Measuring Sectoral Supply and Demand Shocks during COVID-19*

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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. Our estimates suggest that two-thirds of the 16.24 percentage point drop in the growth rate of hours worked in April 2020 are attributable to supply. Most sectors were subject to historically large negative labor supply and demand shocks in March and April, but there is substantial heterogeneity in the size of shocks across sectors. We show that our estimates of supply shocks are correlated with sectoral measures of telework.

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1 Introduction

The on-going COVID-19 outbreak and subsequent 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 self-impose social distancing. There are many aspects that make studying this combined shock interesting. First, its unprecedented and unexpected nature. Second, the fact that it combined features that are traditionally associated with both demand and supply shocks. Third, the fact that its effect across sectors in the economy was 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, it is not clear whether this is mostly a demand or a supply shock.

This paper attempts to contribute to answering that question by constructing estimates of labor demand and supply shocks at the sectoral level. We apply the 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 informative priors on labor demand and supply elasticities, we use sign restrictions to identify and estimate sequences of structural demand and supply shocks. Our latest historical decomposition estimates are for April 2020, the month in which the effects of the controlled shutdown of the US economy on the labor market were mostly felt.

For April 2020, we find that total private employment was subject to negative supply and demand shocks totaling -16.24 percentage points, with supply accounting for 68.83% of this decrease. This means that total private employment grew by 16.04 percentage points less than its historical average in April 2020 (non-annualized), and that two-thirds of this negative growth was 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 was by far the sector subject to a larger disruption (-9.55 pp in March, 59% of which was supply, -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).

Confinement measures such as lockdowns force people to stay at home, which prevents many from being able to perform their jobs (which cannot be done at home). The outbreak itself also induces people to stay at home, regardless of lockdown measures (Baek et al., 2020). Our econometric model captures these situations as negative labor supply shocks. On the other hand, these confinement measures also prevent people from engaging in the consumption of certain goods and services whose enjoyment requires some degree of physical contact. This results in lower product demand for some firms, which results in less labor demand. Additionally, the decline in personal incomes also leads to reductions in expenditure in other goods or services, regardless of the associated degree of physical contact. This can also lead to negative labor demand shocks in sectors that are not directly affected by the lockdown. Both of these economic forces are identified as negative labor demand shocks in our model. For that reason, we argue that, while conceptually different, there is a close relationship between "aggregate" demand and supply, and the measures of shocks that we estimate. We validate our shock identification estimates by showing that the estimated (negative) supply shocks in March 2020 and April 2020 are correlated to measures of sectoral exposure to confinement policies, such as the share of jobs that can be done at home in each sector.

We think that our measurement exercise is relevant for policy making during the COVID-19 crisis. First, and more generally, it is well accepted among macroeconomists that conventional fiscal policy (in the form of stimulus policy, for example) and monetary policy are well suited to respond to aggregate demand shocks, i.e. shocks that reduce both inflation and aggregate activity. It is not clear, however, whether these policies are appropriate for aggregate supply shocks, shocks that increase inflation and reduce aggregate activity as in this case both policies exacerbate the inflation-activity trade-off. The specificities of the COVID-19 crisis add another layer of complexity, as there is doubt whether stimulating activity in sectors that are subject to lockdown should be a goal for policymakers as that could defeat the purpose of the lockdown itself. The fall in employment and aggregate expenditure that is caused by the outbreak and the lockdown can, however, lead to a reduction of activity in sectors that are not 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 this reason, we believe that 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 shock decomposition and measurement exercise also provide natural moment conditions to help discipline quantitative work on the COVID-19 crisis. 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 during COVID-19. 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. Our measurement exercise restricts the set of of models and shocks that are empirically plausible.

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

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

shocks are stagflationary and 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 potential 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. 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 (what they refer to as "Keynesian supply shocks"). The shocks we estimate are not structural under 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 aspects in standard macroeconomic models, and where epidemics generate reductions in economic activity that would be captured by our framework as 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 industry sector $l \in L$. 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. We normalize these parameters so that they are interpreted as elasticities of the growth rate of hours with respect to the growth rate of real wages.

Given this, the labor market demand and supply equations in sector l are given by

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

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

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 demand is downward sloping and supply is upward sloping we have the standard result that, *ceteris paribus*, a positive shift in the demand curve makes equilibrium hours increase and wage 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 effect 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) is the supply curve relative to the demand curve, the weaker (stronger) is the relative impact a supply shock on hours, and the stronger (weaker) is its impact on real wages.[2]

The reduced-form 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

[2] 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.

$$\Phi_0^l = (\boldsymbol{A}^l)^{-1}\boldsymbol{B}_0^l$$
$$\Phi^l(L) = (\boldsymbol{A}^l)^{-1}\boldsymbol{B}^l(L)$$
$$\boldsymbol{u}_t^l = (\boldsymbol{A}^l)^{-1}\boldsymbol{\varepsilon}_t^l \tag{6}$$
$$E[\boldsymbol{u}_t^l(\boldsymbol{u}_t^l)'] = \Omega = (\boldsymbol{A}^l)^{-1}\boldsymbol{D}((\boldsymbol{A}^l)^{-1})' \tag{7}$$

We assume that prior beliefs about the values of the structural parameters are represented by a joint density $p(\boldsymbol{A}, \boldsymbol{D}, \boldsymbol{B})$. We then revise these beliefs when confronting them with sectoral data in our sample $\boldsymbol{Y}_T = (\boldsymbol{y}_1, \boldsymbol{y}_2, \cdots, \boldsymbol{y}_T)$. Importantly, Baumeister and Hamilton (2015) show how these beliefs can be updated for any arbitrary prior distribution $p(\boldsymbol{A})$. In principle this prior $p(\boldsymbol{A})$ could incorporate any combination of exclusion restrictions, sign restrictions, and informative prior beliefs about elements of $\boldsymbol{A}$.

Priors Following Baumeister and Hamilton (2015), we use past studies to form informative priors about α^l and β^l. In particular, we impose sign restrictions on sectoral demand and supply elasticities – β^l is negative and α^l is positive – and that they fall somewhere in the range of the literature estimates for the aggregate economy. Lichter et al. (2015), building on information from 151 different studies containing 1334 estimates in total, find that, except for Construction and Manufacturing, the labor demand elasticity does not seem to vary substantially across the remaining 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 that reason, we apply the same prior distribution $p(\boldsymbol{A})$ for all sectors in our sample.

The sign restriction reflects our belief that the labor demand curve should be downward sloping while the supply curve should be upward sloping. However, we do not place a uniform probability on all values that respect these sign restrictions. We assume a truncated Student's t distribution for β^l with location parameter -0.6, scale parameter 0.6 and 3 degrees of freedom, so that we place 90% probability on values of β^l being in the range of $[-2.2, -0.1]$. This range reflects the labor demand elasticity estimates found in the micro and macro literatures[3]. In terms of the labor supply elasticity, based on the findings of Chetty et al. (2011), we also use a Student's t distribution for α^l with location parameter -0.6, scale parameter 0.6 and 3 degrees of freedom, so that we place 90% probability on values of α^l being in $[-2.2, -0.1]$ interval. This interval thus includes both the lower estimates reported by microeconometric estimates and by macro estimates when movements in wages are persistent, as well as the high Frisch elasticities

[3]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) or Galí et al. (2012) find that the labor demand elasticity can be -2.5 or even higher.

reported by macro studies of the business cycle such as 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.

Next, we define our conditional prior distributions $p(\boldsymbol{D}|\boldsymbol{A})$ and $p(\boldsymbol{B}|\boldsymbol{A},\boldsymbol{D})$ specifications. For the elements of the diagonal matrix $\boldsymbol{D}$, we assume that their reciprocal (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 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. With this setting, $p(\boldsymbol{D}|\boldsymbol{A})$ is just 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 (Doan et al. (1984) and Sims and Zha (1998)) on the reduced-form coefficients Φ. Note that placing a prior on the reduced-form coefficients and conditioning on $\boldsymbol{A}$ implicitly places a prior on $\boldsymbol{B}$ because $\boldsymbol{B} = \boldsymbol{A}\Phi$. Hence the normally distributed coefficients b_i have mean a_i for elements corresponding to own lags and zero to 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, $\lambda_1 = 1$ that 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 $\boldsymbol{Y}_T$. Baumeister and Hamilton (2015) show that 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 Note that given (6), structural demand and supply shocks are only set identified, reflecting uncertainty regarding the labor elasticities that can be summarized by $p(\boldsymbol{A}|\boldsymbol{Y}_T)$. We do not impose any long-run restrictions. The final identified set is a function of our specified prior beliefs and data on the growth rates of hours and real wages. It is worth remarking that, as shown by Baumeister and Hamilton (2015), prior beliefs about $\boldsymbol{A}$ will not vanish asymptotically.

3 Data

Our main source of data is the Current Employment Statistics (CES) database from the Bureau of Labor Statistics, from where we obtain monthly real wages and hours worked by sector from March 2006 to April 2020[4]. 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 and excluding the last two months in the sample. We use the model estimated until February 2020 to perform a historical decomposition of the shocks in these last two months.

We also rely on the measure constructed by Dingel and Neiman (2020) using survey data from the Occupational Information Network (O*NET) for how feasible it is to perform work at home for each sector.

4 Results

Posteriors For most sectors the beliefs about the elasticities are greatly revised upwards, towards the macro literature estimates. This revision is particularly strong in the Leisure and Hospitality, and Utilities sectors. Likewise, in absolute value the demand elasticities are mostly revised upwards, especially in the Construction and Leisure and Hospitality sectors. Hence, we conclude that our identification of supply and demand shocks is strongly influenced by the data. Figure 6 in the Appendix plots the prior distribution for the demand α^l and supply β^l elasticities (red line) as well as a histogram of posterior draws (blue bars).

Historical Decompositions Figure 1 plots the historical decomposition of the growth rate of hours into estimated supply and demand shocks for Total Private employment and the Leisure and Hospitality sector. The top panels exclude March and April 2020, which as we will explain, were historically large shocks. These top panels show that the growth rate of hours was subject to large negative shocks both to demand and to supply during the period corresponding to the Great Recession. Consistent with standard narratives, the Great Recession begins with negative

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

demand shocks in late 2007 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). The bottom panels include March and April 2020, showing that the magnitude of these shocks dwarf anything experienced during the Great Recession (particularly April). Figures 7 and 8 in the Appendix plot the estimated sequences of demand and supply shocks for each sector back to the beginning of 2006 (without and with the months of March and April 2020, respectively).

[FIGURE 1 GOES HERE]

4.1 The Great Lockdown: March and April 2020

We now take a closer look at the results for the month of March and April 2020. Figures 2 and 3 are our main set of results and plot estimated median demand and supply shocks across sectors for the months of March and April, respectively. Tables 1 and 2 report the median values and 95% credible intervals for these shocks. The combined negative effect of supply and demand on the growth rate of hours for total private employment was −2.59 pp in March and −16.24 in April.[5] Negative supply shocks accounted for 64.8% and 68.8% of these effects, respectively.

[FIGURE 2 GOES HERE]

[FIGURE 3 GOES HERE]

[TABLE 1 GOES HERE]

[TABLE 2 GOES HERE]

Figure 2 shows considerable heterogeneity in sectoral exposure to supply and demand shocks. In terms of total exposures, Leisure and Hospitality is the most negatively affected sector, with a combined effect of −9.55 of which 59% is supply. While most sectors receive negative supply shocks, the size of these shocks is very heterogeneous. 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 very small positive demand shocks. The most significant demand shock is 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 could partly benefit. Finally, the Information sector benefits from a boost of demand as many firms increase their demand for technology services to implement telework arrangements. For comparison, Figure 9 in the Appendix performs the same decomposition but one year earlier, in March 2019, a "normal" period. For March 2019, we find a completely different pattern of shocks, of much smaller magnitudes.

[5] This is the effect on the monthly growth rate, and is not annualized.

Figure 3 shows the shock decomposition or April, the first full month of lockdown. Note that the scale is very different, reflecting the much larger magnitude of the shocks: Total Private employment receives a combined negative shock of -16.24 pp in the growth rate of hours, of which 68.8% is attributable to supply. Leisure and Hospitality is by far the most affected sector, as before, with a total shock of -63.17 pp of which 63% is supply. This is to be expected for a sector that relies substantially in 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 or Other Services also experienced negative supply and demand shocks on par with those experienced during the Great Recession, even if those shocks do not look very large when compared to the shocks in other sectors.

Note that, now, essentially all sectors in the economy are negatively affected including sectors that had experienced positive shocks in March (such as Information). The least affected sectors are Utilities (+0.09 pp), Financial Activities (-3.06 pp), and Information (-8.89 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. The 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.

Decomposition by Subsector Figure 4 performs the same decomposition for selected subsectors in March 2020.[6] It clearly shows the shifting of consumption patterns in the early stages of the lockdown: Food services and drinking places, and Acommodation experienced large negative supply and demand shocks. In the case of Food services and drinking places, the demand shock was larger than the supply shock. As people switched their food consumption patterns, Food and Beverage sectors experienced a positive demand shock, while Food manufacturing experienced very small shocks. Also note that Air Transportation seems to have experienced positive demand and supply shocks, as the collapse in passenger air travel was not yet visible in the March BLS statistics.

[FIGURE 4 GOES HERE]

4.2 Challenges posed by COVID-19

The sheer size of shocks during the COVID-19 pandemic can pose challenges to our exercise for a number of reasons. First, it can threaten the assumption of Gaussian errors that is essential for constructing the likelihood function. Second, it can make the residuals non-stationary, thus rendering the Wold decomposition invalid. Third, it can put into question the assumption of

[6] April 2020 data for subsectors was not yet available at the time this draft was written.

linearity due to either 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.

We address the first and second concerns by estimating the model excluding the COVID-19 periods (March and April 2020). The third issue, regarding linearity, is harder to address. We choose to treat the unknown nonlinear mechanics as unknown at the moment and hence as part of the shock. Moreover, identifying the structural break or nonlinear structure is impossible given the size of the sample during the COVID-19 period. We attempt to assuage concerns regarding this third 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.

One challenge to our identification assumptions (that is not directly related to the econometric model per se) is related to composition effects and heterogeneous exposure of occupations to the demand and supply shocks. 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.[7] The only way to address this issue is to control for wage heterogeneity across sectors, which we partly do by separately estimating shocks for different sectors.

4.3 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 the labor supply shocks we identify be positively correlated with the possibility for workers to perform their tasks from home. In Figure 5 we plot our estimated supply shocks (y-axis) for April 2020 against the share of jobs that can be done at home by sector (x-axis). Panel (a) confirms that to be the case. 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), where we remove this sector. 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

[7] Mongey et al. (2020) document that workers predicted to be employed in low work-from-home jobs tend to have lower income and experienced greater declines in employment according to the March 2020 CPS.

(Figure 10). We also repeat the analysis for the months of March and April 2019: Figure 11 shows that the statistically significant and positive correlation vanishes when this measure is compared to supply shocks estimated during a "normal" period.

[FIGURE 5 GOES HERE]

5 Conclusion

In this paper, we estimated Bayesian SVARs on the growth rates of hours worked and real wages for each major sector of the US economy. Our identification strategy, based on sign restrictions and informative priors, allowed us to estimate sequences of labor supply and demand shocks for each sector. Focusing on the on-going 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 negligible 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.

We believe that properly measuring demand and supply shocks is essential for the design and implementation of economic policy during the COVID-19 outbreak. The objective of economic policy during the lockdown should not be to stimulate or stabilize sectors that are directly affected by the lockdown, but rather ensure that aggregate demand externalities do not cause inefficient slowdowns in other sectors (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. 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.

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Table 1: Median and 95% credible interval of the effects of demand and supply shocks on the growth rate of hours, March 2020

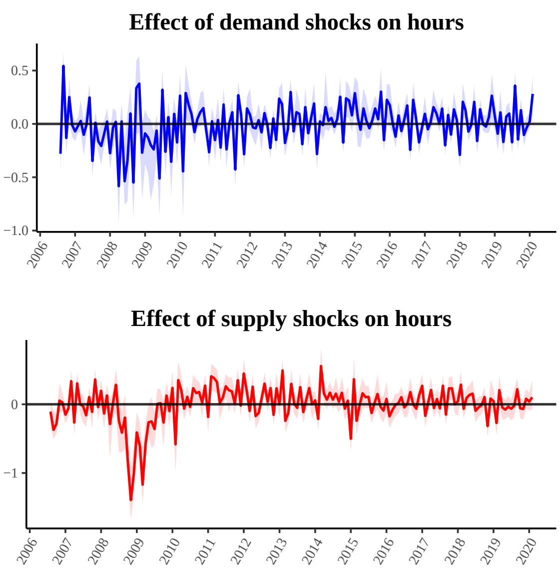
	Demand			Supply		
Sector	Median	2.5p	97.5p	Median	2.5p	97.5p
Total Private	-0.43	-1.05	-0.02	-1.18	-1.62	-0.56
Mining and Logging	-0.57	-1.44	-0.01	-1.30	-2.14	-0.44
Construction	0.10	-0.37	0.36	-1.05	-1.45	-0.57
Manufacturing	-0.12	-0.64	0.17	-0.83	-1.27	-0.30
Wholesale Trade	0.08	-0.06	0.16	-0.14	-0.29	0.00
Retail Trade	0.12	-0.18	0.38	-0.73	-0.99	-0.43
Transport & Warehousing	-0.12	-0.53	0.12	-0.66	-0.95	-0.27
Utilities	-0.09	-0.55	0.20	-0.57	-0.87	-0.12
Information	0.47	0.26	0.63	-0.30	-0.46	-0.08
Financial Activities	-0.01	-0.12	0.10	-0.07	-0.19	0.03
Prof. and Business Services	-0.01	-0.23	0.07	-0.48	-0.66	-0.24
Education and Health	-0.42	-1.00	0.00	-0.79	-1.22	-0.21
Leisure and Hospitality	-3.91	-7.39	-0.75	-5.64	-8.80	-2.16
Other Services	-0.91	-1.85	-0.13	-1.68	-2.47	-0.74

Table 2: Median and 95% credible interval of the effects of demand and supply shocks on the growth rate of hours, April 2020

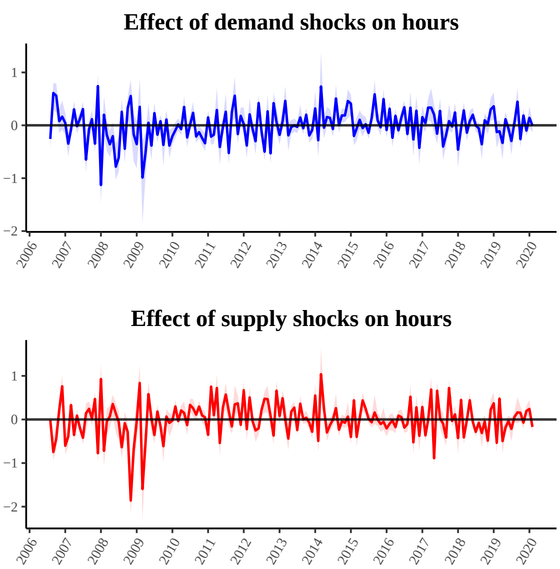
	Demand			Supply		
Sector	Median	2.5p	97.5p	Median	2.5p	97.5p
Total Private	-5.06	-11.28	-0.31	-11.18	-15.94	-4.97
Mining and Logging	-4.78	-9.50	-0.84	-7.34	-11.32	-2.62
Construction	-3.65	-12.78	-0.32	-13.47	-16.82	-4.33
Manufacturing	-6.36	-12.93	-1.14	-9.89	-15.13	-3.32
Wholesale Trade	-3.82	-8.23	-0.37	-5.66	-9.10	-1.25
Retail Trade	-3.65	-9.25	-0.04	-10.82	-14.43	-5.23
Transport. & Warehousing	-3.61	-9.06	-0.01	-9.26	-12.85	-3.81
Utilities	1.17	0.41	1.49	-1.08	-1.40	-0.32
Information	-3.51	-6.95	-0.63	-5.39	-8.26	-1.95
Financial Activities	-0.34	-2.00	0.52	-2.72	-3.59	-1.05
Prof. and Business Services	-3.29	-8.05	-0.15	-8.31	-11.44	-3.53
Education and Health	-5.47	-10.77	-0.63	-6.92	-11.76	-1.62
Leisure and Hospitality	-23.26	-46.70	-3.63	-39.92	-59.55	-16.47
Other Services	-6.32	-14.23	-0.48	-15.39	-21.24	-7.47

Figure 1: Historical decomposition of the growth rate of hours: Total Private Employment, Leisure and Hospitality

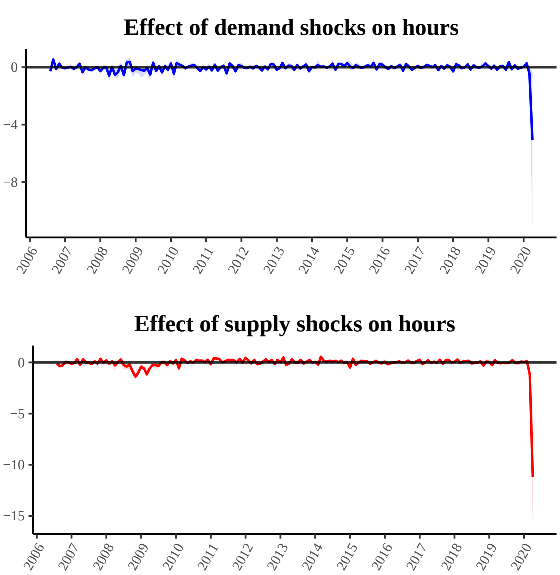
(a) Total Private Employment until February 2020



(b) Leisure and Hospitality until February 2020



(c) Total Private Employment, Full Sample



(d) Leisure and Hospitality, Full Sample

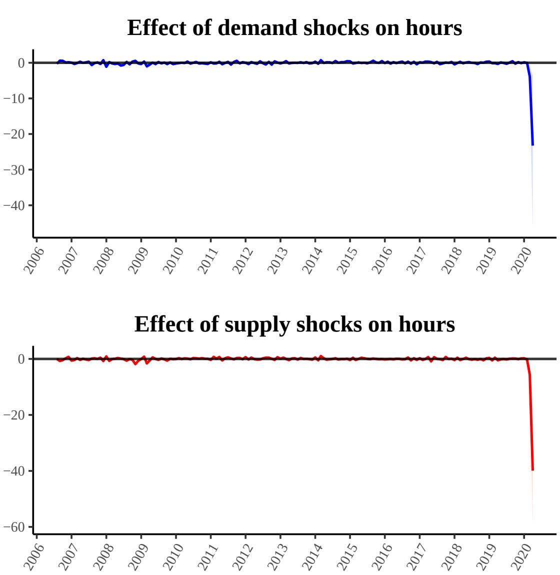


Figure 2: Historical decomposition of the growth rate of hours by sector in March 2020

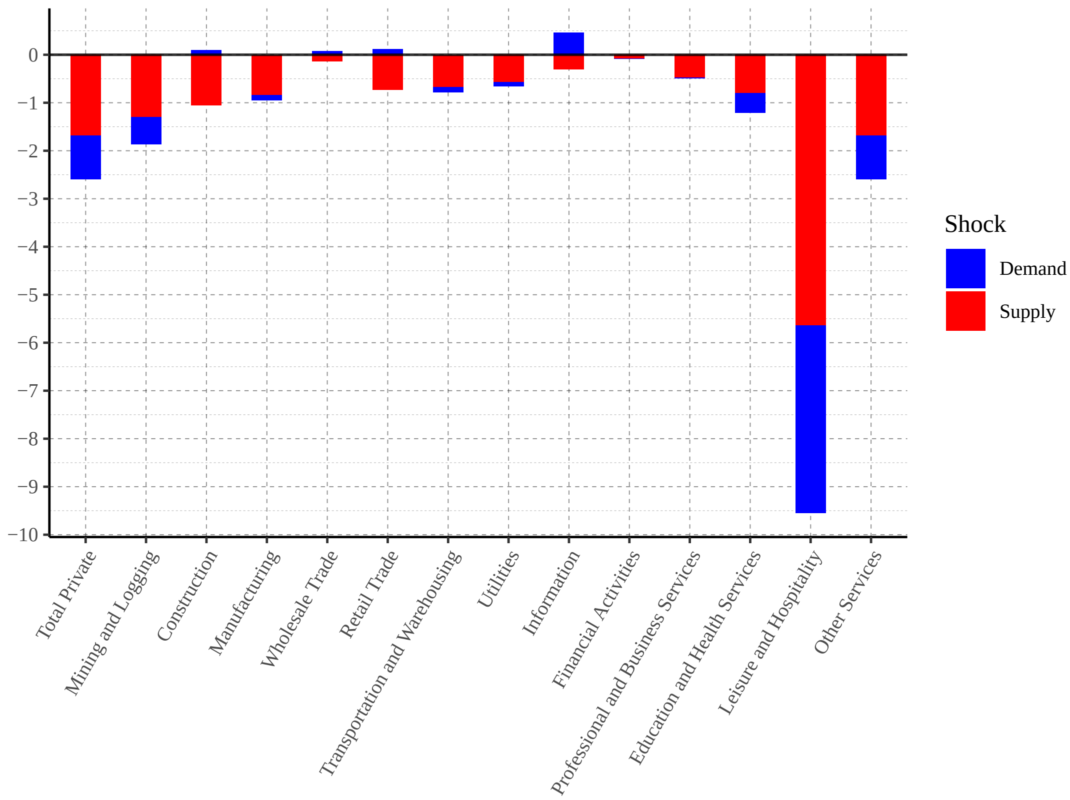


Figure 3: Historical decomposition of the growth rate of hours by sector in April 2020

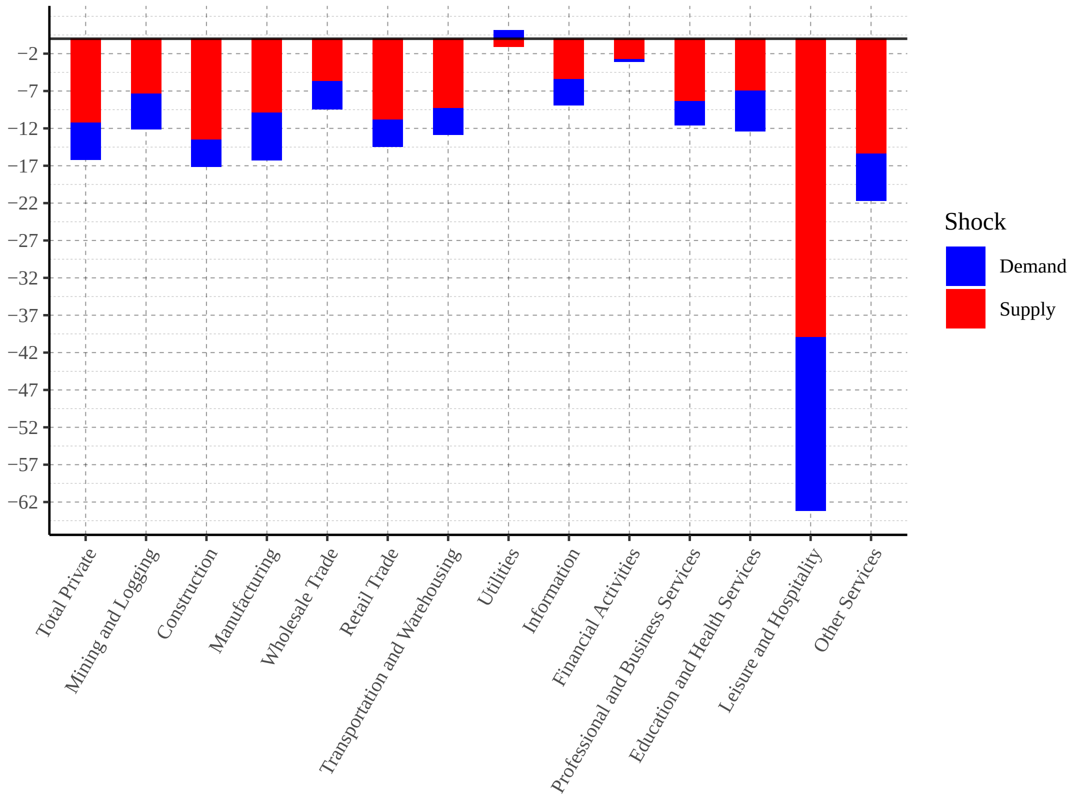


Figure 4: Historical decomposition of the growth rate of hours for selected subsectors in March 2020

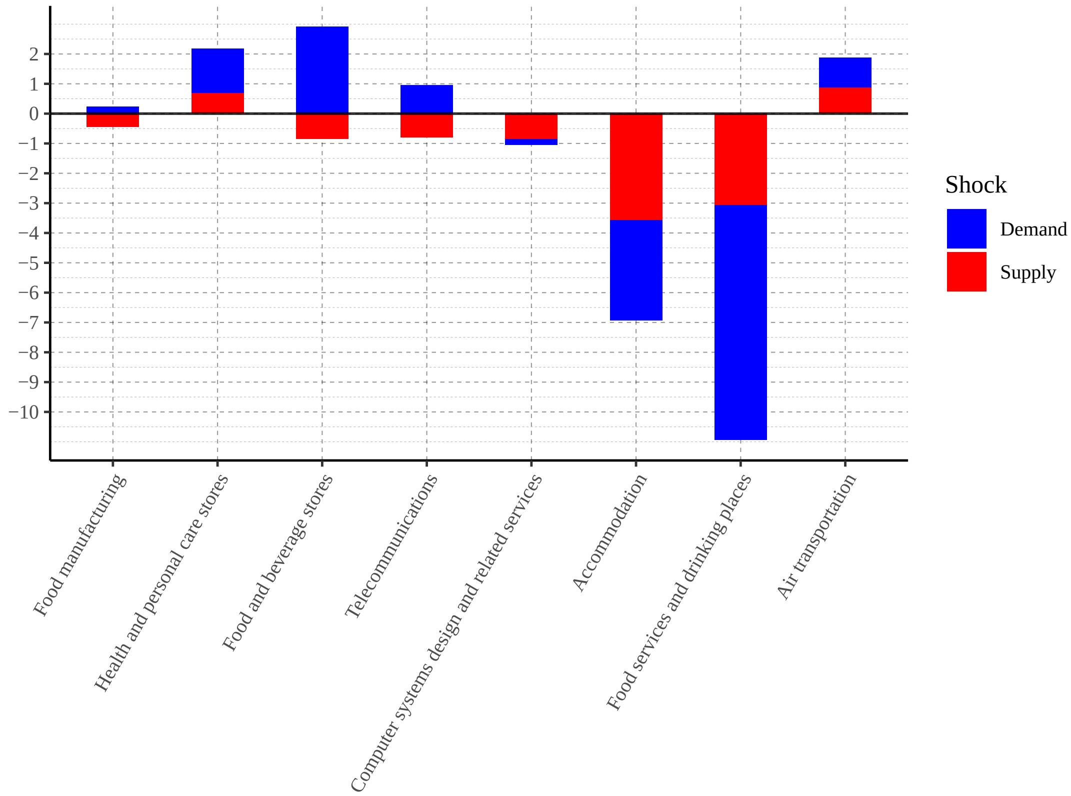
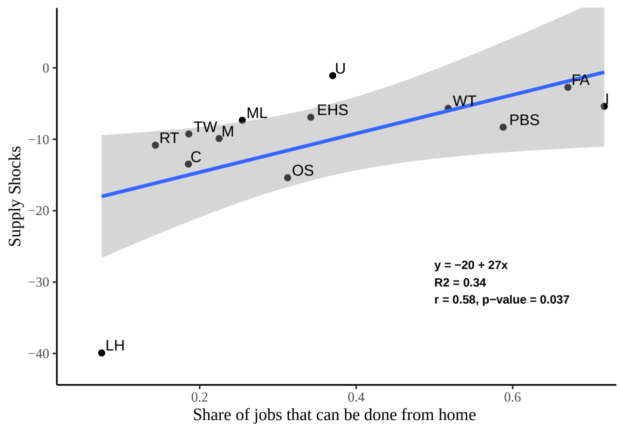
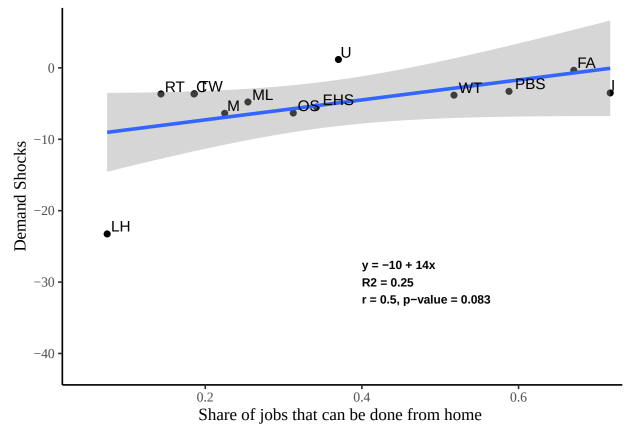


Figure 5: Correlation between sectoral shocks in April 2020 and sectoral share of jobs that can be done at home

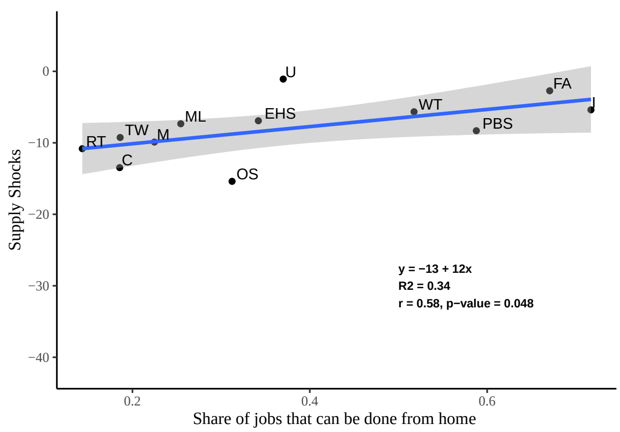
(a) Supply



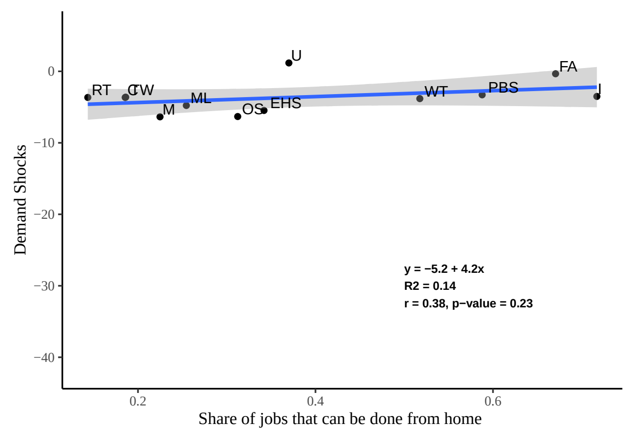
(b) Demand



(c) Supply - Removing Leisure and Hospitality



(d) Demand - Removing Leisure and Hospitality



ML: Minning 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.

Appendix

A Data sources and sectors 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 3 lists all used CES industry classifications as well as the associated NAICS codes.

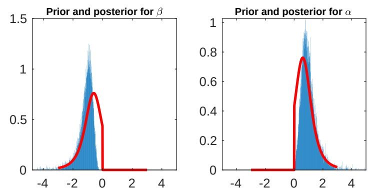
Table 3: CES industry classification

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

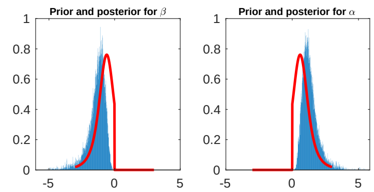
B Additional figures

Figure 6: Prior and posterior distribution of labor demand and supply elasticities by sector

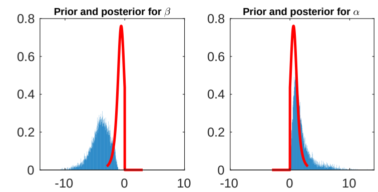
(a) Total Private



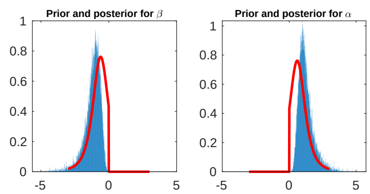
(b) Mining and Logging



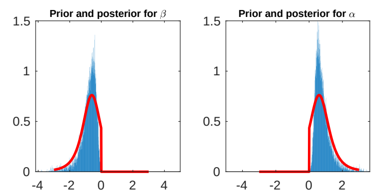
(c) Construction



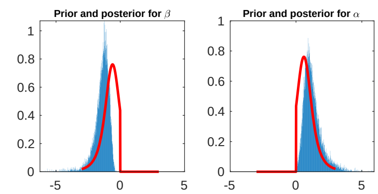
(d) Manufacturing



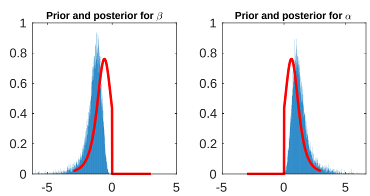
(e) Wholesale Trade



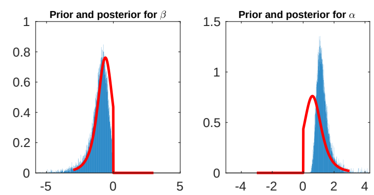
(f) Retail Trade



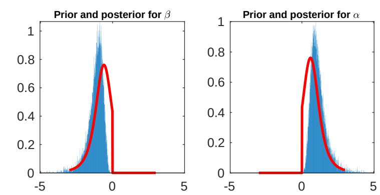
(g) Transportation and Warehousing



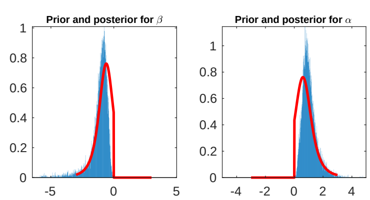
(h) Utilities



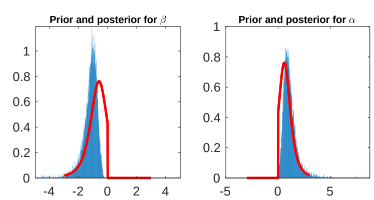
(i) Information



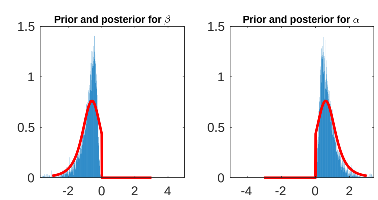
(j) Financial Activities



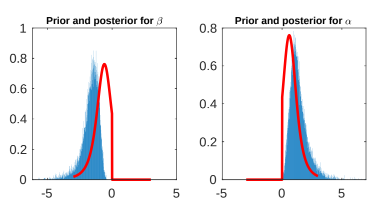
(k) Professional and Business Services



(l) Education and Health Services



(m) Leisure and Hospitality



(n) Other Services

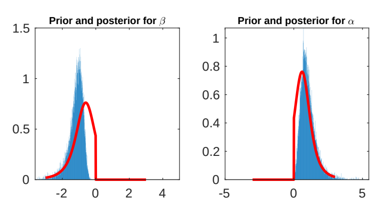
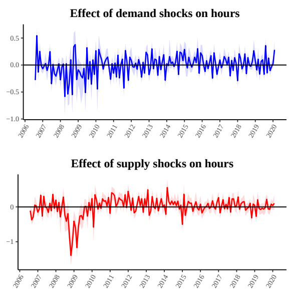
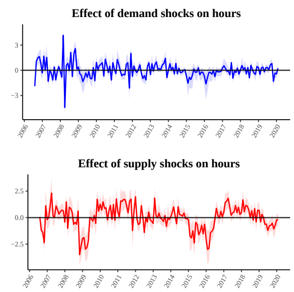


Figure 7: Historical decomposition of the growth rate of hours by sector, excluding March and April 2020

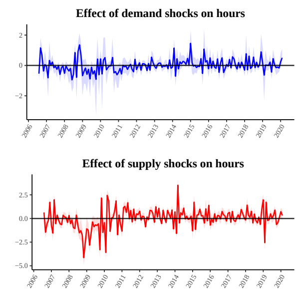
(a) Total Private



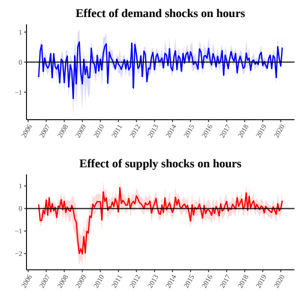
(b) Mining and Logging



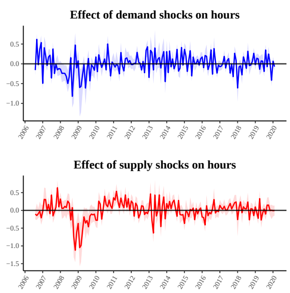
(c) Construction



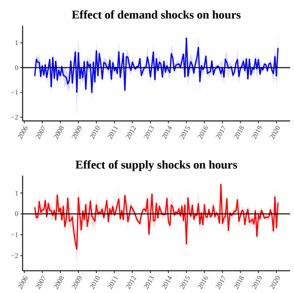
(d) Manufacturing



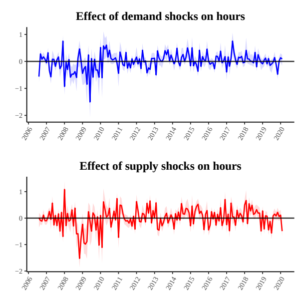
(e) Wholesale Trade



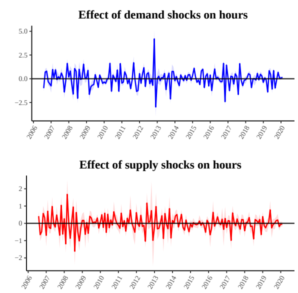
(f) Retail Trade



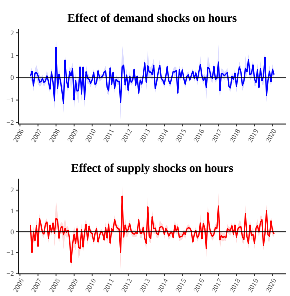
(g) Transportation and Warehousing



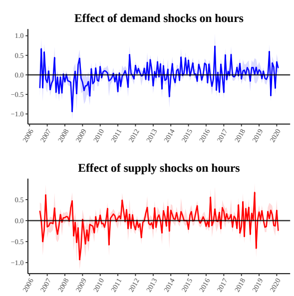
(h) Utilities



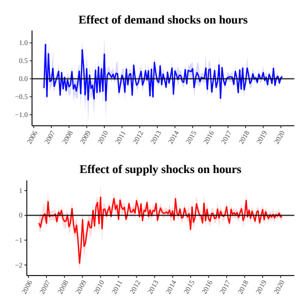
(i) Information



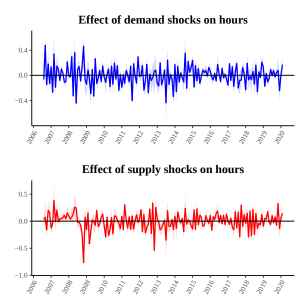
(j) Financial Activities



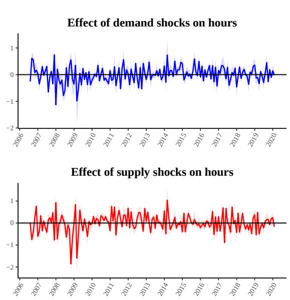
(k) Professional and Business Services



(l) Education and Health Services



(m) Leisure and Hospitality



(n) Other Services

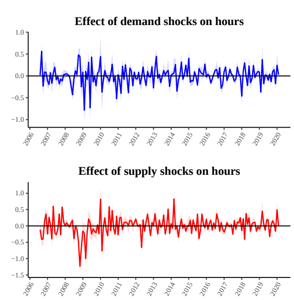
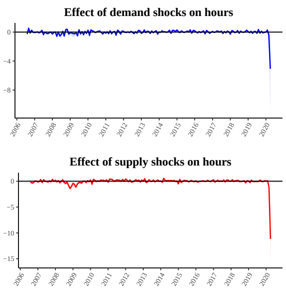
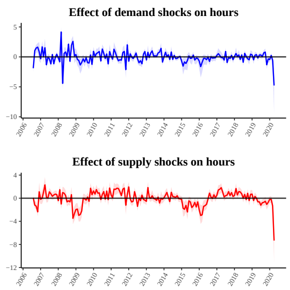


Figure 8: Historical decomposition of the growth rate of hours by sector, full sample

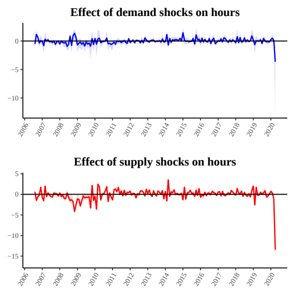
(a) Total Private



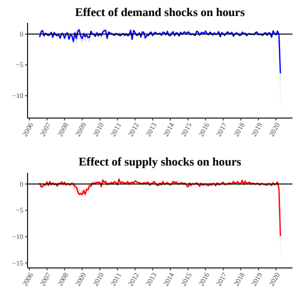
(b) Mining and Logging



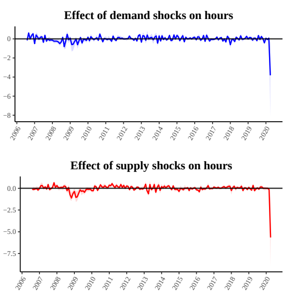
(c) Construction



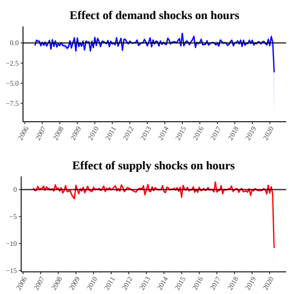
(d) Manufacturing



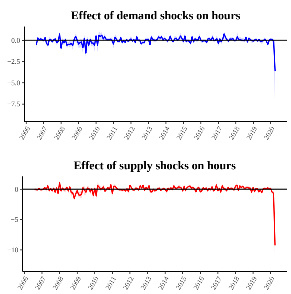
(e) Wholesale Trade



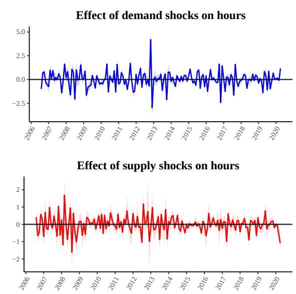
(f) Retail Trade



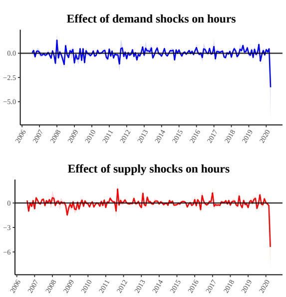
(g) Transportation and Warehousing



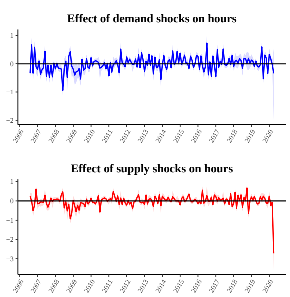
(h) Utilities



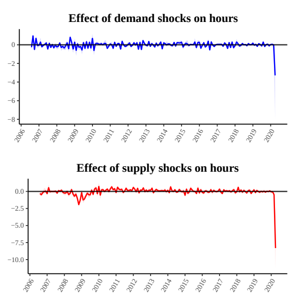
(i) Information



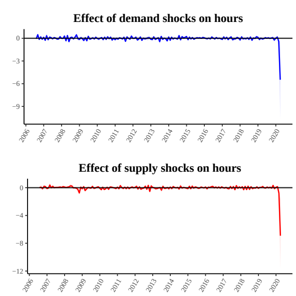
(j) Financial Activities



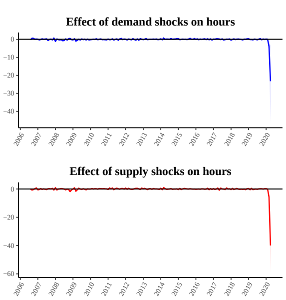
(k) Professional and Business Services



(l) Education and Health Services



(m) Leisure and Hospitality



(n) Other Services

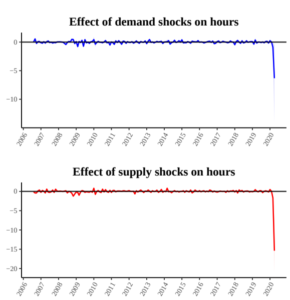


Figure 9: Historical decomposition of the growth rate of hours across sectors, March 2019

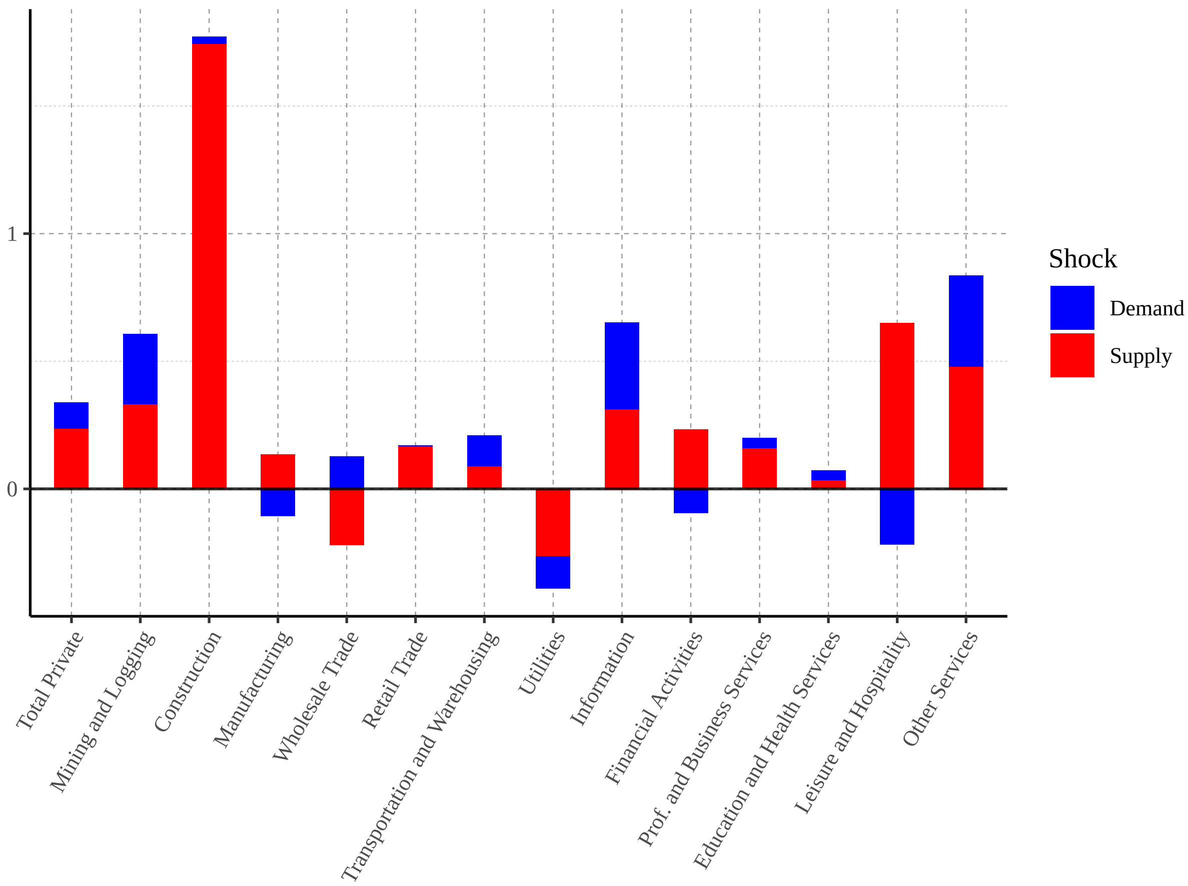
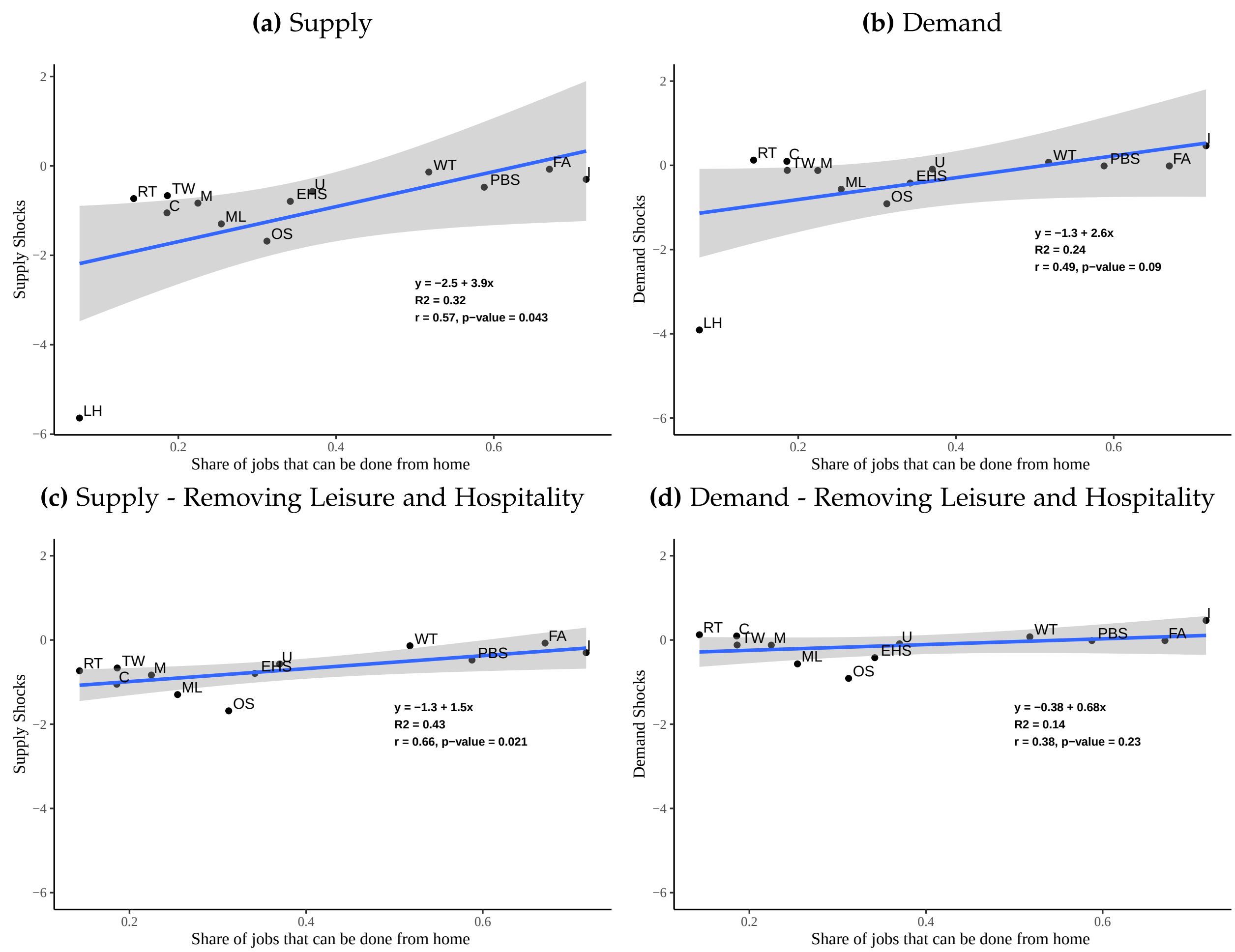


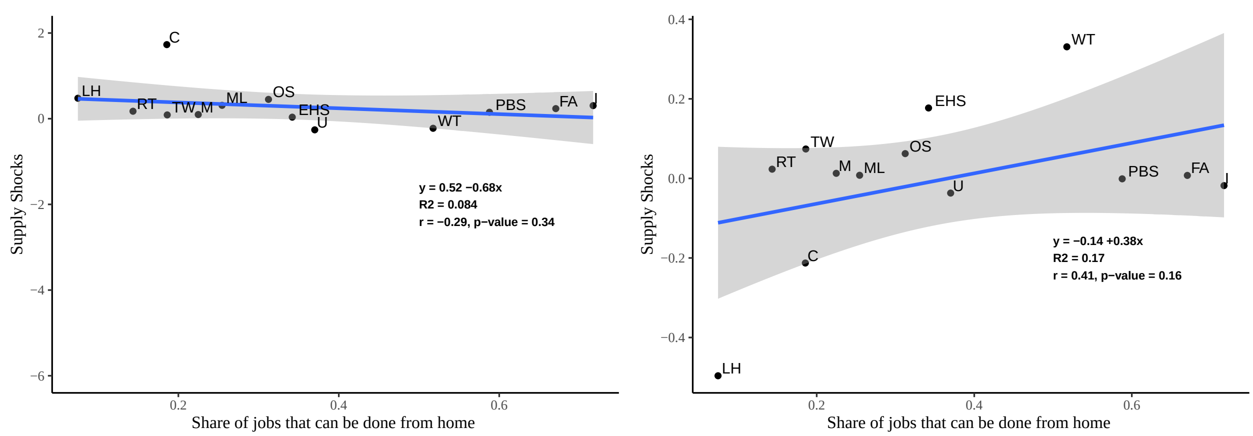
Figure 10: Correlation between sectoral shocks in March 2020 and sectoral share of jobs that can be done at home



ML: Minning 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 11: Supply Shocks in 2019 vs. Share of jobs that can be done from home

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



ML: Minning 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.