it},\mathbf{s}_t)\,(K+\lambda I)^{-1}\,\frac{\partial c}{\partial i}(\mathbf{s}_{t+1}) - \mathrm{E}\left[\frac{\partial \pi}{\partial k}\widehat{(k_{t+1},s_{t+1})}|s_t,k_{t+1}\right]\right)^2.$$

Marginal product of capital hovers around previous estimates



Northeast has the highest regulatory costs

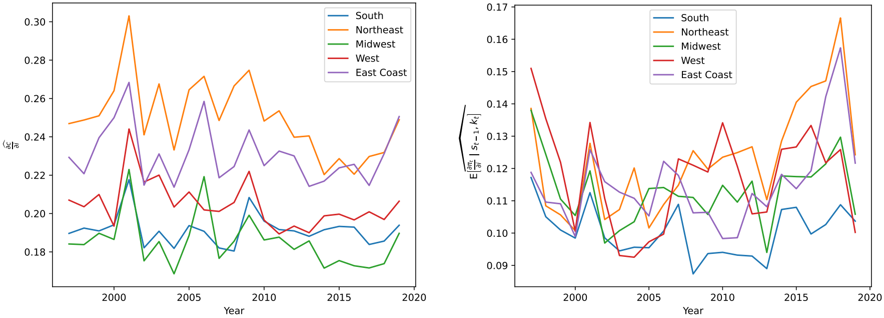


Figure: Investment projects in the Northeast are profitable, so investment distortion is driven primarily by increased regulatory costs.

Unbalanced distribution of costs

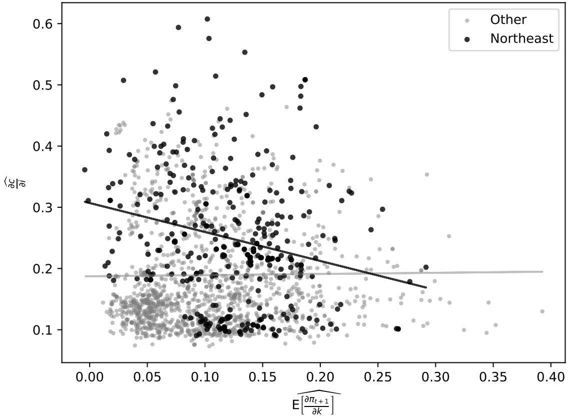


Figure: Investment costs in the northeast are lowest for investments that are likely to be the most profitable.

Prices and social value

- How do these estimated regulatory costs compare to the optimal regulation?

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- How do these estimated regulatory costs compare to the optimal regulation?
- To find out, make a further assumption that there is a continuum of marketers (marketers are perfectly competitive).
- Under this assumption, prices arise from the optimal dispatch problem with a flow constraint (similar to the model used in Cremer, Gasmi and Laffont, 2003)

Optimal dispatch

Demand — Supply — Flow of gas from state i to state j

$$\max_{\mathbf{q},\mathbf{d},\Phi} \sum_{i=1}^{n} \left(u_i(d_i) - c_i^e(q_i) \right) - \sum_{i=1}^{n} \sum_{j=1}^{n} c_{ij}\, \phi_{ij}$$

$$\text{subject to } q_i, d_i \geq 0, \quad \forall i \in \mathcal{A}$$

Capacity constraint

$$0 \leq \phi_{ij} \leq \kappa_{ij}, \quad \forall i,j \in \mathcal{A}$$

$$q_i + \sum_{\ell=1}^{n} \phi_{i\ell} = \sum_{\ell=1}^{n} \phi_{\ell i} + d_i, \quad \forall i \in \mathcal{A}.$$

Conservation of flow constraint

- A social planner wants to choose where to expand capacity constraints κ_{ij}
- **Key finding:** The Lagrange multiplier on the capacity constraint is equal to the difference in prices across a state border details

Social planner invests to minimize price gaps

- Envelope theorem: $\frac{\partial v}{\partial \kappa_{ij}} = \lambda_{ij} = \max\{p_i - p_j - c_{ij}, 0\}$. Under the same boundary condition, Euler can be written as

$$\frac{\partial c}{\partial i}(i_t, k_t, s_t) - \beta \mathrm{E}\left[\frac{\partial c}{\partial i}(i_{t+1}, k_{t+1}, s_{t+1}) \,\middle|\, s_t, k_{t+1}\right] = \beta \sum_{m=1}^{12} \sum_{j=1}^{n} \sum_{\ell=1}^{n} \mathrm{E}\left[\frac{\partial \kappa_{j\ell}}{\partial k} \max\{p_{jmt+1} - p_{\ell mt+1} - c_{j\ell}, 0\} \,\middle|\, s_t, k\right.$$

- This is identical to the firm's Euler equation, except:
  1. The objective on the right hand side is marginal social value of capital, instead of marginal profit
  2. c, not c, on the left hand side. (c does not contain the extra regulatory cost)

- Right hand side can be estimated using a similar Auto-DML procedure.

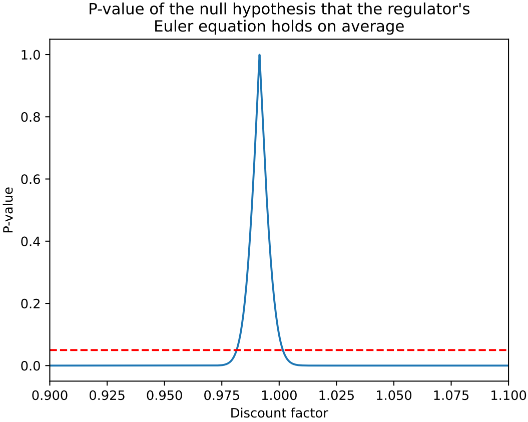


Figure: Assuming that the regulator’s Euler equation holds on average point-identifies the discount factor at 0.99

Measuring social value

- Subtract planner's Euler from firms' to obtain the PDE for optimal regulation

$$\beta \mathrm{E}\left[\lambda_{t+1}\frac{\partial R^*}{\partial i}(i_{t+1},k_{t+1},s_{t+1}) - \lambda_{t+1}\frac{\partial R^*}{\partial k}(i_{t+1},k_{t+1},s_{t+1})\Big| s_t, k_{t+1}\right] - \lambda_t \frac{\partial R^*}{\partial i}(i_t,k_t,s_t) =$$

$$\beta \mathrm{E}\left[\left(\sum_{r=1}^{12}\sum_{j=1}^{n}\sum_{\ell=1}^{n}\frac{\partial \kappa_{j\ell}}{\partial k}\max\{p_j - p_\ell - c_{j\ell}, 0\}\right) - \frac{\partial \pi}{\partial k}(k_{t+1},s_{t+1}) \;\Big|\; s_t, k_{t+1}\right].$$

- **Note:** If the right hand side is negative, capital is overincentivized and at least some additional regulation must be used to get optimal investment

- Denote the right hand side difference as Δ. Estimate $\hat{\Delta}$ using the same debiased method used to recover profits

Negative delta indicates there is need for regulation

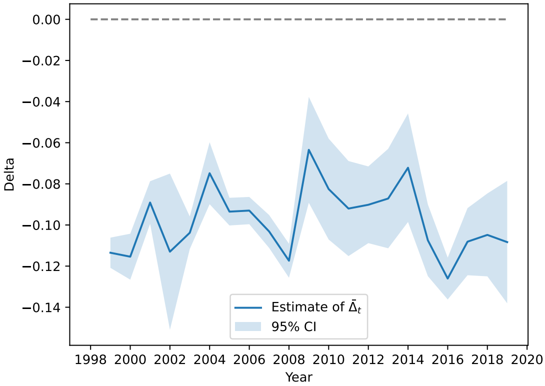


Figure: Delta is consistently negative – fixed rates universally exceed social value so some regulation is needed to realign incentives

Regulatory costs are too stringent in New England

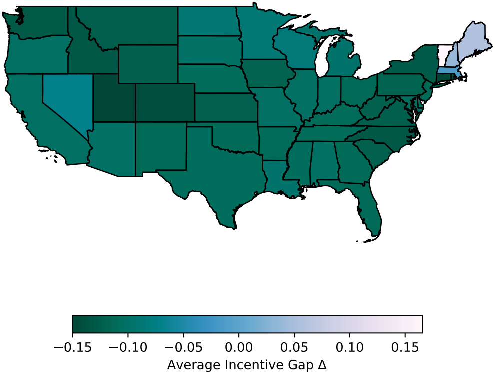
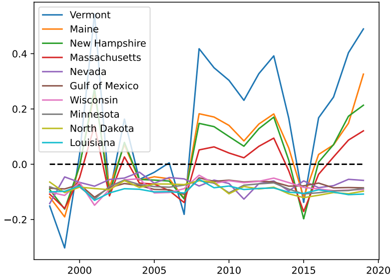


Figure: In the northeast, firms are not incentivized to invest under the current regime; but there may be overinvestment in parts of the midcoast and mountain west

How well targeted is investment regulation?



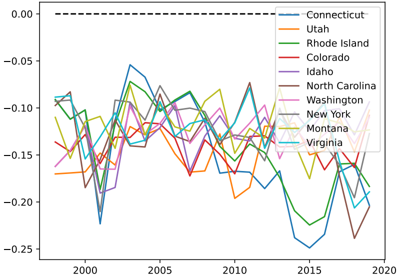


Figure: Regulation costs have risen in the northeast and are decreasing in parts of the southern and mountain regions

Summary

- We set out to investigate whether the regulatory incentives for pipeline development are distorting the growth of the natural gas pipeline network.
- Develop a structural model to estimate firm investment incentives
  - Novel method uses deep networks and RKHS embeddings to estimate network investment incentives from firm Euler equations
  - Estimated on firm-level administrative data from FERC Form 2A and EIA Form 176

Summary

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- Develop a structural model to estimate firm investment incentives
  - Novel method uses deep networks and RKHS embeddings to estimate network investment incentives from firm Euler equations
  - Estimated on firm-level administrative data from FERC Form 2A and EIA Form 176
- Solve a benchmark model of optimal pipeline investment by a social planner
  - Social planner would place new capacity in areas with large price gaps, instead of those with potential profit
  - Regulator can realign incentives by limiting investment through a costly approval process

Summary

- Find that investment incentives of pipelines were not aligned with social value of investment over the time period from 1996-2019
  - Large investment overall but has not improved the bottleneck into New England

Summary

- Find that investment incentives of pipelines were not aligned with social value of investment over the time period from 1996-2019
  - Large investment overall but has not improved the bottleneck into New England
- Most of the variation in investment is driven by the costly approval process, as opposed to varying rates.
- Using our model, characterized the importance of costly investment approvals as a secondary control.
  - Over this time period, investment costs in New England were too high
  - In the lower east coast and parts of the mountain west, there is overinvestment relative to social value. Regulation could be tightened in these areas

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