Measuring Labor Supply and Demand Shocks during COVID-19*

Pedro Brinca† Joao B. Duarte‡ Miguel Faria-e-Castro§

October 2020

Abstract

We measure labor demand and supply shocks at the sector level around the COVID-19 outbreak by estimating a Bayesian structural vector autoregression on monthly statistics of hours worked and real wages. Most sectors were subject to large negative labor supply and demand shocks in March and April, with substantial heterogeneity in the size of shocks across sectors. Our estimates suggest that two-thirds of the drop in the aggregate growth rate of hours in March and April 2020 are attributable to labor supply. We validate our estimates of supply shocks by showing that they are correlated with sectoral measures of telework.

JEL: E24, E30, J20
Keywords: Supply and Demand Shocks, COVID-19, Structural Vector Autoregressions, Sign Restrictions.

*We thank Christiane Baumeister, Jesús Fernández-Villaverde, Erik Hurst, and Peter Klenow for very helpful comments and discussions. We thank seminar participants at the Bank of England, Bank of Portugal, Federal University of Pernambuco, Federal Reserve Bank of St. Louis, Bank of Mexico, and conference participants at the NBER SI 2020 Micro Data and Macro Models session for comments and suggestions. We also thank Joao Barata and Serdar Birinci for enlightening conversations regarding the micro data. Joao Duarte and Pedro Brinca acknowledge funding from Fundação para a Ciência e a Tecnologia (UID/ECO/00124/2013, UID/ECO/00124/2019 and Social Sciences DataLab, LISBOA-01-0145-FEDER-022209), POR Lisboa (LISBOA-01-0145-FEDER-007722, LISBOA-01-0145-FEDER-022209), POR Norte (LISBOA-01-0145-FEDER-022209) and CEECIND/02747/2018. The views expressed here are those of the authors and do not necessarily reflect the views of the Federal Reserve Bank of St. Louis or the Federal Reserve System. First version: May 12th, 2020.

†Nova School of Business and Economics. Email: pedro.brinca@novasbe.pt.

‡Nova School of Business and Economics. Email: joao.duarte@novasbe.pt.

§Federal Reserve Bank of St. Louis. Email: miguel.fariaecastro@stls.frb.org.

1 Introduction

The ongoing COVID-19 outbreak and subsequent public health policy response have caused widespread disruption in most economies. On one hand, authorities around the world have enforced containment and mitigation measures that entailed the supervised shutdown of entire sectors of their economies. On the other hand, in face of health safety uncertainty, agents voluntarily engaged in self-imposed social distancing. There are many aspects that make studying this shock interesting. First, there is its unprecedented nature, both in terms of magnitude and uncertainty regarding its persistence. Second, it combined features that are traditionally associated with both demand and supply shocks. Third, its effects across sectors in the economy were extremely heterogeneous, with some industries shutting down almost completely (such as movie theaters), while others potentially benefiting from increased demand (such as general merchandise retailers). For many sectors, it is not clear whether this is mostly a demand or a supply shock.

This paper attempts to help answering that question by estimating labor demand and supply shocks at the sectoral level. We apply the general methodology proposed by Baumeister and Hamilton (2015) and use Bayesian structural vector autoregressions (SVAR) to model the joint dynamics of monthly real wages and hours worked for each 2-digit NAICS sector of the US economy, as well as for total private employment. Combined with priors on labor demand and supply elasticities that are informed by the literature, we use sign restrictions to identify and estimate sequences of labor demand and supply shocks. Our latest historical decomposition estimates are for the months of March-May 2020 that featured the controlled shutdown and subsequent reopening of parts of the US economy.

Total private employment fell by 16.24 percentage points in April 2020; we find that supply shocks accounted for 68.83% of this decrease. In other words, total private employment grew by 16.04 pp less in April 2020 (non-annualized) than its historical average and two-thirds of this negative growth is attributed to a negative labor supply shock. While most sectors that we consider were subject to negative supply shocks in this period, there is some heterogeneity in the size of both demand and supply shocks. Leisure and Hospitality experienced the largest disruption by far (-9.55 pp in March, 59% of which was supply, and -63.18 pp in April, 63% of which was supply). The least-affected sectors were Utilities, Information, and Financial Activities. In fact, Information experienced positive demand shocks in March (+0.46 pp), and Utilities was the only sector with positive demand shocks in April (+1.173 pp). These patterns revert in May, with most sectors experiencing positive supply and demand shocks, particularly Leisure and Hospitality and Construction.

The fall in economic activity reflects both negative labor supply and demand shocks. Negative supply shocks arise from workers either not being able to work due to lockdown measures, especially if the jobs cannot be done at home, or not wanting to, due to risk of infection or unemployment benefits (Baek et al., 2020). Negative demand shocks also arise from firms not being able to produce, due to supply chain disruptions, or not wanting to, due to deficient demand. As demand for firm product falls and these firms hire less labor, personal incomes may also fall, leading to reductions in expenditures in other goods or services (even those for which consumption is safe from infection) in general equilibrium. Disentangling between these two types of shocks is therefore important for the design of economic policy during this crisis (Baqaee and Farhi, 2020). Conceptually, our measure of labor supply shocks should be directly related to the state of the public health crisis: once the crisis is brought under control, negative supply shocks should disappear as lockdowns are lifted and workers are no longer reluctant to go to work. While demand shocks may also have a public health-related component (especially in sectors where consumption of goods and services involves a social component), they may be more related to the general state of the economy (reflecting low demand due to loss of income from workers or high uncertainty, for example). More specifically, the fall in employment and aggregate expenditure that are caused by this shock can lead to a reduction of activity in sectors that are not explicitly subject to the lockdown. This reduction in activity in non-lockdown sectors, which we identify as sectoral demand shocks, can be addressed via targeted stabilization policies, such as fiscal or credit policies. For these reasons, measuring demand and supply shocks at the sectoral level is essential for the design of public policies that are aimed at minimizing long-term effects of this crisis.

Our sectoral shock decomposition also provides natural moment conditions to help discipline quantitative work not only on the COVID-19 crisis, but also in other periods. There is a large set of shocks and models that are observationally equivalent in terms of being consistent with a number of standard moments while at the same being consistent with movements in hours worked and real earnings. One can formulate models in which the entirety of the drop in hours worked is attributed to shifts in the demand for labor, and other models where all of these movements arise from shifts in the labor supply. The results of our analysis restrict the set of models and shocks that are empirically plausible. Our estimated sectoral shock measures can also be potentially used as instruments for labor supply and demand shocks in empirical work in a variety of different settings, including, but not restricted to, the COVID-19 crises.

Our paper relates to the emerging literature on the economic effects of the COVID-19 outbreak, especially to studies related to the nature of the shocks affecting multi-sector economies.[1] Baqaee and Farhi (2020) study the effects of the COVID-19 crisis in a disaggregated Keynesian model with multiple sectors, factors, and input-output linkages. They find that negative supply shocks are stagflationary and that negative demand shocks are deflationary, which serves as the basis for our identification. Similar to us, del Rio-Chanona et al. (2020) perform a sectoral analysis of demand and supply shocks in the US economy. Their measure of exposure to supply shocks aggregates a remote labor index across occupations at the sector level, while their exposure to demand shocks is based on Congressional Budget Office estimates. Instead, we jointly measure demand and supply shocks using a unified econometric framework and a single source of data.

[1]Examples include Danieli and Olmstead-Rumsey (2020), Barrot et al. (2020), Bodenstein et al. (2020) and Faria-e-Castro (2020).

Guerrieri et al. (2020) show that under certain assumptions in a model with multiple sectors and incomplete markets, supply shocks can have effects that resemble those of demand shocks ("Keynesian supply shocks"). The shocks we estimate are not structural through the lens of their economic model, which means that we cannot disentangle these from other types of demand shocks. Their insights suggest that we may be underestimating the size of supply shocks in our exercise. Finally, there is a new literature embedding epidemiology features in standard macroeconomic models and where epidemics generate reductions in economic activity that would be captured by our framework as both negative supply and demand shocks (Eichenbaum et al., 2020).

This paper is organized as follows: section 2 describes the econometric framework; section 3 describes the data; section 4 presents the results from our historical decomposition exercise as well as some validation exercises; and section 5 concludes.

2 Methodology

We use the methodology proposed by Baumeister and Hamilton (2015) to identify labor supply and demand shocks in each sector $l \in L$.[2] The methodology can be generally applied to any market, provided that data on prices and quantities are available; we specifically apply it to the US labor market. We use a structural vector autoregression (SVAR) to describe the joint dynamics of the growth rate of real wages Δw_t^l and the growth rate of hours worked Δh_t^l in a given sector. Let $\boldsymbol{y}_t^l = (\Delta w_t^l, \Delta h_t^l)$ be the 2×1 vector of observables. Then the SVAR for sector l takes the form

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

where $\boldsymbol{A}^l$ is a 2×2 matrix describing the contemporaneous relations, $\boldsymbol{B}_0^l$ is a 2×1 vector of constants, $\boldsymbol{B}^l(L) = \boldsymbol{B}_1^l + \boldsymbol{B}_2^l L + \boldsymbol{B}_3^l L^2 + \cdots + \boldsymbol{B}_m^l L^{m-1}$ are the 2×2 matrices associated with each lag of $\boldsymbol{y}_t^l$, and $\boldsymbol{\varepsilon}_t^l$ is a 2×1 vector of structural shocks that are assumed to be i.i.d. $N(0, \boldsymbol{D})$ and mutually uncorrelated ($\boldsymbol{D}$ is diagonal).

Let $\boldsymbol{\varepsilon}_t^l = (\varepsilon_{d,t}^l, \varepsilon_{s,t}^l)$ so that the first equation corresponds to labor demand and the second equation to labor supply. We assume that the contemporaneous relation matrix $\boldsymbol{A}^l$ takes the form

$$\boldsymbol{A}^l = \begin{bmatrix} -\beta^l & 1 \\ -\alpha^l & 1 \end{bmatrix}, \tag{2}$$

where β^l is interpreted as the elasticity of labor demand and α^l as the elasticity of labor supply in sector l.

The equations for labor market demand and supply in sector l are then given by

[2] L also includes a "Total Private" employment sector.

$$\Delta h_t^l = b_{10}^{d,l} + \beta^l \Delta w_t^l + \sum_{i=1}^{m} b_{11}^{i,d,l} \Delta w_{t-i}^l + \sum_{i=1}^{m} b_{12}^{i,d,l} \Delta h_{t-i}^l + \varepsilon_{d,t}^l \tag{3}$$

$$\Delta h_t^l = b_{20}^{s,l} + \alpha^l \Delta w_t^l + \sum_{i=1}^{m} b_{21}^{i,s,l} \Delta w_{t-i}^l + \sum_{i=1}^{m} b_{22}^{i,s,l} \Delta h_{t-i}^l + \varepsilon_{s,t}^l. \tag{4}$$

It is important to emphasize that under this framework, the relative sizes of the impact of supply and demand shocks on equilibrium movements in the growth rate of hours depend crucially on the relative size of demand and supply elasticities. For example, assuming no intercepts and no lags, solving for the growth rates of hours and real wages yields

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

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

If we assume that the demand curve is downward sloping and the supply curve is upward sloping, we have the standard result that, *ceteris paribus*, a positive shift in the demand curve makes equilibrium hours increase and wages increase, while, *ceteris paribus*, a positive shift in the supply curve makes hours rise and wages fall. That is, if $\beta^l < 0$ and $\alpha^l > 0$, then $\frac{\partial \Delta h_t^l}{\partial \varepsilon_{d,t}^l} > 0$ and $\frac{\partial \Delta h_t^l}{\partial \varepsilon_{s,t}^l} > 0$, while $\frac{\partial \Delta w_t^l}{\partial \varepsilon_{d,t}^l} > 0$ and $\frac{\partial \Delta w_t^l}{\partial \varepsilon_{s,t}^l} < 0$. Moreover, note that the relative size effects of supply vs. demand shocks on employment and wages depend on the relative labor demand and supply elasticities $\frac{\alpha^l}{\beta^l}$. The flatter (steeper) the supply curve is relative to the demand curve, the weaker (stronger) the relative impact of a supply shock is on hours, and the stronger (weaker) its impact is on real wages.[3]

The reduced-form vector autoregression (VAR) associated with the SVAR model (1) is given by

$$\boldsymbol{y}_t^l = \Phi_0^l + \Phi^l(L)\boldsymbol{y}_{t-1}^l + \boldsymbol{u}_t^l, \tag{5}$$

where

[3] Uhlig (2017) explicitly lays out all the basic assumptions required for identifying demand and supply shocks. There may be other shocks that shift both demand and supply; our framework is without loss of generality as long as those other shocks do not affect demand and supply in a systematic way.

$$
\begin{aligned}
\Phi_0^l &= (A^l)^{-1} B_0^l \\
\Phi^l(L) &= (A^l)^{-1} B^l(L) \\
u_t^l &= (A^l)^{-1} \varepsilon_t^l \qquad (6) \\
E[u_t^l (u_t^l)'] &= \Omega = (A^l)^{-1} D ((A^l)^{-1})'. \qquad (7)
\end{aligned}
$$

We assume that prior beliefs about the values of the structural parameters are represented by a joint density $p(A, D, B)$. We then revise these beliefs when confronting them with sectoral data in our sample $Y_T = (y_1, y_2, \cdots, y_T)$. Importantly, Baumeister and Hamilton (2015) show how these beliefs can be updated for any prior distribution $p(A)$ that best summarizes prior available information. In principle this prior $p(A)$ could incorporate any combination of exclusion restrictions, sign restrictions, and informative prior beliefs about elements of A.

Priors Following Baumeister and Hamilton (2015), we use past studies to form informative priors about α^l and β^l. First, we impose sign restrictions on sectoral demand and supply elasticities: β^l is negative and α^l is positive. The sign restriction reflects our belief that the labor demand curve should be downward sloping and that the supply curve should be upward sloping. However, we do not place a uniform probability on all values that respect these sign restrictions. In particular, we assume prior distributions that reflect uncertainty about the true values for these parameters and that encompass both micro and macro estimates in the literature.

For the labor demand elasticity β^l, we assume a truncated Student's t distribution (Baumeister and Hamilton, 2015, 2018) with location parameter -0.6, scale parameter 0.6 and 3 degrees of freedom, so that we place 90% probability on $\beta^l \in [-2.2, -0.1]$. This range reflects the labor demand elasticity estimates found in the micro and macro literatures.[4] In terms of the labor supply elasticity, based on the findings of Chetty et al. (2011), we also use a Student's t distribution (Baumeister and Hamilton, 2015, 2018) with location parameter 0.6, scale parameter 0.6 and 3 degrees of freedom, so that we place 90% probability on $\alpha^l \in [0.1, 2.2]$. This interval thus includes the lower estimates reported by microeconometric estimates and by macro estimates when movements in wages are persistent, and includes the high Frisch elasticities reported by macro studies of the business cycle, such as in Smets and Wouters (2007). Since we use the same prior for both elasticities, we have an implicit prior belief that unit supply and demand shocks have an equal impact on hours. Finally, our priors for labor demand and supply are assumed to be independent.[5]

In a meta-analysis that uses information from 151 different studies and encompasses a total

[4] Hamermesh (1996) provides a survey of microeconometric estimates of labor demand elasticity and finds them to be between -0.15 and -0.75, while Lichter et al. (2015) find that 80% of the estimates are between 0 and -1. Some macro studies such as Akerlof and Dickens (2007) and Galí et al. (2012) find that the labor demand elasticity can be -2.5 or even higher.

[5] Our prior beliefs on distributions for labor demand and supply elasticities also reflect a variety of labor market frictions, such as wage stickiness.

of 1334 estimates, Lichter et al. (2015) find that, except for Construction and Manufacturing, the labor demand elasticity does not seem to vary substantially across the other sectors we consider. For Construction and Manufacturing, they find a point difference of demand elasticity relative to the aggregate economy of -0.25 and -0.35, respectively. In addition, since the labor supply elasticity should primarily be a function of household behavior, there is no *a priori* reason to believe that it should vary significantly across industries. For these reasons, we apply the same prior distribution $p(\boldsymbol{A})$ for all sectors in our sample.

Next, we define the specification for our conditional prior distributions $p(\boldsymbol{D}|\boldsymbol{A})$ and $p(\boldsymbol{B}|\boldsymbol{A},\boldsymbol{D})$. For the elements of the diagonal matrix $\boldsymbol{D}$, we assume that their reciprocals (the precision of the structural shocks) follow a gamma distribution with shape parameter κ_i and scale parameter τ_i. We set κ_i to $2, \forall i = \{d, s\}$, which puts a small weight on our prior of just 4 months of data, and set the scale parameter τ_i so that the prior mean of each element $\frac{\kappa_i}{\tau_i}$ matches the precision of the structural shocks after orthogonalization of univariate autoregressions with 4 lags under $\boldsymbol{A}$. That is, $\tau_i = \kappa_i a_i' \hat{\boldsymbol{S}} a_i$, where $\hat{\boldsymbol{S}}$ is the variance-covariance of the univariate residuals series. $p(\boldsymbol{D}|\boldsymbol{A})$ is then the product of the two gamma distributions. Finally, $p(\boldsymbol{B}|\boldsymbol{A},\boldsymbol{D})$ is set in a way that conforms with the Bayesian VAR Minnesota priors on the reduced-form coefficients Φ (Doan et al., 1984; Sims and Zha, 1998; Baumeister and Hamilton, 2019). Note that placing a prior on the reduced-form coefficients and conditioning on $\boldsymbol{A}$ implicitly places a prior on $\boldsymbol{B}$ since $\boldsymbol{B} = \boldsymbol{A}\Phi$. Hence the normally distributed coefficients b_i have mean a_i for elements corresponding to their own lags and zero for all others. Moreover, our beliefs place a higher degree of certainty that higher lags should be zero. We follow Baumeister and Hamilton (2015) and set the hyperparameter $\lambda_0 = 0.2$, which controls the overall tightness of the prior; $\lambda_1 = 1$, which governs how quickly the prior for lagged coefficients tightens to zero for higher lags; and $\lambda_3 = 100$, which places essentially zero weight on the prior when estimating $\boldsymbol{B}_0$. The joint prior distribution is then given by:

$$p(\boldsymbol{A},\boldsymbol{D},\boldsymbol{B}) = p(\boldsymbol{A})p(\boldsymbol{D}|\boldsymbol{A})p(\boldsymbol{B}|\boldsymbol{A},\boldsymbol{D}). \tag{8}$$

Estimation Based on the Akaike information criterion, we set the number of lags to $m = 4$. We then use Bayesian methods to update our prior beliefs given the data $\boldsymbol{Y}_T$. The posterior can be written as

$$p(\boldsymbol{A},\boldsymbol{D},\boldsymbol{B}|\boldsymbol{Y}_T) = p(\boldsymbol{A}|\boldsymbol{Y}_T)p(\boldsymbol{D}|\boldsymbol{A},\boldsymbol{Y}_T)p(\boldsymbol{B}|\boldsymbol{A},\boldsymbol{D},\boldsymbol{Y}_T). \tag{9}$$

The conditional posterior on the structural coefficients $\boldsymbol{B}$ is a multivariate normal density because of natural conjugacy, and the updating follows the standard convex combination of prior means and OLS estimates where the weights are based on the relative precision of the prior mean versus OLS estimates of the reduced-from representation (5) and (7). Also because of natural conjugacy, the conditional posterior $p(\boldsymbol{D}|\boldsymbol{A},\boldsymbol{Y}_T)$ is also a gamma distribution. Finally, $p(\boldsymbol{A}|\boldsymbol{Y}_T)$ does not have a known distribution, and we use a random-walk Metropolis-Hastings algorithm to draw from it.

Identification It is important to note that the model is only set identified. The identified set is a function of both prior and data. This allows us to account not just for estimation uncertainty due to the limited amount of data but also for the fact that we do not have perfect knowledge about the underlying structure of the economy. The latter is particularly relevant in analyses of the COVID-19 pandemic period as this shock triggered historically large changes in macroeconomic variables such as hours worked.

3 Data

Our main source of data is the Current Employment Statistics (CES) database from the Bureau of Labor Statistics (BLS), from where we obtain monthly real wages and hours worked by sector from March 2006 to May 2020.[6] The CES provides data for 14 main aggregate sectors: total private, mining and logging, construction, manufacturing, wholesale trade, retail trade, transportation and warehousing, utilities, information, financial activities, professional and business services, education and health services, leisure and hospitality, and other services. For each sector, we compute the monthly growth rate for real wages as the log-difference of monthly average hourly earnings of all employees in 1982-1984 dollars. The growth rate of hours worked in a given sector is computed by taking the log-difference of aggregate weekly hours of all employees in that sector. Given the unprecedented nature of the shocks, and as we discuss in more detail in the following section, we estimate the SVAR using data until February 2020. We then use the estimated model to perform a historical decomposition for the full sample.

4 Results

Posteriors For most sectors the beliefs on elasticities are significantly revised towards macro literature estimates, namely for Leisure and Hospitality and Utilities. Demand elasticities are mostly revised upward (in absolute value), especially in the Construction and the Leisure and Hospitality sectors. Hence, we conclude that our identification of supply and demand shocks is strongly influenced by the data. A detailed description of the posterior estimates is in the Appendix.[7]

Historical Decompositions pre-COVID-19 Figure 1 plots the historical decomposition of the growth rate of hours for Total Private employment and the Leisure and Hospitality sector. These panels include only the estimation period, and exclude March-May 2020 which are analyzed separately in the following sections. They show that the growth rate of hours was subject to large negative shocks both to demand and to supply during the Great Recession. Consistent with standard narratives, the Great Recession begins with negative demand shocks in late 2007

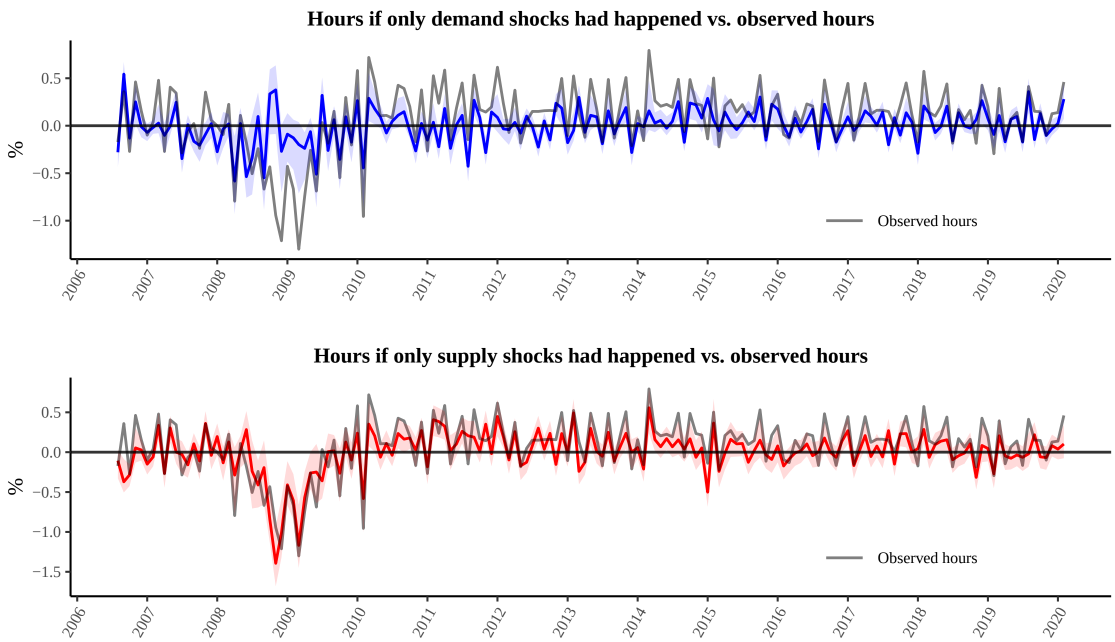
[6] Section A in the appendix provides further details on the data and sector classification.

[7] Figure 7 plots the prior distribution for the elasticities along a histogram of draws from the posterior. Table 5 presents moments of the posterior distributions and Figure 8 plots impulse response functions.

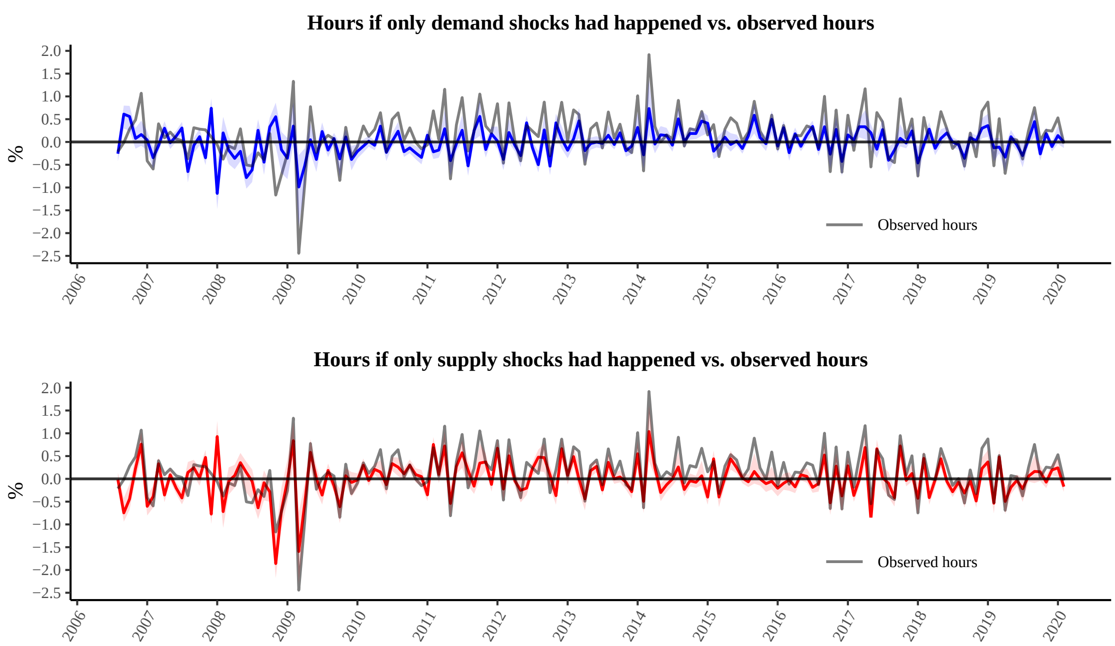
and early 2008. Starting in late 2008 we also identify large negative labor supply shocks, which is consistent with a large literature on labor markets during this period (Elsby et al., 2010).[8]

Figure 1: Historical decomposition of the growth rate of hours: Total Private Employment, Leisure and Hospitality. Median and 95% credible sets.

(a) Total Private Employment until February 2020



(b) Leisure and Hospitality until February 2020

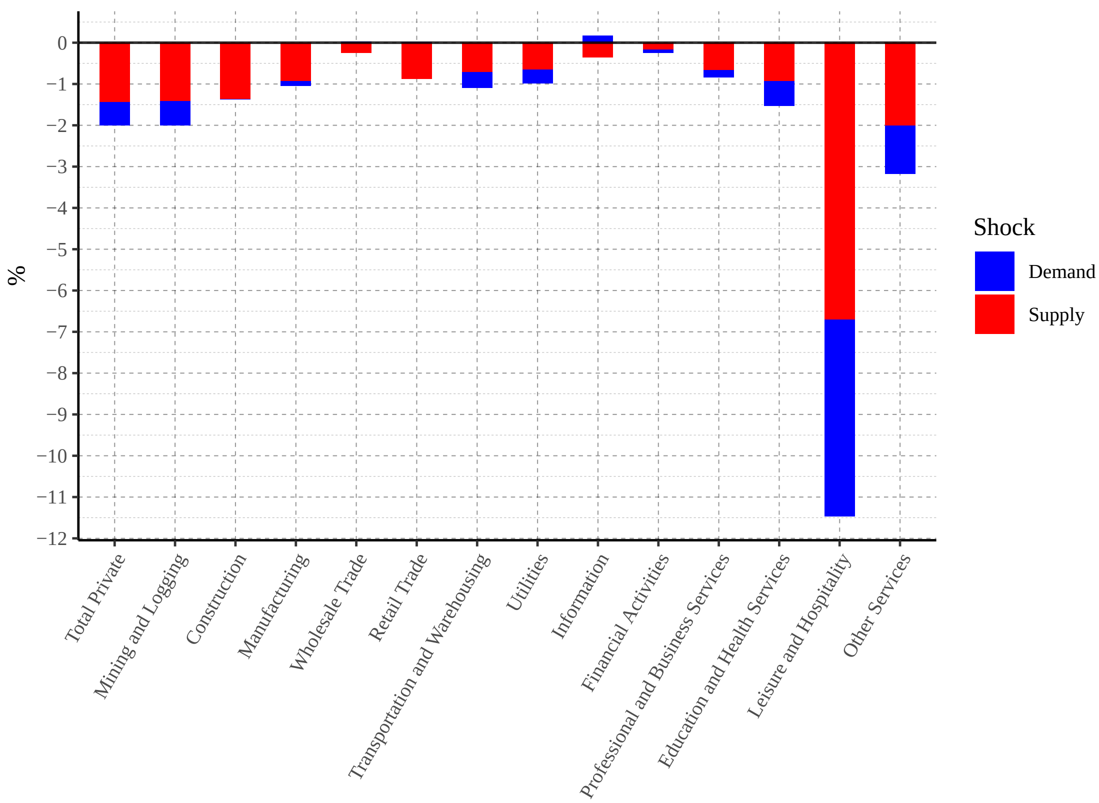


[8]Figures 9 and 10 in the Appendix plot the estimated shocks for all other sectors.

4.1 The COVID-19 Recession: March and April 2020

We now take a closer look at the results for the months of March and April 2020: the two months that featured a significant reduction in economic activity in the US.[9] Figures 2 and 3 contain our main set of results and plot the medians of the historical decomposition of the growth rate of hours across sectors for March and April, respectively.[10] The historical contribution of demand (supply) shocks to sectoral growth rate of hours is the cumulative effect of all past and present demand (supply) shocks to the growth rate of hours. The combined negative effect of supply and demand on the growth rate of hours for total private employment was -2 pp in March and -16.26 in April. Negative supply shocks accounted for 71.5% and 68.8% of these effects, respectively.

Figure 2: Historical decomposition of the growth rate of hours by sector in March 2020



[9]This coincides with "the Great Lockdown", but we are agnostic regarding the extent to which the slowdown is driven directly by lockdown measures and by endogenous, voluntary behavior on the part of workers and consumers.

[10]Tables 6 and 7 in the Appendix report the median values along with 95% credible intervals for these shocks and a test for difference of supply and demand.

Figure 3: Historical decomposition of the growth rate of hours by sector in April 2020

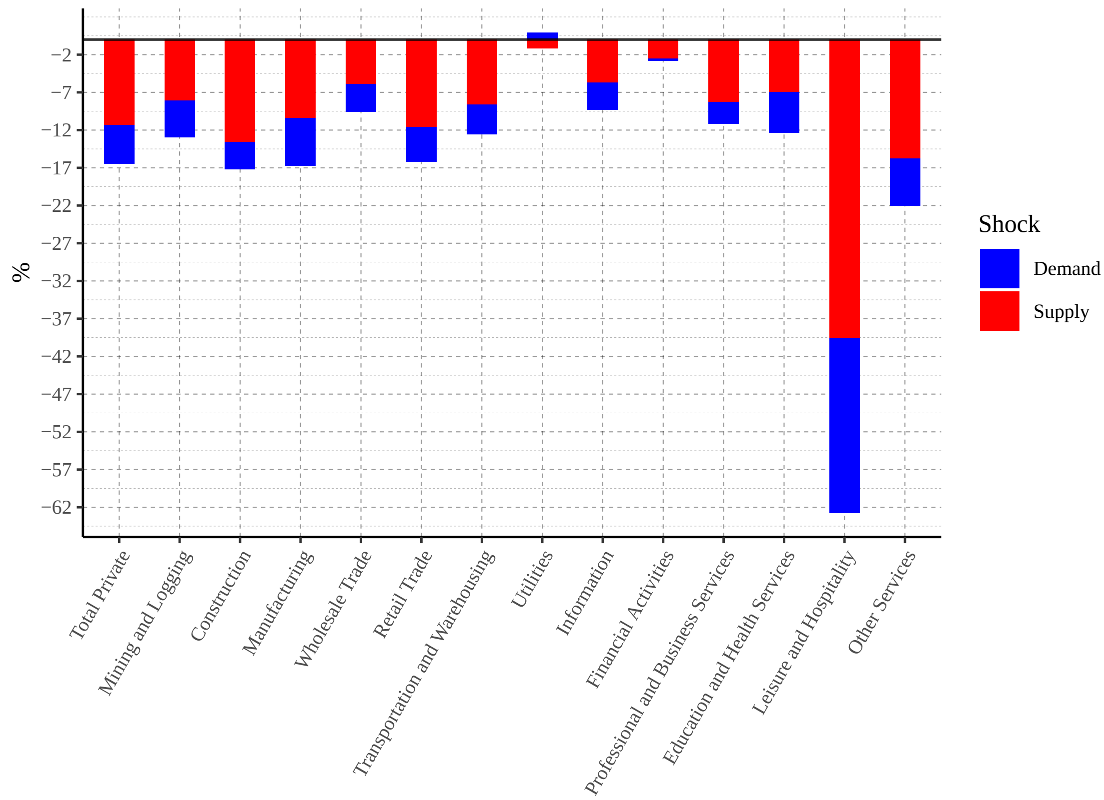


Figure 2 shows considerable heterogeneity in sectoral exposure to shocks. Leisure and Hospitality is the most negatively affected sector, with a combined effect of −9.55, of which 59% is supply. The least-affected sectors are Wholesale Trade (−0.06 pp), Financial Activities (−0.09 pp), and Information (+0.16 pp). Retail Trade, Wholesale Trade, and Construction experience small positive demand shocks, the most significant demand shock being to Information (+0.46 pp). These results are consistent with the narrative regarding the beginning of the lockdown: high physical-contact services, concentrated on Leisure and Hospitality (and Other Services), experience large negative shocks to both demand and supply. As agents shift their consumption patterns, sectors such as Retail Trade and Wholesale Trade partly benefit. Finally, the Information sector benefits from a demand boost as many firms increase their demand for technology services to implement telework arrangements. For comparison, Figure 15 in the Appendix performs the same decomposition but one year earlier, in March 2019, a "normal" period, for which we find a completely different pattern of shocks of much smaller magnitudes. Figure 13 in the Appendix repeats the analysis at the 3-digit NAICS level. It shows, for example, Food Services and Drinking Places experiencing large negative supply and demand shocks, while Food and Beverage Stores experienced a positive demand shock, reflecting substitution in consumption patterns during the lockdown.

Figure 3 presents the shock decomposition or April, the only full month of lockdown. Note the difference in scale that reflects the much larger magnitude of the shocks: the total decline in Total Private hours is of 16.24 pp in the growth rate of hours, out of which 68.8% is attributable to supply. Leisure and Hospitality is the most-affected sector, as before, with a decline of 63.17 pp, of which 63% is supply. This is expected for a sector that relies on physical contact-intensive activities. The negative labor supply shock results from lockdown measures that prevent workers from actually going to work, while the negative labor demand shock results from consumers not undertaking those activities. It should also be noted that other service sectors such as Education and Health Services also experienced negative supply and demand shocks comparable in magnitude to those experienced during the Great Recession.

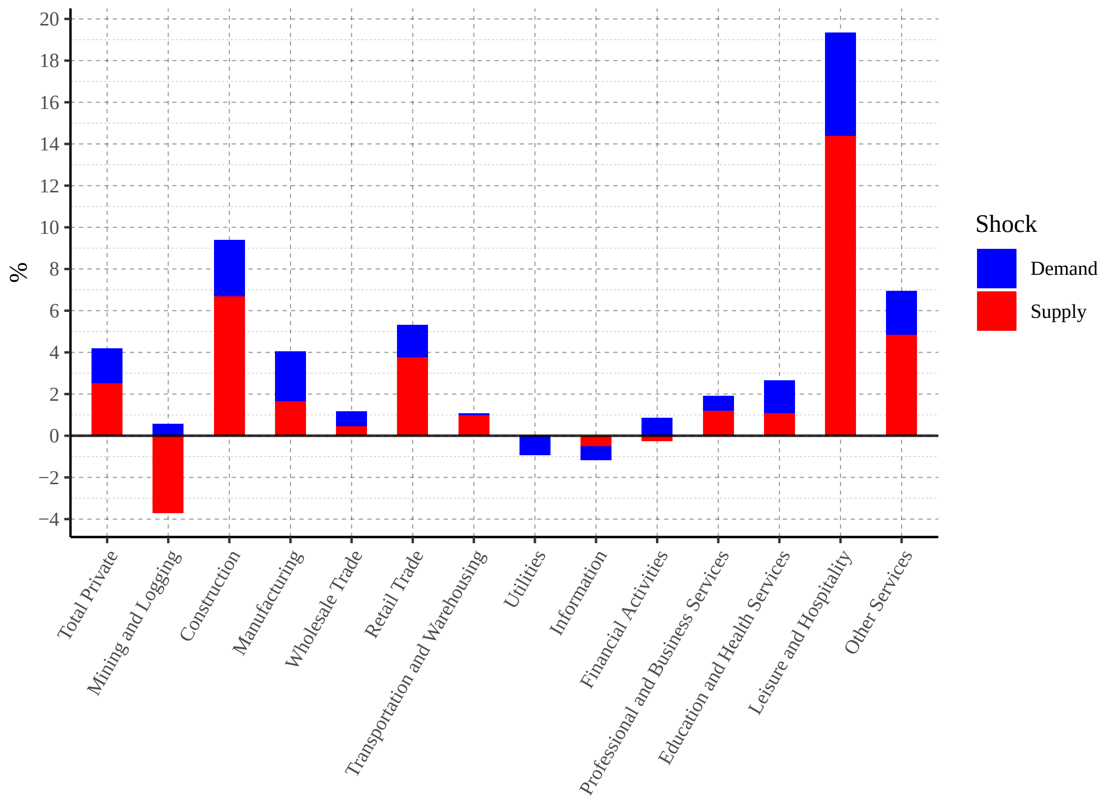
Essentially all sectors in the economy are negatively affected in April, including sectors that experienced positive shocks in March (such as Information). The least-affected sectors are Utilities (+0.09 pp) and Financial Activities (−3.06 pp). As we show in the next section, these are sectors where a high percentage of jobs can be done at home. The supply/demand composition is overall similar across sectors. Sectors where demand was more relevant were Manufacturing (40%), Information (40%) and Education and Health Services (45%). This is consistent with the idea that even sectors that are not necessarily exposed to the lockdown measures can be affected by a fall in aggregate demand. Figure 14 in the Appendix repeats the analysis at the 3-digit NAICS level.

4.2 Reopening: May 2020

We now turn to the shock decomposition in May 2020, which corresponds to the reopening of the economy after a 2-month lockdown. By this month, most states and local governments that had imposed stay-at-home or shelter-in-place orders started lifting these restrictions, triggering positive demand and supply shocks. Consistent with our previous results, we find that labor supply shocks were more positive in sectors that were most affected by the lockdown orders: Leisure and Hospitality (+19.35 pp, 74% supply) and Construction (+9.39 pp, 71% supply). Sectors such as Financial Activities and Information remained largely unaffected, consistent with the fact that these sectors are the ones with the largest shares of workers who can perform their tasks remotely.[11]

[11]Figure 16 in the Appendix shows that this in fact is a systematic pattern: sectors with the smallest shares of jobs that can be done at home are the precisely the ones who are most affected by the easing of restrictions and that experienced larger labor supply shocks in May.

Figure 4: Historical decomposition of the growth rate of hours by sector in May 2020



4.3 Challenges posed by COVID-19

Methodological Challenges The different nature and sheer size of shocks during COVID-19 can pose challenges to our empirical exercise for a number of reasons; this section enumerates them and shows how we address them. First, it can make the residuals non-stationary, thus rendering the Wold decomposition invalid. Second, it can put into question the assumption of linearity either due to a structural break or because large shifts in supply and demand curves may push them into a region where their elasticities are no longer constant. Third, given that different occupations have different wages within each sector, if some occupations are affected differently during COVID-19, then changes in sectoral wages may be purely coming from changes in the composition of occupations.

We address the first concern by estimating the model excluding the COVID-19 months (March-May 2020)[12]. The second issue, regarding linearity, is addressed by allowing for uncertainty regarding the underlying structure of the labor market. Our methodology explicitly allows for uncertainty regarding the labor demand and supply elasticities, which captures the possibility of jumping into different elasticities in reaction to large wage changes[13]. We believe this to be cor-

[12] Lenza and Primiceri (2020) conclude that this approach is acceptable for the purpose of parameter estimation.

[13] The bounds on these elasticities are reported in Table 4, and the bounds on the relative importance of supply vs.

rect approach in dealing with nonlinearities because identifying the structural break or nonlinear structure is impossible given the size of the sample during the COVID-19 period. Nevertheless, we attempt to assuage concerns regarding this second aspect by performing a validation exercise, in which we argue that our identified shock series correlate with externally measured series such as a telework index. Next, we address the third and final issue.

Composition Effects One challenge to our identification assumptions (that is not directly related to the econometric model) is related to composition effects. A situation where a negative labor demand shock leads to the destruction of mostly low-wage jobs is consistent with a fall in the number of hours and an increase in the average real wage, which could be captured as a supply shock. Mongey et al. (2020), for example, document that workers employed in jobs with low ability to work-from-home tend to have lower income and were more likely to lose their job according to the March 2020 CPS. This concern is hard to address due to the lack of high quality disaggregate data at a sufficiently high frequency.

To address this, our main robustness check consists of repeating the baseline exercise for all sectors at NAICS-2 and -3, but using data on hours and earnings for employees in production and nonsupervisory roles. By using more disaggregated industry data and production only employees we are getting data on workers that are more homogeneous. Thus, this data is less prone to be contaminated with composition effects. We find that our baseline results do not change much. For total private employment, the fall in the growth rate of hours is slightly smaller in March (-1.91 pp vs. -2.59 pp), but larger in April (-18.6 pp vs. -16.24 pp). Supply shocks account for 77% of this drop in March, and 68% in April. Overall, we find similar patterns across sectors. The importance of demand shocks increases in some sectors, namely in Leisure and Hospitality (56% in March, 43% in April) and Transportation (65% in March), but it falls in other sectors, suggesting that that while there could be some composition bias our baseline results seem to be relatively robust.[14]

In addition, Appendix B uses micro data from the CPS to conduct a counterfactual exercise where the joint dynamics between hours worked and hourly wages are completely driven by labor demand shocks and composition effects. We find that this would have generated large increases in hourly earnings that are at odds with the micro data for March and April 2020. While this does not completely exclude the possibility that composition effects may be playing a role, we believe that it is a useful exercise to bound the magnitude of these effects. In fact, we provide a lower bound to the relative importance of supply shocks by doing a historical decomposition for three of the most hit sectors in April by the COVID-19 crisis—Accommodation, Clothing and clothing accessories stores, and Food Services and Drinking Places—under the assumption that wage increase in those sectors was purely driven by composition effects. In doing so, we find that the relative importance of supply shocks in explaining hours in April in Accommodation,

demand shocks are reported in Tables 5, 6 and 7 in the Appendix.

[14]Figures 11 and 12 in the Appendix present the shock decomposition for March and April 2020 for the model re-estimation. Tables 9 and 10 in the Appendix present the shocks along with 95% credible intervals.

Clothing and clothing accessories stores, and Food Services and Drinking Places, goes from 51.7% , 73.9% and 51.0%, to 48.7%, 63.3% and 51.9%, respectively. Hence, even assuming that all of the change in the wages is driven by composition effects, the relative importance of supply decreases at most by 10.6 percentage points.

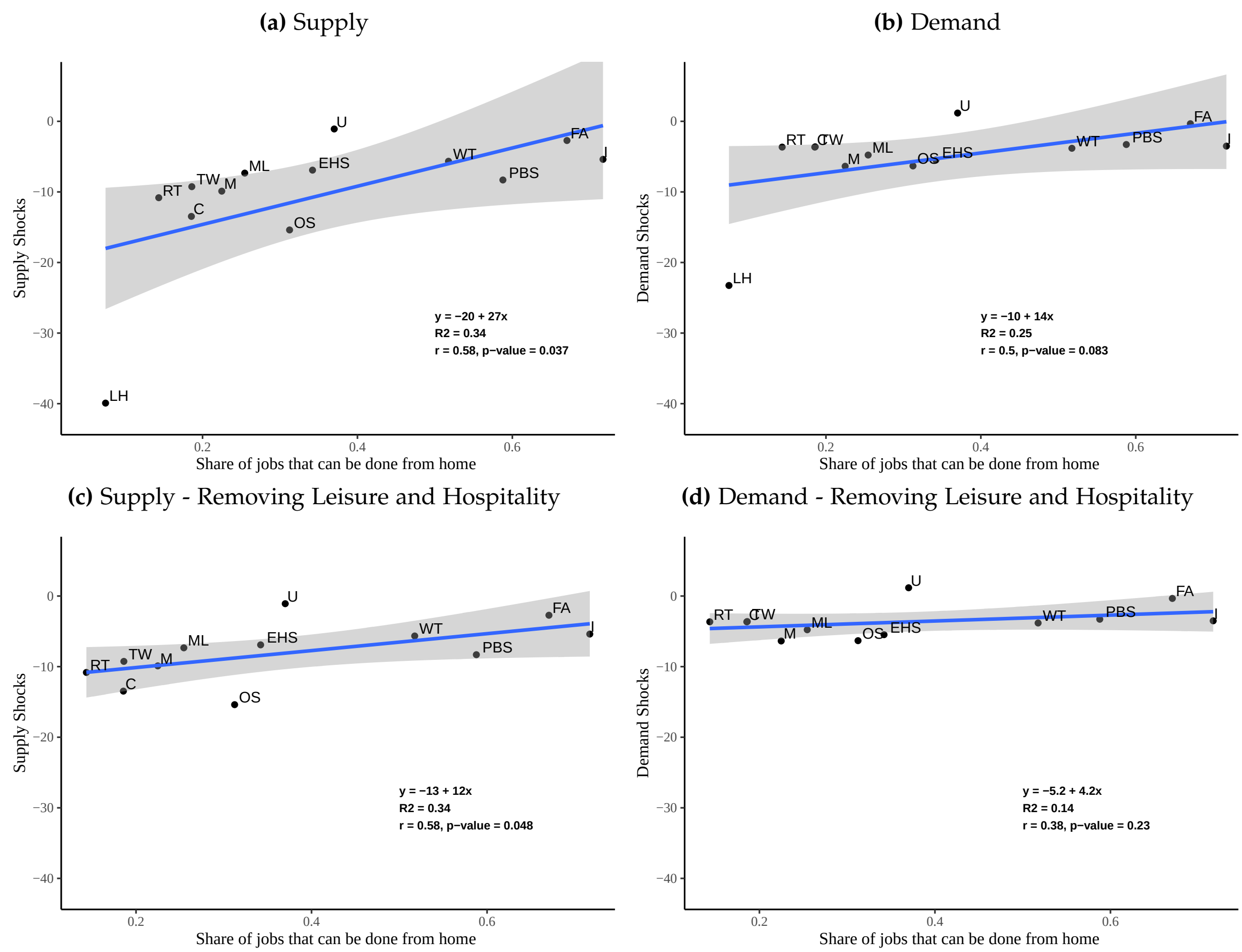
4.4 Validating the Results: share of jobs that can be performed from home by sector

If confinement measures are empirically meaningful for labor supply, we should expect that our estimates of labor supply shocks be positively correlated with the ability of workers to perform their tasks at home. Figure 5 plots our estimated supply shocks (y-axis) for April 2020 against the share of jobs that can be done at home by sector (x-axis), taken from Dingel and Neiman (2020). Panel (a) confirms that such correlation exists. Leisure and Hospitality, the sector with the smallest share of jobs that can be performed from home, was precisely the sector that was hit the hardest by a negative labor supply shock. Sectors where such share is higher endured smaller labor supply shocks, such as Financial Activities and Information. Despite the small number of observations, the relationship is statistically significant at the 5% level ($p-val$ = 0.037), and the share of workers that can perform their job at home per sector explains 34% of the variation of estimated supply shocks. Note also that this relationship is robust to excluding the Labor and Hospitality sector from the analysis; see panel (c). Panel (b) shows that there is also some correlation between the share of jobs that can be done at home and the estimated demand shock in March 2020, but panel (d) shows that this correlation is no longer statistically significant once we remove Labor and Hospitality.

Furthermore, the relationship between this measure and the supply shocks is consistently stronger than that with demand shocks, even when we remove Leisure and Hospitality (which experienced both the largest demand and the largest supply shock during this period).

In the appendix, we show that the validation exercise also holds for the month of March (Figure 16). We also repeat the analysis for the months of March and April 2019: Figure 17 shows that the statistically significant and positive correlation vanishes when this measure is compared with to supply shocks estimated during a "normal" period. Additionally, Figure 16 shows that we obtain the opposite pattern in May 2020, with sectors where a smaller share of jobs can be done at home experiencing the most positive supply shocks.

Figure 5: Correlation between sectoral shocks in April 2020 and the sectoral share of jobs that can be done at home



ML: Mining and logging; **C**: Construction; **M**: Manufacturing; **WT**: Wholesale trade; **RT**: Retail trade; **TW**: Transportation and warehousing; **U**: Utilities; **I**: Information; **FA**: Financial activities; **PBS**: Professional and business services; **EHS**: Education and health services; **LH**: Leisure and hospitality; **OS**: Other services. Grey bands represent 95% confidence intervals.

5 Conclusion

In this paper, we employed Bayesian SVARs and informative priors to estimate sequences of labor supply and demand shocks for each major sector of the US economy. Focusing on the ongoing COVID-19 outbreak, we found that two-thirds of the fall in the growth rate of hours worked in March and April 2020 could be attributed to negative labor supply shocks. Most NAICS-2 sectors were subject to negative labor supply and demand shocks. One sector in particular – Leisure and Hospitality – was subject to historically large negative supply and demand shocks. Other sectors, such as Information and Retail Trade, experienced small supply shocks and, in some cases, positive demand shocks. We showed that the size of our estimated supply shocks correlates with other measures, such as the fraction of jobs in each sector that can be performed from home. We believe that this serves as a validation of our shock identification strategy.

Properly measuring demand and supply shocks is essential for the design and implementation of economic policy during the COVID-19 outbreak. Negative labor supply shocks are more directly related to the on-going public health crisis (and public health policy response), while labor demand shocks reflect economic forces that may persist beyond the public health crisis. Particularly in sectors that are not directly affected by the lockdown, negative demand shocks may reflect a fall in aggregate demand that can be addressed via fiscal policy, for example (Guerrieri et al., 2020; Faria-e-Castro, 2020). Our shock decomposition allows policymakers to identify which sectors are being mostly affected by lack of demand, and to appropriately design and target policies aimed at minimizing the effects of the current crisis on those sectors.[15] We also think that our measurement exercise is useful for those conducting work on quantitative models of the COVID-19 crisis, as it provides moment conditions regarding movements in labor supply and demand that empirically plausible models should be able to match. Finally, the estimated series of shocks can also be used as instruments for labor supply and demand shocks in applied work.

[15]A natural caveat to this is that aggregate shocks may manifest themselves differently across sectors. That is, some aggregate shocks may be demand shocks in some sectors and supply shocks in others.

References

Akerlof, G. A. and W. T. Dickens (2007). Unfinished business in the macroeconomics of low inflation: A tribute to george and bill by bill and george. *Brookings Papers on Economic Activity 2007*(2), 31–46.

Baek, C., P. B. McCrory, T. Messer, and P. Mui (2020, April). Unemployment effects of stay-at-home orders: Evidence from high frequency claims data. Technical Report 101-20, Institute for Research on Labor and Employment, UC Berkeley.

Baqaee, D. and E. Farhi (2020). Supply and demand in disaggregated keynesian economies with an application to the covid-19 crisis. Technical report, Harvard University.

Barrot, J.-N., B. Grassi, and J. Sauvagnat (2020, April). Sectoral effects of social distancing. *Covid Economics* (3).

Baumeister, C. and J. D. Hamilton (2015). Sign restrictions, structural vector autoregressions, and useful prior information. *Econometrica 83*(5), 1963–1999.

Baumeister, C. and J. D. Hamilton (2018). Inference in structural vector autoregressions when the identifying assumptions are not fully believed: Re-evaluating the role of monetary policy in economic fluctuations. *Journal of Monetary Economics 100*(C), 48–65.

Baumeister, C. and J. D. Hamilton (2019). Structural interpretation of vector autoregressions with incomplete identification: Revisiting the role of oil supply and demand shocks. *American Economic Review 109*(5), 1873–1910.

Bodenstein, M., G. Corsetti, and L. Guerrieri (2020). Social distancing and supply disruptions in a pandemic. Technical report, CEPR Discussion Paper No. DP14629.

Chetty, R., A. Guren, D. Manoli, and A. Weber (2011). Are micro and macro labor supply elasticities consistent? a review of evidence on the intensive and extensive margins. *American Economic Review 101*(3), 471–75.

Danieli, A. and J. Olmstead-Rumsey (2020, April). Sector-specific shocks and the expenditure elasticity channel during the covid-19 crisis. Manuscript, Northwestern University.

del Rio-Chanona, R. M., P. Mealy, A. Pichler, F. Lafond, and D. Farmer (2020). Supply and demand shocks in the covid-19 pandemic: An industry and occupation perspective.

Dingel, J. I. and B. Neiman (2020, April). How many jobs can be done at home? Working Paper 26948, National Bureau of Economic Research.

Doan, T., R. Litterman, and C. Sims (1984). Forecasting and conditional projection using realistic prior distributions. *Econometric reviews 3*(1), 1–100.

Eichenbaum, M. S., S. Rebelo, and M. Trabandt (2020, March). The macroeconomics of epidemics. Working Paper 26882, National Bureau of Economic Research.

Elsby, M. W. L., B. Hobijn, and A. Sahin (2010). The Labor Market in the Great Recession. *Brookings Papers on Economic Activity 41*(1 (Spring), 1–69.

Faria-e-Castro, M. (2020, March). Fiscal Policy during a Pandemic. Working Papers 2020-006, Federal Reserve Bank of St. Louis.

Galí, J., F. Smets, and R. Wouters (2012). Unemployment in an estimated new keynesian model. *NBER macroeconomics annual 26*(1), 329–360.

Guerrieri, V., G. Lorenzoni, L. Straub, and I. Werning (2020, April). Macroeconomic implications of covid-19: Can negative supply shocks cause demand shortages? Working Paper 26918, National Bureau of Economic Research.

Hamermesh, D. S. (1996). *Labor Demand*. Princeton University press.

Lenza, M. and G. E. Primiceri (2020). How to estimate a var after march 2020. Technical report, National Bureau of Economic Research.

Lichter, A., A. Peichl, and S. Siegloch (2015). The own-wage elasticity of labor demand: A meta-regression analysis. *European Economic Review 80*, 94–119.

Mongey, S., L. Pilossoph, and A. Weinberg (2020, May). Which workers bear the burden of social distancing policies? Working Paper 27085, National Bureau of Economic Research.

Sims, C. A. and T. Zha (1998). Bayesian methods for dynamic multivariate models. *International Economic Review*, 949–968.

Smets, F. and R. Wouters (2007). Shocks and frictions in us business cycles: A bayesian dsge approach. *American economic review 97*(3), 586–606.

Uhlig, H. (2017). Shocks, sign restrictions, and identification. In *Advances in Economics and Econometrics: Volume 2: Eleventh World Congress*, Volume 59, pp. 95. Cambridge University Press.

Appendix

A Data sources and sector classification

We use the Current Employment Statistics (CES) database from the Bureau of Labor Statistics (BLS) to obtain monthly average hourly earnings of all employees in 1982-1984 dollars (CES code: 13) and aggregate weekly hours of all employees (CES code: 56). The data starts in March 2006 and goes until April 2020, and all series are seasonally adjusted. Table 1 lists all used CES industry classifications as well as the associated NAICS codes.

Table 1: CES industry classification

Sector	BLS Code	NAICS Code
Total private	05000000	-
Mining and logging	10000000	11-21
Construction	20000000	23
Manufacturing	30000000	31-33
Wholesale trade	41420000	42
Retail trade	42000000	44-45
Transportation and warehousing	43000000	48-49
Utilities	44220000	22
Information	50000000	51
Financial activities	55000000	52-53
Professional and business services	60000000	54-56
Education and health services	65000000	61-62
Leisure and hospitality	70000000	71-72
Other services	80000000	81

Regarding concerns on data quality during the months of the pandemic, a BLS press release published on May 8, 2020 reveals that the response rate was lower than in previous months but not as low as initially predicted. See https://www.bls.gov/news.release/archives/empsit_05082020.pdf.

B Composition Effects

In this appendix, we use data from the Current Population Survey (CPS, sourced from IPUMS) to argue that our results are not completely driven by "composition effects". The main concern regarding composition arises from the fact that if a negative demand may lead to a decrease in hours worked in a given sector that is mostly driven by workers in lower wage occupations. This then generates opposite movements in hours worked and average wages in that sector even in the absence of a labor supply shock.

As a first step, we compute counterfactual changes in wages in specific sectors under the assumption that there are no labor supply shocks and that all changes in wages are attributed to composition effects. We focus on three subsectors for which hours fell the most in April 2020: Clothing and accessories stores (NAICS: 448), Traveler accommodation (7211), and Restaurants and other food services (including Drinking places, 722). We use the 2020 Annual CPS data refering to occupations and industries worked in 2019 due to better and more consistent data quality versus the 2020 Monthly CPS, and assume that data to be representative of the pre-pandemic period (February 2020).

We compute hours worked in the pre-pandemic period using the `uhrsworkly` variable for each sector s and occupation o, $h_{s,o,0}$. We also compute average hourly earnings for each occupation and sector using `incwage`, `uhrsworkly`, and `wkswork1`, $w_{s,o,0}$. We excude observations for which `incwage` is either zero or missing, observations for each `uhrsworkly` is either missing or smaller or equal than 1, and observations for which `wkswork1` is smaller than 20. All sector-occupation variables are computed by using the appropriate sample weights. We focus on production and non-supervisory employees. There is no CPS flag that is consistent with the CES definition; we exclude any occupations whose labels include the strings `manage` or `supervis`.

We then take the observed (month-on-month) changes in hours worked in each of the sectors: -2.48% and -92.83% in Clothing Stores for March and April, respectively; -14.36% and -71.01% for Food & Drinking Places; -9.79% and -78.52% for Accommodation. For each sector, we rank occuppations by hourly earnings. Given that we observe hours worked for each occupation and in each sector, we drop the appropriate number of hours worked starting with the lowest-earning occupations, until the fall in hours corresponds to the one observed in the data and we then recompute the average hourly earnings in that sector. We do this first for March, taking the 2019 CPS distribution of hours across occupations and sectors as the benchmark and applying the observed sectoral drop in hours for March. We then apply the April drop in hours to the resulting distribution in March. This allows us to compute two coutnerfactual hourly earnings for each sector, one for each month. The results are shown in table 3.

	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%

Table 2: Counterfactual hourly earnings for selected sectors, assuming extreme composition effects. Note that these are not hourly wages, hence the differences in levels.

By construction, given that all these sectors experienced drops in hours in both March and April, the composition-effect counterfactual hourly earnings rise in these two months. Importantly, they rise by considerably more than in the data. In order to reconcile these composition effects with the observed changes in the data, these sectors would need to have suffered extreme labor demand shocks that would result in considerable drops in the hourly earnings of the workers who remain employed so as to offset the large increase driven by the composition effects.

We proceed to document that there is no evidence of large drops in wages for workers in occupations that would remain employed under the composition effects-only counterfactual. To do this, we use data from the 2020 Monthly CPS (also sourced from IPUMS) to track hourly earnings of workers who work in these sectors, in occupations that did not experience a fall in hours under our counterfactual scenario. We focus on the occupation with the largest percentage of hours worked in our counterfactual scenario for each sector: Customer service representatives for Clothing Stores (34.7% of hours worked in the April counterfactual, occupation code 5240) and Chefs and head cooks for both Accommodation (17.6% of hours worked in the April counterfactual, occupation code 4000) and Food & Drink (28.3% of hours worked in the April counterfactual). Figure 6 shows that these hourly wages were relatively stable during March and April 2020, if anything increasing slightly.

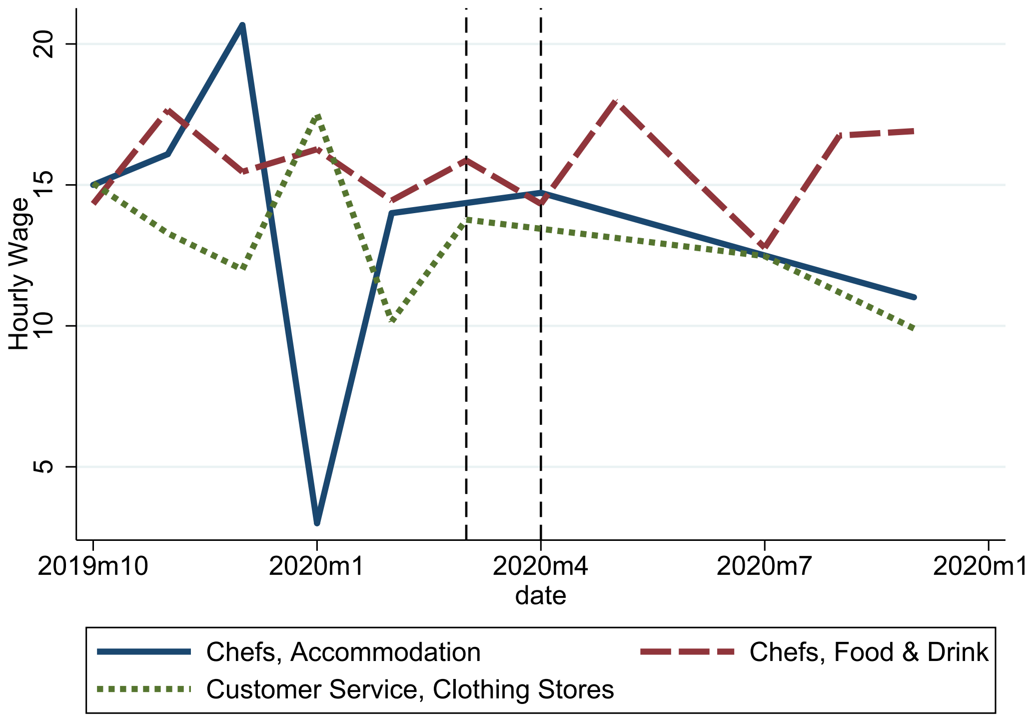


Figure 6: Hourly wages for occuppations with largest share of hours worked under composition effect counterfactual in each sector. Source: 2020 Monthly CPS (IPUMS).

Taken together, our analysis of the micro data does not invalidate the possibility that composition effects played a role in explaining the joint dynamics of hours and hourly wages during the months of March and April 2020, but we hope to have convinced the reader that an extreme scenario in which there are no negative labor supply shocks, and all movements are caused by demand shocks and composition effects, would result in dynamics that are at odds with the micro data.

Next, we provide a lower bound to the relative importance of supply shocks by doing a historical decomposition for three of the most hit sectors in April by the COVID-19 crisis—Accommodation, Clothing and clothing accessories stores, and Food Services and Drinking Places—under the assumption that wage increase in those sectors was purely driven by composition effects. In doing so, we find that the relative importance of supply shocks in explaining hours in April in Accommodation, Clothing and clothing accessories stores, and Food Services and Drinking Places, goes from 51.7% , 73.9% and 51.0%, to 48.7%, 63.3% and 51.9%, respectively. Hence, assuming that all of the wage changes is driven by composition effects, the relative importance of supply decreases at most by 10.6 percentage points.

	Clothing Stores	Accommodation	Food & Drink Places
April Benchmark Historical Decomposition	73.9%	51.7%	51.0%
April Counterfactual Historical Decomposition	63.3%	48.7%	51.9%

Table 3: Counterfactual historical decomposition for selected sectors, assuming composition effects drive all the observed wage increase.

C Tables

Table 4: Descriptive statistics of hours and real wage growth rates by BLS 2-digit sector

		March	April	Mean	SD	Min	Max
Construction	hours	−0.94	−17.10	−0.08	1.78	−17.10	2.84
	wages	0.50	0.90	0.07	0.42	− 1.24	2.39
Education and Health Services	hours	−1.02	−12.19	0.11	0.99	−12.19	0.91
	wages	0.65	2.01	0.06	0.39	− 0.91	2.48
Financial Activities	hours	−0.03	− 3.01	0.03	0.44	− 3.01	1.06
	wages	0.28	2.49	0.12	0.44	− 1.49	2.49
Information	hours	0.14	− 8.93	−0.09	0.90	− 8.93	2.17
	wages	1.02	1.95	0.15	0.57	− 1.33	1.95
Leisure and Hospitality	hours	−9.41	−63.03	−0.29	4.94	−63.03	1.92
	wages	0.61	7.22	0.12	0.66	− 1.17	7.22
Manufacturing	hours	−1.00	−16.29	−0.15	1.38	−16.29	1.06
	wages	0.73	3.58	0.05	0.51	− 0.99	3.58
Mining and Logging	hours	−1.87	−12.09	−0.01	1.82	−12.09	3.96
	wages	0.45	1.55	0.11	1.07	− 5.73	5.56
Other Services	hours	−2.53	−21.65	−0.09	1.72	−21.65	1.32
	wages	0.71	7.26	0.12	0.66	− 0.87	7.26
Professional and Business Services	hours	−0.37	−11.46	0.07	1.01	−11.46	1.55
	wages	0.60	4.32	0.10	0.52	− 0.82	4.32
Retail Trade	hours	−0.61	−14.48	−0.09	1.26	−14.48	1.38
	wages	1.02	5.08	0.05	0.61	− 1.28	5.08
Total Private	hours	−1.54	−16.17	−0.03	1.30	−16.17	0.79
	wages	0.90	5.43	0.09	0.54	− 0.80	5.43
Transportation and Warehousing	hours	−0.65	−12.73	0.07	1.13	−12.73	1.34
	wages	0.51	3.91	0.04	0.49	− 1.58	3.91
Utilities	hours	−0.65	0.10	0.02	1.01	− 3.95	4.95
	wages	0.61	2.39	0.09	0.89	− 2.90	2.86
Wholesale Trade	hours	−0.05	− 9.45	−0.03	0.83	− 9.45	0.86
	wages	0.41	2.56	0.06	0.55	− 1.30	2.81

Table 5: Quantiles for the posterior distributions of labor demand and supply elasticities

	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

Table 6: Median and 95% credible interval of the effects of demand and supply shocks on the growth rate of hours, March 2020

	Demand			Supply			Difference 68% Credible Interval
Sector	50p	2.5p	97.5p	50p	2.5p	97.5p	
Total Private	-0.57	-1.33	-0.03	-1.43	-1.99	-0.67	[-1.557, -0.068]
Mining and Logging	-0.59	-1.53	0.00	-1.41	-2.28	-0.50	[-1.605, 0.079]
Construction	-0.00	-0.70	0.27	-1.36	-1.79	-0.68	[-1.702, -0.816]
Manufacturing	-0.12	-0.69	0.20	-0.93	-1.38	-0.35	[-1.223, -0.258]
Wholesale Trade	0.03	-0.17	0.14	-0.24	-0.42	-0.05	[-0.410, -0.095]
Retail Trade	0.02	-0.37	0.28	-0.88	-1.16	-0.50	[-1.194, -0.525]
Transportation and Warehousing	-0.39	-0.89	-0.01	-0.70	-1.12	-0.22	[-0.753, 0.185]
Utilities	-0.34	-0.87	0.05	-0.65	-1.04	-0.12	[-0.762, 0.230]
Information	0.18	-0.00	0.32	-0.36	-0.51	-0.18	[-0.673, -0.377]
Financial Activities	-0.10	-0.23	0.03	-0.16	-0.29	-0.04	[-0.185, 0.059]
Professional and Business Services	-0.17	-0.52	0.01	-0.66	-0.92	-0.31	[-0.744, -0.162]
Education and Health Services	-0.60	-1.30	-0.03	-0.92	-1.50	-0.23	[-1.107, 0.535]
Leisure and Hospitality	-4.76	-8.94	-0.93	-6.70	-10.54	-2.53	[-6.275, 2.823]
Other Services	-1.18	-2.33	-0.19	-2.00	-3.00	-0.85	[-1.984, 0.431]

Table 7: Median and 95% credible interval of the effects of demand and supply shocks on the growth rate of hours, 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]

Table 8: Median and 95% credible interval of the effects of demand and supply shocks on the growth rate of hours, May 2020

	Demand			Supply			Difference 68% Credible Interval
Sector	50p	2.5p	97.5p	50p	2.5p	97.5p	
Total Private	1.68	-0.38	4.37	2.50	-0.19	4.57	[-1.999, 3.353]
Mining and Logging	0.57	-1.28	2.00	-3.71	-5.24	-1.86	[-5.764, -2.548]
Construction	2.71	0.04	8.33	6.68	1.07	9.38	[-2.033, 7.448]
Manufacturing	2.40	-0.61	5.67	1.65	-1.63	4.67	[-4.330, 2.678]
Wholesale Trade	0.72	-0.45	2.07	0.44	-0.91	1.62	[-1.741, 1.077]
Retail Trade	1.56	-0.38	4.40	3.76	0.93	5.70	[-0.715, 4.615]
Transport. & Warehousing	0.12	-1.13	1.53	0.97	-0.44	2.21	[-0.517, 2.079]
Utilities	-0.92	-1.30	-0.55	0.01	-0.36	0.38	[0.570, 1.230]
Information	-0.66	-1.76	0.31	-0.50	-1.46	0.59	[-0.864, 1.271]
Financial Activities	0.85	0.24	1.38	-0.26	-0.79	0.36	[-1.657, -0.523]
Prof. and Business Services	0.72	-0.66	2.58	1.19	-0.67	2.59	[-1.433, 2.115]
Education and Health Services	1.59	-0.03	3.30	1.06	-0.66	2.68	[-2.490, 1.461]
Leisure and Hospitality	4.97	-2.50	14.92	14.38	4.43	21.85	[-0.933, 18.138]
Other Services	2.12	-0.46	5.82	4.82	1.13	7.40	[-1.080, 5.908]

Table 9: Median and 95% credible interval of the effects of demand and supply shocks on the growth rate of hours using production and nonsupervisory employees only, March 2020

	Demand			Supply		
Sector	Median	2.5p	97.5p	Median	2.5p	97.5p
Total Private	-0.43	-1.17	0.02	-1.48	-1.94	-0.74
Mining and Logging	-0.37	-1.16	0.19	-1.33	-1.96	-0.57
Construction	0.64	0.13	0.96	-1.18	-1.51	-0.66
Manufacturing	-0.04	-0.53	0.19	-0.98	-1.25	-0.49
Wholesale Trade	-0.03	-0.30	0.11	-0.65	-0.81	-0.39
Retail Trade	0.24	-0.13	0.41	-0.64	-0.81	-0.27
Transportation and Warehousing	-0.92	-1.41	-0.31	-0.49	-1.11	-0.01
Utilities	-0.19	-0.67	0.14	-0.67	-1.01	-0.19
Information	0.31	0.13	0.41	-0.40	-0.51	-0.23
Financial Activities	-0.18	-0.54	0.03	-0.53	-0.75	-0.18
Professional and Business Services	-0.20	-0.63	0.03	-1.02	-1.27	-0.59
Education and Health Services	-0.40	-0.93	0.03	-0.81	-1.24	-0.28
Leisure and Hospitality	-6.44	-10.69	-2.04	-5.06	-9.47	-0.82
Other Services	-0.90	-2.25	-0.04	-1.97	-2.82	-0.61

Notes: The data sample for production and nonsupervisory employees we use to estimate our SVAR starts in 1984. Production and nonsupervisory employees CES series code for real wages is 32 and for aggregate weekly hours is 81.

Table 10: Median and 95% credible interval of the effects of demand and supply shocks on the growth rate of hours using production and nonsupervisory employees only, April 2020

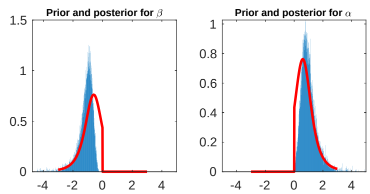
	Demand			Supply		
Sector	Median	2.5p	97.5p	Median	2.5p	97.5p
Total Private	-5.98	-12.99	-0.50	-12.62	-18.09	-5.61
Mining and Logging	-5.43	-11.91	-0.85	-9.68	-14.26	-3.18
Construction	-6.93	-19.39	-0.67	-13.20	-19.46	-0.75
Manufacturing	-8.42	-16.14	-2.19	-11.23	-17.45	-3.52
Wholesale Trade	-4.07	-8.16	-0.33	-6.90	-10.63	-2.81
Retail Trade	-4.91	-12.75	-0.52	-10.18	-14.57	-2.34
Transportation and Warehousing	-3.52	-9.54	0.21	-10.92	-14.65	-4.91
Utilities	0.16	-0.87	0.70	-1.46	-2.00	-0.43
Information	-1.85	-6.01	0.80	-7.31	-9.96	-3.16
Financial Activities	-2.14	-5.03	-0.20	-3.91	-5.85	-1.02
Professional and Business Services	-3.05	-7.91	0.01	-10.27	-13.32	-5.41
Education and Health Services	-5.54	-10.75	-0.60	-7.75	-12.69	-2.54
Leisure and Hospitality	-30.65	-58.66	-7.44	-41.02	-64.23	-13.03
Other Services	-8.69	-20.02	-0.95	-16.03	-23.77	-4.69

Notes: The data sample for production and nonsupervisory employees we use to estimate our SVAR starts in 1984. Production and nonsupervisory employees CES series code for real wages is 32 and for aggregate weekly hours is 81.

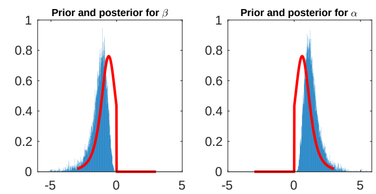
D Additional Figures

Figure 7: Prior and posterior distribution of labor demand and supply elasticities by sector

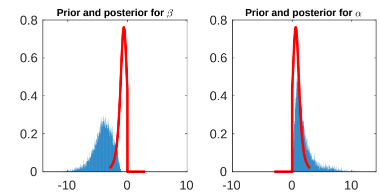
(a) Total Private



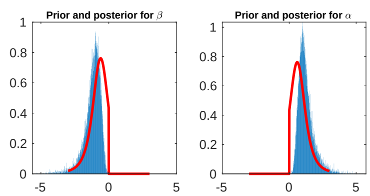
(b) Mining and Logging



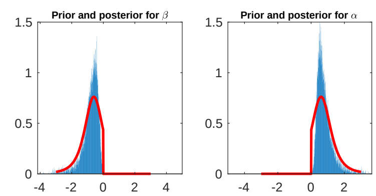
(c) Construction



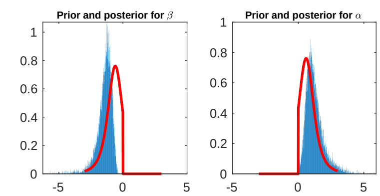
(d) Manufacturing



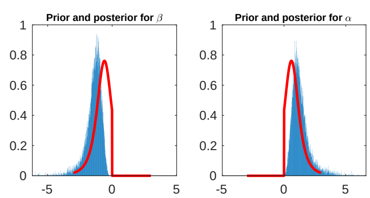
(e) Wholesale Trade



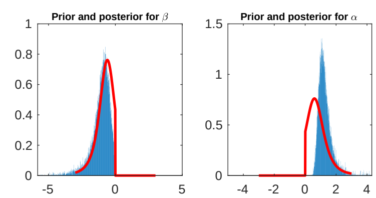
(f) Retail Trade



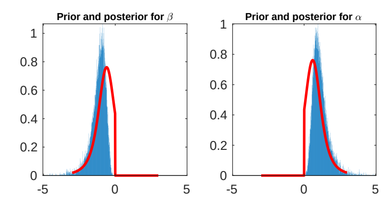
(g) Transportation and Warehousing



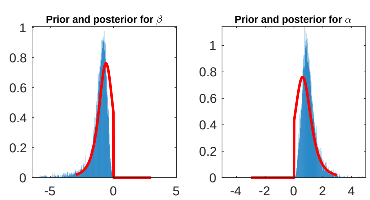
(h) Utilities



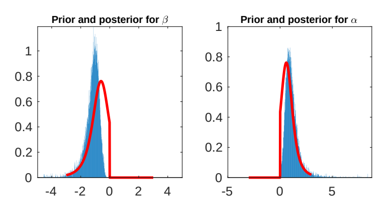
(i) Information



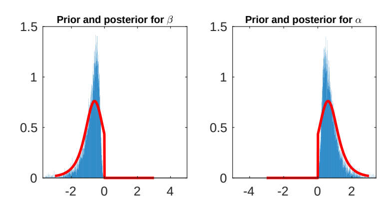
(j) Financial Activities



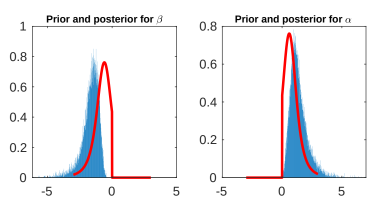
(k) Professional and Business Services



(l) Education and Health Services



(m) Leisure and Hospitality



(n) Other Services

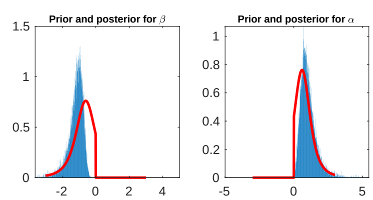
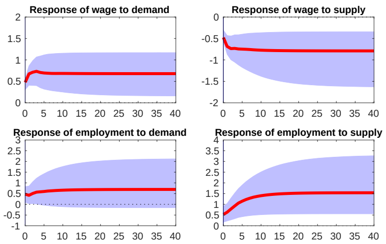
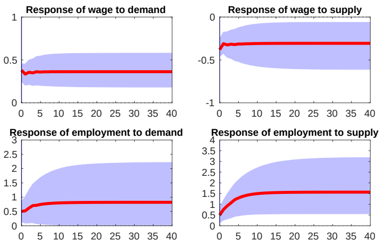


Figure 8: Impulse response functions by sector with 95% credible bands

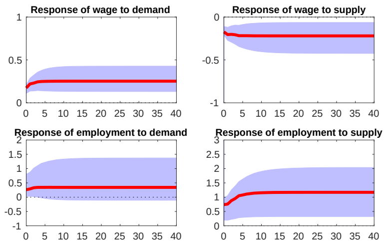
(a) Total Private



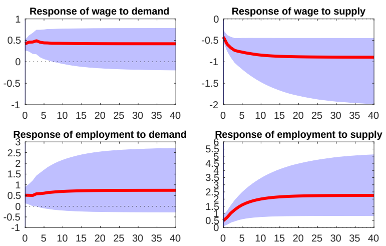
(b) Mining and Logging



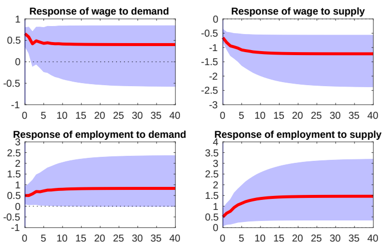
(c) Construction



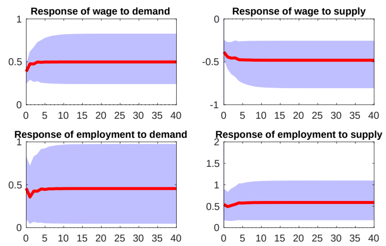
(d) Manufacturing



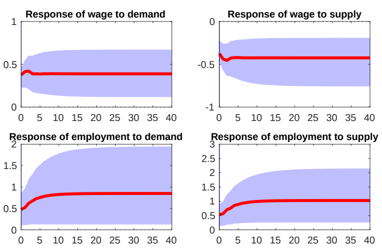
(e) Wholesale Trade



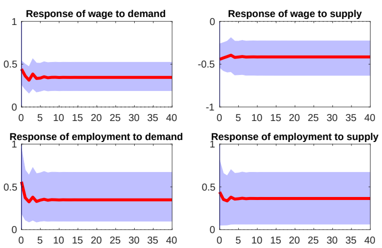
(f) Retail Trade



(g) Transportation and Warehousing

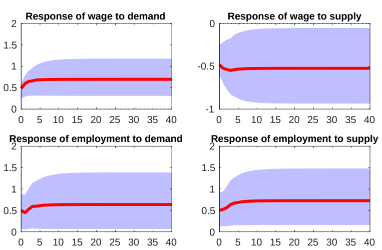


(h) Utilities

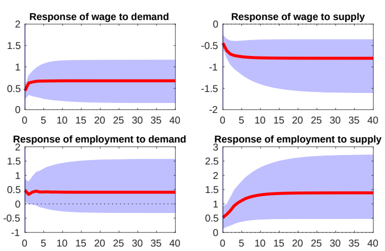


(i) Information

(j) Financial Activities

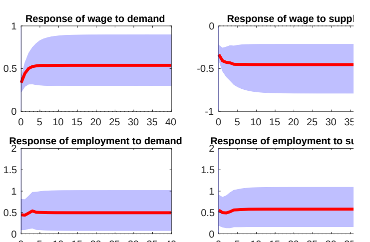


(k) Professional and Business Services



(l) Education and Health Services

(m) Leisure and Hospitality



(n) Other Services

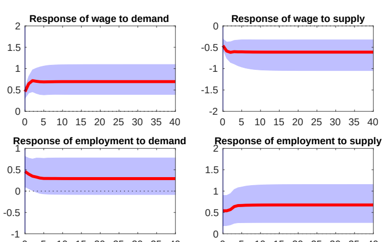
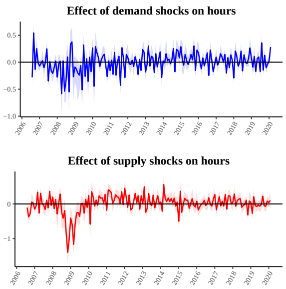
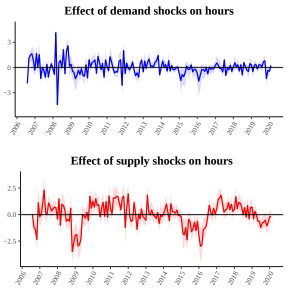


Figure 9: Historical decomposition of the growth rate of hours by sector, excluding March, April and May 2020

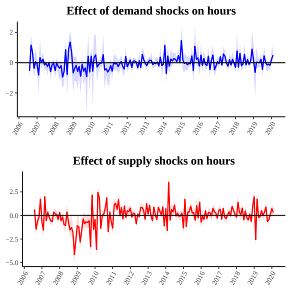
(a) Total Private



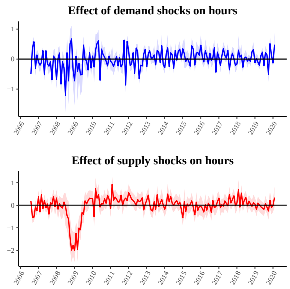
(b) Mining and Logging



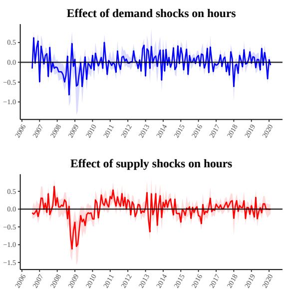
(c) Construction



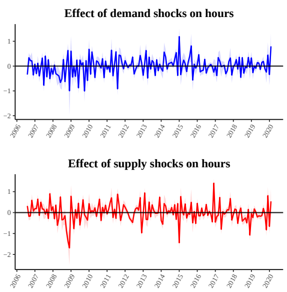
(d) Manufacturing



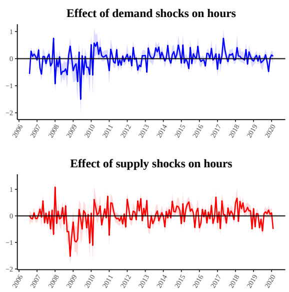
(e) Wholesale Trade



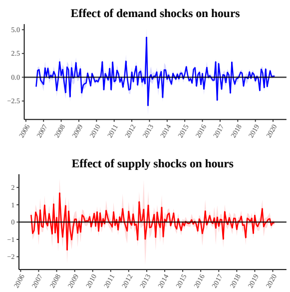
(f) Retail Trade



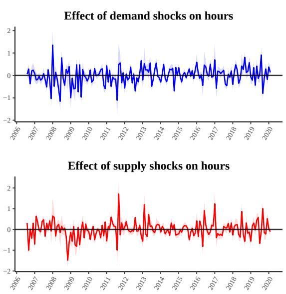
(g) Transportation and Warehousing



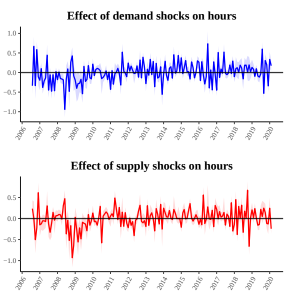
(h) Utilities



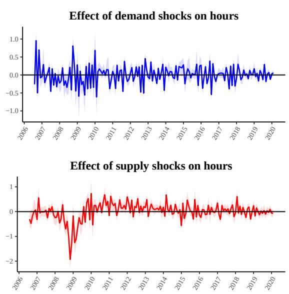
(i) Information



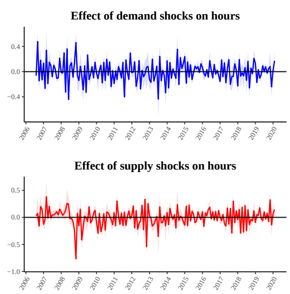
(j) Financial Activities



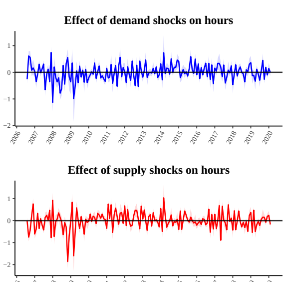
(k) Professional and Business Services



(l) Education and Health Services



(m) Leisure and Hospitality



(n) Other Services

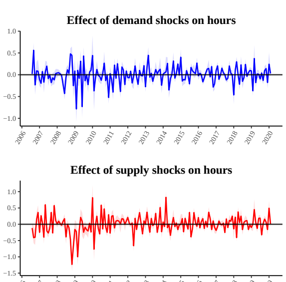
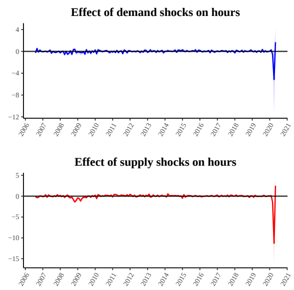
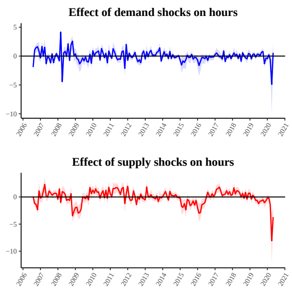


Figure 10: Historical decomposition of the growth rate of hours by sector, full sample

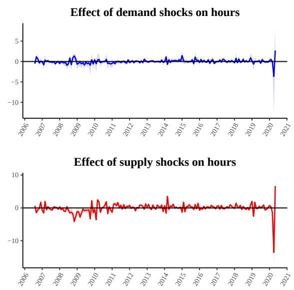
(a) Total Private



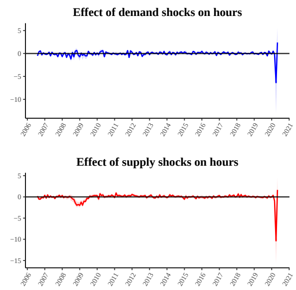
(b) Mining and Logging



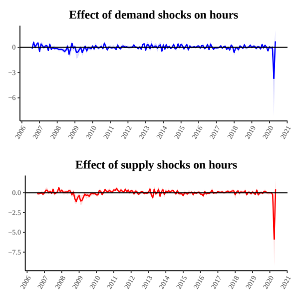
(c) Construction



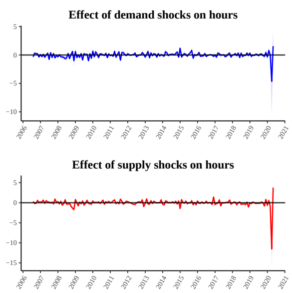
(d) Manufacturing



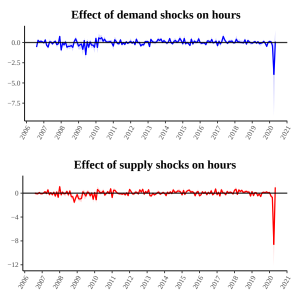
(e) Wholesale Trade



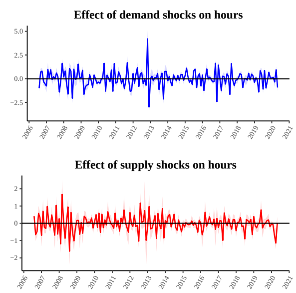
(f) Retail Trade



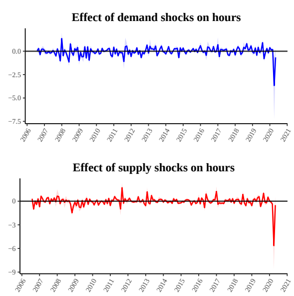
(g) Transportation and Warehousing



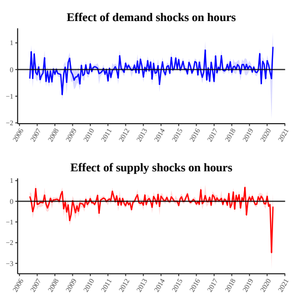
(h) Utilities



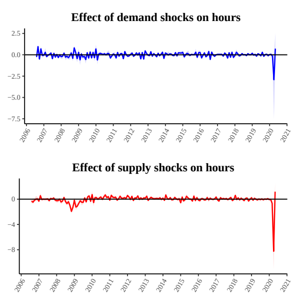
(i) Information



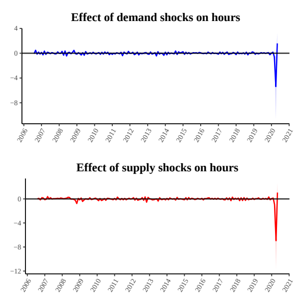
(j) Financial Activities



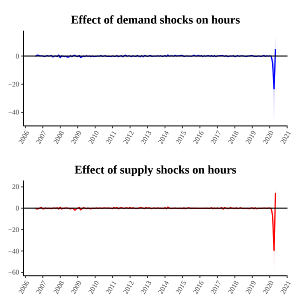
(k) Professional and Business Services



(l) Education and Health Services



(m) Leisure and Hospitality



(n) Other Services

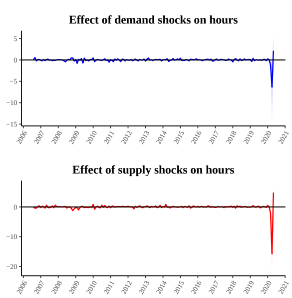
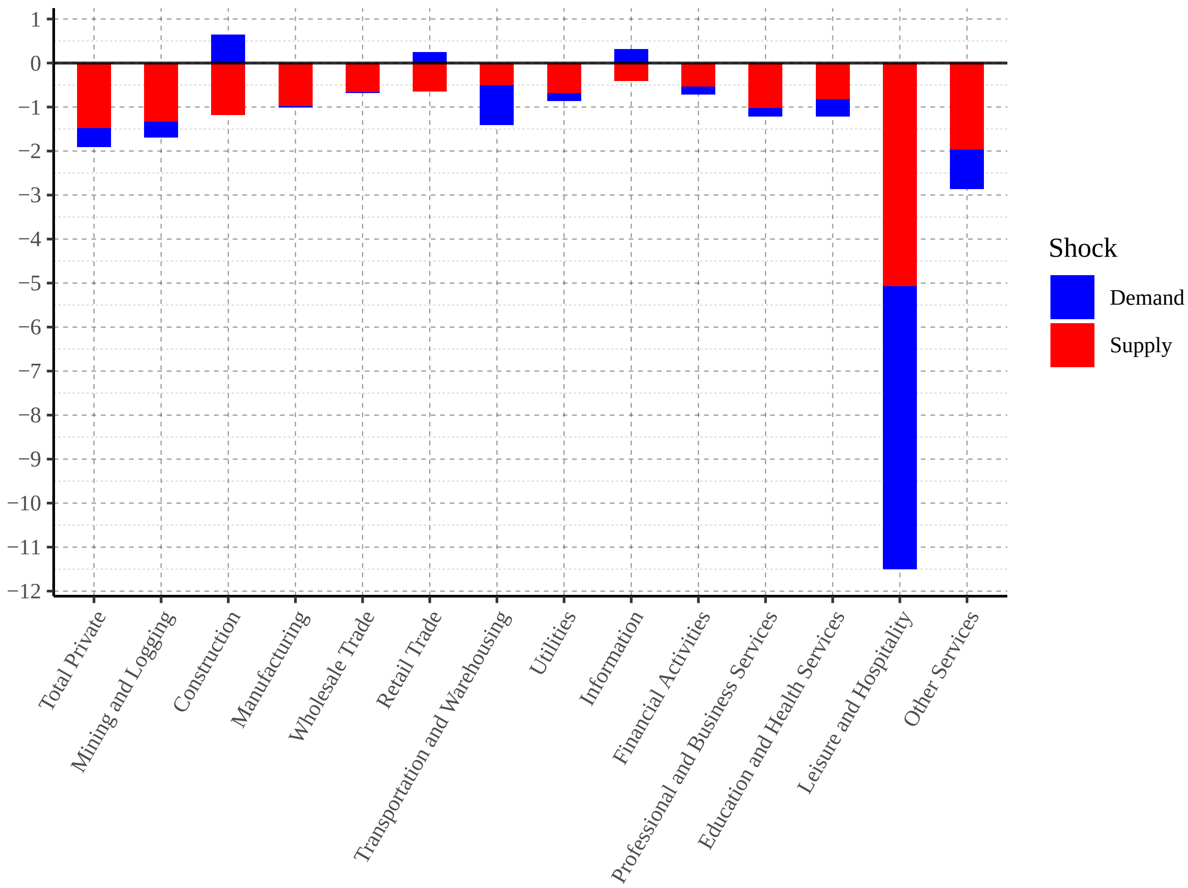
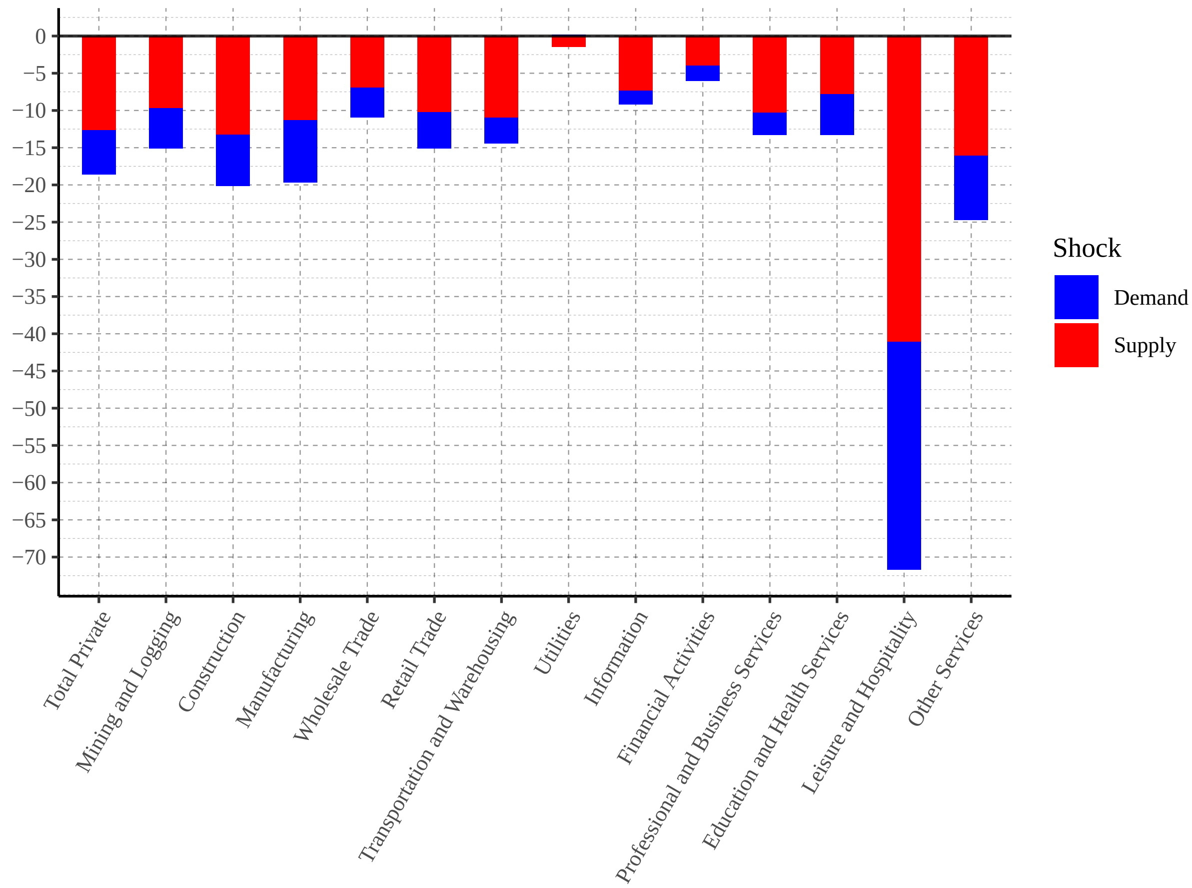


Figure 11: Historical decomposition of the growth rate of hours across sectors using production and nonsupervisory employees only, March 2020



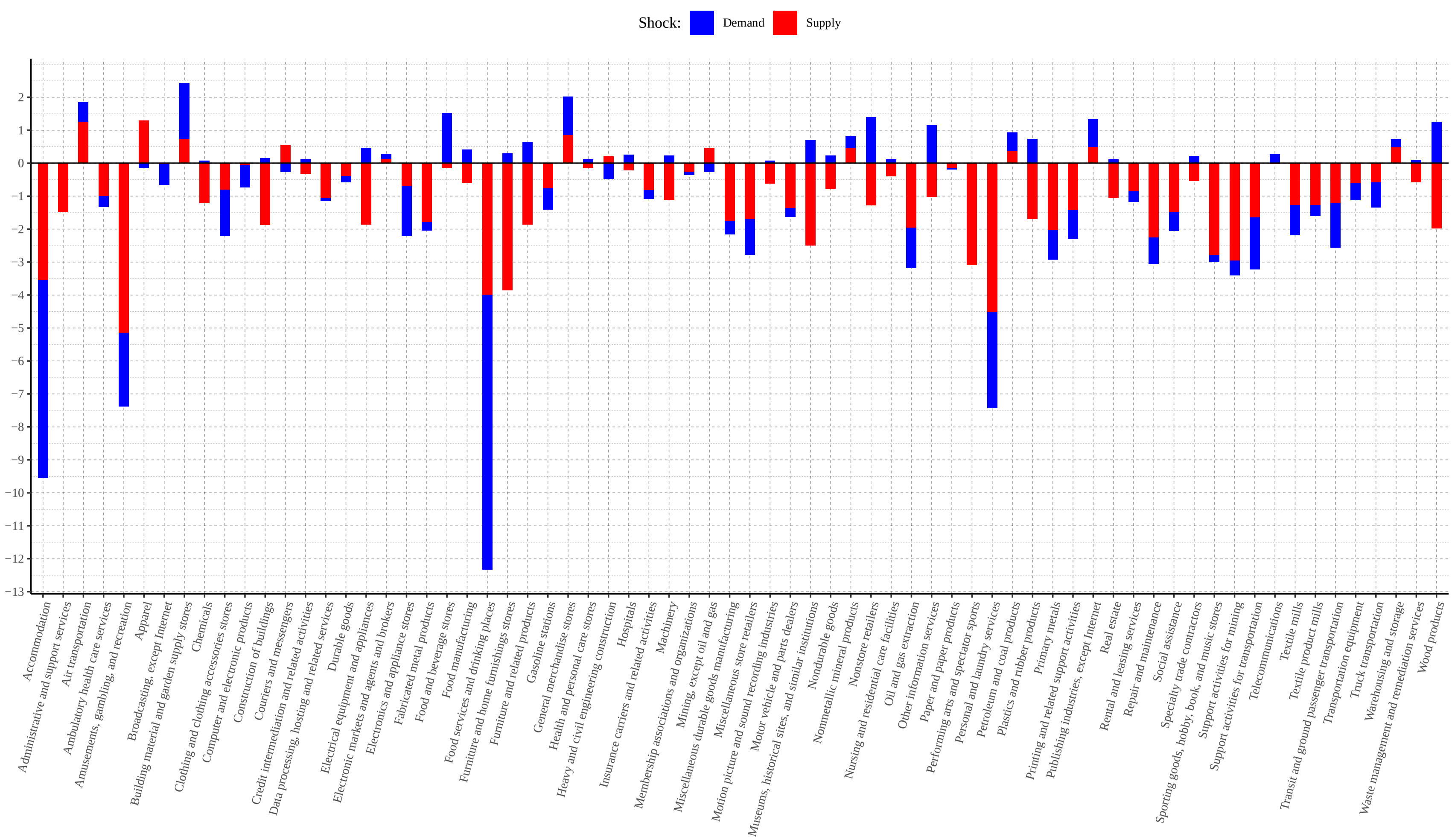
Notes: The data sample for production and nonsupervisory employees we use to estimate our SVAR starts in 1984. Production and nonsupervisory employees CES series code for real wages is 32 and for aggregate weekly hours is 81.

Figure 12: Historical decomposition of the growth rate of hours across sectors using production and nonsupervisory employees only, April 2020



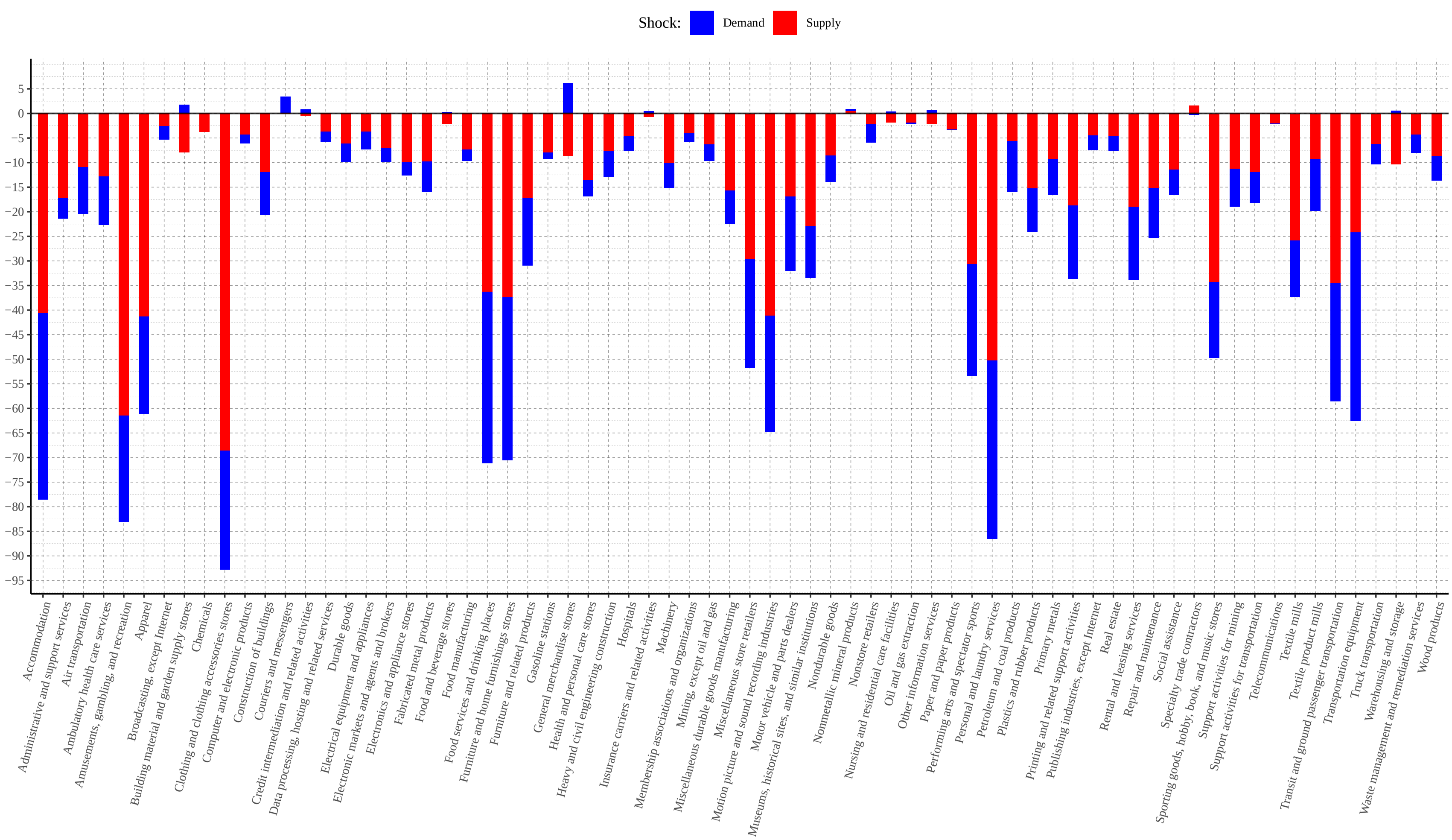
Notes: The data sample for production and nonsupervisory employees we use to estimate our SVAR starts in 1984. Production and nonsupervisory employees CES series code for real wages is 32 and for aggregate weekly hours is 81.

Figure 13: Historical decomposition of the growth rate of hours across NAICS 3-digit sectors using production and nonsupervisory employees only, March 2020



Notes: The data sample for production and nonsupervisory employees we use to estimate our SVAR starts in 1984. Production and nonsupervisory employees CES series code for real wages is 32 and for aggregate weekly hours is 81.

Figure 14: Historical decomposition of the growth rate of hours across NAICS 3-digit sectors using production and nonsupervisory employees only, April 2020



Notes: The data sample for production and nonsupervisory employees we use to estimate our SVAR starts in 1984. Production and nonsupervisory employees CES series code for real wages is 32 and for aggregate weekly hours is 81.

Figure 15: Historical decomposition of the growth rate of hours across sectors, March 2019

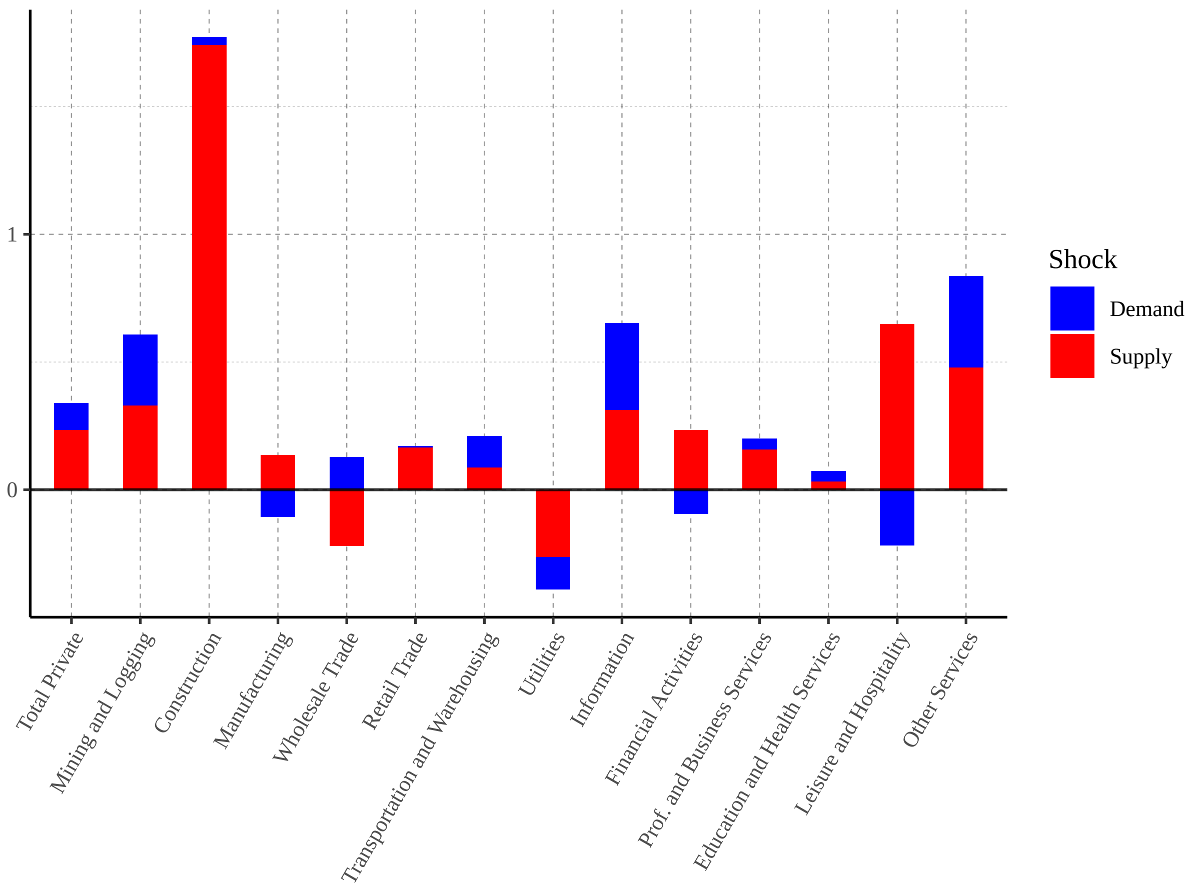
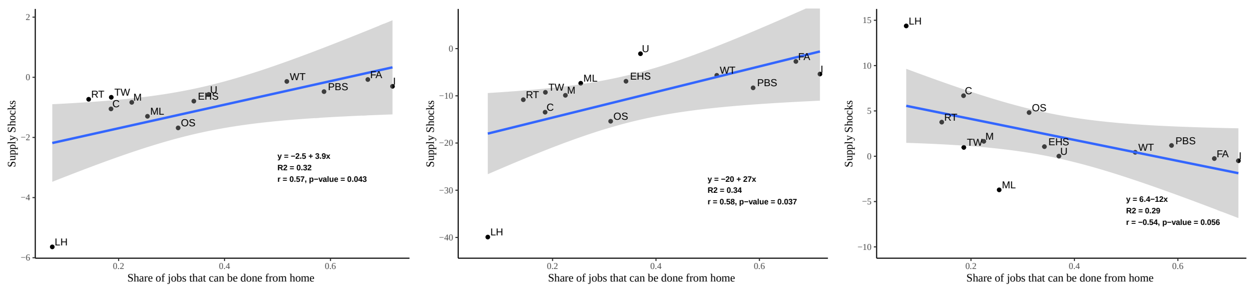


Figure 16: Correlation between sectoral supply shocks the sectoral share of jobs that can be done at home

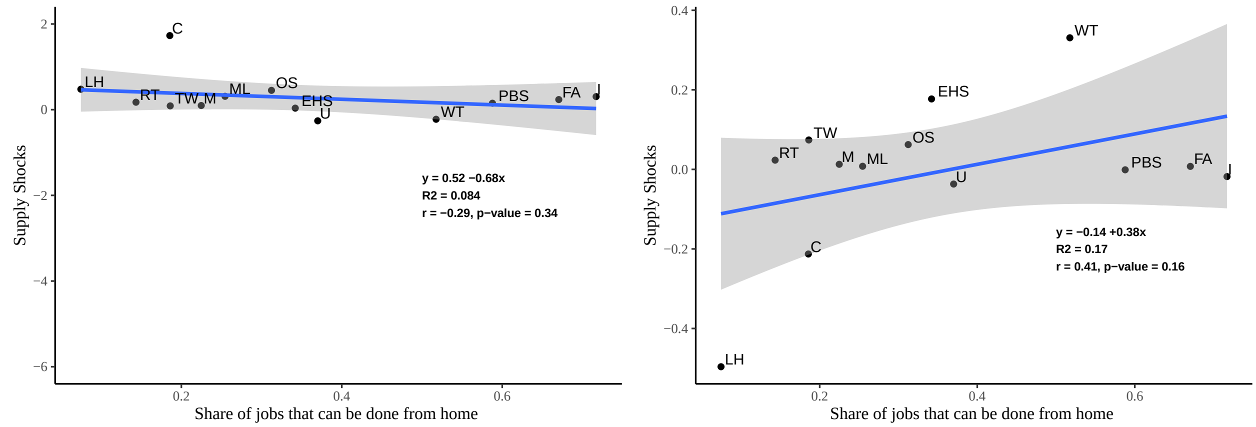
(a) March **(b)** April **(c)** May



ML: Mining and logging; **C**: Construction;**M**: Manufacturing; **WT**: Wholesale trade; **RT**: Retail trade; **TW**: Transportation and warehousing; **U**: Utilities; **I**: Information; **FA**: Financial activities; **PBS**: Professional and business services; **EHS**: Education and health services; **LH**: Leisure and hospitality; **OS**: Other services. Grey bands represent 95% confidence intervals.

Figure 17: Supply Shocks in 2019 vs. Share of jobs that can be done from home

(a) March 2019 **(b)** April 2019



ML: Mining and logging; **C**: Construction;**M**: Manufacturing; **WT**: Wholesale trade; **RT**: Retail trade; **TW**: Transportation and warehousing; **U**: Utilities; **I**: Information; **FA**: Financial activities; **PBS**: Professional and business services; **EHS**: Education and health services; **LH**: Leisure and hospitality; **OS**: Other services. Grey bands represent 95% confidence intervals.