Economic Winners versus Losers

and

The Unequal Pandemic Recession

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Abstract

As is understood, during the pandemic recession firms directly exposed to the virus, i.e. the "contact" sector, contracted sharply and have been recovering slowly relative to the rest of the economy. Less understood is how firms that "won" by offering safer substitutes for contact sector goods have affected this unequal downturn. Using both firm and industry data, we first construct disaggregated measures of revenue growth that distinguish between contact sector losers, contact sector winners, and the non-contact sector. We show that contact sector losers contracted roughly fifty percent more than the sector average, while winners grew. Further, forecast data suggests that the gap between winners and losers will persist beyond the pandemic. We then develop a simple three sector New Keynesian model, in which a sector of firms offers safe substitutes for risky contact sector goods. We also allow for learning by doing to help explain the persistent gap between contact sector winners and losers. Overall, the simple model is reasonably consistent with the basic features of the data.

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1 Introduction

As has been well documented the recent recession has hit sectors of the economy unevenly. Sectors where market activity involves exposure to the virus experienced a much sharper downturn and a much slower recovery than those sectors where exposure is minimal. Figure 1 illustrates: Following Kaplan, Moll, and Violante (2020) (KMV), we aggregate exposed industries into the "contact" sector and non-exposed industries into the "non-contact" sector. Then for the period 2019Q1 to 2021Q1, we plot revenue relative to trend for the contact sector (red line), the non-contact sector (blue) and the aggregate (black). The contact sector, which accounts for roughly thirty percent of total revenue, contracts roughly twenty-two percent relative to trend during the height of the recession, more than double that of the non-contact sector, which drops nine percent.[1] Further, while the non-contact sector returns to trend in 2021Q1 and the aggregate economy is close to full recovery, the contact sector remains eight percent below.

A second important feature of the recession, which is also known but perhaps less well documented, is that there has been a spending shift from contact sector goods and services to safer substitutes. Common examples include the shift from restaurants to grocery stores, from retail stores to online delivery companies, from airlines to teleconferencing equipment and from movie theaters to in-home streaming. This substitution behavior is significant for at least two reasons. First, it may enhance inequality as relative revenues rise for economic winners such as Domino's, Amazon, Zoom and Netflix at the further expense of economic losers in the contact sector. Second, to the extent that this substitution effect enhances the revenue contraction among firms in the contact sector, it could amplify the overall contraction in aggregate economic activity, depending on the complementarities between this sector and the rest of the economy.

In this paper we attempt to both measure and model the uneven sectoral dynamics of the

[1] Note that the value added share of the contact sector in thirty two percent, which is very close to the revenue share of thirty percent.

pandemic recession, with particular emphasis on the role of substitution between economic winners versus losers in the contact sector. We attempt to capture not only the unequal initial contraction in economic activity shown in Figure 1, but also the persistence in sectoral inequality during the recovery period.

In the first part of the paper, we disaggregate economic activity over the crisis into the three sectors we have just described: (1) contact sector losers (firms exposed to the virus), (2) contact sector winners (firms offering safe substitutes), and (3) the non-contact sector. To identify winners versus losers, we start with firm level stock market responses to news about Covid, using news dates constructed by Davis, Hansen, and Seminario-Amez (2020). We then classify firms with high relative stock market responses as winners and those with low relative responses as losers. We show that by and large the winners we measure indeed offer goods that are contact sector substitutes. Then using relative stock market performance, we compare how being a winner versus a loser affected revenue growth during the crisis as well as projected revenue growth several years ahead.[2]

In the end, we are able to disaggregate the contact sector revenues presented in Figure 1 into revenues by losers versus winners. The results are consistent with a significant amount of substitution, as winners gain and losers contract nontrivially relative to the contact sector mean. At the height of the recession, contact sector losers drop roughly forty to fifty percent more than the sector as whole.[3] This gap persists through the crisis. By contrast, winners revenues increase relative to expectation, peaking at ten percent above trend in 2020Q4. We show further using forecast data that the gap between winners and losers is expected to persist well into 2022.

We next develop a simple model with output disaggregated into contact versus non-contact sectors to explain the data, following Guerrieri, Lorenzoni, Straub, and Werning

[2]To control for pre-existing trends (e.g. high trend growth in the IT sector), we examine revenue behavior relative to the pre-recession forecast.

[3]Our measure of the contact sector differs slightly from KMV in that we include some firms from information technology that offer substitutes for contact sector goods, such as Amazon. With this in mind, we measure total revenues of winners as a quarter of the contact sector total at the beginning of the crisis (and thus the number is three quarters for losers.)

(2020) (GLSWa), Baqaee and Farhi (2020) (BF), Faria-e Castro (2021), KMV and others. The specific baseline framework is a simple three sector New Keynesian model, where we allow for contact sector winners and losers that provide substitute goods. As in GLSWa, we allow for incomplete markers that in our case introduces a complementarity between the contact sector losers and the non-contact sector. Similar to BF, we capture the virus as a combination of demand and supply shocks to the contact sector. In addition, because our measures suggest that the sectoral inequality will persistent well into 2022, (hopefully) well after the pandemic, we add to the framework learning by doing in the contact winning and losing sectors. Learning by doing introduces persistent productivity declines among workers in the losing sector and persistent increases in the winning sector.

We then simulate the pandemic recession, picking the demand and supply shocks to match the quarterly behavior of output and inflation. Overall, the simple model does reasonably well in capturing both the aggregate and disaggregated data. We are also able to clearly illustrate both qualitatively and quantitatively how "substitution" can enhance both the unevenness of the sectoral contraction as well as the combined aggregate effect. The learning by doing mechanism helps capture some of the persistent gap between winners and losers, though a good fraction remains unexplained. Interestingly, because learning by doing leads to a reduction in productive capacity over time in the contact losing sector, it helps the model explain the recent increase in inflationary pressures.

Our paper follows the huge literature motivated by the Covid-19 pandemic. As noted earlier, GLSWa and BF develop a multi-sector economy with complementarities between the contact and non-contact sectors. Other examples of Covid-related multi-sector models include Faria-e Castro (2021), Kaplan, Moll, and Violante (2020), Bigio, Zhang, and Zilberman (2020), Buera, Fattal-Jaef, Hopenhayn, Neumeyer, and Shin (2021) and Guerrieri, Lorenzoni, Straub, and Werning (2021). Also relevant is Fornaro and Wolf (2020) and Alon, Doepke, Olmstead-Rumsey, and Tertilt (2020) who consider how output declines during the pandemic could have persistent effects via endogenous productivity. Our paper is also related to Krueger,

Uhlig, and Xie (2020) which similarly explores the implication of substitution between goods with different levels of Covid exposure. These authors instead focus on the implications of substitution for the path of the virus in a framework with an explicit epidemiological model. We instead analyze the implications for observed sectoral output dynamics during the crisis and beyond. We note though that we do not provide and explicit epidemiological model, as in this paper, Eichenbaum, Rebelo, and Trabandt (2020), KMV and others. Rather, as in BF, we identify reduced form demand and supply shocks to the Covid sensitive sector by matching output and inflation.[4]

On the empirical side, a number of papers have developed measures of the heterogeneous impact of the crisis across sectors. Papanikolaou and Schmidt (2020) develop a measure of industry Covid exposure based inversely on the degree of remote work within the industry. They show that industry revenue and stock price surprises are negatively related to this measure. Davis, Hansen, and Seminario-Amez (2020) use 10-K filings to identify firm exposure to Covid. They show that Covid exposed firms experienced greater stock market losses on days when Covid news were released and also lower earnings for at least several quarters. Furthermore, Barrero, Bloom, and Davis (2020) present descriptive evidence of labor reallocation between firms during the pandemic crisis using data from the Survey of Business Uncertainty. We differ from these papers by using stock market data to construct measures of winners' versus losers' revenue within the contact sector that we can use to construct sectoral aggregate revenue quantities that our model can target. Lastly, Bloom, Davis, and Zhestkova (2021) show evidence on how shifts in demand for remote activity during the pandemic triggered innovation on working-from-home technologies which increases the productivity of firms that rely more on remote interactions. Our paper complements theirs by focusing on learning-by-doing in the winning sector as a source of productivity growth and by quantifying the relevance of the mechanism through our model results.

Section 2 presents our measures of sectoral revenue behavior over the pandemic. Section 3

[4]The limitation of the approach is that while we capture the impact of the virus on the economy, we ignore the feedback of the economy on the virus.

develops our model. Section 4 first illustrates the key properties of the model. It then presents a numerical simulation of the pandemic recession with the aim of accounting for both aggregate and sectoral behavior. We then illustrate the role of each of the key features, including substitution between safe and risky contact sector goods and learning by doing. Finally, we show our results are robust to allowing for a reasonable degree of labor mobility between sectors.

2 Measuring Sectoral Behavior Over the Covid Recession

In this section we disaggregate total revenue growth over the recent recession into series for the contact sector losers, contact sector winners and the non-contact sector. We also derive projected revenue growth as far out as 2022 for both winners and losers. We use revenue rather than value added because some of our firm level data is only available in revenue form. But as Figure 14 in the appendix shows, the cyclical properties of revenue and output are very similar, at least at the aggregate level. In constructing our measures we will make use of both firm level data from Compustat and industry level data from BEA.

As noted earlier, we begin with the industry classification by KMV into contact versus non-contact sectors as shown in the Table 1. We differ slightly by including in the contact sector a number firms from the Information category that provide substitutes for contact sector goods (e.g., Amazon, Zoom, etc.) One interesting feature of this classification is that since 2009 the share of the contact sector in total revenues is quite stable at roughly thirty percent until it contracts several percentage points during the pandemic, as Figure 2 shows. We return to this point later when we discuss our model structure.

The challenge now is to divide up revenues in the contact sector between winners and losers. We first use Compustat data to identify winners versus losers. To do so we follow Davis, Hansen, and Seminario-Amez (2020) by examining the response of firm stock prices to

news about Covid on nine different dates from February 24 to March 27, 2020. In particular, we construct a "Covid resilience" measure for each firm as follows: Let $\text{median}_t(Ret_{ft})$ be the median return of firm f across Covid days; $\text{median}_f(\text{median}_t(Ret_{ft}))$ be the revenue weighted median of all firms' median return; and $\sigma\left(\text{median}_t(Ret_{ft})\right)$ be the standard deviation of the median across firms, again revenue weighted. Then we constructed the normalized Covid resilience for each firm f, (CR_f), as

$$CR_f = \frac{\text{median}_t(Ret_{ft}) - \text{median}_f(\text{median}_t(Ret_{ft}))}{\sigma\left(\text{median}_t(Ret_{ft})\right)} \tag{1}$$

A firm is Covid resilient if its median return on Covid news days is high relative to the sector median.

We accordingly use a firm's Covid resilience measure to classify it as a winner or loser. Before doing so, we first confirm that there is a positive link between Covid resilience and revenue performance over the crisis. Measuring how the crisis affected revenue performance is a bit tricky since it is necessary to control for pre-crisis trends for each firm. To do so we use the February 2020 analysts' forecasts of firm revenues, restricting attention to firms with at least 3 forecasters. These forecasts are available for Q1, Q2, Q3, Q4 in 2020 and for 2021, 2022. We then construct 2020 quarterly revenue surprises as the log difference between realized quarterly revenue and the February 2020 forecast. To get a measure of the expected longer term impact of Covid resilience, we also construct a measure of 2021 and 2022 forecast surprises, using the log difference between May 2021 and February 2020 forecasts.

Table 2 presents regressions of the firm level quarterly revenue surprises over 2020 on our measure of Covid resilience. The first four columns present the regressions for each four quarters without controls, while the last four add controls for industry and size. In all cases the Covid resilience measure is statistically significant and positive, as we would expect. The effect is also big, with the largest impact for Q2, where unconditionally a one standard deviation in Covid resilience implies a twenty-five percent revenue surprise. The effects on revenue surprises remain large in Q3 and Q4, at seventeen and fourteen percent respectively.

With controls, the coefficient on Covid resilience drops by a factor of four but remains significant and nontrivial in size. In our view, this largely reflects the fact that our resilience measure is quite imprecise.[5] Industry controls (e.g. information versus retail) are likely capturing some revenue substitution. So too is size as, for example larger retailers, (e.g.Walmart) were able to take business from smaller ones. In the case of controls, what the Covid resilience measure can still isolate is revenue substitution occurring with firms within an industry or size group. In any event, as we show shortly, firms that are "winners" in the contact sector generally offer products that are safer substitutes for the products of losing firms.

To get a visual feel for the strong positive correlation between Covid resilience and firm revenue surprise, the four panels in Figure 3 provide a bin scatter plot of firm revenue surprises predicted by Covid resilience across firms for each quarter. The horizontal dashed line is the revenue surprise within the quarter for firms with exposure equal to the median. This measure drops nearly thirty percent in Q2 before steadily increasing to roughly minus ten percent. Across each quarter, firm revenue surprises vary sharply with Covid resilience.

To assess the longer term effects, we next regress the revenue forecast surprises for 2021 and 2022 on our measure of Covid resilience. One complication is that not all firms have a sufficient number of analysts' forecast over this period. Dropping all firms that do not have a complete set of forecasts would make the sample too small. We accordingly run an unbalanced panel, keeping each period all the firms that have the relevant forecasts for the period. Table 3 shows the results both without controls (top panel) and with them (bottom panel). The first four columns confirm that with our unbalanced panel we are able to replicate the results in Table 2 for 2020 with the balanced panel. Importantly, the last two columns in each panel show the responses of the forecast surprises for 2021 and 2022. In each case the effect is significant. Without controls, a one standard deviation in Covid resilience implies an eight percent positive forecast surprise and a seven percent surprise for 2022. With controls the numbers are five and four percent respectively, in either case

[5]It is reasonable to presume that stock market participants' estimates of firms' Covid resilience in Feb/March 2020 had a good deal of imprecision.

suggesting a highly persistent effect.

We now are in a position to extract contact sector winners and losers from the Compustat data, along with their respective revenue surprises. After doing so, we can then combine with the BEA data (which includes nontraded firms) to construct sectoral measures. We define a winner among Compustat firms in the contact sector as one with a positive Covid resilience (i.e. Covid news returns above the sector median) and conversely a loser as a firm with a negative one. For comparison we do the same with the non-contact sector.

We next aggregate the revenue surprises for winning versus losing firms. Figure 4 plots total revenue surprises relative to the sector median for winners versus losers. The left and right panels are for the contact and non-contact sectors respectively. Each panel plots the quarterly revenue surprises for 2020 and annual forecast surprises for 2021 and 2022. The gap between winners and losers revenue performance in the contact sector is huge, peaking at nearly thirty five percent in 2020Q2 and expected to persist at nearly twenty percent in 2021 and 2022. While there is also dispersion in the non-contact sector it is less than half that in the contact sector.

What is also important for our purpose is that winners in the contact sector appear to typically offer products that are safe substitutes for the products elsewhere in the sector that involve Covid exposure. The left side of Table 4 lists some representative winners and losers in the contact sector, along with their respective Covid resilience numbers. Among the winners: Amazon, Domino's Pizza, Walmart, Zoom, Netflix, Dropbox, all companies that were able to compete away business from the pandemic "losers" listed at the bottom. By contrast, as the right side of the table shows, in the non-contact sector winning versus losing reflected different considerations than substitution. For example, drug and pharmaceutical companies naturally came out ahead. So too did companies offering cleaning products (famously Clorox.) Losers like the automobile and airline companies suffered complementary effects from the drop in travel and auto demand. Accordingly, because there is much less dispersion in the non-contact sector and because this dispersion reflected factors other than substitution, we

restrict attention to winners versus losers in the contact sector.

Since Compustat firms only represent roughly half of total firm revenues, we need to combine our firm level data with the BEA measures to get a comprehensive revenue measure for each sector. We proceed as follows. We first assume that the only winners in the contact sector are among publicly traded firms: All non-traded firms are losers. Here the idea is that the firms best able to quickly offer innovate substitutes for Covid exposed products are large and experienced (e.g. Amazon), which tend to be publicly traded firms. While our assumption may be extreme, it is not unreasonable. Also, if anything, it stacks the deck against ourselves by limiting the number of winners. Given this assumption we can directly use our Compustat measure of contact sector winners to get a total revenue measure for this group. To obtain a measure of losers, take the contact sector total revenue from BEA and then subtract winners' revenues.

Figure 5 then presents our disaggregated sectoral series. We plot the revenue deviation from trend from 2019Q4 through 2021Q1. From 2021Q2 on we plot the May 2021 forecast relative to trend. The blue line reflects contact sector winners (about a quarter of the contact sector), the red line losers, the purple line the total contact sector, the yellow line the non-contact sector and the black line the aggregate.

There are several key points to note: First contact sector losers do much worse than the sector as a whole, with revenues dropping thirty three percent in Q2 as opposed to twenty two percent. The recovery is also slower. Indeed in Q4, contact sector losers are down nearly twenty percent as compared to ten percent for the sector as a whole, not to mention just two percent for the non-contact sector. By contrast, winners did quite well, steadily rising to ten percent above trend in Q4. As the figure makes clear, further, the gap between winners and losers is expected to persist well into 2022.

In the next section we develop a model to account for the data in Figure 5. Our goal is to explain both the sectoral and aggregate data.

3 Model

The core framework is a standard New Keynesian model with consumption goods only and with labor as the only production input. We introduce four main modifications: First we allow for three sectors, corresponding to contact winners, contact losers and the non-contact sector. Second, we allow for two sectoral shocks: a demand shock that affects contact losers directly and a labor supply shock that hits the contact losing sector directly as well. Third, we allow for incomplete markets in a very tractable way. Doing so motivates complementarities between the contact losing sector and the non-contact sector, as in GLSWa. Finally we allow for learning by doing in the contact sector. This feature introduces persistence owing to scarring effects in the contact losing sector, as well as endogenous productivity gains in the contact winning sector. For pedagogical purposes we present the baseline without learning by doing and then add this feature at the end.

Lastly, while we allow for variable labor within a sector, for simplicity our baseline does not have mobility across sectors. Accordingly, in Section 4.4 we introduce imperfect labor mobility and show that our results are largely unaffected under reasonable circumstances.

3.1 Sectors and Goods

There are two broad sectors: sector 1 where contact goods c_{1t} are produced and sector 2 where non-contact goods c_{2t} are made. Contact goods, further, are composites of goods where market activity makes them susceptible to the virus, c_{at}, and non-susceptible goods that are substitutes, c_{bt}. Thus, overall there are three sectors corresponding to c_{at}, c_{bt} and c_{2t}.

Let ρ be the inverse intratemporal elasticity of substitution and ϵ_t a taste shock that obeys a stationary first order process. Then we express c_{1t} as the following CES composite of c_{at} and c_{bt}:

$$c_{1t} = [\zeta(\epsilon_t) c_{at}^{1-\rho} + (1 - \zeta(\epsilon_t)) c_{bt}^{1-\rho}]^{\frac{1}{1-\rho}} \tag{2}$$

with

$$\zeta(\epsilon_t) = \frac{(1-\epsilon_t)\zeta}{1-\epsilon_t\zeta} \tag{3}$$

We suppose $0 < \rho < 1$ so that c_{at} and c_{bt} are substitutes.

The taste shock is meant to capture the impact of the virus on the demand for susceptible contact sector goods. It does so by affecting (1) the overall demand for contact sector goods c_{1t} -as it will become clear shortly- and, (2) holding constant c_{1t}, the relative demand for c_{at} versus c_{bt}. We start with (2): From equations (2) and (3) we see how ϵ_t affects the relative demands. Since $\zeta'(\epsilon_t) < 0$, an increase in ϵ_t shifts demand from c_{at} to c_{bt}, holding constant c_{1t}. We next describe how ϵ_t affects the overall demand for c_{1t}.

Let C_t denote the following homogeneous composite of broad sectoral consumptions c_{1t} and c_{2t}:[6]

$$C_t = \Theta(\epsilon_t) \cdot c_{1t}^{\phi(\epsilon_t)} c_{2t}^{1-\phi(\epsilon_t)} \tag{4}$$

with

$$\phi(\epsilon_t) = \frac{(1-\epsilon_t\zeta)\phi}{1-\epsilon_t\zeta\phi} \tag{5}$$

$$\Theta(\epsilon_t) = [\phi(\epsilon_t)^{\phi(\epsilon_t)}(1-\phi(\epsilon_t))^{1-\phi(\epsilon_t)}]^{-1} \tag{6}$$

The composite C_t is Cobb Douglas in c_{1t} and c_{2t}, with share parameters that depend on the taste shock. Given $\phi'(\epsilon_t) < 0$, an increase in ϵ_t reduces the weight on c_{1t} relative to c_{2t}.

We next suppose that period utility from C_t is given by[7]

$$\begin{aligned} u(C_t) &= \log C_t^{(1-\epsilon_t\zeta\phi)} \\ &= (1-\epsilon_t\zeta\phi)\log\Theta(\epsilon_t) + \log(c_{1t}^{(1-\epsilon_t\zeta)\phi} c_{2t}^{1-\phi}) \end{aligned} \tag{7}$$

[6]Given ϵ_t is zero prior to the pandemic recession, the log preferences appear consistent with Figure 2, which shows that from 2010 through 2019, the contact share of total revenue was fairly stable.

[7]See BF for a similar representation of preferences for the case where the shock hits only one of the sectors directly.

The bottom right hand side of equation (7) shows that the virus-induced taste shock directly affects the demand for contact sector goods c_{1t}. The top right hand side shows that there will be an implied impact of the shock on the aggregate composite C_t. In turn, from (2) and (3) earlier we see how, conditional on c_{1t}, the shock ϵ_t affects the relative preference for c_{at} versus c_{bt}. As in GSLWa, incomplete markets will spread the effect of the shock to the non-contact sector, amplifying the contraction of C_t, though we defer this discussion to Section 3.3.

3.2 Household Behavior

Each sector has one type of household. A household attached to a given sector supplies labor and receives profit income only in that sector. However, the household consumes goods from all sectors.

Preferences are the same across households, with one exception: The pandemic induces a negative shock to labor supply for households attached to sector a, the contact sector with susceptible goods. With the aim of making the steady state equilibrium as simple as possible, we set the number of households in each sector as follows: The number in $a = \phi$; in $b = \phi$; in $2 = 1 - \phi$.

Finally, to introduce a complementary spillover between the contact losing sector a and the non-contact sector 2, we introduce incomplete markets, in the spirit of GLSWa. To keep things as simple as possible, in our baseline setup we allow for complete insurance between agents in sectors b and 2, while we have agents in sector a credit-constrained.[8]

An upper case j denotes a choice by an agent in sector j. Let l_t^j denote labor supply, β the subjective discount factor, and η_{jt} a shock to labor supply in sector j. Then for $j = a, b, 2$,

[8]We are conservative in the amount of credit market friction we are introducing in the following respect. The average marginal propensity to consume out of wealth in our model is roughly 0.22 (the fraction of income of constrained households.) Elsewhere in the literature the average MPC is much higher: e.g., 0.3 in Kaplan, Moll, and Violante (2018) and 0.45 - 0.5 in Auclert, Rognlie, and Straub (2018). Another reason we are being conservative is that the contact sector is more labor intensive than the non-contact sector. This sector has thirty two percent of value added but fifty six percent of employment. Thus in practice the spillover effect on the demand for sector 2 coming from sector a households could be larger than our model suggests, even if there are a smaller fraction of constrained households in this sector than we assume.

preferences for a sector j household are given by:

$$E_0\{\sum_{t=0}^{\infty}\beta^t[\log(C_t^j)^{1-\epsilon_t\zeta\phi} - \frac{\eta_{jt}\kappa}{1+\varphi}l_t^{j(1+\varphi)}]\} \tag{8}$$

where η_t is a labor supply shock specific to sector a:

$$\eta_{at} = \eta_t; \qquad \eta_{bt} = \eta_{2t} = 1$$

Let B_t^j denote holdings of short term nominal bonds, T_t^j denote lump sum taxes,Υ_t^j denote insurance transfers, i_t the nominal interest rate, W_{jt} the sector j real wage rate and P_t the price level (i.e. the nominal price of the consumption composite). Then the period budget constraint for a sector j household is given by

$$C_t^j + B_t^j/P_t = (1+i_{t-1})B_{t-1}^j/P_t + \Pi_t^j + \Upsilon_t^j + W_{jt}l_{jt} - T_t^j \tag{9}$$

Since sector b and sector 2 agents insure each other, net transfers between the groups must equal zero:

$$\phi\Upsilon_t^b + (1-\phi)\Upsilon_t^2 = 0 \tag{10}$$

On the other hand, sector a agents are uninsured and cannot borrow, implying

$$\Upsilon_t^a = 0 \tag{11}$$

$$0 \leq B_t^a \tag{12}$$

Each household chooses, consumption, labor supply and nominal bonds to maximize utility given by (8). Each must satisfy the budget constraint (9). Households in sectors b and 2 must also satisfy the insurance transfer constraint, given equation (10). We suppose

further that under the insurance arrangement, the relative consumption levels of sector b and 2 households are the same as in the steady state. Given that they are not participating in the insurance arrangement and are credit constrained, each household in sector a must satisfy equations (11) and (12), instead of (10)

From the first order conditions of each household $j = a, b, 2$, consumption across the contact and non-contact sector goods (c_{1t}^j versus c_{2t}^j) must satisfy

$$c_{1t}^j = \phi(\epsilon_t)(\frac{P_{1t}}{P_t})^{-1} C_t^j \tag{13}$$

$$c_{2t}^j = (1 - \phi(\epsilon_t))(\frac{P_{2t}}{P_t})^{-1} C_t^j \tag{14}$$

In turn, the allocation of contact sector consumption between susceptible versus nonsusceptible consumption is given by

$$c_{at}^j = \zeta(\epsilon_t)^{1/\rho}(\frac{P_{at}}{P_{1t}})^{-1/\rho} c_{1t}^j \tag{15}$$

$$c_{bt}^j = (1 - \zeta(\epsilon_t))^{1/\rho}(\frac{P_{bt}}{P_{1t}})^{-1/\rho} c_{1t}^j \tag{16}$$

Since $\phi'(\epsilon_t) < 0$, a taste shock reduces the share of contact sector goods c_{1t}^j in total consumption C_t^j and increases the share of non–contact sector goods, c_{2t}^j. Similarly, since $\zeta'(\epsilon_t) < 0$, the shock reduces the share of susceptible goods c_{at}^j in c_{1t}^j and increases the share of nonsusceptible goods c_{bt}^j. Finally, as we show shortly, the taste shock will also reduce consumption of the aggregate composite C_t^j. Thus the sectoral shock will have aggregate effects on consumption demand and not simply a reallocative effects between sectors.

Next we turn to households' labor supply choices. For households in sector $k = b, 2$

$$(1 - \epsilon_t \zeta \phi)\frac{W_{kt}}{C_t^k} = \kappa(l_t^k)^{\varphi} \tag{17}$$

For households in sector a

$$(1-\epsilon_t\zeta\phi)\frac{W_{at}}{C_t^a}=\eta_t\kappa(l_t^a)^{\varphi} \tag{18}$$

The shock η_t directly affects labor supply in sector a. A positive innovation in η_t reduces labor supply by sector a households. As we show later, wages and prices in sector a increase as well, inducing substitution to sector b. Note also that the taste shock ϵ_t reduces labor supply in all three sectors by reducing the marginal utility of consumption.

Finally, sectoral household consumption/savings decisions are as follows: Let R_{t+1} denote the real ex post return on the nominal bond. Then for households in sector $k=b,2$ the consumption Euler equation is given by

$$\frac{1-\epsilon_t\zeta\phi}{C_t^k}=E_t\{\beta\frac{1-\epsilon_{t+1}\zeta\phi}{C_{t+1}^k}R_{t+1}\} \tag{19}$$

where, given complete insurance:

$$\frac{C_{t+1}^b}{C_t^b}=\frac{C_{t+1}^2}{C_t^2} \tag{20}$$

Next, let λ_t the Lagrange multiplier on the borrowing constraint (12) facing sector a households. Then the consumption Euler equation for sector a households is given by

$$\frac{1-\epsilon_t\zeta\phi}{C_t^a}=E_t\{\beta\frac{1-\epsilon_t\zeta\phi}{C_{t+1}^a}R_{t+1}\}+\lambda_t \tag{21}$$

Note that when the borrowing constraint is binding, consumption spending by a sector a household C_t^a is simply equal to current after tax income:

$$P_tC_t^a=\Pi_t^a+W_{at}l_{at}-T_t^a$$

Finally, we suppose that the sectoral demand and labor supply shocks obey the following first order processes

$$\begin{aligned}\epsilon_t &= \rho_\epsilon\epsilon_{t-1}+\xi_{\epsilon t} \\ \eta_t &= \rho_\eta\eta_{t-1}+\xi_{\eta t}\end{aligned} \tag{22}$$

where $\xi_{\epsilon t}$ and $\xi_{\eta t}$ are mean zero i.i.d. shocks.

3.3 Aggregate Demand, Sectoral Demand Shocks and the Interest Rate

The previous section characterized sectoral consumption demand by households conditional on the demand for the aggregate composite C_t. Before moving on to the supply side of the model, we briefly sketch how C_t is determined, as well as its dependence on the sectoral demand shock ϵ_t. For ease of exposition, we follow GLSWa by assuming that the taste shock is i.i.d. and is realized only in period t.[9] Also for simplicity, assume that nominal prices are fixed during both period t and $t+1$.

Accordingly, we begin by expressing the Euler equation for a sector 2 household in the following form:

$$C_t^2 = (1 - \epsilon_t \zeta \phi) E_t \{\beta \frac{1}{C_{t+1}^2} R_{t+1}\}^{-1}$$

where C_t^2 is consumption of the aggregate composite by type 2 households. The equation gives a standard inverse relation between C_t^2 and the interest rate R_{t+1}. Note also that the taste shock induces an intertemporal substitution effect: an increase in ϵ_t reduces C_t^2.

To derive an expression for total consumption demand, we need to derive a relation between C_t^2 and C_t. First, let $\alpha(\epsilon_t, \frac{P_{at}}{P_{1t}})$ be the share of consumption by type a households in total consumption. Then given that sector a households are borrowing constrained, their consumption just equals their income, implying[10]

$$\begin{aligned} \alpha(\epsilon_t, \frac{P_{at}}{P_{1t}}) &= \frac{P_{at} c_{at}}{PtC_t} \\ &= (\frac{P_{at}}{P_{1t}})^{\frac{\rho-1}{\rho}} \zeta(\epsilon_t)^{\frac{1}{\rho}} \phi(\epsilon_t) \end{aligned}$$

[9] To be clear, after this section we return to allowing ϵ_t to arise each period and be serially correlated.
[10] For the time being we ignore fiscal policy.

where we make use of equation (15) to derive the last expression, implying

$$\alpha_1(\epsilon_t, \frac{P_{at}}{P_{1t}}) < 0; \alpha_2(\epsilon_t, \frac{P_{at}}{P_{1t}}) < 0$$

A taste shock that reduces the demand for sector a goods (i.e. an increase in ϵ_t), reduces the consumption share of sector a households. So too does an increase in the relative price of sector a goods.

Given the insurance arrangement between sector b and 2 agents, C_t^2 is proportionate to total consumption minus the consumption by type a households, as follows:

$$C_t^2 \propto [1 - \alpha(\epsilon_t, \frac{P_{at}}{P_{1t}})]C_t$$

Combining with the Euler equation for type 2 households then yields the following expression for aggregate consumption demand

$$C_t = \frac{1 - \epsilon_t \zeta \phi}{1 - \alpha(\epsilon_t, \frac{P_{at}}{P_{1t}})} E_t\{\beta \frac{1}{[1 - \alpha(0, \frac{P_{at+1}}{P_{1t+1}})]C_{t+1}} R_{t+1}\}^{-1}$$

As in the standard one sector New Keynesian model, C_t falls as the interest rate R_{t+1} increases. The sectoral demand shock also affects C_t: An increase in ϵ_t, which reduces the demand for sector a goods, reduces C_t through two channels. The first channel is an intertemporal substitution effect, captured by the numerator in $(1 - \epsilon_t \zeta \phi)/[1 - \alpha(\epsilon_t, \frac{P_{at}}{P_{1t}})]$ Households delay some consumption to the next period, when the taste shock has disappeared. The second channel, captured by the denominator reflects the effect of incomplete markets. The decline in sector a income leads to a sharp drop in consumption by sector a households who are borrowing constrained. This drop in consumption by type a households affects the demand for goods in the non-contact sector 2.

As in GLSWa, incomplete markets introduces a complementarity between the Covid susceptible sector a and the non-contact sector 2. Combining the demand function for sector

2 goods (14) with the Euler equation for C_t yields

$$c_{2t} = (\frac{P_{2t}}{P_t})^{-1} \frac{1-\phi}{1-\alpha(\epsilon_t, \frac{P_{at}}{P_{1t}})} E_t\{\frac{1}{1-\alpha(0, \frac{P_{at+1}}{P_{1t+1}})} \beta \frac{1}{C_{t+1}} R_{t+1}\}^{-1}$$

The key takeaway is that the impact of the taste shock on the demand for sector 2 goods works only through the incomplete markets complementarity effect, since an increase in ϵ_t affects c_{2t} only by affecting the share of consumption going to sector a households, $\alpha(\epsilon_t, \frac{P_{at}}{P_{1t}})$. One significant difference from GLSWa is that the strength of this complementarity effect depends on the substitutability between Covid susceptible contact sector goods c_{at} and non-susceptible substitutes c_{bt}. High substitutability amplifies the contraction in c_{at} induced by an increase in ϵ_t, which in turn amplifies the spending drop by sector a households, leading to a greater reduction in demand for sector 2 goods.

To isolate the role of incomplete markets, we briefly present the complete markets benchmark. With complete markets, $C_t^2 \propto C_t$, implying that we can express the demand for total consumption C_t and for sector 2 goods c_{2t} as, respectively

$$C_t = (1 - \epsilon_t \zeta \phi) E_t\{\beta \frac{1}{C_{t+1}} R_{t+1}\}^{-1}$$

$$c_{2t} = (\frac{P_{2t}}{P_t})^{-1} (1-\phi) E_t\{(\beta \frac{1}{C_{t+1}} R_{t+1}\}^{-1}$$

With complete markets, ϵ_t affects affects C_t only through intertemporal substitution, as the top equation indicates. There is no spillover effect of ϵ_t on the demand for c_{2t} coming from households in sector a. Given the log preference structure (7), there is no direct intertemporal substitution effect on c_{2t}, implying that the only way ϵ_t can affect c_{2t} is via complementarity effects from incomplete markets which are absent in this example.

3.4 Production and Firms

The supply side of the model is conventional, except for there being three sectors. Within each sector there are final goods firms and intermediate goods firms. The former package together intermediate goods into final output and are competitive. The latter produce differentiated intermediate goods using labor. They are monopolistic competitors and set prices on a staggered basis.[11]

There is a continuum of measure unity intermediate goods firms in each sector. Let $Y(f)_{jt}$ be output of intermediate goods firm f in sector $j = a, b, 2$. Output Y_{jt} of a representative final goods firm in sector j is then the following CES aggregate of intermediate goods

$$Y_{jt} = [\int_0^1 Y(f)_{jt}^{\frac{\varepsilon-1}{\varepsilon}} df]^{\frac{\varepsilon}{\varepsilon-1}} \tag{23}$$

where $\varepsilon > 1$ is the elasticity of demand. From cost minimization, we get the final goods firms' demand for $Y(f)_{jt}$

$$Y(f)_{jt} = \left(\frac{P(f)_{jt}}{P_{jt}}\right)^{-\varepsilon} Y_{jt} \tag{24}$$

Combining with the production function then yields the price index:

$$P_{jt} = \left[\int_0^1 P(f)_{jt}^{1-\varepsilon} df\right]^{\frac{1}{1-\varepsilon}} \tag{25}$$

Intermediate goods firms produce output using a technology that is linear in total labor input $L(f)_{jt}$

$$Y(f)_{jt} = L(f)_{jt}$$

[11] Our choice to make prices sticky as opposed to wages creates some tension between the model and our identification of winners if one takes the model literally. In the model, we measure winners by their total income equal to profits plus labor income. Accordingly households in sector b are winners in the model by this definition, as they are in the data. However, our empirical work measures the response of profits which increase in sector b in the data but decline in the model due to the price rigidity. There are two ways to fix this without materially affecting the results: One is to use wage rather than price rigidity, which makes profits in sector b procyclical. The second would be to add capital which would also make profits procyclical. Since the substantive results are unaffected, we opt for the simpler and more standard approach that appeals to price rigidity.

These firms adjust prices on staggered basis (as in Calvo). Firms not setting price simply hire labor input to meet output demand. Firms adjusting price choose the optimal sector-specific reset price P^*_{j0}. Let $1-\theta$ be the adjustment probability each period, $\Lambda^j_{0,t} = \beta^t \frac{1-\epsilon_t\zeta\phi}{1-\epsilon_0\zeta\phi}\frac{C_0}{C_t}$ the stochastic discount for a sector j household and $1+\mu = \frac{1}{1-1/\varepsilon}$ the gross desired markup. The reset price decision for a sector j firm is given by

$$\max_{P^*_{j0}} E_0\{\sum_{t=0}^{\infty}\theta^t[\Lambda^j_{0,t}(\frac{P^*_{j0}}{P_t} - W_{j,t})\cdot(\frac{P^*_{j0}}{P_{jt}})^{-\varepsilon}Y_{jt}\}$$

The standard first order condition is given by

$$E_0\{\sum_{t=0}^{\infty}\theta^t[\Lambda^j_{0,t}(\frac{P^*_{j0}}{P_t} - (1+\mu)W_{j,t})\cdot(\frac{P^*_{j0}}{P_{jt}})^{-\varepsilon}Y_{jt}]\} = 0 \tag{26}$$

Finally, given that the reset probability is independent of firm characteristics, we can express the price index for sector $j = a, b, 2$ as

$$P_{jt} = [\theta P^{1-\varepsilon}_{jt-1} + (1-\theta)P^{*1-\varepsilon}_{jt}]^{\frac{1}{1-\varepsilon}} \tag{27}$$

3.5 Equilibrium

The link between aggregate output and labor input in sector j is given by

$$Y_{jt} = [\int_0^1 L(f)_{jt}^{\frac{\varepsilon-1}{\varepsilon}}df]^{\frac{\varepsilon}{\varepsilon-1}} \tag{28}$$

In turn, the link between labor firms use in each sector and household labor supply is given by

$$\begin{aligned}\int_0^1 L(f)_{at}df &= L_{at} = \phi l_{at} \\ \int_0^1 L(f)_{bt}df &= L_{bt} = \phi l_{bt} \\ \int_0^1 L(f)_{2t}df &= L_{2t} = (1-\phi) l_{2t}\end{aligned} \tag{29}$$

Next we turn to resource constraints. The sum of the demand across households for the sector j good equals the total sector output of the good:

$$\phi c_{jt}^a + \phi c_{jt}^b + (1-\phi) c_{jt}^2 = c_{jt} = Y_{jt} \tag{30}$$

Similarly the sum of the household demand for the consumption composite equals total output

$$\phi C_t^a + \phi C_t^b + (1-\phi) C_t^2 = C_t = Y_t \tag{31}$$

Sectoral and aggregate price indices are given by

$$P_{1t} = [\zeta(\epsilon_t)^{1/\rho} P_{at}^{\frac{\rho-1}{\rho}} + (1-\zeta(\epsilon_t))^{1/\rho} P_{bt}^{\frac{\rho-1}{\rho}}]^{\frac{\rho}{\rho-1}} \tag{32}$$

$$P_t = P_{1t}^{\phi_t} P_{2t}^{1-\phi_t} \tag{33}$$

We model fiscal stimulus during the pandemic as lump sum transfers financed by lump sum taxes. Accordingly, the government budget constraint requires:

$$\phi T_t^a + \phi T_t^b + (1-\phi) T_t^2 = 0 \tag{34}$$

Finally, the real interest is given by the Fisher identity:

$$R_{t+1} = (1+i_t)\frac{P_t}{P_{t+1}} \tag{35}$$

Let i be the steady state nominal rate given a zero inflation steady state. Then we suppose that the central bank sets the nominal rate according to a simple Taylor rule, subject to the zero lower bound constraint:

$$\begin{aligned} 1 + i_t &= (1 + i)(\frac{P_t}{P_{t-1}})^{\phi_\pi} \\ i_t &\geq 0 \end{aligned} \tag{36}$$

This completes the description of the baseline model.

3.6 Deterministic Steady State

The steady state provides a useful benchmark. In this instance there are no shocks, prices are flexible and there is zero inflation. We also assume that fiscal policy is used only outside the steady state.

With flexible prices, firms in sector j set prices equal to a constant desired markup μ over the steady state real wage.

$$\frac{P_j}{P} = (1 + \mu)W_j$$

Given the absence of shocks, labor supply is each sector satisfies

$$\frac{W_j}{C_j} = \kappa l_j^{\varphi}$$

Let $\kappa = \frac{1}{1+\mu}$ and assume household budget constraints are satisfied. Then we can combine the two equations above to obtain that steady state equilibrium labor supply is simply unity in each sector.

$$l_j = 1$$

Given each household supplies one unit of labor and sectoral output equals labor input,

sectoral consumption equals total sectoral labor input, as follows

$$c_a = c_b = c_1 = \phi$$

$$c_2 = 1 - \phi$$

Aggregate consumption, in turn is given by

$$C = \phi^{\phi}(1-\phi)^{1-\phi}/\phi^{\phi}(1-\phi)^{1-\phi} = 1$$

Relative prices are obtained from the sectoral demand functions, given the equilibrium quantities:

$$\frac{P_a}{P} = \zeta; \qquad \frac{P_b}{P} = 1 - \zeta$$

$$\frac{P_1}{P} = \frac{P_2}{P} = 1$$

where ζ is the steady state relative preference weight for susceptible contact sector goods.

Finally, given the insurance arrangement between households in sectors b and 2, we need to know the steady state relative consumption shares of the two types of agents. Given $\frac{P_b}{P} = 1 - \zeta$ and $\frac{P_2}{P} = 1$ in steady state, it is straightforward to show that the steady state ratio of consumption per household in sector b versus sector 2 is simply $1 - \zeta$:

$$\frac{C^b}{C^2} = 1 - \zeta$$

The optimal insurance arrangement maintains this relative consumption ratio across households in b and 2.

3.7 Sketch of the Flexible Price Benchmark

Because it is useful to compare the behavior of the model with nominal rigidities with the flexible equilibrium, in this section we sketch how the latter is determined. In particular we focus on how employment is determined across sectors. Then, given employment, it is straightforward to use the rest of the model described earlier to pin all the sectoral quantities and relative prices.

Because prices are perfectly flexible, as in the steady state a sector j firm charges a price that is the fixed desired markup μ above marginal cost W_{jt}

$$\frac{P_{jt}}{P_t} = (1+\mu)W_{jt}$$

The difference from the steady state, of course, is that prices and wages are not constant and in general will depend on the sectoral demand and supply shocks that hit the economy. Combining this pricing equation with the sectoral labor supply conditions given by (17) and (18) then yields equilibrium household labor supply for each sector:

$$\begin{aligned} l_{at} &= (\frac{1-\epsilon_t\zeta\phi}{\eta_t})^{\frac{1}{1+\varphi}} \\ l_{bt} &= \{\frac{\frac{\phi}{1-\phi}(1-\zeta)+1}{\frac{\phi}{1-\phi}(1-\zeta)+\Omega_t^{1-\rho}} \cdot (1-\epsilon_t\zeta\phi)\}^{\frac{1}{1+\varphi}} \\ l_{2t} &= \Omega_t^{\frac{1-\rho}{1+\varphi}} l_{bt} \end{aligned}$$

with

$$\Omega_t = [\zeta(\epsilon_t)(\frac{l_{at}}{l_{bt}})^{1-\rho} + (1-\zeta(\epsilon_t))]^{\frac{1}{1-\rho}}$$

and where we continue to assume $\kappa = 1/(1+\mu)$. To gain some intuition it is useful to consider the equilibrium with one shock at a time.

With only demand shocks, employment is the same across sectors and is given by

$$l_{at} = l_{bt} = l_{2t} = (1 - \epsilon_t \zeta \phi)^{\frac{1}{1+\varphi}}$$

As we noted earlier, the sectoral taste shock reduces the marginal utility of the consumption aggregate C_t, reducing labor supply in the flexible price equilibrium. How much depend positively on the Frisch elasticity of labor supply given by $1/\varphi$. Because labor co-moves perfectly across sectors, so will output in the flexible price equilibrium, even though this shock only hits directly the susceptible contact sector. What happens is that relative prices adjust (with a fall in sector a and an increase in b and 2) in a way that keeps relative output shares constant. By contrast, as we will show in the equilibrium with nominal rigidities inertia in relative prices will lead to a sharp drop in sector a output, an increase in the output of the substitute good b, and a drop in the non-contact sector 2 that is milder than the drop in a. Thus in our three sector model, nominal rigidities distort not only the absolute price level (and hence the markup) but also sectoral relative prices. We expand on this discussion later.

With only a labor supply shock, sectoral employment allocations are given by

$$\begin{aligned} l_{at} &= \eta_t^{-\frac{1}{1+\varphi}} \\ l_{bt} &= [\frac{\phi(1-\zeta)+1-\phi}{\phi(1-\zeta)+(1-\phi)\Omega_t^{1-\rho}}]^{\frac{1}{1+\varphi}} \\ l_{2t} &= \Omega_t^{\frac{\rho-1}{1+\varphi}} l_{bt} \end{aligned}$$

with $\Omega'(\eta_t) < 0$. In contrast to the sectoral demand shock, the supply shock that hits a causes the flexible price equilibrium sectoral output shares to vary. An increase in η_t reduces l_{at}, which in turn reduces output in this sector. Given $\Omega'(\eta_t) < 0$, the rise in η_t leads to an increase in employment in the substitute sector l_{bt}. Finally, the impact of the labor supply shock in the contact subsector a on employment in the non-contact sector 2 is ambiguous. We only know that sector 2 output is below that of sector b.

As we noted above, given the equilibrium sectoral labor supplies described in this section, we can then use the model equations presented in Section 3.2-3.5 to derive the complete flexible price equilibrium.

3.8 Learning by Doing

As we noted earlier, we try to capture some of the persistent effects of the crisis on earnings of winners versus losers in the contact sector by introducing learning by doing in these two sub-sectors. Let X_{ht} be efficiency units of labor for a person in sector $h = a, b$. Then we introduce a simple learning by doing mechanism originally proposed by Chang, Gomes, and Schorfheide (2002) which relates the evolution of X_{ht} to the intensity of labor input, as follows:

$$X_{ht+1} = l_{ht}^{\sigma_h} X_{ht}^{\rho_h} \tag{37}$$

with $0 \leq \rho_h < 1$ and $\sigma_h > 0$. Note that equation (37) relates the log of labor efficiency to a distributed lag of the log of past labor input. Accordingly, periods where there has been a rapid and persistent decrease in hours, such as what happened to workers in the susceptible contact sector, will produce a scarring effect that reduces labor productivity. Conversely, the rise in hours in substitute goods sector b will yield improvements in labor productivity.

Note that since $\rho_h < 1$, we are allowing for some obsolescence in labor productivity (as do Chang, Gomes, and Schorfheide (2002)). We do so to keep the steady state growth rate equal to zero for technical simplicity. However, in our numerical simulations we keep ρ_h close to unity so that the learning by doing has persistent effects.

The learning by doing makes the labor supply decision dynamic. We can express the objective for households in sector $h = a, b$ as

$$V(X_{ht}) = \max_{l_t^h} \log(C_t^h)^{1-\epsilon_t\zeta\phi} - \frac{\eta_{ht}\kappa}{1+\varphi} l_t^{h(1+\varphi)} + E_t\{\beta V(X_{ht+1})\} \tag{38}$$

Let Q_{ht} be the time t present discounted value to a sector h household of a unit increase in labor efficiency at $t+1$. Then the first order condition for labor supply is given by

$$W_{ht}X_{ht} + \sigma_h \frac{X_{ht+1}}{l_{ht}} Q_{ht} = \eta_{ht}\kappa l_t^{h\varphi} C_t^h / (1 - \epsilon_t \zeta \phi) \tag{39}$$

with

$$Q_{ht} = \rho_h \Lambda^h_{t,t+1}\{W_{ht+1}l_{t+1} + \rho \Lambda^h_{t+1,t+2} Q_{ht+1}\} \tag{40}$$

With learning by doing, the marginal benefit of supplying labor now includes the gain in subsequent labor productivity: the product of the additional efficiency units from an additional of work, $\sigma_h \frac{X_{ht+1}}{l_t^h}$, times the present value of an efficiency unit, Q_{ht}

Adding learning by doing to the baseline model is simple. The labor supply conditions (39) and (40) for workers in sectors a and b replace the corresponding conditions in the baseline model. Wherever labor supply enters the baseline model, it is now augmented by efficiency units. Finally, note that given the steady state value of l_t^h is unity, equation (37) implies that the steady state of X_{ht} is also unity.

4 Quantitative (and Qualitative) Analysis

In this section we analyze how the model captures the unequal sectoral recession described in Section 3, with particular emphasis on the role of winners versus losers. We present the model calibration. Then to clarify the mechanisms, we analyze the model response to sectoral demand and supply shocks, both under sticky and flexible prices. We next flesh out some implications for monetary policy. We then explore the extent to which our simple model can capture the sectoral dynamics over the pandemic recession, as well as the expected persistence in the gap between winners and losers. As noted earlier, our baseline does not allow for labor mobility across sectors. Accordingly, in the last part of this section we consider imperfect labor mobility.

4.1 Calibration

The model is quarterly.[12] There are thirteen parameters, as listed in Table 5. Four are "standard" New Keynesian parameters, for which we choose conventional values. Note though that we set the degree of price rigidity to be consistent with empirical estimates of the slope of the Phillips curve as opposed to the length time prices are fixed.[13]

Five parameters are "sectoral": We set ϕ, the steady state revenue share of the contact sector relative to the aggregate, to be thirty percent, consistent with what we found in the data. Similarly, we set ζ, the steady state revenue share of losing firms in the contact sector, to be seventy five percent, again consistent with our data. For the intra-temporal sectoral substitution $1/\rho$ across contact sector goods, we choose a value of two, which is within the range of estimates of this parameter using industry data[14]. Finally, we choose the persistence of the demand shocks ρ_ϵ and supply shocks, ρ_η such that the shocks are expected to last about a year, which we believe was the rough prediction of the length of the pandemic when it began, as well as the updated prediction when the new wave hit in the fall of 2020. In particular we choose a value of 0.5 for each shock, which implies that three quarters after a shock, only about ten percent of the initial shock is left.

Finally, there are four parameters that reflect "learning by doing." We set σ_a, the elasticity of human capital with respect to labor input in sector a, equal to 0.1, the estimate in Chang, Gomes, and Schorfheide (2002). What this number implies, is that to increase productivity by ten percent, an employee must work ten percent more than normal for ten quarters. For σ_b, the elasticity for the contact sector winners, we choose a higher value, 0.2, to capture the idea that this subsector is more technology intensive, with more scope for effective learning by doing. Finally, to capture the idea that gains in skills may be highly persistent, we set the parameters ρ_a and ρ_b each equal to 0.95.[15]

[12] While a monthly model would be desirable, the shortest frequency the firm level data is available is quarterly.

[13] See Hazell, Herreño, Nakamura, and Steinsson (2020) for empirical estimates of the slope.

[14] See Broda and Weinstein (2006).

[15] We make ρ_a and ρ_b less than unity for technical reasons: to ensure that the learning by doing does not

4.2 Illustrating Model Behavior

We begin with several experiments designed to illustrate how the model behaves.

4.2.1 Demand versus Supply Shocks

We examine the response of the model first to a sectoral demand shock and then to a sectoral labor supply shock. To disentangle the effect of the shocks from the response of monetary policy, we suppose the central bank adjusts the nominal rate to keep the real rate essentially fixed.[16] We normalize the size of the shocks so that each inititally generates a five hundred basic point change in the natural rate of interest. The top row in Figure 6 gives the response to the demand shock and the second row shows the results for the supply shock.

The demand shock is an increase in ϵ_t that directly reduces demand for contact sector goods and induces substitution from the exposed subsector a to the safe subsector b. Note first that the shock produces a decline in the natural rate of interest. It does so for two reasons: First, as discussed in Section 3.3, the shock induces intertemporal substitution, reducing current demand. In the flexible equilibrium the drop in demand requires the interest rate to fall to offset the drop. Second, as emphasized by GSLWa and also discussed in Section 3.3, incomplete markets amplifies the drop in demand, pushing down further the natural rate.

By contrast, an increase in η_t, which reduces labor supply in sector a, increases the natural rate. As we show in the next figure, the supply shock reduces current output in the flexible price equilibrium, causing expected output growth to rise, placing upward pressure on the natural rate. As in GLSWa there is an effect of incomplete markets that works in the opposite direction as constrained households in sector a are reducing demand, placing downward pressure on the natural rate. In our quantitative framework the former effect

lead to permanent changes in winners' and losers' respective contact sector output shares, which enables us to easily solve the model via loglinear approximation. However, our own evidence and Barrero, Bloom, and Davis (2020) argue that a fraction of the reallocation has been permanent. We accordingly approximate a permanent change in winners and losers relative output shares with a highly persistent departure from steady state.

[16] We assume that the Taylor rule coefficient on inlfation is 1.01 which effectively keeps the real rate fixed.

dominates the latter.

The middle column in each row shows the response of sectoral and aggregate revenues in our baseline model with nominal rigidities, given that the central bank is keeping the real rate effectively fixed. Since the effective real rate is far above the natural rate, the sectoral demand shock induces a contraction in real activity. Intertemporal substitution, which pushes the natural rate down, leads to an output contraction in the sticky price case. In addition, the drop in spending by constrained households in sector a magnifies the overall contraction. The recession is also highly unequal. The directly affected sector a (the losers), experiences the largest drop. The sector offering safe substitutes b (the winners) grows. The non-contact sector 2 experiences a milder contraction, driven mainly by the drop in spending by constrained households in sector a. In addition, even though the shock mostly dies out after four quarters, the gap between winners and losers persists due to learning by doing.

In the case of nominal rigidities, the effect of the supply shock on aggregate and sector 2 output is minimal since output is demand determined. However, there is a nontrivial effect on the allocation of contact sector revenues between winners and losers. The shock increases relative price of sector a inducing substitution to sector b. The learning by doing makes the effect strongly persistent.

Finally, we see sharp differences between the demand and supply shock in the response of inflation, as the last column illustrates. The demand shock reduces wages and hence marginal cost, while the supply shock does the opposite. Indeed we will make use of the inflation data to help identify demand versus supply shocks in the next section.

4.2.2 Limits to Monetary Policy

Before turning to the recession simulation, we consider one more exercise designed to illustrate the distortions in the model economy. In particular, we analyze the extent to which the central bank could improve welfare if it was unconstrained by the zero lower bound and instead chose to set the real rate equal to the natural rate. Of course in the standard one

sector New Keynesian model, this policy recovers the first best.[17] In our case, however, not only is the aggregate price level distorted due to nominal rigidities, so to are the sectoral relative prices.

In order to provide a benchmark for policy, the first column in Figure 7 shows the responses of sectoral and aggregate quantities under flexible prices. The second shows the responses under nominal rigidities when the central bank is able to set the interest rate equal to the natural rate. The last column shows the response of inflation.

With flexible prices, the sectoral demand shock reduces output in all sectors proportionately. As discussed in Section 3.7, relative prices adjust instantly to offset the shift in sectoral demand, implying a huge fall in the relative price of the directly affected sector a. With nominal rigidities, monetary policy stimulates demand by tracking the natural rate but it has minimal effect on the sectoral misallocation since relative prices are slow to adjust. As compared to when the central bank keeps the real rate fixed (see Figure 6), output increases across sectors. Indeed, output in the non-contact sector returns to steady state. However, the output improvement for the contact sector losers is modest in percentage terms, while the winners also gain, placing them in an even better situation. Finally, the policy does stabilize inflation, as comparison of Figure 6 and Figure 7 suggests. However, in contrast to the one sector NK model, stabilizing the price level does not lead to the first best outcome, a point that has been made by Guerrieri, Lorenzoni, Straub, and Werning (2021) in a somewhat related context.

In contrast to the demand shock, the labor supply shock has a big impact on sectoral and total output in the flexible price equilibrium as the bottom left panel of Figure 7 shows. On impact sector a falls significantly and sector b jumps as relative prices instantly rise in sector a and fall in sector b. The main difference with the case of nominal rigidities and a fixed real rate (see Figure 6), is that sector 2 is largely unaffected as wages adjust to stabilize employment. As with the demand shock however, with nominal rigidities the central bank

[17] Assuming lump sum transfers eliminate the distortion due to monopolistic competition.

cannot recover the flexible price equilibrium simply by setting the real rate equal to the natural rate. Doing so in this case requires raising rates which depresses demand across sectors without correcting the sectoral distortions. Inflation moderates as a result, but there is still a nontrivial positive bump in the short run. In the end, as with the demand shock, the combination of multiple sectors and nominal rigidities implies the central bank has insufficient instruments to recover the first best[18].

4.3 Simulating the Covid-19 Pandemic Recession

Next we use our model to simulate the pandemic recession. In order to do it we select realizations of the demand and supply shocks to minimize the distance of our model from four targets: aggregate revenue, sector a revenue, sector b revenue and inflation.[19] For inflation, we use Cavallo's core Covid CPI index detrended by its mean for 2019.[20] We select only shocks between Q1-2020 and Q1-2021 the period through which we have realized data for all series. We also allow for direct fiscal transfers (stimulus checks) and unemployment insurance both in a manner consistent with the data. We pick the size and timing of the direct transfers to match the data on stimulus checks. We suppose the checks are distributed evenly per capita across sectors. Because we do not explicitly model unemployment, we pick the size and timing of enhanced unemployment benefits to match the estimated impact on consumption, according to Farrell, Ganong, Greig, Liebeskind, Noel, and Vavra (2020). For monetary policy, we suppose the central bank moves the interest rate to the zero lower bound in Q2-2020, as happened in practice, and allow for four quarters of forward guidance at the zero lower bound. Appendix 6 provides details of the identification of the shocks, along with the implementation of policy.

Because we have fewer shocks than targets, the model will not fit perfectly. But our simple framework does a reasonable job of describing the data. Figure 8 illustrates. Overall,

[18]This point is well developed in Rubbo (2020) and Guerrieri, Lorenzoni, Straub, and Werning (2021).

[19]We do not have a separate target for sector 2 revenue since it is implied from the other sector revenues and aggregate revenue.

[20]See Baqaee and Burstein (2021) for some pitfalls of using this index.

the model does well in capturing both the unequal sectoral decline in economic activity as well as the overall contraction. Given its simple structure, the model does not capture all the quarterly bumps, but it does a good job capturing the average behavior over the first year of the crisis. Table 6 shows the average quarterly decline for aggregate and sectoral output over 2020. For aggregate output and output in sectors a and b the model is close. For sector 2, the model explains only about sixty percent of the drop. One likely factor is that we did not include the lockdown that occurred in March and April, which may led us to understate the drop in sector 2 output during Q2.

Due to the learning by doing mechanism, the model is able to replicate some of the persistence in the revenue gap between sectors a and b, though a large amount is left unexplained, as we discuss shortly. An interesting result is that partly as a product of the learning by doing the model predicts an increase in inflationary pressure by early 2021, consistent with the data. We also elaborate on this point later.

4.3.1 Inspecting the Mechanisms

In this section we explore the role of the distinctive features of the model, including substitution between safe and risky contact sector goods and learning by doing, as well as the role of fiscal policy in sectoral and aggregate dynamics.

No Substitution

What would happen if there was no substitution between expenditures on safe versus risky goods in the contract sector. The scenario corresponds to an intra-sectoral elasticity of substitution of one ($\rho = 1$). We keep all other features the same as in the baseline model (shocks, policy, etc), but adjust ρ to unity. Figure 9 shows the results, where the dashed lines correspond to our benchmark economy. Several results are clear: First, the risky sector drops notably less than in the case with substitution and, second, the safe sector does not win, both results that one would expect. In addition, the drop in both sector 2 and the aggregate

is smaller than in our benchmark case. Because the drop in the Covid exposed part of the contact sector is lower than with substitution, the spillover effect of spending on sector 2 is lower, which weakens the overall aggregate effect of the shocks.

Table 6 provides exact numbers. It shows the average quarterly revenue change over 2020 for each sector for the baseline model and various alternative scenarios.[21] With no substitution, the decline in sector a revenue is smaller by roughly twenty percent, going from -22% in the case with substitution to -17.3%. Sector b now loses -1.3% instead of winning. The effects on the aggregate are nontrivial. Without substitution, the drop in sector 2 (due to spillovers from sector a) is nearly half, going from -2.5 percent to -1.3%. The drop in aggregate revenues is also smaller in the case without substitution, going from -6.15 percent to -4.9 percent, a nearly twenty five percent increase.

No Learning-by-Doing

Figure 10 illustrates the role of learning by doing by comparing our baseline model to the case without this mechanism. Not surprisingly there is no significant impact the first year of the pandemic: It takes time for effects of employment on productivity to cumulate. After a year, we can begin to see the scarring effect on workers in sector a, who have suffered significant employment losses. As the bottom left panel illustrates, as the shocks are wearing off in year two of the crisis, output in sector a remains persistently below trend due to the productivity loss from scarring. Conversely, by virtue of "winning" during the first year of the crisis, workers in sector b enjoy enhanced productivity in the second. As a result, sector b output increases persistently relative to trend. The net effect is a gap in output between sectors a and b that persists beyond the (expected) time the pandemic ends.

Our data, however, is in terms of revenue as opposed to output. While the revenue gap between sectors a and b persists, it narrows a bit relative to the output gap, as the upper left panel in the figure illustrates. The reason is that relative prices adjust in each sector in

[21] In Table 6 we exclude the counterfactual for learning-by-doing since this feature does not generate a noticeable impact on the first year of the pandemic.

an offsetting direction: The productivity decline in sector a raises the costs of these goods, while the productivity improvement leads to a decline in the cost of sector b goods.

There are two ways to reconcile our model with the data. One is that the measure of the forecasted gap between winners and losers is likely quite imprecise, given that it is based on the analysts forecasts for a relative small set of firms. Second, it may be necessary to consider other possible sources of persistence such as habit formation that could prolong the substitution from risky to safe contact sector goods.

A result worth highlighting is that learning by doing helps the model account for the rise in inflation in early 2021, as the upper right panel shows. Intuitively, the loss in productivity reduces supply in sector a at the same time the waning of the pandemic shocks increases demand. The excess demand pushes up prices in sector a, enhancing inflationary pressures during the recovery period.

The Role of Fiscal Policy

As discussed earlier, we allow for fiscal transfers to mimic the effects of the stimulus checks and expanded unemployment insurance, both in terms of magnitude and timing. As Section 3 describes, for simplicity we model the stimulus as lump sum transfers to all households funded by lump sum taxes on sectors b and 2. Accordingly, the extra cash payments only directly affect spending by the constrained households in sector a. Figure 10 characterizes the effect of the fiscal stimulus by comparing the model with and without policy.

As one would expect, the fiscal stimulus increases both aggregate and sectoral revenues. It does little however to reduce sectoral revenue inequality (though of course it does more to reduce consumption inequality, as it is a direct transfer to sector a households.) Indeed, in percentage terms, the non-contact sector 2 benefits the most in terms of the impact of the stimulus on revenues. As Table 6 shows, for 2020, the fiscal stimulus reduces the revenue loss from -3.3 percent absent fiscal action to -2.5 percent. Intuitively, the fiscal stimulus helps offset the negative spillover effect on sector 2 of the pandemic induced drop in spending by

constrained households in sector a. It moves the economy closer to the complete markets solution, where the complementarity between sectors a and 2 vanishes.

4.4 Allowing for Labor Reallocation

In our baseline, we allowed for variable labor input within a sector, but did not allow for labor mobility across sectors. This begs the question of how the results would be affected if some workers from the losing sector a move to the winning sector b. Accordingly, in this section we allow for some cross sector labor mobility. Given the high level of unemployment in sector a type industries, we think it is reasonable to presume that mobility was far less than perfect. Here we allow labor reallocation for workers in sector a to b that involves some costs that we describe shortly.

We present only the parts of the model that involve some change. For simplicity, we exclude learning by doing.

4.4.1 Households

To minimize complexity, we introduce costly labor reallocation from a to b in a very simple way. We assume that workers in sector a can work in b but at a cost that involves increasing marginal disutility. Put differently, rather than depend just on total hours worked, the disutility from labor also depends on the allocation of hours across sectors, with increasing disutlity of hours in each sector.[22]

Let l_{at}^a be labor in sector a supplied by households in sector a, l_{bt}^a labor in sector b supplied by households in sector a, and $\Phi < 0$ a parameter that governs the disutility for sector a households working in b. Then we suppose that the utility function for a sector a household is given by

$$E_0\{\sum_{t=0}^{\infty}\beta^t[\log(C_t^a)^{1-\epsilon_t\zeta\phi} - \frac{\eta_t\kappa}{1+\varphi}\left[(\Psi_t)^{\frac{1}{1-\Phi}}\right]^{(1+\varphi)}]\} \tag{41}$$

[22]To keep the model simple, we model the reallocation cost as a flow instead of a fixed cost (see e.g. Guerrieri, Lorenzoni, Straub, and Werning (2021)). In practice, this cost may involve both.

where Ψ_t is the following composite of l_{at}^a and l_{bt}^a.

$$\Psi_t = \nu_a \left(l_{at}^a\right)^{1-\Phi} + (1-\nu_a)\left(l_{at}^a + l_{bt}^a\right)^{1-\Phi}$$

Note that the utility function has the property that l_{at}^a and l_{bt}^a separately affect the disutility from supplying labor. We choose this particular functional form for two reasons: First, it is possible to have l_{bt}^a equal zero in the steady state, which makes the steady state the same as in our baseline model. Second, $\frac{1}{\Phi}$ is the semi-elasticity of substitution between l_{bt}^a and l_{at}^a at steady state. Thus, in the limiting case where Φ goes to minus infinity, the semi-elasticity goes to zero, implying the household in sector a will not supply labor to sector b. Conversely, at Φ equal zero, there is perfect mobility since at the margin there will be a fixed rate of transformation in the utility cost of supplying labor between sectors a versus b.

The first order condition for the household's labor supply in sector a, l_{at}^a, is now given by,

$$\frac{1-\epsilon_t\zeta\phi}{C_t^a} = \frac{\eta_t\kappa}{W_{at}}\left[(\Psi_t)^{\frac{1}{1-\Phi}}\right]^{\varphi} \times (\Psi_t)^{\frac{\Phi}{1-\Phi}}\left(\nu_a\left(l_{at}^a\right)^{-\Phi} + (1-\nu_a)\left(l_{at}^a + l_{bb}^a\right)^{-\Phi}\right) \tag{42}$$

while the household's intra-sector allocation of labor is,

$$\frac{\nu_a\left(l_{at}^a\right)^{-\Phi} + (1-\nu_a)\left(l_{at}^a + l_{bt}^a\right)^{-\Phi}}{(1-\nu_a)\left(l_{at}^a + l_{bt}^a\right)^{-\Phi}} = \frac{W_{at}}{W_{bt}} \tag{43}$$

Given wages and consumption, equations (42) and (43) pin down l_{at}^a and l_{bt}^a.

Finally, we select ν_a such that in steady state, no households from a work in b, i.e., $l_b^a = 0$.

$$\frac{1}{(1-\nu_A)} = \frac{w_A}{w_B} \rightarrow \nu_A = 1 - \frac{w_B}{w_A} \tag{44}$$

4.4.2 Firms

Production is linear in labor, but now sector b incorporates potential hiring from sector a.

$$\begin{aligned} Y_a &= \phi l_a \\ Y_b &= \phi \left[l_b + l_b^a \right] \\ Y_2 &= (1-\phi)\, l_2 \end{aligned} \tag{45}$$

Finally, we will assume that profits from sector a continue to be sent to workers in that sector, even those who work in sector b. The latter, however, only receive the profits from a and not from b.

4.4.3 The Model with Labor Reallocation

We now ask how allowing labor mobility from sector a to b affects our simulation of the crisis. To do so we explore how the model behaves under different values of the parameter Φ, which governs the marginal cost of sector a households supplying labor to b. In our benchmark case, we pick a value of Φ equal to minus ten. This value implies that the amount of labor that shifts from a to b during the height of the crisis equals ten percent of steady state labor supplied by households in a, which we consider a fairly sizable shift.

Figure 12 shows the results. The solid line is the model with labor mobility, while the dashed line is our baseline. As the figure shows, there is no tangible impact. While labor mobility reduces the decline in income suffered by sector a households, it also reduces the gains by sector b workers which works in an offsetting direction. The increased supply of labor to sector b dampens wages in this sector, which hurts sector b workers and limits the gains to sector a workers that cross over. As a result, the decline in sector 2 ,which comes largely from the decline in spending by contact sector households, is largely unaffected.

We next consider what happens as we increase labor mobility. Figure 13 considers three

cases, which correspond to different values of Φ: $-10, -5$ and -0.5. Increasing Φ increases mobility by reducing the marginal cost of crossing from a to b. We then show the impact on the decline in sector 2, where we would expect the impact of mobility to show up. As we raise mobility by increasing Φ from -10 to -5, hours that sector a households work in b as a percent of steady state hours goes up from ten to eighteen percent. However, there is still no tangible impact on the sectoral revenue decline. With Φ as high as -0.5, there is a difference. In this case, sector 2 revenues fall only by a third the amount in the baseline. However, in this case, the amount of reallocation is huge: sector a households work nearly forty five percent of their steady state hours in sector b at the peak of the crisis. Given the behavior of unemployment in the data, this level of reallocation does not seem plausible.

5 Conclusion

We have analyzed how reallocation due to shifts from Covid susceptible contact sector products to safe substitutes has affected the unequal pattern of the pandemic recession, including the contraction phase, the recovery phase and expected future behavior. We first develop measures of aggregate revenue behavior for three sectors, including: contact sector losers, contact sector winners and the non-contact sector. We find that contact sector losers experienced the sharpest contraction and slowest recovery. Contact sector winners gained throughout the crisis. Further, using analyst's forecast data, we find that the gap between winners and losers is expected to persist well beyond the pandemic.

To explain the data we develop a simple three sector New Keynesian model with incomplete markets. There are two key differences from the recent literature: First, we disaggregate the contact sector into an "exposed" sub-sector (losers) and a subsector (winners) that offers safe substitute goods. Second, we allow for learning by doing to introduce some persistence in the gap between winners and losers. Beyond this, the model is quartely and there are both demand and suppy shocks to the Covid exposed sub-sector. Overall, the model does

a reasonable job of capturing the data, particularly the uneven sectoral contraction and recovery phase. The learning by doing, however, only accounts for a fraction of the expected persistence between winners and losers revenue growth. Though as we have noted, our measure of forecasted persistence is quite imprecise. Nonetheless, it may be necessary to consider other sources of persistence such as habit formation.

Finally, it is worth considering whether our model of sectoral substitution and business cycles may be relevant beyond the pandemic recession. One potential application may be an open economy framework, where domestic and foreign producers produce tradable goods that are close substitutes. A shock that favors foreign producers (e.g., a large exchange rate appreciation or a significant trade liberalization) will then induce substitution from domestic to foreign producers. To the extent there are complementarities between the domestic tradable and non-tradable sectors (due either to incomplete markets or input/output links), the sectoral shock will generate a decline in the nontradable goods sector. The magnitude of the decline, further, will be increasing in the substitutability between domestic and foreign tradables. Finding and fleshing out examples like this is something on the agenda for future research.

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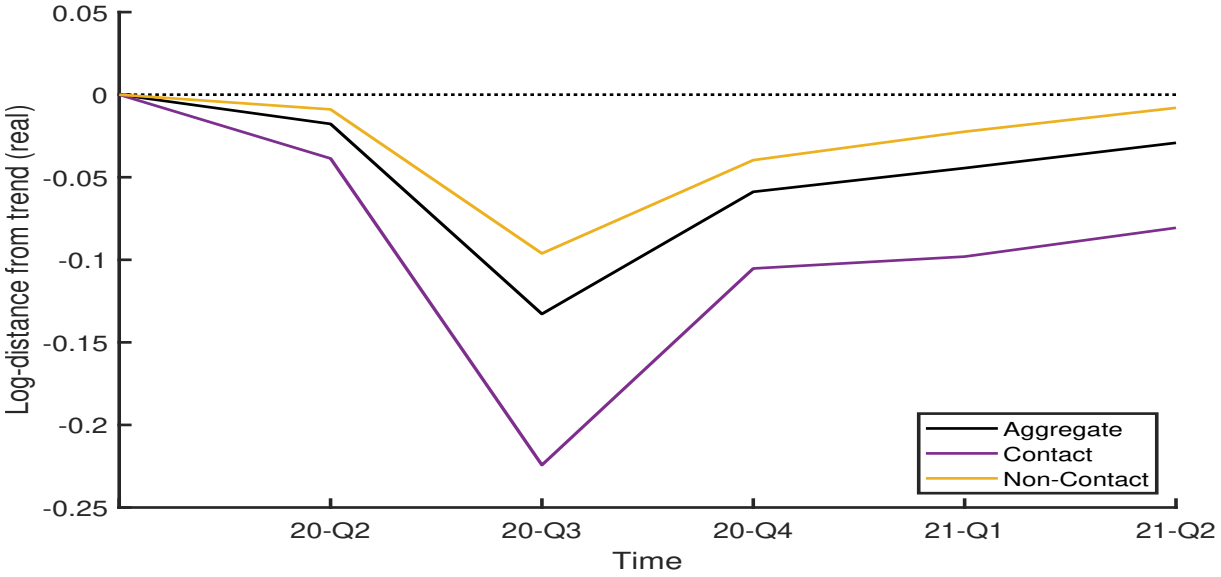
6 Figures and Tables

Table 1: Contact and Non-Contact Classification

Non Contact		Contact
Agriculture, fishing, and hunting (11)		Retail trade (44-45)
Mining, Quarrying, and Oil and Gas (21)		Air, rail, and water; Transit and Sc transportation (481-483,485,487,488)
Construction (23)		Educational services (61)
Manufacturing (31-33)		Health care and social assist.(62)
Wholesale trade (42)		Arts, Entertainment, and Recreation (71)
Truck and Pipeline transportation (484,486)		Accommodation and Food Services (72)
Postal transportation (491,492)		Other services (excluding P.A.) (81)
Warehousing and storage (493)		Real estate, rental and leasing services (531-3)
Real estate (53)		Information (51)*
Professional and business services (54)		
Management of Companies and Enterprises (55)		
Administrative and Support and Waste Management and Remediation Services(56)		
Information (51)*		
Revenue share:	70%	30%
Value added share:	68%	32%
Employment share:	46%	54%

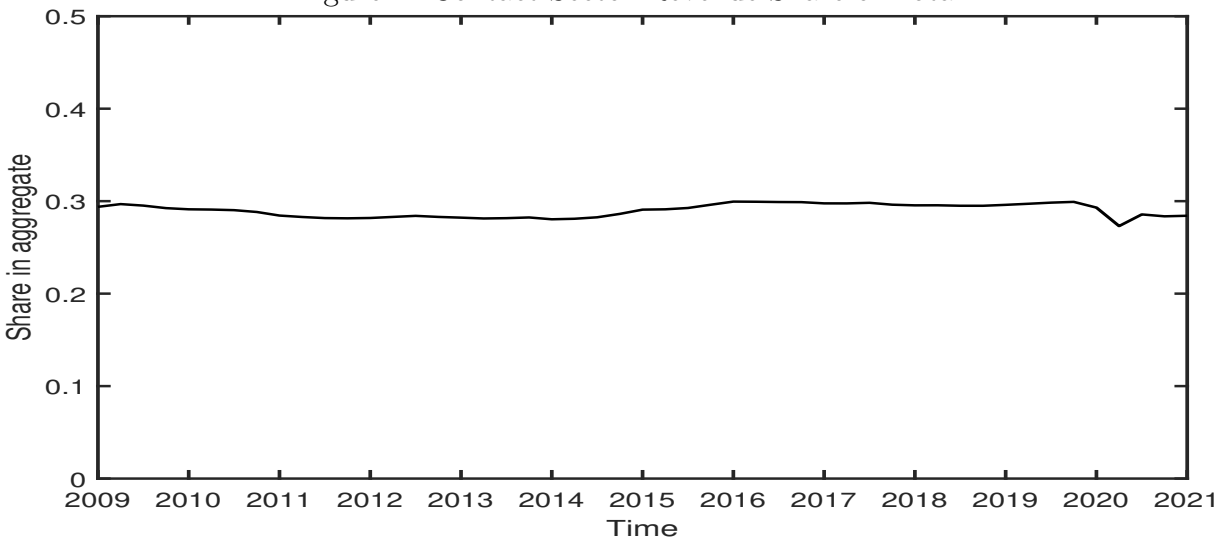
Note: Table shows our classification of sectors between Contact and Non-Contact using NAICS codes. Information sector (51) companies that offer a close substitute good or service to Contact sub-sectors are included in the Contact sector. Details for the classification are in Appendix 6. Employment share excludes agricultural employment.

Figure 1: Revenue During Recession: Contact vs Non-Contact Sector



Note: Figure shows the log-distance from trend of real revenue of the aggregate economy, the contact and the non-contact sector as classified in Table 1. Nominal output data comes from the BEA and is transformed to real using the Chain-Type Price Indexes for Gross Output for Private Industries. Trends assumed are 4% for nominal output and 2% for prices.

Figure 2: Contact Sector Revenue Share of Total



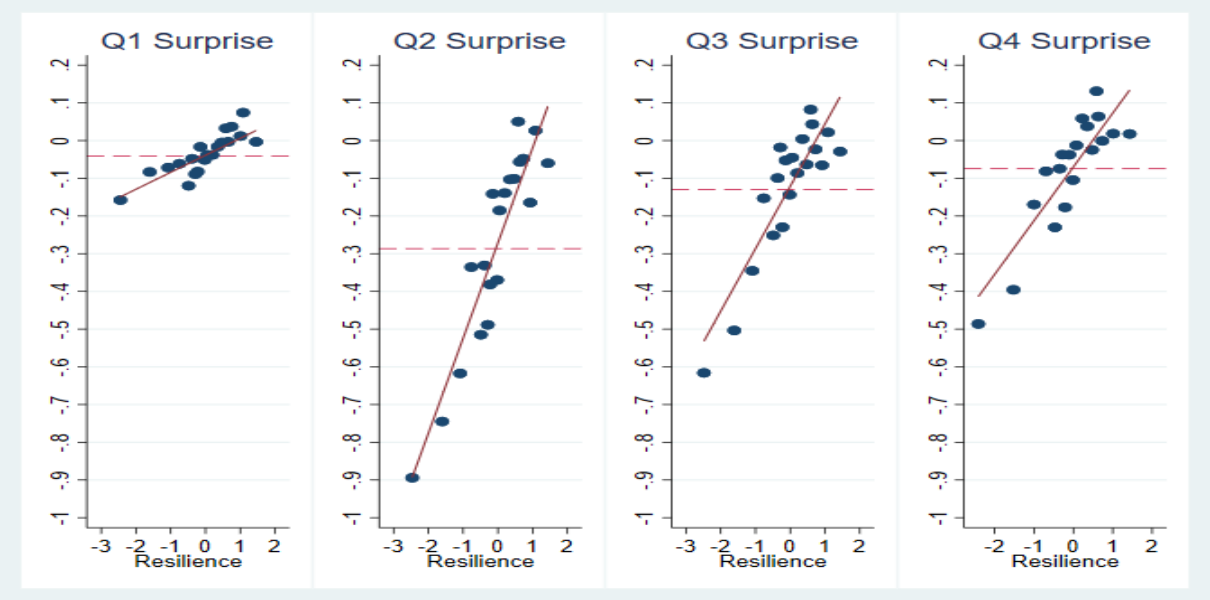
Note: Figure shows the share of the contact sector, as defined in Table 1, in aggregate output.

Table 2: Covid Resilience and Revenue Surprises

	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
Resilience	0.045***	0.252***	0.165***	0.143***	0.010	0.049*	0.043**	0.042**
	(6.69)	(8.59)	(7.54)	(7.60)	(1.75)	(2.53)	(2.69)	(2.71)
Industry FE (NAICS 4)	N	N	N	N	Y	Y	Y	Y
Size (revenue 2019)	N	N	N	N	Y	Y	Y	Y
R^2	0.217	0.280	0.262	0.241	0.751	0.888	0.859	0.819
N	960	960	960	960	960	960	960	960

Note: The dependent variable is the difference between the log of realized revenue from Compustat with the log of the median expected revenue from IBES reported in February 2020 for each firm in the sample. The independent variable in columns 1-4 is our measure of Covid resilience. Columns 4-8 include NAICS 4 fixed effect and revenue in 2019 fiscal year for each company. The sample of firms is the same across periods and the regression is weighted using previous year quarterly revenue for each quarter. Standard errors are robust to heteroskedasticity (White (1980)).

Figure 3: Covid Resilience and Revenue Surprises



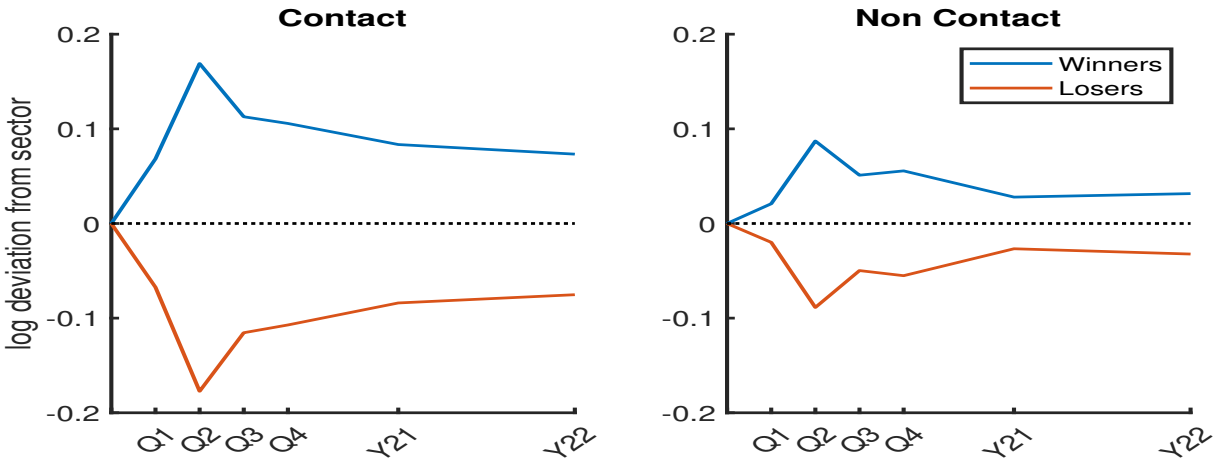
Note: Figure shows a binscatter for each quarter of the weighted revenue surprises defined as the log of realized revenue from Compustat with the log of the median expected revenue from IBES reported in February 2020 for each firm in the sample plotted as a function of our measure of Covid resilience. The regression line is the slope estimated in columns 1-4 of Table 2. The dash horizontal line reports the surprise for the median firm for that quarter.

Table 3: Covid Resilience and Revenue Surprises: Long-Term

No Fixed Effects:						
	Q1	Q2	Q3	Q4	Y21	Y22
Exposure	0.049***	0.229***	0.149***	0.142***	0.083***	0.069***
	(8.38)	(9.72)	(8.28)	(7.60)	(6.37)	(4.35)
Industry FE (NAICS 4)	N	N	N	N	N	N
Size (revenue 2019)	N	N	N	N	N	N
R^2	0.160	0.250	0.225	0.241	0.155	0.154
N	1644	1622	1591	967	1539	711
Fixed Effects:						
	Q1	Q2	Q3	Q4	Y21	Y22
Exposure	0.016**	0.068***	0.046***	0.042**	0.048***	0.039
	(3.02)	(3.94)	(3.69)	(2.74)	(3.69)	(1.82)
Industry FE (NAICS 4)	Y	Y	Y	Y	Y	Y
Size (revenue 2019)	Y	Y	Y	Y	Y	Y
R^2	0.701	0.831	0.815	0.819	0.609	0.542
N	1644	1622	1591	967	1539	711

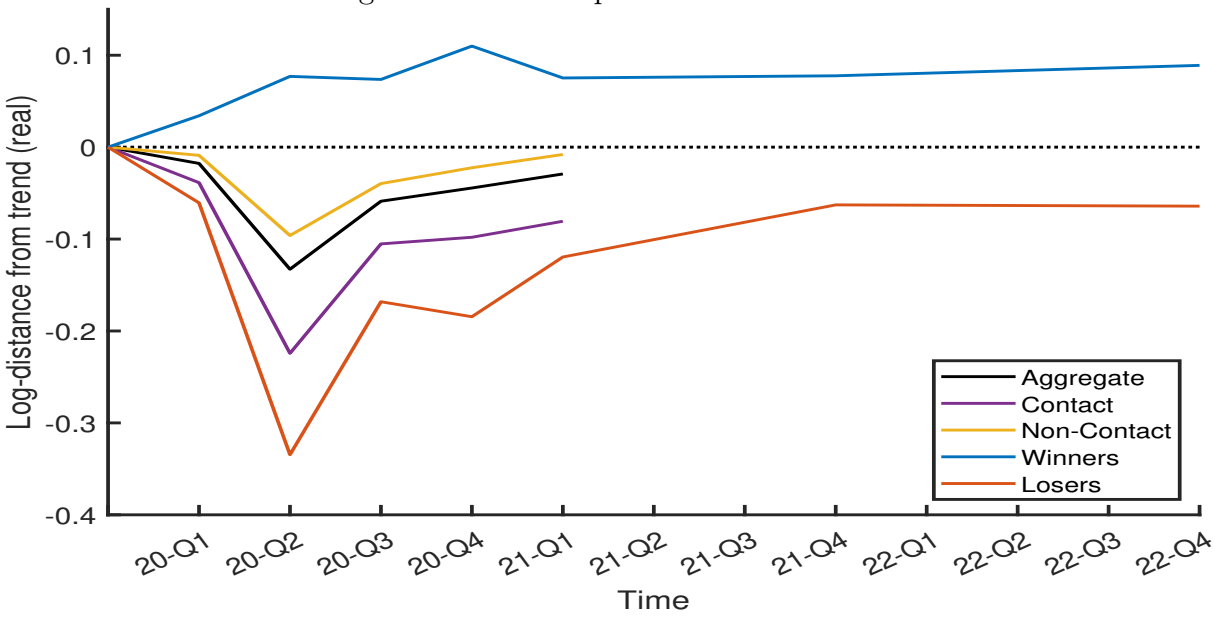
Note: For Q1-Q4 the dependent variable is the difference between the log of realized revenue from Compustat with the log of the median expected revenue from IBES reported in February 2020 for each firm in the sample. For Y21 and Y22 the realized revenue is replace by the updated forecast reported in May 2021. The independent variable in the upper panel is our measure of Covid resilience. The bottom panel include NAICS 4 fixed effect and revenue in 2019 fiscal year for each company. The sample of firms varies across quarter depending whether a forecast was available for that time. The regression is weighted using previous year revenue for each period. Standard errors are robust to heteroskedasticity (White (1980)).

Figure 4: Winners vs Losers: Deviation from Sector Mean



Note: Figure shows the evolution of the sum of revenue surprises for winners and losers of each sector relative to the sectoral aggregate surprise. Surprises in revenue are defined as the difference between the log of realized revenue from Compustat with the log of the median expected revenue from IBES reported in February 2020 for each firm in the sample. For Y21 and Y22 the realized revenue is replace by the updated forecast reported in May 2021. Winners in each sector are defined as those with positive Covid resilience relative to sectoral revenue weighted median.

Figure 5: The Unequal Pandemic Recession



Note: Figure shows the log-distance from expectations of real revenue of the aggregate economy, Contact and Non-Contact sector as classified in Table 1, and winners and losers as classified in Section 2. Nominal output data for aggregate and sectors come from the BEA and is transformed to real using the Chain-Type Price Indexes for Gross Output for Private Industries. Trends assumed are 4% for nominal output and 2% for prices. Nominal output data for winners comes from Compustat. Surprises in revenue for the winners are defined as the difference between the log of realized revenue with the log of the median expected revenue from IBES reported in February 2020 for each firm in the sample. For Y21 and Y22 the realized revenue for winners is replace by the updated forecast reported in May 2021 and the annual growth is interpolated between quarters. Losers are defined as any revenue in BEA that is not winning in Compustat. The surprise for the losers is obtain as the residual between winners the Contact sector.

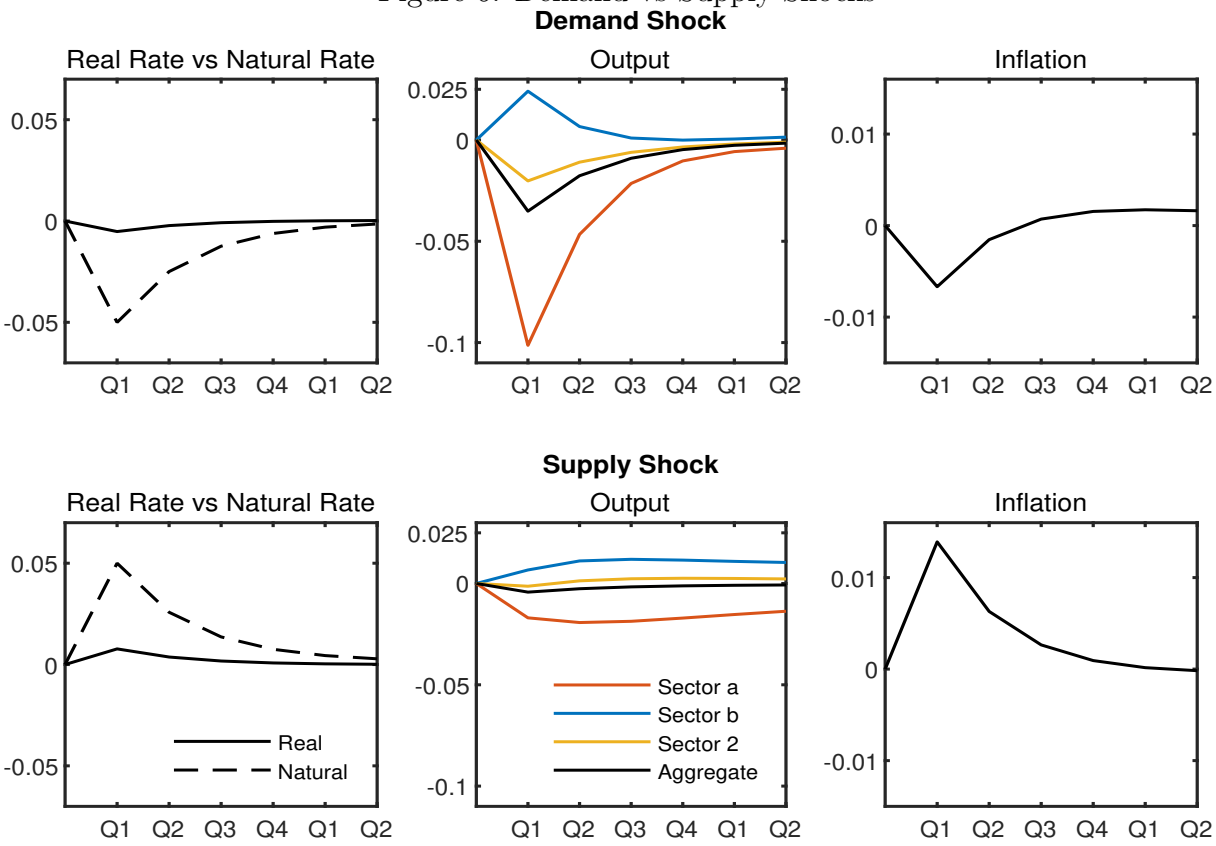
Table 4: Winners and Losers Examples

	Contact			Non - Contact	
	Sub - Sectors	**Examples (Resilience)**		**Sub - Sectors**	**Examples (Resilience)**
Winners			**Winners**		
	Non-Store retailers	Amazon (0.59) Ebay (0.34) Domino's Pizza (0.71)		Pharma companies	Johnson and Johnson (0.66) Pfizer (0.72) MaKesson (0.41)
	Supercenters	Walmart (1.08) Target (0.74)		Covid related	Procter and Gamble (0.87) 3M (0.61) Clorox (2.3)
	Work from Home	Zoom (4.15)		Transportation	UPS (0.11) CH Robinson (0.77)
	Online entertainment	Netflix (0.57) Spotify (0.8) Electronic Arts (0.96)			
	Cloud and Software Services	Dropbox (0.46) Carecloud (2.3)			
	Supermarkets	Kroger (2.03) Costco (0.65)			
Losers			**Losers**		
	Airlines	United (-1.36) American (-2.44) Delta (-1.25)		Air industry	Boeing (-2.2) Raytheon (-1.7)
	Cruise	Norwegian (-2.88) Carnival (-1.76)		Automobile	General Motors (-0.3) Ford (-0.3) Goodyear (-0.67)
	Transportation	Uber (-1.3) Lyft (-2.06)			
	Retail chains	Macy's (-1.6) Bed Bath and Beyond (-0.8) Nordstrom (-0.87)			
	Hotels	Marriot (-1.66) Hilton (-0.85)			
	Casinos	Golden (-5.2) Caesars (-4.2)			
	Restaurants	Darden (-1.9) BJ's restaurants (-3.8)			

Table 5: Parameter Selection

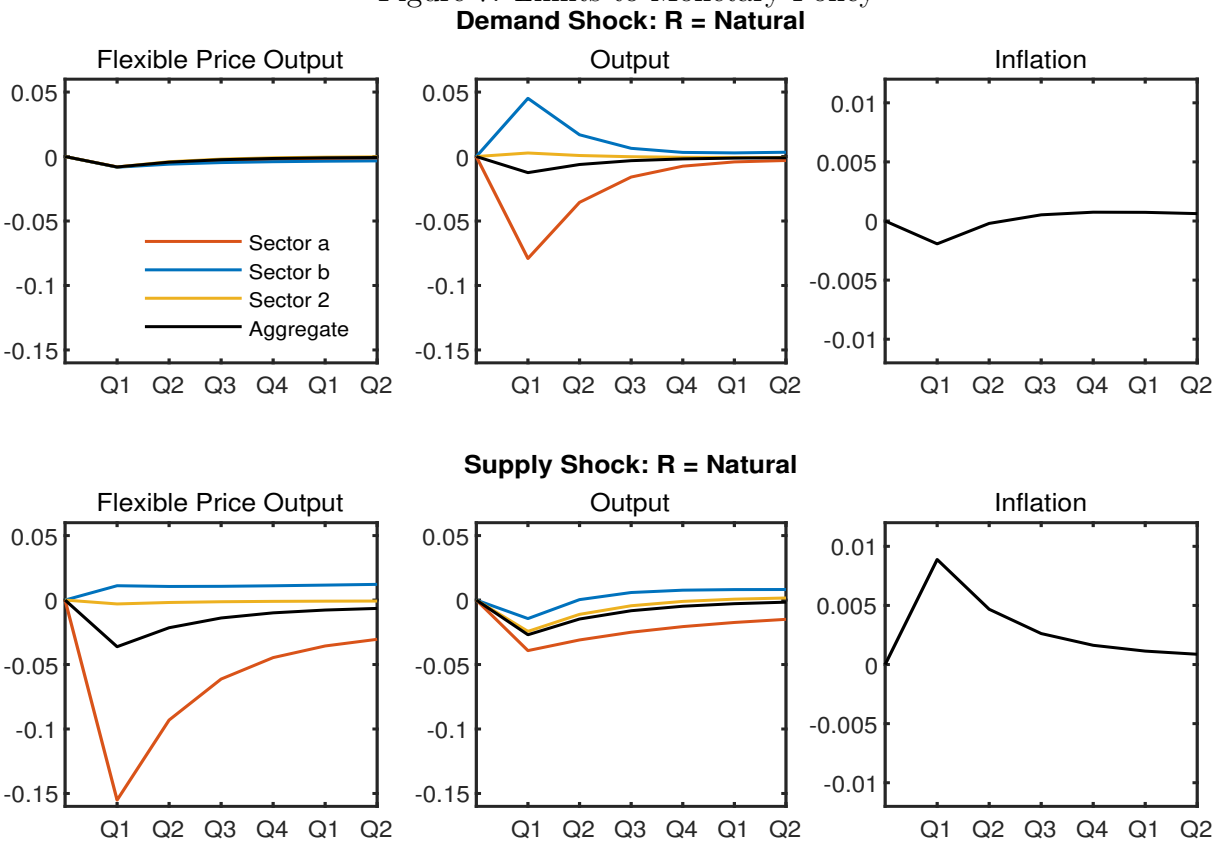
Parameter	Value	Description
Standard Parameters		
β	0.995	$r = 2p.p.$
φ	1	Labor elasticity
γ	0.9	Calvo parameter
ε	6	Final good elasticity. Markup of 20%
Sectoral Parameters		
ϕ	0.3	Contact Sector as a fraction of Total
ζ	0.75	Losers as a fraction of Contact sector
$1/\rho$	2	Intra-temporal sectoral substitution
ρ_ϵ	0.5	Persistence of labor supply shock
ρ_η	0.5	Persistence of demand shock
Learning by Doing Parameters		
σ_a	0.1	Sensitivity of Losers
σ_b	0.2	Sensitivity of Winners
ρ_a	0.95	Persistence of Losers
ρ_b	0.95	Persistence of Winners

Figure 6: Demand vs Supply Shocks



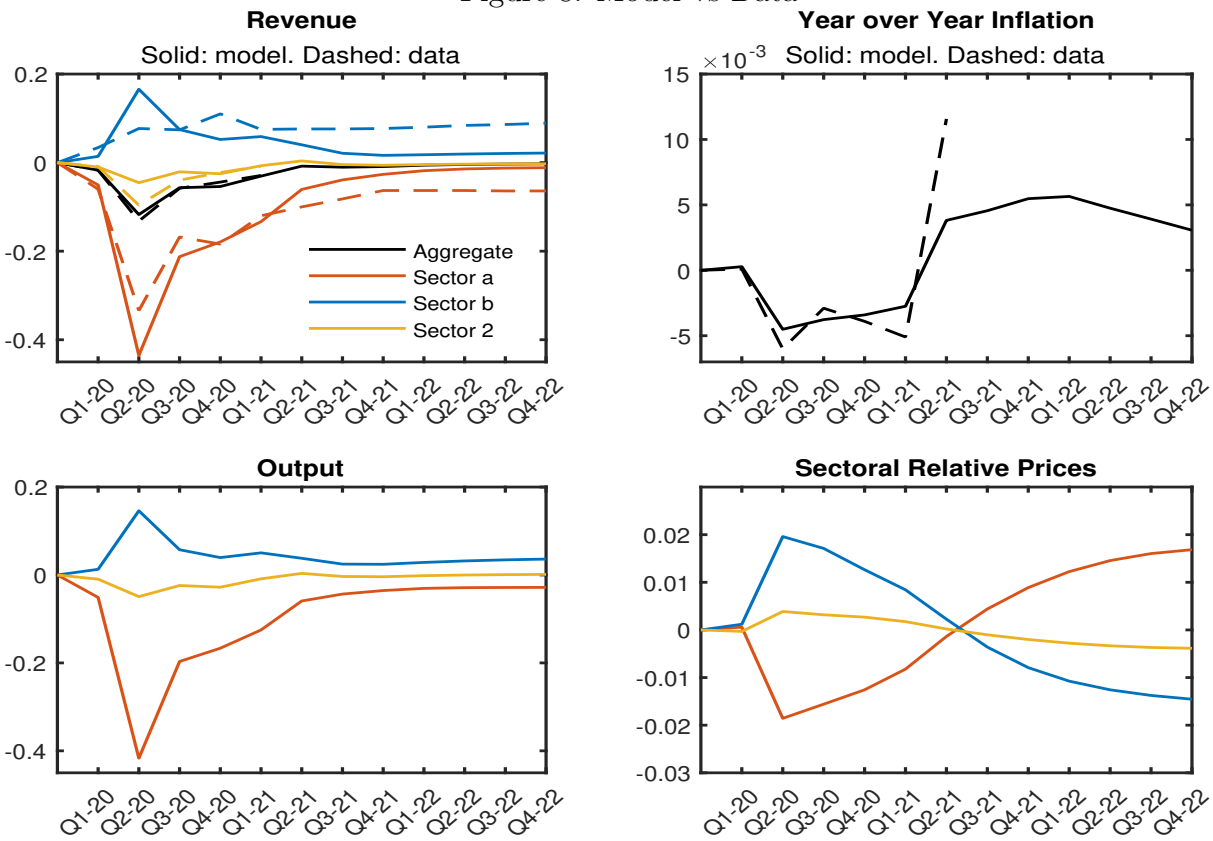
Note: Figure shows the response of the model to a one time negative demand (first row) and supply (second row) shocks. Shocks are normalized so that each initially generates a five hundred basic point change in the natural rate of interest.

Figure 7: Limits to Monetary Policy



Note: Figure shows the response of the model to a one time negative demand (first row) and supply (second row) shocks under flexible prices (first column), with nominal rigidities but the real rate tracking the natural (second column) and inflation (third column). Shocks are normalized so that each initially generates a five hundred basic point change in the natural rate of interest.

Figure 8: Model vs Data

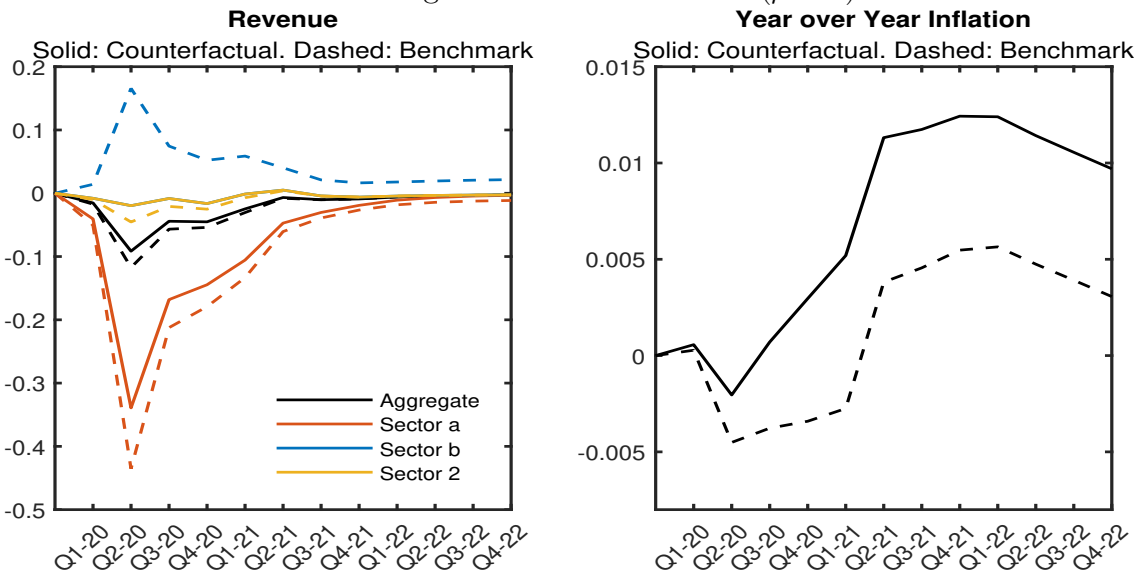


Note: Figure shows the response of our benchmark model to the estimated shocks (solid line) and the data (dashed line).

Table 6: Average Revenue Change in 2020

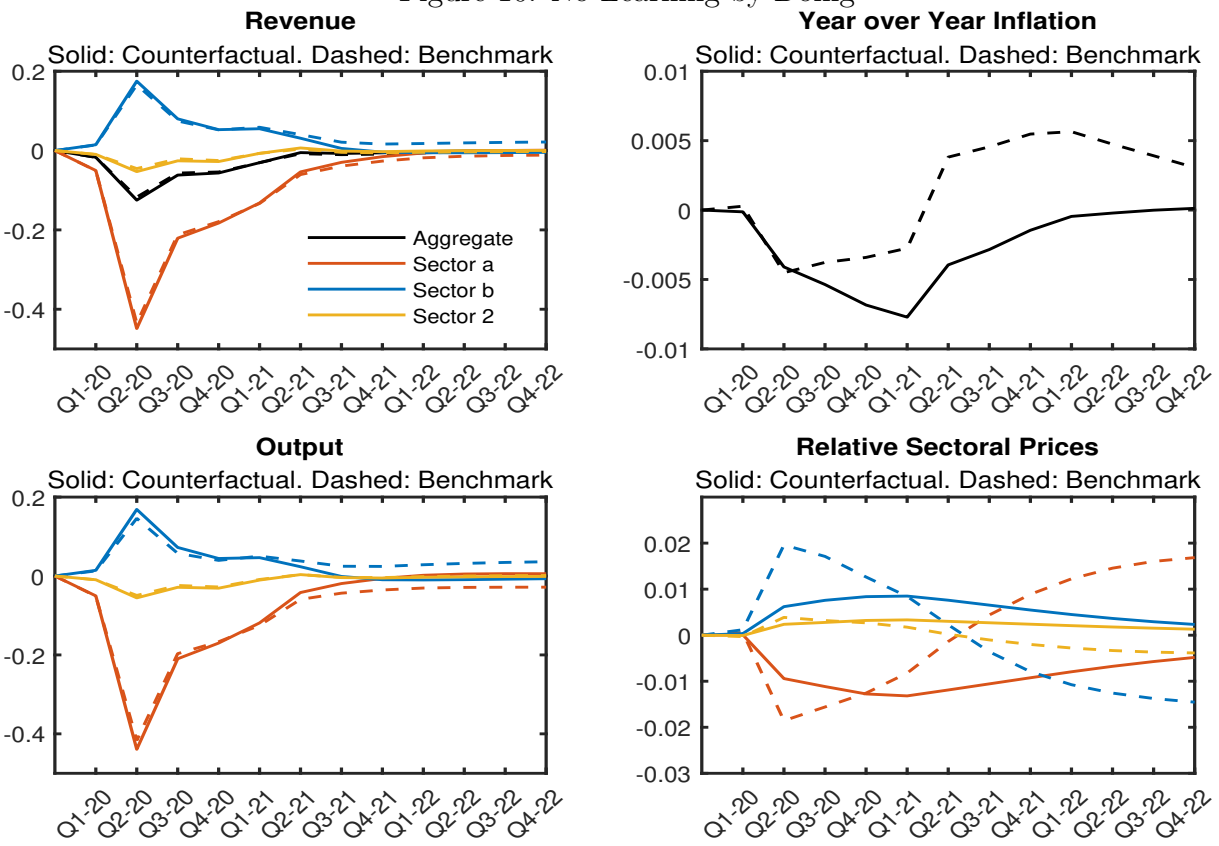
	Aggregate	Sector a	Sector b	Sector 2
Data	-6.28	-18.65	7.38	-4.17
Benchmark	-6.13	-21.94	7.66	-2.53
No Substitution	-4.90	-17.31	-1.30	-1.30
No Fiscal Policy	-6.94	-22.73	6.81	-3.34
No Monetary Easing	-7.22	-23.03	6.60	-3.62

Figure 9: No Substitution ($\rho = 1$)



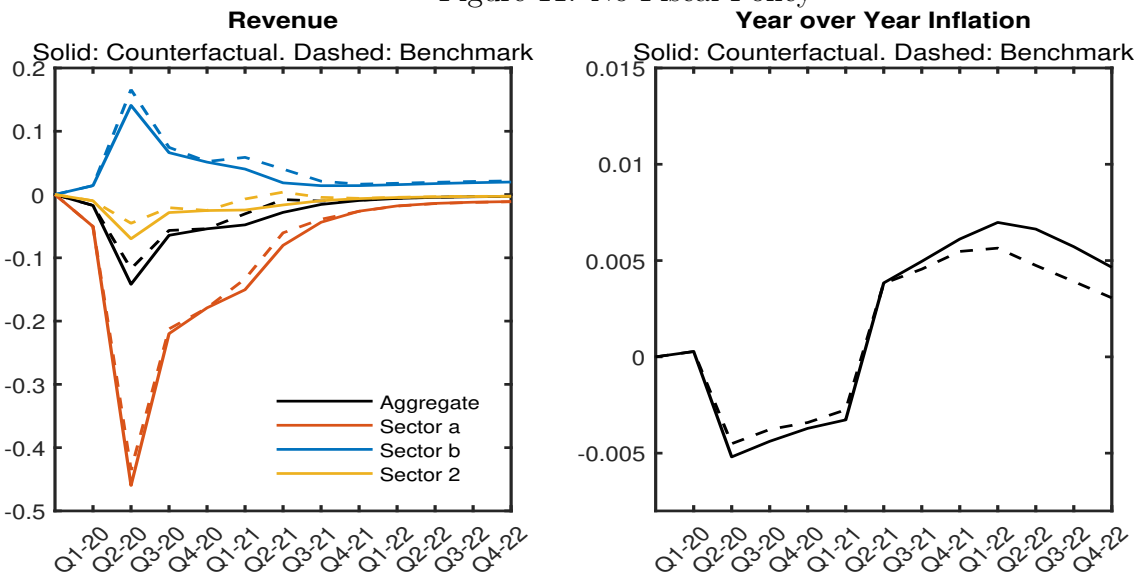
Note: Figure compares response to the estimated shocks of our benchmark model (dashed line) and the counterfactual with perfect substitution between subsectors.

Figure 10: No Learning by Doing



Note: Figure compares response to the estimated shocks of our benchmark model (dashed line) and the counterfactual without learning by doing $\sigma_{a,b} = 0$ (solid line).

Figure 11: No Fiscal Policy



Note: Figure compares response to the estimated shocks of our benchmark model (dashed line) and the counterfactual with no transfer not unemployment benefits.

Figure 12: Labor Reallocation

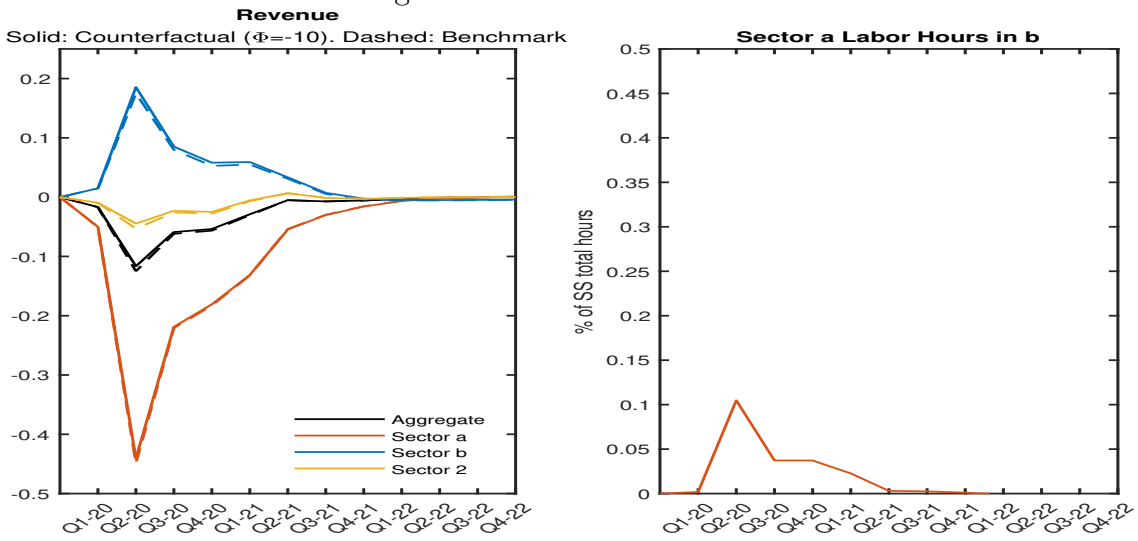
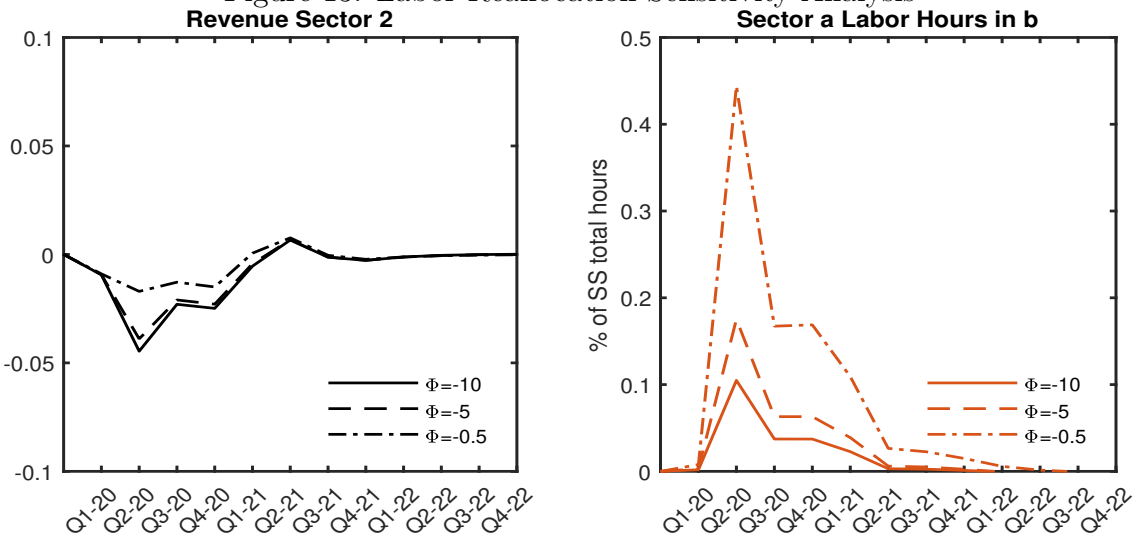


Figure 13: Labor Reallocation Sensitivity Analysis



Appendix A: Data

We make use of the following seven data series:

1. Quarterly gross output by industry: Bureau of Economic Analysis (BEA)
2. Chain-Type Price Indexes for Gross Output by Industry (BEA)
3. Compustat Fundamentals of Public Firms, Quarterly: Wharton Research Data Services (WRDS)
4. Stock market prices: Compustat security daily table (WRDS)
5. Revenue Forecast of Public Firms: I/B/E/S Academic Summary History from Thomson Reuters (WRDS).
6. Consumer price index: Cavallo (2020) Covid adjusted core CPI.
7. Aggregate data forecasts: International Monetary Fund World Economic Outlook October 2019.

Figure 1: Detrended Aggregate and Sectoral Revenue Growth

Figure 1 shows the log-distance between realized real output and its trend. In order to construct the series for real sectoral output, we first aggregate realized nominal output from BEA following our classification in Table 1 of contact and non-contact sectors. Then, we deflate using the price index. Finally, real output trend is constructed assuming a two percent annual trend real growth based on the 2019Q4 IMF World Economic Outlook October 2019.

Issues Involving Compustat Data

Sample Selection

We follow a criteria similar to Dinlersoz, Hyatt, Kalemli-Ozcan, and Penciakova (2019) on selecting firms: We do not include firms that do not report a NAICS code or have a NAICS 3 code equal to 525 (Financial Instruments). We also delete those that do not have EIN and are not incorporated in the US or do not report a US State in the address. Finally, we exclude the utilities sector because its heavily regulated price collapsed at the same time that the Covid pandemic started for reasons not captured in our model. Also, we exclude financial industries that were the target of regulations not included in our model that could affect their performance during the crisis.

Exposure Creation

We calculate the percent change in the daily closure price of each stock on Covid news days which we define following Davis, Hansen, and Seminario-Amez (2020). The dates include February 24, 25 and 27, and March 03, 05, 11, 16, 18 and 27, of 2020. We keep firms' tickers with at least 90 observations in 2019 and calculate the median percent change in prices for each ticker across all Covid days. Since each company can have more than one actively traded ticker in the stock market, we take the mean across all tickers for each company. We then merge this measure with its fundamentals using the provided "gvkey" in Compustat. In order to normalize the exposure, we calculate the median and standard deviation across firms weighted by the yearly revenue in the 2019 fiscal year. We keep firms that have reported revenues in every quarter of 2019 and 2020.

Merging Compustat with Forecast Data from I/B/E/S

Forecasts data from I/B/E/S is performed at the ticker level and merging this data with company fundamentals in Compustat is not straightforward. We use the Linking Suite tables provided by Wharton Research Data Services that use PERMNO to first link I/B/E/S with CRSP tickers, and then CRSP with Compustat using the CRSP/Compustat Linking table.

Calendar versus Fiscal Time Periods

A public firm reports quarterly/yearly revenue following its own fiscal timeline that might not correspond with the same calendar quarter/year the BEA reports output. Following Compustat procedures, we define a firm's fiscal quarter as belonging to a calendar quarter if two out of three months of its fiscal quarter are included in the calendar quarter. In the same fashion, a firm's fiscal year belongs to a calendar year if seven out of twelve months of its fiscal year are included in the calendar year.

When we compute the moments for calibration, we keep firms whose fiscal quarter timeline coincides with the calendar periods in order to correctly capture the revenue dynamics of Q2-2020. Our results are robust to using the entire universe of firms.

Revenue Surprises

The expected path of revenues are computed using forecasts reported on February 20, 2020. For each period, we keep firms with at least three forecasts and we obtain a profile of expected revenue as the median estimate across all forecasts. We do this for the calendar periods: Q1-2020, Q2-2020 Q3-2020, Q4-2020, Year 2021 and Year 2022. We define the revenue surprise for each firm/period as the linear difference between the logarithm of the realized revenue with the logarithm of the expected one in February 2020. For the year 2021 and 2022 we compared the revisited forecast in May 2021 with the one in February 2020.

For the analysis up to Q4-2020 we keep a stable panel of firms with no missing data for any quarter. For the analysis that involve surprises of year 2021 and 2022 the sample of firms without missing data is small. Accordingly, we keep the entire universe of firms in this latter case.

Winners and Losers

We define a publicly traded firm as a winner if its Covid resilience measure (see equation (1)) is positive. This means that the firm's resilience is above the median of resilience for the

firms in its respective sector. We use the entire universe of Compustat firms to identify a firm Covid resilience measure. When we construct measures of revenue surprises for winners versus losers, though, we do not include firms that have missing values for forecasts. As we note in the text, we focus on winners in the contact sector since these firms appear to offer substitutes for the losing firms, in contrast to their counterparts in the non-contact sector. Also, the gap between winners and losers in the contact sector is more than double that in the non-contact sector.

In order to construct the series of revenue surprises for contact sector winners that appears in Figure 5, we first assume that only publicly traded firms are winners. Next, we compute the aggregate revenue surprise across our identified winners in the contact sector. Then, to construct the measure for contact sector losers, we subtract the revenue surprises for winners from the corresponding aggregate revenue surprise from BEA, which includes the entire universe of firms. For years 2021 and 2022 we do not have an ex-post revenue surprise. We accordingly make use of the surprise in the May 2021 forecast relative to the February 2020 forecast.

Information Sector: Contact - Non-Contact Sector Subdivision

A firm in our sample that belongs to the information sector (NAICS code 51) will be classified as non-contact unless it supplies a good or service that is a close substitute to one in the contact sector, in which case will be classified as a contact sector firm. In order to identify firms in the information sector that do provide good substitutes we combine two industry classifications: the NAICS and the GICS.

We do not find it possible to use NAICS sub-sectors classification to point to firm groups that simultaneously provide good substitutes to those in the contact sector and are also information firms. Alternatively, we use the GICS (Global Industry Classification Standard), another industry classification, that is better for subtracting close substitutes for risky contact sector goods.

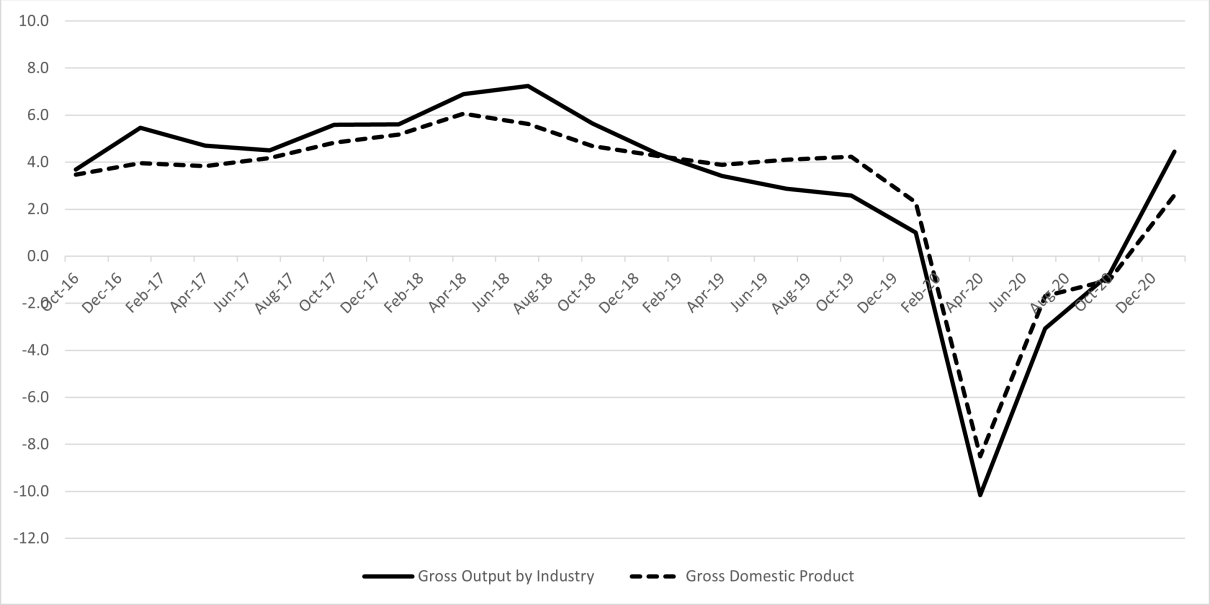
Then, we can make sure that a firm belongs to the information sector by fixing its NAICS code to be equal 51, and then use the GICS classification to match a similar sub-sector with one in the contact sector. Then, we call a firm in the information sector a close substitute (and re-classify it as contact) if this any of these criteria are met:

- Close substitute to Retail: firms in GICS 2550 (Retailing) and NAICS 51.
- Close substitute to Health care and social assist: GICS 3510 (Health Care Equipment & Services) and NAICS 51.
- Close substitute to Arts, Entertainment, and Recreation: GICS 502020 (Entertainment) and NAICS 51.
- Close substitute to Air, rail, and water transportation, Educational services and Accommodation: These activities were replaced partially by remote work substitutes: IT services. We can identify these companies by those classified as,
  - Education: GICS 25302010 (Education Services) and NAICS 51.
  - IT services: GICS 4510 (Software & Services)

We correct our aggregate sectoral data from BEA to account for this partition of the Information sector. In order to do this, we calculate the share of close substitutes in the Information sector in Compustat. We assume this share is representative and split the BEA Information sector between Contact and Non-Contact using this fraction.

GDP and Gross Output During the Crisis

Figure 14: Gross Domestic Product vs Gross Output by Industry



Note: Figure shows the percent change year over year for the GDP and Gross Output by Industry for Private Industries. Data is obtained from FRED (https://fred.stlouisfed.org/)

Appendix B: Simulating the Pandemic

Shock Selection

Demand and supply shocks are selected to minimize the distance between the model and the data. Specifically, we use data between Q1-2020 and Q1-2021 on revenue surprises and inflation. For revenue surprises, we use the data from Figure 5 on winners, losers and the aggregate. For consumer inflation, we use Cavallo's (2020) core Covid CPI index detrended using its mean realization for 2019. The selection of shocks is performed by minimizing the quadratic distance where each sectoral revenue surprise is weighted by the size of the sector.

Monetary Policy

We assume that the central bank sets the nominal rate to zero in Q2-2020 and is expected to keep it at zero for four quarters before resuming its policy rule of a (nearly) constant real rate.

Fiscal Policy

Fiscal Policy in our model consists of transfers and unemployment benefits to sector a financed by lump-sum taxes in sector b and 2. This assumption is based on the fact that Ricardian equivalence holds for sector b and 2 agents and so any lump-sum transfer that is directed to them will not produce any output change. The timeline and size of the transfers are,

Table 7: Fiscal Policy as a share of Q4 annualized GDP

	Q1-20	**Q2-20**	**Q3-20**	**Q4-20**	**Q1-21**	**Q2-21**	**Q3-21**	**Q4-21**
Transfers	0	0.013	0	0	0.01	0.013	0	0
Unemployment Benefits	0	0.009	0.007	0	0.005	0.005	0.005	0

Sources: https://www.covidmoneytracker.org/, Faria-e Castro (2021) and authors' assumptions on timing.

We assume that transfers are distributed on a per-capita basis, which gives agents in sector a a share of $\frac{1}{1+\phi}$ per-capita of each quarterly direct payment. Since unemployment benefits depend on the employment condition, and we do not have a direct measure of unemployment in our model, we choose the share of the transfers that goes to agents in sector a in order to match the partial equilibrium contribution of 2% extra spending for the first round of payments, as estimated by Farrell, Ganong, Greig, Liebeskind, Noel, and Vavra (2020).[23]

[23]Since our model has only consumption goods, and consumption is roughly 2/3 of spending, we actually match 2/3 of the estimated contribution.