Sectoral effects of social distancing

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The global health crisis caused by the outbreak of the Covid-19 virus has led many countries to implement drastic measures of social distancing. These include shutting down public spaces, restaurants and shops, closing schools, and restricting any economic activity inducing close physical contact between workers.

The economic effects of these restrictions depend on the structure of production networks. Modern economies are indeed characterized by the many interdependencies formed by companies in their production processes. These interdependencies are well identified in the literature as facilitating the propagation of non-systemic shocks (Barrot and Sauvagnat, 2016) and their aggregation (Acemoglu et al., 2012; Baqaee and Farhi, 2019), with applications for policies (Liu, 2019; Grassi and Sauvagnat, 2019). In this paper, we build on the findings of this literature and analyze the effects of social distancing in production networks.

For this, we calibrate a standard production network model to the U.S. economy. We use data from the U.S. Census to determine the share of workers affected by social distancing, and show how it disrupts national production through the network of input-output linkages.

We contribute to the recent stream of work on the macroeconomic implications of the Covid-19 virus. Our paper is closely related to Baqaee and Farhi (2020*a*) and Baqaee and Farhi (2020*b*) who study the implications of Covid-19 using a quantitative production network. This literature has also focused on business failures (Gourinchas et al., 2020), the interaction beetwen epidemiologic models of contagion and the macroeconomy (see Eichenbaum, Rebelo and Trabandt (2020) among others), and the role of complementarities and incomplete markets in generating supply-driven demand shortages as in Guerrieri et al. (2020).

I. Measuring Social Distancing

The Covid-19 virus first spreads to the U.S. in January, and caused deaths in February of 2020. A Public Health Emergency was declared on January 31 by the federal government. On March 19, the Department of State advised U.S. citizens to avoid all international travels. In turn, U.S. State governors issued various Executive Orders restricting social activities.

To estimate the overall reduction in active workforce in each sector due to the implementation of social distancing measures in the U.S., we proceed as follows. We define restricted labor as the sum of the set of workers that have dependent children and therefore are forced into inactivity due to the closure of schools (that have been enforced in all States), and the set of workers (without dependent children) in non-essential sectors that cannot work from home. We use data from the American Community Survey (ACS) in order to compute the share of working people with children under 15 in each sector.[1] Then, we focus on Executive Orders closing businesses deemed as non-essential. 45 States issued such orders between March 19 (California) and April 6

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[1] We consider that an active person has dependent children if there is not another inactive person in the household who could take care of them. If there are several active adults in the household, we consider that the lowest earning adult is in charge of childcare.

Table 1—Summary Stats

	#Obs	Mean	Sd	Min	Med	Max
BEA Sector-level sample						
Emp. share with kids	390	0.098	0.029	0.039	0.092	0.256
Emp. share in non-essential businesses	390	0.158	0.290	0.000	0.032	0.986
... which cannot work from home	390	0.120	0.233	0.000	0.016	0.965
Restricted labor	390	0.206	0.213	0.039	0.117	0.971
BLS Sector-level sample						
January-April emp. growth	221	-0.141	0.165	-0.803	-0.078	0.077
FRB Sector-level sample						
January-April (log) output change	82	-0.295	0.432	-2.414	-0.211	0.070

Note: This Table presents the summary statistics for the employment share with kids, $kids$, the employment share in non-essential businesses, $close$, the employment share in non-essential businesses that cannot work from home $close \times (1 - wfh)$, and the overall restricted labor share, $kids + (1 - kids) \times close \times (1 - wfh)$ for each BEA industry, as well as the change in employment between February and April 2020 for BLS industry data.
Source: BLS, American Community Survey, O*NET, Fed Industrial Production and Capital Utilization, and, data collected by the authors. Authors calculation.

(Missouri). We read each State's Executive Orders and classify for each of them, each 4-digit NAICS industry (310 industries) as either essential (i.e., open) or non-essential (i.e. closed).[2] To get the share of workers in closed sectors that can still work from home, we borrow data from Dingel and Neiman (2020) who classify the feasibility of working at home for all occupations based on responses to two Occupational Information Network (O*NET) surveys, and merge them with information from the U.S. Bureau of Labor Statistics (BLS) on the prevalence of each occupation across 4-digit NAICS industries.[3]

Formally, if we denote in each sector i, $kids_i$, the fraction of workers with children under 15 forced into inactivity, $close_i$, the fraction of workers in non-essential businesses, and wfh_i the share of workers that can work from home, we get that the overall share of restricted workers in sector i, is equal to:

$$kids_i + (1 - kids_i) \times close_i \times (1 - wfh_i) \quad (1)$$

Table 1 presents summary statistics for our data across 390 BEA industries. Importantly for our analysis, there is significant heterogeneity across industries in the share of workers in non-essential businesses who cannot work from home, less so for the share of workers with children under 15 forced into inactivity (the standard deviation is 0.03 only). When considered together, the fraction of the labor force that cannot work due to social distancing measures ranges from 4% to 97% across industries.

As shown in Figure 1, we find that the restricted labor share has a strong predictive power for the drop in employment observed between January and April 2020. A cross-sectional OLS regression gives an estimated coefficient of -0.4 with a t-statistics of 6.5.

II. A Production Network Model

We use a production network model to evaluate the sectoral impact of social distancing, as measured by the restricted labor share. In this framework, there is a representative household who consumes a bundle of N goods, and supplies inelastically sector-specific labor, l_i, and capital, k_i. In each sector, there is a representative firm which produces the sector good using sector-specific labor and capital to-

[2] States vary in the set of businesses they decide to close. We use the same data in a companion paper in which we estimate the effect of state-mandated business closures on employment, firms' market values, Covid-19 infections, and death rates, see Barrot et al. (2020).

[3] As shown in Dingel and Neiman (2020), the classification implies that 37 percent of U.S. jobs can plausibly be performed at home. This estimate exceeds the share of jobs that in fact have been performed entirely at home in recent years (According to the 2018 American Time Use Survey, less than a quarter of all full-time workers work at all from home on an average day). This means that we probably underestimate the fraction of the labor force that cannot work in non-essential sectors.

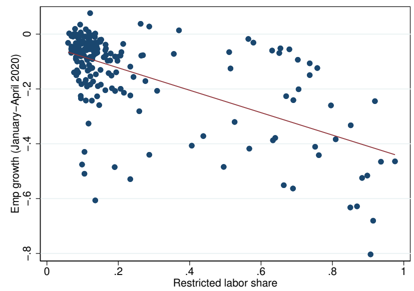

FIGURE 1. RESTRICED LABOR SHARE AND EMPLOYEMENT GROWTH

Note: Each dot represents one of the 221 sectors in our BLS sample. The x-axis represents the restricted labor share defined in Equation (1). The y-axis represents employement growth between January and April 2020.
Source: BLS and author calculation.

gether with other goods used as intermediate inputs. There is no nominal friction, and prices are equal to marginal costs. All markets clear. We use the "exact-hat algebra" notation, that is, for an equilibrium variable X whose value at an initial equilibrium is $\overline{X}$, we denote $\widehat{X} = X/\overline{X}$, the change from the initial equilibrium (due to the implementation of social distancing policies). The household utility is given by:

$$\left(\sum_{i=1}^{N} \psi_i \widehat{f_i}^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}}$$

where f_i is the final demand of good i, $\psi_i = \overline{p}_i \overline{f}_i / \sum_i \overline{p}_i \overline{f}_i$ is the share on good i in total expenditure, and, σ is the (constant) elasticity of substitution across goods. In our application, N is equal to 390, the number of sectors in the detailed BEA input-output classification. The representative firm in sector i produces y_i units of its good using the following production function:

$$\widehat{y}_i = \widehat{z}_i \left(\eta_i \widehat{a}_i^{\frac{\theta-1}{\theta}} + (1-\eta_i)\widehat{X}_i^{\frac{\theta-1}{\theta}}\right)^{\frac{\theta}{\theta-1}},$$

$$\text{where } \widehat{a}_i = \left(\widehat{l}_i\right)^{\gamma_i} \left(\widehat{k}_i\right)^{1-\gamma_i},$$

$$\text{and } \widehat{X}_i = \left(\sum_{j=1}^{N} \Omega_{ij} \widehat{x}_{ij}^{\frac{\varepsilon-1}{\varepsilon}}\right)^{\frac{\varepsilon}{\varepsilon-1}}.$$

where the change in productivity, $\widehat{z}_i$, in capital supply, $\widehat{k}_i$, and in labor supply, $\widehat{l}_i$, are exogenous. In our baseline, the first two are set to one, while the change in labor supply is given by the restricted labor share discussed above. The change in output, y_i, capital/labor bundle, a_i, intermediate input bundle, X_i, and the intermediate demand for good j, x_{ij}, are endogenous and need to be solved for. At the initial equilibrium, the share of value-added in production is given by η_i, the labor share in value added is given by γ_i, while $\Omega_{ij} = \overline{p}_j \overline{x}_{ij} / \sum_j \overline{p}_j \overline{x}_{ij}$ is the share of expenditure on good j in total intermediate inputs used by sector i. These variables are read off directly from the detailed BEA input-output table for the U.S. Finally, θ is the (constant) elasticity of substitution between the capital/labor bundle and the intermediate input bundle, and ε is the (constant) elasticity of substitution between intermediate inputs.[4]

III. Network effect of social distancing

We compute the equilibrium effect of social distancing measures by solving the model of section II. We choose the values of the elasticities $(\sigma, \theta, \varepsilon) = (0.9, 0.5, 0.001)$. These values are the ones used by Baqaee and Farhi (2019) and are consistent with estimates in the production network literature.

[4]We report in the Online Appendix all the remaining equations of the model. Given exogenous variables, z_i, k_i, l_i, elasticities $(\sigma, \theta, \varepsilon)$, input-output parameters, the solution of the equilibrium equations gives the change in endogenous variables.

Table 2—Effect on GDP

	Scenarios		
	(i) admin	(ii) school	(iii) admin+school
GDP dev. %	-25.18%	-5.96%	-30.52%
GDP dev. % (Cobb-Douglas)	-10.58%	-5.89%	-15.66%

Note: For a given scenario and calibration, we report $100 * (\widehat{Y} - 1)$. First row: baseline calibration $(\sigma, \theta, \varepsilon) = (0.9, 0.5, 0.001)$. Second row: Cobb-Douglas case $(\sigma, \theta, \varepsilon) = (1, 1, 1)$.

We consider three scenarios below: (i) the "administrative closure" scenario where non-essential businesses are closed while allowing people to work from home, in which case labor supply is given by $l_i = 1 - close_i * (1 - wfh_i)$, (ii) the "school closure" scenario where $l_i = 1 - kids_i$, and, (iii) our baseline "administrative+school" scenario where both administrative and school closures are enforced, that is, l_i is equal to one minus the restricted labor share of Equation (1).

Table 2 reports the percentage change in aggregate output for the baseline, $(\sigma, \theta, \varepsilon) = (0.9, 0.5, 0.001)$, and Cobb-Douglas calibrations, $(\sigma, \theta, \varepsilon) = (1, 1, 1)$. Under our baseline calibration and scenario (iii), the GDP is 31% below its pre-social distancing level. Importantly, this number represents the level of GDP when social distancing measures are active. To compute annualized GDP loss, one would need to take into account the duration of these measures. Since in the Cobb-Douglas case, the Hulten (1978)'s theorem applies exactly, the difference between the baseline calibration and the Cobb-Douglas case is a measure of the contribution of non-linearities (Baqaee and Farhi, 2019). These non-linearities account for more than half of the change in GDP in the "administrative closure" scenario while they play virtually no role in the "school closure" scenario. As shown in Table 1, the "school closure" shock is affecting labor supply of all sectors in a relatively homogeneous way, while the effect of the administrative closure of non-essential businesses is concentrated on a few sectors. The results in Table 2 indicate that non-linearities matter more for asymmetric shocks.

Figure 2 displays the kernel density estimate of the (log) change in quantity across sectors in the data and the three scenarios of the model. Comparing the baseline calibration (left panel) with the Cobb-Douglas case (right panel) shows that non-linearities are important to replicate the large heterogeneity in the quantity change across sectors observed in the data. For the "school closure" shock, the model does not generate much heterogeneity in output changes across sectors both in the baseline calibration and in the Cobb-Douglas case. Instead, for concentrated shocks such as "administrative closure" and "administrative+school", the model generates sizeable dispersion in (log) quantity changes across sectors under the baseline calibration, in line with the data.

IV. Conclusion

We measure social distancing policies as labor-supply shocks using U.S. States executive orders, occupation and survey data, and evaluate their effects through the lens of a parsimonious production network model. We show that when these labor supply shocks are heterogeneous across sectors, non-linearities in the production network model generate realistic dispersion in sectoral output change.

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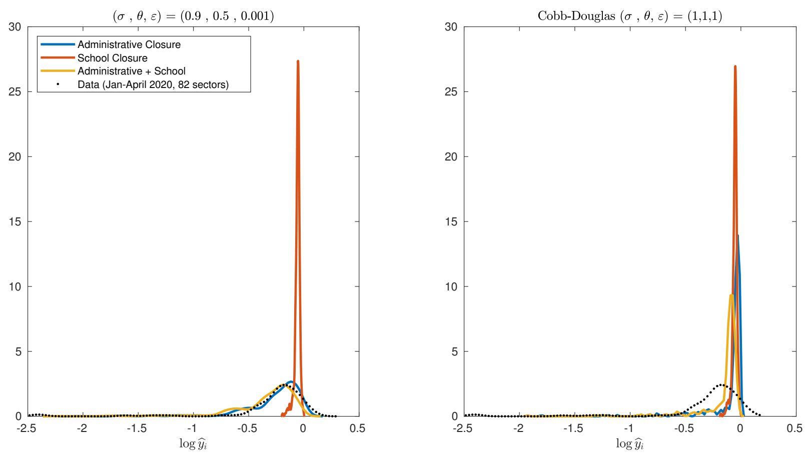

FIGURE 2. KERNEL DISTRIBUTION ESTIMATE OF (LOG) SECTOR QUANTITY CHANGE

Note: Kernel density estimate of sector output (log) change in model and data. Left panel: baseline calibration $(\sigma, \theta, \varepsilon) = (0.9, 0.5, 0.001)$. Right panel: Cobb-Douglas calibration $(\sigma, \theta, \varepsilon) = (1, 1, 1)$. Black dotted line: (log) change in sector output between January and April 2020 from 82 sectors. Source: BLS.

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