

Measuring Labor 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. 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.

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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, 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 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 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 ([Baqae 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 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 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 [Baqae 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. [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

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

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 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 $\mathbf{y}_t^l = (\Delta w_t^l, \Delta h_t^l)$ be the 2×1 vector of observables. Then the SVAR for sector l takes the form

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

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

$$\mathbf{A}^l = \begin{bmatrix} -\beta^l & 1 \\ -\alpha^l & 1 \end{bmatrix}, \quad (2)$$

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.

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

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

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

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

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 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

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

where

³Uhlig (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.

$$\begin{aligned}\Phi_0^l &= (A^l)^{-1} B_0^l \\ \Phi^l(L) &= (A^l)^{-1} B^l(L) \\ \mathbf{u}_t^l &= (A^l)^{-1} \boldsymbol{\varepsilon}_t^l\end{aligned}\tag{6}$$

$$E[\mathbf{u}_t^l(\mathbf{u}_t^l)'] = \Omega = (A^l)^{-1} D((A^l)^{-1})'. \tag{7}$$

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 $\mathbf{Y}_T = (y_1, y_2, \dots, y_T)$. 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 microeconomic 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 microeconomic 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.

⁵Our 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 $p(A)$ for all sectors in our sample.

Next, we define the specification for our conditional prior distributions $p(D|A)$ and $p(B|A, D)$. For the elements of the diagonal matrix 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 A . That is, $\tau_i = \kappa_i a_i' \hat{S} a_i$, where \hat{S} is the variance-covariance of the univariate residuals series. $p(D|A)$ is then the product of the two gamma distributions. Finally, $p(B|A, D)$ 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 A implicitly places a prior on B since $B = A\Phi$. Hence the normally distributed coefficients b_i have mean a_i for elements corresponding to their 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; $\lambda_1 = 1$, 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 B_0 . The joint prior distribution is then given by:

$$p(A, D, B) = p(A)p(D|A)p(B|A, D). \quad (8)$$

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 Y_T . The posterior can be written as

$$p(A, D, B|Y_T) = p(A|Y_T)p(D|A, Y_T)p(B|A, D, Y_T). \quad (9)$$

The conditional posterior on the structural coefficients 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-form representation (5) and (7). Also because of natural conjugacy, the conditional posterior $p(D|A, Y_T)$ is also a gamma distribution. Finally, $p(A|Y_T)$ 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 fact 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 into estimated supply and demand shocks 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

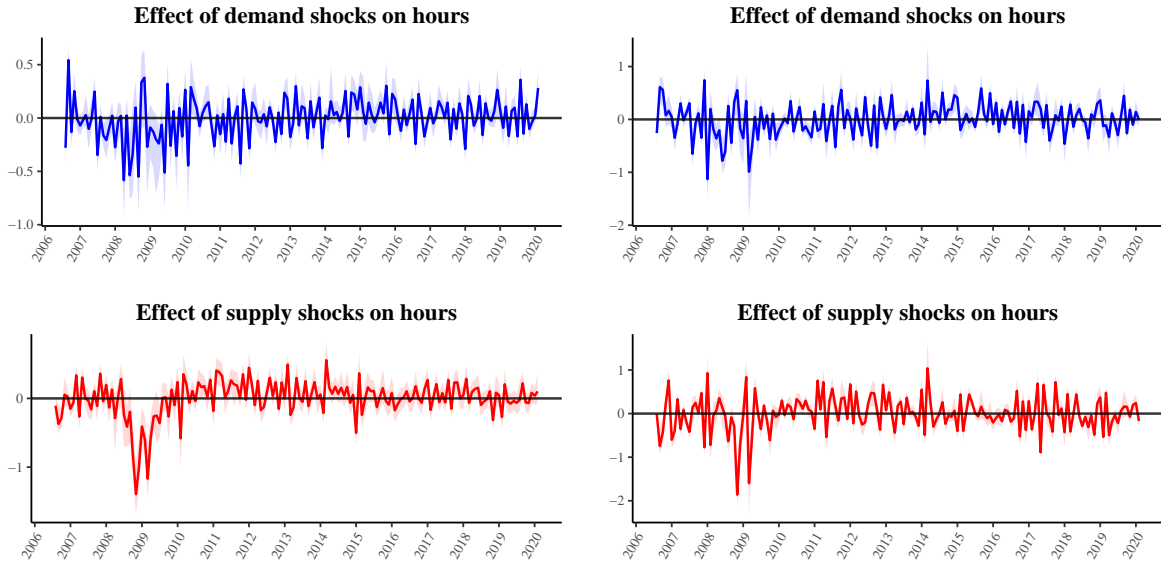
⁶Section A in the appendix provides further details on the data and sector classification.

⁷Figure 6 plots the prior distribution for the elasticities along a histogram of draws from the posterior. Table 3 presents moments of the posterior distributions and Figure 7 plots impulse response functions.

negative 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).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



4.1 The Great Lockdown: March and April 2020

We now take a closer look at the results for the months of March and April 2020: the months of the “Great Lockdown” in the US. Figures 2 and 3 contain our main set of results and plot the medians of estimated demand and supply shocks across sectors for March and April, respectively.⁹ 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. Negative supply shocks accounted for 64.8% and 68.8% of these effects, respectively.

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

⁹Tables 4 and 5 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 2: Historical decomposition of the growth rate of hours by sector in March 2020

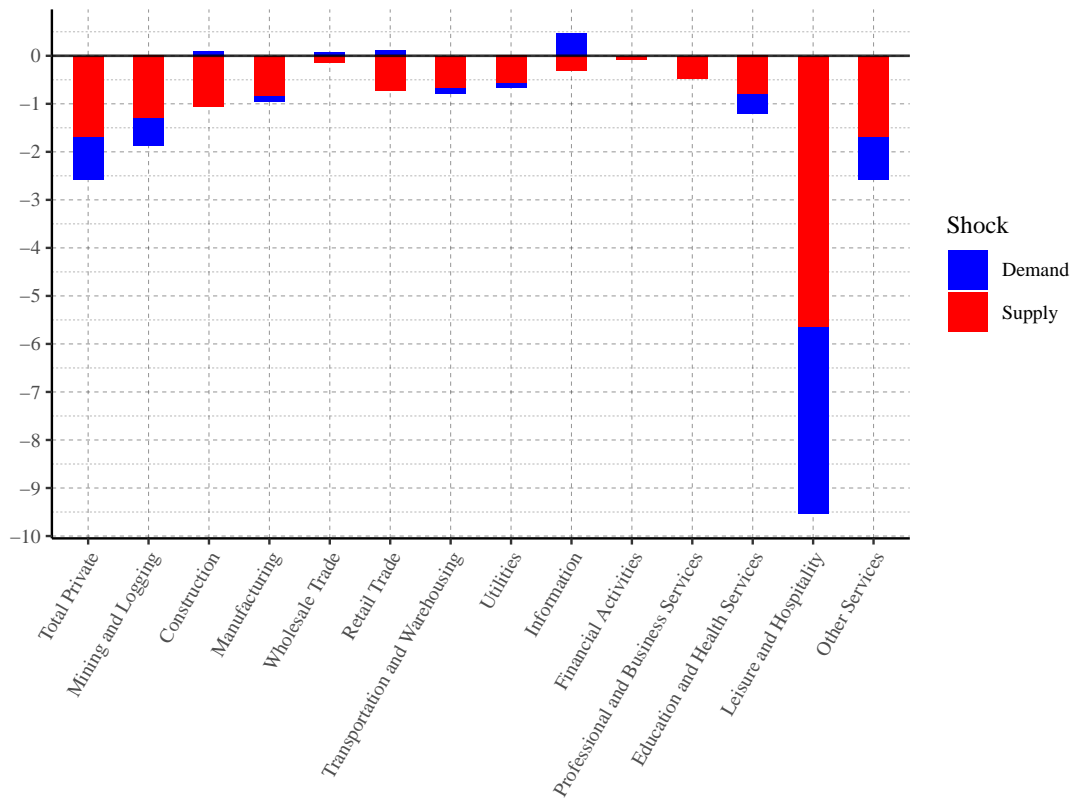


Figure 3: Historical decomposition of the growth rate of hours by sector in April 2020

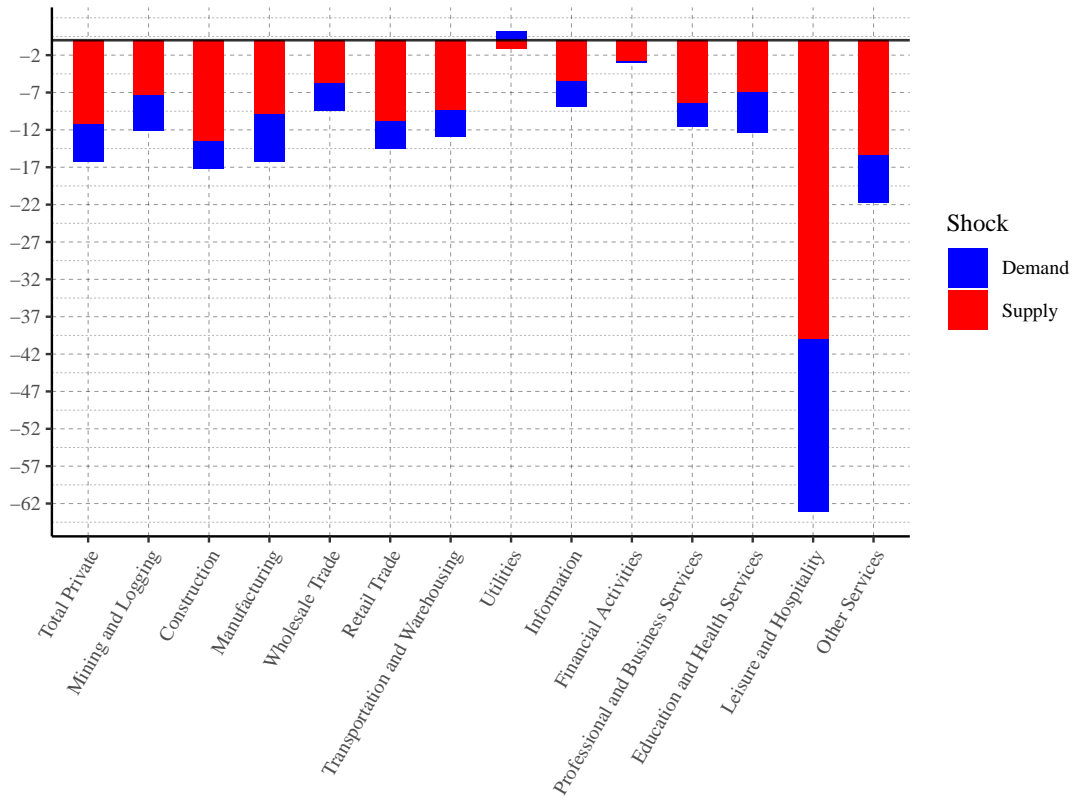


Figure 2 shows considerable heterogeneity in sectoral exposure to shocks. Leisure and Hospitality is the most negatively affected sector, with a combined effect of -9.55 , of which 59% is supply. The least-affected sectors are Wholesale Trade (-0.06 pp), Financial Activities (-0.09 pp), and Information ($+0.16$ 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 14 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 12 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 for 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 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 also experienced negative supply and demand shocks comparable in magnitude to those experienced during the Great Recession.

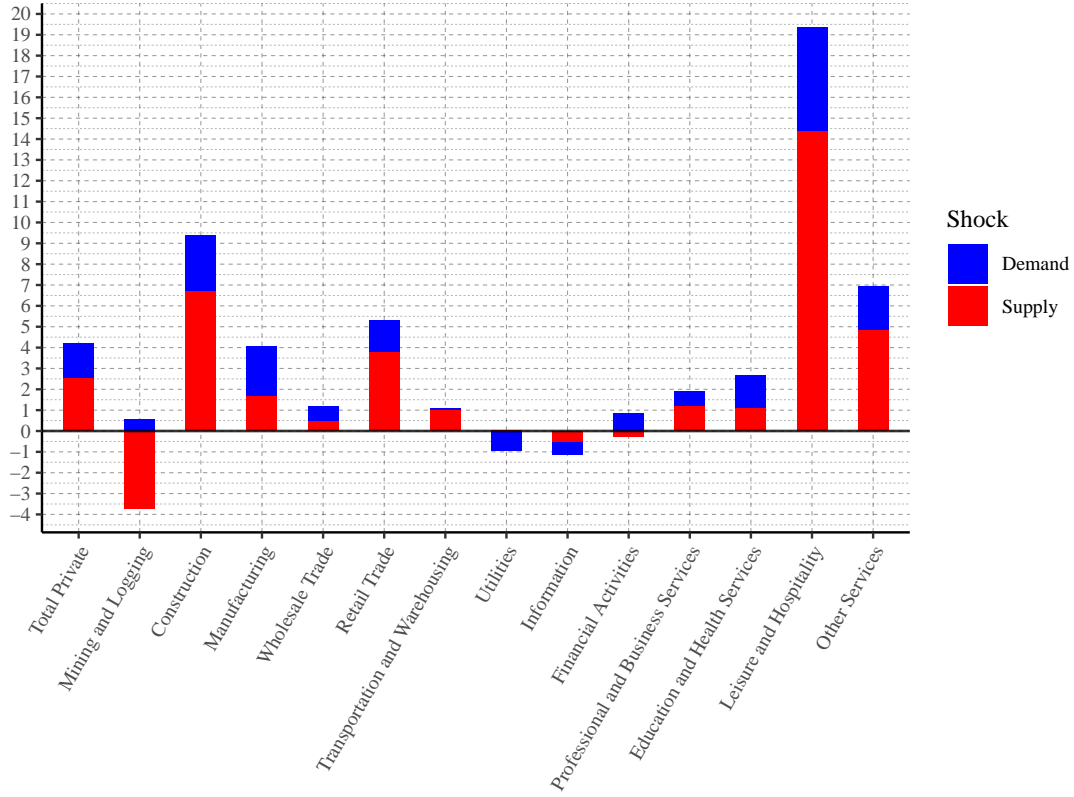
Essentially all sectors in the economy are negatively affected in April, including sectors that experienced positive shocks in March (such as Information). The least-affected sectors are Utilities (+0.09 pp) and Financial Activities (−3.06 pp). As we show in the next section, these are sectors where 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 13 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.¹⁰

¹⁰Figure 15 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

The sheer size of shocks during COVID-19 can pose challenges to our empirical 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 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.

We address the first and second concerns by estimating the model excluding the COVID-19 months (March-May 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.

Another concern is related to the fact that the CES data for the COVID-19 months is only preliminary at the moment and the BLS has reported that data collection during these months

for the CES surveys was impacted by the coronavirus.¹¹

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 disaggregate data at a sufficiently high frequency, ideally monthly data on hours and earnings by occupation-sector.

We repeat our exercise for all sectors, but using data on hours and earnings for employees in production and nonsupervisory roles. Under the assumption that these employees tend to receive lower wages, this re-estimation should partly address this issue. We also believe that estimating the model at the sector-level already controls to a certain extent for differences in occupational wage composition.

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.¹²

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 ($p\text{-val} = 0.037$), 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

¹¹A 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/empst_05082020.pdf.

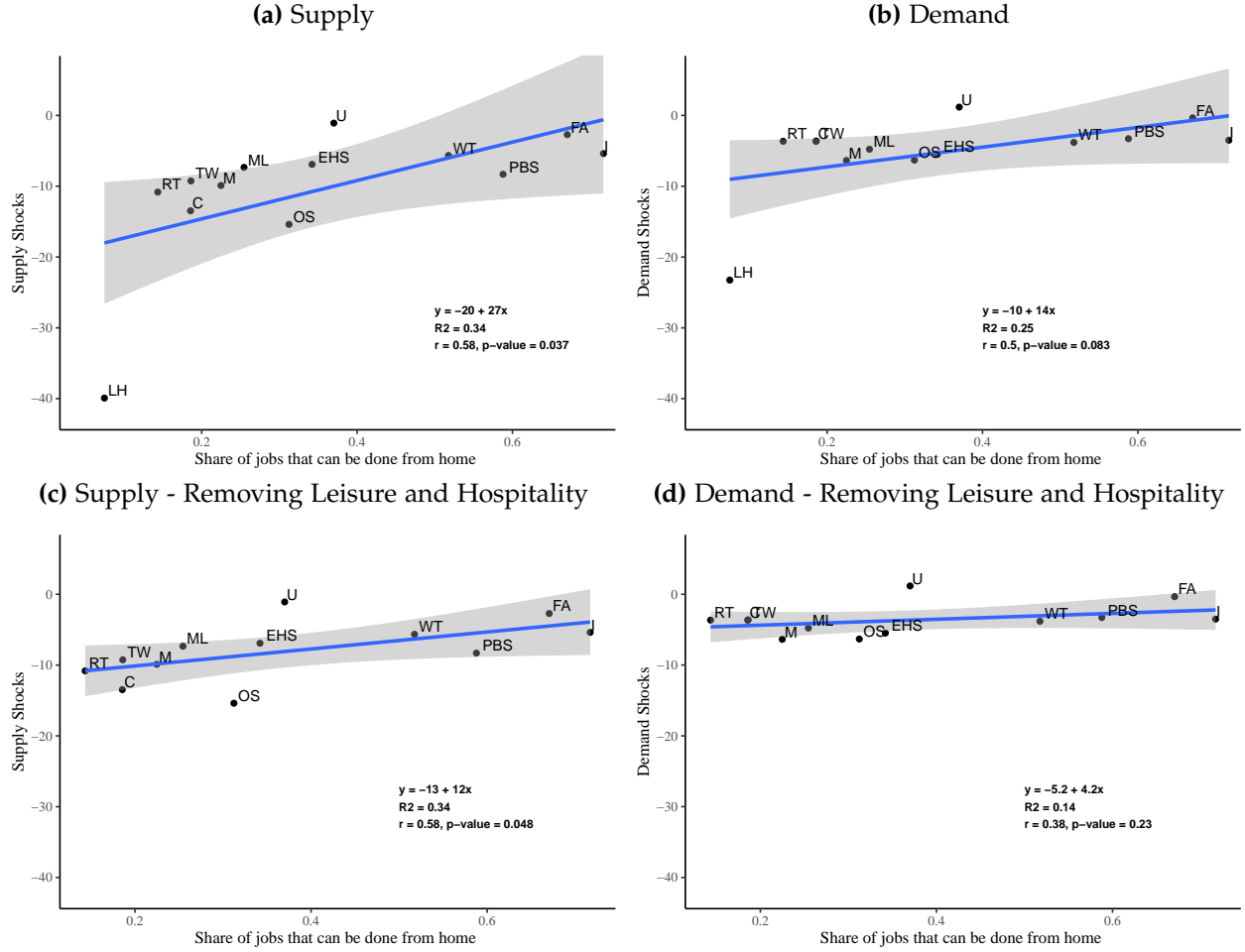
¹²Figures 10 and 11 in the Appendix present the shock decomposition for March and April 2020 for the model re-estimation. Tables 7 and 8 in the Appendix present the shocks along with 95% credible intervals.

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 15). We also repeat the analysis for the months of March and April 2019: Figure 16 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 15 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.¹³ 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.

¹³A 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.

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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

B Tables

Table 2: 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 3: Quantiles for the posterior distributions of labor demand and supply elasticities

Sector	β^l (demand)			α^l (supply)		
	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 4: Median and 95% credible interval of the effects of demand and supply shocks on the growth rate of hours, March 2020

Sector	Demand			Supply			Difference 68% Credible Interval
	50p	2.5p	97.5p	50p	2.5p	97.5p	
Total Private	-0.43	-1.05	-0.02	-1.18	-1.62	-0.56	[-1.557, -0.068]
Mining and Logging	-0.57	-1.44	-0.01	-1.30	-2.14	-0.44	[-1.605, 0.079]
Construction	0.10	-0.37	0.36	-1.05	-1.45	-0.57	[-1.702, -0.816]
Manufacturing	-0.12	-0.64	0.17	-0.83	-1.27	-0.30	[-1.223, -0.258]
Wholesale Trade	0.08	-0.06	0.16	-0.14	-0.29	0.00	[-0.410, -0.095]
Retail Trade	0.12	-0.18	0.38	-0.73	-0.99	-0.43	[-1.194, -0.525]
Transport & Warehousing	-0.12	-0.53	0.12	-0.66	-0.95	-0.27	[-0.753, 0.185]
Utilities	-0.09	-0.55	0.20	-0.57	-0.87	-0.12	[-0.762, 0.230]
Information	0.47	0.26	0.63	-0.30	-0.46	-0.08	[-0.673, -0.377]
Financial Activities	-0.01	-0.12	0.10	-0.07	-0.19	0.03	[-0.185, 0.059]
Prof. and Business Services	-0.01	-0.23	0.07	-0.48	-0.66	-0.24	[-0.744, -0.162]
Education and Health	-0.42	-1.00	0.00	-0.79	-1.22	-0.21	[-1.107, 0.535]
Leisure and Hospitality	-3.91	-7.39	-0.75	-5.64	-8.80	-2.16	[-6.275, 2.823]
Other Services	-0.91	-1.85	-0.13	-1.68	-2.47	-0.74	[-1.984, 0.431]

Table 5: Median and 95% credible interval of the effects of demand and supply shocks on the growth rate of hours, April 2020

Sector	Demand			Supply			Difference 68% Credible Interval
	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 6: Median and 95% credible interval of the effects of demand and supply shocks on the growth rate of hours, May 2020

Sector	Demand			Supply			Difference 68% Credible Interval
	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 7: 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

Sector	Demand			Supply		
	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 8: 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

Sector	Demand			Supply		
	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.

C Additional Figures

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

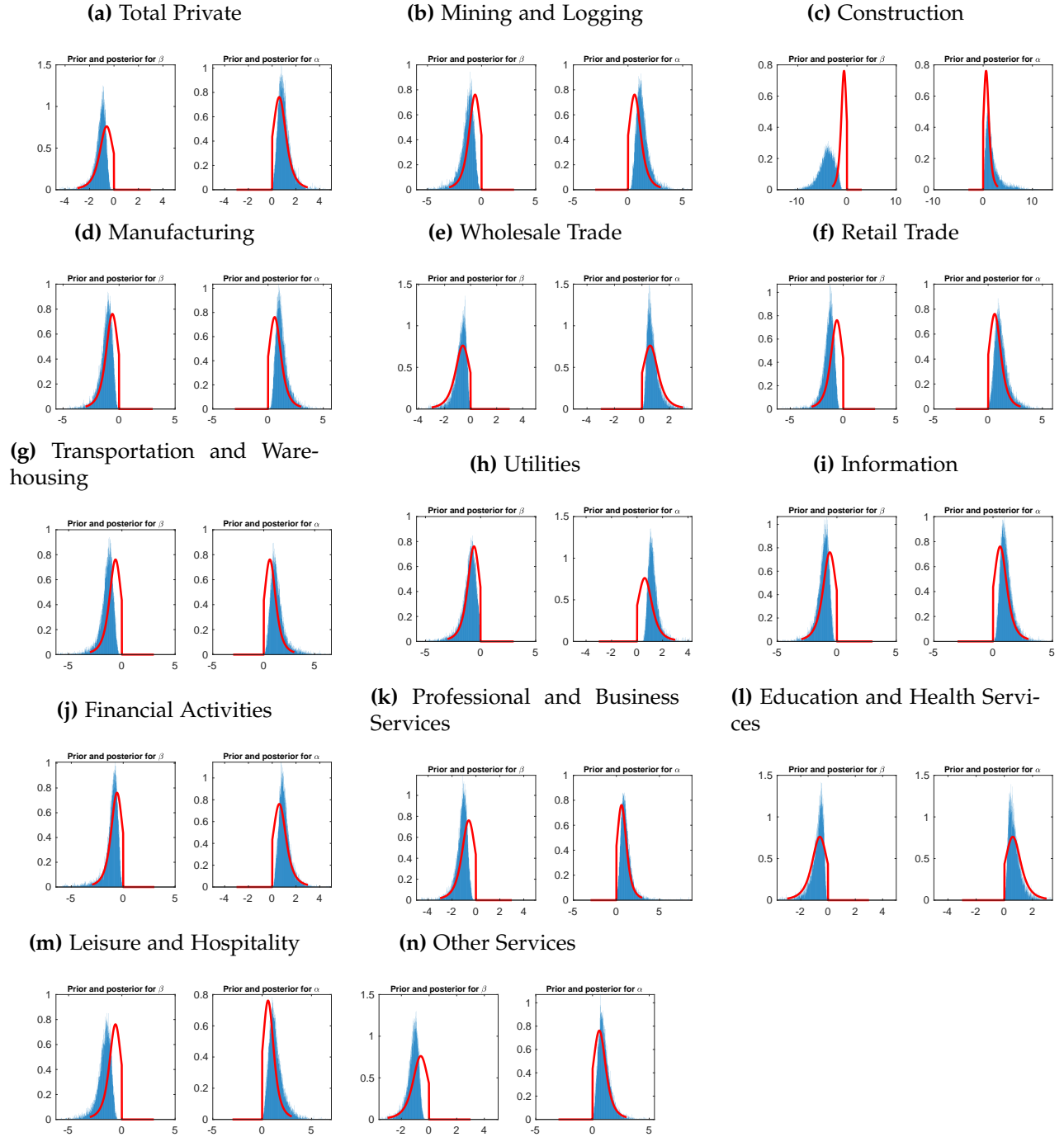


Figure 7: Impulse response functions by sector with 95% credible bands

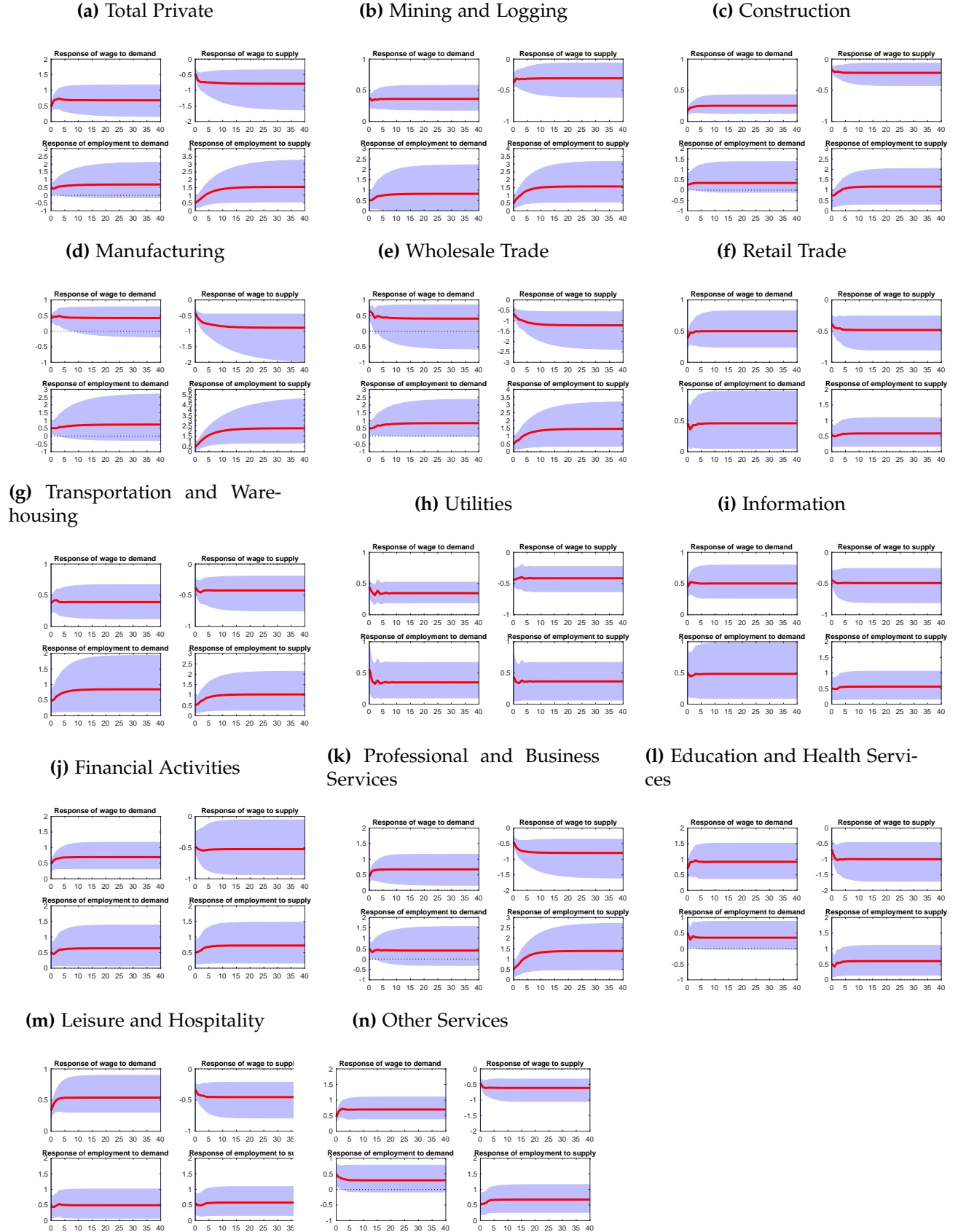


Figure 8: Historical decomposition of the growth rate of hours by sector, excluding March, April and May 2020

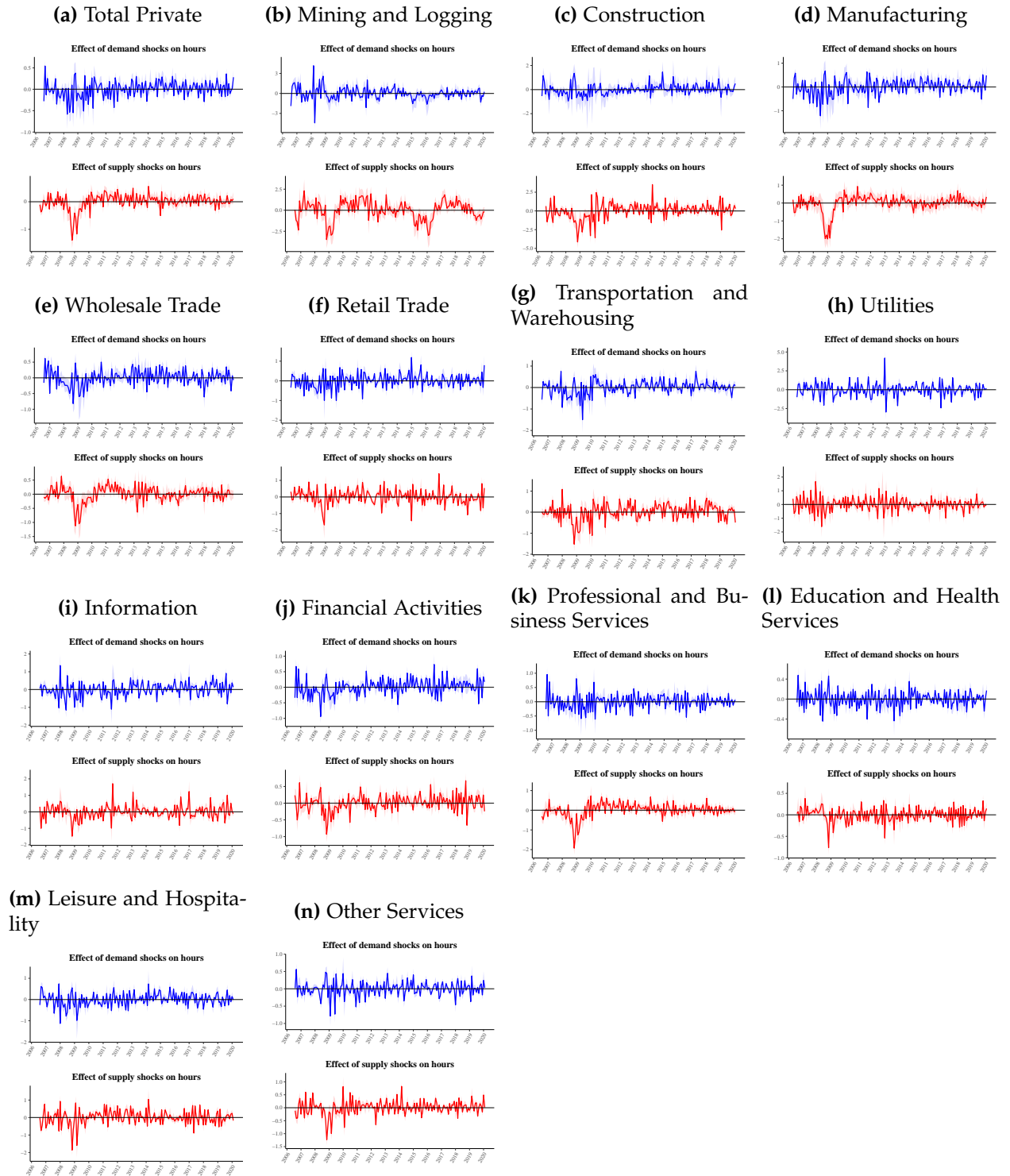


Figure 9: Historical decomposition of the growth rate of hours by sector, full sample

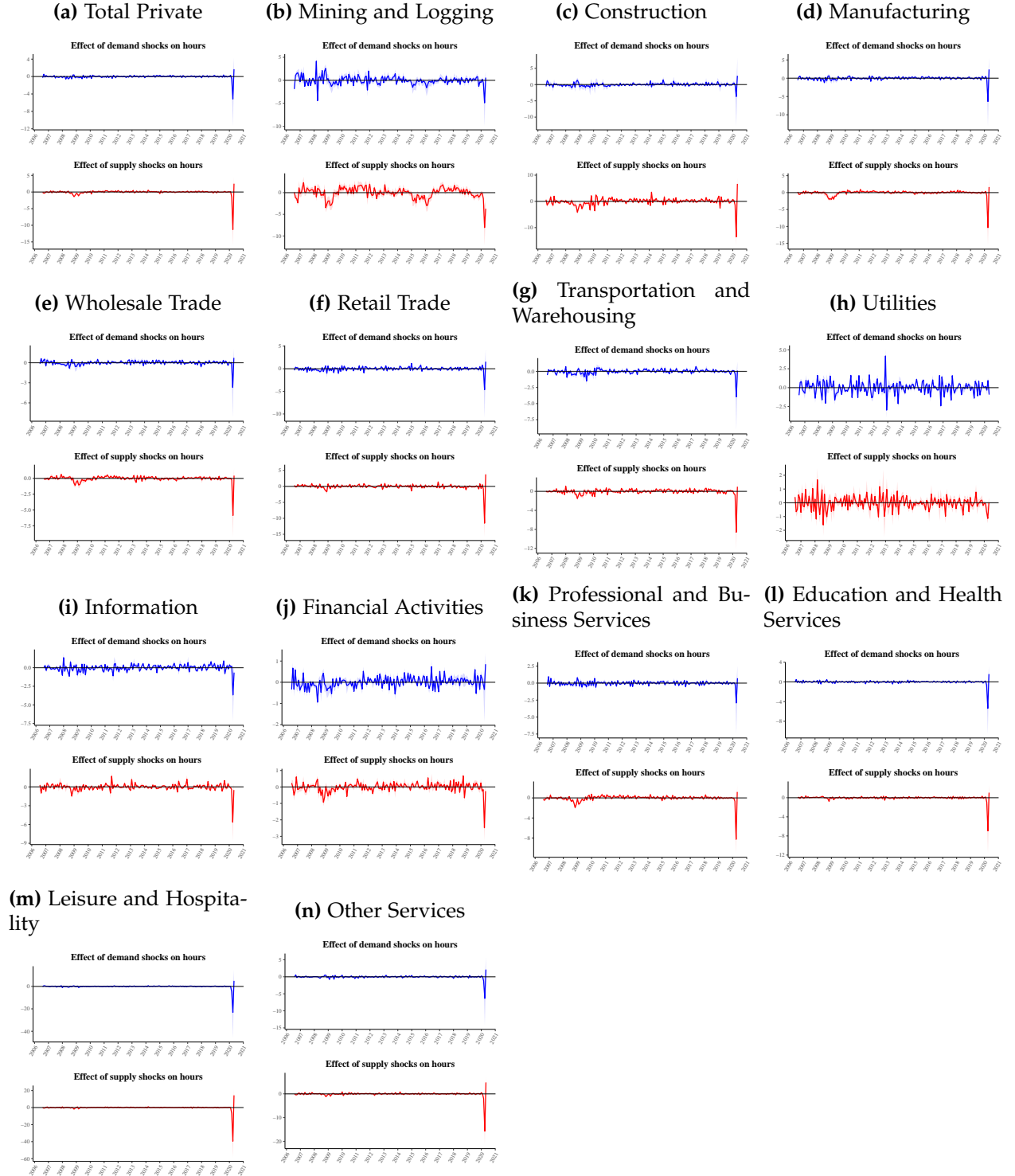
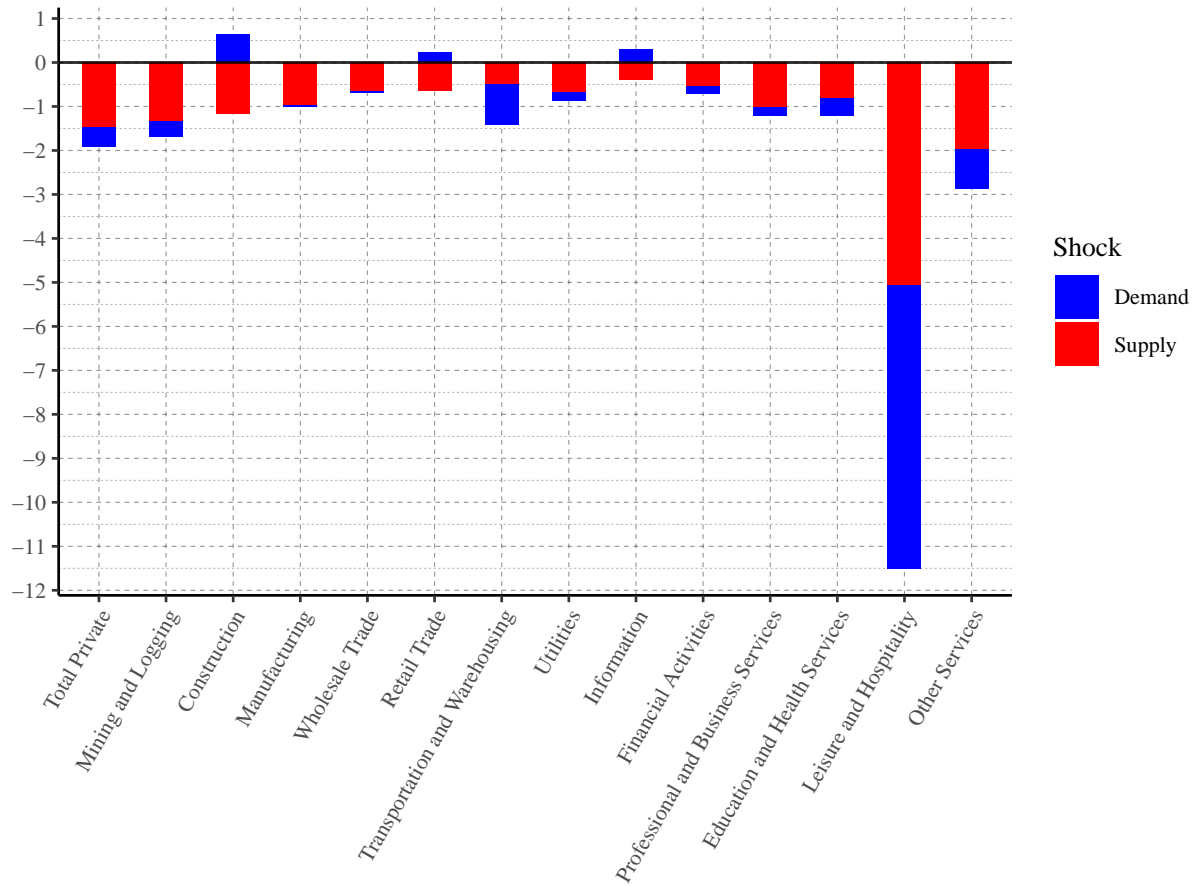
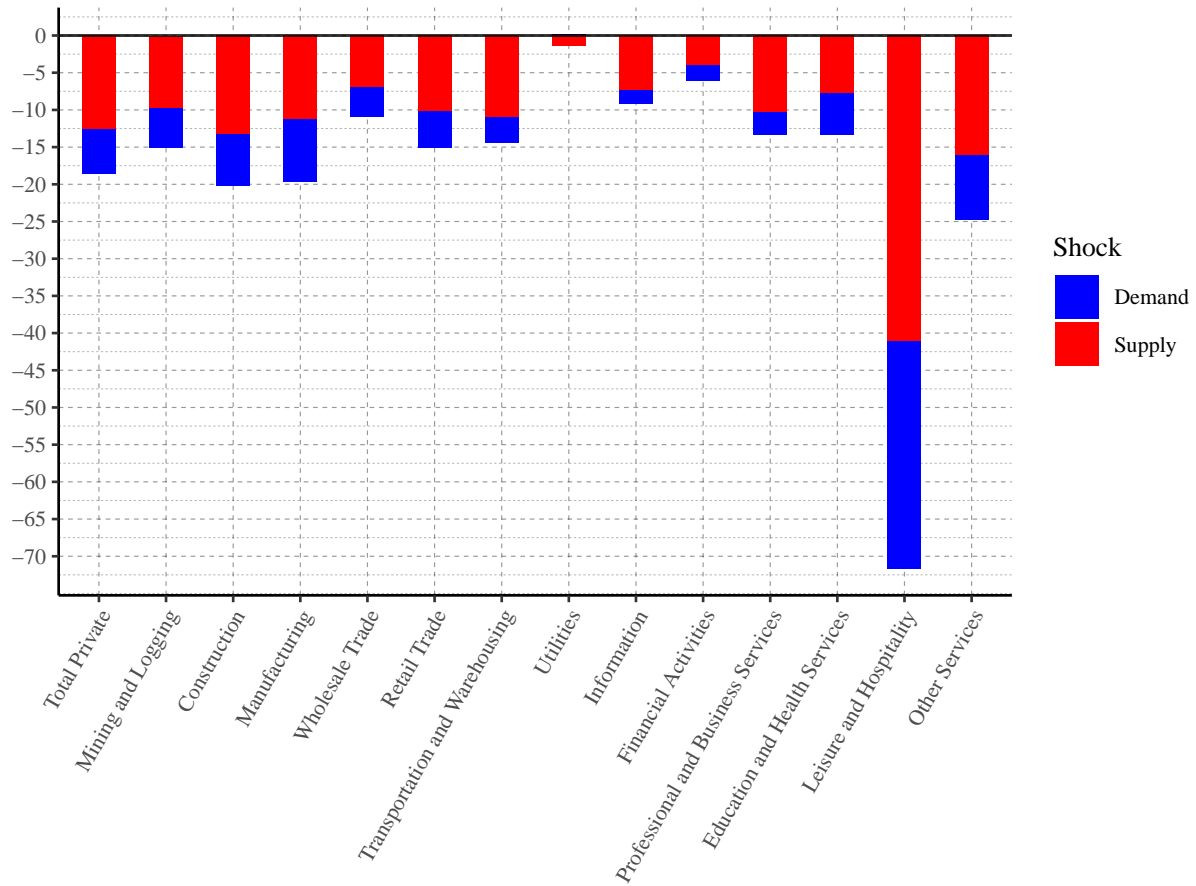


Figure 10: Historical decomposition of the growth rate of hours across sectors using production and nonsupervisory employees only, March 2020



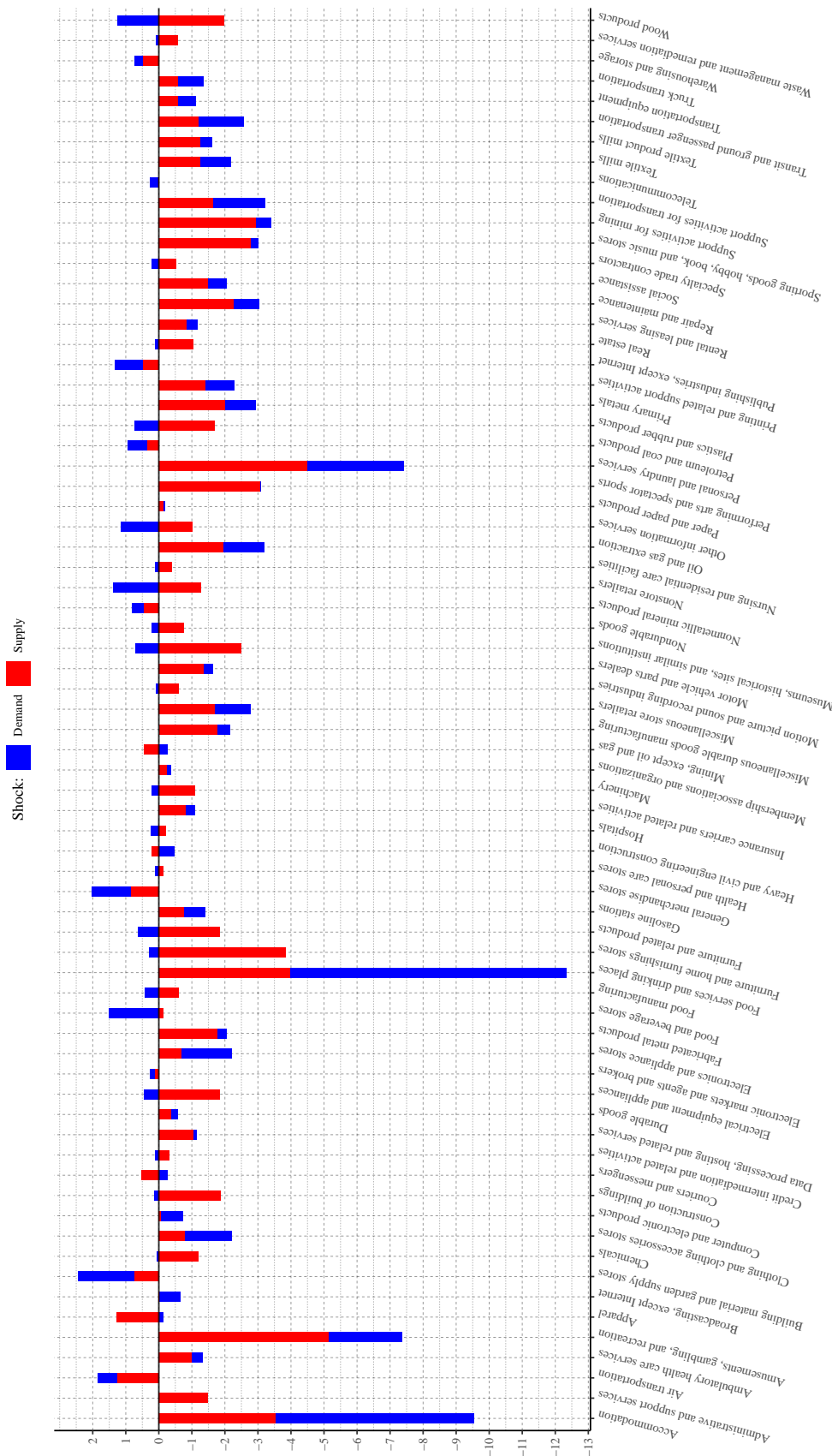
Notes: The data sample for production and nonsupervisory employees we use to estimate our SVAR starts in 1984. Production and nonsupervisory employees CES series code for real wages is 32 and for aggregate weekly hours is 81.

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



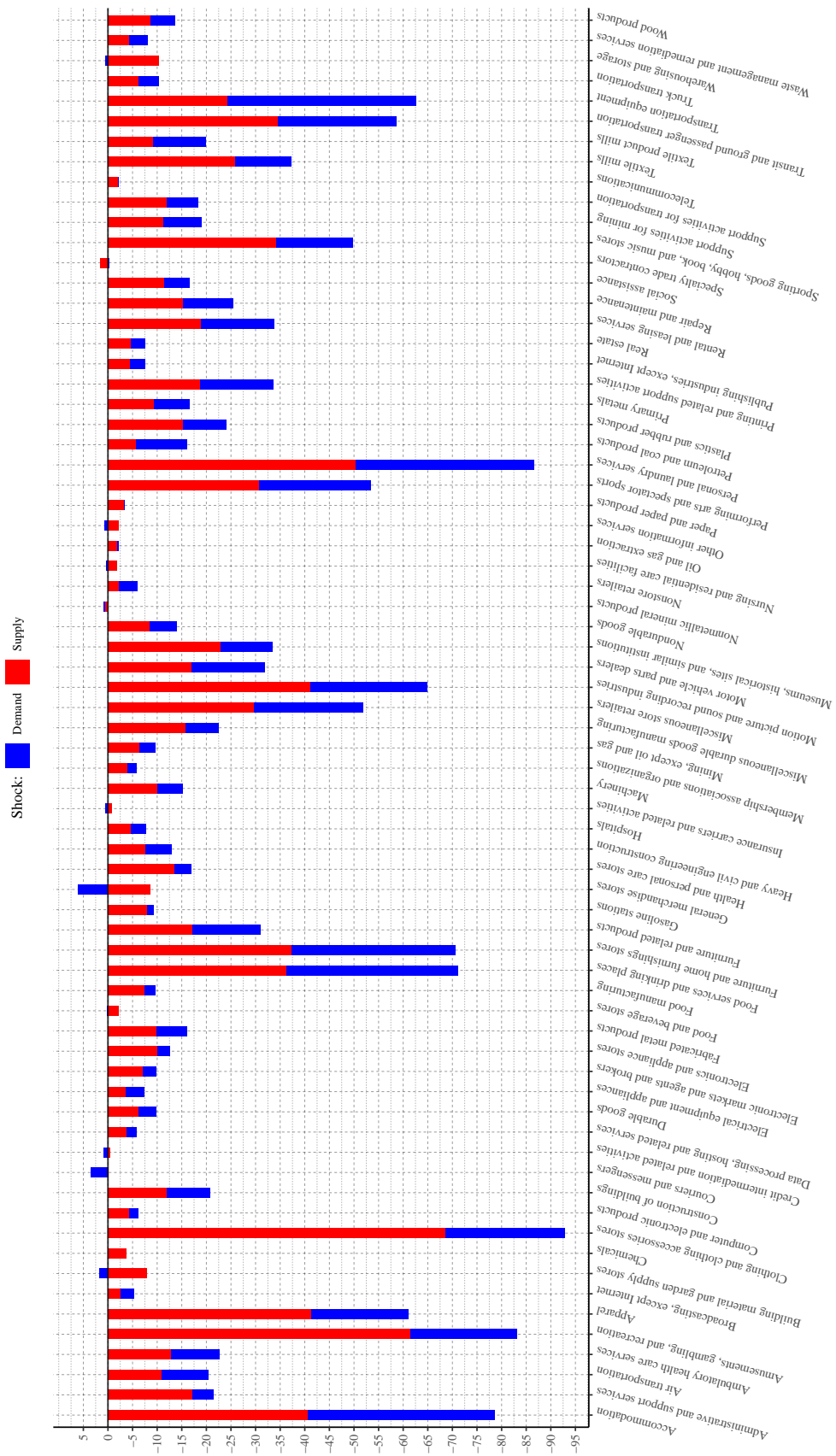
Notes: The data sample for production and nonsupervisory employees we use to estimate our SVAR starts in 1984. Production and nonsupervisory employees CES series code for real wages is 32 and for aggregate weekly hours is 81.

Figure 12: 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 13: 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 14: Historical decomposition of the growth rate of hours across sectors, March 2019

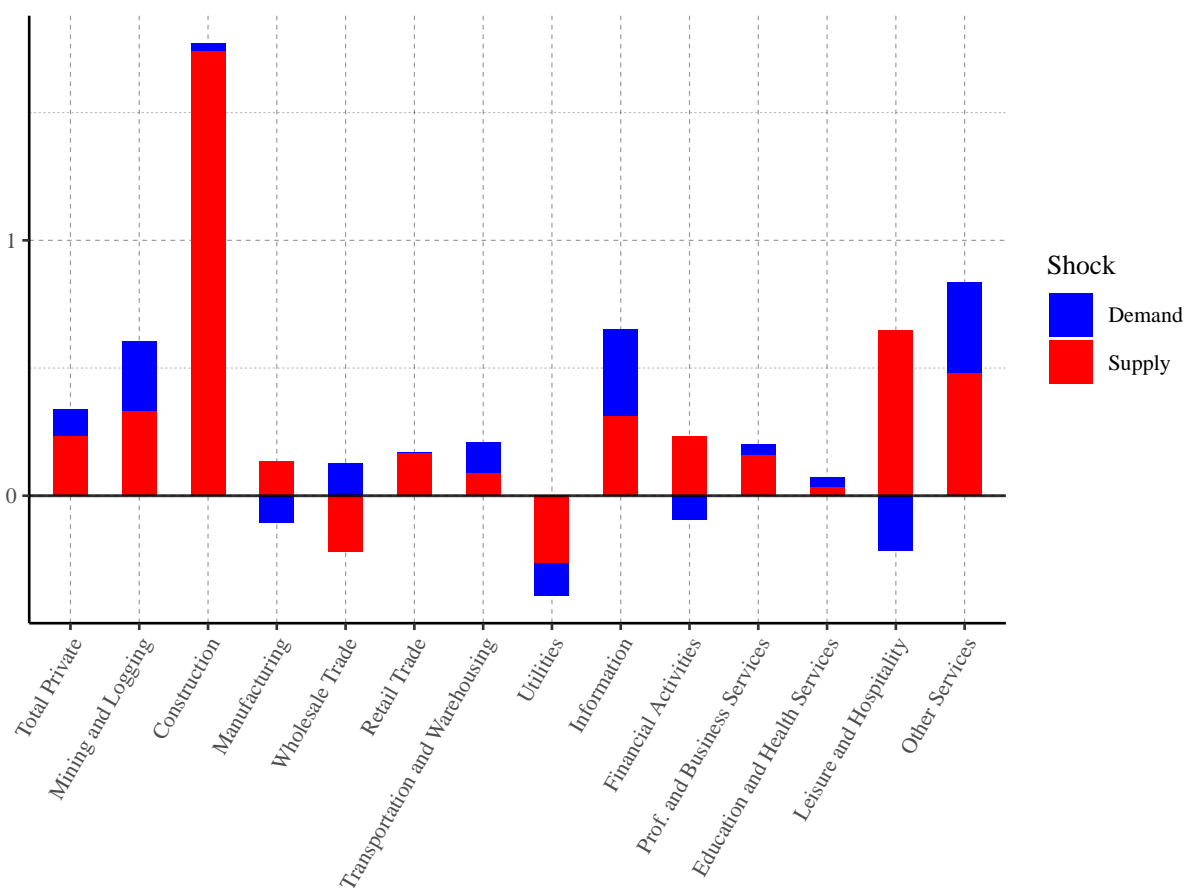
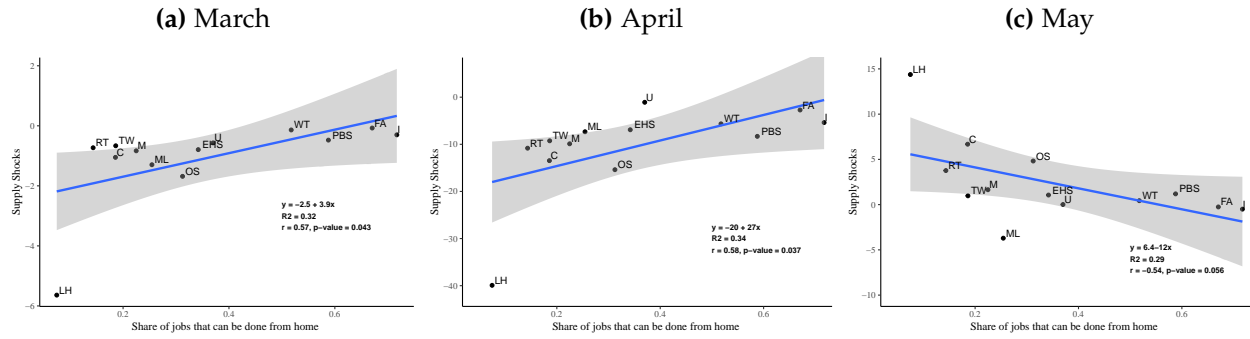
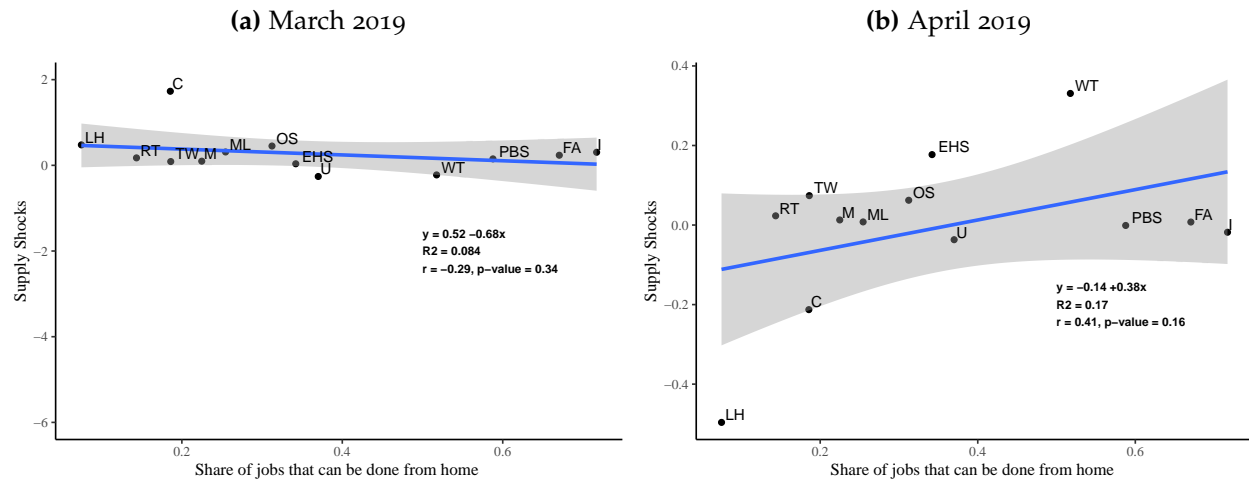


Figure 15: Correlation between sectoral supply shocks the sectoral share of jobs that can be done at home



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.

Figure 16: Supply Shocks in 2019 vs. Share of jobs that can be done from 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.