# Measuring Labor Demand and Supply Shocks during COVID-19

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*The views expressed on this presentation do not necessarily reflect the positions of the Federal Reserve Bank of St. Louis or the Federal Reserve System.*

# Introduction

# COVID-19 fall in hours: Labor supply or demand shock?

Reduction in hours worked in a given **sector** due to:

1. Supply ← Workers behavior
   - Increase in health risk
   - Policy
     - Containment and mitigation measures (lockdowns)
     - Fiscal: e.g. CARES act
     - Monetary
2. Demand ← Firms behavior
   - Demand shortages (GLSW 2020; Baqaee and Farhi 2020)
     - Increase in Health risk
     - Complementarities across sectors (input-output — preferences)
     - Aggregate demand
   - Supply chain disruptions
   - Policy (monetary & fiscal policy)

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# Labor supply or demand shocks definition

**Definition**

*Labor supply shocks are defined as unforeseen changes in workers willingness to work given the observed wage.*

*Labor demand shocks are defined as unforeseen changes in employers willingness to hire given the observed wage.*

**Remarks**

- Labor supply and demand shocks here are interpreted as shifts in the supply and demand curve, respectively.
- They are structural insofar as disentangling workers vs. employers behavior goes. They are not fundamental shocks to preferences, market structure or technology.
- They are best described as reduced form shocks that net out how fundamental shocks shift the demand or supply curves.

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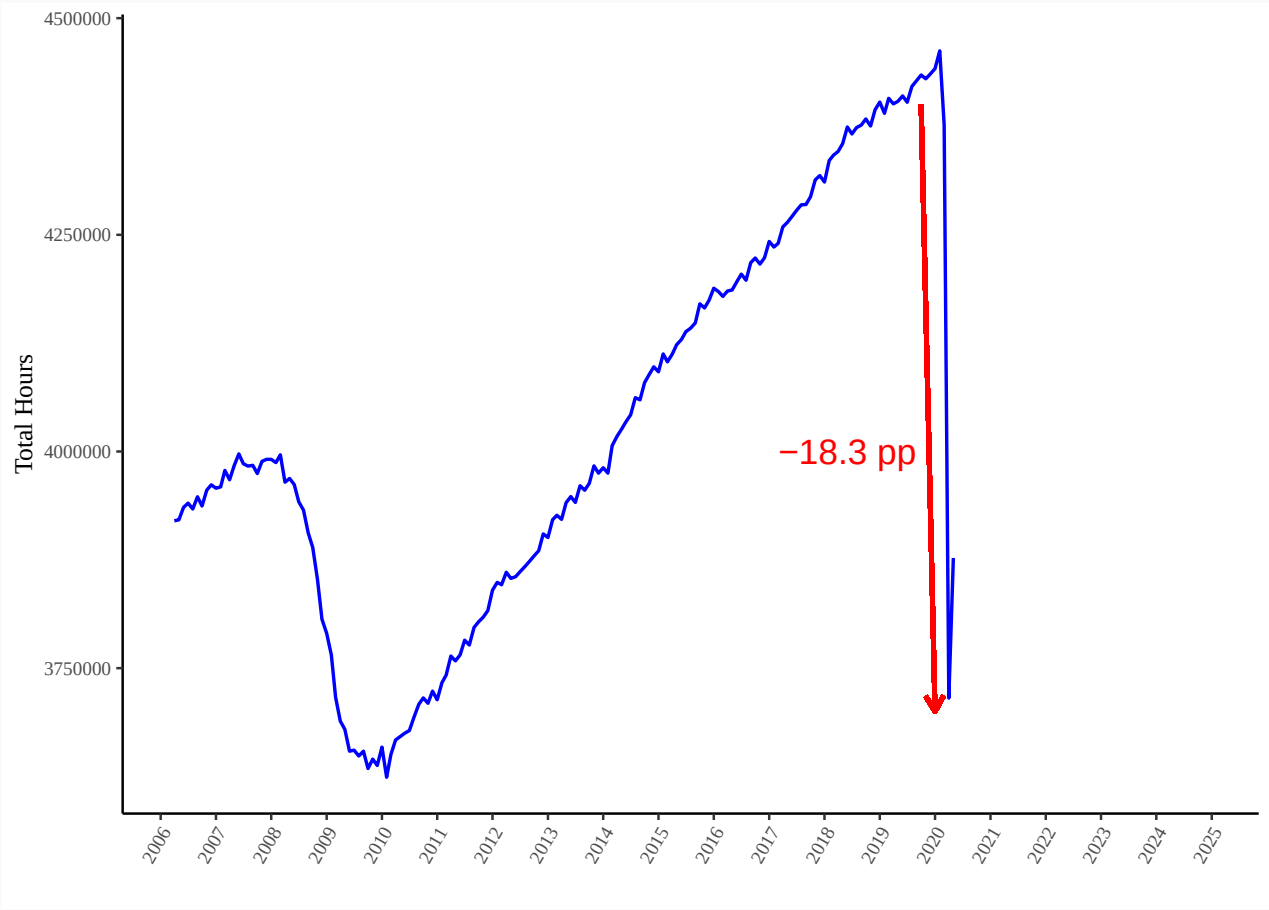
# This paper

1. How much of the drop in hours worked is explained by shifts in labor supply and demand?
2. How does that vary across sectors?



# Why does this decomposition matter?

1. The need of useful moments and parameters to calibrate models
   - How large were the shifts in labor supply and demand during COVID-19?
   - We provide sectoral labor elasticities (multisector models are key to model COVID-19)
2. Policy guidance
   - Labor supply shocks more closely related w/ state of public health
     - Persistence linked to that of public health crisis
     - Policy recommendation: **Social insurance for workers (preferably preserving job matches)**
   - Labor demand shocks more closely related w/ state of the economy (labor earnings collapsing)
     - Potentially more persistent (job destruction, business exit)
     - Policy recommendation: **Targeted fiscal and credit policies (especially in non-lockdown sectors)**

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**Approach**:

Measure monthly **labor** demand and supply shocks w/ econometric model

- Using monthly hours and real wage per hour (CES from BLS)
- Estimate Bayesian SVAR ($\Delta h_t$, $\Delta w_t$) with informative prior (Baumeister & Hamilton, 2015, 2018, 2019)
  - Accounts for estimation uncertainty + uncertainty about the underlying structure of the economy
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- Identification of relative size of demand and supply shocks driven by:
  - Changes in hours and wages per hour
  - Ratio of labor demand and supply elasticities (prior: ratio$=1$)
- Analysis by
  1. Sector (NAICS-2 and -3)
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# Results

- Supply accounts for 2/3 of 16.24 pp drop in the growth rate of hours worked in April 2020
- Large negative demand & supply shocks in March, April
- Huge heterogeneity across sectors:
  1. Leisure and Hospitality: -63.18 pp in April, 63% supply
  2. Utilities, Information, Financial Activities least affected
  3. Positive demand shocks are observed in March for many sectors, but not in April
- Validation:
  1. Supply shocks correlate strongly with measures of telework
  2. No correlation for "normal" months
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# Relation to the Literature

1. COVID shock in multi-sector economies

   Bodenstein, Corsetti, & Guerrieri (2020); Barrot, Grassi, & Sauvagnat (2020); Faria-e-Castro (2020); ...

2. Effects of voluntary & mandated confinement

   Eichenbaum, Rebelo & Trabandt (2020); Kaplan, Moll, and Violante (2020); ...

3. Supply vs. demand shocks

   Guerrieri, Lorenzoni, Straub, & Werning (2020); Baqaee & Fahri (2020); del Rio-Chanona et al. (2020); ...

# Outline of the Talk

1. Econometric model
2. Data
3. Results: estimation & decomposition
4. Validation
5. Conclusion

# Model

# Econometric Model

Framework based on Baumeister & Hamilton (2015, ECTA)

- Sector $l \in L$, month $t \in T$
- Growth rate of wages $\Delta w_t^l$, hours $\Delta h_t^l$
- Observables

$$\boldsymbol{y}_t^l = (\Delta w_t^l, \Delta h_t^l)$$

- SVAR for sector $l$

$$\boldsymbol{A}^l \boldsymbol{y}_t^l = \boldsymbol{B}_0^l + \boldsymbol{B}^l(L)\boldsymbol{y}_{t-1}^l + \boldsymbol{\varepsilon}_t^l$$

- Structural demand and supply shocks

$$\boldsymbol{\varepsilon}_t^l = (\varepsilon_{d,t}^l, \varepsilon_{s,t}^l) \sim \mathcal{N}(\mathbf{0}, \boldsymbol{D})$$

# Identification

- Assume that

$$\boldsymbol{A}^l = \begin{bmatrix} -\beta^l & 1 \\ -\alpha^l & 1 \end{bmatrix}$$

$$\alpha^l \geq 0$$

$$\beta^l \leq 0$$

- $\alpha_l \geq 0$: supply slopes up
- $\beta_l \leq 0$: demand slopes down
- Prior beliefs over $\{\alpha^l, \beta^l\}_{l \in L}$ incorporate these sign restrictions

# Identification: Example

- Write the SVAR as supply/demand system

$$\Delta h_t^l = b_{20}^{s,l} + \alpha^l \Delta w_t^l + \sum_{i=1}^{m} b_{21}^{i,s,l} \Delta w_{t-i}^l + \sum_{i=1}^{m} b_{22}^{i,s,l} \Delta h_{t-i}^l + \varepsilon_{s,t}^l$$

$$\Delta h_t^l = b_{10}^{d,l} + \beta^l \Delta w_t^l + \sum_{i=1}^{m} b_{11}^{i,d,l} \Delta w_{t-i}^l + \sum_{i=1}^{m} b_{12}^{i,d,l} \Delta h_{t-i}^l + \varepsilon_{d,t}^l$$

- Assume (i) no intercept, (ii) no lags. That yields

$$\Delta h_t^l = \left( \frac{1}{1 - \left( \frac{\alpha^l}{\beta^l} \right)^{-1}} \right) \varepsilon_{d,t}^l + \left( \frac{1}{1 - \frac{\alpha^l}{\beta^l}} \right) \varepsilon_{s,t}^l$$

$$\Delta w_t^l = \left( \frac{1/\beta^l}{\frac{\alpha^l}{\beta^l} - 1} \right) \varepsilon_{d,t}^l + \left( \frac{1/\beta^l}{1 - \frac{\alpha^l}{\beta^l}} \right) \varepsilon_{s,t}^l$$

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# Estimation

Reduced form model

$$\boldsymbol{y}_t^l = \Phi_0^l + \Phi^l(L)\boldsymbol{y}_{t-1}^l + \boldsymbol{u}_t^l$$

where

$$\begin{aligned}
\Phi_0^l &= (\boldsymbol{A}^l)^{-1}\boldsymbol{B}_0^l \\
\Phi^l(L) &= (\boldsymbol{A}^l)^{-1}\boldsymbol{B}^l(L) \\
\boldsymbol{u}_t^l &= (\boldsymbol{A}^l)^{-1}\varepsilon_t^l \\
E[\boldsymbol{u}_t^l(\boldsymbol{u}_t^l)'] &= \Omega = (\boldsymbol{A}^l)^{-1}\boldsymbol{D}((\boldsymbol{A}^l)^{-1})'
\end{aligned}$$

Joint density for prior beliefs over parameter values:

$$p(\boldsymbol{A}, \boldsymbol{D}, \boldsymbol{B}) = p(\boldsymbol{A})p(\boldsymbol{D}|\boldsymbol{A})p(\boldsymbol{B}|\boldsymbol{A}, \boldsymbol{D})$$

# Priors (BH (2015, ECTA), BH (2018, JME), BH (2019, AER))

1. $p(\boldsymbol{A})$
   - Encompass estimates from micro & macro lit. (Lichter et al., 2015)

     prior for $\alpha^l \sim t(0.6, 0.6, 3)$, 90% of mass on $[0.1, 2.2]$

     prior for $\beta^l \sim t(-0.6, 0.6, 3)$, 90% of mass on $[-2.2, -0.1]$

   - Same prior for all sectors $l \in L$
2. $p(\boldsymbol{D}|\boldsymbol{A})$
   - gamma distribution w/ shape $\kappa_i = 2$ and scale $\tau_i$
   - set $\kappa_i/\tau_i$ to match precision of structural shocks from univariate 4-lag autoregs under $\boldsymbol{A}$
3. $p(\boldsymbol{B}|\boldsymbol{A}, \boldsymbol{D})$
   - set to conform to Minnesota priors (Sims & Zha, 1998) on reduced form coefs. $\boldsymbol{\Phi}$

# Posteriors

- Posterior given by

$$p(\boldsymbol{A}, \boldsymbol{D}, \boldsymbol{B}|\boldsymbol{Y}_T) = p(\boldsymbol{A}|\boldsymbol{Y}_T)p(\boldsymbol{D}|\boldsymbol{A}, \boldsymbol{Y}_T)p(\boldsymbol{B}|\boldsymbol{A}, \boldsymbol{D}, \boldsymbol{Y}_T)$$

- Natural conjugacy:
  - $p(\boldsymbol{B}|\boldsymbol{A}, \boldsymbol{D}, \boldsymbol{Y}_T)$ follows multivariate normal
  - $p(\boldsymbol{D}|\boldsymbol{A}, \boldsymbol{Y}_T)$ follows gamma distribution
- $p(\boldsymbol{A}|\boldsymbol{Y}_T)$ has no closed form distribution, use Metropolis-Hastings to draw from it

Other estimation details:

- Lag length set at $m = 4$ based on Akaike IC

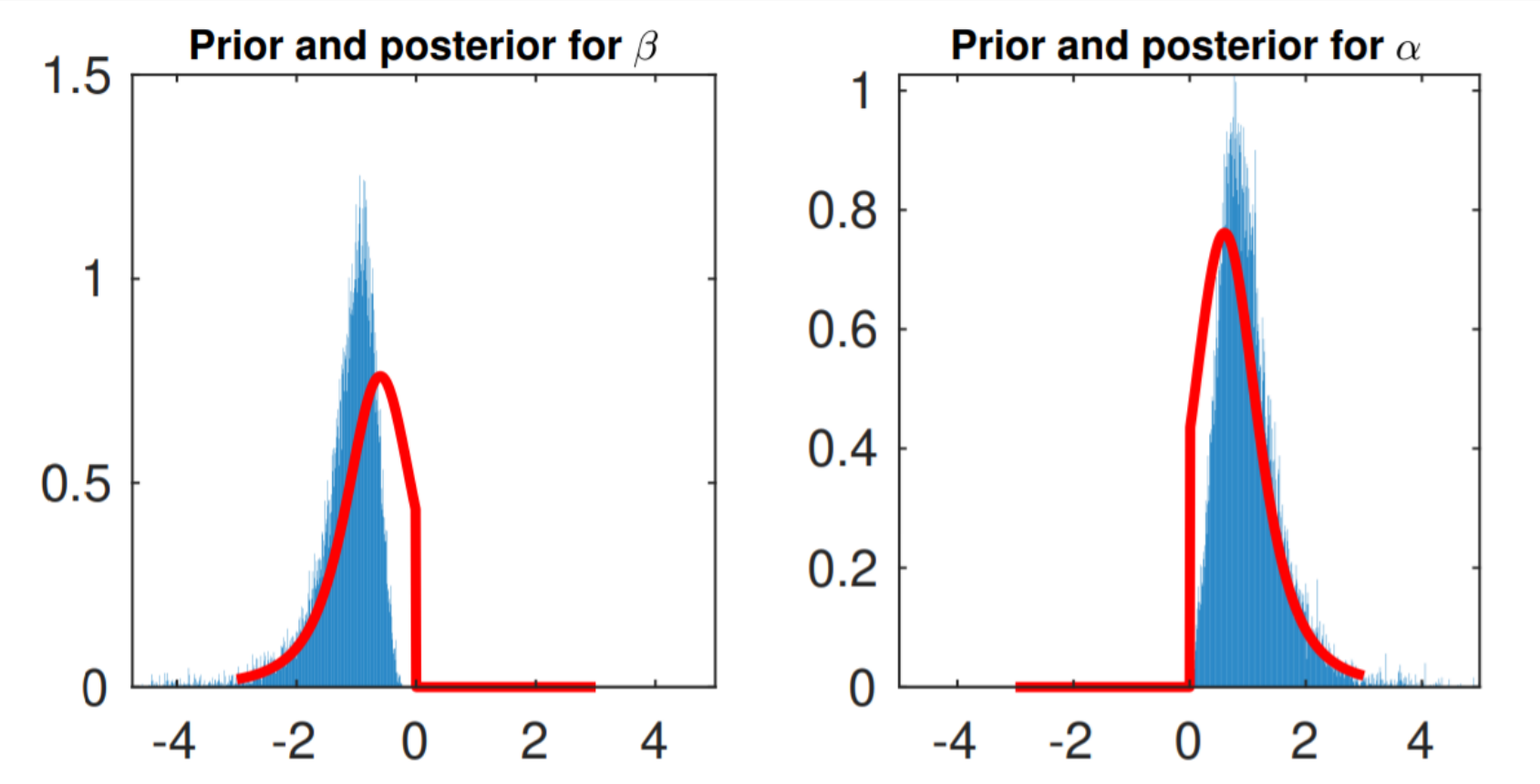
# Data

# Data

- Current Employment Statistics (CES) from the Bureau of Labor Statistics (BLS)
- Monthly data on hours worked and average hourly wages by sector, March 2006-May 2020 (log differences of both hours and wages)
- 14 aggregate sectors, roughly map to NAICS-2 (68 sectors NAICS-3)
- Estimate SVAR until February 2020, use estimated model+data to estimate shocks for March-May 2020 (Lenza and Primiceri (2020))

# Estimation Results

# Estimation Results: Total Private Employment




▸ All sectors ▸ Table with Results

# Estimated Shocks: until February 2020

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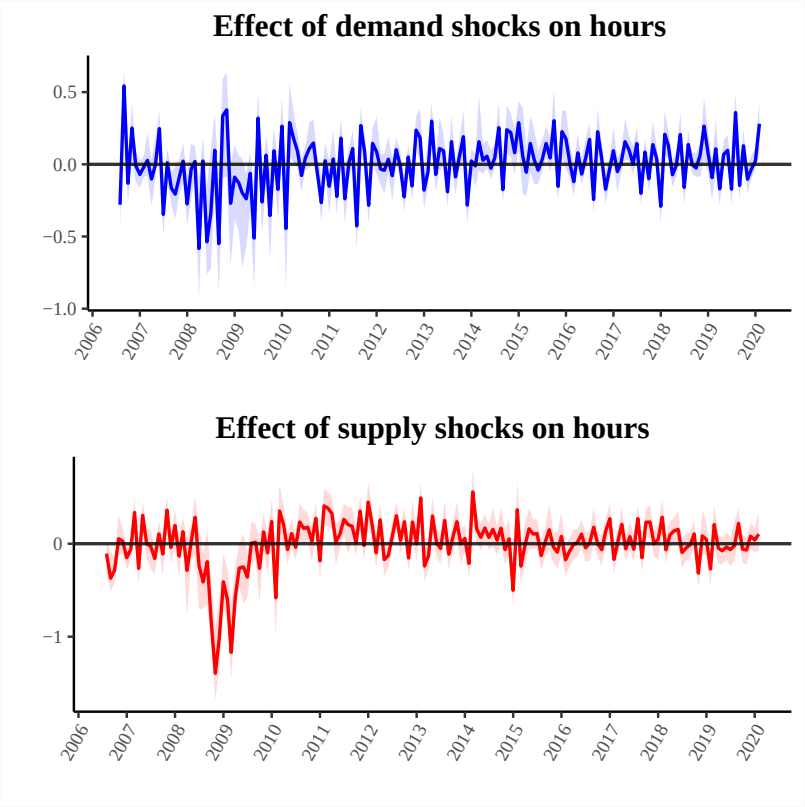
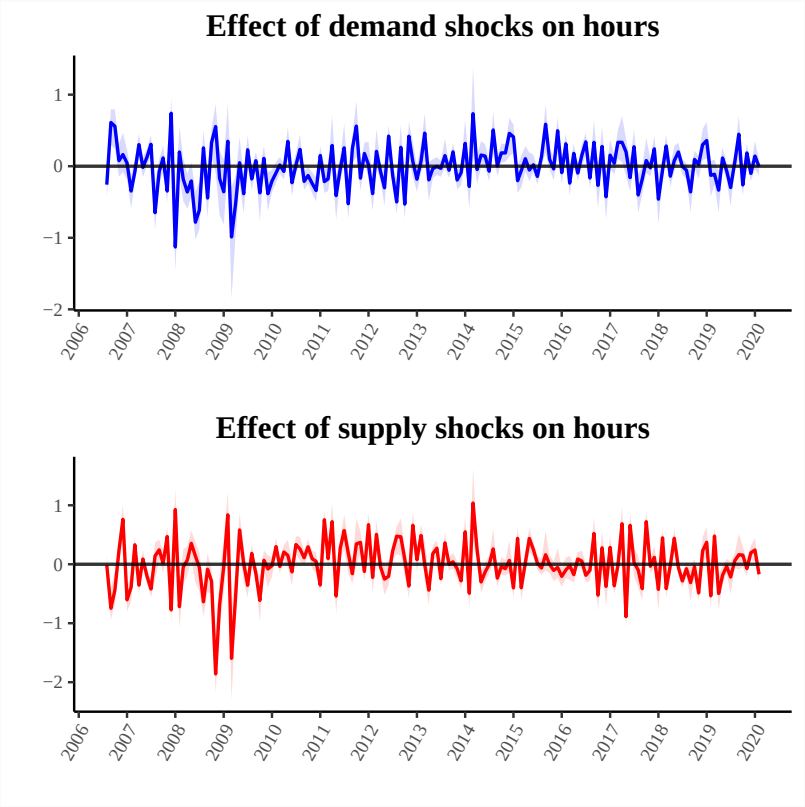
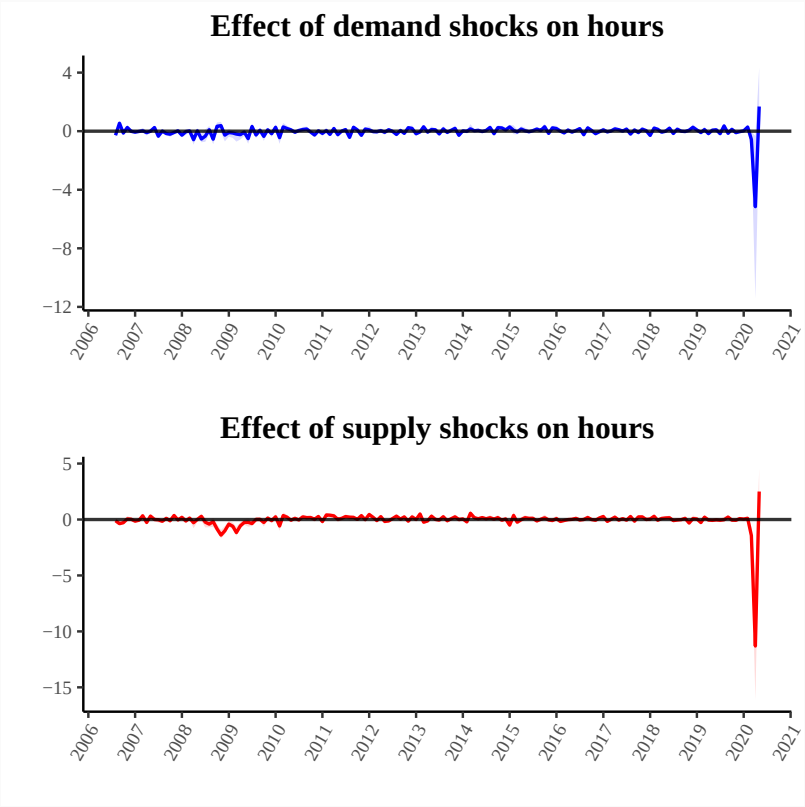



**(b)** Leisure and Hospitality

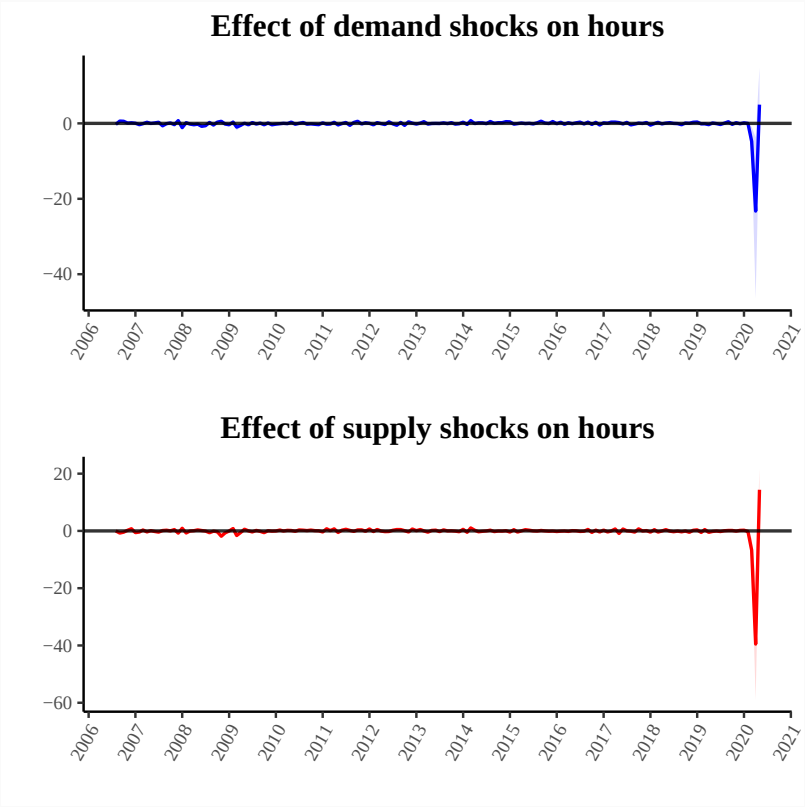


# Estimated Shocks: full sample

**(a)** Total Private Employment

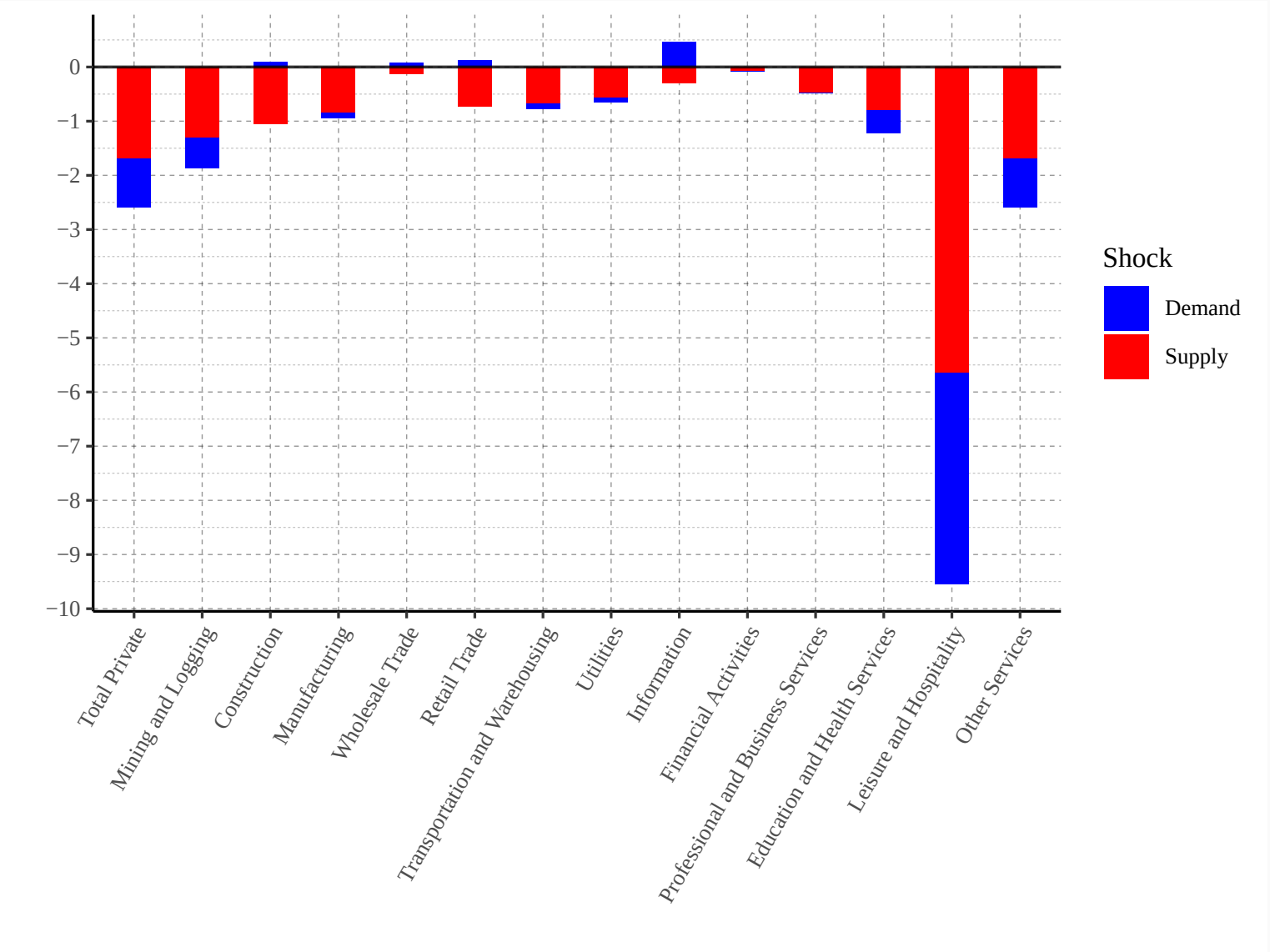



**(b)** Leisure and Hospitality



# Shock Decomposition

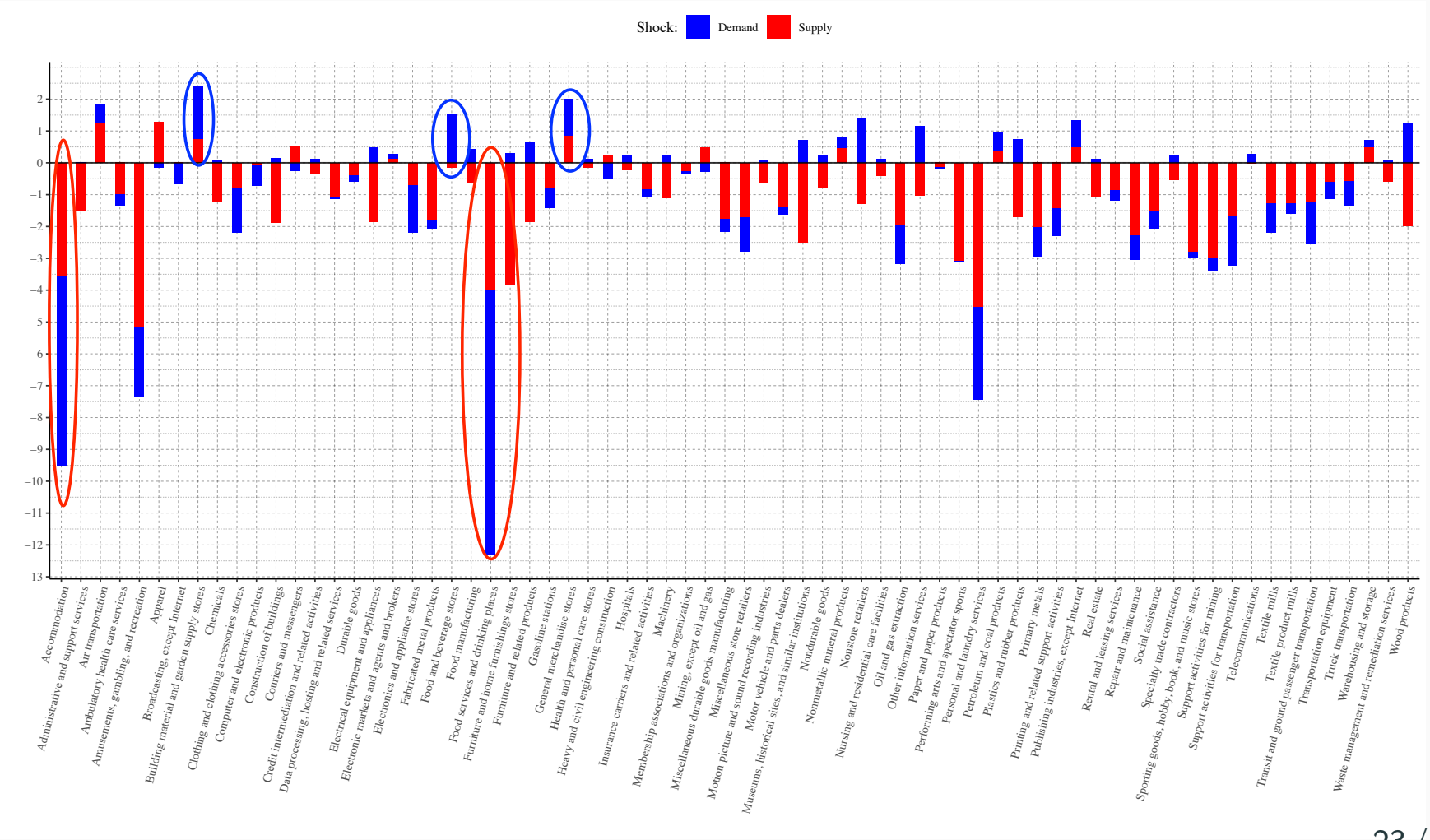
# Shock Decomposition by NAICS-2, March 2020



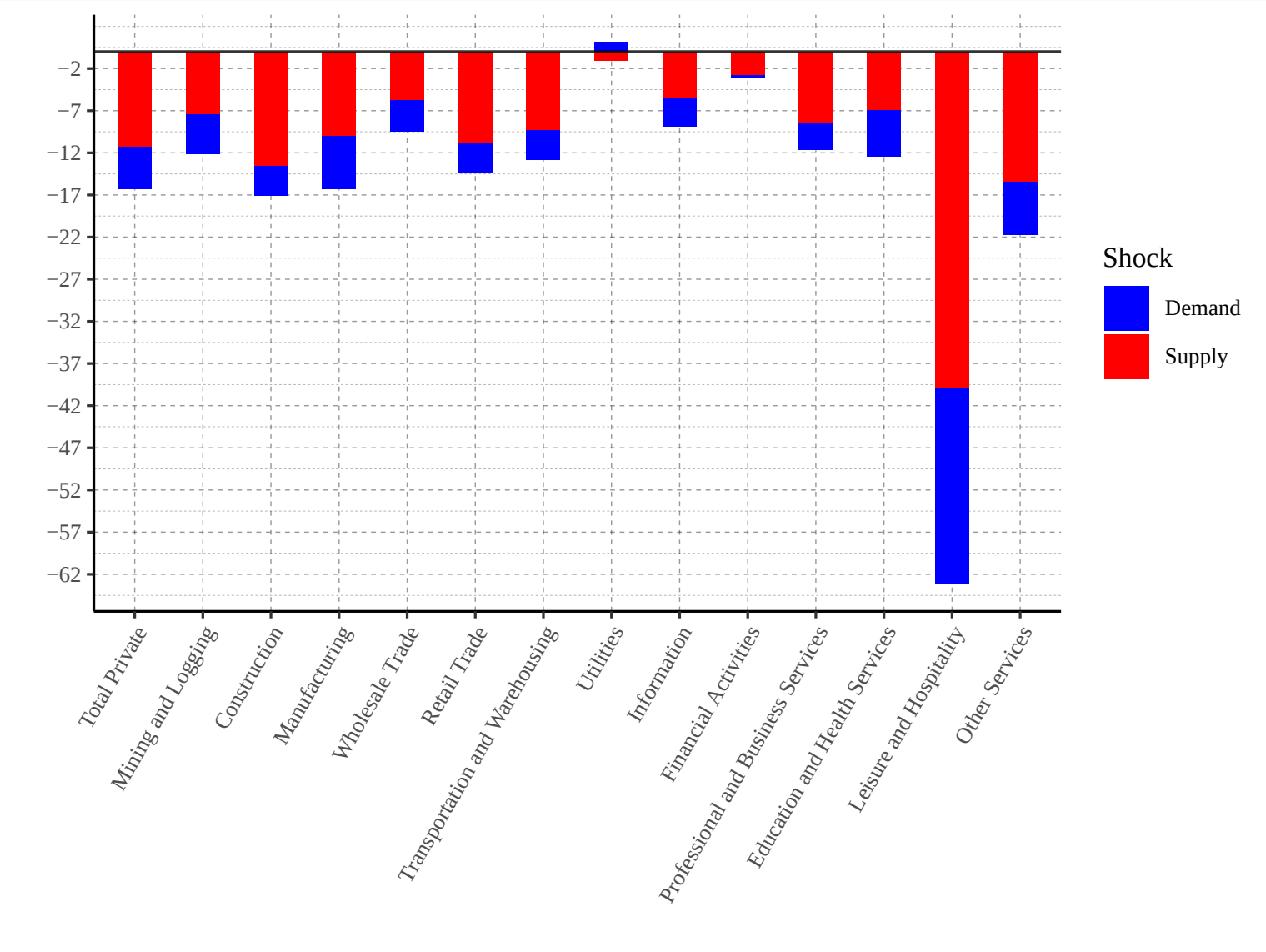
# Shock Decomposition by NAICS-2, March 2020

- Total private: $-2.59$ pp, supply accounts for 64.8%
- Leisure and Hospitality most negatively affected sector ($-9.55$, of which 59% supply)
- Least-affected sectors: Wholesale Trade ($-0.06$ pp), Financial Activities ($-0.09$ pp), Information ($+0.16$ pp)
- Positive demand shocks: Information, Retail Trade, Wholesale Trade, Construction
- Very different from March 2019 ▸ March 2019

# Shock Decomposition by NAICS-3, March 2020



# Shock Decomposition by NAICS-2, April 2020

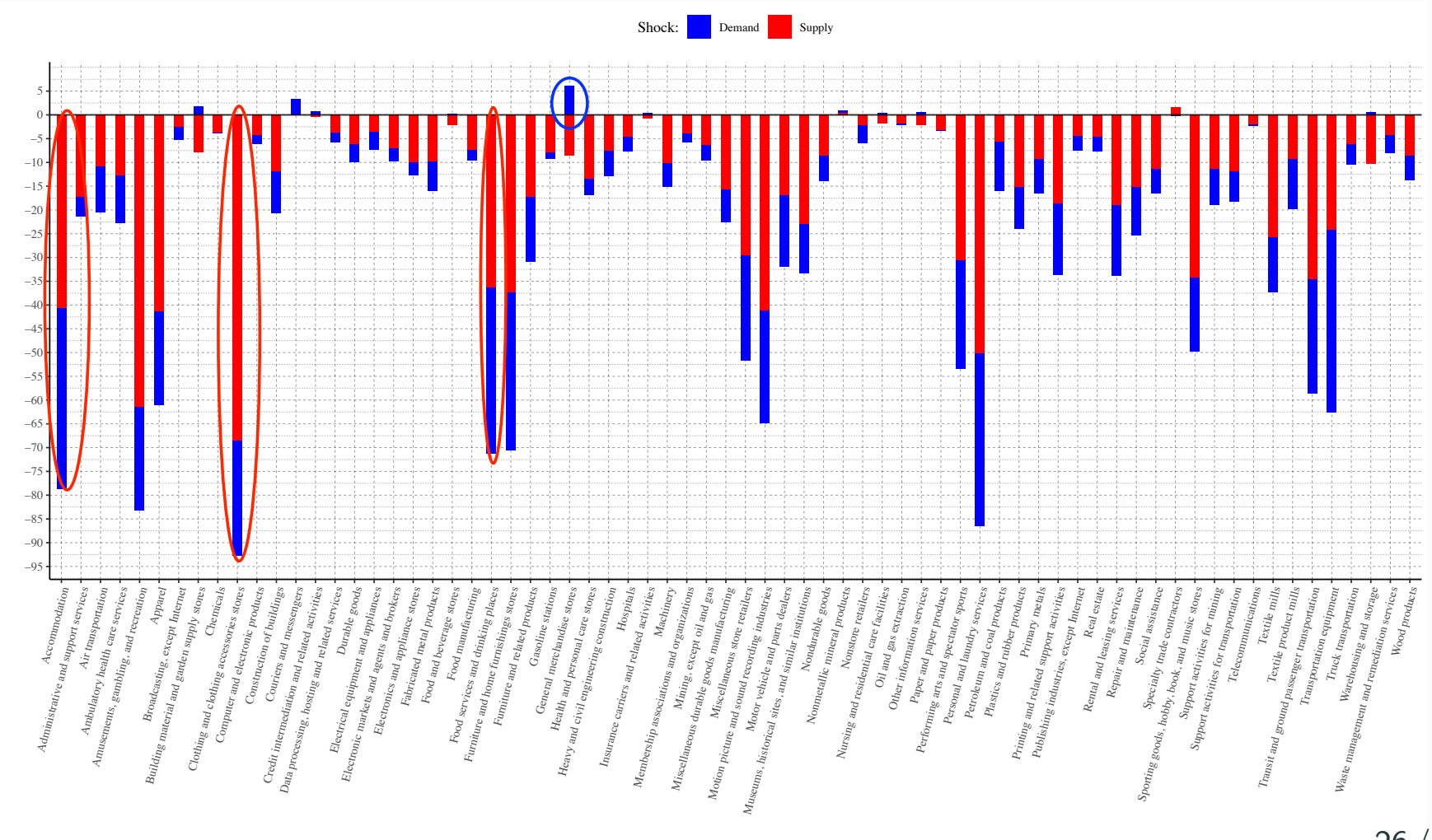


# Shock Decomposition by NAICS-2, April 2020

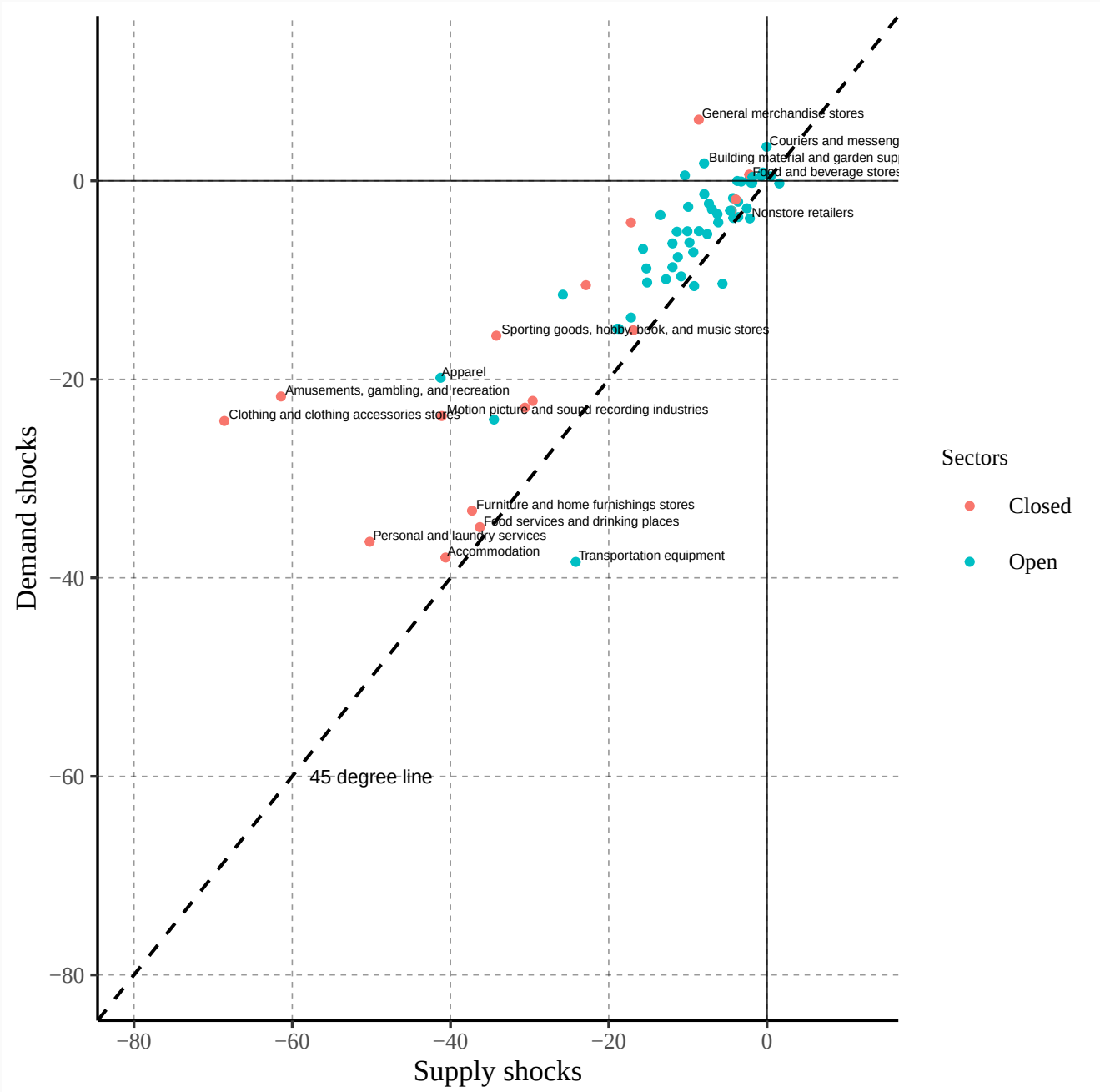
- Combined effect: $-16.24$ pp, supply accounted for 68.8%
- Leisure and Hospitality most-affected sector ($-63.17$ pp, of which 63% supply)
- Least-affected sectors: Utilities ($+0.09$ pp), Financial Activities ($-3.06$ pp), Information ($-8.89$ pp)
- Sectors where demand was relevant: Manufacturing (40%), Information (40%), Education and Health Services (45%)
- Sectors not directly exposed to lockdown measures more affected by demand

▸ Shock distributions for April

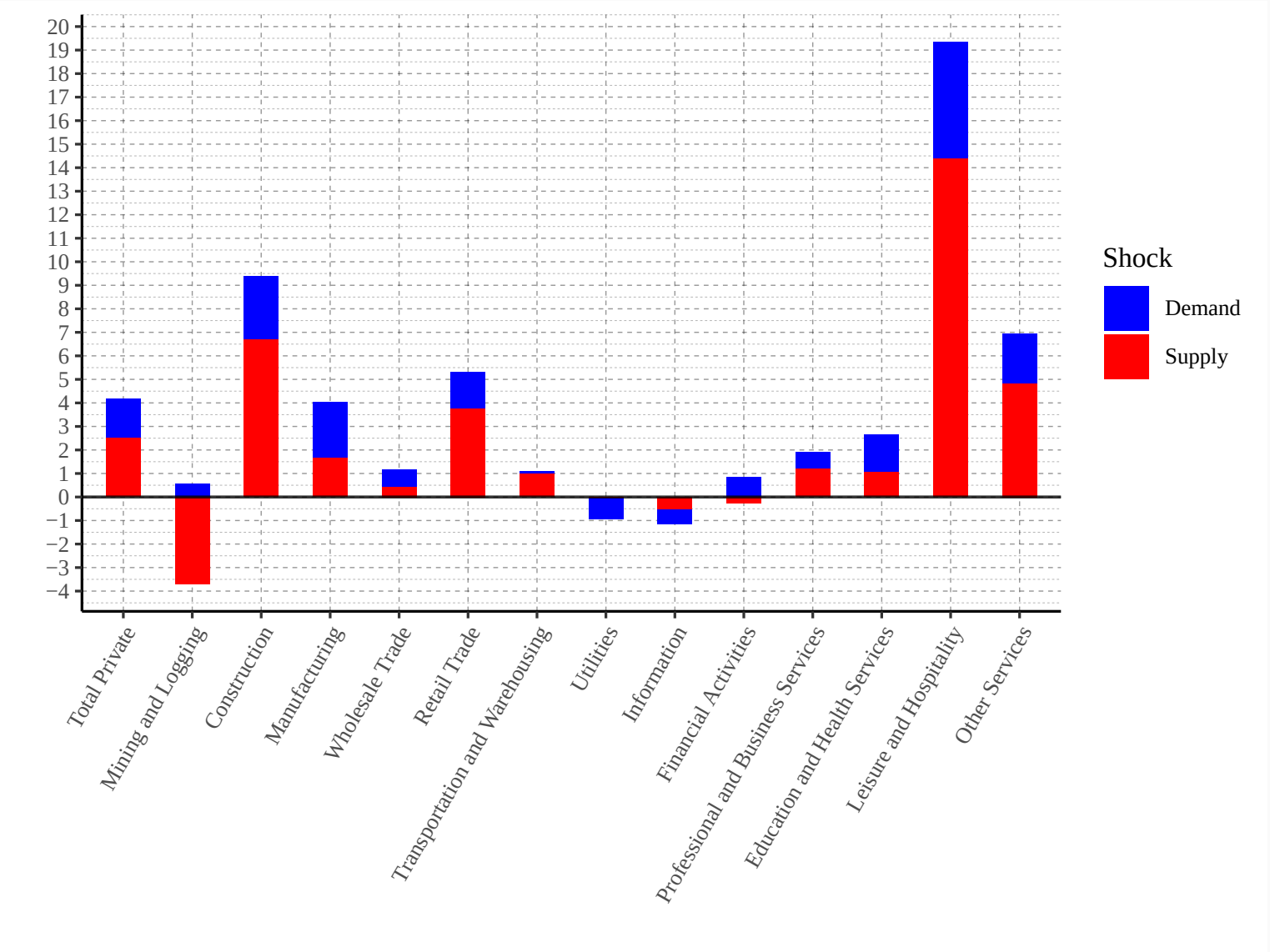
# Shock Decomposition by NAICS-3, April 2020



# Lockdown - closed vs. open sectors in April 2020



# Shock Decomposition, May 2020



# Challenges and Robustness

# Empirical Challenges

Large unprecedented shock, may threaten some important assumptions

1. Gaussian errors, needed to construct likelihood
2. Stationarity of residuals, needed for the Wold decomposition
3. **Model linearity (structural breaks, non-constant elasticities...)**

- (1) and (2) addressed by estimating model up to February 2020
- (3) harder to address; validate shocks w/ external measures

Other challenges:

4. Quality of BLS data (Establishment survey was not significantly affected by COVID-19)
5. **Composition effects**
6. Labor demand shocks driven by supply shocks of goods and services (e.g. TFP shocks)?

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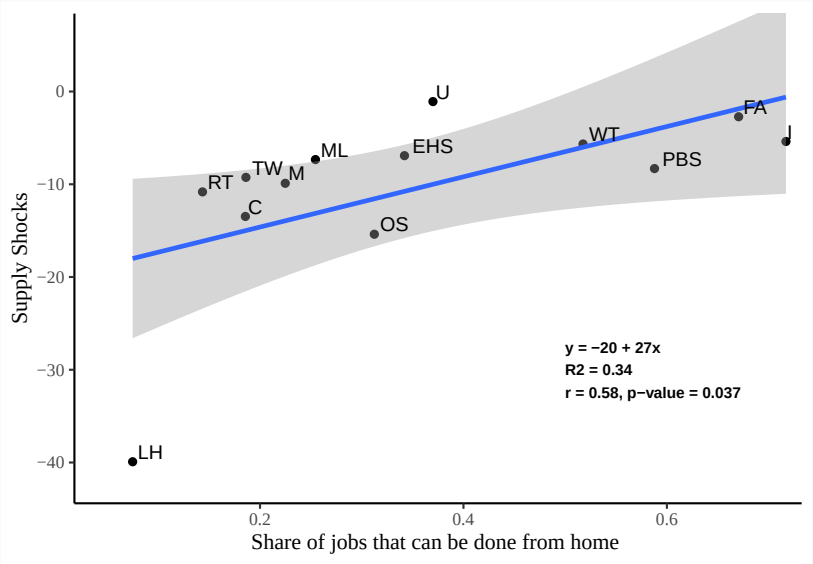
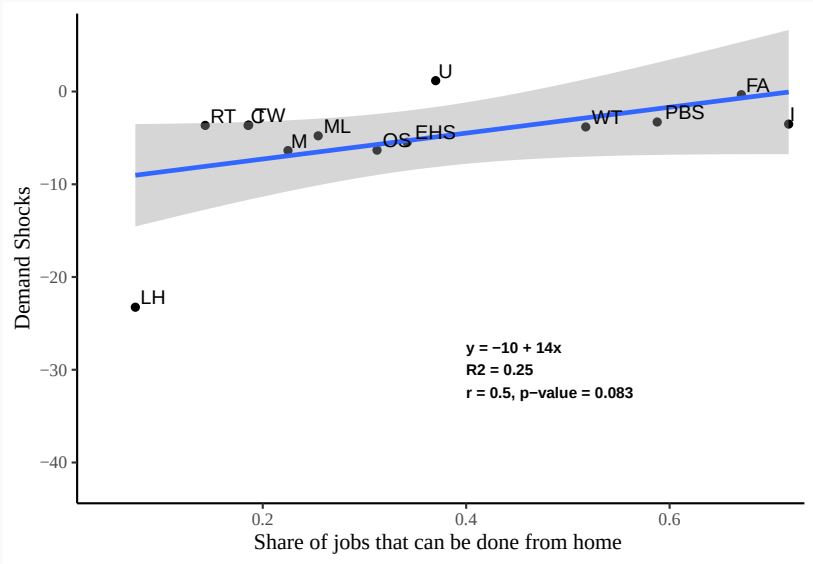
# Robustness I: external validation

Telework measure from Dingel & Neiman (2020)

**(a)** Supply




**(b)** Demand

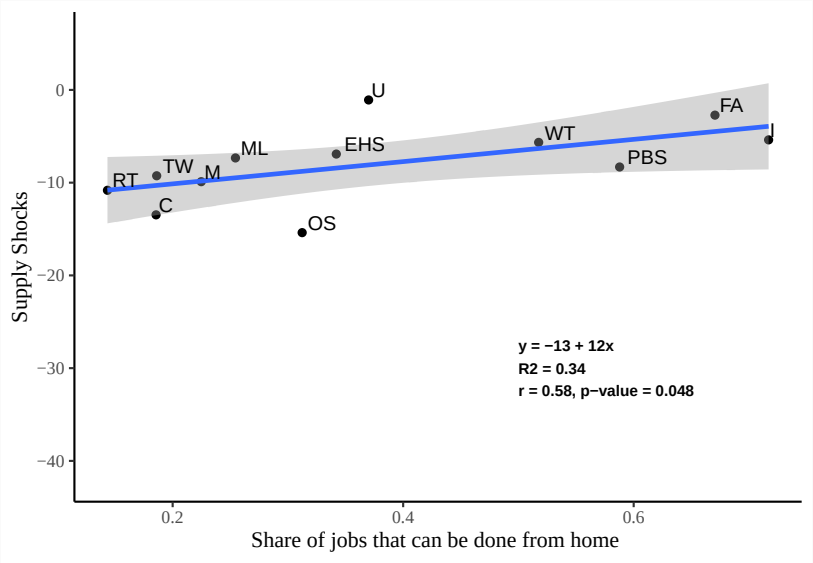



No significant relationship in other months ▸ April 2019

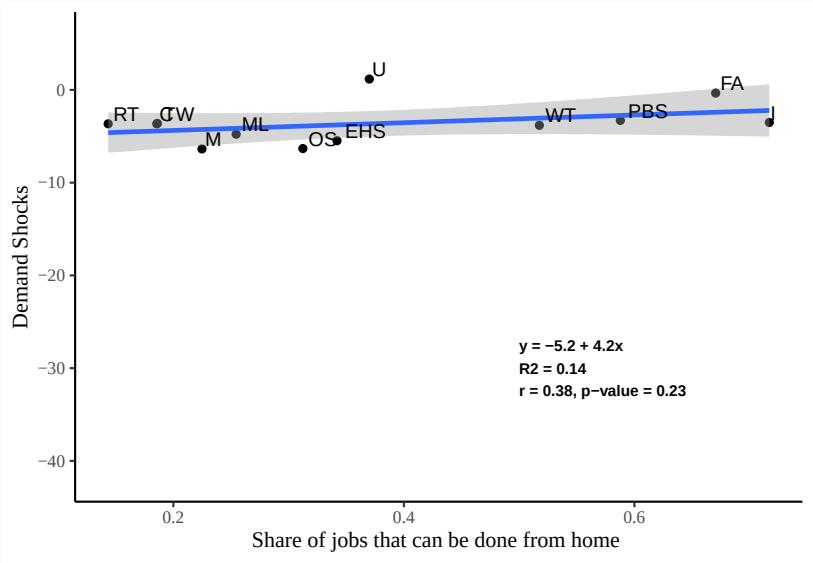
# Robustness I: external validation

## Removing Leisure and Hospitality

**(a)** Supply



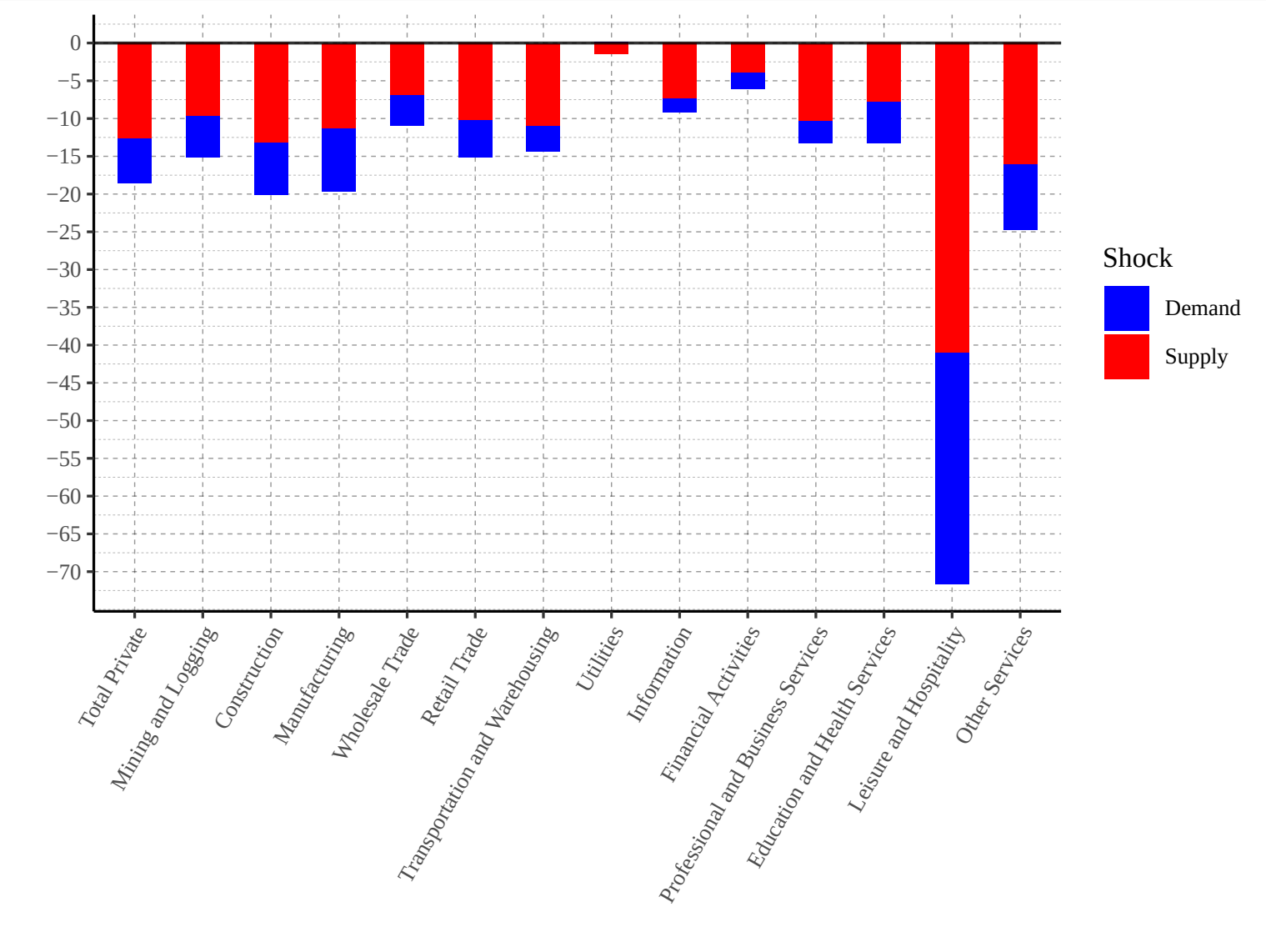

**(b)** Demand



# Robustness II: composition effects

- Job losses concentrated in low-paying jobs (i.e., Mongey et al. 2020)
- Negative labor demand shock leading to destruction of low-wage jobs may "look like" a negative supply shock
- Re-estimate VAR on data for "production and non-supervisory" and "supervisory" employees
- Results for "production and non-supervisory" employees change little

# Robustness II: composition effects, April 2020



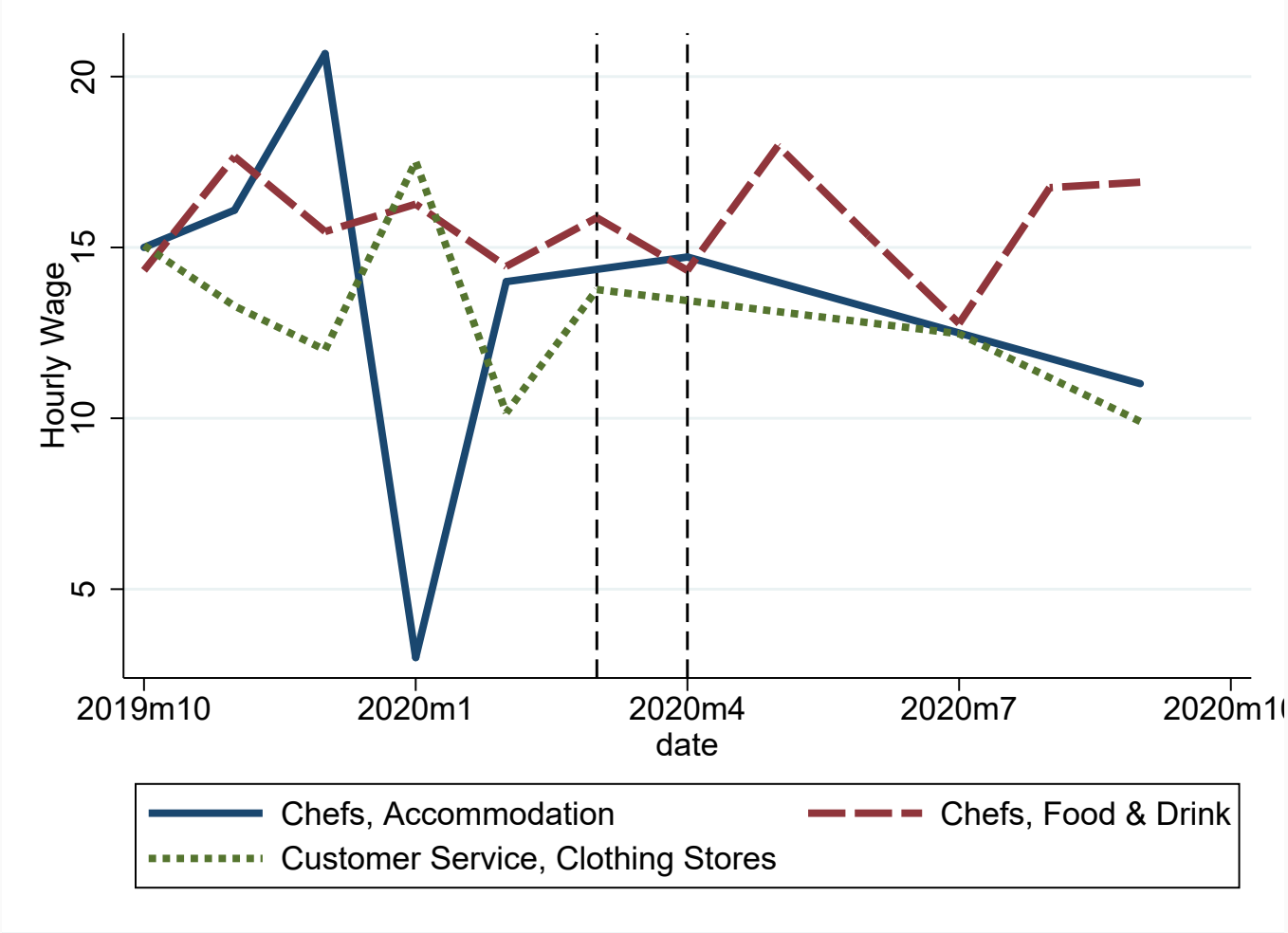
# Robustness II: composition effects, April 2020

- Use CPS monthly data to check the plausibility of composition effects and demand explaining all the labor dynamics

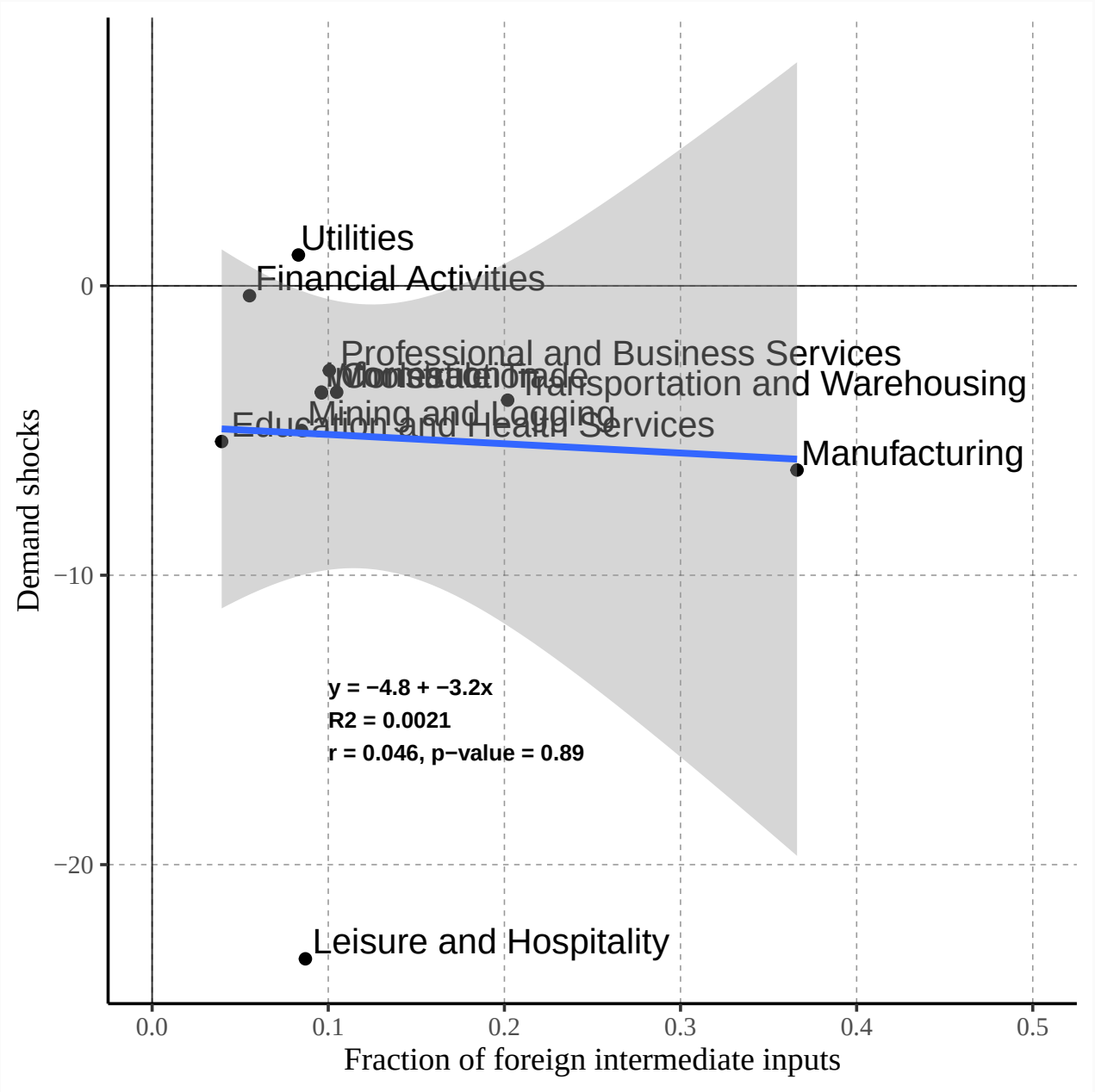
- We conclude this extremely unlikely as wages would have had to increase by much more

| | Clothing Stores | Accommodation | Food & Drink Places |
|---|---|---|---|
| 2019 CPS Hourly Earnings | 21.16 | 17.61 | 14.82 |
| Counterfactual March 2020 | 21.47 | 18.55 | 15.35 |
| % Δ March 2020 CF vs. 2019 CPS | +1.45% | +5.29% | +3.59% |
| % Δ, data | -0.061% | -1.62% | -2.54% |
| Counterfactual April 2020 | 65.35 | 38.28 | 24.54 |
| % Δ April 2020 CF vs. March 2020 CF | +204.43% | +106.39% | +59.80% |
| % Δ, data | +11.33% | +3.05% | -1.11% |

# Robustness II: composition effects, April 2020



# Robustness III: labor demand shocks $\neq$ TFP shocks, April 2020

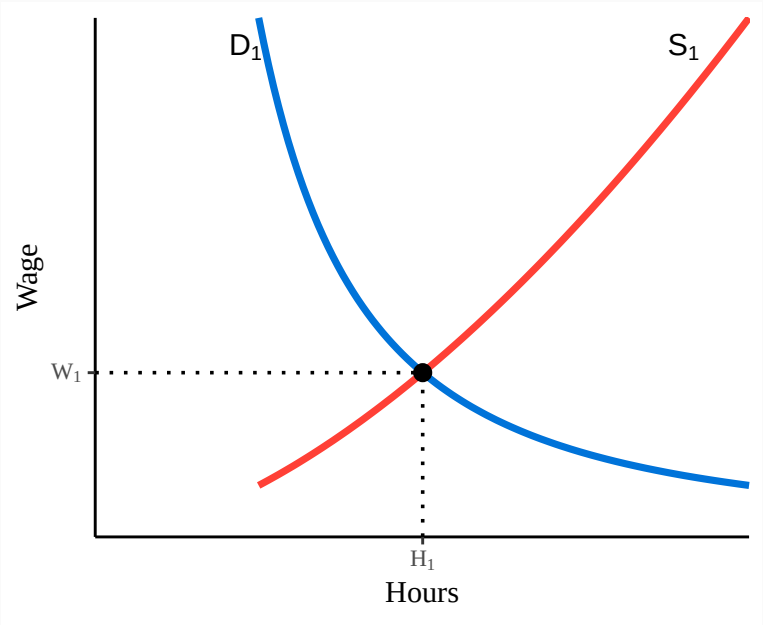


# Conclusion

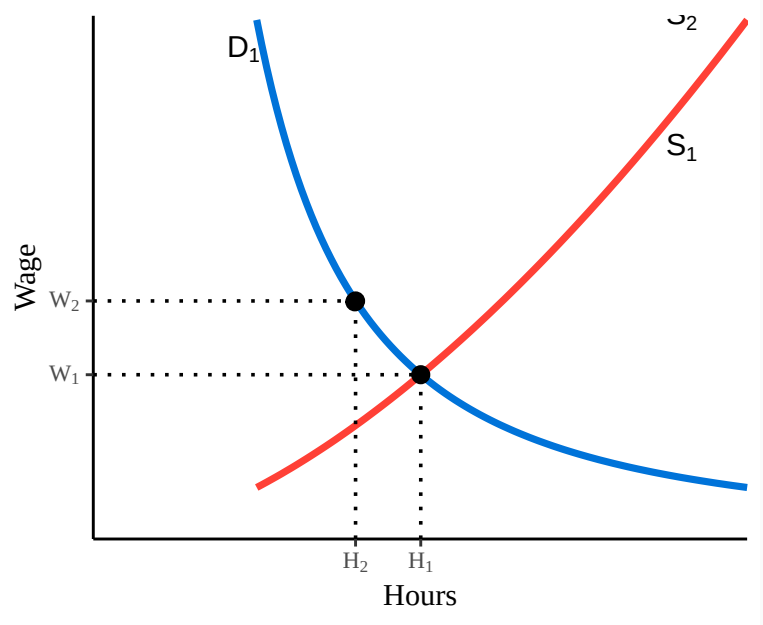
- Econometric model of the labor market to decompose supply & demand in March-May 2020
- 2/3 of the fall in hours during March & April 2020 attributable to negative supply shocks
- Contributions:
  1. Provide useful moments to calibrate/discipline models
  2. Important for the design of public policies (targeted policies, etc.)
- In progress:
  - MSA-level analysis
  - Effects of UI expansion
  - Demand vs. "Keynesian supply shocks" (Guerrieri et al., 2020)

# Identification Illustrated

**(a)** Equilibrium at t=0




**(b)** Equilibrium at t=1

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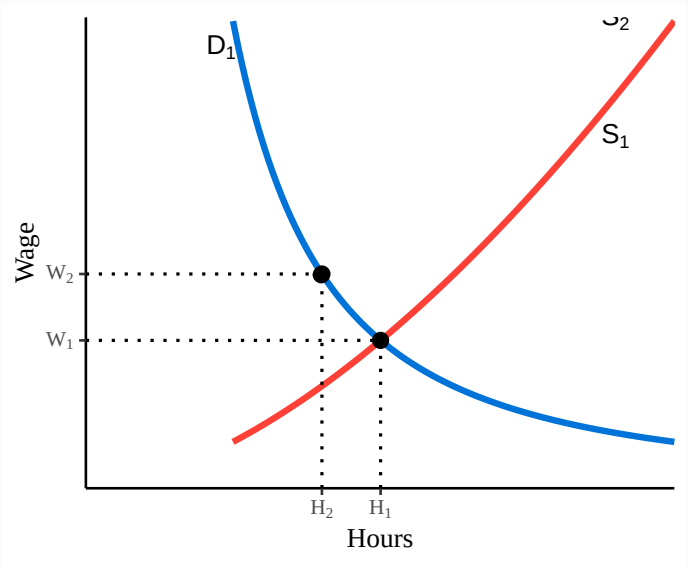
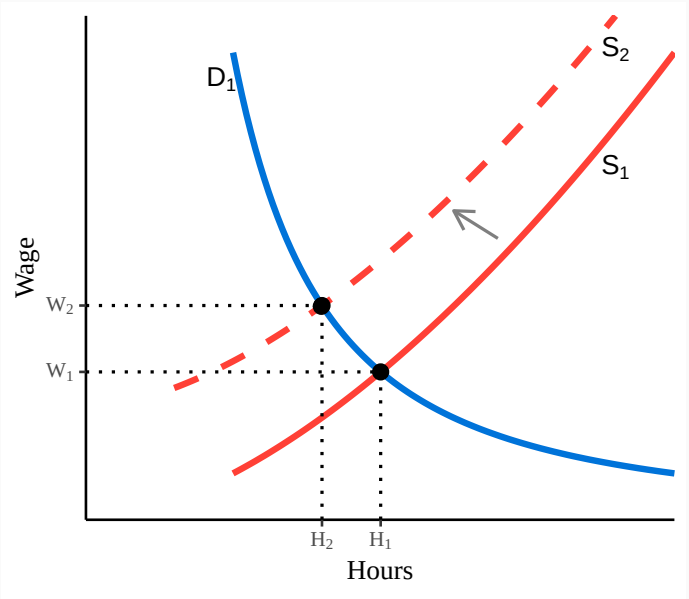
# Identification Illustrated

**(a)** Equilibrium at t=1




**(b)** Equilibrium at t=1

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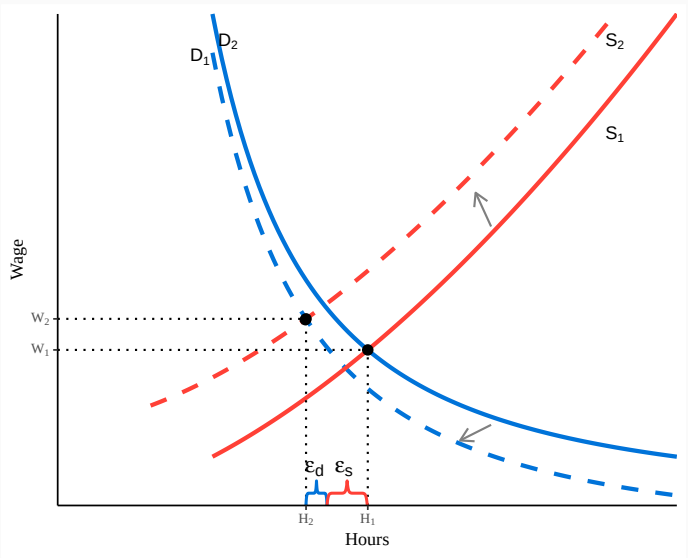
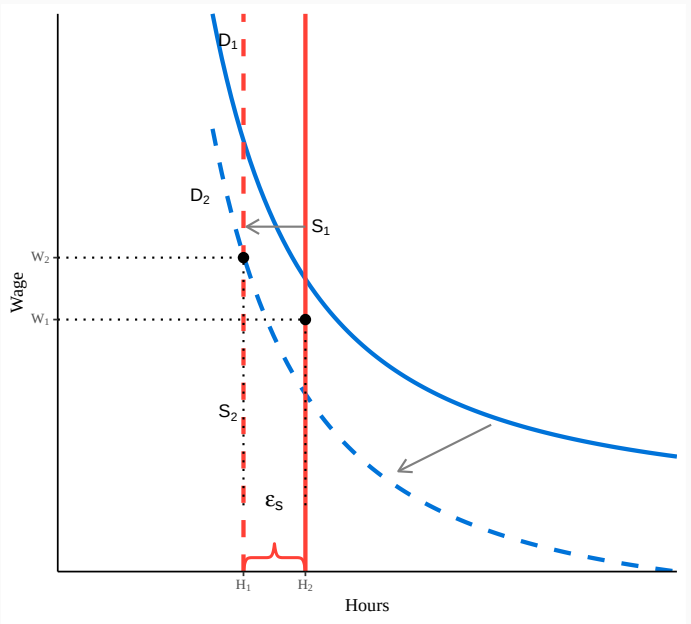
# Identification Illustrated - Hours Decomposition

**(a)** A) Depends on new wage-hours locus




**(b)** B) Depends on relative labor elasticities

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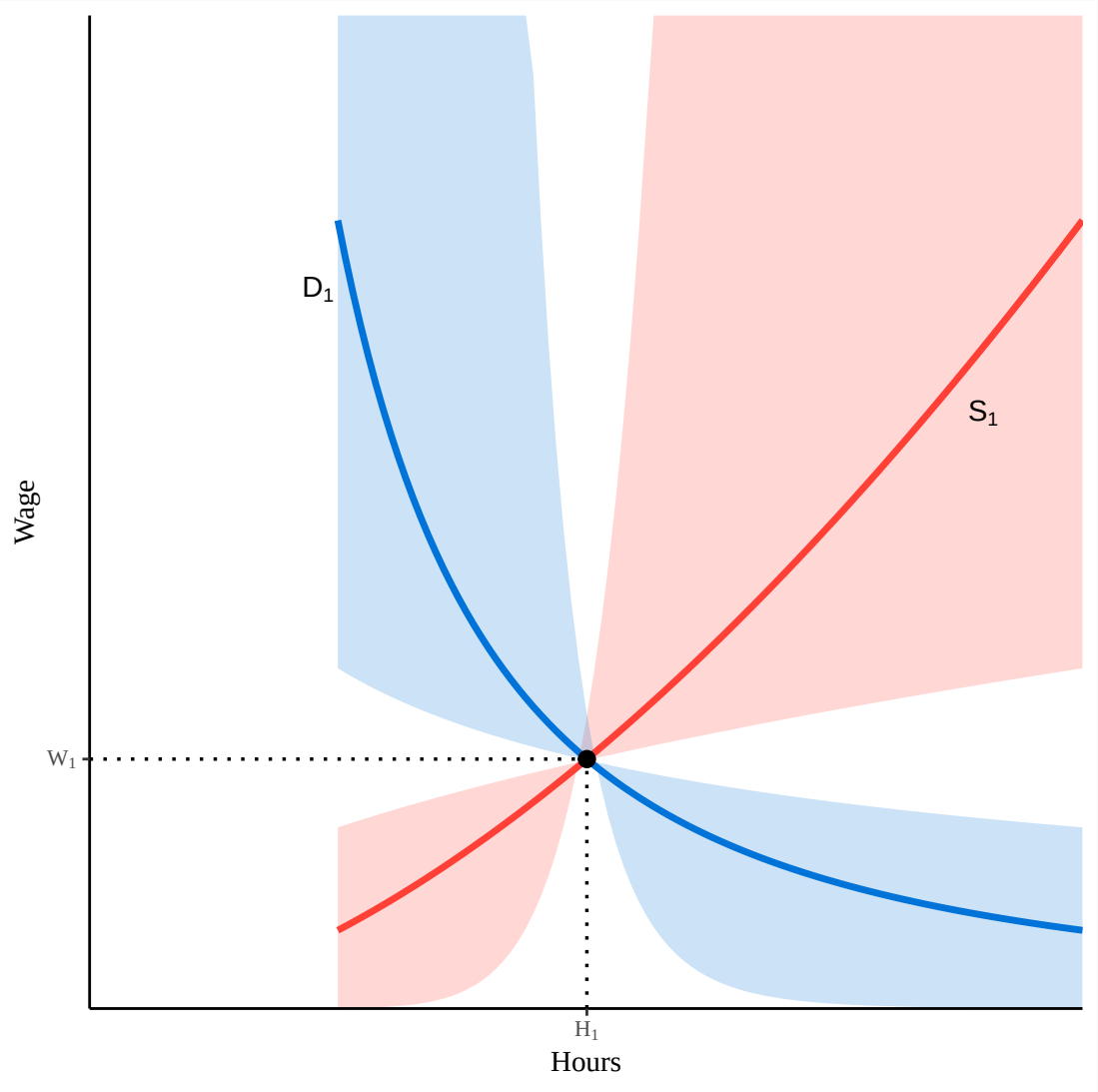
# Identification Illustrated - Add Prior

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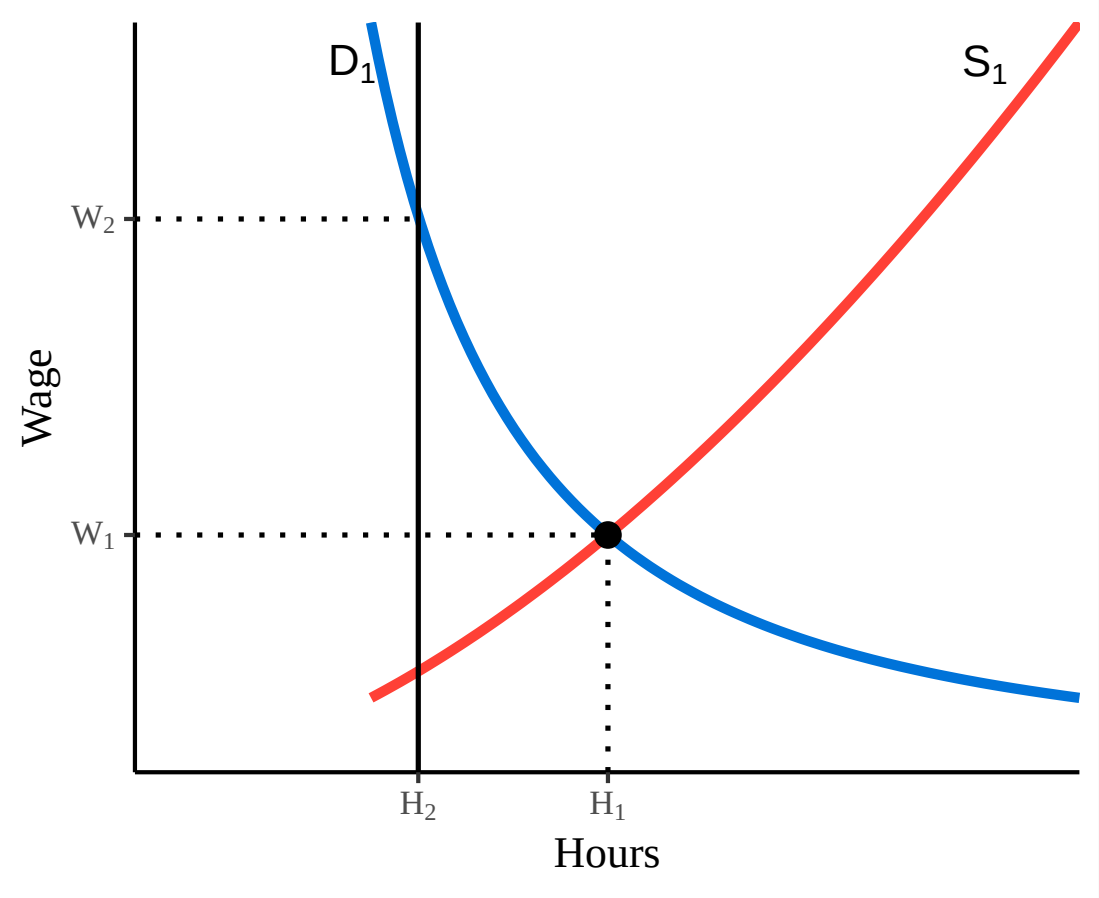
# Identification Illustrated - Lockdown

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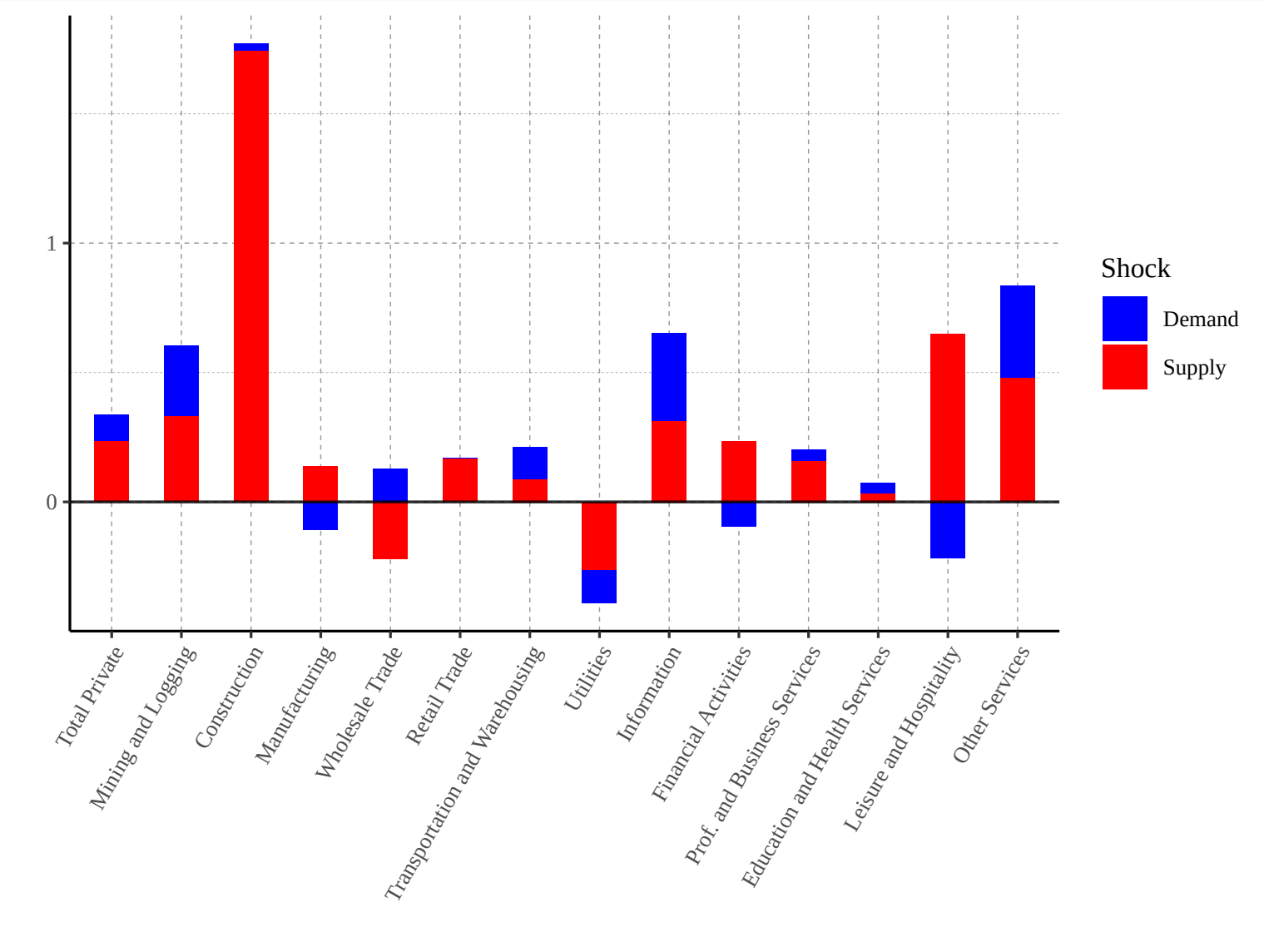
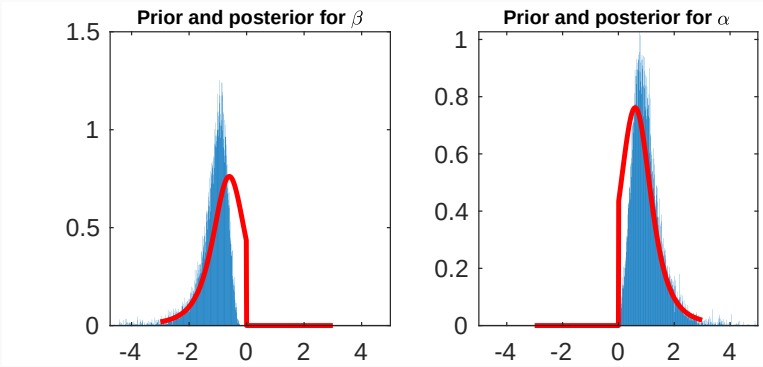
# Shock Decomposition, March 2019



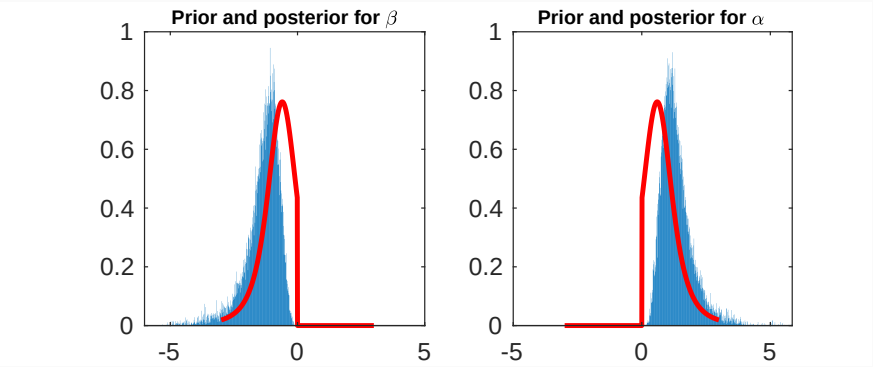

return

# Prior and posterior distribution of labor demand and supply elasticities by sector (1/4)

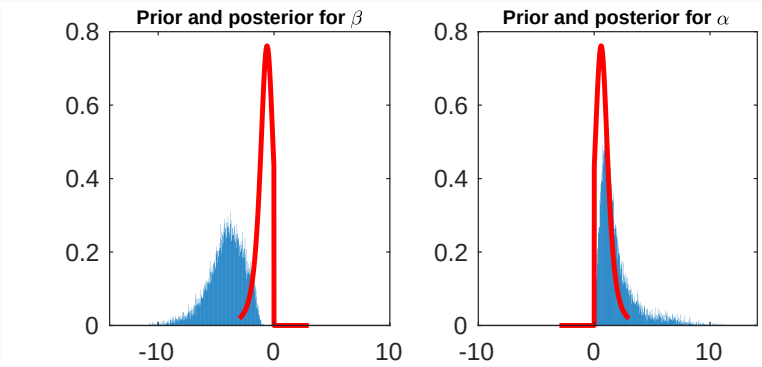
**(a)** Total Private



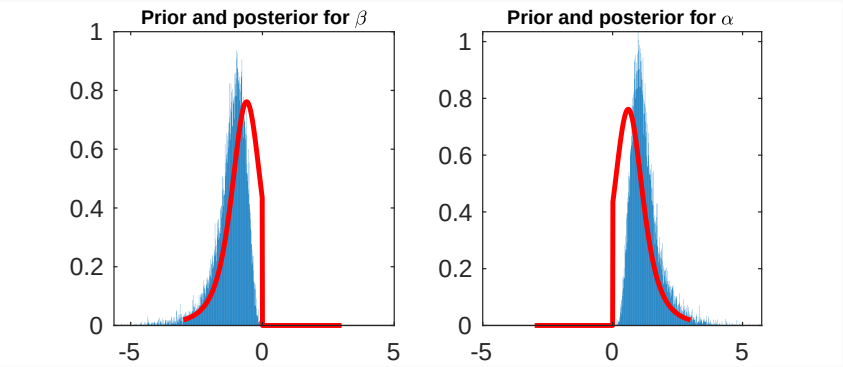

**(b)** Mining and Logging




**(c)** Construction




**(d)** Manufacturing

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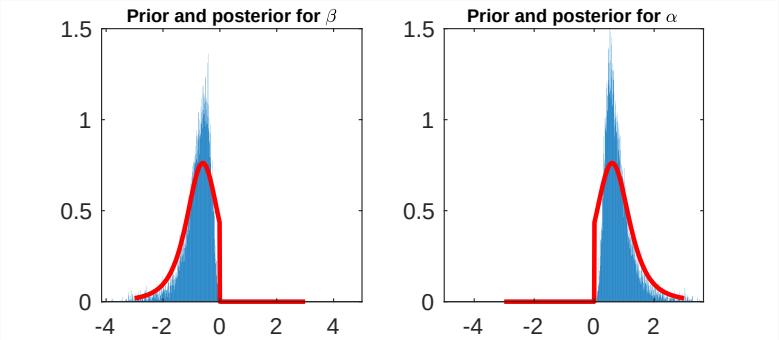
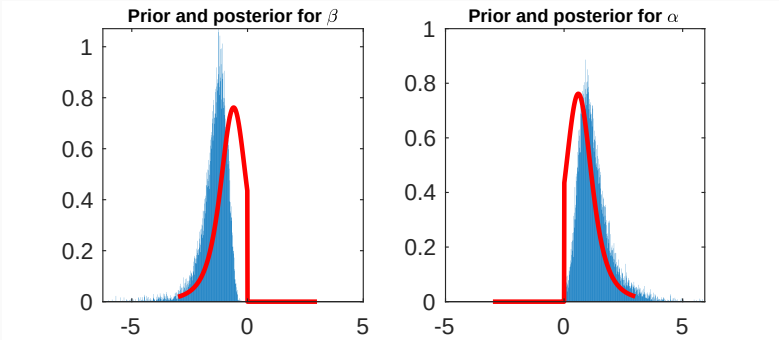
# Prior and posterior distribution of labor demand and supply elasticities by sector (2/4)

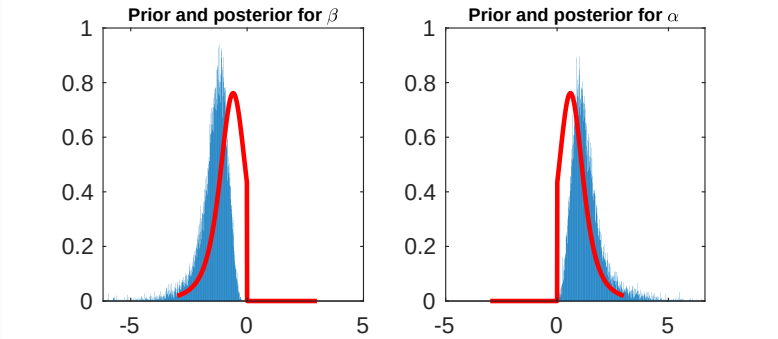
**(a)** Wholesale Trade



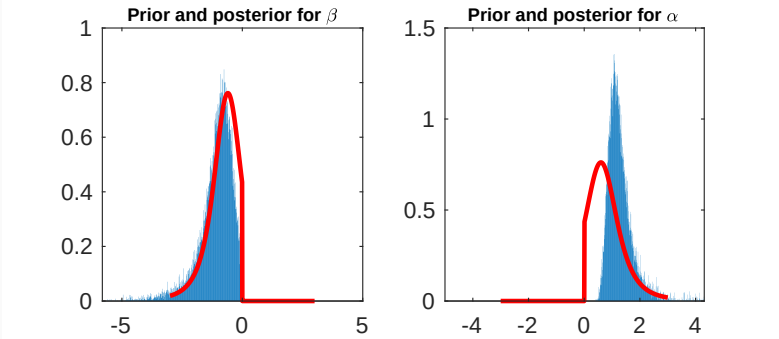

**(b)** Retail Trade




**(c)** Transportation and Warehousing




**(d)** Utilities

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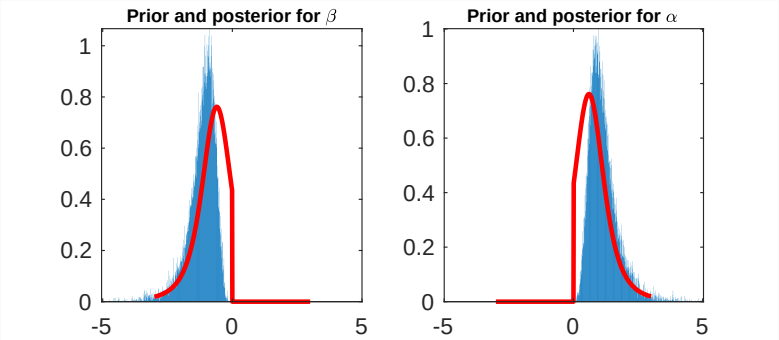
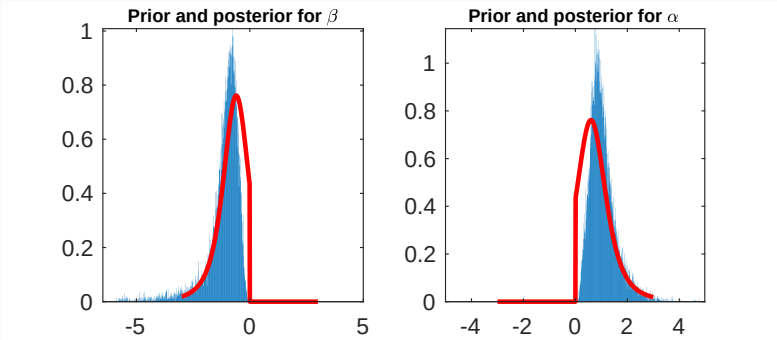
# Prior and posterior distribution of labor demand and supply elasticities by sector (3/4)

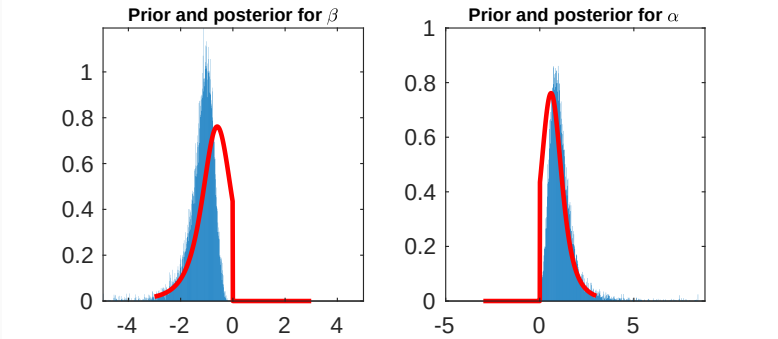
**(a)** Information



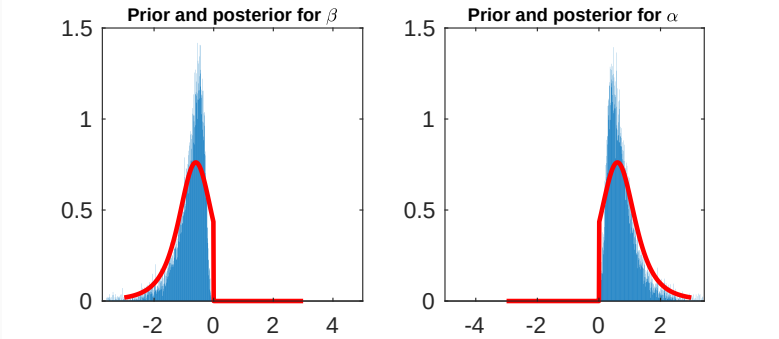

**(b)** Financial Activities




**(c)** Professional and Business Services




**(d)** Education and Health Services

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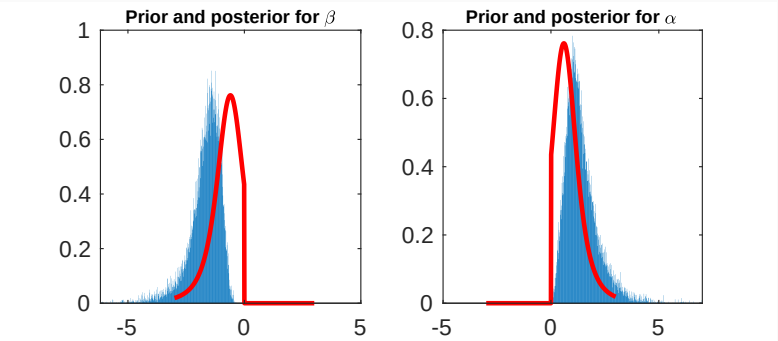
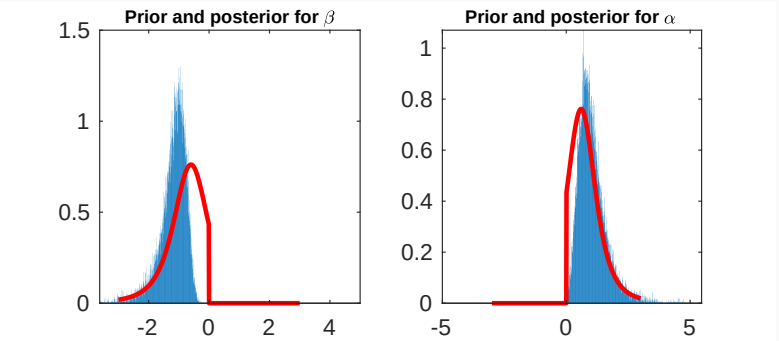
# Prior and posterior distribution of labor demand and supply elasticities by sector (4/4)

**(a)** Leisure and Hospitality




**(b)** Other Services

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# Posterior Estimates

| | $\beta^l$ (demand) | | | $\alpha^l$ (supply) | | |
|---|---|---|---|---|---|---|
| Sector | p5 | p50 | p95 | p5 | p50 | p95 |
| Mining and Logging | -3.4985 | -1.4533 | -0.57036 | 0.51094 | 1.3784 | 3.331 |
| Utilities | -2.7957 | -1.0508 | -0.2748 | 0.72259 | 1.3686 | 2.6255 |
| Construction | -14.443 | -4.4111 | -0.70444 | 0.45431 | 2.3951 | 16.097 |
| Manufacturing | -3.813 | -1.4151 | -0.45704 | 0.8067 | 1.8056 | 3.8972 |
| Wholesale Trade | -1.9119 | -0.74404 | -0.21297 | 0.25625 | 0.73813 | 1.7147 |
| Retail Trade | -4.6419 | -2.4711 | -1.2466 | 0.32368 | 1.2577 | 3.7929 |
| Transportation and Warehousing | -2.2208 | -1.2205 | -0.67791 | 0.2437 | 0.95951 | 2.4964 |
| Information | -2.0643 | -0.90012 | -0.34388 | 0.32847 | 0.92223 | 2.1588 |
| Financial Activities | -2.1287 | -1.0533 | -0.49371 | 0.26154 | 0.93418 | 2.3441 |
| Professional and Business Services | -2.9516 | -1.4611 | -0.72686 | 0.34512 | 1.1377 | 2.9259 |
| Education and Health Services | -2.2529 | -1.0778 | -0.47521 | 0.3506 | 1.0614 | 2.5915 |
| Leisure and Hospitality | -4.4276 | -1.9899 | -0.84574 | 0.45443 | 1.4753 | 4.1884 |
| Other Services | -2.9106 | -1.4046 | -0.63227 | 0.42351 | 1.193 | 2.8501 |
| Total Private | -2.6593 | -1.1375 | -0.40432 | 0.53653 | 1.2244 | 2.6541 |

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# Shock Decomposition, April 2020

| | Demand | | | Supply | | | Difference 68% Credible Interval |
|---|---|---|---|---|---|---|---|
| Sector | 50p | 2.5p | 97.5p | 50p | 2.5p | 97.5p | |
| Total Private | -5.06 | -11.28 | -0.31 | -11.18 | -15.94 | -4.97 | [-12.204, 0.5492] |
| Mining and Logging | -4.78 | -9.50 | -0.84 | -7.34 | -11.32 | -2.62 | [-8.076, 2.293] |
| Construction | -3.65 | -12.78 | -0.32 | -13.47 | -16.82 | -4.33 | [-14.443, -0.375] |
| Manufacturing | -6.36 | -12.93 | -1.14 | -9.89 | -15.13 | -3.32 | [-10.365, 3.447] |
| Wholesale Trade | -3.82 | -8.23 | -0.37 | -5.66 | -9.10 | -1.25 | [-6.556, 3.101] |
| Retail Trade | -3.65 | -9.25 | -0.04 | -10.82 | -14.43 | -5.23 | [-12.276, -0.285] |
| Transport. & Warehousing | -3.61 | -9.06 | -0.01 | -9.26 | -12.85 | -3.81 | [-9.090, 0.655] |
| Utilities | 1.17 | 0.41 | 1.49 | -1.08 | -1.40 | -0.32 | [-2.467, -1.416] |
| Information | -3.51 | -6.95 | -0.63 | -5.39 | -8.26 | -1.95 | [-5.545, 1.967] |
| Financial Activities | -0.34 | -2.00 | 0.52 | -2.72 | -3.59 | -1.05 | [-3.241, -0.610] |
| Prof. and Business Services | -3.29 | -8.05 | -0.15 | -8.31 | -11.44 | -3.53 | [-9.086, -0.780] |
| Education and Health | -5.47 | -10.77 | -0.63 | -6.92 | -11.76 | -1.62 | [-8.005, 5.076] |
| Leisure and Hospitality | -23.26 | -46.70 | -3.63 | -39.92 | -59.55 | -16.47 | [-38.955, 9.722] |
| Other Services | -6.32 | -14.23 | -0.48 | -15.39 | -21.24 | -7.47 | [-16.701, -0.876] |

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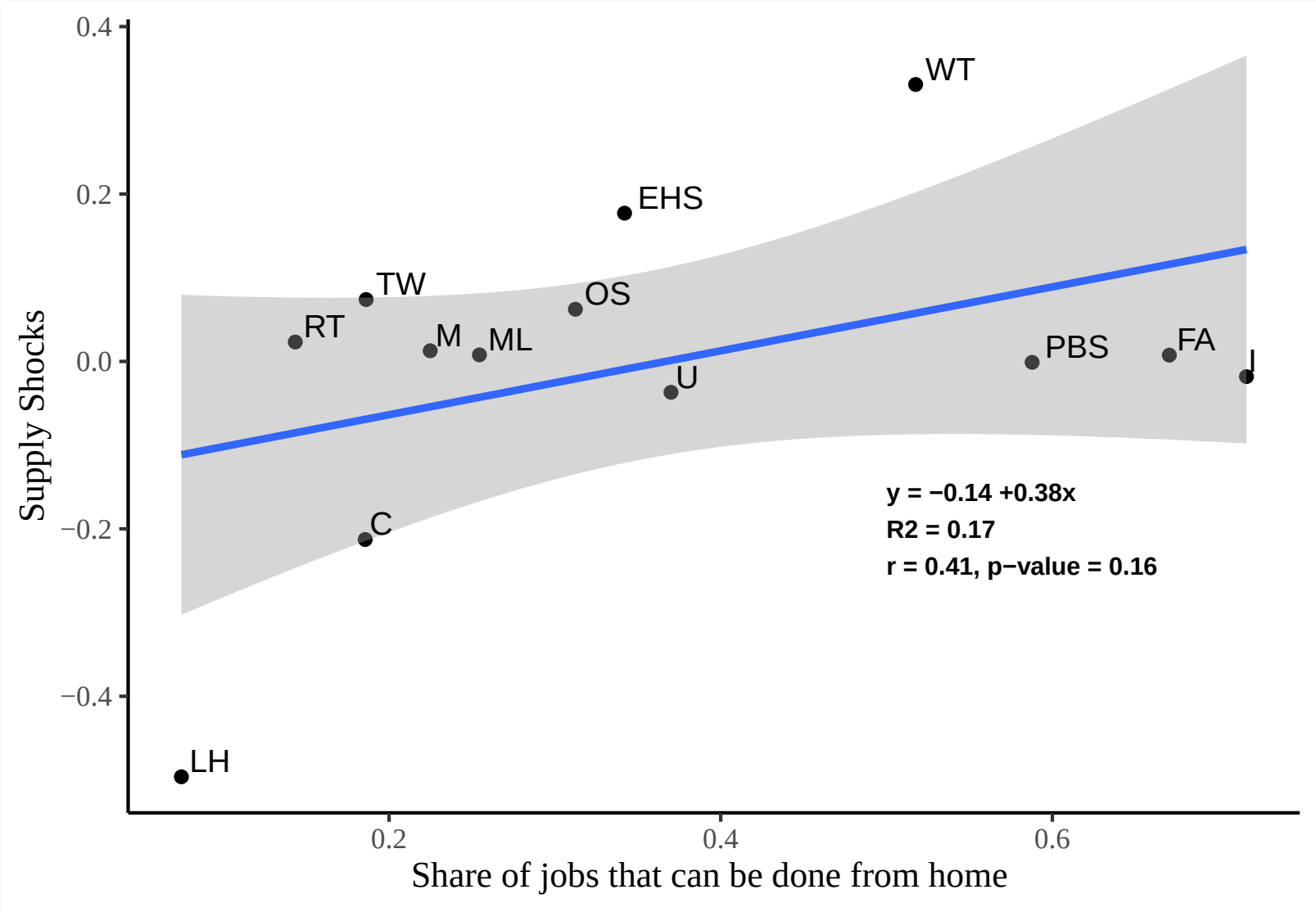
# Estimated Shocks vs. Telework Measure, April 2019

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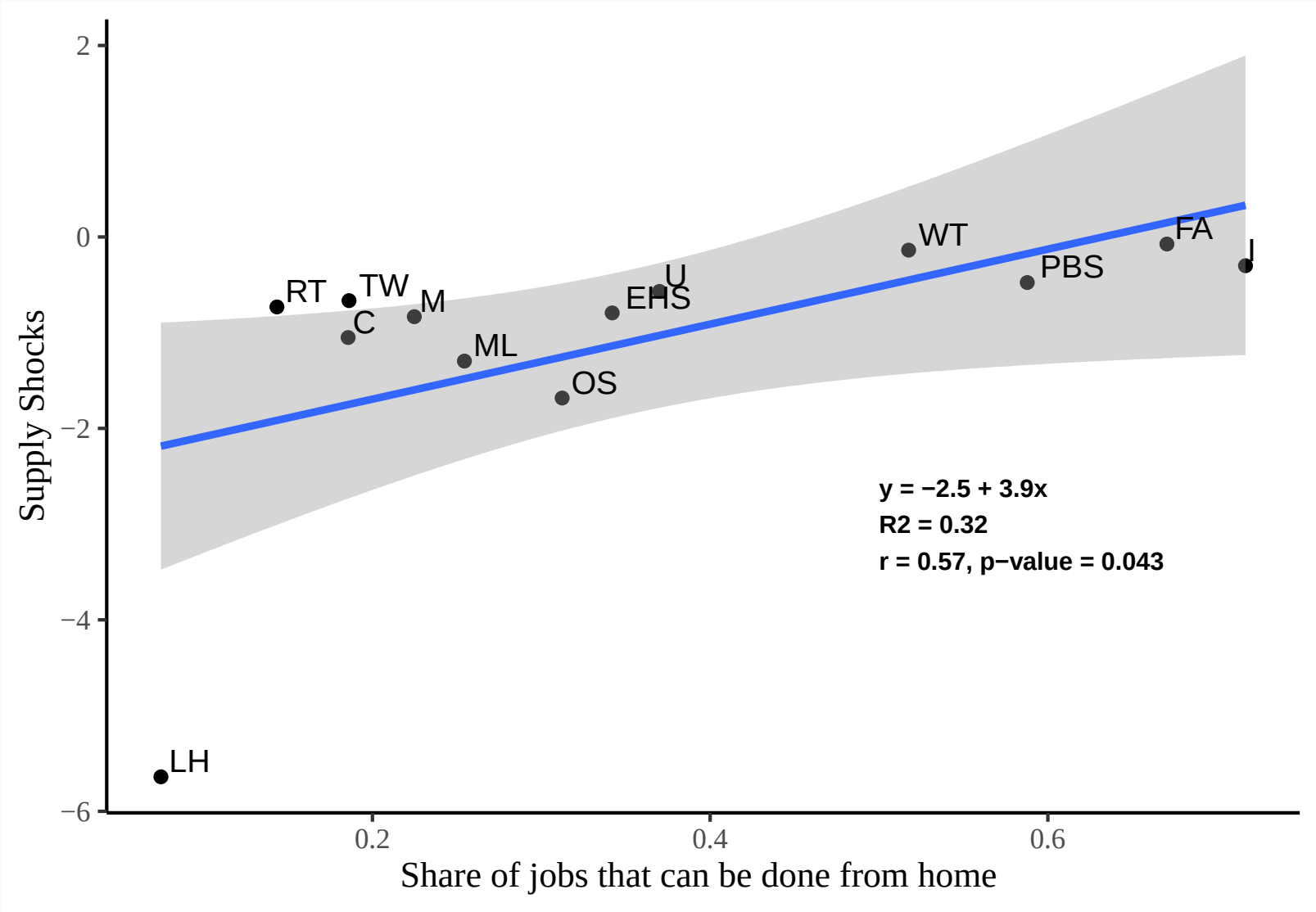
# Estimated Shocks vs. Telework Measure, March 2020

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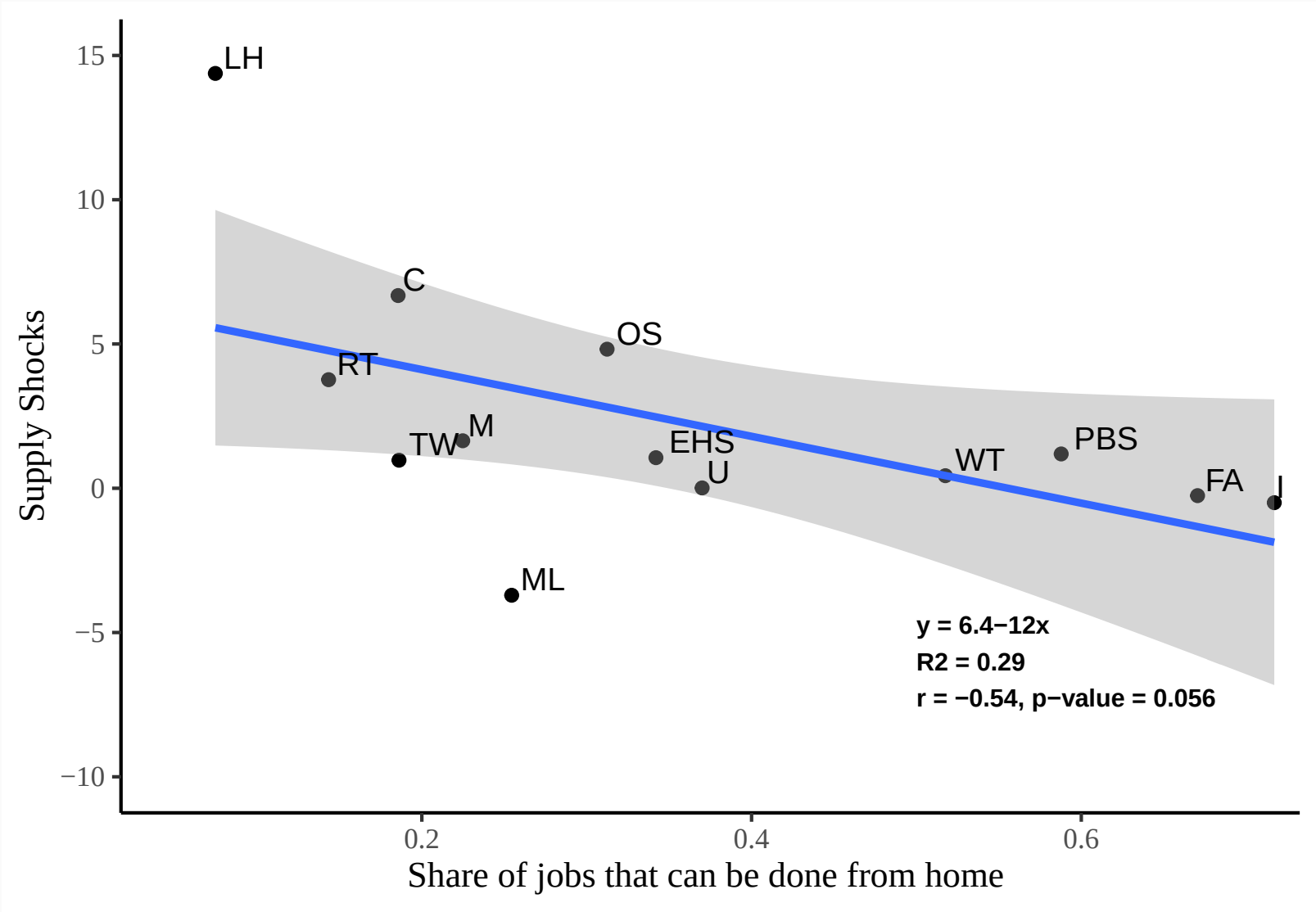
# Estimated Shocks vs. Telework Measure, May 2020

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