Measuring Labor Demand and Supply Shocks during COVID-19

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Introduction

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

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

1. Supply ← Household behavior
   - Increase in health risk
   - Policy
     - Containment and mitigation measures (lockdowns)
     - CARES act
2. Demand ← Firm 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 (closures/monetary/fiscal policy)

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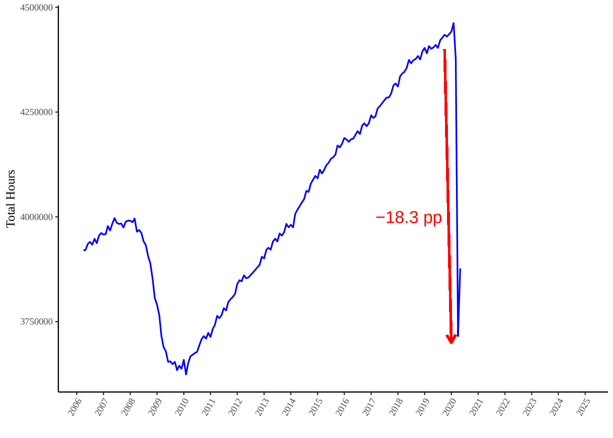
This paper

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**
    - Labor demand shocks more closely related w/ state of the economy
        - Potentially more persistent (job destruction, business exit)
        - Policy recommendation: **Targeted stimulus**

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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 (Δh_t, Δw_t) with informative prior (Baumeister & Hamilton, 2015, 2018, 2019)
  - Accounts for estimation uncertainty + uncertainty about the underlying structure of the economy
  - Prior beliefs are explicitly acknowledged: labor supply & demand elasticity estimates from literature

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Approach:

- 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 ▸ NAICS-3 results)
  2. Occupational category (production vs. non-production)

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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
- 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 in some of these sectors
- Validation:
  1. Supply shocks correlate strongly with measures of telework
  2. No correlation for "normal" months
  3. Low correlation w/ demand shocks

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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 Δw_t^l, hours Δh_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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- Assuming $\beta^l < 0, \alpha^l > 0$, we get:
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  2. $\frac{\partial \Delta w_t^l}{\partial \varepsilon_{d,t}^l} > 0$ and $\frac{\partial \Delta w_t^l}{\partial \varepsilon_{s,t}^l} < 0$

▸ Graphical Illustration

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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 τ_i
   - set κ_i/τ_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

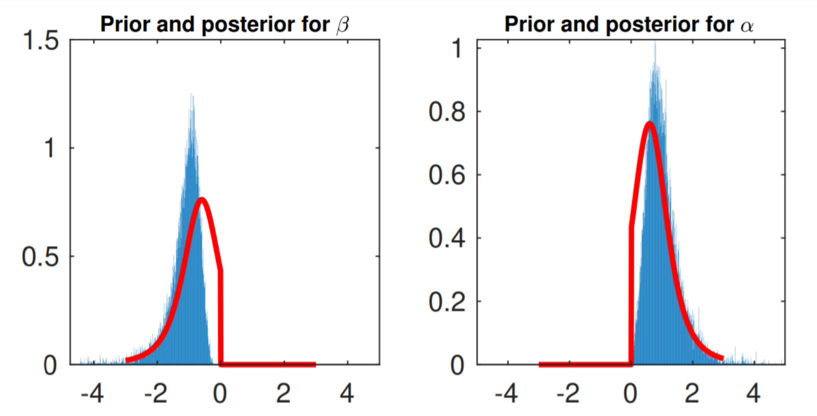
Data

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
- 14 aggregate sectors, roughly map to NAICS-2
- Estimate SVAR until February 2020, use estimated model+data to estimate shocks for March-May 2020

Estimation Results

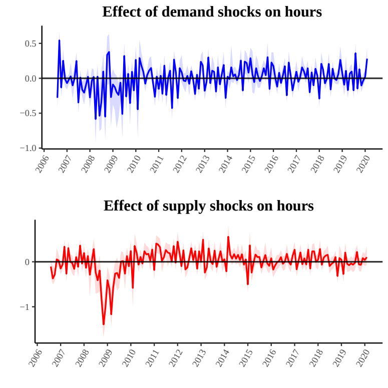
Estimation Results: Total Private Employment



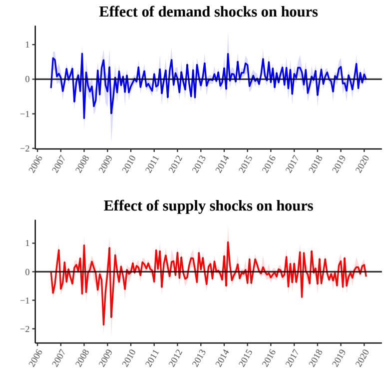
▸ All sectors ▸ Table with Results

Estimated Shocks: until February 2020

(a) Total Private Employment

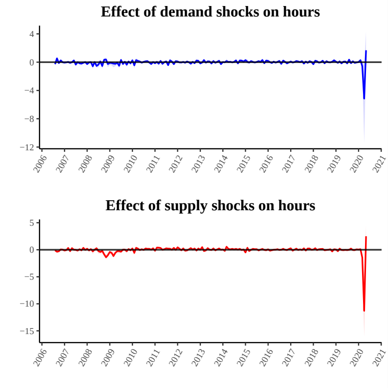


(b) Leisure and Hospitality

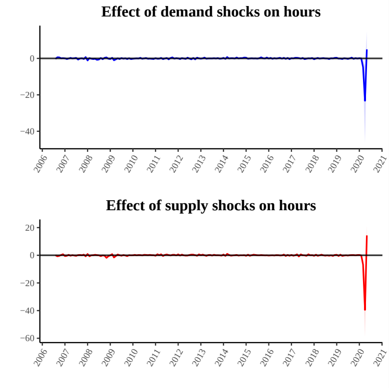


Estimated Shocks: full sample

(a) Total Private Employment

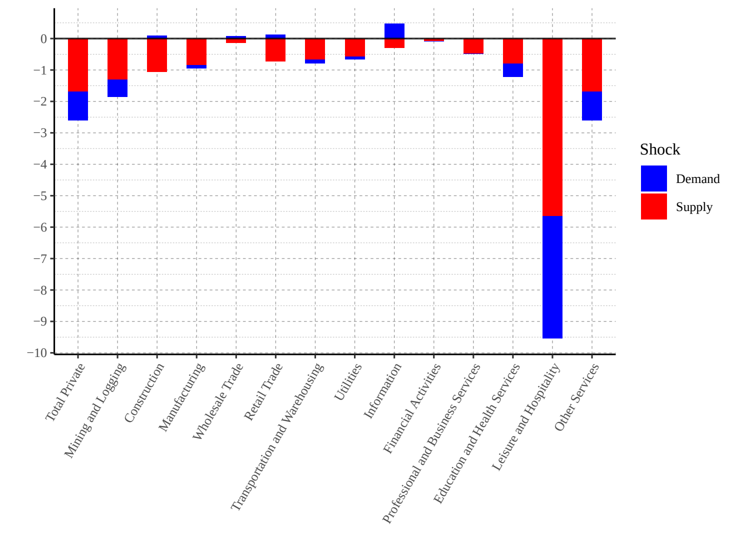


(b) Leisure and Hospitality



Shock Decomposition

Shock Decomposition, March 2020

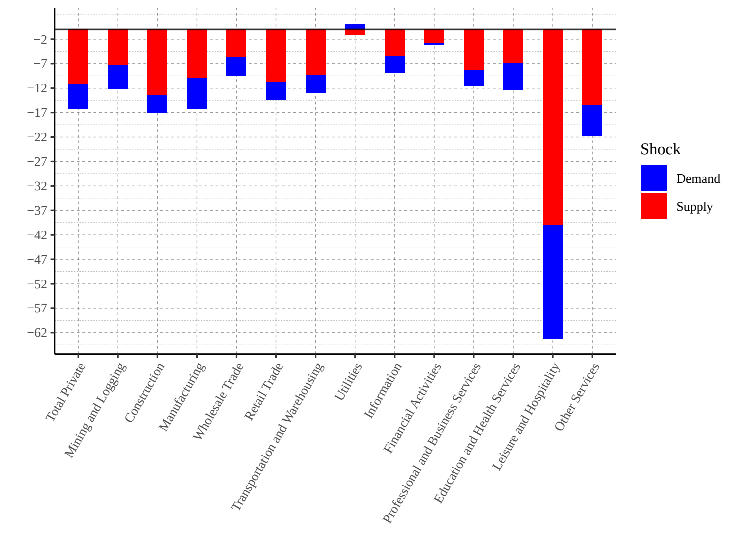


Shock Decomposition, March 2020

- 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

▸ March 2020, NAICS-3

Shock Decomposition, April 2020

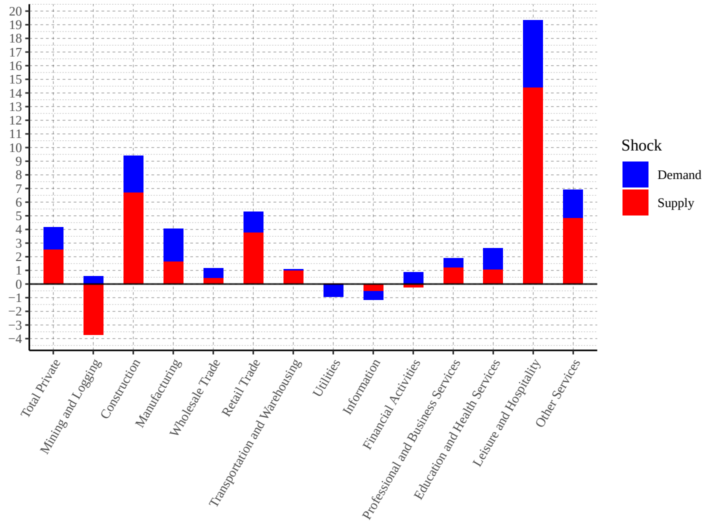


Shock Decomposition, April 2020

- 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 ▸ NAICS-3 for April

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 (preliminary) BLS data
5. **Composition effects**

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:

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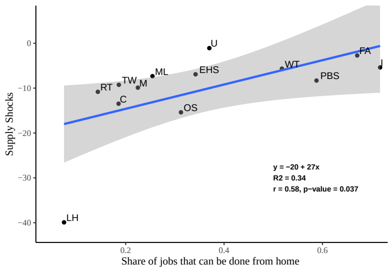
5. **Composition effects**

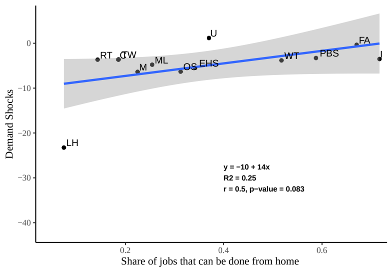
Robustness I: external validation

Telework measure from Dingel & Neiman (2020)

(a) Supply



(b) Demand

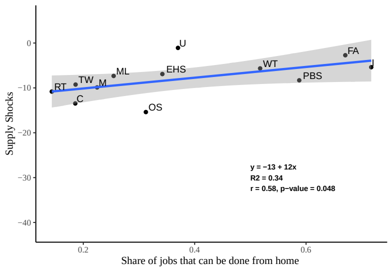


No significant relationship in other months ▸ April 2019

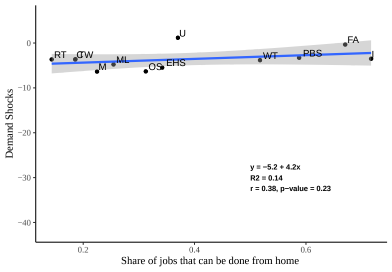
Robustness I: external validation

Removing Leisure and Hospitality

(a) Supply



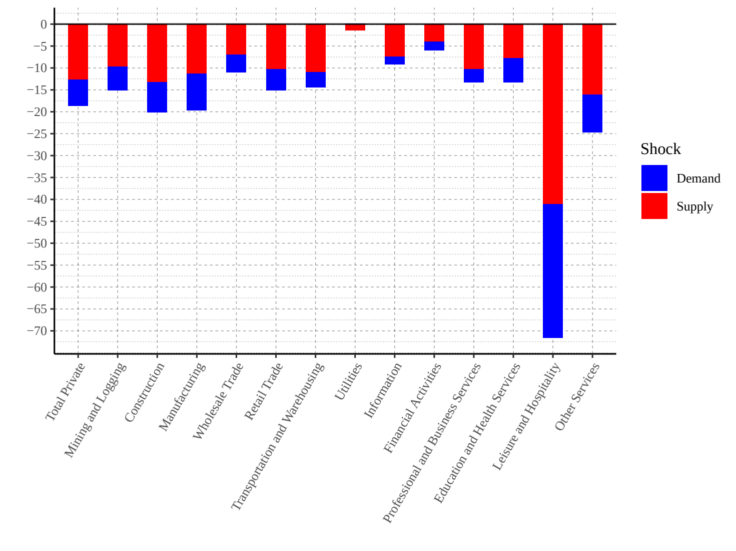
(b) Demand



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

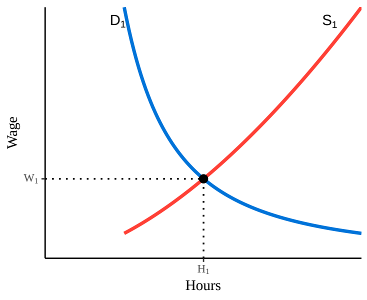


Conclusion

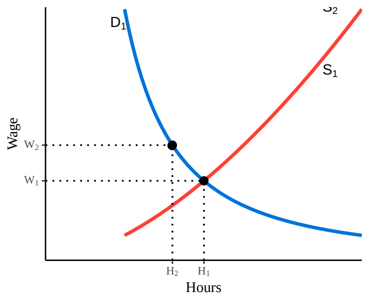
- Econometric model of the labor market to decompose supply & demand in March-May 2020
- 2/3 of the fall in hours during March & April 2020 attributable to negative supply shocks
- Contributions:
    1. Provide useful moments to calibrate/discipline models
    2. Important for the design of public policies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

Identification

(a) Equilibrium at t=0



(b) Equilibrium at t=1



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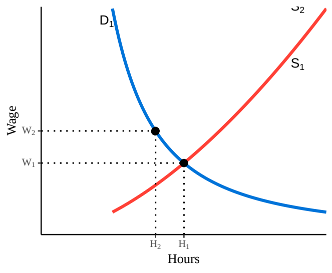
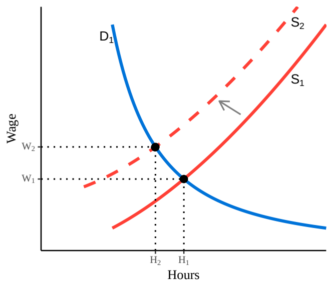
Identification

(a) Equilibrium at t=1



(b) Equilibrium at t=1



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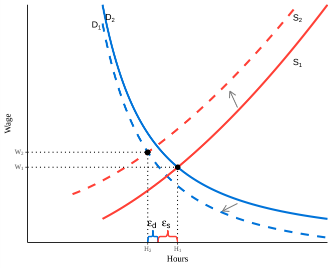
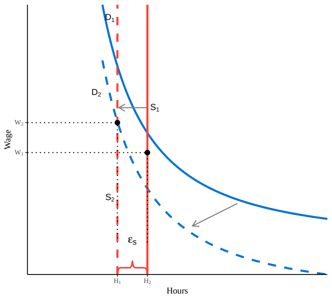
Identification - Hours Decomposition

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



(b) B) Depends on relative labor elasticities



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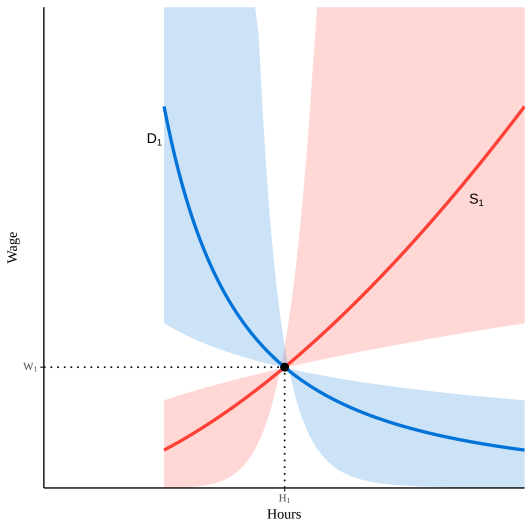
Identification - Prior



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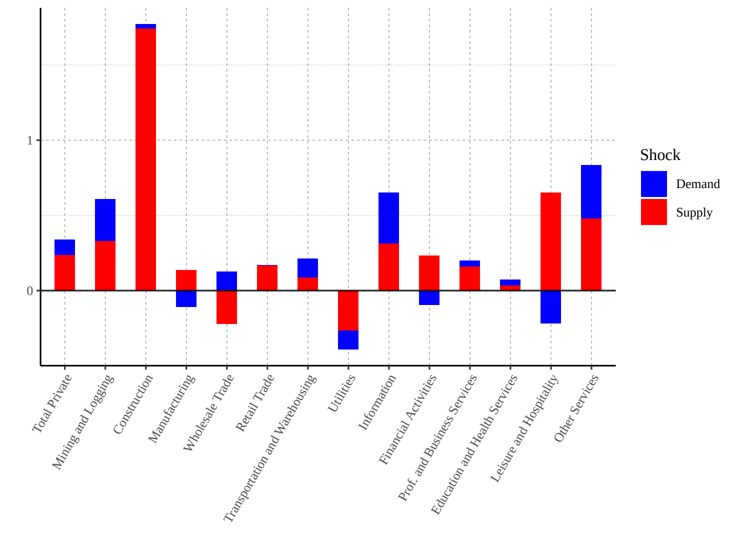
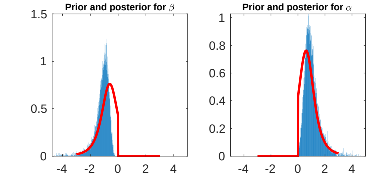
Shock Decomposition, March 2019



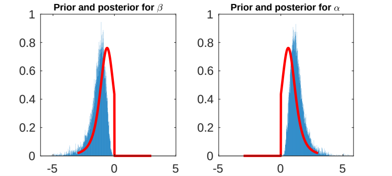
return

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

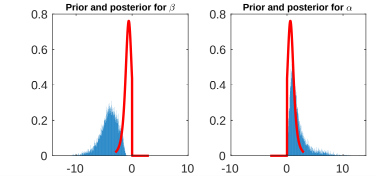
(a) Total Private



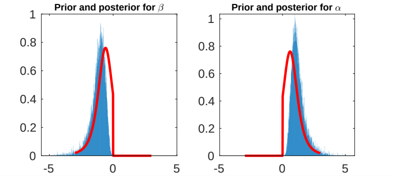
(b) Mining and Logging



(c) Construction



(d) Manufacturing



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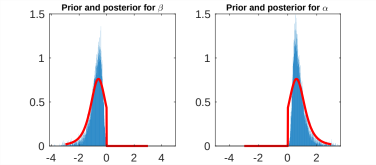
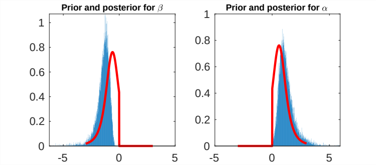
Prior and posterior distribution of labor demand and supply elasticities by sector (2/4)

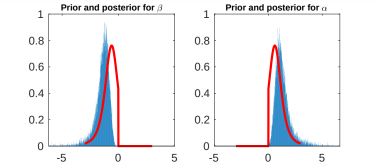
(a) Wholesale Trade



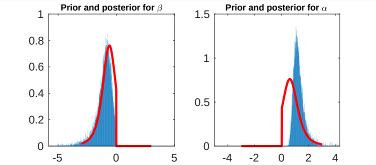
(b) Retail Trade



(c) Transportation and Warehousing



(d) Utilities



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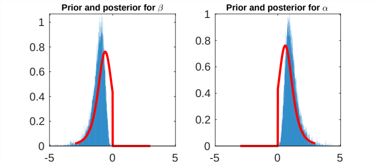
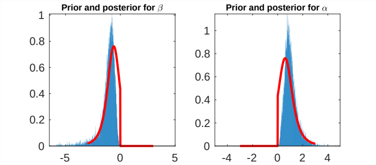
Prior and posterior distribution of labor demand and supply elasticities by sector (3/4)

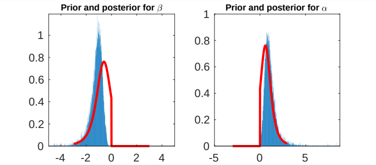
(a) Information



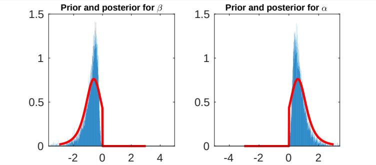
(b) Financial Activities



(c) Professional and Business Services



(d) Education and Health Services



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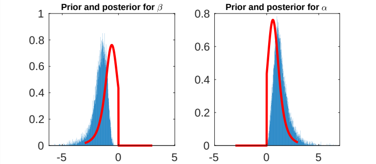
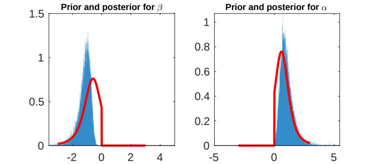
Prior and posterior distribution of labor demand and supply elasticities by sector (4/4)

(a) Leisure and Hospitality



(b) Other Services



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Posterior Estimates

	β^l (demand)			α^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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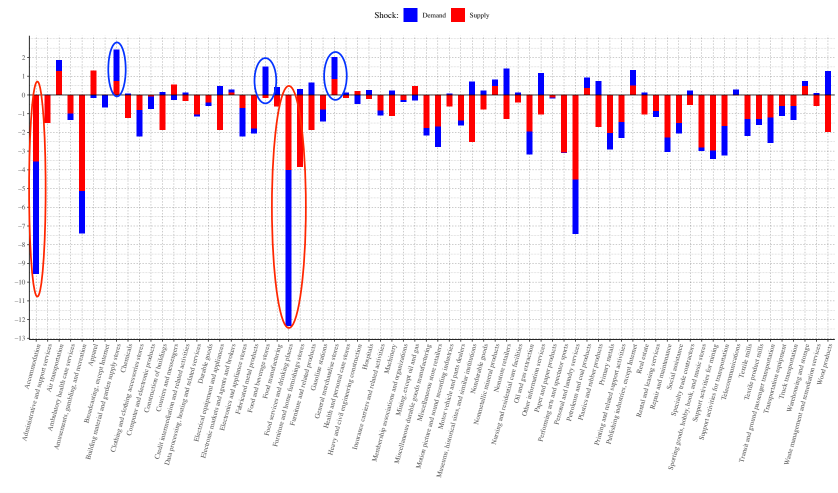
Shock Decomposition NAICS-3, March 2020



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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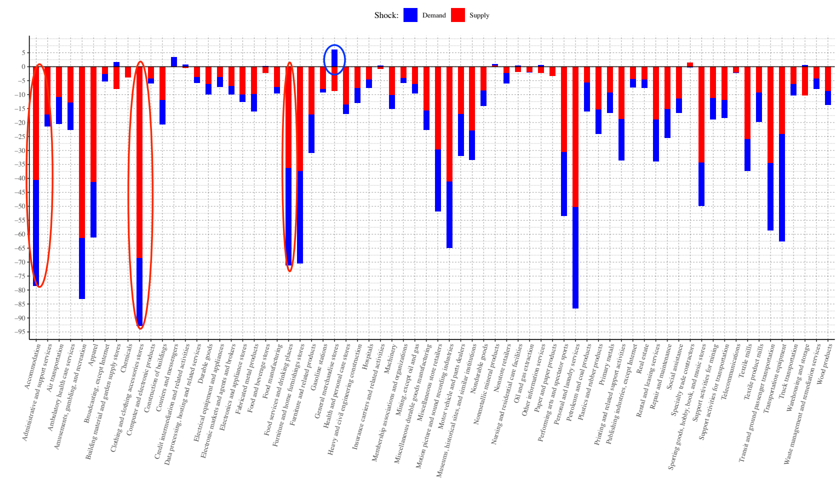
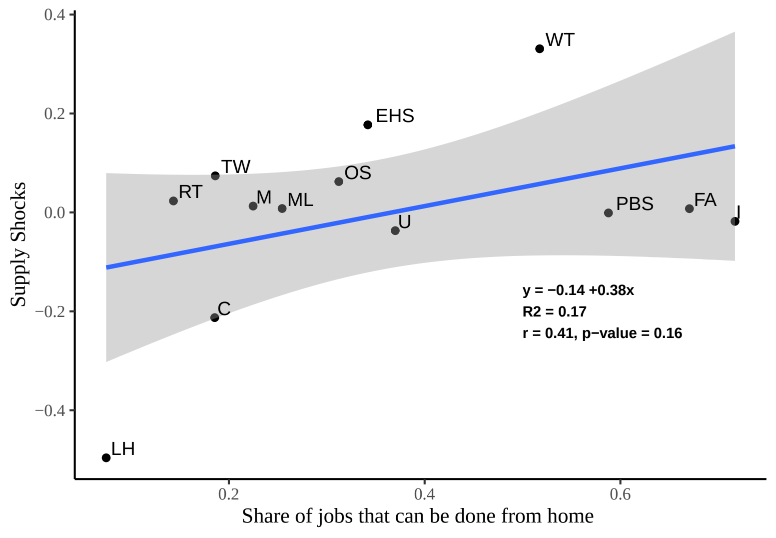
Shock Decomposition NAICS-3, April 2020



Estimated Shocks vs. Telework Measure, April 2019



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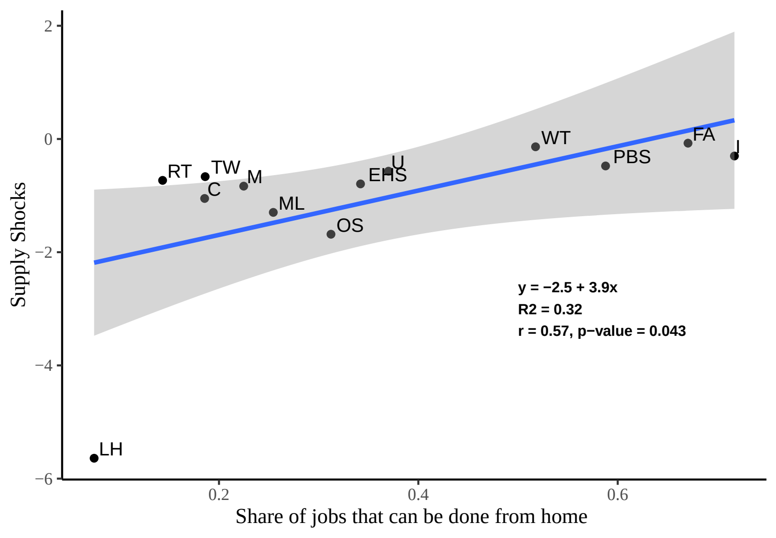
Estimated Shocks vs. Telework Measure, March 2020



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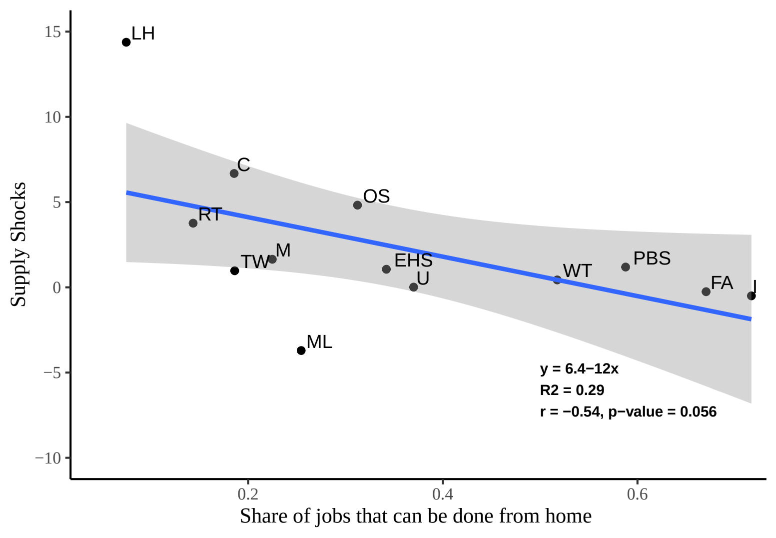
Estimated Shocks vs. Telework Measure, May 2020



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