Imperfect Competition and Rents in Labor and Product Markets:

The Case of the Construction Industry

Kory Kroft, Yao Luo, Magne Mogstad, Bradley Setzler

CESifo Area Conference on Labor Economics – May 2022

Disclaimer: The opinions expressed here are those of the authors alone and do not reflect the views of the Internal Revenue Service or the U.S. Treasury Department.

Motivation

Our primary goal is to quantify the importance of imperfect competition in the U.S. construction industry by estimating the **size and sharing of rents** between **firms** and **workers**.

Motivation

Our primary goal is to quantify the importance of imperfect competition in the U.S. construction industry by estimating the **size and sharing of rents** between **firms** and **workers**.

To **measure rents and understand its sources**, we take into account imperfect competition in two markets:

- **Labor market:** firms may markdown wages below MRPL.
- **Product market:** firms may markup prices above MC.
- **Interactions:** impacts of **labor market power** depend on degree of **product market power**, and vice versa.

Motivation

Our primary goal is to quantify the importance of imperfect competition in the U.S. construction industry by estimating the **size and sharing of rents** between **firms** and **workers**.

To **measure rents and understand its sources**, we take into account imperfect competition in two markets:

- **Labor market:** firms may markdown wages below MRPL.
- **Product market:** firms may markup prices above MC.
- **Interactions:** impacts of **labor market power** depend on degree of **product market power**, and vice versa.

Empirical context: We link the universe of U.S. **firm** and **worker** tax returns with records we collected from **procurement auctions**.

Related Literature

Wage inequality, imperfect competition, compensating differentials

- Rosen 1986; Murphy and Topel 1990; Gibbons and Katz 1992; Abowd Lemieux 1993; Abowd et al 1999; Hamermesh 1999; Pierce 2001; Bhaskar et al 2002; Manning 2003, 2011; Mas and Pallais 2017; Wiswall and Zafar 2017; Card et al 2013, 2016, 2018; Maestas et al 2018; Caldwell Oehlsen 2018; Berger et al 2019; Jarosch et al 2019; Chan et al 2020; Bassier et al 2020; Hershbein et al 2020; Azar Berry Marinescu 2020; many more

Inferring monopsony from pass-through of firm-specific shocks

- van Reenen 1996; Kline et al 2019; Howell Brown 2020; Lamadon Mogstad Setzler 2022

Empirical designs for auctions

- Ferraz et al 2015; Lee 2017; Cho 2018; Hvide Meling 2019; Gugler et al 2020

Brief Overview of the Model

In the interest of time, I will only briefly outline the purpose and features of the model.

Brief Overview of the Model

In the interest of time, I will only briefly outline the purpose and features of the model.

Structure of the model: Firms compete in 3 markets:

- **Monopsony power:** Upward-sloping labor supply curve with slope $1/\theta$, constant wage markdown $(1+\theta)^{-1}$.
- **Monopoly power:** Downward-sloping product demand curve with slope $1/\epsilon$, constant price markup $(1-\epsilon)^{-1}$.
- Bid in **first-price auctions** for government procurements.

Brief Overview of the Model

In the interest of time, I will only briefly outline the purpose and features of the model.

Structure of the model: Firms compete in 3 markets:

- **Monopsony power:** Upward-sloping labor supply curve with slope $1/\theta$, constant wage markdown $(1+\theta)^{-1}$.
- **Monopoly power:** Downward-sloping product demand curve with slope $1/\epsilon$, constant price markup $(1-\epsilon)^{-1}$.
- Bid in **first-price auctions** for government procurements.

Uses of the model:

- **Framework** for jointly analyzing **labor** and **product** power.
- **Distinguish** supply and demand factors in both markets.
- **Closed-form** identification of all model parameters.
- **Measures** of rents and incidence of procurement.
- **Counterfactual** changes to power in either market.

Data Sources (1/2)

US tax data 2001-15 universe of business and worker tax returns

Firms: Business tax returns include balance sheet and other information for C-corps, S-corps, and partnerships

- **firm:** tax entity (EIN)
- **sales:** gross receipts from business operations (not dividends)
- **profits:** EBITD (earnings before interest, taxes, deductions)
- **intermediate inputs:** COGS (cost of goods sold)
  - includes intermediate goods, transit costs, etc
  - excludes durables, overhead, labor costs, etc

Data Sources (1/2)

US tax data 2001-15 universe of business and worker tax returns

Firms: Business tax returns include balance sheet and other information for C-corps, S-corps, and partnerships

- **firm:** tax entity (EIN)
- **sales:** gross receipts from business operations (not dividends)
- **profits:** EBITD (earnings before interest, taxes, deductions)
- **intermediate inputs:** COGS (cost of goods sold)
  - includes intermediate goods, transit costs, etc
  - excludes durables, overhead, labor costs, etc

Workers: W-2 records on employment and total earnings

- **labor:** link workers to their highest-paying employer with earnings above FTE threshold, restrict to age 25-60
- **contractors:** also observe indep. contractors (Form 1099)

Data Sources (2/2)

Auction data Firm-auction records on bids and winners of department of transportation (DOT) procurement contracts

- state DOTs use auctions to procure construction and landscaping work on roads and bridges
- First-price sealed-bid auctions (output price = lowest bid), where we observe bid of each firm, not only the winner
- FOIA or webscraped from BidX.com & state-specific websites
- Cover more than **100,000** auctions by 28 state DOTs, including large states like California, Texas, and Florida
- No evidence of collusion test results

Data Sources (2/2)

Auction data Firm-auction records on bids and winners of department of transportation (DOT) procurement contracts

- state DOTs use auctions to procure construction and landscaping work on roads and bridges
- First-price sealed-bid auctions (output price = lowest bid), where we observe bid of each firm, not only the winner
- FOIA or webscraped from BidX.com & state-specific websites
- Cover more than **100,000** auctions by 28 state DOTs, including large states like California, Texas, and Florida
- No evidence of collusion test results

Final data Link tax returns to auction records by fuzzy matching on firm name and address

- Final data: **8,000** unique firms, **360,000** unique workers
- 6 states provide EIN, used for training algorithm & robustness

Labor Supply Elasticity (1/5)

Model: Log inverse labor supply curve is,

$$w_{jt} = \theta \ell_{jt} + u_{jt} = \theta \ell_{jt} + \psi_j + \xi_t + \nu_{jt} \tag{1}$$

Goal: Identify the labor supply elasticity, $1/\theta$.

Labor Supply Elasticity (1/5)

Model: Log inverse labor supply curve is,

$$w_{jt} = \theta \ell_{jt} + u_{jt} = \theta \ell_{jt} + \psi_j + \xi_t + \nu_{jt} \tag{1}$$

Goal: Identify the labor supply elasticity, $1/\theta$.

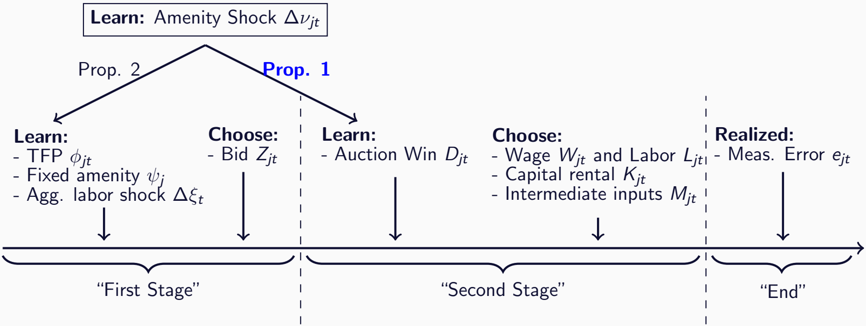
Easy to deal with:

- Time-invariant firm-specific amenities ψ_j (take differences)
- Aggregate labor supply shocks $\Delta \xi_t$ (add year fixed effects)

$$\Delta w_{jt} = \theta \Delta \ell_{jt} + \Delta \xi_t + \Delta \nu_{jt} \tag{2}$$

Challenge: Regression of change in log wage on change in log employment biased for θ due to firm-specific amenity shock $\Delta \nu_{jt}$

Sequence of Events within Time Period t



Labor Supply Elasticity (2/5)

Assumption 1. $\Delta\nu_{jt}$ not in information set at "First Stage" of t when bid is placed in auction $\implies D_{jt} \perp \nu_{jt} | (\psi_j, \xi_t)$.

- Time delay assumptions are standard for identification in empirical IO (Ackerberg et al 2015; Gandhi et al 2020).
- Delay is between *estimating* labor cost (bidding at beginning of period t) and actually hiring labor (middle of period t)

Labor Supply Elasticity (2/5)

Assumption 1. $\Delta\nu_{jt}$ not in information set at "First Stage" of t when bid is placed in auction $\implies D_{jt} \perp \nu_{jt} | (\psi_j, \xi_t)$.

- Time delay assumptions are standard for identification in empirical IO (Ackerberg et al 2015; Gandhi et al 2020).
- Delay is between *estimating* labor cost (bidding at beginning of period t) and actually hiring labor (middle of period t)

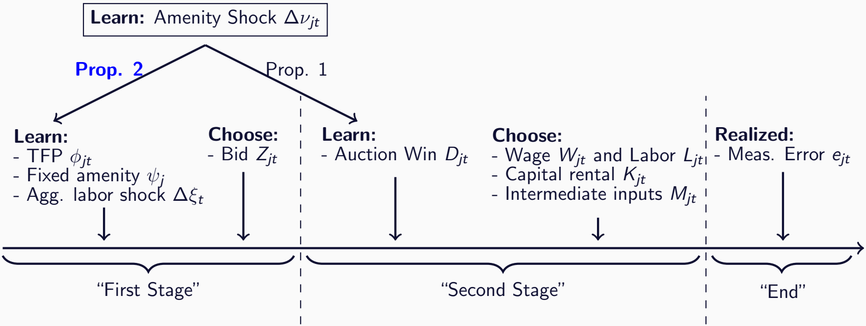
Proposition 1. θ is recovered by the IV estimator,

$$\theta_{\text{IV}} \equiv \frac{\text{Cov}\left[\Delta w_{jt}, D_{jt}\right]}{\text{Cov}\left[\Delta \ell_{jt}, D_{jt}\right]} \tag{3}$$

Important to emphasize what is **not** restricted by Assumption 1:

- no additional restrictions on joint dist of $(Z_{jt}, D_{jt}, \phi_{jt}, \psi_j, \xi_t)$.
- allows $\text{Var}(\Delta\nu_{jt}) > 0$, clear step forward in this literature.
- allows $\Delta\ell_{jt}, \Delta w_{jt}$ to depend on $\Delta\nu_{jt}$, no time delay here.

Sequence of Events within Time Period t



Labor Supply Elasticity (3/5)

Alternative: Leverage auction structure to relax Assumption 1.

Labor Supply Elasticity (3/5)

Alternative: Leverage auction structure to relax Assumption 1.

Loss margin: For a firm j that bids in auction ι at time t, define $\tau_{jt} \equiv \frac{Z_{jt} - Z_{\iota}^{*}}{Z_{\iota}^{*}}$, where Z_{ι}^{*} is the winning bid in auction ι.

Labor Supply Elasticity (3/5)

Alternative: Leverage auction structure to relax Assumption 1.

Loss margin: For a firm j that bids in auction ι at time t, define $\tau_{jt} \equiv \frac{Z_{jt}-Z_{\iota}^{*}}{Z_{\iota}^{*}}$, where Z_{ι}^{*} is the winning bid in auction ι.

Intuition:

- First-price auctions $\implies$ winning fully determined by bids Z_{jt}.
- Restrict sample to $\tau_{jt} \leq \overline{\tau}$. As $\overline{\tau} \to 0^{+}$, Z_{jt} of winners=losers.
- Therefore, $\mathbb{E}[\Delta\nu_{jt}]$ of winners and losers converges as $\overline{\tau} \to 0^{+}$

Labor Supply Elasticity (3/5)

Alternative: Leverage auction structure to relax Assumption 1.

Loss margin: For a firm j that bids in auction ι at time t, define $\tau_{jt} \equiv \frac{Z_{jt} - Z_\iota^*}{Z_\iota^*}$, where Z_ι^* is the winning bid in auction ι.

Intuition:

- First-price auctions $\implies$ winning fully determined by bids Z_{jt}.
- Restrict sample to $\tau_{jt} \leq \overline{\tau}$. As $\overline{\tau} \to 0^+$, Z_{jt} of winners=losers.
- Therefore, $\mathbb{E}[\Delta \nu_{jt}]$ of winners and losers converges as $\overline{\tau} \to 0^+$

Proposition 2: θ is recovered by the RDD estimator,

$$\theta_{\overline{\tau}} \equiv \frac{\mathbb{E}\left[\Delta w_{jt} | \tau_{jt} = 0\right] - \mathbb{E}\left[\Delta w_{jt} | 0 < \tau_{jt} \leq \overline{\tau}\right]}{\mathbb{E}\left[\Delta \ell_{jt} | \tau_{jt} = 0\right] - \mathbb{E}\left[\Delta \ell_{jt} | 0 < \tau_{jt} \leq \overline{\tau}\right]} \quad (4)$$

where $\overline{\tau}$ is a proximity parameter and the conditioning on ι is implicit. Then, $\lim_{\overline{\tau} \to 0^+} \theta_{\overline{\tau}} = \theta$.

Labor Supply Elasticity (4/5)

Results using multiplicity of approaches:

- Estimator of Proposition 1: $1/\theta = 4.1$, markdown $= 0.80$
- Estimator of Proposition 2: $1/\theta = 3.5$, markdown $= 0.78$
- Estimator of Lamadon Mogstad Setzler (2022) panel-IV for full construction sample: $1/\theta = 4.0$, markdown $= 0.80$

Labor Supply Elasticity (4/5)

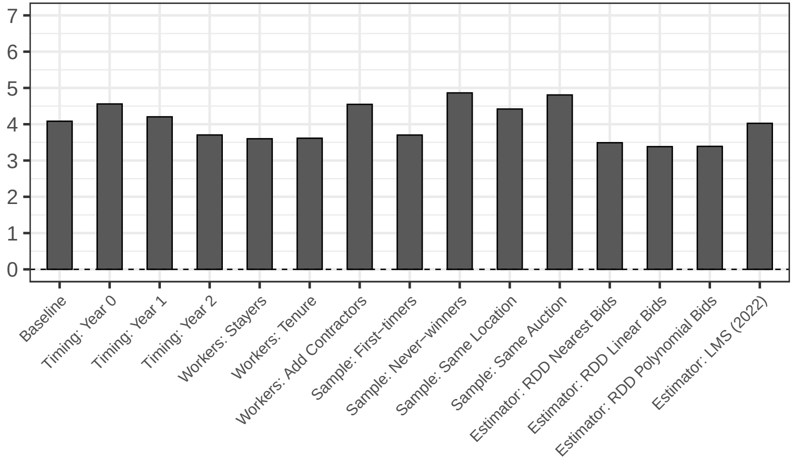
Results using multiplicity of approaches:

- Estimator of Proposition 1: $1/\theta = 4.1$, markdown $= 0.80$
- Estimator of Proposition 2: $1/\theta = 3.5$, markdown $= 0.78$
- Estimator of Lamadon Mogstad Setzler (2022) panel-IV for full construction sample: $1/\theta = 4.0$, markdown $= 0.80$

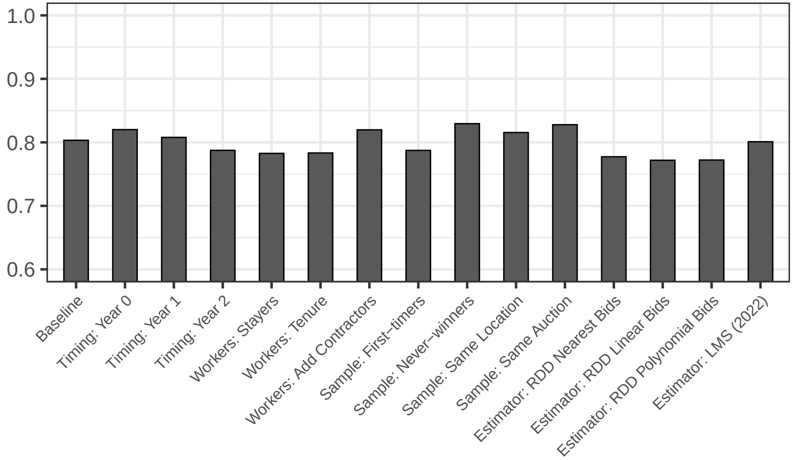
Sensitivity checks:

- Passes falsification test using IV on the pre-period outcomes
- No evidence of bias from slow adjustments over time
- No evidence of bias from worker composition changes
- No evidence of bias from local aggregate shocks
- Not sensitive to alternative choices of auction loser sample
- Not sensitive to right-to-work or prevailing wage law coverage
- Not sensitive to alternative parameterizations of Proposition 2
- Various checks using this sample and external BLS and Census wage surveys indicate wage effects not due to hours responses
- ... more

Labor Supply Elasticity (5/5)



Wage Markdown



Technology and Product Demand Elasticities (1/2)

Model: Optimal intermediate inputs imply,

$$x_{jt} = \kappa_X + \rho \ell_{jt} + \phi_{jt} \tag{5}$$

Goal: Identify the composite returns to labor, ρ.

Challenge: log TFP ϕ is a determinant of both log labor ℓ and log intermediate input expenditures x.

Technology and Product Demand Elasticities (1/2)

Model: Optimal intermediate inputs imply,

$$x_{jt} = \kappa_X + \rho \ell_{jt} + \phi_{jt} \tag{5}$$

Goal: Identify the composite returns to labor, ρ.

Challenge: log TFP ϕ is a determinant of both log labor ℓ and log intermediate input expenditures x.

"Invert the bidding strategy": Inverse equilibrium bidding strategy is $\phi_{jt} = s_{u_{jt}}^{-1}(Z_{jt})$, so TFP pinned down by (Z_{jt}, u_{jt}).

Technology and Product Demand Elasticities (1/2)

Model: Optimal intermediate inputs imply,

$$x_{jt} = \kappa_X + \rho \ell_{jt} + \phi_{jt} \tag{5}$$

Goal: Identify the composite returns to labor, ρ.

Challenge: log TFP ϕ is a determinant of both log labor ℓ and log intermediate input expenditures x.

"Invert the bidding strategy": Inverse equilibrium bidding strategy is $\phi_{jt} = s^{-1}_{u_{jt}}(Z_{jt})$, so TFP pinned down by (Z_{jt}, u_{jt}).

Recovering amenities: Given the estimate of the labor supply elasticity $\widehat{\theta}$, we can recover amenities as $\widehat{u}_{jt} = w_{jt} - \widehat{\theta} l_{jt}$.

Technology and Product Demand Elasticities (1/2)

Model: Optimal intermediate inputs imply,

$$x_{jt} = \kappa_X + \rho \ell_{jt} + \phi_{jt} \tag{5}$$

Goal: Identify the composite returns to labor, ρ.

Challenge: log TFP ϕ is a determinant of both log labor ℓ and log intermediate input expenditures x.

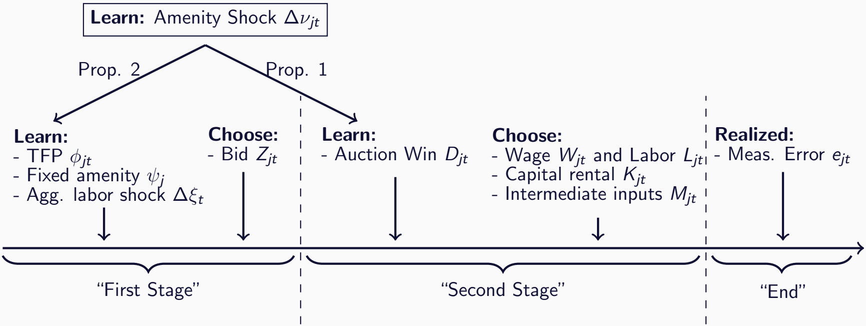
"Invert the bidding strategy": Inverse equilibrium bidding strategy is $\phi_{jt} = s_{u_{jt}}^{-1}(Z_{jt})$, so TFP pinned down by (Z_{jt}, u_{jt}).

Recovering amenities: Given the estimate of the labor supply elasticity $\widehat{\theta}$, we can recover amenities as $\widehat{u}_{jt} = w_{jt} - \widehat{\theta} l_{jt}$.

Proposition 3: Controlling for (Z_{jt}, u_{jt}) controls for ϕ_{jt}:

$$\frac{\text{Cov}\left[x_{jt}, \ell_{jt} | \widehat{u}_{jt}, Z_{jt}\right]}{\text{Var}\left[\ell_{jt} | \widehat{u}_{jt}, Z_{jt}\right]} = \frac{\text{Cov}\left[x_{jt}, \ell_{jt} | \widehat{u}_{jt}, \phi_{jt}\right]}{\text{Var}\left[\ell_{jt} | \widehat{u}_{jt}, \phi_{jt}\right]} = \rho \tag{6}$$

Sequence of Events within Time Period t



Technology and Product Demand Elasticities (2/2)

Goal: Identify the product demand elasticity, $1/\epsilon$.

Two approaches, both relying on Leontief technology:

- We extend the de Loecker Eeckhout Unger (2020) measure of inverse markups to incorporate labor market power ($\theta > 0$):

$$\overbrace{(1-\epsilon)}^{\text{markup}^{-1}} = \frac{\overbrace{(1+\theta)}^{\text{markdown}^{-1}}}{\beta_L} \frac{B_{jt}}{R_{jt}} + \frac{X_{jt}}{R_{jt}} \tag{7}$$

Technology and Product Demand Elasticities (2/2)

Goal: Identify the product demand elasticity, $1/\epsilon$.

Two approaches, both relying on Leontief technology:

- We extend the de Loecker Eeckhout Unger (2020) measure of inverse markups to incorporate labor market power ($\theta > 0$):

$$\overbrace{(1-\epsilon)}^{\text{markup}^{-1}} = \frac{\overbrace{(1+\theta)}^{\text{markdown}^{-1}}}{\beta_L} \frac{B_{jt}}{R_{jt}} + \frac{X_{jt}}{R_{jt}} \tag{7}$$

- The paper provides another moment, as well as an over-identifying condition which we use in GMM estimation.

Technology and Product Demand Elasticities (2/2)

Goal: Identify the product demand elasticity, $1/\epsilon$.

Two approaches, both relying on Leontief technology:

- We extend the de Loecker Eeckhout Unger (2020) measure of inverse markups to incorporate labor market power ($\theta > 0$):

$$\overbrace{(1-\epsilon)}^{\text{markup}^{-1}} = \frac{\overbrace{(1+\theta)}^{\text{markdown}^{-1}}}{\beta_L} \frac{B_{jt}}{R_{jt}} + \frac{X_{jt}}{R_{jt}} \tag{7}$$

- The paper provides another moment, as well as an over-identifying condition which we use in GMM estimation.

Product demand elasticity: We estimate $1/\epsilon = 7.3$, which gives a **price markup**, $(1/\epsilon)/(1/\epsilon - 1)$, that is 16% above marginal cost.

Composite returns to labor: We estimate $\rho = 1.09$, just above **constant returns to scale** (like Levinsohn and Petrin 2003).

Results from Estimated Model (1/2): Double Markdown

$$W_{jt} = \overbrace{\frac{1}{1+\theta}}^{\text{markdown}} \times \mathsf{MRPL}_{jt}$$

A natural measure of monopsony power is the **markdown**

- We estimate a **markdown** of 0.80, so workers are paid 20% below the marginal revenue product of labor (MRPL)

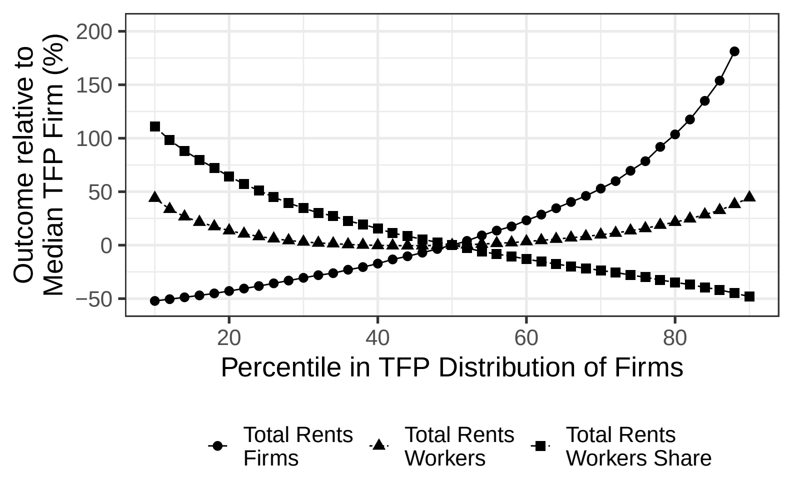
Results from Estimated Model (1/2): Double Markdown

$$W_{jt} = \overbrace{\frac{1}{1+\theta}}^{\textbf{markdown}} \times \text{MRPL}_{jt} = \underbrace{\overbrace{\frac{\theta}{1+\theta}}^{\textbf{markdown}} \times \overbrace{\left(\frac{1/\epsilon}{1/\epsilon - 1}\right)^{-1}}^{\textbf{inverse markup}}}_{\textbf{double markdown}} \times \underbrace{P_{jt} \times \text{MPL}_{jt}}_{\textbf{VMPL}}$$

A natural measure of monopsony power is the **markdown**

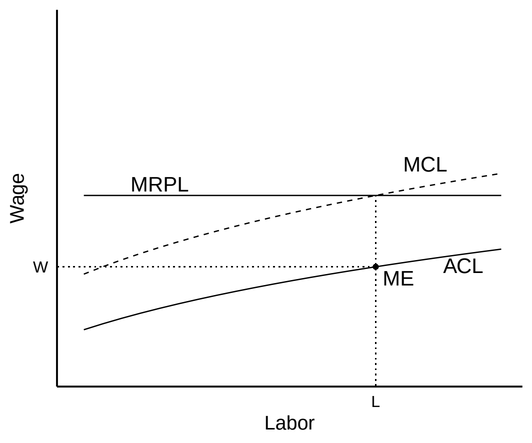
- We estimate a **markdown** of 0.80, so workers are paid 20% below the marginal revenue product of labor (MRPL)
- But MRPL depends on **product market power**
- Special case w/o intermediate inputs: MRPL equals **inverse markup** times the value of the marginal product of labor (MPL) at fixed prices, so **higher markup** $\implies$ **lower wage**
- We estimate a **composite markdown** of 0.69, so workers are paid 31% below VMPL, versus 20% if ignoring the markup

Results from Estimated Model (2/2): Rents and Rent-sharing



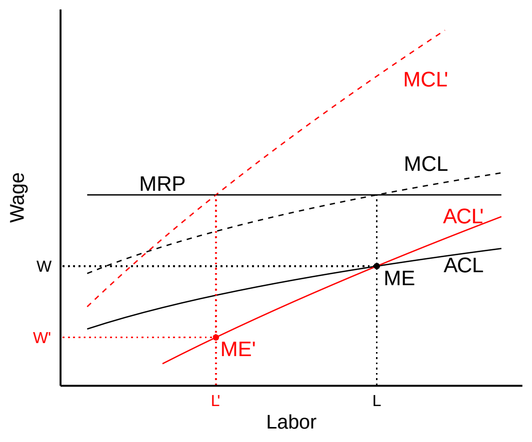
- **Rents:** per capita, workers earn \$12k and firms capture \$43k.
- **Rent heterogeneity:** higher TFP $\implies$ **lower rent-share**.
- See paper for results on **incidence of govt procurements**.

Theory: Impacts of Labor Market Power (1/3)



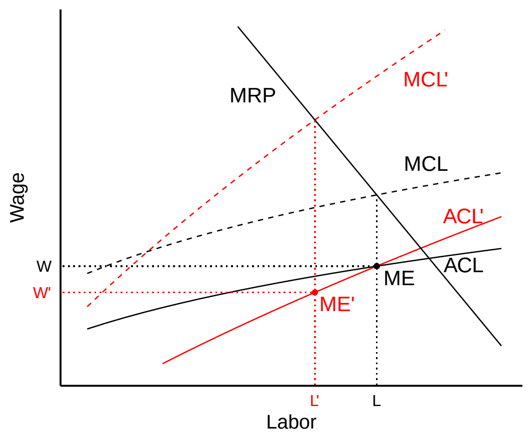
- No price-setting power $\implies$ flat MRPL curve
- Labor market power: upward-sloping MCL
  - Firm chooses L such that MRPL = MCL, W < MRPL

Theory: Impacts of Labor Market Power (2/3)



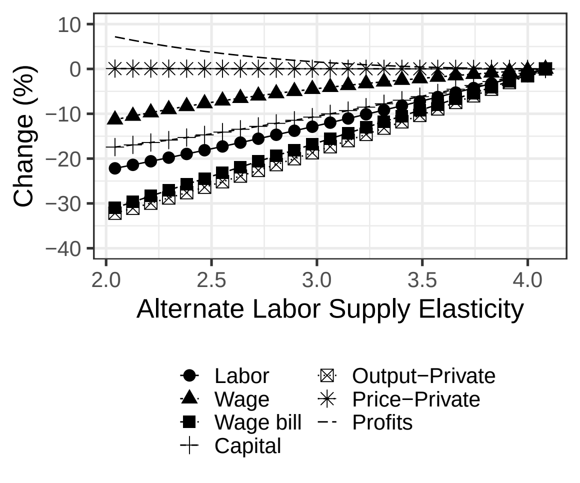
- No price-setting power $\implies$ flat MRPL curve
- More labor market power $\implies$ steeper MCL (red) $\implies$ less employment, greater wage markdown

Theory: Impacts of Labor Market Power (3/3)



- Firm has price-setting power $\implies$ downward-sloping MRPL
- Cut employment $\implies$ cut output $\implies$ higher output price $\implies$ incentive not to cut employment as much

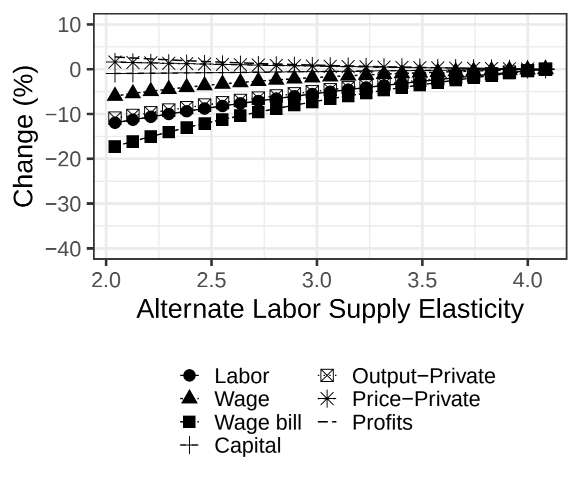
Model Simulation: Impacts of Labor Market Power (1/2)



Consider reducing LS elasticity $1/\theta$ in half

- Simulate from estimated model, counterfactually set $\epsilon = 0$
- Employment $\downarrow$ 22%, wages $\downarrow$ 11%, profits $\uparrow$ 7%

Model Simulation: Impacts of Labor Market Power (2/2)



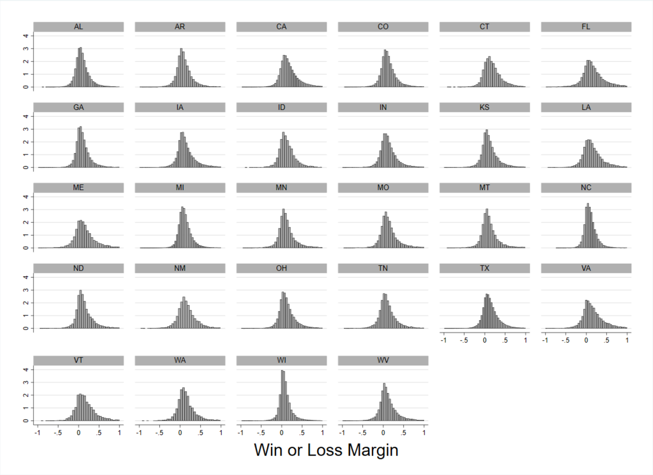
- Simulate from estimated model, use estimated $1/\epsilon = 7.3$
- Employment $\downarrow$ 12%, wages $\downarrow$ 6%, profits $\uparrow$ 3% $\implies$ impacts of labor market power mitigated by product market power

Conclusions

- Developed a framework for jointly analyzing **labor** and **product** market power
- Leveraged features of **procurement auctions** to recover **labor supply**, **technology**, and **product demand**
- The wage markdown is 20%, and there is a **double wage markdown** of 31% accounting for **product** market power
- Firms capture more than 3/4 of rents, high productivity firms share less, but workers capture a high share of incidence
- Simulations from estimated model show that impacts of **labor** market power depend on degree of **product** market power

Appendix

Visual test of collusion from Chassang et al (2022)

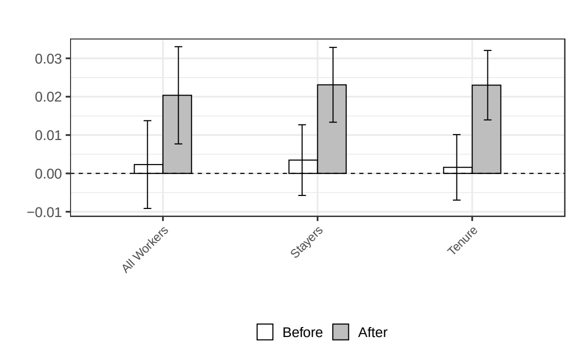


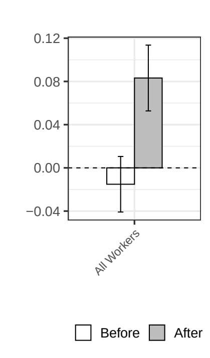
None of our 28 states has a "missing mass" of close losing bids. Chassang Kawai Nakabayashi Ortner (2022 ECMA) show that such patterns should be found broadly under collusive behavior.

Back

Falsification using Pre-period

Effects on wages (left) and employment (right):

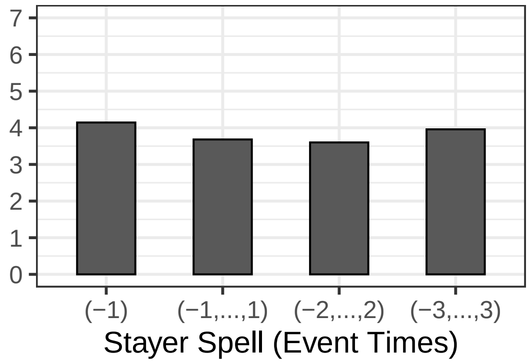




Back

Stayers and Tenure Samples (1/2)

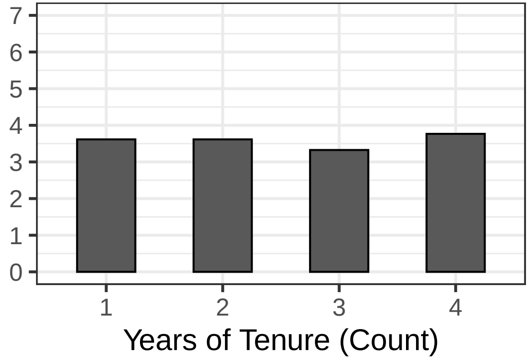
Labor supply elasticity by stayer spell:



◂ Back

Stayers and Tenure Samples (2/2)

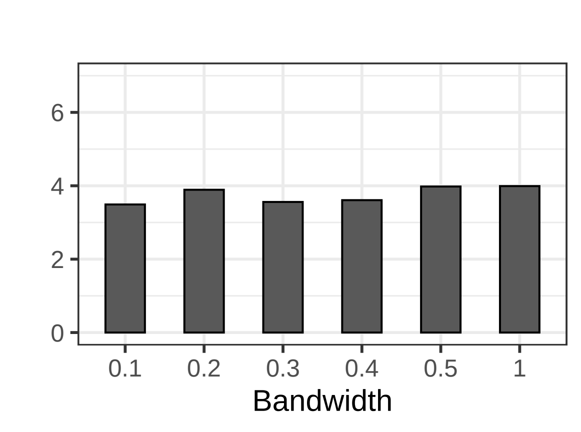
Labor supply elasticity by tenure length:



Back

Bandwidths in the Prop 2 estimator (1/1)

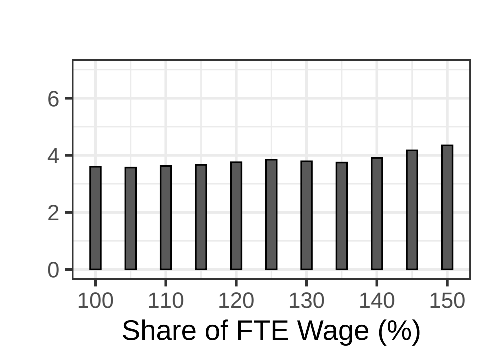
Labor supply elasticity for alternative bandwidths ($\bar{\tau}$):



Back

Hours and full-time status (1/2)

Labor supply elasticity by FTE threshold (as % of min. wage):



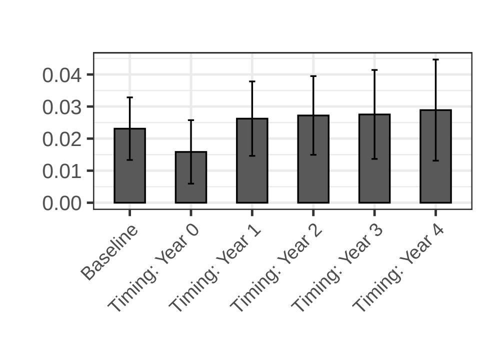
Other notes:

- US construction industry during 2001-2015 was 4.6% part-time labor vs 13.9% in entire private sector (BLS)
- LMS estimator in Norway: revenue shock pass-through of 0.092 (annual earnings) and 0.091 (hourly wages)

Back

Hours and full-time status (2/2)

Wage effects persist over time (inconsistent with over-time pay):



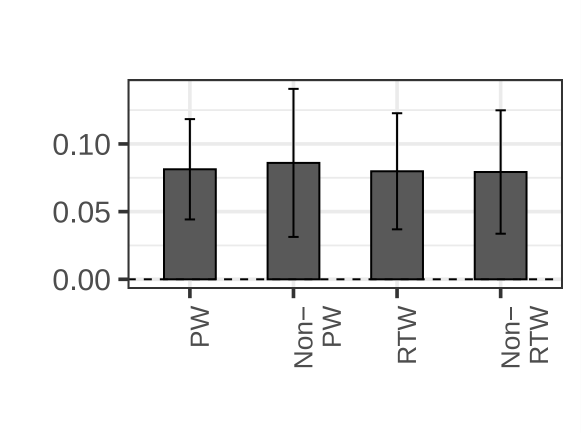
Other notes:

- US construction industry during 2001-2015 was 4.6% part-time labor vs 13.9% in entire private sector (BLS)
- LMS estimator in Norway: revenue shock pass-through of 0.092 (annual earnings) and 0.091 (hourly wages)

Back

Right-to-Work and Prevailing Wage States (1/2)

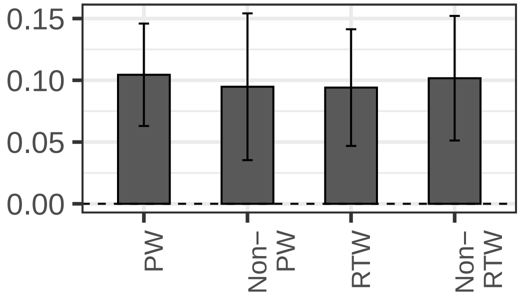
Effects on employment:



◂ Back

Right-to-Work and Prevailing Wage States (2/2)

Effects on wage bill:



Back

Measurement Error Orthogonality

The goal is to estimate $1-\epsilon$ using the relationship:

$$r_{jt} = \kappa_R + (1-\epsilon)\, x_{jt} + (1-\epsilon)\, e_{jt}$$

where e_{jt} is the error in the relationship between log revenues r_{jt} and log intermediates x_{jt}. The key identifying restriction is,

$$\mathrm{Cov}(x_{jt}, e_{jt}) = 0$$

This orthogonality condition is satisfied under the assumption by Ackerberg et al. (2015) that the firm has no information about e_{jt} at the time inputs are chosen:

> *"The [e_{jt}] represent shocks to production or productivity that are* **not observable (or predictable)** *by firms before making their input decisions at t... [e_{jt}] can also represent (potentially serially correlated) measurement error in the output variable." Ackerberg et al. (2015, ECMA)*

Indeed, x_{jt} should be uncorrelated with e_{jt} if e_{jt} is completely unpredictable at the time x_{jt} is chosen. Back