

Economic Winners versus Losers and The Unequal Pandemic Recession

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September 11, 2024

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, the data suggests that the gap between winners and losers persisted 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) a set of demand and supply shocks meant to capture the impact of the virus. Overall, the model accounts for the unequal sectoral recession. It also captures some of the runup in inflation.

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1 Introduction

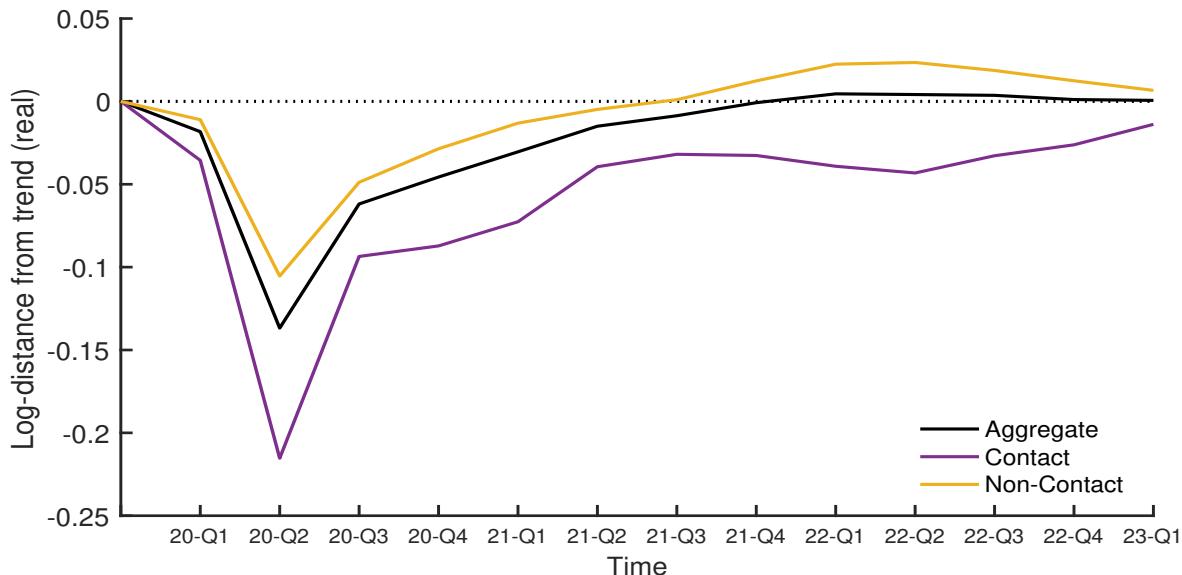
As has been well documented, the recent recession has hit sectors of the economy unevenly. Sectors where market activity involves exposure to the virus experienced a much sharper downturn and a much slower recovery than those sectors where exposure is minimal. [Figure 1](#) illustrates: Following [Kaplan, Moll, and Violante \(2020\)](#) (KMV), we aggregate exposed industries into the “contact” sector and non-exposed industries into the “non-contact” sector. Then for the period 2019:Q1 to 2023:Q1, we plot revenue relative to trend for the contact sector (purple line), the non-contact sector (yellow) and the aggregate (black).¹ The contact sector, which accounts for roughly thirty percent of total revenue, contracts approximately twenty percent relative to trend during the height of the recession, doubling the non-contact sector, which drops about ten percent.² Further, while the non-contact sector returns to trend in 2021:Q3 and the aggregate economy is fully recovered by 2021:Q4, the contact sector remains around four percent below trend until the end of 2022.

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.

¹[Figure 12](#) in the appendix shows the analogous to [Figure 1](#) without detrending.

²Note that the value added share of the contact sector is 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 5](#). 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.

In this paper we both measure and model the uneven sectoral dynamics of the pandemic recession, with particular emphasis on the role of substitution between economic winners versus losers in the contact sector. We attempt to capture not only the unequal initial contraction in economic activity shown in [Figure 1](#), but also the persistence in sectoral inequality during the recovery period. As a byproduct, our framework also accounts for some of the runup in inflation.

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 losers³. 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.⁴

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 fifty percent more than the sector as whole.⁵ 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 that the gap between winners and losers persisted 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), [Baqae 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. The main way we differ is by allowing for contact sector winners and losers that provide substitute goods.

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. Overall, the simple model does reasonably well in capturing both the aggregate and disaggregated data. We are also able to clearly illustrate both qualitatively and quantitatively how “substitution” can enhance both the unevenness of the sectoral contraction as well as the combined aggregate effect. Similar to

³Note that in every recession there are winners and losers. By using the stock market response to Covid, we are isolating the component of winning versus losing associated with the virus.

⁴To control for pre-existing trends (e.g. high trend growth in the IT sector), we examine revenue behavior relative to the pre-recession forecast.

⁵Our 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.)

GLSW, incomplete markets introduces a complementarity between the contact sector losers and the non-contact sector. Interestingly, the model explains some of the rise inflation. In doing so it also generates some patterns in sectoral inflation consistent with the data.

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.

[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 the individual contributions of supply and demand shocks. Finally, we present evidence of sectoral inflation consistent with the data.

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 15](#) 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 5](#). Their logic behind the classification is to sort industries based on the degree of social interaction, either with other customers or with workers. We differ slightly by including in the contact sector a number firms from the Information industry that primarily offer substitutes for contact sector goods and services.⁶ Notable examples of these Information sector firms we include in the contact sector are eBay—an online retailer offering a safer alternative to traditional in-person retail—and

⁶It would be more precise to call this sector “Contact plus close substitutes.” But in the interest of brevity we will stick with the label “Contact.” For details on the classification see [Appendix B.3.7](#).

Zoom—a technology company providing communication services that act as a substitute for transportation, allowing households to avoid risky trips. 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 14](#) 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 $\text{med}_t(\Delta p_{ft})$ be the median stock return of firm f across Covid days⁷; $\text{med}_f(\text{med}_t(\Delta p_{ft}))$ be the revenue weighted median of all firms’ median stock return; and $\sigma_f(\text{med}_t(\Delta p_{ft}))$ 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

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

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 loser⁸. 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

⁷Stock return for firm f at each Covid day t , Δp_{ft} , is measured as the log price change at closure.

⁸As detailed later in this section, winners and losers are sector-specific. A firm is considered a winner in its sector (Contact or Non-Contact) if its Covid resilience is above the sectoral median.

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. We then construct quarterly revenue surprises as the log difference between realized quarterly revenue and the February 2020 forecast⁹.

Table 1 presents regressions of the firm level quarterly revenue surprises on our measure of Covid resilience for the two years, 2020 and 2021, during which Covid had the most pronounced impact on the economy.¹⁰ We also examine the non-contact sector as a control group. Accordingly, we divide firms between the contact and non-contact sectors. In the eight 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-six percent revenue surprise increase relative to the median firm. The effects on realized revenue surprises remain large from 20:Q3 through 21:Q4, declining smoothly from twenty-three to seven 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 twenty to forty percent, typically more than double that for the non-contact sector.

⁹The expected quarterly revenue in 2021 and 2022 is not directly available every firm. Therefore, we use the February 2020 forecast of 2021 and 2022 revenue to compute the expected yearly growth and update the quarterly forecasts of 2020 assuming equal expected growth for each quarter.

¹⁰One 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 7 we show that the estimates for 20:Q1 through 21:Q4 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	Q4-21
Resilience	0.069*** (0.008)	0.362*** (0.053)	0.228*** (0.04)	0.210*** (0.039)	0.174*** (0.034)	0.127*** (0.027)	0.1*** (0.024)	0.074*** (0.019)
R^2	0.251	0.425	0.354	0.433	0.321	0.258	0.231	0.191
N	480	476	475	287	438	432	424	266
Non Contact								
	Q1-20	Q2-20	Q3-20	Q4-20	Q1-21	Q2-21	Q3-21	Q4-21
Resilience	0.039*** (0.008)	0.167*** (0.021)	0.115*** (0.02)	0.116*** (0.022)	0.072*** (0.016)	0.042*** (0.012)	0.05** (0.021)	0.006 (0.028)
R^2	0.115	0.169	0.192	0.18	0.098	0.036	0.044	0.001
N	1141	1121	1093	662	1004	986	970	612

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 on whether a forecast was available for that time. The regression is weighted using the 2019 quarterly revenue for the same quarter. Standard errors are robust to heteroskedasticity [White \(1980\)](#)

We next present suggesting evidence that spending substitution was likely at work in the 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 2](#) 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 bottom¹¹. 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

¹¹We focus on between firms substitution. There was certainly within firm substitution—for example, a shift from offline to online sales in Walmart—that also contributed to winners’ revenue evolution during the pandemic.

and auto demand, as opposed to a loss of business to companies offering substitute products.

Table 2: Winners and Losers Examples

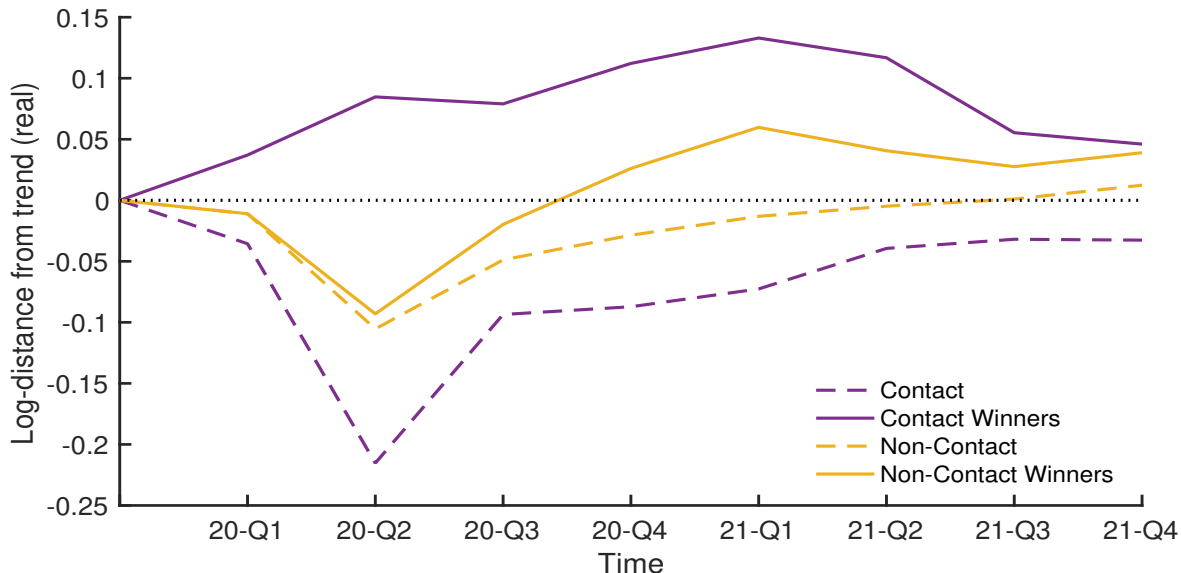
Contact		Non-Contact	
Winners	Examples (Resilience)	Winners	Examples (Resilience)
Non-Store retailers	Domino's Pizza (0.72)	Pharma companies	Pfizer (0.72)
	Amazon (0.59)		Johnson and Johnson (0.66)
	Ebay (0.34)		McKesson (0.42)
Online entertainment	Electronic Arts (0.97)	Covid related	Clorox (2.33)
	Spotify (0.81)		Procter and Gamble (0.87)
	Netflix (0.57)		3M (0.61)
Supercenters	Walmart (1.09)	Transportation	CH Robinson (0.77)
	Target (0.75)		UPS (0.11)
Work from Home	Zoom (4.19)		
Cloud and Software Services	Carecloud (3.02)		
	Dropbox (0.46)		
Supermarkets	Kroger (2.04)		
	Costco (0.65)		
Losers		Losers	
Airlines	American (-2.47)	Automobile	Goodyear (-0.68)
	United (-1.37)		Ford (-0.3)
	Delta (-1.27)		General Motors (-0.3)
Cruise	Norwegian (-2.91)	Air industry	Boeing (-2.2)
	Carnival (-2.97)		Raytheon (-1.73)
Transportation	Lyft (-2.09)		
	Uber (-1.28)		
Retail chains	Macy's (-1.59)		
	Nordstrom (-0.88)		
	Bed Bath and Beyond (-0.8)		
Hotels	Marriot (-1.68)		
	Hilton (-0.86)		
Casinos	Golden (-5.3)		
	Caesars (-4.2)		
Restaurants	BJ's restaurants (-3.84)		
	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:Q4 (the solid lines) relative

to the respective sector means (the dotted lines).¹² 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 5](#), 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 resilience predicted a larger increase in revenues

¹²Figure 13 in the appendix shows the analogous to [Figure 2](#) without detrending.

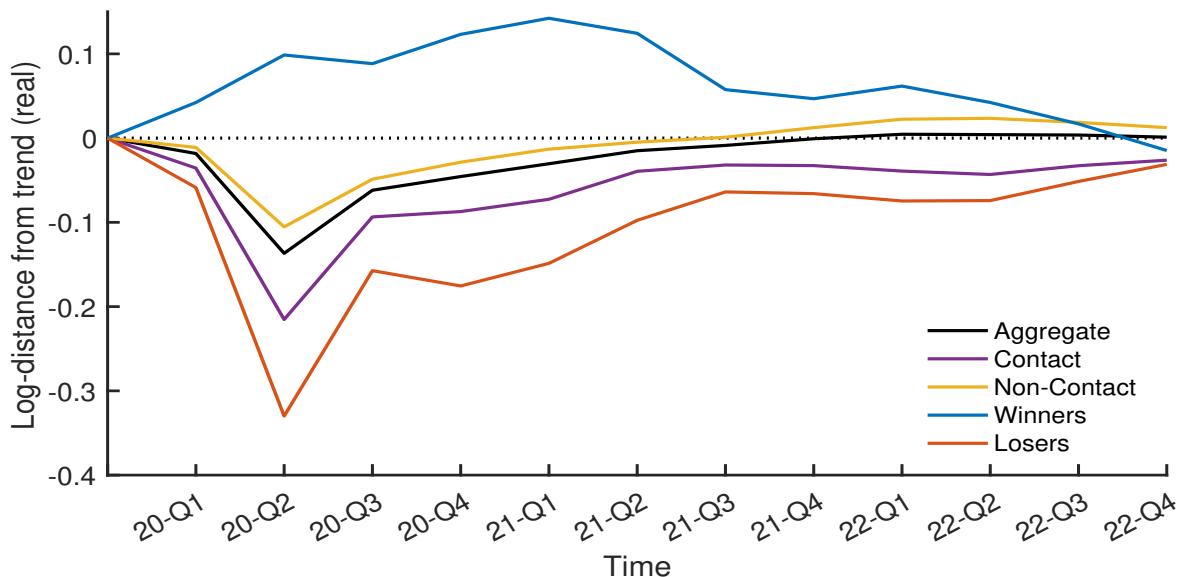
in the contact sector relative to the non-contact; 2. Representative winners in the contact sector appear to offer substitute products for losers, while this was not the case in the non-contact sector; and 3. Total revenues of contact sector winners rose substantially through the crisis and significantly 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 2022:Q4. 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 one percent. The recovery is also slower. Indeed in 20:Q4, contact sector losers are down nearly seventeen percent as compared to nine percent for the sector as a whole, not to

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 5](#), 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. Losers realized and expected revenue is obtained as a residual between public firms winners and aggregate from BEA.

mention just three percent for the non-contact sector. By contrast, winners did quite well, steadily rising to twelve percent above trend in 20:Q4. As the figure makes clear, further, the gap between winners and losers persisted well into 2022 when it appears to converge back only in 22:Q4. 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 three 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 hit the contact losing sector directly: One is a shock that reduces product demand that captures how the virus increases households' aversion to shopping. The other is a shock that reduces sectoral labor supply meant to capture the forces that affected the labor market, including: increases in the aversion to work due to contagion, changes in the household preference for remote work, and increases in the value of unemployment due to transfers. 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.

Lastly, while we allow for variable labor within a sector, for simplicity our baseline does not have mobility across sectors. Accordingly, in [Appendix A.4](#) we introduce imperfect labor mobility and show that our results are largely unaffected under reasonable circumstances.

3.1 Sectors and Goods

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

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

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

with

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

where $0 < \zeta < 1$. 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

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} :¹³

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

with

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

and $0 < \phi < 1$. 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 by¹⁴

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

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

¹³Given ϵ_t is zero prior to the pandemic recession, the log preferences appear consistent with Figure 14, which shows that from 2009 through 2019, the contact share of total revenue was fairly stable.

¹⁴See BF for a similar representation of preferences for the case where the shock hits only one of the sectors directly.

for non-contact sector goods c_{2t} , amplifying the contraction of C_t . We defer this discussion to [Section 3.3](#).

3.2 Household Behavior

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

Preferences are the same across households, with one exception: The pandemic induces a negative shock to labor supply for households attached to sector a , the contact sector with susceptible goods.¹⁵ With the aim of making the steady state equilibrium as simple as possible, we set the number of households in sector a equal to ϕ , in b to ϕ , and in sector 2 to $1 - \phi$.

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.¹⁶

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:

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

¹⁵We restrict the supply shock to sector a households mainly for parsimony. While it is acknowledged that many sectors in the economy experienced some problems in retaining workers, data suggests that labor supply disruptions affected disproportionately the losing sectors.

¹⁶Our 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 \(2018\)](#).

where η_t is a labor supply shock specific to sector a ¹⁷:

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

Let B_t^j denote holdings of short term nominal bonds, T_t^j denote lump sum taxes, Υ_t^j denote insurance transfers, i_t the nominal interest rate, W_{jt} the sector j real wage 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

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

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

$$\phi\Upsilon_t^b + (1 - \phi)\Upsilon_t^2 = 0 \quad (9)$$

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

$$\Upsilon_t^a = 0 \quad (10)$$

$$0 \leq B_t^a \quad (11)$$

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).

¹⁷As noted earlier, in [Appendix A.4](#) we allow for costly mobility of labor across sectors.

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

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

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

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

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

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

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 reallocation effects between sectors.

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

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

For households in sector a

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

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

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

where, given complete insurance:

$$\frac{C_{t+1}^b}{C_t^b} = \frac{C_{t+1}^2}{C_t^2} \quad (19)$$

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

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

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:

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

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

$$\epsilon_t = \rho_\epsilon \epsilon_{t-1} + \xi_{\epsilon t} \quad (21)$$

$$\eta_t = \rho_\eta \eta_{t-1} + \xi_{\eta t} \quad (22)$$

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 future¹⁸. Also for simplicity, assume 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 as¹⁹

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

¹⁸To be clear, after this section we return to allowing ϵ_t to arise each period and be serially correlated.

¹⁹To 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).

The first term on the right is demand by unconstrained households, which depends on their consumption/saving behavior.²⁰ The second term is the demand by constrained households, which simply equals their income. Rearranging yields

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

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 delay some consumption to the next period, when the taste shock (i.e. virus) has disappeared. The second channel, captured by the multiplier $1/[1 - \alpha(\epsilon_t, \frac{P_{at}}{P_{1t}})]$, 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

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

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

²⁰This 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.)

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} ²¹. 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.

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.²²

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

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

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

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

²¹The degree of substitutability enters through equation (23).

²²Our 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.

Combining with the production function then yields the price index:

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

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

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

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, $\Lambda_{0,t}^j = \beta^t \frac{1-\varepsilon_t \zeta \phi}{1-\varepsilon_0 \zeta \phi} \frac{C_0^j}{C_t^j}$ 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

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

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

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

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 substitute 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 equilibrium behavior.

3.5 Equilibrium

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

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

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

$$\int_0^1 L(f)_{at} df = L_{at} = \phi l_t^a \quad (34)$$

$$\int_0^1 L(f)_{bt} df = L_{bt} = \phi l_t^b \quad (35)$$

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

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:

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

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

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

Sectoral and aggregate price indices are given by

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

$$P_t = P_{1t}^{\phi(\epsilon_t)} P_{2t}^{1-\phi(\epsilon_t)} \quad (40)$$

Lump sum transfers are financed by lump sum taxes. Accordingly, the government budget constraint requires:

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

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

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

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:

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

$$i_t \geq 0 \quad (44)$$

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 in [Appendix A.2](#). 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.

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 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.4](#) 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.²³ There are nine parameters, as listed in [Table 3](#). 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.²⁴

Five parameters are “sectoral”: We set ϕ , the steady state revenue share of the contact

²³While a monthly model would be desirable, the shortest frequency the firm level data is available is quarterly.

²⁴See [Hazell, Herreño, Nakamura, and Steinsson \(2020\)](#) for empirical estimates of the slope.

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 data²⁵.

We choose the persistence of the demand shocks ρ_ϵ such that the shock is expected to die out after about a year, which we believe was the rough prediction of the length of the first wave of the virus, as well as the updated prediction when the new wave hit in the fall of 2020. Specifically, we opt for a value of 0.5 for the persistence of the demand shock. This implies that three quarters after a shock, only about ten percent of the initial shock remains.

Similarly, the persistence of the supply shock ρ_η is selected to capture the duration of the factors affecting the labor market during this period. These factors include health risks, the expansion of unemployment insurance, and shifts in preferences toward remote work, among others. We choose a persistence of 0.75, corresponding to the average persistence of the supply shocks affecting the labor market during the Covid recession and recovery considered in [Bagga, Mann, Sahin, and Violante \(2023\)](#).

4.2 Illustrating Model Behavior

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

4.2.1 Demand versus Supply Shocks

We examine the response of the model first to a sectoral demand shock and then to a sectoral labor supply shock. To disentangle the effect of the shocks from the response of monetary policy, we suppose the central bank adjusts the nominal rate to keep the real rate essentially fixed.²⁶ We normalize the size of the shocks so that each initially generates a one hundred

²⁵See [Broda and Weinstein \(2006\)](#).

²⁶We assume that the Taylor rule coefficient on inflation is 1.01 which keeps the real rate relatively fixed.

Table 3: Parameter Selection

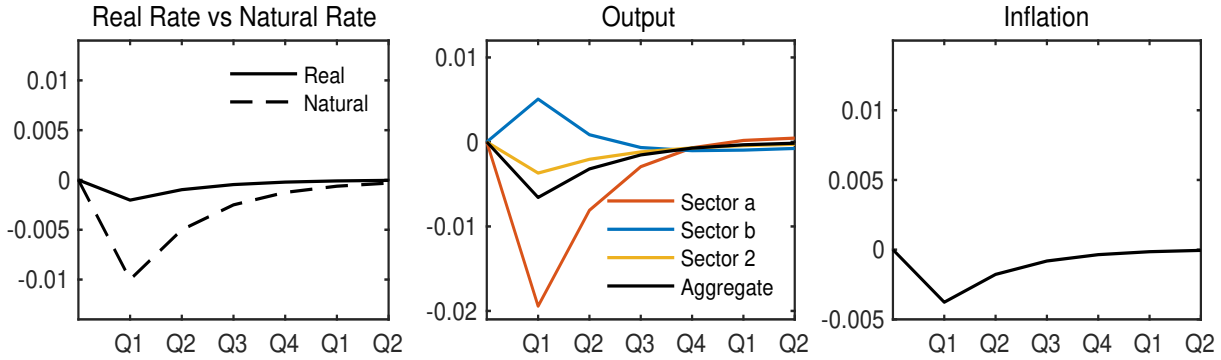
Parameter	Value	Description
Standard Parameters		
β	0.995	$r = 2p.p.$
φ	1	Labor elasticity
γ	0.8	Calvo parameter
ε	6	Final good elasticity. Markup of 20%
Sectoral Parameters		
ϕ	0.3	Contact Sector as a fraction of Total
ζ	0.75	Losers as a fraction of Contact sector
$1/\rho$	2	Intra-temporal sectoral substitution
ρ_ϵ	0.5	Persistence of demand shock
ρ_η	0.75	Persistence of labor supply shock

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.

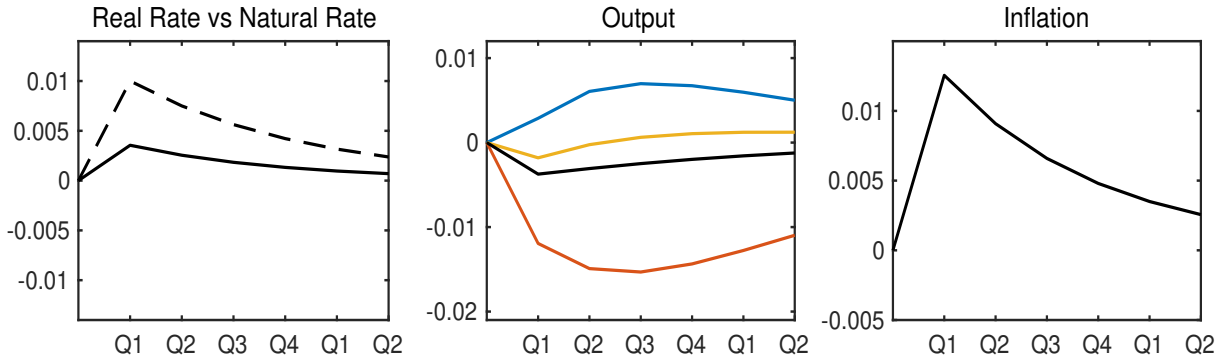
The demand shock is an increase in ϵ_t that directly reduces demand for contact sector goods and induces substitution from the exposed subsector a to the safe subsector b . Note first that the shock produces a decline in the natural rate of interest. It does so for two reasons: First, as discussed in [Section 3.3](#), the shock induces intertemporal substitution, reducing current demand. In the flexible 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. 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.

Figure 4: Demand vs Supply Shocks
Demand Shock



Supply Shock



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 one hundred basis point change in the natural rate of interest.

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*.

The supply shock leads to a more substantial reduction in both aggregate and sector 2 output, primarily due to its greater persistence. There is also a nontrivial effect on the allocation of contact sector revenues between winners and losers. The shock increases the relative price of sector a goods, inducing substitution to sector b .

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.

4.3 Simulating the Covid-19 Pandemic Recession

Next we use our model to simulate the pandemic recession.²⁷ In order to do it we select realizations of the demand and supply shocks to minimize the distance of our model from three targets: aggregate revenue, sector a revenue and inflation. For inflation, we use Cavallo’s core Covid CPI index, which adjusts for changes in spending shares induced by the virus.²⁸ We select only shocks from 2020:Q1 through 2021:Q4 as we want to capture the time in which Covid had the most severe and direct impact on the economy and avoid cofunding it with other posterior shocks like the war in Ukraine. As we discussed earlier, the behavior of inflation helps us disentangle demand from supply shocks.

Figure 5 shows our identified shocks. The left panel represents the demand shock, ϵ_t —in negative terms—, while the right panel portrays the supply shock, η_t . Our estimations reveal a significant negative demand shock at the onset of the Covid recession. However, these negative demand pressures dissipate relatively quickly, nearly disappearing by the end of 2021, coinciding with the point when over 60% of the US population had been fully vaccinated.²⁹

In contrast, the supply shock exhibits a gradual buildup over time. It initially peaks in 2020 concurrently with the demand shock, possibly reflecting challenges faced by firms in

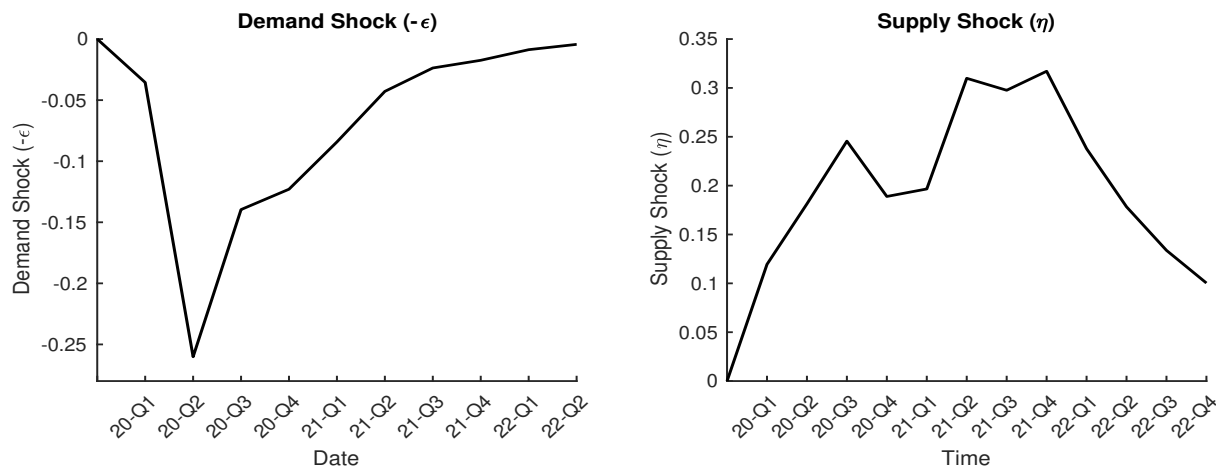
²⁷Appendix A.3 provide details on model simulation and shocks selection.

²⁸See Baqaee and Burstein (2021) for some pitfalls of using this index.

²⁹See data from CDC at <https://usafacts.org/>.

operating under the health risks of workers. The supply shock experiences a more pronounced peak in 2021, corresponding to the period recognized as the “Great Resignation.” Various factors have contributed to the observed labor market problems during 2021, including the rise in unemployment insurance, a shift in preferences towards remote work, and the deterioration of workers’ health conditions³⁰.

Figure 5: Estimated Shocks



Note: The figure shows the selection of demand shocks in negative values ϵ (left panel) and supply shocks η (right panel) for the simulated economy.

For monetary policy, we assume that the 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.³¹

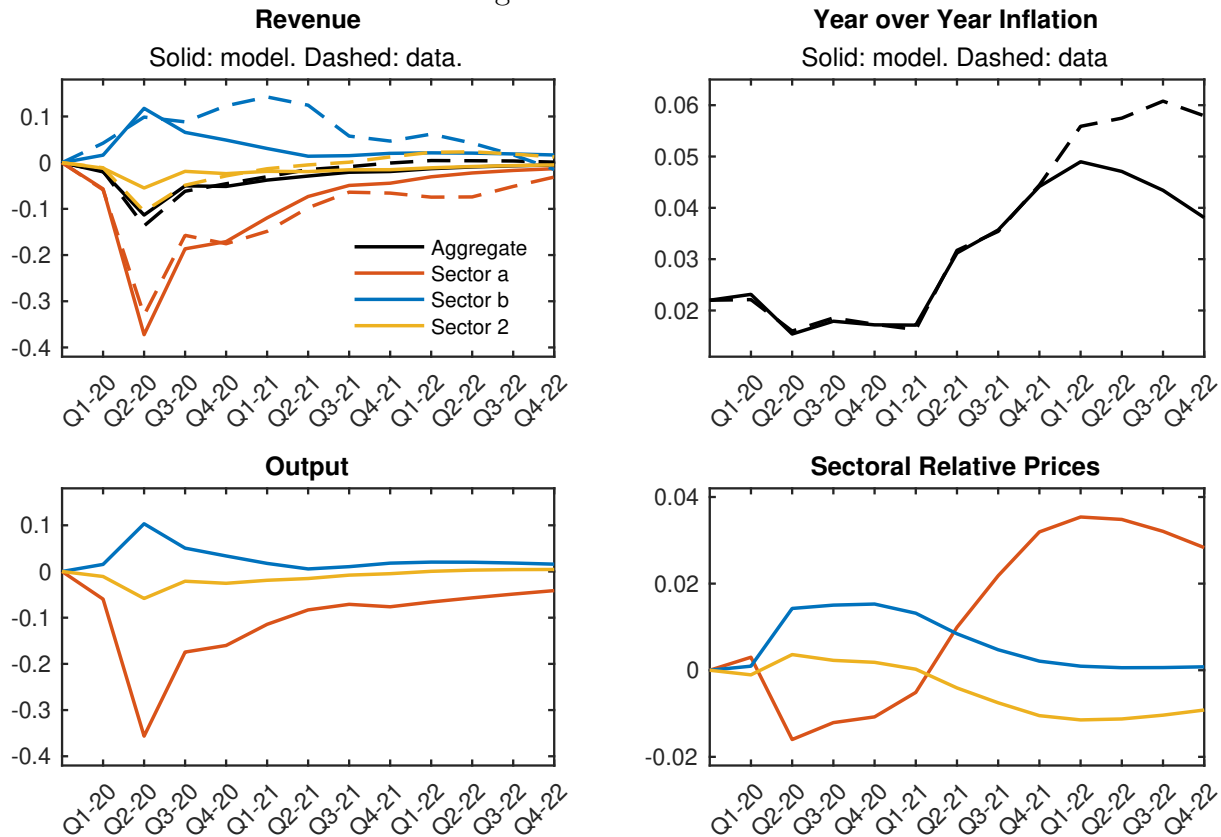
Because we have fewer shocks than targets, the model will not fit perfectly. But our simple framework does a reasonable job of describing the data. [Figure 6](#) illustrates. As the top left panel shows, the model does well overall in capturing both the unequal sectoral decline in economic activity as 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 4](#) shows the average quarterly decline

³⁰Refer to [Bagga, Mann, Sahin, and Violante \(2023\)](#) for a detailed decomposition of these forces.

³¹In a prior iteration of this paper, we introduced direct fiscal transfers funded by lump-sum taxes of comparable magnitude to those witnessed during the recession. However, our analysis, consistent with findings presented in [Bianchi et al. \(2022\)](#), indicated that these transfers had a modest impact on our results. To enhance clarity and simplicity, we have elected to exclude them in this revised version.

for aggregate and sectoral revenue over 2020. For aggregate revenue and revenue 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 revenue during Q2.

Figure 6: 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).

The model is able to replicate a good deal of the persistence in the revenue and output gap between sectors a and b . 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.

Finally, the model also does well in capturing inflation through 21-Q4, as the top right panel shows. 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 in early 2021 is then the product of two factors: the wearing off the negative demand shock and the large supply shocks in mid 2021 (see [Figure 5](#)). The model then has inflation level off at around four percent in 21-Q4, while it continues to increase to roughly six percent in the data. This discrepancy is likely due to several factors missing from the model relevant to the inflation surge, such as the spike in energy prices, including the dramatic jump associated with the Ukraine war, along with supply chain disruptions.

Table 4: Average Revenue Change and Inflation in 2020

	Aggregate	Sector a	Sector b	Sector 2	YoY Inflation
Data	-6.6	-18	8.8	-4.9	1.85
Benchmark	-5.9	-19.7	6.2	-2.7	1.85
No Substitution	-4.9	-15.7	-1.8	-1.8	2.3
Demand shocks only	-5.2	-18.5	5.3	-2.1	0.6

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

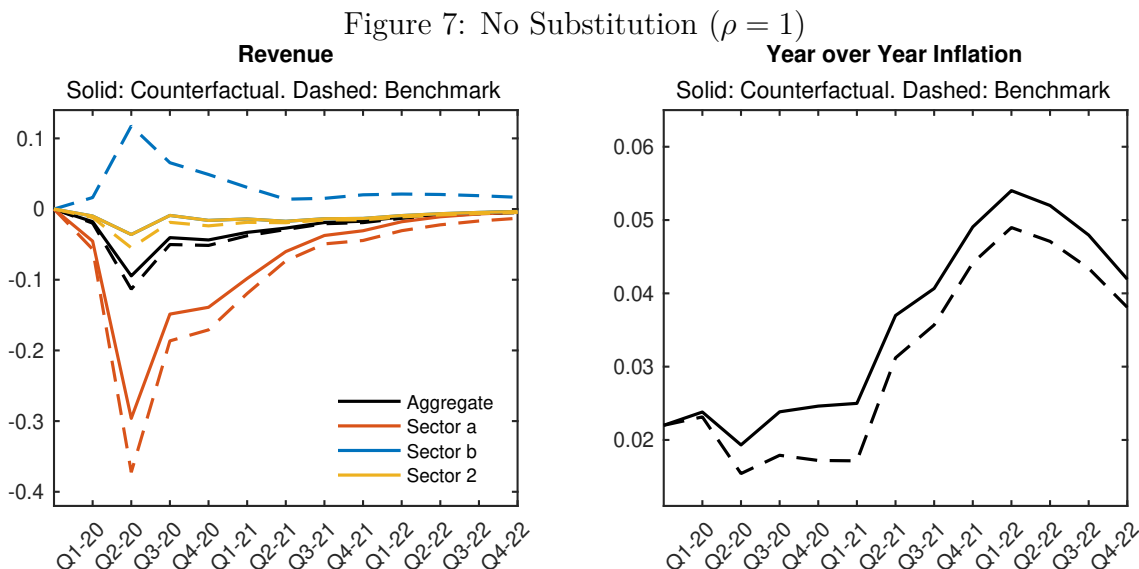
In this section, we explore the role of the distinctive features of the model, including substitution between safe and risky contact sector goods and the role of supply and demand shocks in driving sectoral and aggregate dynamics.

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 7](#) 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. In other words, when sectors were substitutes, the inability of the losing sector to smooth the shock due to incomplete markets was spilling over to the rest of the economy.³² However, this effect is smaller when sectors become independent since the drop in income of constrained households is smaller.



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

Table 4 provides exact numbers. It shows the average quarterly revenue change over 2020 for each sector for the baseline model and various alternative scenarios. With no substitution, the decline in sector *a* revenue is smaller by roughly twenty percent, going from -19.7% in the case with substitution to -15.7% . Sector *b* now loses -1.8% instead of winning. The effects on the aggregate are nontrivial. Without substitution, the drop in sector 2 (due to

³²We find it reasonable to concentrate the borrowing constraints on the losing sector *a* since this sector is mostly populated by low income service workers, in contrast to the winning sectors, which included among others information technology.

smaller spillovers from sector a) is sixty percent, going from -2.7 percent to -1.8% . The drop in aggregate revenues is also smaller in the case without substitution, going from -5.9 percent to -4.9 percent, a twenty percent increase.

Decomposition of Shocks

In this section, we decompose the role of demand (ϵ and forward guidance) and supply (η) shocks in driving the dynamics of revenue and prices. [Figure 8](#) plots the decomposition. The solid black line reproduces the evolution of revenue and inflation in our benchmark economy. The shaded red area represents the contribution of the demand shock to the dynamics of each variable, while the blue area corresponds to the contribution of the supply shock.

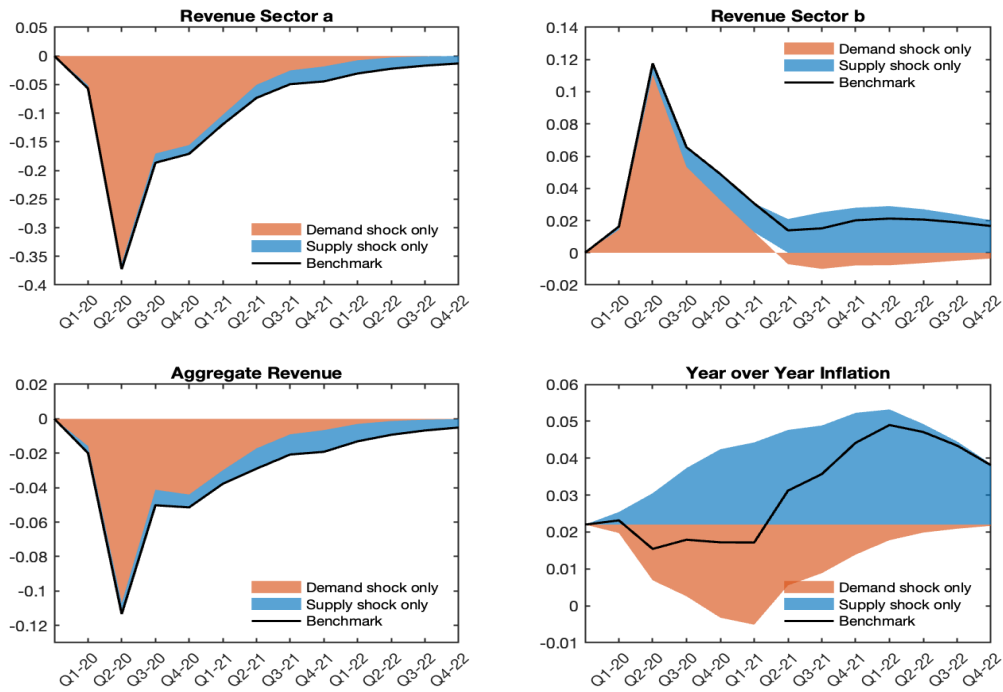
The demand shock plays a key role in explaining the initial dynamics of revenue in every sector. Yet, after the demand shock vanishes, the supply shock plays a key role in explaining the persistence of the revenue during the recovery. As the [Figure 8](#) shows, revenue would have returned to trend several quarters before if it were not for the supply shocks that hit the economy during 2021.

For the dynamics of prices, the supply shock plays a critical role. At the beginning of the pandemic, disruptions in the supply of labor prevented prices from experiencing a decline in response to the fall in demand. Subsequently, these supply shocks emerged as the primary driver behind the significant inflation observed in our benchmark economy during 2021 and 2022. [Table 4](#) shows that, in the absence of supply shocks, around 90% of the fall in revenues in 2020 would have occurred anyway. For inflation, however, the level would have been markedly lower: 0.6% instead of 1.85%.

4.3.2 Evidence on Inflation Dynamics on Winners and Losers

While our model is not designed to provide a complete description of the inflation surge, it does have implications for the heterogenous behavior of pricing dynamics across firms that are winners versus losers. In particular, the model predicts that when the pandemic hits,

Figure 8: Supply and Demand Shocks Decomposition



Note: The figure shows the contribution of supply (blue area) and demand (red area) shocks in the dynamics of the benchmark economy (solid black line).

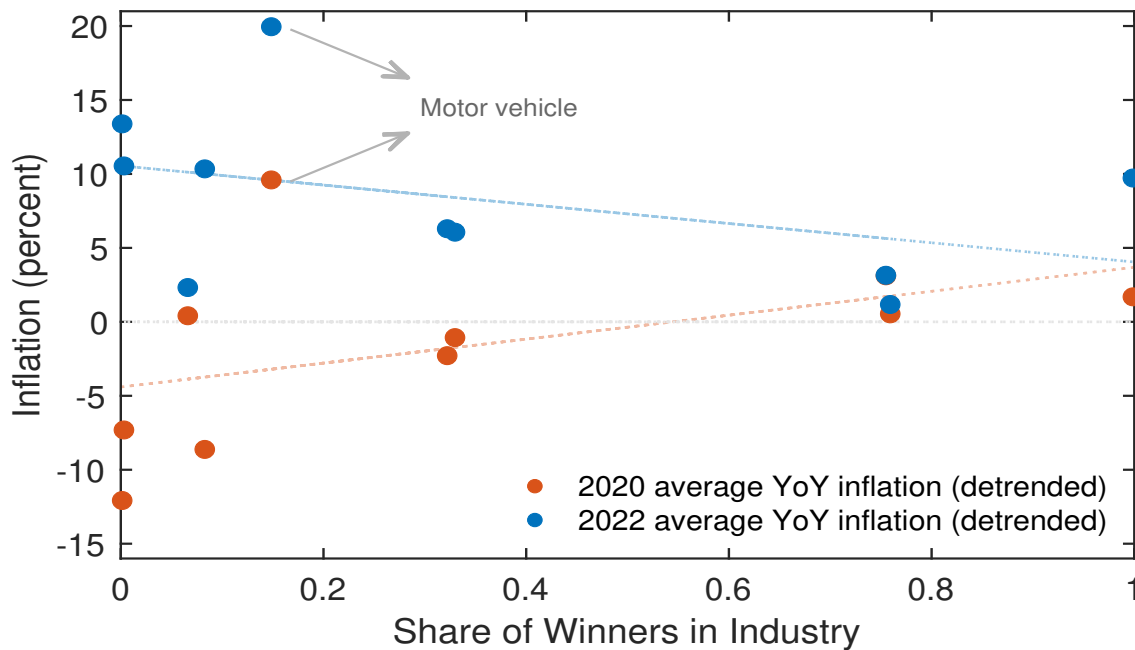
losers initially experience a drop in inflation due to the contraction in demand. Then, as the demand shock wanes and the supply shock kicks in, inflation in this sector picks up. Conversely, winners experience an initial rise in inflation due to the reallocation of spending from the demand shock and another rise later on due to the reallocation of spending from the supply shock. In this subsection we show that these implications are consistent with the available evidence.

A challenge in doing so is that we only possess price data at the industry level: This is problematic because industries contain both losers and winners. To address this challenge, we adopt the following approach: we calculate the share of revenue generated by winner firms within industries and pair this metric with the corresponding industry-level inflation rates for 2020 and 2022.³³ Further details of this calculation can be found in [Appendix B.3.8](#).

³³We appreciate the suggestion from Referee 1 to use the share of winners' revenue as a proxy for the level

As shown in Figure 9, we plot the share of revenue contributed by winner firms within industries in the Contact sector³⁴ together with data on industry-level inflation. The horizontal axis represents the share of winners' revenue within each industry, while the vertical axis illustrates the average detrended inflation for the years 2020 and 2022. Each point on the scatter plot represents a combination of an industry's 'winner' status and its corresponding inflation experience during the specified period. The figure illustrates that industries primarily comprised of losers witnessed significant deflation in 2020 and a sharp inflation increase in 2022. In contrast, industries with a higher prevalence of winner firms experienced relatively mild inflation in both 2020 and 2022.³⁵

Figure 9: Industry Exposure and Inflation Dynamics



Note: The horizontal axis shows the revenue generated by winner firms as a share of the total public firms in its industry for industries in the Contact sector. Vertical axis industry inflation is the average (over each quarter) year over year inflation for each industry from the Chain-Type Price Indexes for Gross Output by Industry. See Appendix B.3.8 for details.

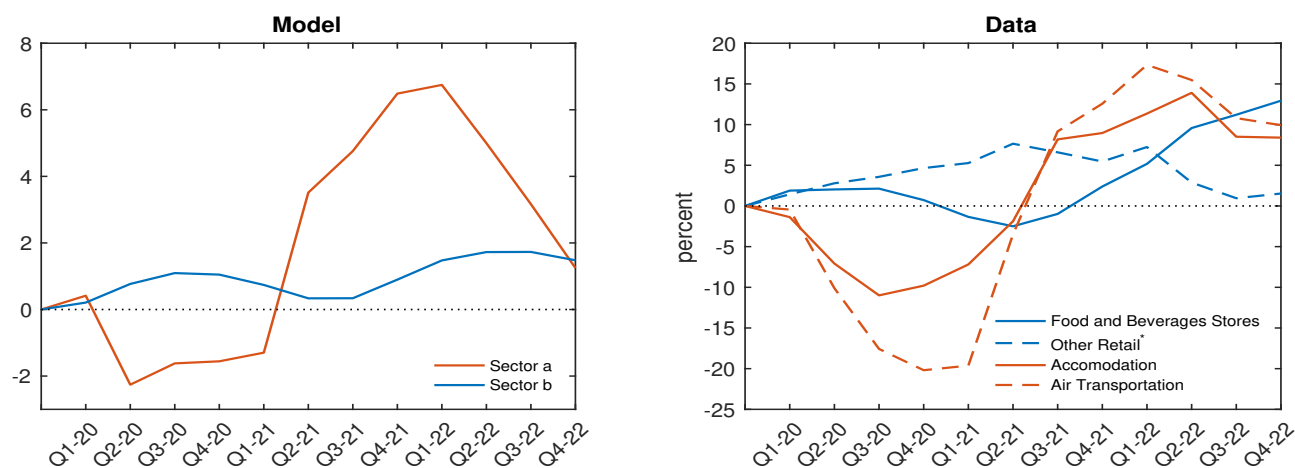
of winners within a sector.

³⁴We keep industries well represented in the public firms dataset. In particular, we keep sectors in which public firms contribute at least 20% of the aggregate revenue (see the full list in Table 6).

³⁵The clear outlier is the motor vehicle industry. We believe it was due to factors such as increased demand for durable goods and supply chain disruptions not fully captured in our model.

Figure 10 shows how our model’s predictions align closely with the observed data. For sector *a*, the loser sector, the model accurately anticipates deflation in 2020, followed by elevated inflation in 2022. In contrast, sector *b*, the winner, consistently avoids deflation. The right panel shows the inflation dynamics for two industries that rank among the top in terms of the largest share of winners and losers. Accommodation and Air Transportation were severely impacted by Covid restrictions and identified as the most affected according to our Covid resilience measure. These industries initially witnessed a significant price decline in 2020 but exhibited a swift rebound in 2022. Conversely, industries like Food Stores and Other Retail—category predominantly inhabited by online shopping companies—provided viable alternatives to dining out and traditional in-person retail, positioning them as winners. Notably, these industries experienced neither price drops in 2020 nor in 2022; instead, they mostly demonstrated inflationary trends. These observations underscore the model’s ability to effectively capture and predict pricing dynamics within sectors.

Figure 10: Inflation: Model Prediction and Selected Industries



Note: The left panel shows the inflation dynamics for sector *a* and *b* in our benchmark economy. The right panel shows the year over year inflation for selected industries from the Chain-Type Price Indexes for Gross Output by Industry. *Other Retail is the name adopted by the BEA. This category in the public firms dataset is predominantly populated by online and large retail department stores.

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 and the recovery phase, as well as relative inflation dynamics. 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.

To explain the data we develop a simple three sector New Keynesian model with incomplete markets. Among other things, we disaggregate the contact sector into an “exposed” subsector (losers) and a subsector (winners) that offers safe substitute goods. Overall, the model does a reasonable job of capturing the data, particularly the uneven sectoral contraction and recovery phase. The model also explains some of the runup in inflation in 2021. In doing so, it predicts heterogeneity in pricing dynamics across winners and losers which we show is consistent with the data. To provide a full accounting of inflation, of course, it is necessary to include other supply factors, including rising energy prices, supply chain disruptions, and exit from the labor force. We leave this on the agenda for future research.

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

tradables. Finding and fleshing out examples like this is something on the agenda for future research.

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Appendix

for Online Publication

A Model

A.1 Deterministic Steady State

We linearize the model around a steady state in which there are no shocks, prices are flexible and there is zero inflation.

With flexible prices, firms in sector j set prices equal to a constant desired markup $1 + \mu = \frac{\varepsilon}{\varepsilon - 1}$ over the steady state real wage.

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

Given the absence of shocks, labor supply in 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

$$\begin{aligned} c_a &= c_b = c_1 = \phi \\ c_2 &= 1 - \phi \end{aligned}$$

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:

$$\begin{aligned} \frac{P_a}{P} &= \zeta; & \frac{P_b}{P} &= 1 - \zeta \\ \frac{P_1}{P} &= \frac{P_2}{P} &= 1 \end{aligned}$$

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

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:

$$\begin{aligned} l_t^a &= \left(\frac{1 - \epsilon_t \zeta \phi}{\eta_t} \right)^{\frac{1}{1+\varphi}} \\ l_t^b &= \left\{ \frac{\frac{\phi}{1-\phi}(1 - \zeta) + 1}{\frac{\phi}{1-\phi}(1 - \zeta) + \Omega_t^{1-\rho}} \cdot (1 - \epsilon_t \zeta \phi) \right\}^{\frac{1}{1+\varphi}} \\ l_t^2 &= \Omega_t^{\frac{1-\rho}{1+\varphi}} l_{bt} \end{aligned}$$

with

$$\Omega_t = [\zeta(\epsilon_t) \left(\frac{l_t^a}{l_t^b} \right)^{1-\rho} + (1 - \zeta(\epsilon_t))]^{\frac{1}{1-\rho}}$$

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

$$l_t^a = l_t^b = l_t^2 = (1 - \epsilon_t \zeta \phi)^{\frac{1}{1+\varphi}}$$

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

$$\begin{aligned} l_t^a &= \eta_t^{-\frac{1}{1+\varphi}} \\ l_t^b &= \left[\frac{\phi(1-\zeta) + 1 - \phi}{\phi(1-\zeta) + (1-\phi)\Omega_t^{1-\rho}} \right]^{\frac{1}{1+\varphi}} \\ l_t^2 &= \Omega_t^{\frac{\rho-1}{1+\varphi}} l_{bt} \end{aligned}$$

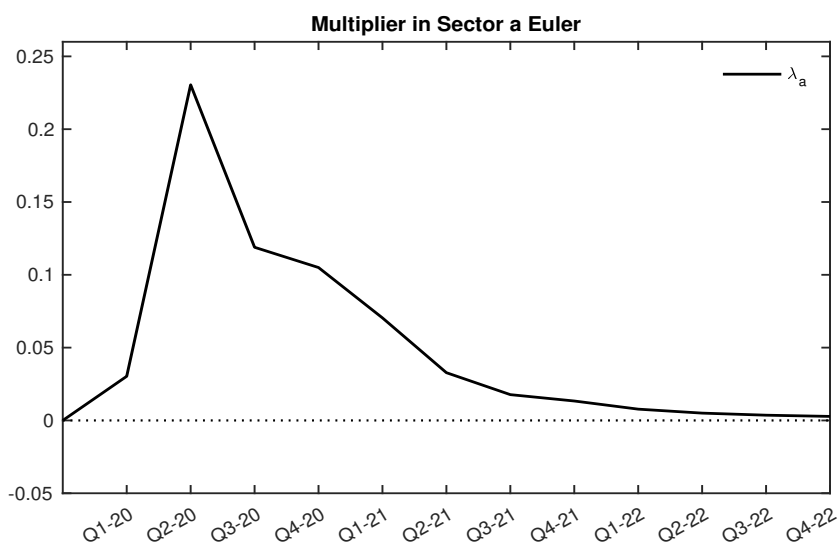
with $\Omega'(\eta_t) < 0$. In contrast to the sectoral demand shock, the supply shock that hits a causes the flexible price equilibrium sectoral output shares to vary. An increase in η_t reduces l_t^a , which in turn reduces output in this sector. Given $\Omega'(\eta_t) < 0$, the rise in η_t leads to an increase in employment in the substitute sector l_t^b . 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](#) - [Section 3.5](#) to derive the complete flexible price equilibrium.

A.3 Model Solution and Shocks Selection

The model is solved using first-order perturbation around the deterministic steady state characterized in [Appendix A.1](#) implemented using Dynare. So long as the borrowing constraint of sector a households binds every period ($\lambda_t^a > 0$ in equation (20) $\forall t$), the model returns to its original steady state after small temporary shocks and the dynamics of the model can be accurately approximated using traditional first-order perturbation techniques. Therefore, we solve the model by assuming that the Euler equation (18) for households in sector b and 2 holds with equality and households in sector a act as hand-to-mouth each period. We then verify that this indeed the right solution in our simulations. [Figure 11](#) show that this is the case for our benchmark economy. It plots the value of the Lagrange multiplier (λ_t^a) on (20) for our benchmark economy, which is always above zero.

Figure 11: Lagrange multiplier in sector a Euler equation



Note: Figure shows the value of the Lagrange multiplier in sector a Euler equation (20) for our benchmark economy.

Our benchmark economy features four quarters of forward guidance with the monetary policy rate expected to be at the zero lower bound, $i_t = 0$, for four quarters starting at Q2:20 ($t = 2$). In order to implement forward guidance using a first-order approximation solution, we incorporate into the monetary policy rule four perfect foresight shocks, $\{\xi_{it}\}_{t=2}^5$, that are

realized to the households every quarter between Q2:20 and Q1:21 ($t = 5$). These shocks are updated each quarter to ensure that households maintain the expected duration of the ZLB until Q1:2021 every quarter given the new demand and supply shocks that hit the economy. The modified monetary policy rule for our benchmark economy is then (in deviations from trend):

$$i_t = \phi_\pi \pi_t + \sum_{t=2}^5 \xi_{it}$$

The realizations of demand (ξ_{et}) and supply ($\xi_{\eta t}$) shocks from equation (21) in our benchmark economy of Section 4.3 are chosen to minimize the distance between our model simulations and data targets. As data targets, we use aggregate and sector a (winners) revenue deviations from trend from Figure 3, and core inflation deviations between 2020:Q1 and 2021:Q4. To match these eight quarters of the three time series we select eight supply and eight demand shocks, one per quarter. In particular, we choose shocks such that:

$$\min_{\{\xi_{et}, \xi_{\eta t}\}_{t=1}^8} d(x_t, \bar{x}_t)' W d(x_t, \bar{x}_t)$$

where $d(x_t, \bar{x}_t)$ is a vector that collects the distance between the deviations from trend in the data \bar{x}_t for each of the series with respect to the deviations from trend in the model simulation x_t given a series of shocks $\{\xi_{et}, \xi_{\eta t}\}_{t=1}^8$, and W is the identity matrix. At each time t , we measure the distance between each series j as a weighted average between a proportional and a linear distance:

$$d_t^j(x_t^j, \bar{x}_t^j) = \omega_t^j \frac{x_t^j - \bar{x}_t^j}{\bar{x}_t^j} + (1 - \omega_t^j) (x_t^j - \bar{x}_t^j)$$

where,

$$\omega_t^j = \frac{|\bar{x}_t^j|}{|\bar{x}_t^j| + \|\bar{x}_t^j\| - \max_j |\bar{x}_t^j|}$$

The weights ω_t^j are purposely chosen such that they go to zero ($\omega_t^j \rightarrow 0$) when the data is very close to trend ($|\bar{x}_t^j| \rightarrow 0$) and therefore measure the distance between data and model using

the linear distance $(x_t^j - \bar{x}_t^j)$ for observations close to trend. Contrarily, if the data series is the furthest possible from its trend measured linearly $(|\bar{x}_t^j| \rightarrow \max_j |\bar{x}^j|)$ then the weight $(\omega_t^j \rightarrow 1)$ and the distance is measured using proportional distance $(\frac{x_t^j - \bar{x}_t^j}{\bar{x}_t^j})$. For realizations in between, the distance is a weighted average of both measures.

This weighted average distance handles well the selection of shocks for our benchmark economy since it prevents the minimizer from attributing disproportionately large weights to observations very close to zero, in the case of proportional distance, or very far from zero, in the case of linear distance. The weighted measure does it by using the distance measure that behaves better for each observation: proportional when the data is far from trend, and linear when is close.

A.4 Allowing for Labor Reallocation

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

A.4.1 Households

To minimize complexity, we introduce costly labor reallocation from a to b in a very simple way. We assume that workers in sector a can work in b but at a cost that involves increasing marginal disutility. Put differently, rather than depend just on total hours worked, the disutility from labor also depends on the allocation of hours across sectors, with increasing disutility of hours in each sector.³⁶

³⁶To 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.

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

$$E_0 \left\{ \sum_{t=0}^{\infty} \beta^t \left[\log(C_t^a)^{1-\epsilon_t \zeta \phi} - \frac{\kappa}{1+\varphi} \left[(\Psi_t)^{\frac{1}{1-\Phi}} \right]^{(1+\varphi)} \right] \right\} \quad (45)$$

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

$$\Psi_t = \nu_a \left(\eta_t^{\frac{1}{1+\varphi}} l_{at}^a \right)^{1-\Phi} + (1 - \nu_a) \left(\eta_t^{\frac{1}{1+\varphi}} l_{at}^a + l_{bt}^a \right)^{1-\Phi} \quad (46)$$

Note that the utility function has the property that l_{at}^a and l_{bt}^a separately affect the disutility from supplying labor. We choose this particular functional form for two reasons: First, it is possible to have l_{bt}^a equal zero in the steady state, which makes the steady state the same as in our baseline model. Second, $\frac{1}{\Phi}$ controls the response of relative labor supply l_{bt}^a/l_{at}^a to relative wages w_{bt}/w_{at} at the steady state.³⁷ 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_{at}^a , is now given by,

$$\frac{1 - \epsilon_t \zeta \phi}{C_t^a} = \frac{\kappa}{W_{at}} \left[(\Psi_t)^{\frac{1}{1-\Phi}} \right]^\varphi \times (\Psi_t)^{\frac{\Phi}{1-\Phi}} \left(\nu_a \eta_t^{\frac{1-\Phi}{1+\varphi}} (l_{at}^a)^{-\Phi} + (1 - \nu_a) \eta_t^{\frac{1}{1+\varphi}} \left(\eta_t^{\frac{1}{1+\varphi}} l_{at}^a + l_{bt}^a \right)^{-\Phi} \right) \quad (47)$$

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

$$\frac{\nu_a \eta_t^{\frac{1-\Phi}{1+\varphi}} (l_{at}^a)^{-\Phi} + (1 - \nu_a) \eta_t^{\frac{1}{1+\varphi}} \left(\eta_t^{\frac{1}{1+\varphi}} l_{at}^a + l_{bt}^a \right)^{-\Phi}}{(1 - \nu_a) \left(\eta_t^{\frac{1}{1+\varphi}} l_{at}^a + l_{bt}^a \right)^{-\Phi}} = \frac{W_{at}}{W_{bt}} \quad (48)$$

³⁷In particular, at steady state $\frac{\partial(l_{bt}^a/l_{at}^a)}{\partial(W_{bt}/W_{at})} \propto -\frac{1}{\Phi}$.

Given wages and consumption, equations (47) and (48) pin down l_{at}^a and l_{bt}^a .

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

$$\frac{1}{(1 - \nu_A)} = \frac{w_A}{w_B} \rightarrow \nu_A = 1 - \frac{w_B}{w_A} \quad (49)$$

A.4.2 Firms

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

$$Y_a = \phi l_a^a \quad (50)$$

$$Y_b = \phi [l_b + l_b^a] \quad (51)$$

$$Y_2 = (1 - \phi) l_2 \quad (52)$$

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.4.3 The Model with Labor Reallocation

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

Figure 16 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 (not shown), 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 17 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 go up from approximately 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 half the amount in the baseline. However, in this case, the amount of reallocation is huge: sector a households work nearly forty 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.

B Data

For details on data and figures and table construction please refer to the replication package provided in the additional material.

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

4. Stock market prices and revenue: 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. Consumer price index: All Items Less Food and Energy in U.S. City Average (FRED).
8. Aggregate data forecasts: International Monetary Fund World Economic Outlook [Fund \(October 2019\)](#).

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 5](#) 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. Also, 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. Finally, 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 use the most traded one on those days. 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 2020.³⁸ Expected revenue for Q1-2020 to Q4-2020 are obtained directly from IBES. For Q1-2021/2022 to Q4-2021/2022 we update the expected revenue for each quarter in 2020 by adding the expected growth between year 2021/2022 and 2020.

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 above the sectoral median. 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.

³⁸We winsorize surprises at 1.5% level in each quarter.

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 Resilience 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 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 any of these criteria are met.³⁹

- A firm is a close substitute to Retail if: its GICS code is 2550 (Retailing) and its NAICS is 51. Also,
- Close substitute to Health care and social assist: GICS 3510 (Health Care Equipment & Services) and NAICS 51.
- Close substitute to Arts, Entertainment, and Recreation: GICS 502020 (Entertainment) and NAICS 51.
- Close substitute to Air, rail, and water transportation, Educational services and Accommodation: These activities were replaced partially by remote work substitutes: IT services. We can identify these companies by those classified as,
 - Education: GICS 25302010 (Education Services) and NAICS 51.
 - IT services: GICS 4510 (Software & Services) 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 in the fourth quarter of 2019. We assume this share is representative and split the BEA Information sector between Contact and Non-Contact using this fraction.

B.3.8 Inflation Dynamics on Winners and Losers

This subsection describes the data used in [Section 4.3.2](#). Industries in [Figure 9](#) are classified as the NAICS 3 industries that belong to the Contact sector defined in [Table 5](#).⁴⁰ [Figure 9](#)

³⁹An exception to this classification is Netflix, which we included as a substitute for the Contact sector despite being categorized under NAICS sector 53 in Compustat, typically associated with real estate and rental companies. However, given Netflix's primary business activities in media streaming, a form of at-home entertainment, we found classifying it under NAICS code 51 (Information) more accurate. For additional details, see <https://www.naics.com/company-profile-page/?co=6063>.

⁴⁰Ideally we would go as narrow as possible on the industry classification, but going below NAICS 3 leaves us with only a few industries well represented in the public sector firms dataset.

shows only industries that are well represented in Compustat, which we define as those NAICS 3 industries whose 2019 sectoral revenue in Compustat is at least 20% as the one reported by the BEA. We do this because the share of winners by industry is defined as the revenue share by winners on the Compustat industry total and we want to ensure correct coverage. Inflation for each industry is computed as the average year over year inflation using Chain-Type Price Indexes for Gross Output by Industry from BEA detrended by the industry average between 2015 and 2019. [Table 6](#) shows the data for all NAICS 3 industries in the Contact sector.

C Extra Figures and Tables

Table 5: 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)*	

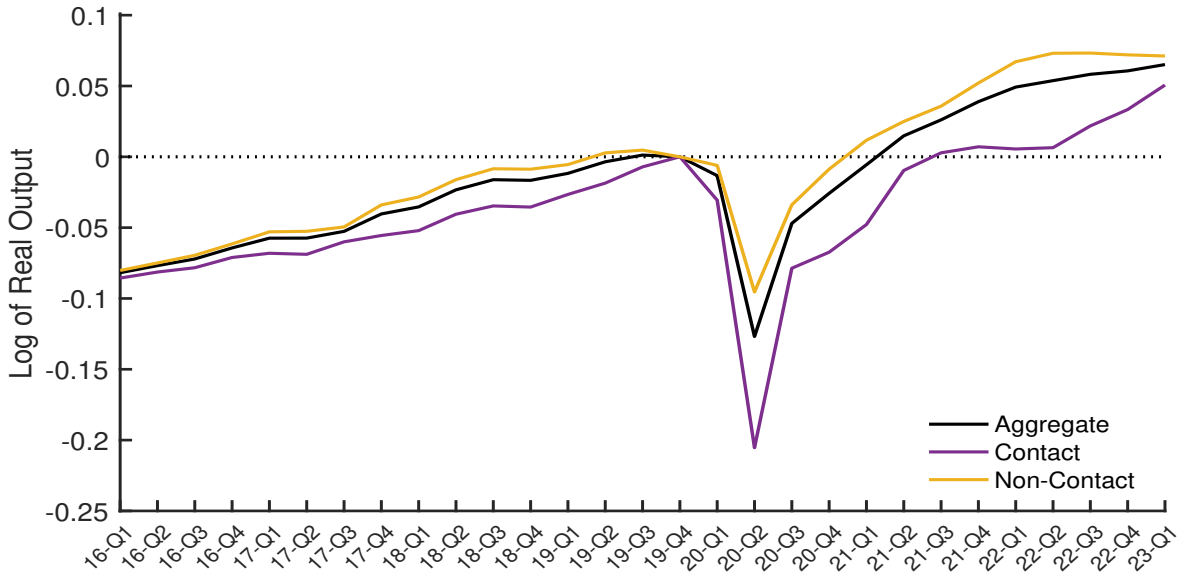
Note: Table shows our classification of sectors between Contact and Non-Contact using NAICS codes. Firms in the Information sector (51) that offer goods or services that are close substitutes for Contact sub-sectors are included in the Contact sector. Details for the classification are in [Appendix B.3.7](#).

Table 6: Sectoral Inflation and Winners Share

Naics code	Description	Share Compustat	Share Winners	Inflation 2020	Inflation 2022
441	Motor vehicle and parts dealers	0.49	0.15	0.1	0.2
445	Food and beverage stores	0.54	1	0.02	0.1
452	General merchandise stores	0.12	0.82	-0.02	0.12
Remaining 44#-45#	Other retail	1.67	0.75	0.03	0.03
481	Air transportation	0.74	0	-0.12	0.13
482	Rail transportation	0.82	0.32	-0.02	0.06
483	Water transportation	0.61	0.08	-0.09	0.1
485	Transit and ground passenger transportation	0.2	0.08	-0.03	-0.01
487-488-492	Other transportation and support activities	0.05	0.62	-0.03	0.09
511	Publishing industries, except internet..	0.06	0.58	0.01	0
512	Motion picture and sound recording industries	0.06	0.09	-0.01	0.03
513	Broadcasting and telecommunications	0.21	0.07	0	0.02
514	Data processing, internet publishing..	0		0.02	0.01
532-533	Rental and leasing services and lessors..	0.2	0.33	-0.01	0.06
611	Educational services	0.03	0.68	0	0.02
621	Ambulatory health care services	0.32	0.76	0.01	0.01
622	Hospitals	0.11	0	0	0.03
623	Nursing and residential care facilities	0.05	0.1	0.01	0.01
624	Social assistance	0.01	1	0.01	0.02
711-712	Performing arts, spectator sports, museums...	0.07	0.01	0.01	0
713	Amusements, gambling,...	0.1	0	0.04	0.03
721	Accommodation	0.28	0	-0.07	0.1
722	Food services and drinking places	0.16	0.09	0.02	0.04
81	Other services, except government	0.02	0.24	0.01	0.04

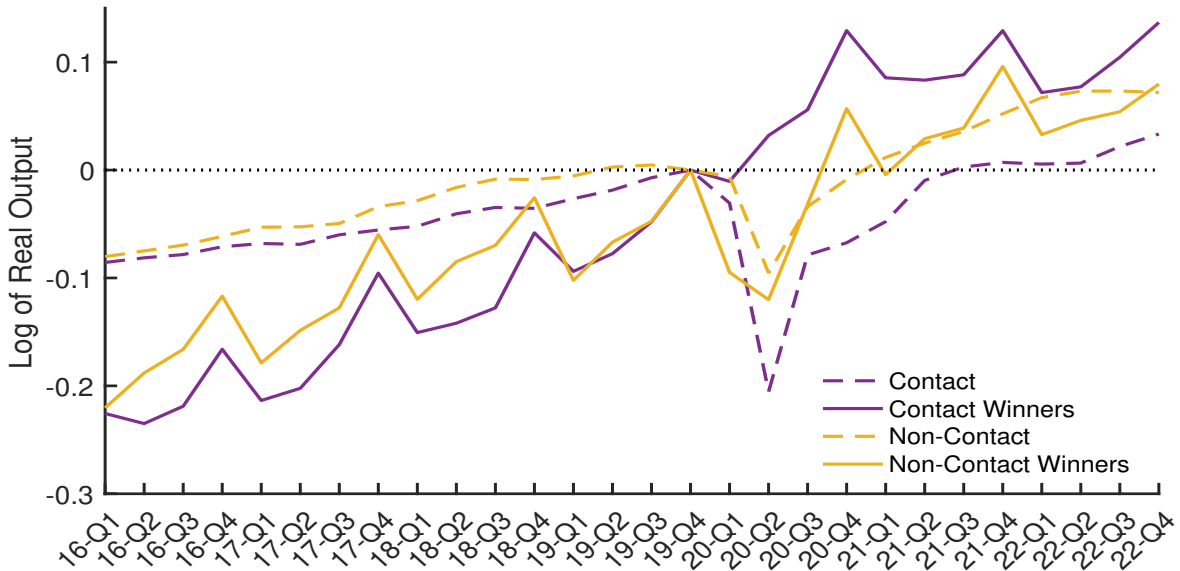
Note: Table shows the data used in [Figure 9](#). Column three shows the 2019 share of revenue in Compustat for each NAICS 3 industry in BEA for the selected group of firms used in [Section 2](#). Column four shows the share of winners' revenue in Compustat. Columns five and six show the average year over year inflation for each industry using the Chain-Type Price Indexes for Gross Output by Industry from BEA detrended by the industry average between 2015 and 2019. Note that the revenue share in Compustat can be above one since public firms' revenue includes sales generated outside the US.

Figure 12: Revenue During Recession: Contact vs Non-Contact Sector



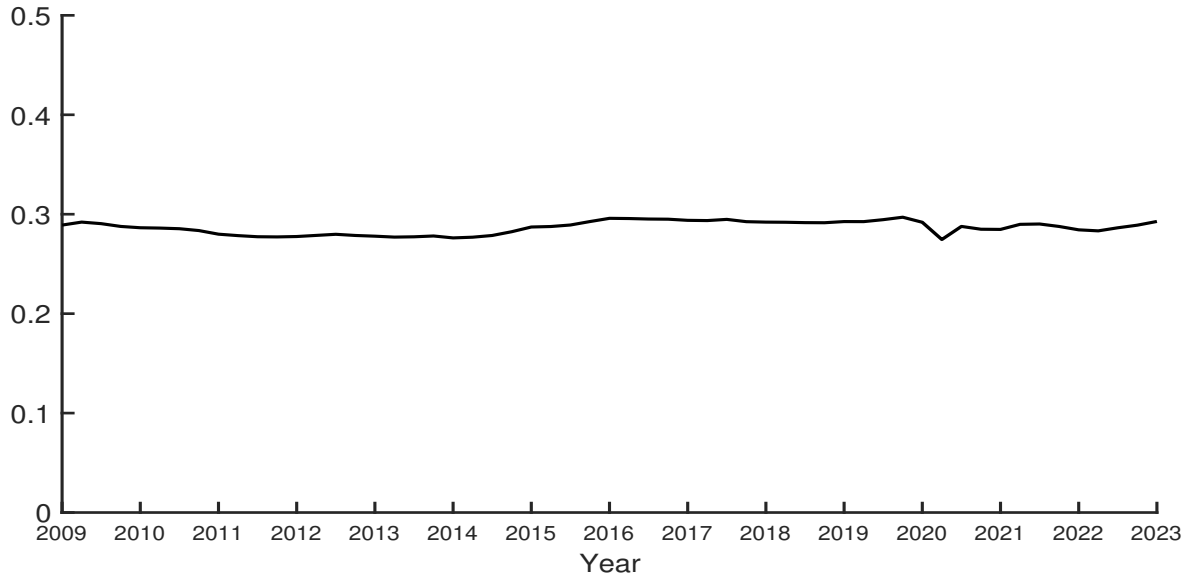
Note: Figure shows the log distance of real revenue from its 2019-Q4 value. The definition of the contact and the non-contact sector is in Table 5. Nominal output data comes from the BEA and is transformed into real using the Chain-Type Price Indexes for Gross Output for Private Industries.

Figure 13: Winners Relative Performance



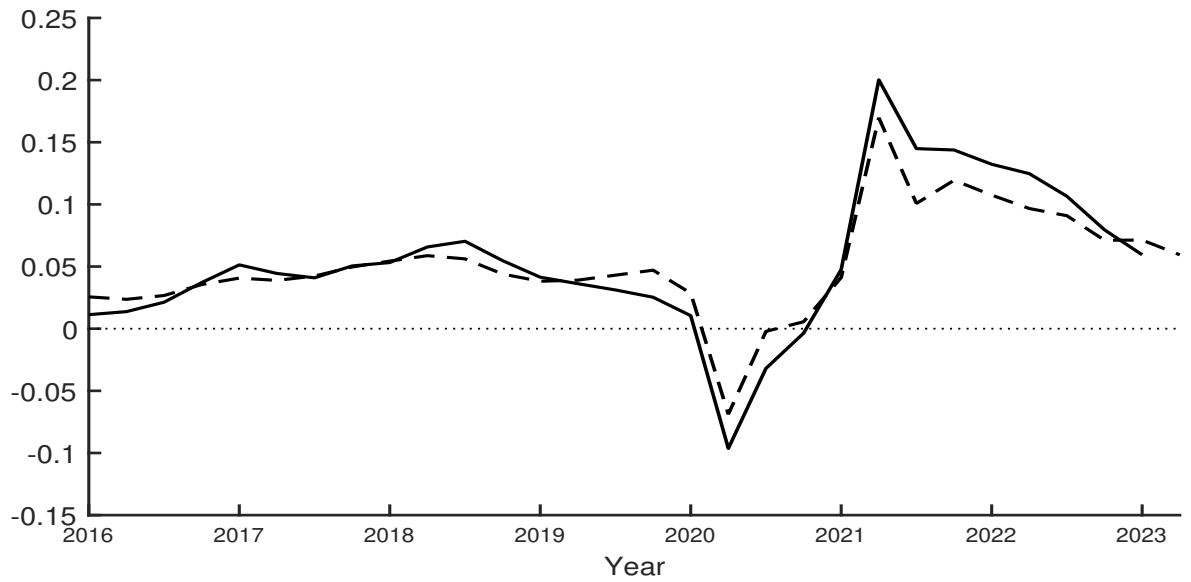
Note: Figure shows the log distance of real revenue from its 2019-Q4 value. Contact and Non-Contact sectors are defined in Table 5, and winners are defined in Appendix B.3.6. Nominal output data for sectors come from the BEA and is transformed to real using the Chain-Type Price Indexes for Gross Output for Private Industries. Nominal output data for winners comes from Compustat.

Figure 14: Contact Sector Revenue Share of Total



Note: Figure shows the share of the contact sector, as defined in [Table 5](#), in aggregate output.

Figure 15: Evolution of Gross Output and GDP



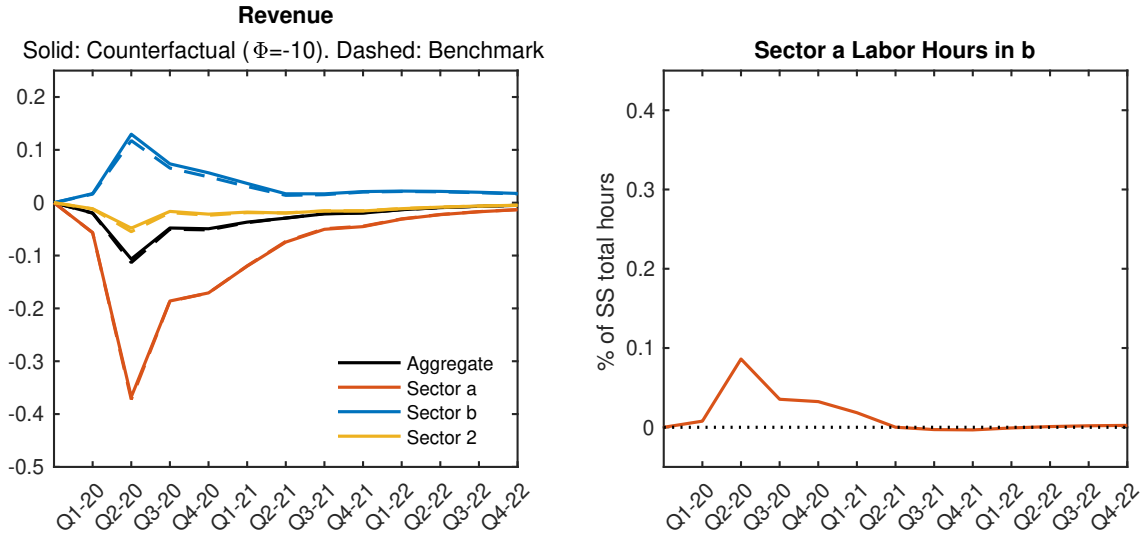
Note: Figure shows year over year growth of nominal GDP and Gross Output by Industry (all industries) for the U.S.

Table 7: Covid Resilience and Revenue Surprises

Contact								
	Q1-20	Q2-20	Q3-20	Q4-20	Q1-21	Q2-21	Q3-21	Q4-21
Resilience	0.055*** (0.009)	0.422*** (0.066)	0.273*** (0.05)	0.210*** (0.039)	0.209*** (0.041)	0.145*** (0.032)	0.118*** (0.031)	0.074*** (0.019)
R^2	0.486	0.51	0.442	0.433	0.413	0.329	0.285	0.191
N	266	266	266	266	266	266	266	266
Non Contact								
	Q1-20	Q2-20	Q3-20	Q4-20	Q1-21	Q2-21	Q3-21	Q4-21
Resilience	0.044*** (0.009)	0.175*** (0.022)	0.122*** (0.024)	0.117*** (0.022)	0.066*** (0.02)	0.031* (0.014)	0.041 (0.024)	0.006 (0.028)
R^2	0.149	0.179	0.206	0.181	0.088	0.021	0.034	0.001
N	608	608	608	608	608	608	608	608

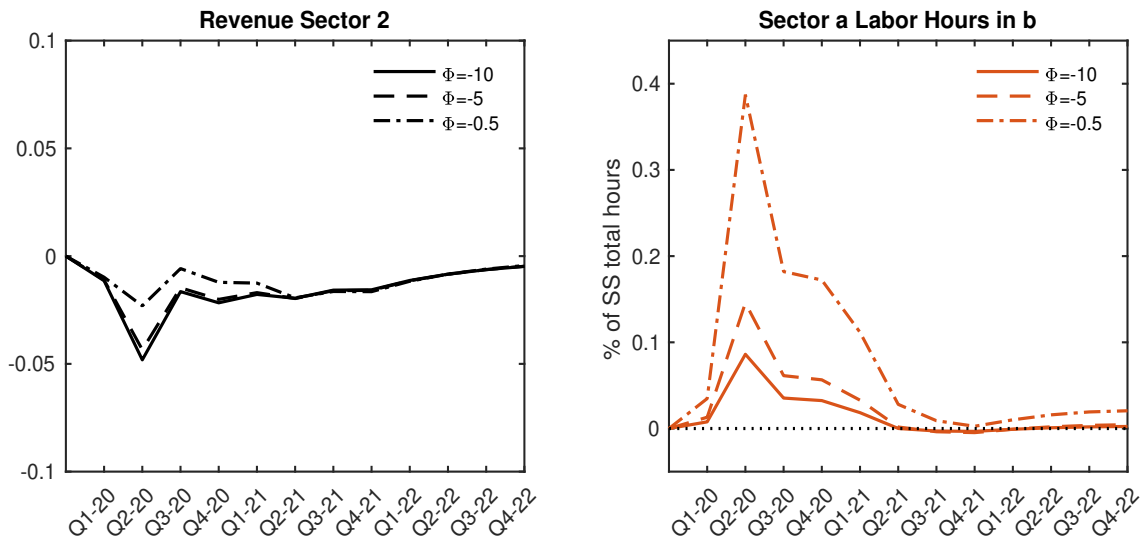
Note: The dependent variable for columns is the log-difference between the quarterly realized revenue and the log of the median expected revenue from IBES reported in February 2020 for each firm in the sample. The independent variable is our measure of Covid resilience. The sample of firms is stable across columns and each firm has at least three active forecasts in per period. The regression is weighted using the 2019 quarterly revenue for the same quarter. Standard errors are robust to heteroskedasticity [White \(1980\)](#)

Figure 16: 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.4](#). Right panel shows hours worked that workers in sector a are working in sector b as a share of steady state.

Figure 17: 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.