Economic Winners versus Losers

and

The Unequal Pandemic Recession

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Abstract

As is well known, during the pandemic recession firms directly exposed to the virus, i.e. the "contact" sector, contracted sharply and recovered 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 at least through 2022. To explain this evidence, we then develop a simple three sector New Keynesian model with (i) a sector of firms that offers safe substitutes for risky contact sector goods and (ii) learning by doing. Overall, the model captures the unequal sectoral recession. It also accounts for inflation, including the sharp runup in 2021.

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 2019:Q1 to 2021:Q3, we plot revenue relative to trend for the contact sector (purple line), the non-contact sector (yellow) and the aggregate (black). The contact sector, which accounts for roughly thirty percent of total revenue, contracts approximately 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 almost returns to trend in 2021:Q1 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 that involve exposure to the virus 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 losing 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 both measure and model the uneven sectoral dynamics of the pandemic

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[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.

Figure 1: Revenue During Recession: Contact vs Non-Contact Sector
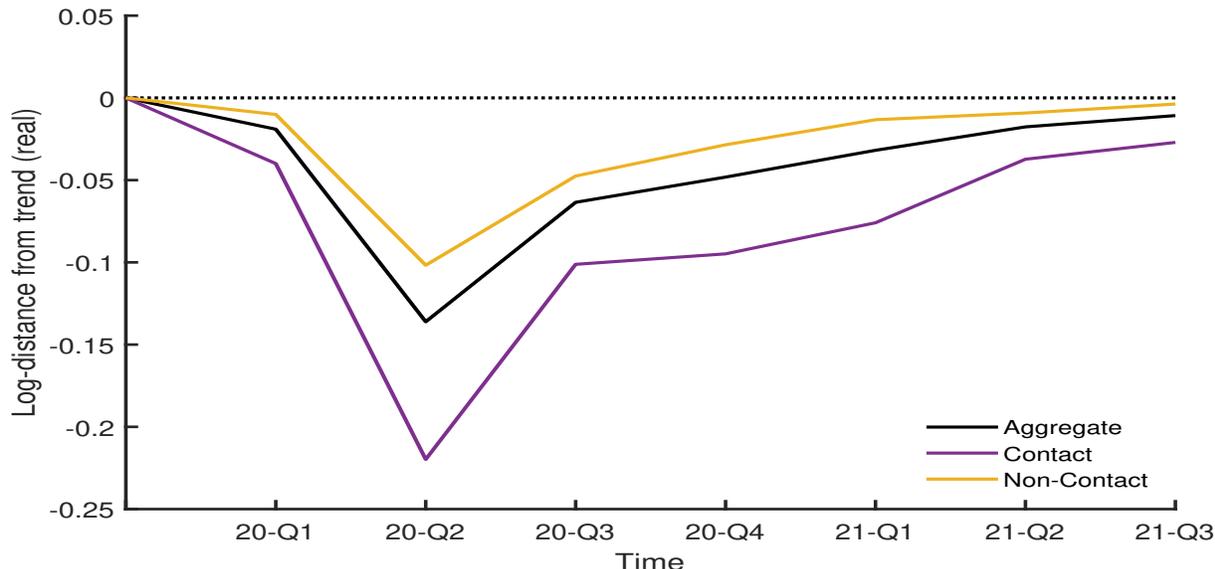
Note: Figure shows the log-distance from trend of real revenue of the aggregate economy, the contact and the non-contact sector as classified in Table 7. Nominal output data comes from the BEA and is transformed to real using the Chain-Type Price Indexes for Gross Output for Private Industries. Trends assumed are 4% for nominal output and 2% for prices.

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. As a byproduct, our framework also accounts for inflation, including the recent increase in 2021.

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, within the contact sector, the winners we measure indeed offer goods that are substitutes for those provided by losers. 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 revenue 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 almost fifteen percent above trend in 2021:Q1. 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 (2020) (GLSW), Baqaee and Farhi (2020) (BF), Faria-e Castro (2021), KMV and others. Our baseline framework is a simple three sector New Keynesian model with incomplete markets. We differ in two main ways: First we allow for contact sector winners and losers that provide substitute goods. Second, because our measures suggest that sectoral inequality will persist well into 2022, 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. Similar to BF, we capture the virus as a combination of demand and supply shocks to the contact sector. To identify these shocks we target the quarterly behavior of sectoral output and inflation. We also present some suggestive evidence in support their plausibility. 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

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[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.)

unevenness of the sectoral contraction as well as the combined aggregate effect. Similar to GLSW, incomplete markets introduces a complementarity between the contact sector losers and the non-contact sector. The learning by doing mechanism helps capture the persistent gap between winners and losers. 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 rise in inflation in the second half of 2021.

Our paper follows the huge literature motivated by the Covid-19 pandemic. As noted earlier, GLSW 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 that for tractability we do not provide an epidemiological model, as in Eichenbaum, Rebelo, and Trabandt (2020), KMV and others.

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 featuring learning by doing as a source of productivity growth in the contact winning sector, as well as a source of productivity decline in the losing sector.

Section 2 presents our measures of sectoral revenue behavior over the pandemic. Section 3 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, as well as inflation. We then illustrate the role of each of the key features, including substitution between safe and risky contact sector goods and learning by doing.

2 Measuring Sectoral Behavior

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 12 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 I/B/E/S, and industry level data from the BEA.

As noted earlier, we begin with the industry classification by KMV into contact versus

non-contact sectors as shown in the Table 7. 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.)[4] 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 11 in the appendix shows. We return to this point later when we discuss our model structure.

The challenge now is to divide up revenues between firms that have been benefited by Covid relative to other firms (winners) and those that have been negatively impacted (losers). We proceed in two steps. First, we identify firms' relative exposure to Covid. Then, we link the revenue performance of each firm to its exposure.

In order to determine firms' exposure to Covid we use stock returns. 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 $\mathrm{med}_t(\Delta p_{ft})$ be the median stock return of firm f across Covid days[5]; $\mathrm{med}_f(\mathrm{med}_t(\Delta p_{ft}))$ be the revenue weighted median of all firms' median stock return; and $\sigma_f(\mathrm{med}_t(\Delta p_{ft}))$ 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

$$CR_f = \frac{\mathrm{med}_t(\Delta p_{ft}) - \mathrm{med}_f(\mathrm{med}_t(\Delta p_{ft}))}{\sigma_f(\mathrm{med}_t(\Delta p_{ft}))} \tag{1}$$

A firm is Covid resilient if its median stock return on Covid news days is high relative to the median of all firms.

We accordingly use a firm's Covid resilience measure to classify it as a winner or loser. Before doing so, we show 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

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[4]For details on the classification see Appendix B.3.7.
[5]Stock return for firm f at each Covid day t, Δp_{ft}, is measured as the log price change.

tricky since it is necessary to control for pre-crisis trends for each firm. Accordingly, to identify the pre-crisis trends we use the February 2020 analysts' forecasts of firm revenues, restricting attention to firms with at least 3 active forecasts. These forecasts are available for 20:Q1 through 20:Q4 and for 2021, 2022. Ex post revenues are available from 20:Q1 through 21:Q3. We then construct quarterly revenue surprises for these seven quarters as the log difference between realized quarterly revenue and the February 2020 forecast[6].

Table 1 presents regressions of the firm level quarterly revenue surprises on our measure of Covid resilience for the quarters with available revenue realization.[7] We also examine the non-contact sector as a control group. Accordingly, we divide firms between the contact and non-contact sectors. In the seven columns for each case, the dependent variable is the revenue surprise for a given quarter.

In all cases the Covid resilience measure is a positive and statistically significant predictor of the respective revenue surprise, as one would expect. The effect is also big, especially for firms in the contact sector. For these firms, the largest impact is for 2020:Q2, where a one standard deviation increase in Covid resilience implies a thirty-five percent revenue surprise increase relative to the median firm. The effects on realized revenue surprises remain large from 20:Q3 through 21:Q3, declining smoothly from twenty-one to nine percent.

Covid resilience also has significant predictive power for revenue surprises in the non-contact sector, but the effects are much weaker than in the contact sector. For each quarter, the response of the revenue surprise varies between a third to half of the respective contact sector response. Another indicator that Covid resilience is less a factor in the non-contact sector is that it explains much less of the overall variation in revenue surprises in this sector relative to the contact sector. For the contact sector the R^2 for each period varies from

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[6]The expected quarterly revenue in 2021 is not directly available for each firm. Therefore, we use the February 2020 forecast of 2021 revenue to compute the expected yearly growth and update the quarterly forecasts of 2020 assuming equal expected growth for each quarter.

[7]One complication is that not all firms have a sufficient number of analysts' forecasts for all the periods. Dropping all firms that do not have a complete set of forecasts for each period 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. In Table 8 we show that the estimates for 20:Q1 through 21:Q3 are robust to using a balanced panel.

Table 1: Covid Resilience and Revenue Surprises

Contact

	Q1-20	Q2-20	Q3-20	Q4-20	Q1-21	Q2-21	Q3-21
Resilience	0.070***	0.346***	0.212***	0.209***	0.169***	0.119***	0.086***
	(0.008)	(0.051)	(0.037)	(0.040)	(0.033)	(0.024)	(0.017)
R^2	0.264	0.396	0.317	0.400	0.290	0.227	0.202
N	509	506	503	302	456	452	443

Non Contact

	Q1-20	Q2-20	Q3-20	Q4-20	Q1-21	Q2-21	Q3-21
Resilience	0.034***	0.150***	0.105***	0.108***	0.068***	0.042***	0.049*
	(0.008)	(0.020)	(0.019)	(0.021)	(0.016)	(0.012)	(0.020)
R^2	0.093	0.147	0.166	0.162	0.087	0.035	0.043
N	1148	1127	1099	671	980	966	953

Note: The dependent variable for columns is the log-difference between the quarterly realized revenue and the median expected revenue from IBES reported in February 2020 for each firm in the sample. The independent variable is our measure of Covid resilience. The sample of firms varies across columns depending whether a forecast was available for that time. The regression is weighted using previous year quarterly revenue. Standard errors are robust to heteroskedasticity White (1980)

twenty-five to forty percent, typically more than double that for the non-contact sector.

As a robustness check in Table 2 we add controls for industry at the four digit level and size. Covid resilience remains a significant predictor of revenue surprises in the contact sector and less so in the non-contact sector. While they remain nontrivial in size, the coefficients on Covid resilience are only a third to half that in the corresponding cases without controls. This effect of controls may reflect that (i) our resilience measure is quite imprecise and (ii) the controls may also be capturing substitution.[8] 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.

We next present suggesting evidence that spending subsitution was likely at work in the

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

Table 2: Covid Resilience and Revenue Surprises

Contact

	Q1-20	Q2-20	Q3-20	Q4-20	Q1-21	Q2-21	Q3-21
Resilience	0.027***	0.150***	0.073**	0.042*	0.079***	0.046*	0.033
	(0.008)	(0.041)	(0.024)	(0.020)	(0.023)	(0.018)	(0.017)
Size	Y	Y	Y	Y	Y	Y	Y
Sector FE (NAICS 4)	Y	Y	Y	Y	Y	Y	Y
R^2	0.853	0.878	0.885	0.932	0.857	0.808	0.731
N	505	503	499	302	452	450	439

Non Contact

	Q1-20	Q2-20	Q3-20	Q4-20	Q1-21	Q2-21	Q3-21
Resilience	0.013	0.044*	0.039*	0.040*	0.037*	0.022	0.046**
	(0.007)	(0.020)	(0.016)	(0.019)	(0.016)	(0.014)	(0.017)
Size	Y	Y	Y	Y	Y	Y	Y
Sector FE (NAICS 4)	Y	Y	Y	Y	Y	Y	Y
R^2	0.535	0.762	0.703	0.721	0.485	0.415	0.444
N	1147	1126	1097	670	980	965	952

Note: The dependent variable for columns (1)-(6) is the log-difference between the quarterly realized revenue and the median expected revenue from IBES reported in February 2020 for each firm in the sample. The independent variable is our measure of Covid resilience. The sample of firms varies across columns depending whether a forecast was available for that time. The regression is weighted using previous year quarterly revenue. The regression includes industry NAICS 4 digit fixed effects and the 2019 fiscal year revenue for each company. Standard errors are robust to heteroskedasticity White (1980).

contact sector but not in the non-contact. It is first instructive to examine some representative winning and losing firms in each sector. For each sector, we define a winner as a firm with a Covid resilience measure above the sector median and vice-versa for a loser. The left side of Table 3 lists some representative winners and losers in the contact sector, along with their respective Covid resilience numbers. Among the contact sector 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 revenue 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, as opposed to a loss of business to companies offering substitute products.

Table 3: Winners and Losers Examples

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

Note: The table shows examples of Winners and Losers firms together with its Covid Resilience measure for the Contact and Non-Contact sector.

We next show that winners in the contact sector did "win" significantly in terms of revenue performance relative to their sector mean. This was not the case for the non-contact sector. For each sector we aggregate the revenue surprises across our public firm winners and compare them with the aggregate BEA sectoral revenue behavior. Figure 2 plots the winners revenue surprises for each sector from 20:Q1 through 21:Q3 (the solid lines) relative

to the respective sector means (the dotted lines). Note first that contact sector winners win significantly in absolute terms, even during recession trough in 20:Q2. Revenue surprises are eight percent above target in 20:Q2, and climb to thirteen percent in 21:Q1. Further, winners' revenues are well above those for the sector as a whole which, as we noted earlier, contracted sharply in 20:Q2 and recovered slowly thereafter. By contrast, the revenue of winners in the non-contact sector contracted until 20:Q3. After that it moved modestly above zero, though well below that of winners in the contact sector. Further the gap between non-contact sector winners and the sector as a whole is much smaller than that for the contact sector.

Figure 2: Winners Relative Performance
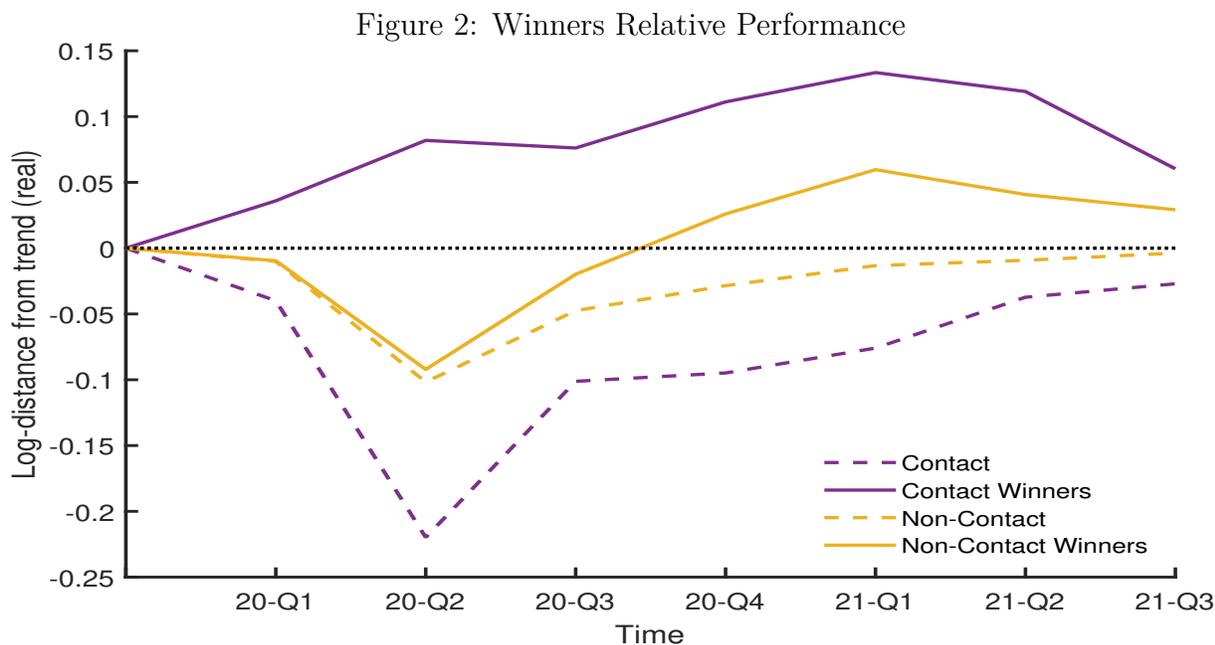
Note: Figure shows the log-distance from expectations of real revenue of Contact and Non-Contact sector as classified in Table 7, and winners as classified in Appendix B.3.6. Nominal output data for sectors come from the BEA and is transformed to real using the Chain-Type Price Indexes for Gross Output for Private Industries. Aggregate nominal series are detrended assuming a expected growth of 4% for nominal output and 2% for prices. Nominal output data for winners comes from IBES. Surprises in revenue for the winners are defined as the log-difference between the realized revenue with the median expected revenue from forecasters reported in February 2020 for each firm in the sample.

To summarize: In both the contact and non-contact sector there were winners and losers. However: 1. Winning as measured by Covid resilance predicted a larger increase in revenues in the contact sector relative to the non-contact; 2. Representative winners in the contact sector appear to offer substitute products for losers, while this was not the case in the

non-contact sector; and 3. Total revenues of contact sector winners rose substantially through the crisis and significantly outperformed the sector as a whole, while the same was not true for their non-contact sector counterparts. Overall, the results are suggestive of a high degree of substitution being at work in the contact sector but not for the noncontact sector. We accordingly restrict attention to winners versus losers in the contact sector.

We are now in a position to construct our sectoral revenue measures. 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 substitutes for Covid exposed products are large and experienced companies (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, we take the contact sector total revenue from BEA and then subtract winners' revenues.

Figure 3 then presents our disaggregated sectoral series. We plot the revenue deviation from trend from 2020:Q1 through 2021:Q3. From 21:Q3 on we plot the October 2021 forecast relative to trend (the dotted lines). 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 20:Q2 as opposed to twenty two percent. The recovery is also slower. Indeed in 20: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,

Figure 3: The Unequal Pandemic Recession
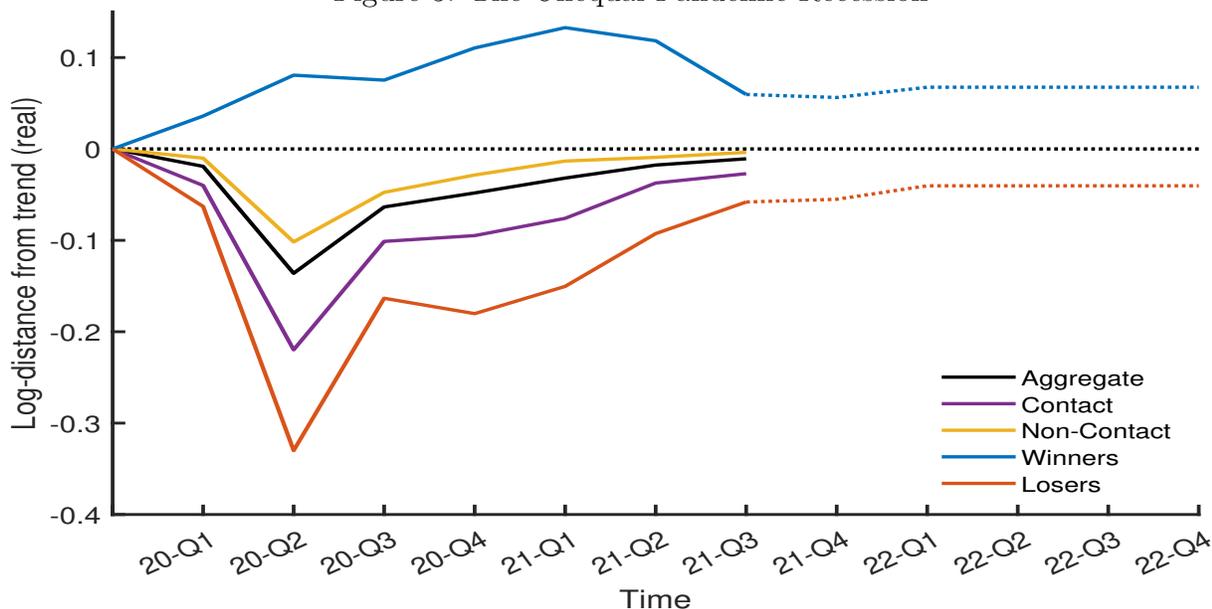
Note: Figure shows the log-distance from expectations of real revenue of the aggregate economy, Contact and Non-Contact sector as classified in Table 7, and winners and losers as classified in Appendix B.3.6. Nominal output data for aggregate and sectors come from the BEA and is transformed to real using the Chain-Type Price Indexes for Gross Output for Private Industries. Aggregate nominal series are detrended assuming a expected growth of 4% for nominal output and 2% for prices. Nominal output data for winners comes from IBES. Surprises in revenue for the winners are defined as the log-difference between the realized revenue and the median expected revenue from IBES reported in February 2020 for each firm in the sample. For 21:Q4 and Y22 the realized revenue for winners is replace by the updated forecast reported in October 2021. The surprise in Y22 is assumed constant for each quarter. Losers realized and expected revenue is obtained as a residual between public firms winners and aggregate from BEA.

steadily rising to ten percent above trend in 20:Q4. As the figure makes clear, further, the gap between winners and losers is expected to persist well into 2022. We next present a model designed to explain these facts.

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 sector winners, contact sector losers and the non-contact sector. Second, to mimic the impact of the virus we allow for two shocks that

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hit the contact losing sector directly: One is a shock that reduces product demand . The other is a shock that reduces sectoral labor supply. 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 GLSW. 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. As we will see, it also helps account for inflation. 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 Appendix A.3 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 contact sector goods. It does so by affecting (1) the overall demand for contact sector goods c_{1t}, as

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we make clear shortly, and (2) given c_{1t}, the relative demand for c_{at} versus c_{bt}. In the latter case, since $\zeta'(\epsilon_t) < 0$, an increase in ϵ_t shifts demand from c_{at} to c_{bt}. 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}:[9]

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

with

$$\begin{aligned}
\phi(\epsilon_t) &= \frac{(1 - \epsilon_t \zeta)\phi}{1 - \epsilon_t \zeta \phi} \\
\Theta(\epsilon_t) &= [\phi(\epsilon_t)^{\phi(\epsilon_t)}(1 - \phi(\epsilon_t))^{1-\phi(\epsilon_t)}]^{-1}
\end{aligned} \tag{5}$$

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[10]

$$\begin{aligned}
u(C_t) &= \log C_t^{(1-\epsilon_t \zeta \phi)} \tag{6} \\
&= \log \Theta(\epsilon_t)^{(1-\epsilon_t \zeta \phi)} + \log(c_{1t}^{(1-\epsilon_t \zeta)\phi} c_{2t}^{1-\phi})
\end{aligned}$$

The bottom right hand side of equation (6) shows that the virus-induced taste shock directly affects the demand for contact sector goods c_{1t}. An increase in ϵ_t reduces the marginal utility of c_{1t} and hence the overall demand for this good. From (2) and (3), the rise in ϵ_t also induces a shift in the composition of c_{1t} from c_{at} toward c_{bt}. The top right hand side of (6) shows that there will be an implied impact of the shock on the demand for the aggregate composite C_t. Further, as in GLSW, incomplete markets will spread the effect of the shock to the demand for non-contact sector goods c_{2t}, amplifying the contraction of C_t. We defer this discussion to

---

[9]Given ϵ_t is zero prior to the pandemic recession, the log preferences appear consistent with Figure 11, which shows that from 2009 through 2019, the contact share of total revenue was fairly stable.

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

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 GLSW. 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.[11]

Let upper case j denote 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 $j = a, b, 2$, preferences for a sector j household are given by:

$$E_0\{\sum_{t=0}^{\infty} \beta^t [\log(C_t^j)^{1-\epsilon_t \zeta \phi} - \frac{\eta_{jt}\kappa}{1+\varphi} l_t^{j(1+\varphi)}]\} \tag{7}$$

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

---

[11]Our assumptions on the amount of credit market frictions are similar to those in the literature. For instance, the marginal propensity to consume in our model is roughly 0.22 (the share of income of sector a households) a number similar to the one implied in Kaplan, Moll, and Violante (2018).

insurance transfers, i_t the nominal interest rate, W_{jt} the sector j real wage 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

$$C_t^j + B_t^j/P_t = (1 + i_{t-1})B_{t-1}^j/P_t + \Pi_t^j + \Upsilon_t^j + W_{jt}l_{jt} - T_t^j \tag{8}$$

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

$$\phi \Upsilon_t^b + (1 - \phi)\Upsilon_t^2 = 0 \tag{9}$$

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

$$\Upsilon_t^a = 0 \tag{10}$$

$$0 \leq B_t^a \tag{11}$$

Each household chooses consumption, labor supply and nominal bonds to maximize utility given by (7). Each must satisfy the budget constraint (8). Households in sectors b and 2 must also satisfy the insurance transfer constraint, given equation (9). 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 (10) and (11), instead of (9).

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

$$c_{1t}^j = \phi(\epsilon_t) \left(\frac{P_{1t}}{P_t}\right)^{-1} C_t^j \tag{12}$$

$$c_{2t}^j = (1 - \phi(\epsilon_t)) \left(\frac{P_{2t}}{P_t}\right)^{-1} C_t^j \tag{13}$$

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

$$c_{at}^j = \zeta(\epsilon_t)^{1/\rho} \left(\frac{P_{at}}{P_{1t}}\right)^{-1/\rho} c_{1t}^j \tag{14}$$

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

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 $j = b, 2$

$$(1 - \epsilon_t \zeta \phi) \frac{W_{jt}}{C_t^j} = \kappa (l_t^j)^\varphi \tag{16}$$

For households in sector a

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

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 consumption 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 $j = b, 2$ the consumption Euler equation is given by

$$\frac{1 - \epsilon_t \zeta \phi}{C_t^j} = E_t \left[\beta \frac{1 - \epsilon_{t+1} \zeta \phi}{C_{t+1}^j} R_{t+1} \right] \tag{18}$$

where, given complete insurance:

$$\frac{C_{t+1}^b}{C_t^b} = \frac{C_{t+1}^2}{C_t^2} \tag{19}$$

Next, let λ_t the Lagrange multiplier on the borrowing constraint (11) facing sector a households. Then the consumption Euler equation for sector a households is given by

$$\frac{1 - \epsilon_t \zeta \phi}{C_t^a} = E_t \left[\beta \frac{1 - \epsilon_t \zeta \phi}{C_{t+1}^a} R_{t+1} \right] + \lambda_t \tag{20}$$

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:

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

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

$$\epsilon_t = \rho_\epsilon \epsilon_{t-1} + \xi_{\epsilon t} \tag{21}$$

$$\eta_t = \rho_\eta \eta_{t-1} + \xi_{\eta t} \tag{22}$$

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

3.3 Aggregate Demand and Sectoral Demand Shocks

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 GLSW by assuming that the taste shock is realized only in period t and there are no shocks in the future [12]. Also for simplicity, assume

---

[12]To be clear, after this section we return to allowing ϵ_t to arise each period and be serially correlated.

that nominal prices are fixed during both period t and $t+1$.

Total consumption spending is the sum of spending by unconstrained households (sectors b and 2) and by constrained households (sector a). Let $\alpha\left(\epsilon_t, \frac{P_{at}}{P_{1t}}\right)$ be the share of income by type a households:

$$
\begin{aligned}
\alpha\left(\epsilon_t, \frac{P_{at}}{P_{1t}}\right) &= \frac{P_{at}c_{at}}{P_t C_t} \\
&= \left(\frac{P_{at}}{P_{1t}}\right)^{\frac{\rho-1}{\rho}} \zeta(\epsilon_t)^{\frac{1}{\rho}}\phi(\epsilon_t)
\end{aligned}
\tag{23}
$$

where we make use of equation (14) to derive the last expression, implying

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

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

It is then possible to express aggregate consumption demand as[13]

$$
C_t = (1 - \epsilon_t\zeta\phi)\frac{1 - \alpha\left(0, \frac{P_{at+1}}{P_{1t+1}}\right)}{\beta R_{t+1}}C_{t+1} + \alpha\left(\epsilon_t, \frac{P_{at}}{P_{1t}}\right)C_t
\tag{24}
$$

The first term on the right is demand by unconstrained households, which depends on their consumption/saving behavior.[14] The second term is the demand by constrained households, which simply equals their income. Rearranging yields

$$
C_t = \frac{1 - \epsilon_t\zeta\phi}{1 - \alpha(\epsilon_t, \frac{P_{at}}{P_{1t}})}\frac{1 - \alpha(0, \frac{P_{at+1}}{P_{1t+1}})}{\beta R_{t+1}}C_{t+1}
\tag{25}
$$

---

[13]To obtain (24) note first that we can express the Euler equation for type 2 households as $C_t^2 = (1 - \epsilon_t\zeta\phi)\frac{C_{t+1}^2}{\beta R_{t+1}}$. Given complete insurance between households in sectors 2 and b, we can write: $C_t^2 \propto [1 - \alpha(\epsilon_t, \frac{P_{at}}{P_{1t}})]C_t$ Combining equations then yields (24).

[14]This term comes from rearranging the consumption Euler equation for unconstrained households. The expression $[1-\alpha(0, \frac{P_{at+1}}{P_{1t+1}})]C_{t+1}$ is total consumption by unconstrained households in $t+1$, with $[1-\alpha(0, \frac{P_{at+1}}{P_{1t+1}})]$ their fraction of total consumption (equal to their fraction of income.)

As in the standard one sector New Keynesian model, C_t falls after an interest rate R_{t+1} increase as it induces unconstrained households to cut back consumption spending.

The sectoral demand shock also affects C_t: An increase in ϵ_t reduces C_t through two channels. The first channel is an intertemporal substitution effect, captured by the term $(1 - \epsilon_t \zeta \phi)$. Unconstrained households households delay some consumption to the next period, when the taste shock (i.e. virus) has disappeared. The second channel, captured by the multiplier $1 / \left[1 - \alpha(\epsilon_t, \frac{P_{at}}{P_{1t}}) \right]$, 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 GLSW, 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 (13) with the Euler equation for C_t yields

$$c_{2t} = \left(\frac{P_{2t}}{P_t} \right)^{-1} \frac{1 - \phi}{1 - \alpha \left(\epsilon_t, \frac{P_{at}}{P_{1t}} \right)} \frac{1 - \alpha \left(0, \frac{P_{at+1}}{P_{1t+1}} \right)}{\beta R_{t+1}} C_{t+1} \tag{26}$$

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, reflected by the multiplier $1 / \left[1 - \alpha(\epsilon_t, \frac{P_{at}}{P_{1t}}) \right]$. The intertemporal substitution effect of ϵ_t is present only for contact sector goods, c_{1t}, which are directly affected by the shock.

One significant difference from GLSW is that the strength of this complementarity effect from incomplete markets depends on the substitutability between Covid susceptible contact sector goods c_{at} and non-susceptible substitutes c_{bt}[15]. 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.

---

[15]The degree of substitutability enters through equation (23).

3.4 Production, Firms and Sectoral Supply Shocks

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.[16]

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

$$Y_{jt} = \left[\int_0^1 Y(f)_{jt}^{\frac{\varepsilon-1}{\varepsilon}} df \right]^{\frac{\varepsilon}{\varepsilon-1}} \tag{27}$$

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

$$Y(f)_{jt} = \left(\frac{P(f)_{jt}}{P_{jt}} \right)^{-\varepsilon} Y_{jt} \tag{28}$$

Combining with the production function then yields the price index:

$$P_{jt} = \left[\int_0^1 P(f)_{jt}^{1-\varepsilon} df \right]^{\frac{1}{1-\varepsilon}} \tag{29}$$

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

$$Y(f)_{jt} = L(f)_{jt} \tag{30}$$

---

[16]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, $\Lambda_{0,t}^j = \beta^t \frac{1 - \epsilon_t \zeta \phi}{1 - \epsilon_0 \zeta \phi} \frac{C_0^j}{C_t^j}$ 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

$$\max_{P_{j0}^*} E_0 \left\{ \sum_{t=0}^{\infty} \theta^t \Lambda_{0,t}^j \left(\frac{P_{j0}^*}{P_t} - W_{j,t} \right) \cdot \left(\frac{P_{j0}^*}{P_{jt}} \right)^{-\varepsilon} Y_{jt} \right\}$$

The standard first order condition is given by

$$E_0 \left\{ \sum_{t=0}^{\infty} \theta^t \Lambda_{0,t}^j \left(\frac{P_{j0}^*}{P_t} - (1 + \mu) W_{j,t} \right) \cdot \left(\frac{P_{j0}^*}{P_{jt}} \right)^{-\varepsilon} Y_{jt} \right\} = 0 \tag{31}$$

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

$$P_{jt} = \left[\theta P_{jt-1}^{1-\varepsilon} + (1 - \theta) P_{jt}^{*1-\varepsilon} \right]^{\frac{1}{1-\varepsilon}} \tag{32}$$

We now briefly discuss how the labor supply shock η_t in the virus exposed sector a affects economic behavior. The real wage that firms in sector $j = a, b, 2$ face must be consistent with household labor supply in sector j, given by equations (16) and (17). Accordingly, a (virus motivated) increase in η_t will drive up the sector a real wage, which in turn will increase the sector a relative price P_{at}/P_t. Because prices are sticky, the full adjustment of sectoral relative prices will take some time. Nonetheless, the increase in the sector a relative price will induce a shift in spending from sector a to the subsitute sector b. As in GLSW, there may be a reduction in aggregate demand due to the borrowing constraint on sector a households. In Section 4.2.1 we examine the impact of both the sectoral demand and supply shocks on equilbirum behavior.

3.5 Equilibrium

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

$$Y_{jt} = \left[\int_0^1 L(f)_{jt}^{\frac{\varepsilon-1}{\varepsilon}} df \right]^{\frac{\varepsilon}{\varepsilon-1}} \tag{33}$$

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

$$\int_0^1 L(f)_{at} df = L_{at} = \phi l_{at} \tag{34}$$

$$\int_0^1 L(f)_{bt} df = L_{bt} = \phi l_{bt} \tag{35}$$

$$\int_0^1 L(f)_{2t} df = L_{2t} = (1-\phi) l_{2t} \tag{36}$$

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:

$$\phi c_{jt}^a + \phi c_{jt}^b + (1-\phi) c_{jt}^2 = c_{jt} = Y_{jt} \tag{37}$$

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

$$\phi C_t^a + \phi C_t^b + (1-\phi) C_t^2 = C_t = Y_t \tag{38}$$

Sectoral and aggregate price indices are given by

$$P_{1t} = \left[\zeta(\epsilon_t)^{1/\rho} P_{at}^{\frac{\rho-1}{\rho}} + (1-\zeta(\epsilon_t))^{1/\rho} P_{bt}^{\frac{\rho-1}{\rho}} \right]^{\frac{\rho}{\rho-1}} \tag{39}$$

$$P_t = P_{1t}^{\phi_t} P_{2t}^{1-\phi_t} \tag{40}$$

24

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

$$\phi T_t^a + \phi T_t^b + (1 - \phi)T_t^2 = 0 \tag{41}$$

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

$$R_{t+1} = (1 + i_t)\frac{P_t}{P_{t+1}} \tag{42}$$

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:

$$1 + i_t \;=\; (1 + i)\left(\frac{P_t}{P_{t-1}}\right)^{\phi_\pi} \tag{43}$$

$$i_t \;\geq\; 0 \tag{44}$$

This completes the description of the baseline model.

In Appendix A.1 we characterize the model's deterministic steady state. Among other things, we show that the steady state ratio of consumption per household in sector b versus sector 2 is $1 - \zeta$: The optimal insurance arrangement then maintains this relative consumption ratio across households in b and 2. We also sketch the flexible price equilibrium. One notable feature of this case is that the sectoral demand shock causes employment and output to co-move perfectly across sectors. Relative prices do all the adjusting: An increase in the sector demand shock ϵ_t reduces the relative price in sector a and increases it in sectors 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.

3.6   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_{jt} be efficiency units of labor for a person in sector $j = a, b$. Then we introduce a simple learning by doing mechanism originally proposed by Chang, Gomes, and Schorfheide (2002) which relates the evolution of X_{jt} to the intensity of labor input, as follows:

$$X_{jt+1} = l_{jt}^{\sigma_j} X_{jt}^{\rho_j} \tag{45}$$

with $0 \le \rho_j < 1$ and $\sigma_j > 0$. Note that equation (45) 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 $\rho_j < 1$, we are allowing for some obsolescence in labor productivity (as do Chang et al. (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_j 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 $j = a, b$ as

$$V(X_{jt}) = \max_{l_t^j} \log(C_t^j)^{1-\epsilon_t \zeta \phi} - \frac{\eta_{jt}\kappa}{1+\varphi} l_t^{j(1+\varphi)} + E_t \left\{ \beta V(X_{jt+1}) \right\} \tag{46}$$

Let Q_{jt} be the time t present discounted value to a sector j household of a unit increase in

labor efficiency at $t+1$. Then the first order condition for labor supply is given by

$$W_{jt}X_{jt} + \sigma_h \frac{X_{jt+1}}{l_t^j}Q_{jt} = \eta_{jt}\kappa l_t^{j\varphi}C_t^h/(1 - \epsilon_t\zeta\phi) \qquad (47)$$

with

$$Q_{jt} = \rho_j\Lambda_{t,t+1}^j\{W_{jt+1}l_{t+1}^j + \rho\Lambda_{t+1,t+2}^jQ_{jt+1}\} \qquad (48)$$

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, $\sigma_j\frac{X_{jt+1}}{l_t^j}$, times the present value of an efficiency unit, Q_{jt}

Adding learning by doing to the baseline model is simple. The labor supply conditions (47) and (48) 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^j is unity (see Appendix A.1), equation (45) implies that the steady state of X_{jt} is also unity.

4   Quantitative (and Qualitative) Analysis

In this section we analyze how the model captures the unequal sectoral recession described in Section 2, with particular emphasis on the role of winners versus losers. We first 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 and also the behavior of inflation. As noted earlier, our baseline does not allow for labor mobility across sectors. Accordingly, in Appendix A.3 we show that our results are robust to including this mobility so long as there is a reasonable degree of imperfection in cross-sectoral labor supply.

4.1 Calibration

The model is quarterly.[17] There are thirteen parameters, as listed in Table 4. 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.[18]

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[19]. Finally, we choose the persistence of the demand shocks ρ_ϵ and supply shocks ρ_η such that the shocks are expected to die out after 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[20]. 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. Note that we choose the quarterly demand and supply shocks to match the sectoral output and inflation data, as we discuss shortly. To provide some support for the validity of our measured shocks, we show they line up well with both OpenTable's measure of restaurant reservations and the Federal Reserve Bank of New York's measure of supply chain disruptions.

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 et al. (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

---

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

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

[19]See Broda and Weinstein (2006).

[20]Since our realized data only goes up to 2021:Q3, we are not considering the Omicron wave.

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.[21]

Table 4: Parameter Selection

| Parameter	Value	Description
Standard Parameters		
β	0.995	$r = 2p.p.$
φ	1	Labor elasticity
γ	0.85	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

4.2   Illustrating Model Behavior

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

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[21]We make ρ_a and ρ_b less than unity for technical reasons: to ensure that the learning by doing does not 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 et al. (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.

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.[22] We normalize the size of the shocks so that each initially generates a five hundred basis point change in the natural rate of interest. The top row in Figure 4 gives the response to the demand shock and the second row shows the results for the supply shock.

Figure 4: Demand vs Supply Shocks
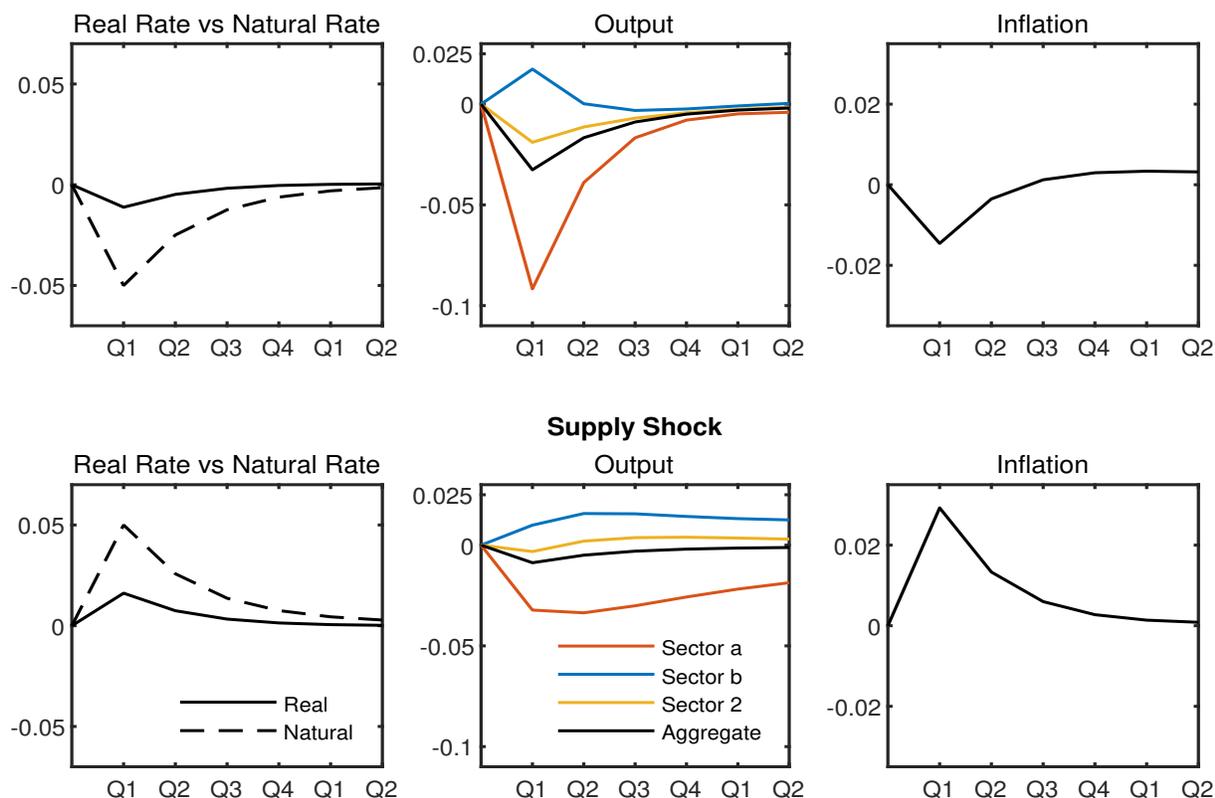
Note: Figure shows the response of the model to a one time negative demand (first row) and supply (second row) shocks. Shocks are normalized so that each initially generates a five hundred basis point change in the natural rate of interest.

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

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

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 price equilibrium the drop in demand requires the interest rate to fall to offset the drop. Second, as emphasized by GLSW 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 GLSW 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 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* goods, 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.[23] In our case, however, not only is the aggregate price level distorted due to nominal rigidities, so too are the sectoral relative prices.

In order to provide a benchmark for policy, the first column in Figure 5 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 Appendix A.2, 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 effects 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 4), output increases across sectors. Indeed, output in the non-contact sector returns to steady state. However, the

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

Figure 5: Limits to Monetary Policy
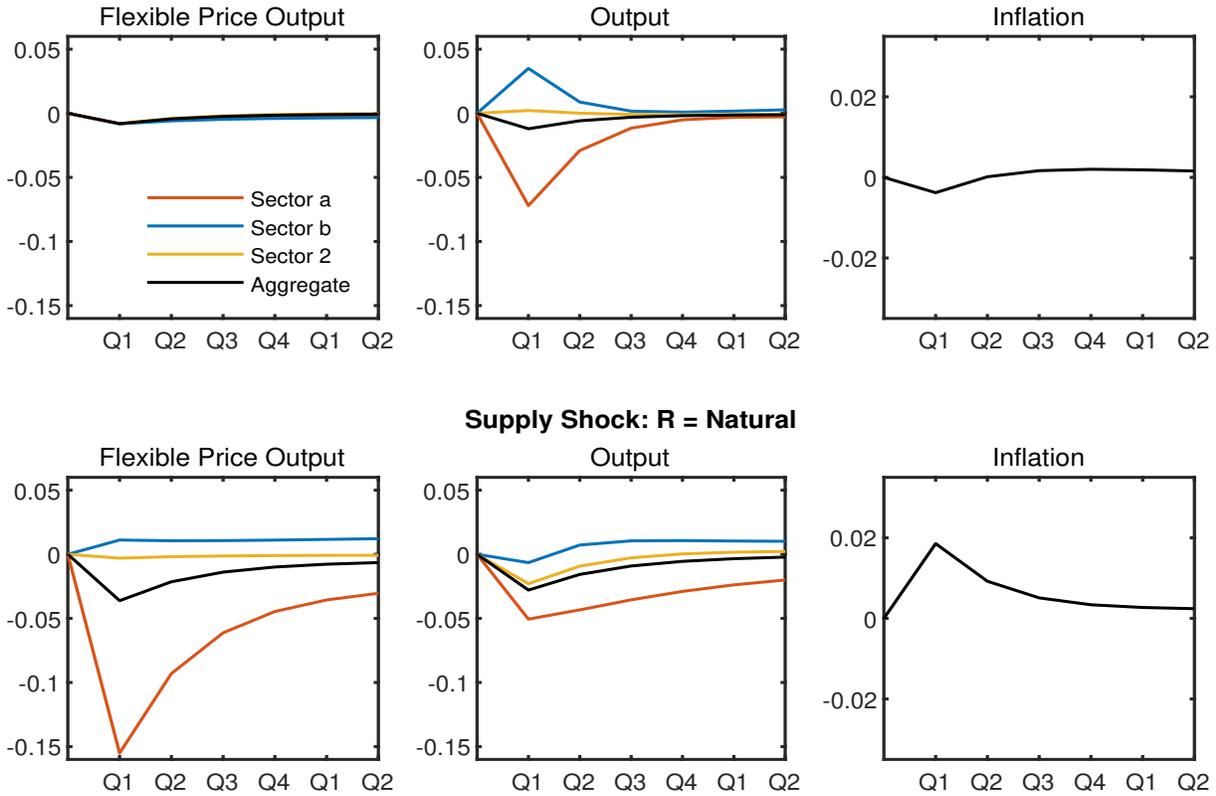
Note: Figure shows the response of the model to a one time negative demand (first row) and supply (second row) shocks under flexible prices (first column), with nominal rigidities but the real rate tracking the natural (second column) and inflation (third column). Shocks are normalized so that each initially generates a five hundred basis point change in the natural rate of interest.

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 4 and Figure 5 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 5 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

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fixed real rate (see Figure 4), is that sector 2 is largely unaffected as wages and prices adjust to stabilize employment. As with the demand shock however, with nominal rigidities the central bank 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[24].

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.[25] For inflation, we use Cavallo's core Covid CPI index, which adjusts for changes in spending shares induced by the virus.[26] We select only shocks from 2020:Q1 through 2021:Q3, the period through which we have realized data for all series. As we discussed earlier, the behavior of inflation helps us disentangle demand from supply shocks.

Figure 6 shows our identified shocks. The left panel plots the demand shock, ϵ_t, (in negative values to improve comparison) along with a measure of dinner reservations from OpenTable. The latter is a popular indicator of the impact of Covid on spending in virus sensitive industries and is highly correlated with spending in the contact sector as a whole (see Figure 1). While it is not possible to directly disentangle demand and supply effects from the OpenTable data, our identified demand shock moves closely with this series, suggesting demand forces at work, at least in the sector as a whole. The right panel plots the supply shock, η_t, along long with an index of supply chain pressure developed by Benigno et al.

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[24]This point is well developed in Rubbo (2020), Guerrieri et al. (2021) and Woodford (2020).

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

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

(2022). The latter is constructed to be orthogonal to demand factors and thus may be considered a measure of supply shocks. Interestingly, our identified supply shock is closely correlated with the supply chain pressure index: Both increase in mid 2020, then soften a bit before increasing to a new peak in mid 2021.

Figure 6: Shocks vs Data
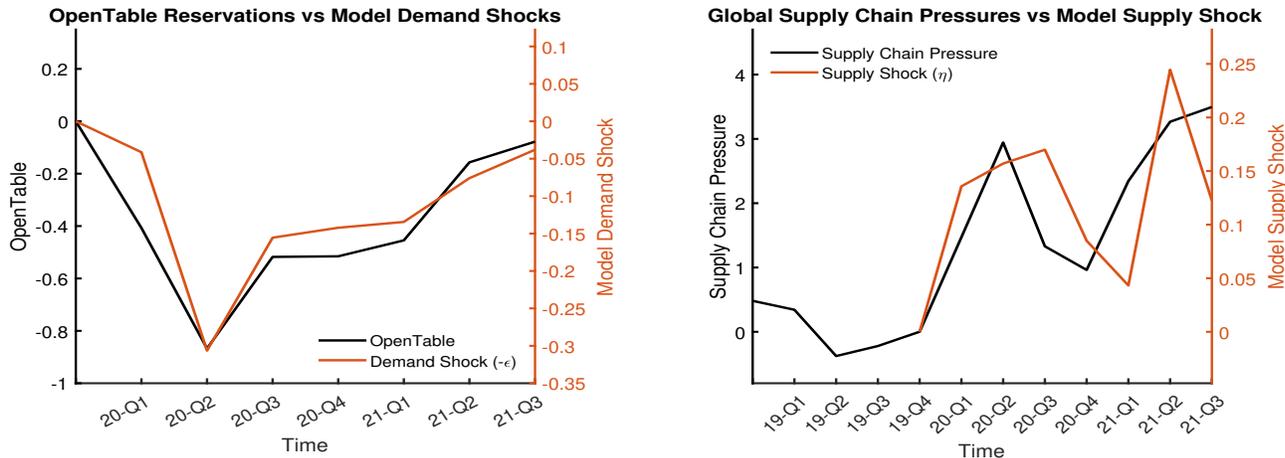
Note: Top panel compares OpenTable's state of the restaurants industry for the US measured as the share of 2019 reservations (left axis) with our calibrated demand shock process ϵ in negative terms (right axis). Bottom panel compares the New York FED Global Supply Chain Pressures index (left axis) with our calibrated supply shock process η (right axis).

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 et al. (2020). For monetary policy, we suppose the central bank moves the interest rate to the zero lower bound in 2020:Q2, as happened in practice, and allow for four quarters of forward guidance at the zero lower bound. Appendix A.4 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 7 illustrates. As the

top left panel shows, the model does well overall 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 5 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.

Figure 7: Model vs Data
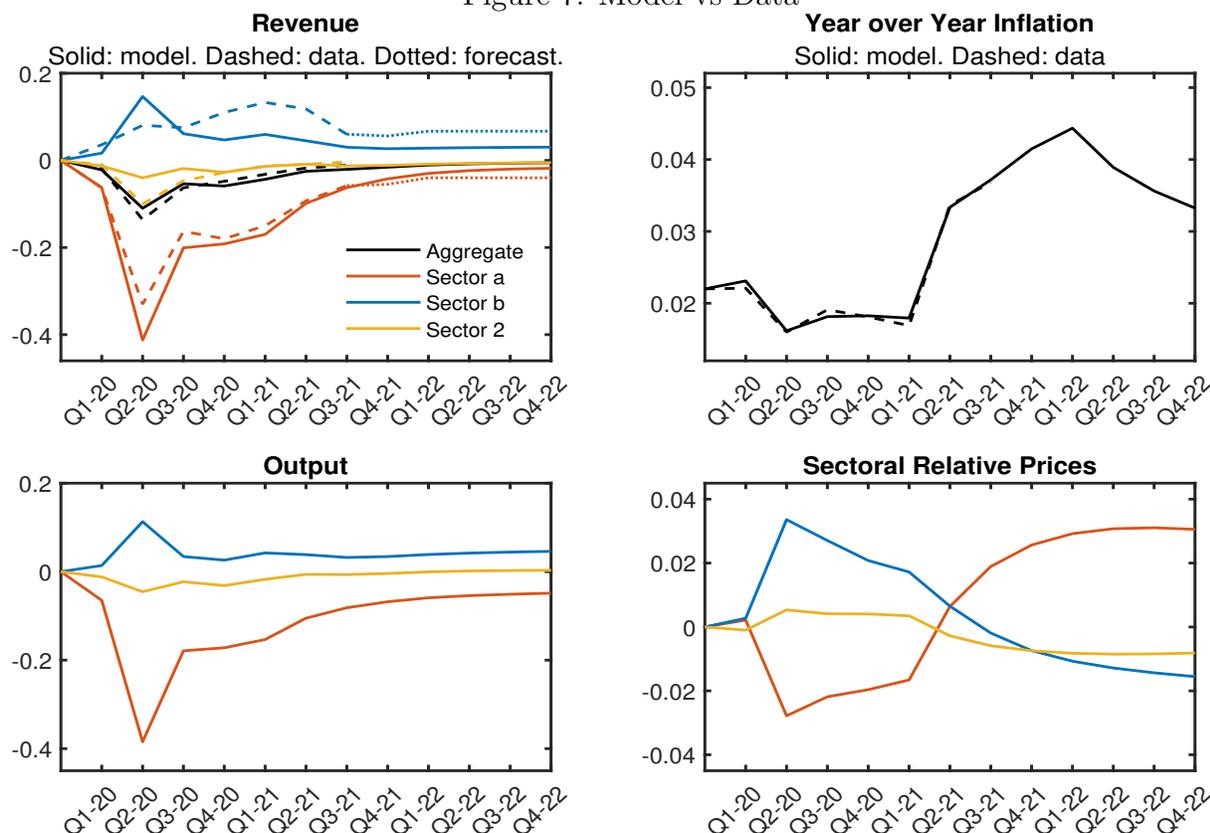
Note: Figure shows the response of our benchmark model to the estimated shocks (solid line), the data (dashed line) and changes in forecasts (dotted lines).

Due to the learning by doing mechanism, the model is able to replicate a good deal of the persistence in the revenue gap between sectors a and b, ranging from about three quarters of the gap by the end of 2021 to a half by the end of 2022. Learning by doing has even

larger effects on the persistence of the output between a and b than on the revenue gap. As the bottom left panel shows, the former is nearly double that of the latter. The reason the persistence of revenue gap is smaller than that of the output gap is that over time relative prices increase in sector a and decline in b, as the bottom right panel indicates. Accordingly, to account fully for the high degree of persistence in the expected revenue gap, 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.[27]

Finally, the model also does well in capturing inflation, as the top right panel shows. An interesting result, we think, is that the learning by doing plays an important role in account for the rise in inflation in mid 2020, as we make clear shortly. The initial softening of inflation in mid 2020 is the product of the demand shock being important in the initial downturn. The pickup of inflation is then the product of three factors: the wearing off the negative demand shock; the supply shocks in mid 2021; and finally the endogenous decline in capacity in the contact sector due to learning by doing.

Table 5: Average Revenue Change and Inflation in 2020

	Aggregate	Sector a	Sector b	Sector 2	YoY Inflation
Data	-6.65	-18.40	7.54	-4.63	1.88
Benchmark	-6.10	-21.69	6.78	-2.48	1.89
No Substitution	-4.86	-17.36	-1.23	-1.23	2.52
No Fiscal Policy	-6.94	-22.50	5.88	-3.31	1.77
No Monetary Easing	-7.10	-22.70	5.83	-3.47	1.57

Note: Table shows the average revenue and inflation deviations from trend in the data and in the model under alternative counterfactual scenarios.

### 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

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[27]Another consideration is that forecasted gap between winners and losers is likely quite imprecise, given that it is based on the analysts forecasts for a relatively small set of firms

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 8 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. Because the drop in demand becomes smaller, inflation becomes higher, as the right panel shows.
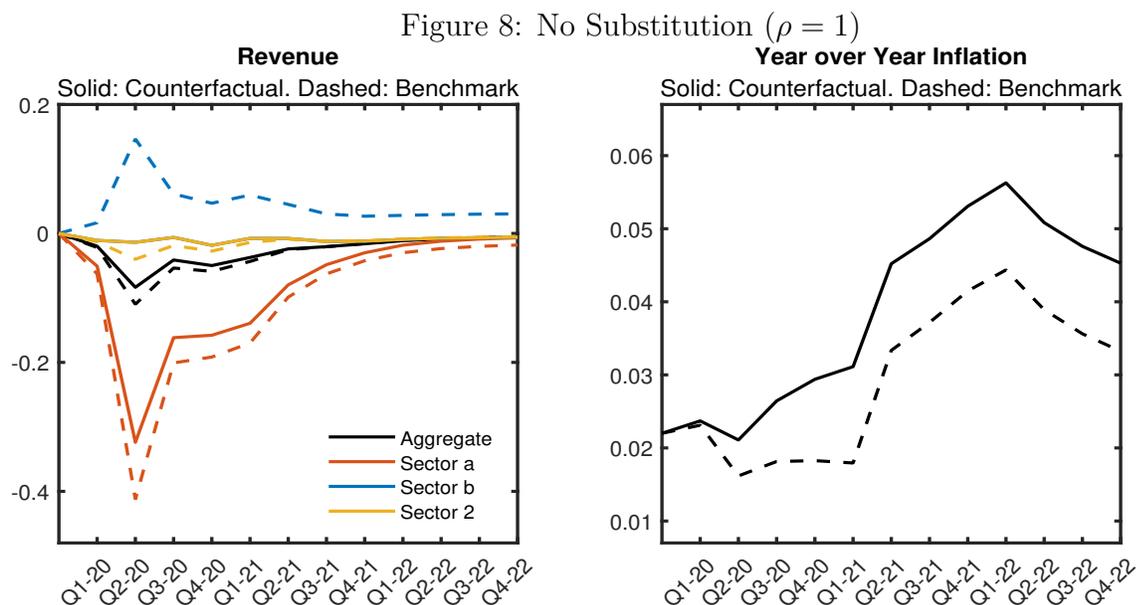
Figure 8: No Substitution ($\rho = 1$)

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

Table 5 provides exact numbers. It shows the average quarterly revenue change over

2020 for each sector for the baseline model and various alternative scenarios.[28] With no substitution, the decline in sector a revenue is smaller by roughly twenty percent, going from -22% in the case with substitution to -17.4%. Sector b now loses -1.2% 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 -1.2%. The drop in aggregate revenues is also smaller in the case without substitution, going from -6.1 percent to -4.9 percent, a nearly twenty five percent increase.
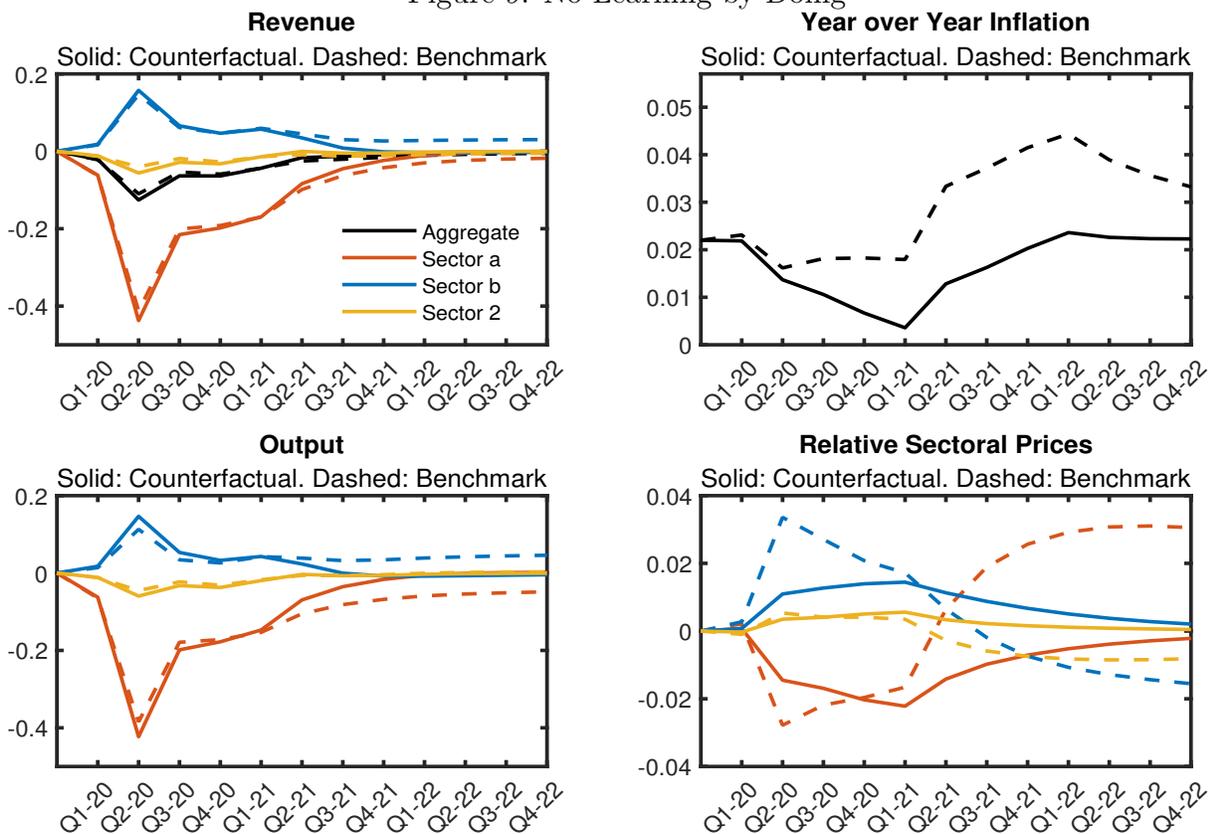
No Learning-by-Doing

Figure 9 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. Without learning by doing, the gap between revenues of winners and losers begins to wear off relative to the baseline in mid 2021 and disappear completely by the end of 2021, as the upper left panel shows. From the bottom left panel we see that the same is true for the output gap between winners and losers.

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. Without learning by doing, inflation would be roughly two hundred basis points lower in 2021.[29]

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[28]In Table 5 we exclude the counterfactual for learning-by-doing since this feature does not generate a noticeable impact on the first year of the pandemic.

[29]Note the impact of learning by doing on inflation shows up in the second half of 2020, before there is a noticeable impact on output. Here expectations of the future play a strong role: Price setting depends on the expected path of marginal cost.
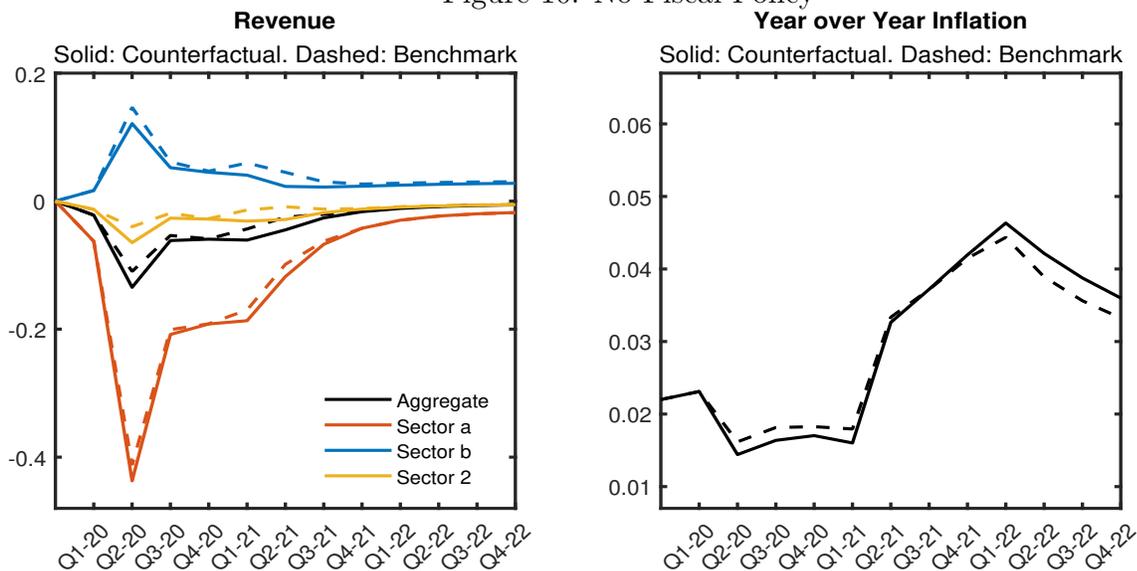
Figure 9: No Learning by Doing

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).

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

Figure 10: No Fiscal Policy

Note: Figure compares response to the estimated shocks of our benchmark model (dashed line) and the counterfactual with no transfer nor unemployment benefits.

percentage terms, the non-contact sector 2 benefits the most in terms of the impact of the stimulus on revenues. As Table 5 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.

Interestingly, fiscal policy does not appear to have much impact on inflation, as the top right panel shows. The demand and supply shocks coupled with learning by doing largely account for inflation, as we have discussed.

Finally, as we noted earlier, we have assumed for our baseline model that labor is variable within a sector but is not mobile across sectors. In Appendix A.3 we show that our results are robust to allowing for a reasonable degree of cross-sectoral labor mobility.

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" subsector (losers) and a subsector (winners) that offers safe substitute goods. Second, we allow for learning by doing to help account for the persistence in the gap between winners and losers. Overall, the model does a reasonable job of capturing the data, particularly the uneven sectoral contraction and recovery phase. However, while it does well in explaining the gap between winner's and losers' revenue throughout most of our sample, it explains only about half the gap expected by the end of 2022. 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, the model also does well in explaining inflation, including the increase that began in early 2021. One unexpected finding is that the learning by doing mechanism plays an important role. As we showed in Section 4.3.1, the resulting endogenous decline in capacity in the contact sector accounted for roughly two percentage points of the increase in inflation in 2021. Given that our model of sectoral imbalances and learning by doing can account for the recent increase in inflation, an interesting question is: How should the central bank respond? We take this as a topic for future research.

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Appendix

for Online Publication

A Model

A.1 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.

A.2   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

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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 down 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 (16) and (17) 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 - 3.6 to derive the complete flexible price equilibrium.

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A.3 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.

A.3.1 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.[30]

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

$$E_0\{\sum_{t=0}^{\infty} \beta^t [\log(C_t^a)^{1-\epsilon_t \zeta \phi} - \frac{\kappa}{1+\varphi} \left[(\Psi_t)^{\frac{1}{1-\Phi}} \right]^{(1+\varphi)}]\} \tag{49}$$

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

$$\Psi_t = \nu_a \left(\eta_t^{\frac{1}{1+\varphi}} l_{at}^a \right)^{1-\Phi} + (1-\nu_a) \left(\eta_t^{\frac{1}{1+\varphi}} l_{at}^a + l_{bt}^a \right)^{1-\Phi} \tag{50}$$

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[30]To keep the model simple, we model the reallocation cost as a flow instead of a fixed cost (see e.g. Guerrieri et al. (2021)). In practice, this cost may involve both.

Note that the utility function has the property that l^a_{at} and l^a_{bt} separately affect the disutility from supplying labor. We choose this particular functional form for two reasons: First, it is possible to have l^a_{bt} equal zero in the steady state, which makes the steady state the same as in our baseline model. Second, $\frac{1}{\Phi}$ controls the response of relative labor supply l^a_{bt}/l^a_{at} to relative wages w_{bt}/w_{at} at the steady state.[31] In the limiting case where Φ goes to minus infinity, the sensitivity of sector b labor to wages 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^a_{at}, is now given by,

$$\frac{1 - \epsilon_t \zeta \phi}{C^a_t} = \frac{\kappa}{W_{at}} \left[(\Psi_t)^{\frac{1}{1-\Phi}} \right]^{\varphi} \times (\Psi_t)^{\frac{\Phi}{1-\Phi}} \left(\nu_a \eta_t^{\frac{1-\Phi}{1+\varphi}} (l^a_{at})^{-\Phi} + (1-\nu_a) \eta_t^{\frac{1}{1+\varphi}} \left(\eta_t^{\frac{1}{1+\varphi}} l^a_{at} + l^a_{bb} \right)^{-\Phi} \right)$$

(51)

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

$$\frac{\nu_a \eta_t^{\frac{1-\Phi}{1+\varphi}} (l^a_{at})^{-\Phi} + (1-\nu_a) \eta_t^{\frac{1}{1+\varphi}} \left(\eta_t^{\frac{1}{1+\varphi}} l^a_{at} + l^a_{bt} \right)^{-\Phi}}{(1-\nu_a) \left(\eta_t^{\frac{1}{1+\varphi}} l^a_{at} + l^a_{bt} \right)^{-\Phi}} = \frac{W_{at}}{W_{bt}}$$

(52)

Given wages and consumption, equations (51) and (52) pin down l^a_{at} and l^a_{bt}.

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

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

(53)

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[31]In particular, at steady state $\frac{\partial (l^a_{bt}/l^a_{at})}{\partial (W_{bt}/W_{at})} \propto -\frac{1}{\Phi}$.

A.3.2 Firms

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

$$Y_a = \phi l_a \tag{54}$$

$$Y_b = \phi\left[l_b + l_b^a\right] \tag{55}$$

$$Y_2 = (1 - \phi)\, l_2 \tag{56}$$

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.

A.3.3 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 13 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 14 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 fifteen 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.

A.4   Simulating the Pandemic

A.4.1   Shock Selection

Demand and supply shocks are selected to minimize the distance between the model and the data. Specifically, we use data between 2020:Q1 and 2021:Q3 on revenue surprises and inflation. For revenue surprises, we use the data from Figure 3 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 a weighted quadratic distance.

A.4.2   Monetary Policy

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

A.4.3 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 6: 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 et al. (2020).[32]

B   Data

B.1   Data Sources

We make use of the following data series:

1. Quarterly gross output by industry: Bureau of Economic Analysis (BEA)

2. Chain-Type Price Indexes for Gross Output by Industry (BEA)

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

3. Compustat Fundamentals of Public Firms, Quarterly: Wharton Research Data Services (WRDS)

4. Stock market prices: Compustat security daily table (WRDS)

5. Revenue and 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 Fund (October 2019).

8. OpenTable State of the Industry (`https://www.opentable.com/state-of-industry`) and New York FED Global Supply Chain Pressures (Benigno, di Giovanni, Groen, and Noble (2022))

B.2   Detrended Aggregate and Sectoral Revenue Growth

In order to get the log-distance between realized real output and its trend, as shown in Figure 1, we first aggregate realized nominal output from BEA following our classification in Table 7 of contact and non-contact sectors. Then, we deflate using the Chain-Type Price Index for Gross Output. Finally, expected real output is constructed assuming a two percent annual trend real growth based on the 2019:Q4 IMF World Economic Outlook Fund (October 2019).

B.3   Issues Involving Compustat Data

B.3.1   Sample Selection

We follow a criteria similar to Dinlersoz, Hyatt, Kalemli-Ozcan, and Penciakova (2019) on selecting firms: We exclude 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.

B.3.2   Exposure Creation

We calculate the percent change in the daily closure price of each stock on Covid news days which we define following Davis et al. (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 the standard deviation of the median return across firms weighted by the yearly revenue in the 2019 fiscal year.

B.3.3   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 (available at https://wrds-www.wharton.upenn.edu/pages/get-data/linking-suite-wrds/ibes-crsp-link/), and then CRSP with Compustat using the CRSP/Compustat Linking table.

B.3.4 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 2020:Q2. Our results are robust to using the entire universe of firms.

B.3.5 Revenue Surprises

The expected path of revenues are computed using forecasts collected by IBES on February 20, 2020. For each period, we keep firms with at least three active forecasts and we obtain a profile of expected revenue as the median estimate across all forecasters. We do this at the quarterly and annual level. 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. Expected revenue for Q1-2020 to Q4-2020 are obtained directly from IBES. For Q1-2021 to Q4-2021 we update the expected revenue for each quarter in 2020 by adding the expected growth between year 2021 and 2020. Revenue on Q4-2021 and for Q4:2021 and year 2022 is not yet reported when we wrote this version and then we replace it with a revisited forecast on October 2021. In order to construct the revenue surprise for those periods, we use the difference between Feburary 20, 2020 an the updated forecast in October 2021.

B.3.6   Winners and Losers

We define a publicly traded firm in each sector (Contact/Non-Contact) as a winner if its Covid resilience measure (see equation (1)) is positive using the sectoral median as reference in the numerator. 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 or those that have less than three active 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 (used in Figure 2 and Figure 3), we assume that winners can only be among publicly traded firms. By selecting firms with a positive Covid Resilience in each sector, we aggregate the revenue surprise across our identified winners. Then, to construct the measure for sectoral losers, we subtract the revenue surprises of winners from the corresponding aggregate revenue surprise from BEA, which includes the entire universe of firms. It is important to notice that winners are identified as those with positive Covid Resileince and their size is calculated by aggregating their revenue in Compustat data, but we can only compute the revenue surprise of subset of those firms in the IBES dataset. We assume that the surprises computed are a representative sample of the winners actual surprises.

B.3.7   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 complement the

NAICS (North American Industry Classification System) classification we have been using to categorize firms with the GICS (Global Industry Classification Standard) classification. We use GICS as a tool to subtract close substitutes for Covid non-resilient Contact sector goods and services.

Each firm in our sample belongs to a sector/sub-sector in the NAICS classification and to another sector/sub-sector in the GICS. We look for close substitutes only on firms with the first two digits of the NAICS code equal to 51 to make sure that a firm belongs to the information sector. We then use the GICS classification to find the main business activity of the company. We try to match the GICS sub-sector in which the company belongs to a NAICS sub-sector in the Contact sector. If that is possible, we re-classify an information firm as belonging to the Contact sector. Specifically, 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:

- A firm is a close substitute to <u>Retail</u> if: its GICS code is 2550 (Retailing) and its NAICS is 51.Also,

- Close substitute to <u>Health care and social assist</u>: GICS 3510 (Health Care Equipment & Services) and NAICS 51.

- Close substitute to <u>Arts, Entertainment, and Recreation</u>: GICS 502020 (Entertainment) and NAICS 51.

- Close substitute to <u>Air, rail, and water transportation, Educational services and Accommodation</u>: 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) and NAICS 51.

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 revenue 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.

C Extra Figures and Tables

Table 7: 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)*	

Note: Table shows our classification of sectors between Contact and Non-Contact using NAICS codes. Firms in the Information sector (51) that offer goods or services that are close substitutes for Contact sub-sectors are included in the Contact sector. Details for the classification are in Appendix B.3.7.

Figure 11: Contact Sector Revenue Share of Total
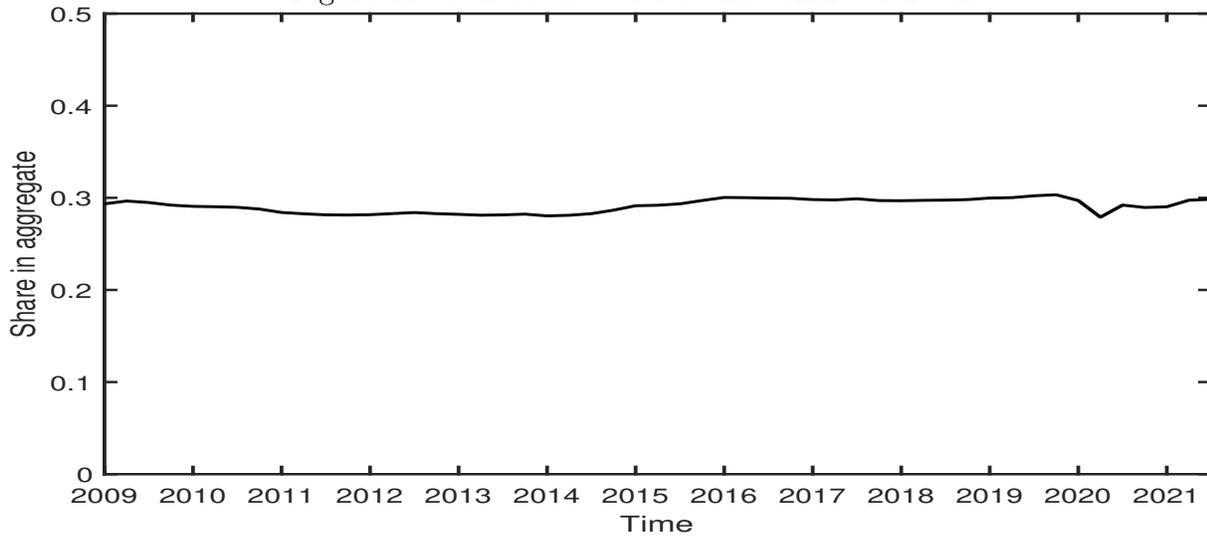
Note: Figure shows the share of the contact sector, as defined in Table 7, in aggregate output.

Figure 12: Evolution of Gross Output and GDP
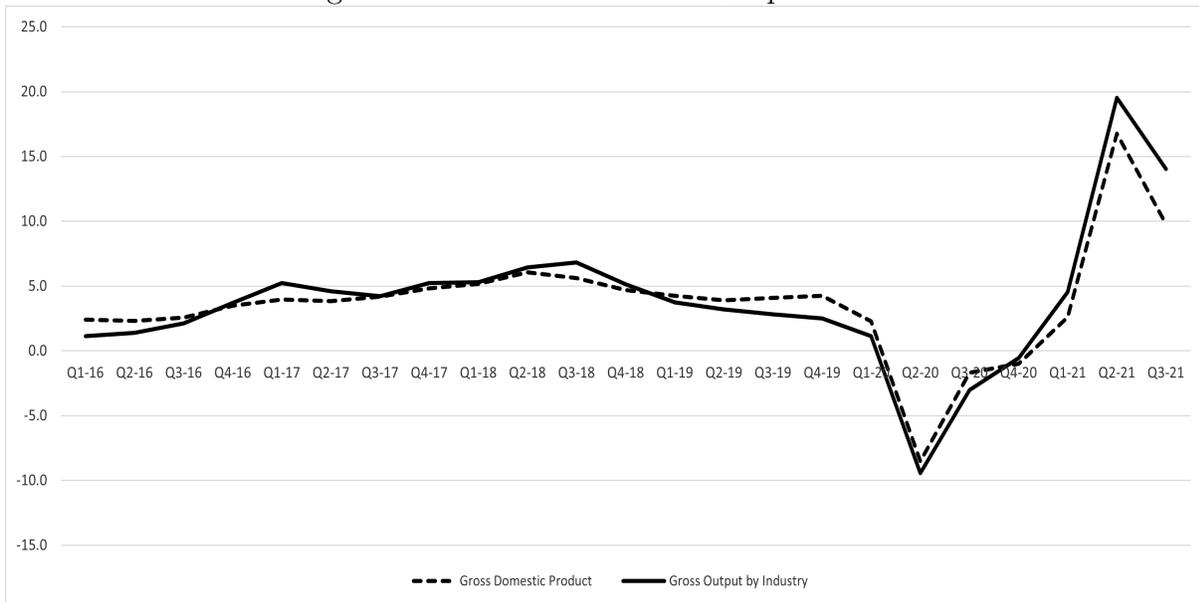
Note: Figure shows year over year growth of nominal GDP and Gross Output by Industry (all industries) for the U.S.

Table 8: Covid Resilience and Revenue Surprises

Contact

	Q1-20	Q2-20	Q3-20	Q4-20	Q1-21	Q2-21	Q3-21
Resilience	0.058***	0.423***	0.267***	0.210***	0.198***	0.130***	0.093***
	(0.009)	(0.070)	(0.051)	(0.040)	(0.040)	(0.028)	(0.020)
R^2	0.523	0.494	0.413	0.411	0.385	0.306	0.281
N	277	277	277	277	277	277	277

Non Contact

|	Q1-20	Q2-20	Q3-20	Q4-20	Q1-21	Q2-21	Q3-21
Resilience	0.038***	0.171***	0.118***	0.111***	0.065***	0.034*	0.045*
	(0.008)	(0.020)	(0.022)	(0.021)	(0.018)	(0.014)	(0.023)
R^2	0.142	0.187	0.204	0.172	0.087	0.027	0.043
N	607	607	607	607	607	607	607

Note: The dependent variable for columns is the log-difference between the quarterly realized revenue and the log of the median expected revenue from IBES reported in February 2020 for each firm in the sample. The independent variable is our measure of Covid resilience. The sample of firms is stable across columns and each firm has at least three active forecasts in per period. The regression is weighted using previous year quarterly revenue. Standard errors are robust to heteroskedasticity White (1980)

Figure 13: Labor Reallocation
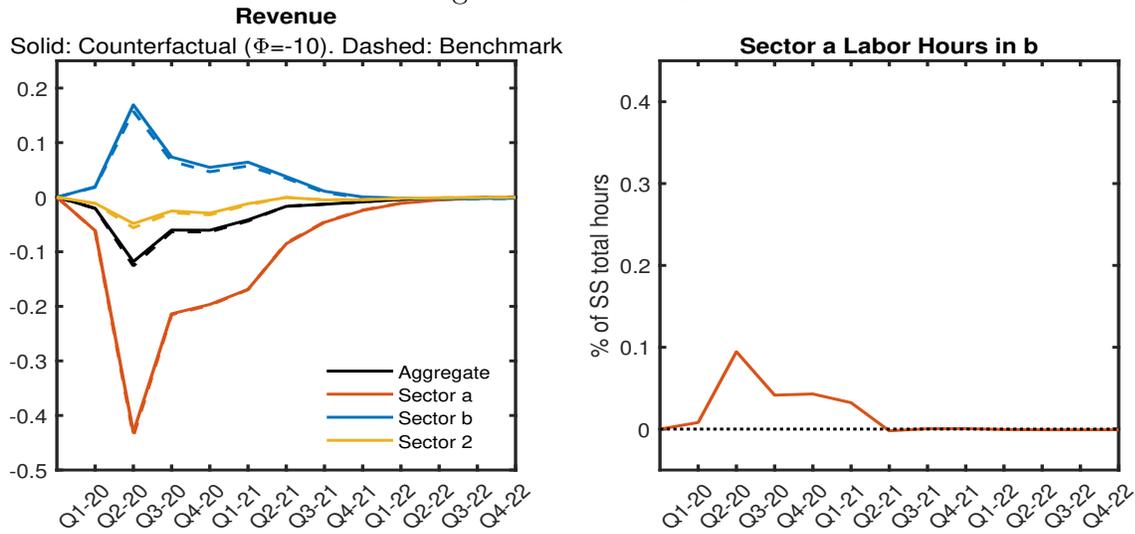
Note: Left panel compares response to the estimated shocks of our benchmark model (dashed line) and the counterfactual (solid line) allowing for labor reallocation of workers from sector a to b as described in Appendix A.3. Right panel shows hours worked that workers in sector a are working in sector b as a share of steady state.

Figure 14: Labor Reallocation Sensitivity Analysis
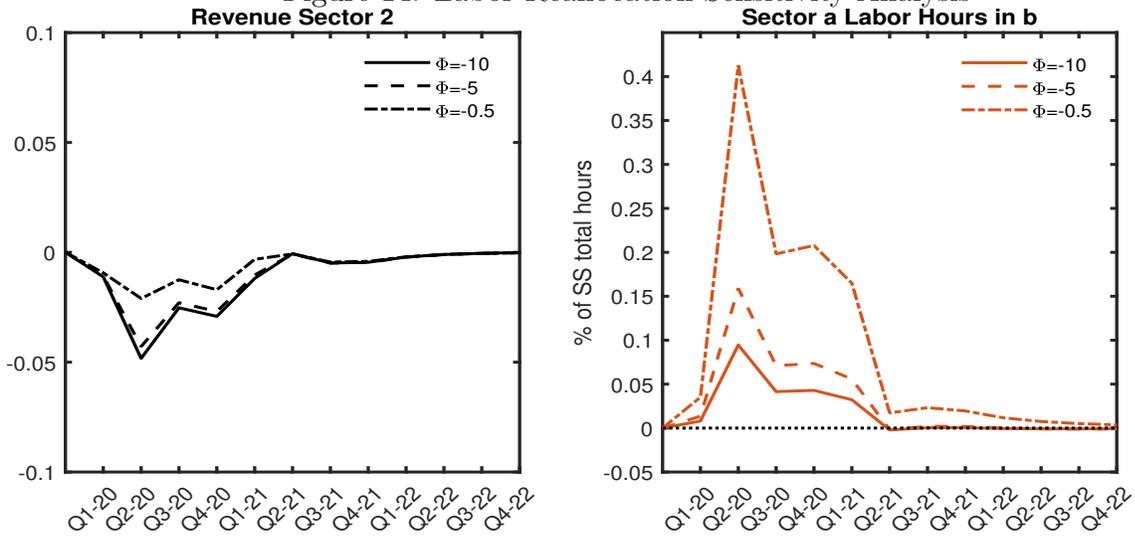
Note: Left panel compares response to the estimated shocks of revenue in sector 2 for different degrees of labor reallocation rigidities parametrized by Φ. Right panel shows hours worked that workers in sector a are working in sector b as a share of steady state.