Sector-Specific Shocks and the Expenditure Elasticity Channel During the COVID-19 Crisis

Ana Danieli   Jane Olmstead-Rumsey

April 27, 2020

Abstract

The COVID-19 economic crisis differs from past recessions in terms of the sectors and occupations that are being hit first. In this paper we propose a model with sectoral and occupational heterogeneity and non-homothetic preferences over sectors. That is, households' consumption bundles depend on income and they cut consumption on high income-elastic sectors when labor income falls. We first document that contact intensive occupations are concentrated in just a few, high-income-elasticity sectors. By contrast, production/manufacturing occupations are distributed widely across sectors. We then compare a COVID-19 type shock affecting service sectors first to a more "standard" recession affecting manufacturing in our model calibrated to match the U.S. economy. Our main result is that the increase in labor income inequality in the COVID-19 recession is one and a half times the increase in a normal recession due to the fact that contact intensive service workers are low income *and* work mainly in high income-elasticity sectors.

1 Introduction

The economic downturn brought about by the COVID-19 pandemic is likely to differ from other recent downturns in potentially important ways. This paper emphasizes the central importance of sectoral and occupational heterogeneity for the propagation and depth of the COVID-19 shock in the U.S., and for its effects on income inequality.

To do this, we modify the dynamic stochastic general equilibrium model with non-homothetic preferences of Danieli (2020) to analyze the present crisis. This model features multiple sectors. Because of the non-homothetic preferences, consumers with different incomes consume different bundles of sector goods. The expenditure elasticities on each of the sectors are estimated from U.S. consumption data. The model also features a different occupational mix within each sector, calibrated to match the occupation shares within sectors in the U.S. Thus, sector-specific demand or productivity shocks fall disproportionately on occupations used intensively in that sector.

We divide occupations into five categories: healthcare, professional, non-contact intensive services, production/laborers, and contact-intensive services. We find that the latter category, those workers most affected by coronavirus-related shutdowns, are concentrated in just a few sectors like arts, entertainment, recreation, accommodation, food services, and non-essential retail. These are not the sectors that typically suffer the most in U.S. recessions. Coskun & Dalgic (2020) find substantial heterogeneity in the sensitivity of employment in different industries to changes in aggregate employment from 1990-2018, with trade, transportation, manufacturing, and construction significantly outranking entertainment, retail, and other services in terms of correlation to the business cycle. However, according to the March Bureau of Labor Statistics Employment Situation report, nearly 459,000 jobs were lost in these leisure and hospitality sectors in March, accounting for nearly two-thirds of the decline in non-farm payrolls.[1]

Previous research shows that the types of workers who are laid off can have an economically significant effect on the size of recessions (Patterson (2019)). Low wage workers' incomes are typically more sensitive to business cycle fluctuations and thus income inequality tends to rise in recessions (Heathcote et al. (2010)), though government transfers to low-income groups can mitigate this rise. Inequality itself can deepen recessions by reducing aggregate demand, since lower income individuals tend to have high-marginal propensities to consume (Auclert & Rognlie (2020); Ahn et al. (2018)). Neglecting sectoral heterogeneity can also result in welfare losses in the evaluation of optimal monetary policy (Kreamer (2019)).

The incorporation of non-homothetic preferences allows us to capture a channel that was important during the great recession: changes in consumer spending habits in response to the recession. For example, Jaimovich et al. (2019) find that changes in consumers' consumption baskets during recessions, specifically reductions in product quality, had significant amplifying effects on the depth and persistence of the great recession. The key mechanism in our model is that a negative shock to labor income causes consumers to change the mix of goods they consume, rather than reduce consumption of all sectors proportionally to the decline in their income. This reshuffling of consumption has disproportionate effects on workers in occupations used intensively in the sectors with high expenditure elasticities that consumers cut back on. We document that these workers are precisely the contact intensive services workers and another low income group: physical laborers/manufacturers.

The economics profession has reacted swiftly to study various aspects of the COVID-19 crisis. Areas of research include the interaction of epidemiology and economic models (see Eichenbaum et al. (2020) Berger et al. (2020) and Kaplan et al. (2020)). Age and sectoral heterogeneity in the analysis of optimal policy responses to the pandemic (Glover et al. (2020)). Measurement of the anticipated effect on different occupations (Dingel & Neiman (2020) and Leibovici et al. (2020)). The effects of the crisis on gender equality in the labor market (Alon et al. (2020)). The use of stock market data to predict the magnitude of the slowdown (Gormsen & Koijen (2020)). The effects of various policies in a DSGE model with a COVID-19 type shock to demand for contact intensive services (Faria-e Castro (2020)). To this line we contribute a model similar to Faria-e Castro (2020) but with an emphasis on inequality and consumption heterogeneity through the incorporation of non-homothetic preferences.

[1] https://www.bls.gov/news.release/pdf/empsit.pdf

To forecast patterns we expect to see in the current crisis, our main exercise with the model is to compare two collections of shocks: one collection to represent the COVID-19 crisis and one collection to represent recent past recessions. We model the COVID-19 crisis as:

1. A negative labor supply shock for all workers (alternately as a negative aggregate total factor productivity shock) calibrated to match a 4% decline in GDP on impact

2. A negative sector specific demand shock to the arts, entertainment, accommodation, food, and day care services sector of our model economy where contact intensive service workers are concentrated

3. A negative sector specific shock to the transportation sector which has also been hit hard

4. A positive demand shock for the healthcare sector

The negative demand shocks are calibrated such that the negatively effected sectors are hit five times harder than the other sectors initially.

For the "standard" recession modeled after U.S. downturns in the past 40 years or so, we similarly use a negatively labor supply shock to yielding a 4% decline in GDP on impact, but give a demand shock to non-essential manufacturing such that it is hit five times harder than other sectors. To be consistent we include a positive healthcare demand shock in the "standard" recession as well.

Our main result is that income inequality is likely to rise by at least one and half times as much during the COVID-19 recession as in past recessions. In particular, because of non-homotheticities, workers in contact-intensive occupations are hit with a "double-whammy" in the COVID-19 scenario: their labor income declines initially, but because they work mainly in a few sectors with high estimated expenditure elasticities, there are second round effects that reduce demand for the sectors they work in. Unlike physical laborers who have been hit hard in past recessions, they cannot easily substitute into other sectors of the economy. Another driver of the rise in inequality is that manufacturing occupations are also hard hit during the COVID-19 crisis through demand effects, whereas in a standard recession professional occupations are the second-hardest hit group.

This paper also contributes to our understanding of characteristics of hard-hit workers and sectors. We find that contact-intensive service workers are low income, but comprise a small fraction of the total workforce (around 9%). A key fact is that about half of total labor income for this group comes from a single sector: leisure activities such as hospitality, arts, and entertainment. So far unemployment insurance claims data show these sectors and workers losing jobs most rapidly, but the scope of the crisis also appears to be spreading beyond this initial group, mainly to production occupations, which is predicted by our model.

The rest of the paper is organized as follows. In section 2 we describe the model. In section 3 we calibrate the model for the U.S. economy and describe the occupational distribution within sectors. Section 4 presents results of a COVID-19 shock in the model and compares these findings to a "typical" recession. Section 5 considers extensions and alternative shock specifications. Section 6 compares the model predictions across sectors to unemployment claims data by sector. Finally, section 7 discusses various policy options we plan to analyze in the context of the model.

2 Model

We use a two-agent New Keynesian (TANK) model with non-homothetic preferences and heterogeneous sectors and occupations to capture the effect of the COVID-19 crisis. Agents in the model belong to five different occupation groups: healthcare, professional, non-contact intensive services, manufacturing/physical laborers, and contact-intensive service occupations. There are two key differences between individuals in different occupations: their labor income and their asset position. While the latter is not an inherent part of the mechanism, it will affect the individual response to an income shock and how these changes propagate to aggregate outcomes. This is especially important since workers in contact-intensive service occupations are more prone to have low liquid asset holdings and face borrowing constraints (Kaplan et al. (2020) and Mongey & Weinberg (2020)).

To capture this effect we use a TANK framework where four of the occupations (healthcare, professional, non-contact intensive services, production/laborers) belong to one big family with access to company profits and government bonds and contact intensive occupations are hand to mouth and consume fully their labor income and have no access to financial markets. While a fully heterogeneous agent framework might allow us to more accurately capture the response of asset holdings for each type of occupation, a TANK framework does allow us to capture the key aggregate dynamics as discussed in Debortoli & Galí (2018) and is more tractable given the richness of the model.

All agents have non-homothetic preferences over J sectors. Formally, the problem of the non-contact intensive household, type $k =$ nc agent is the following:

$$\max_{\{c^k_{j,t}\}_{j\in J}, L^k_t, B^k_{t+1}} E_0 \sum_{t=0}^{\infty} \beta^t \left[\frac{C_t^{k\,1-\theta}}{1-\theta} - \psi_t \sum_{o\in ns} n_o \frac{L_{o,t}^{1+\gamma}}{1+\gamma} \right]$$

$$\sum_{j\in J} p_{j,t} c^k_{j,t} + \frac{B^k_{t+1}}{1+i_t} \leq \sum_{o\in ns} n_o W_{o,t} L_{o,t} + B^k_t + T^k_t$$

$$C^k_t = \sum_{j\in J} \xi_{j,t}^{\frac{1}{\sigma}} c_{j,t}^{k\,\frac{\sigma-1}{\sigma}} C_t^{k\,\frac{\epsilon_j}{\sigma}+1} \tag{1}$$

$$\forall j : ln(\xi_{j,t}) = (1-\rho_\xi) ln(\xi_{j,ss}) + \rho_\xi ln(\xi_{j,t-1}) + u_{\xi,j,t},\ u_{\xi,t} \sim N(0, \sigma^2_\xi)$$
$$ln(\psi_t) = (1-\rho_\psi) ln(\psi_{ss}) + \rho_\psi ln(\psi_{t-1}) + u_{\psi,t},\ u_{\psi,t} \sim N(0, \sigma^2_\psi)$$

Where $c^k_{j,t}$ is households type k consumption of sector j at time t and C^k_t is a non-homothetic CES consumption aggregate defined by equation (1). The components of this consumption aggregate are sector taste parameters $\xi_{j,t}$ that follow AR(1) processes in logs, price elasticity σ that is common across sectors and a set of expenditure elasticity parameters $\{\epsilon_j\}_{j\in J}$ that differ across sectors and determine the expenditure elasticity of each sector.[2] These preferences are identical to a standard CES aggregate if ϵ_j the same for all sectors. We use that case as our benchmark homothetic model. The effect of ϵ_j on the expenditure elasticity of each sector can be seen in equation (2) that computes the elasticity of sector j with respect to all consumption expenditures $\sum\limits_{j\in J} p_{j,t}c^k_{j,t} \equiv E^k_t$:

$$\eta_{c^k_{j,t},E^k_t} = \frac{dlogc^k_{j,t}}{dlogE^k_t} = \sigma + (1-\sigma)\frac{\epsilon_j}{\bar{\epsilon}^k_t} \tag{2}$$

Where $\bar{\epsilon}^k_t = \sum\limits_j \frac{c^k_{j,t}p_{j,t}}{E^k_t}\epsilon_j = \sum\limits_j s^k_{j,t}\epsilon_j$, which is the weighted average of elasticity parameters $\{\epsilon_j\}$ weighted by their share in household expenditures $s^k_{j,t}$. This elasticity is larger for larger values of ϵ_j and defines a good as a luxury if $\epsilon_j > \bar{\epsilon}^k_t$. Notice that the elasticity varies across households and over time depending on the household's consumption composition. In particular, it might be that a sector will transition from a luxury to necessity if the household's income increases enough.

$L_{o,t}$ denotes occupation $o \in O$ employment choice and n_o is their share in household k with $\sum_{o\in ns} n_o = 1$. ψ is the labor dis-utility parameter that follows an AR(1) in logs. The household chooses how to optimally allocate labor across the four occupations and then collects all labor income into a single budget constraint to make mutual decisions of consumption and savings. This problem describes the labor choice when no wage frictions are in place in order to simplify the description of the model and focus the discussion on the new presence of non-homotheticity. When simulating the model it is nevertheless key to introduce wage rigidities to get a reasonable representation of labor markets as will be discussed below. Lastly, B^k_t are one period bonds and T^k_t are transfers that include company profits and government transfers for $k = nc$ and only government transfers for $k = c$.

The problem of the contact intensive services household, type $k =$ c agent is the following, where the key difference in the lack of ability to hold bonds or corporate profits as part of T^k_t. Notice that all the preference parameters are identical between the two types of households, therefore the differences in their consumption choices only result from differences in wages and assets.

[2]For a detailed discussion of non-homothetic CES preferences see Comin et al. (2019).

$$
\begin{aligned}
&\max_{\{c^k_{j,t}\}_{j\in J},L_{o,t},B^k_{t+1}} E_0 \sum_{t=0}^{\infty} \beta^t \left[\frac{C_t^{k1-\theta}}{1-\theta} - \psi_t \frac{L_{o,t}^{1+\gamma}}{1+\gamma}\right]\\
&\sum_{j\in J} p_{j,t} c^k_{j,t} \le W_{o,t} L_{o,t} + T^k_t\\
&C^k_t = \sum_{j\in J} \xi_{j,t}^{\frac{1}{\sigma}} c_{j,t}^{k\frac{\sigma-1}{\sigma}} C_t^{k\frac{\epsilon(j)}{\sigma}+1}\\
&\forall j : ln(\xi_{j,t}) = (1-\rho_\xi) ln(\xi_{j,ss}) + \rho_\xi ln(\xi_{j,t-1}) + u_{\xi,j,t},\ u_{\xi,t} \sim N(0,\sigma^2_\zeta)\\
&ln(\psi_t) = (1-\rho_\psi) ln(\psi_{ss}) + \rho_\psi ln(\psi_{t-1}) + u_{\psi,t},\ u_{\psi,t} \sim N(0,\sigma^2_\psi)
\end{aligned}
$$

2.1 Solution to the household problem with non-homothetic demand

The solution to type $k = nc$ household's problem can be split into three parts: an inter temporal problem, a intra temporal consumption vs leisure problem and an intra temporal allocation of consumption across sectors. The solution for type $k = c$ household includes only the intra-temporal parts of the solution but is otherwise equivalent.

The solution to the inter-temporal problem is characterized by the Euler equation written (3)

$$
\frac{1}{C_t^{k\theta} P_t^k \bar{\epsilon}_t^k} = E_t \frac{\beta(1+i_t)}{C_{t+1}^{k\theta} P_{t+1}^k \bar{\epsilon}_{t+1}^k}, \text{if } k = nc \tag{3}
$$

There are two components that differentiate this Euler equation from the standard one. First, the presence of $\bar{\epsilon}^k_t$, which is the expenditure share weighted average of the elasticity parameters $\{\epsilon_j\}$ discussed above. Second, the definition of P^k_{t+1} which is the household specific price index, equivalent to the price index for CES preferences, however adjusted for the non-homothetic effect. This price index is defined by equation (4).

$$
\begin{aligned}
P^k_t C^k_t &= \sum_{j\in J} p_{j,t} c^k_{j,t}\\
P^k_t &= \left[\sum_{j\in J} \xi_j C_t^{k\epsilon_j-(1-\sigma)} p_{j,t}^{1-\sigma}\right]^{\frac{1}{1-\sigma}}
\end{aligned} \tag{4}
$$

This price index differs from the standard CES price index by the presence of C^k_t, which means that the household's price index will increase as the consumption aggregate increases reflecting the desire to spend more on more expensive higher elasticity sectors.[3]

We next turn to the household's labor supply decision. The solution to the household labor choice is given by equation (5). This equation differs from the standard labor choice condition by

[3] For a more detailed discussion of the Euler equation adjusted for non-homotheticity see Danieli (2020).

the same components $\bar{\epsilon}_t^k$ and P_t^k. This equation implies a different marginal rate of substitution between consumption and leisure than in the standard model, since the marginal benefit from an increase in total consumption expenditures is not only an increase in the consumption aggregate but also reallocation towards more elastic sectors. This implies a stronger wealth effect manifested by a positive effect on the real wage $\frac{W_{o,t}}{P_t^k \bar{\epsilon}_t^k}$ when C_t^k declines.

$$\psi_t L_{o,t}^{\gamma} = \frac{W_{o,t}(1-\sigma)}{P_t^k C_t^{k\theta} \bar{\epsilon}_t^k} \tag{5}$$

Finally, the solution to the household intra-temporal allocation of consumption across sectors is given by equation (6). This equation demonstrates directly the effect of non-homotheticity since demand for sectors j increases with the consumption aggregate C_t^k, and this increase is larger for sectors with higher value of ϵ_j.

$$c_{j,t}^k = \xi_{j,t} \left(\frac{p_{t,j}}{P_t^k} \right)^{-\sigma} C_t^{k\epsilon_j + \sigma} \tag{6}$$

2.2 Production

Each of the J sectors is sold in a competitive market and is produced using a measure 1 of intermediate inputs denoted by $y_{i,j,t}$ and aggregated using a standard CES aggregator as described in equation (7). These intermediate inputs operate in a monopolistically competitive environment that is sector specific, i.e each input is only sold to a specific fixed sector j.

$$Y_{j,t} = \left[\int\limits_{i \in I} y_{i,j,t}^{\frac{\nu-1}{\nu}} \right]^{\frac{\nu}{\nu-1}} \tag{7}$$

Each intermediate input is produced using a Cobb-Douglass combination of the five occupations as described in equation (8) where $l_{ijo,t}$ is labor supplied by occupation o to intermediate input i that belongs to sector j at time t. α_{jo} is intensity of occupation o in the production of intermediate inputs that produce for sector j. Notice that this value is common to all i that produce for sector j. Lastly, Z_{jt} is a sector j specific TFP factor that follows an AR(1) process in logs.

$$\begin{aligned} & y_{ij,t} = Z_{j,t} \prod_o l_{ijo,t}^{\alpha_{jo}} \\ & \forall j : \, ln(Z_{j,t}) = (1-\rho_z) ln(Z_{j,ss}) + \rho_z ln(Z_{j,t-1}) + u_{zj,t}, \; u_{z,t} \sim N(0, \sigma_z^2) \end{aligned} \tag{8}$$

Each intermediate firm faces two choices. First, how to optimally allocate production across employees for any given output level. Second, how to set its prices and production to maximize profits given the demand from producer j and Rotemberg price rigidities. These problem are given by equations (9) and (10). In this setting the discount factor for the firms Λ_t is given by the stochastic discount factor for type $k = nc$ households since they are the shareholders. The cost of adjusting prices in this setting is paid in units of sector j output.

$$\begin{aligned} &\min \sum_{o} W_{o,t} l_{ijo,t} \\ &\text{s.t } exp(Z_t) \prod_{O} l_{ijo,t}^{\alpha_{jo}} \geq y_{ij,t} \end{aligned} \tag{9}$$

$$\max E_t \sum_{\tau=0}^{\infty} \Lambda_{t+\tau} \left[p_{ij,t+\tau} y_{ij,t+\tau} - MC_{ij,t+\tau} y_{ij,t+\tau} - \frac{\psi}{2} \left(\frac{p_{ij,t+\tau}}{p_{ij,t+\tau-1}} - 1 \right)^2 y_{j,t+\tau} \right] \tag{10}$$

2.3 Wage Rigidity

Since this model focuses on labor market outcomes it is important to capture a realistic representation of wage setting and labor allocation. We do so by introducing wage rigidities following Erceg et al. (2000). We assume each occupation is composed of a measure one continuum of differentiated labor services, which are all used by the firms. Each period, only a randomly selected subset of workers $1 - \xi_{w,o}$ can adjust their nominal wage. A labor company collects all the differentiated labor services from each individual in each occupation and translates it into occupation specific labor that is then used in the firms. The technology of the labor company is described by equation (11).

$$L_{o,t} = \left(\int_0^1 h_{om,t}^{\frac{\nu_w - 1}{\nu_w}} dm \right)^{\frac{\nu_w}{\nu_w - 1}} \tag{11}$$

The demand for each labor service is given by equation (12).

$$h_{om,t} = \left(\frac{W_{om,t}}{W_{o,t}} \right)^{-\nu_w} L_{o,t} \tag{12}$$

Where

$$W_{o,t} \equiv \left(\int_0^1 W_{om,t}^{1-\nu_w} dm \right)^{\frac{1}{1-\nu_w}} \tag{13}$$

Nominal wages are set by a union that represents each worker's specific type and occupation. They are taken as given by the firms and households. The union chooses an optimal $W_{o,t}^*$ wage for occupation o in a way that is consistent with utility maximization of the households, taking as given the demand schedule for the labor type and occupation as well as all choices made by other unions in all occupation and the path for consumption and prices. The union's optimization problem yields the following FOC described in equation (14).

$$\sum_{s=0}^{\infty} (\beta \xi_{w,o})^s \left[\frac{L_{o,t+s}}{C_{t+s}^{k\theta} \bar{\epsilon}_{t+s}^k} (1-\sigma) \left(\frac{W_{o,t+s}^*}{P_{t+s}^k} - \lambda_w MRS_{o,t+s}^k \right) \right] \tag{14}$$

Where $MRS_{o,t+s}^k = \frac{\psi_t L_{o,t+s}^{\gamma} C_{t+s}^{k\theta} \bar{\epsilon}_{t+s}^k}{1-\sigma}$ and $\lambda_w = \frac{\nu_w}{\nu_w - 1}$. This solution is equivalent to the original

Erceg et al. (2000) paper with two modifications. First, the wage determination process is occupation specific. Second, the marginal rate of substitution between consumption and labor and the price index are adjusted for non-homotheticity.

2.4 Monetary Policy

Monetary policy takes the form of a Taylor rule specified in equation (15). From a theoretical perspective, the correct form of inflation is a weighted average of sector specific inflation rates, where they are weighted by their share in household $k = nc$ expenditures multiplied by their expenditure elasticity for household $k = nc$ as discussed in Danieli (2020). However such a rule is hard to implement in practice since expenditure elasticities vary across households and are hard to estimate at the household level. Furthermore Danieli (2020) shows that the difference between the two inflation specifications is not significant.

$$i_t = \varphi i_{t-1} + (1-\varphi)\left[\phi_\pi \sum_{j\in J} s_{j,t}\hat{\pi}_{j,t} + \phi_x \hat{X}_t\right] + u_{mt} \tag{15}$$

2.5 Equilibrium

An equilibrium in the economy is defined by a set of prices $\{p_{j,t}\}_{j\in J}$ and allocations $\{\{c^k_{j,t}\}_{j\in J}\}_{k\in\{s,ns\}}, \{\{l_{jo,t}\}_{j\in J}\}_{o\in O}$ such that each type of household maximizes its utility given their budget constraints and labor bargaining process, intermediate firms in each sector maximize profits given price rigidities and the demand for their products, final good firms in each sector maximize profits and markets clear. Notice that since all intermediate firms in sector $j \in J$ will be making the same price and allocation decisions, the subscript i is dropped from the equilibrium description for notation simplification.

3 Quantitative Model

This section turns to calibrating the model for the U.S. economy. We describe our classifications of sectors and occupations for the U.S. economy, as well as the estimates of the expenditure elasticities for each sector. To discipline the production function of each sector we characterize the occupational mix across sectors using labor income data by occupation within sectors.

In doing so, we uncover several new facts that will be important for how the COVID-19 crisis affects different sectors and groups of workers compared to past recessions. We find that contact-intensive service workers are the lowest income occupation group and are highly concentrated in arts, entertainment, accommodation, food and day care services. This group is fairly small, however, accounting for about 9% of total employment in the U.S. The group that is typically hit hardest in recessions, production workers, are spread more broadly across multiple sectors of the economy and are a much larger group: about 25% of all workers.

3.1 Sector classification

For our sector classifications, we modify the existing 2-digit North American Industrial Classification System (NAICS) codes with special attention to the current crisis. For computational ease we combine sectors that are intuitively similar that also have similar estimated expenditure elasticities in an estimation including all traditional 2-digit NAICS sectors. For example, code 11, "Agriculture, Forestry, Fishing and Hunting" has a similar estimated elasticity to code 21, "Mining, Quarrying, and Oil and Gas Extraction" and to code 22, "Utilities" so we combine all three into a single sector in the model. Moreover, all three of these sectors are considered critical during the crisis.

For manufacturing and retail however, some subsectors are critical and thus labor demand and supply are mostly unaffected by the initial shock, while others subsectors are not. We separate these two broad sectors into four sectors in the model. Table 1 provides the full classification as well as the share of value added and the share of labor income using 2016 data for the U.S. We match the value added shares in the model by calibrating the sector taste parameters $\{\zeta_j\}_{j\in J}$. In addition we match relative sectoral prices in 2016 by calibrating the sector specific TFP $\{Z_j\}_{j\in J}$.

Sector	VA share	Labor comp. share
Mining, utilities, agriculture, forestry, forestry, fishing, and hunting	0.039	0.021
Construction	0.043	0.049
Essential manufacturing	0.039	0.023
Non-Essential manufacturing	0.078	0.078
Essential retail	0.017	0.019
Non-Essential retail	0.101	0.092
Transportation	0.030	0.033
Health care and social assistance	0.066	0.103
Professional, finance, real estate, information and other services	0.400	0.316
Arts, entertainment, accommodation, food and day care services	0.047	0.057
Government and education (excl. day care)	0.140	0.209

Table 1: 11 sectors in the model. "VA share" is share of total value added, 2016. "Labor comp share" is share of total labor compensation, 2016. Data from the BEA.

We use the CEX interview data and follow Aguiar & Bils (2015) in estimating the expenditure elasticities reported in column (3) in table (2). We deviate from their estimation process by using value added shares rather than expenditure shares by connecting the CEX data to the BEA's input-output tables following Buera et al. (2018). We apply the same sample restrictions as Aguiar & Bils (2015) and focus the estimation on Urban households with ages of the reference person between 25 and 64. We drop households if they report spending less than 100 dollars on food in 3 months per individual in the household, they have negative total or food consumption expenditure, total income is reported incomplete, they have not responded all (four quarterly) interviews, income is below 50% of minimum wage or if they earn money but do not work. To mitigate measurement error concerns, we drop the top and bottom 5% richest households according to their total income

Sector	Elasticity Parameters ϵ_j	Expenditure Elasticity
Health care and social assistance	3.20	2.33
Arts, entertainment, accommodation, food and day care services	1.85	1.54
Government and education (excl. day care)	1.20	1.16
Non-Essential manufacturing	1.19	1.16
Professional, finance, real estate, information and other services	1	1.07
Transportation	0.98	1.03
Non-Essential retail	0.87	0.96
Construction	0.52	0.76
Mining, utilities, agriculture, forestry, forestry, fishing, and hunting	0.45	0.72
Essential manufacturing	0.21	0.58
Essential retail	0.12	0.52
σ	0.45	

Table 2: Estimated expenditure elasticities and elasticity parameters for each sector. Estimation is constructed using CEX interview data. Expenditure elasticities are estimated following Aguiar and Bils (2015) methodology and elasticity parameters are estimated following Comin, Danieli and Mestieri (2020). Professional, finance, real estate, information and other services is normalized to 1.

(after taxes). While these restrictions are important for consistency with Aguiar & Bils (2015), the estimation is robust to releasing most of them. We use data from the years 2000-2007, however the results are robust to other time periods as well. One potential problem with the CEX data is they do not include public spending on health and education which are fairly significant. Comin, Danieli and Mestieri (2020) impute public expenditures from hospital referral region medicare and medicare spending and expenditure per pupil at school district and show that the elasticities of these sector decrease a little, yet remain high. We then follow Comin, Danieli and Mestieri (2020) and use GMM estimation for the demand system specified by (6) to get the expenditure elasticity parameters $\{\epsilon_j\}_{j\in J}$ and price elasticity parameter σ presented in column (2) of table (2).

The most expenditure elastic sector is healthcare, followed by the "leisure" sector: arts, entertainment, accommodation, food and day care services as the next most expenditure elastic sector. The expenditure elasticity estimates also align with sectors that we classify as essential: essential manufacturing and essential retail are the least expenditure elastic sectors, meaning households cut back least on these sectors when their income falls.

3.2 Occupation classification

We divide occupations into five broad categories with special attention to the nature of the COVID-19 crisis. We follow Leibovici et al. (2020) for guidance on "contact-intensive" occupations but account for whether some of these occupations are critical and thus not affected by shelter-in-place orders. The classification of Leibovici et al. (2020) uses O*NET data on each occupation's physical proximity to others at work and assigns an index value to each occupation in the American

Community Survey (ACS).[4] Barbers and cosmetologists score highest. Our occupation categories are:

1. Managerial and professional excluding:
   - Medical occupations
   - Contact intensive professional occupations as art/entertainment performers
2. Medical occupations, including health service occupations and excluding:
   - Dentists and dental assistants, optometrists and podiatrists
   - Dietitians and nutritionists
   - Therapists
   - Pharmacists
3. Technical, sales, and non contact-intensive service occupations such as protective services
4. Production, craft, repair, operator, fabricators and laborers
5. Contact intensive occupations:
   - Services excluding protective service occupations and health services
   - Recreation and religious workers
   - Artists, entertainers, and athletes

3.3 Stylized facts by occupation

Table 3 documents key facts about all five occupation categories. Note that contact intensive service workers have the lowest average hourly wage at $15.26 dollars per hour. However, this occupation category accounts for a relatively small share of both employment (8.8%) and labor income (5.7%). The second lowest income group is production occupations, with an average hourly wage of $19.20 per hour. This group is much larger, accounting for nearly a quarter of total employment.

Table 3 also gives the labor compensation share of each occupation in each sector based on U.S. data for 2016. These shares are used to calibrate the occupation intensities in each sector $\{\{\alpha_{jo}\}_{j\in J}\}_{o\in O}$. Several points are worth noting. Because contact-intensive service (CIS) workers are low paid, their labor income share in most sectors is quite low. The one exception is the arts, entertainment, accommodation, food and day care services sector, where these workers are concentrated and account for 38% of labor compensation. Hence shocks to these workers can be modelled as specific shocks to this sector. Production occupations, by contrast, are employed intensively in a variety of sectors, from mining and agriculture to manufacturing, transportation, and

[4]Their findings suggest contact intensive workers account for about 20% of labor income in the U.S., but they do not adjust for medical and other critical occupations that have generally continued working despite social distancing and shutdowns. We estimate that non-essential contact intensive workers account for around 6% of labor income, see table (3).

construction. Table (4) drives these facts home: depicting instead the share of each occupation's total income coming from each sector, it shows that 47% of CIS workers' total labor income comes from the leisure sector. The greatest share of production workers' income comes from non-essential manufacturing, but about construction and transportation are also important.

Sector	CIS	Prod.	NCIS	Med.	Prof.
Mining, utilities, agriculture, forestry, fishing, and hunting	0.011	0.471	0.186	0.001	0.331
Construction	0.059	0.620	0.0789	0	0.242
Essential manufacturing	0.012	0.468	0.181	0.001	0.338
Non-Essential manufacturing	0.024	0.584	0.158	0.001	0.233
Essential retail	0.043	0.117	0.748	0.001	0.091
Non-Essential retail	0.009	0.186	0.613	0.003	0.189
Transportation	0.022	0.613	0.214	0	0.151
Health care and social assistance	0.036	0.029	0.278	0.454	0.202
Professional, finance, real estate, information and other services	0.044	0.090	0.338	0.008	0.519
Arts, entertainment, accommodation, food and day care services	**0.380**	0.044	0.141	0.033	0.402
Government and education (excl. day care)	0.0359	0.031	0.259	0.016	0.658
Share in total labor income	0.057	0.204	0.294	0.052	0.393
Share in total employment	0.088	0.247	0.309	0.050	0.306
Average wage	15.24	19.20	22.17	24.24	29.84

Table 3: Share of labor compensation in each sector to each occupation. "CIS"=Contact intensive services, "NCIS"=Non-contact intensive services. Data is taken from American Community Survey (ACS) 2016.

Sector	CIS	Prod.	NCIS	Med.	Prof.
Mining, utilities, agriculture, forestry, fishing, and hunting	0.003	0.041	0.011	0	0.015
Construction	0.052	0.156	0.014	0	0.032
Essential manufacturing	0.008	0.053	0.010	0	0.011
Non-Essential manufacturing	0.030	0.327	0.088	0.004	0.123
Essential retail	0.024	0.018	0.080	0	0.007
Non-Essential retail	0.012	0.071	0.162	0.005	0.038
Transportation	0.019	0.147	0.036	0	0.019
Health care and social assistance	0.062	0.014	0.092	0.859	0.050
Professional, finance, real estate, information and other services	0.239	0.137	0.357	0.046	0.412
Arts, entertainment, accommodation, food and day care services	**0.470**	0.015	0.034	0.045	0.073
Government and education (excl. day care)	0.083	0.020	0.259	0.040	0.221

Table 4: Share of labor compensation in each sector out of the total labor compensations of each occupation. "CIS"=Contact intensive services, "NCIS"=Non-contact intensive services. Data is taken from ACS 2016.

3.4 Additional Model Parameters

Other model parameters that are standard and are taken from the literature are reported in table (5). We set a more persistent wage process for managerial and medical occupations since they are likely to have long term contracts that are not easily adjusted during a crisis.

Table 5: Additional Parameters

β	$(1.03)^{-0.25}$	discount factor
θ	1	IES parameter
$1/\gamma$	1	Frisch elasticity
ψ	1	labor coefficient
ν	12 (1.1 markup in SS)	intermediate goods substitution
ψ	116.5 (average price duration 0.75-year)	price adjustment cost
ϕ_π	1.5	monetary policy- inflation
ϕ_x	0	monetary policy- output gap
φ	0.8	monetary policy- persistence
λ_w	1.285	wage markup
$\xi_{w,1}$	0.95	wage persistence - managerial and medical occupations
$\xi_{w,2}$	0.7	wage persistence- other occupations
ρ_ξ	0.9	Taste shock persistence
σ_ξ	1	Taste shock standard deviation
ρ_ψ	0.9	Labor dis-utility shock persistence
σ_ψ	1	Labor dis-utility shock standard deviation
n_l	0.088	Share of contact intensive occupations
$nh * nh1$	0.306	Share of managerial and professional occupations
$nh * nh2$	0.050	Share of medical occupations
$nh * nh3$	0.309	Share of technical, sales and non contact services occupations
$nh * nh4$	0.247	production/laborers

4 Results

This section discusses the results from various exercises with the quantitative model. One challenge is to approximate the forces of the COVID-19 crisis with the shocks available in the model and allow for a consistent comparison with previous recessions.

Many states and local governments have implemented shelter-in-places orders that can be modelled as a negative demand shock for sectors that are intensive in contact-intensive service occupations. Sectors with a large share of critical workers and occupations that can telework are not affected as hard initially by shelter-in-place orders (see Dingel & Neiman (2020) and Alon et al. (2020) for discussions of which occupations can telework and/or are critical). Even in places without explicit orders, to the extent that consumers understand that going out increases their risk of infection (as in the model of Eichenbaum et al. (2020)), sectors with a large share of contact-intensive workers will suffer from this negative demand shock.

However, workers in contact intensive sectors are also more likely to get sick because of the nature of their jobs (second only to healthcare workers) and their productivity/labor supply is likely to decline as a result. Thus we can think of a supply and demand shock hitting sectors with a high share of contact-intensive sectors simultaneously, with opposite effects on relative prices.

Another sector that has been hit extremely hard in this crisis is the transportation sector because using any means of public transportation and especially air-travel increases the chance of infection a great deal. Furthermore many restrictions on travel have been put in place preventing people from using means of transportation, so we also give a negative demand shock to the transportation sector.

While contact intensive and transportation sectors are most affected by this crisis we can expect employees in other sectors to be affected directly as well. That is since working from home presents many challenges to employees in all sectors as lack of childcare or convenient work space. We model this as an aggregate increase in the dis-utility from work or, alternatively, a negative productivity shock. Either shock will lead to an increase in the marginal cost of production and result in a decrease in output. In fact, the aggregate decline in output is expected to be very large, e.g., the International Monetary Fund forecasts a contraction of 5.9% in U.S. GDP in 2020.[5]

We use a more conservative decline in our model and calibrate an aggregate shock to dis-utility from labor that leads to a 2% drop in GDP in the first quarter. We then add a sector specific demand shock that hits the contact intensive industry art, entertainment, accommodation, food and day care services as well as the transportation sectors and double the size of the drop in GDP to 4% in the first quarter. In addition, since demand for healthcare is peaking in this crisis for exogenous reasons, we include a positive demand shock to the health care sector. We call this a "COVID 19" recession in the figures below.

We compare the COVID-19 crisis to a similar size recession that follows a more standard pattern: a recession where the industry that is hit most is non-essential manufacturing (five times harder than the rest of the sectors initially) which has been usually the case in the US. The sizes of the sectors are comparable, since manufacturing is 7.8% of value added and art, entertainment, accommodation, food, day care and transportation are 7.7% of value added. We also keep the size of the shocks the same, therefore this can be viewed as a particularly strong, yet standard recession, which we label "Standard Recession" in subsequent figures. In addition we present the results for a recession with only the aggregate income shock (that is, with no sector-specific shock to any sector) as a benchmark. We call this a "labor income" recession.

In section 5 we examine alternative shocks specifications such as negative demand shocks to non-essential retail which has also been hit hard, or a negative shock to the population size as a way to model people's unwillingness or inability (because of illness) to both work and consume.

4.1 Labor income and inequality

Figure (1) compares the responses of aggregate output and the Gini coefficient to each type of recession shock using our non-homothetic model.[6][7] There is little difference in the response of aggregate output between the two sector-specific recessions in the non-homothetic model. However, the response of the Gini coefficient substantially differs between the recession types, with the current crisis expected to lead to an increase in inequality that is about 50% larger than in a

[5] https://www.imf.org/en/Publications/WEO/Issues/2020/04/14/weo-april-2020

[6] The Gini coefficient is computed as follows: $Gini = \frac{\sum_{o\in O}\sum_{o'\in O} n_o n_{o'} |W_{o,t}L_{o,t} - W_{o',t}L_{o',t}|}{2N\sum_{o\in O} W_{o,t}L_{o,t}}$

[7] We focus our analysis on inequality in non-medical occupations, since medical occupation compensation is almost exclusively affected by exogenous forces in this crisis. The results however are not largely affected by including the medical occupations as well as can be seen in Appendix B.

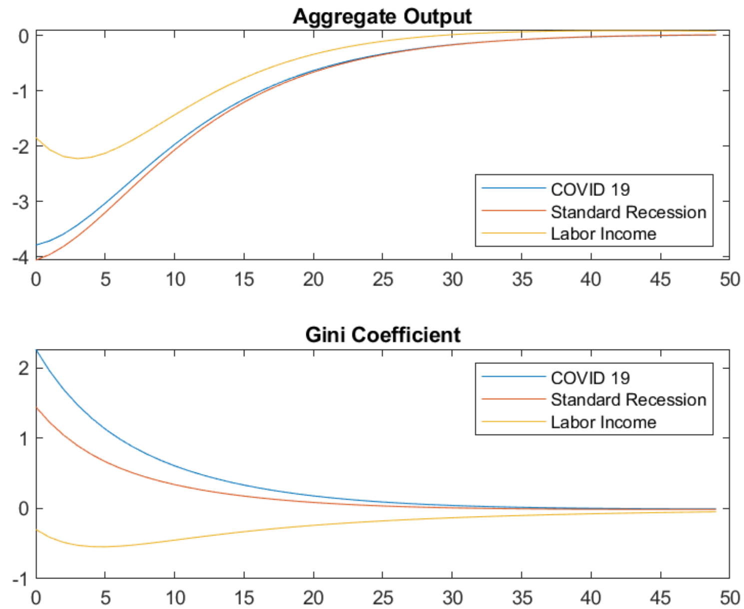


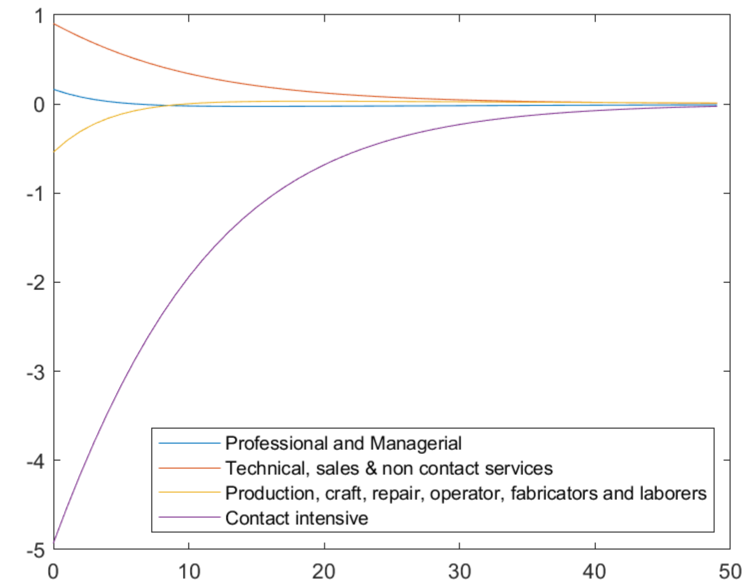
Figure 1: Impulse responses of GDP and inequality (Gini coefficient) at quarterly frequency. See text for description of the shocks in each case.

recession where manufacturing is being hit the most and 100% larger than in a recession where there is only an aggregate labor income shock. A 2.3% increase in the Gini coefficient in the COVID-19 crisis is equivalent to the observed increase in the Gini coefficient since 2004, making it economically significant both in absolute terms and in comparison to the alternative specifications.

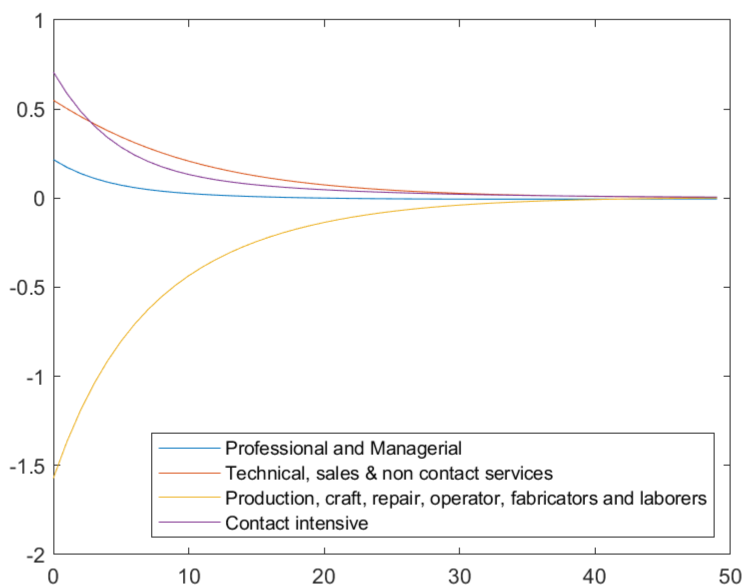
We can explain these differential effects on inequality in the COVID-19 crisis and past recessions by looking at the evolution of the income shares of each occupation that are presented in figure (2). The key difference can be seen by comparing the effects of each recession the two lowest income groups, contact intensive occupations and production occupations.

As can be seen in figure (2), in both recessions, the sector specific shock leads to a large drop in the income share of employees that are used most intensely in the affected sector. The size of this drop, however, is not equal in both cases. The labor compensations share of contact intensive occupations drops by 5 percentage points while the labor compensation share of production workers falls only by 1.5 percentage points.

The key driver of the strong decline in the compensation share of contact intensive occupations lies in their concentration in a single sector as can be seen in table (3). These employees are only used with high intensity in the arts and entertainment sector which leads to this sector employing 47% of all contact intensive employees. In contrast, production employees are used very intensely in the non-essential manufacturing sector, but they are also employed intensively in other sectors such as essential manufacturing, transportation, and agriculture which leads to only 33% percent



(a) COVID-19 Recession



(b) Standard Recession

Figure 2: Impulse responses of labor compensation shares of each non-medical occupation at quarterly frequency to COVID-19 shocks (panel a) and standard recession shocks (panel b) in the non-homothetic model.

of them being employed in the effected non-essential manufacturing sector. This difference in the allocation of employees across sectors means that when a specific sector is hit, production employees have more alternatives and therefore their relative income declines by less.

The difference in the response to the sector specific shock between the two low income occupations is further amplified by the income effect arising from non-homothetic preferences as can be seen in figure (3). This figure plots the response of the relative income for each occupation in both the baseline non-homothetic model and a standard homothetic model with $\epsilon_j = 1 - \sigma$ for all j.[8] The income effect in the non-homothetic model leads to lower relative income for contact intensive occupations, and a higher income for production occupations. This is because contact intensive occupations are concentrated in the sector with the second highest income elasticity (e.g., arts and entertainment), while production occupations are employed intensely is low elasticity sectors as well (e.g., essential manufacturing, agriculture).

Another interesting dimension of these figures is the second-hardest hit occupation in each recession. In the COVID-19 recession, manufacturing occupation's share of labor income falls. In the standard manufacturing recession, the other occupations generally increase their income share. The COVID-19 recession hits both low-income groups, contact-intensive services and manufacturing/laborers, hardest which explains the greater increase in inequality.

4.2 Role of Non-Homotheticity

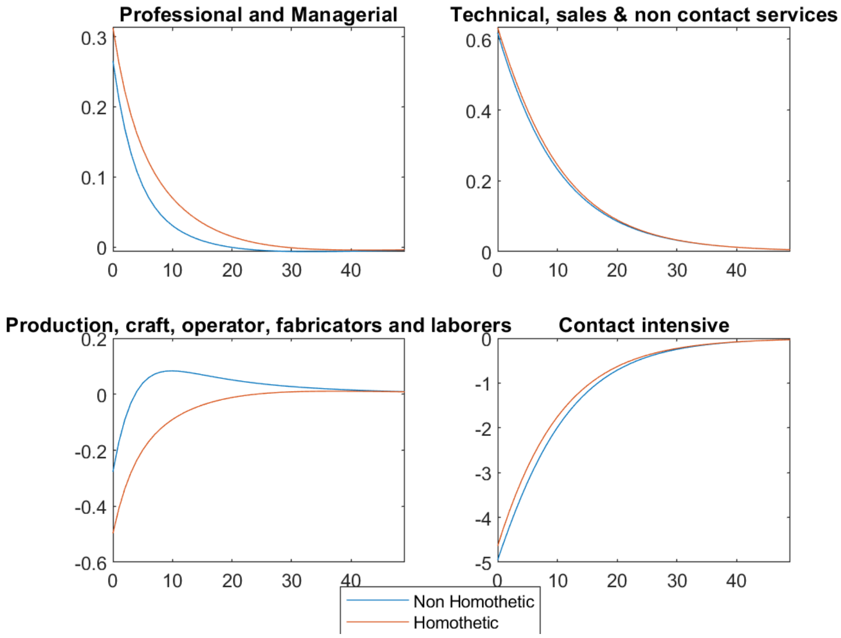
As shown in figure (4), incorporating non-homothetic preferences dampens the decrease in aggregate output in all three different recessions we consider by 0.3 percent. This is driven primarily by a negative effect from the decrease in total consumption expenditures on the price index relevant for the household that in given by equation (4). This negative effect reflects the choice of the household to reallocate its consumption towards less income elastic sectors. This decrease in the household specific price index leads to a lower decline in the real interest rate and a higher real wage, pushing the aggregate effect in different directions. The substitution effect arising from the real wage dominates leading to a smaller decline in aggregate output than the homothetic benchmark.[9]

The increase in inequality is slightly larger in the homothetic model. The reason for this is the opposite effect non-homotheticity has on the two poorest occupations, production and contact intensive occupations. Because contact intensive occupations work mainly in the arts and entertainment sector which is highly income elastic, the drop in aggregate income leads to a lower income share of contact intensive occupations, which pushes inequality further up. That is, there is a second round effect on contact intensive service workers from the crisis that is not present in a standard homothetic DSGE model.

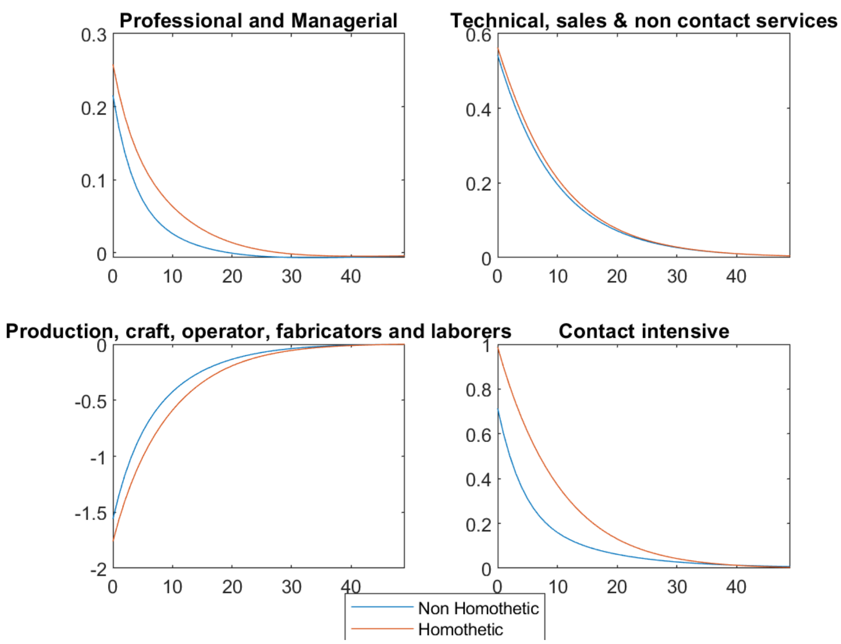
On the other hand, income effects lead to a higher income share of production occupations in the non-homothetic model compared to the homothetic baseline because they work in low income-

[8] The $\{\zeta_j, A_j\}_{j \in J}$ are recalibrated in the homothetic model to match VA shares and relative prices in 2016.

[9] These effects are analyzed in Appendix A.



(a) COVID-19 Recession



(b) Standard Recession

Figure 3: Impulse responses of relative income by occupation at quarterly frequency in the non-homothetic preferences vs. a homothetic benchmark model where all $\{\epsilon_j\}_{j\in J}$ are set to $1-\sigma$.

elastic sectors, which pushes inequality down. Since the share of production occupations is more than twice the share of contact intensive occupations, the positive effect on their relative income dominates, leading to lower inequality. In addition, income effects lead to a smaller increase in the income share of managerial and professional employees, leading to further decline in inequality. This effect is relatively small, however.

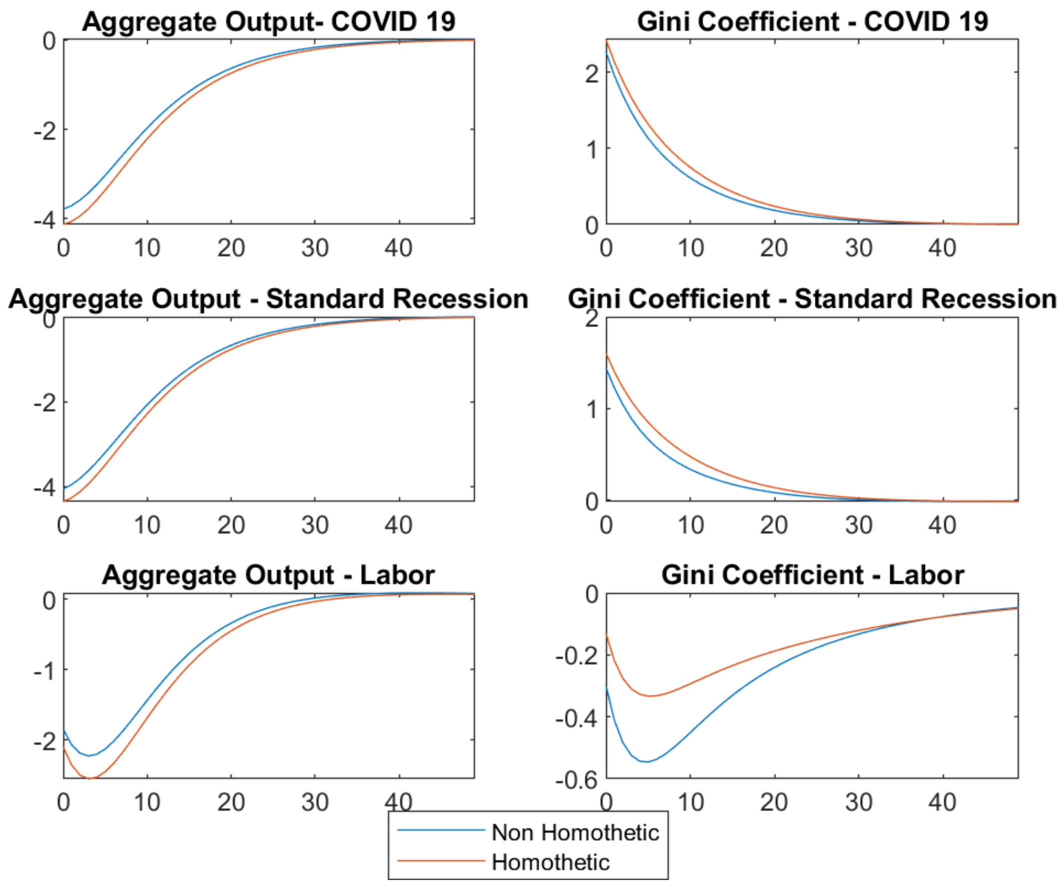


Figure 4: Impulse responses of GDP and Gini coefficient to 3 different recession shocks described in the text, at quarterly frequency in the non-homothetic model vs. a homothetic benchmark model where all $\{\epsilon_j\}_{j\in J}$ are set to $1-\sigma$.

The role of non-homotheticity increases with the size of the shock. Since the size of the COVID-19 shock has not been fully understood yet, while estimates suggest it is very large we examine the robustness of the model to a labor shock that is double in size in figure (5). This results in a smaller increase in inequality, since as described above, with stronger income effects the positive effect on the income share of production occupations dominates the negative effect on contact intensive occupations. These effects on the different occupations are presented in figure (6). This figure shows that with a stronger income shock the positive effect on production employees is so strong it reverses the effect on their labor share in the COVID-19 crisis.

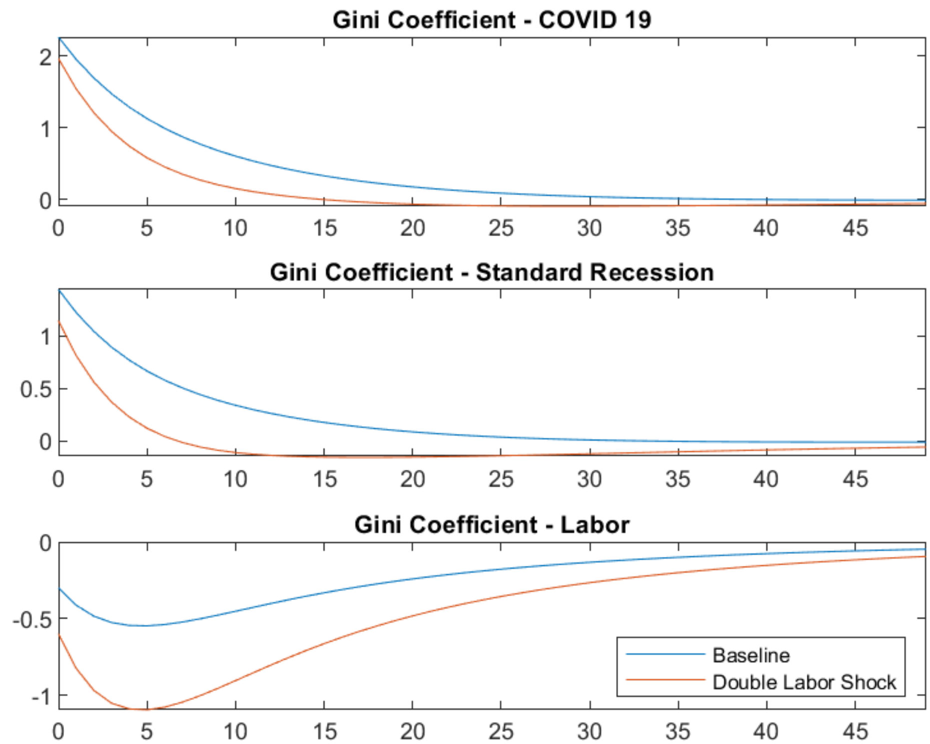


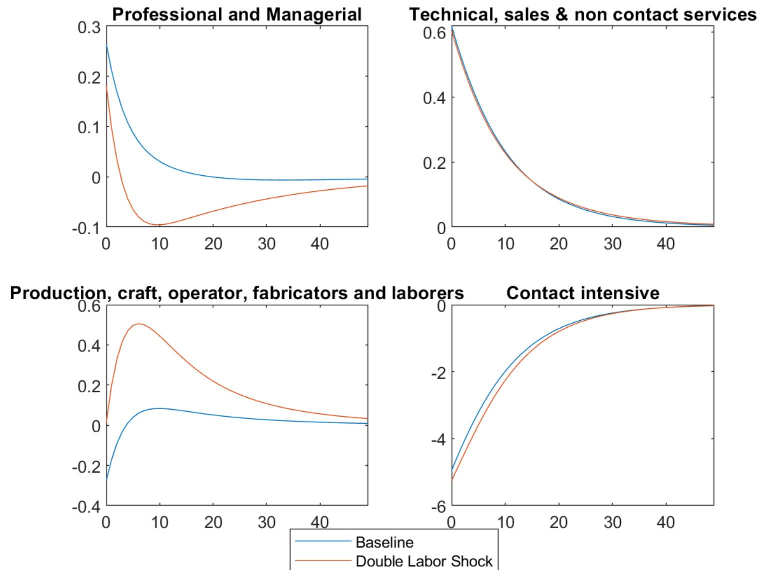
Figure 5: Impulse responses of output and inequality to labor shocks of different sizes in the non-homothetic model.

Another way to examine the role of non-homotheticity is by looking at the response of different sectors that is presented in figure (7) for the COVID-19 crisis. Income effects lead to an increase in the share of low elasticity sectors during a recession.[10] These are mainly essential manufacturing, essential retail and agriculture. The relative increase in these sectors can account for the positive effect non-homotheticity has on production employees. In the current crisis, there are exogenous reasons for a an increase in the share of these low elasticity sectors as well due to the peak demand for basic food and paper products, which can further decrease the effect on inequality.

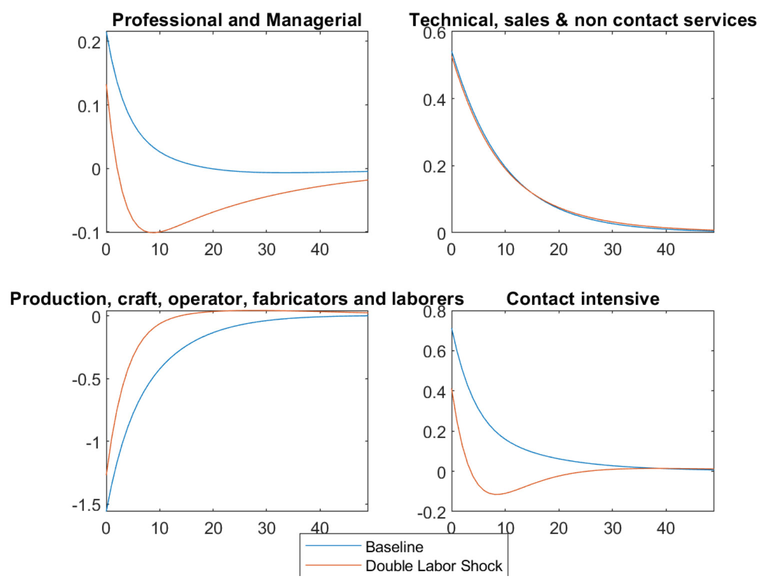
5 Extensions

In this section we consider two extensions to the baseline exercise. First, we reconsider how to model the demand effects related to coronavirus. So far we mainly considered the effects of social distancing by focusing on contact intensive service workers. But many states have now issued

[10]The sector *level* responses are given in Appendix C.



(a) COVID-19 Recession



(b) Standard Recession

Figure 6: Impulse responses of relative income by occupation with non-homothetic preferences in the non-homothetic model vs. a homothetic benchmark model where all $\{\epsilon_j\}_{j \in J}$ are set to $1 - \sigma$.

broader orders to shut down non-essential retail and other businesses. We expand the affected sectors to include non-essential retail and find that this partially mitigates the difference in the rise in inequality between the COVID-19 crisis and the standard recession. Second, we consider an alternative way of modeling the coronavirus shock. Rather than modeling it as mainly a labor

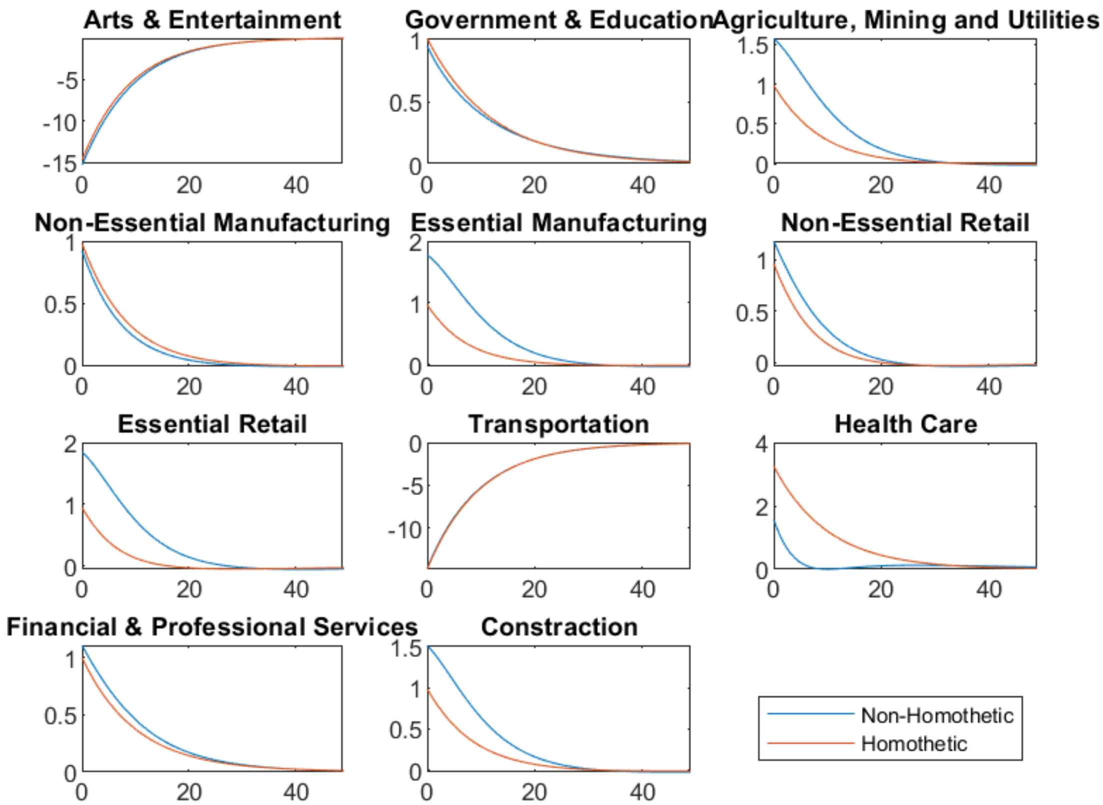


Figure 7: Impulse responses of sector value added shares at quarterly frequency in COVID-19 recession in the non-homothetic model vs. a homothetic benchmark model where all $\{\epsilon_j\}_{j\in J}$ are set to $1-\sigma$.

disutility shock, we instead give a negative shock to the population size as a way to model a decline in demand *and* labor supply of workers, either because they are sick or because they are unwilling to go to work.

5.1 COVID-19 Extended to Additional Sectors

In this extension we take into account additional sectors that have been affected by the COVID-19 crisis. The non-essential retail sector was almost entirely shut down by orders issued in many states. The essential retail and essential manufacturing sectors on the other hand experienced a large increase in demand due to the fear of shortages and lack of access during the pandemic (Baker et al. (2020)). We add these demand effects to the baseline model and re-calibrate the shock to maintain the same decrease in output as in our baseline model. We do so to examine the effect of the distribution of the demand shock across sectors, while maintaining the average income effect largely unchanged.

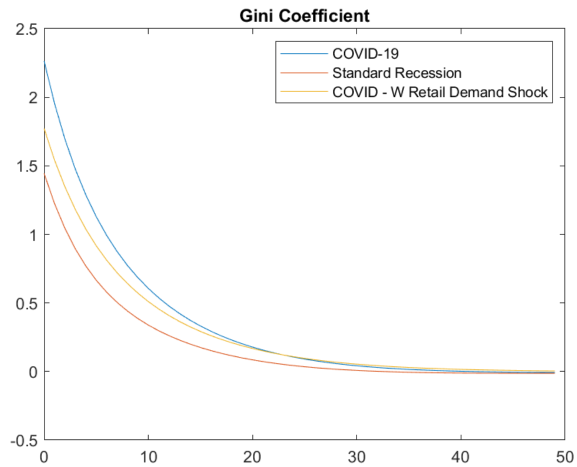


Figure 8: Impulse responses of the Gini coefficient to different recession types at quarterly frequency comparing the baseline model with a standard recession and a COVID-19 recession extended to include the direct effect on the retail and essential manufacturing sectors.

Figure (8) plots the response of the Gini coefficient in this alternative specification compared to the baseline COVID-19 recession and the standard manufacturing recession. This figure shows that the effects on the additional sectors leads to a decline of 0.33 percentage points in the Gini coefficient relative to the baseline exercise. Nevertheless, inequality increases by significantly more than in a standard manufacturing recession.

We analyze this decline in inequality by looking at the effect on the relative income of different occupations that is presented in figure (9). The key difference is the dramatic decline in the income share of technical, sales and non contact intensive occupations. These are employed very intensely in both retail sectors that experience opposite effects. However, the non essential retail sector is dramatically larger than the essential retail sector so that the negative effect dominates. In addition, the further increase in the essential manufacturing sector benefits the production employees leading to further decline of the effect on inequality.

5.2 Population Size Shock

Next we examine an alternative shock specification where instead of the dis-utility from labor we shock the size of the population uniformly across all occupations. We calibrate the size of the shock to match the size of the decrease in total output in our main exercise. In addition we maintain the sector specific demand shock. This shock specification operates mainly through the demand side and the key difference is that it leads to a decrease in prices, while in the previous exercise

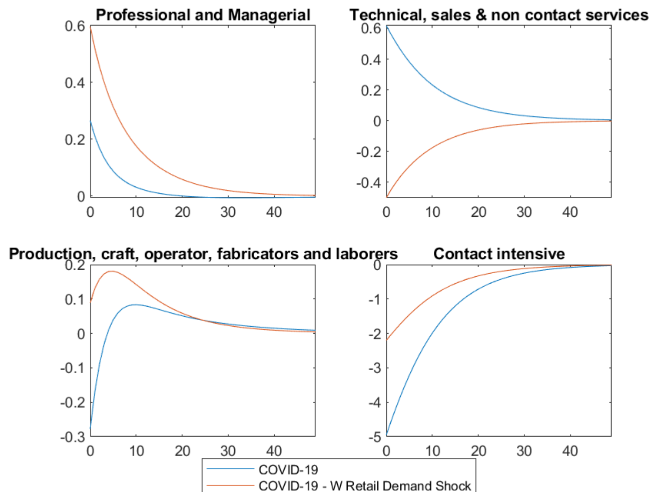


Figure 9: Impulse responses of relative income by occupation comparing the baseline model and a COVID-19 recession extended to include the direct effect on the retail and essential manufacturing sectors.

the effect of the supply side dominated, leading to an increase in prices.[11]

Figure (10) plots the response of the Gini coefficient comparing the baseline simulation with this alternative specification. This figure shows that inequality increases even more using population size shock, however the gap between both recessions is maintained.

The increase in inequality is arising from the decline in prices, that leads to a smaller decline in the household real consumption aggregate C_t^k. This increase is amplified by a positive income effect that is generated from a drop in the demand for two relatively income elastic sectors, creating new available income.[12] This means that the reallocation from high elasticity sectors toward low elasticity sectors is less than in the baseline. This has dampening effects on inequality because it benefits contact intensive occupations and hurts production occupations, as can be seen in Figure 11. The latter effect again dominates due to the sizes of each group.

6 Empirical Validation

The lack of real-time data makes it hard to compare the model predictions to data. Ideally, we would like to know sector value added shares and occupation income shares to make a direct comparison to the model, but these are not yet available for the crisis period. Data on household consumption by sector would also be useful but is not yet available. Instead, in table (6) we use unemployment insurance (UI) claims by industry as a proxy for the effects by sector, since these

[11]The decrease in population size affects both demand and supply and these effects balance one another, the sector specific demand shock then dominates the effect on prices.

[12]This effect is present in the baseline exercise as well, however it is fairly small and is dominated by the large negative income shock.

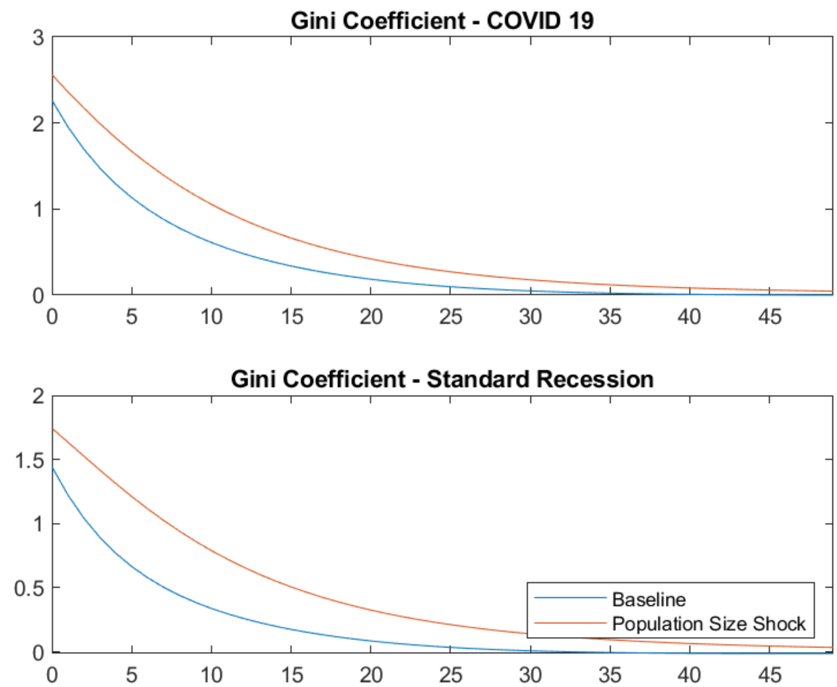
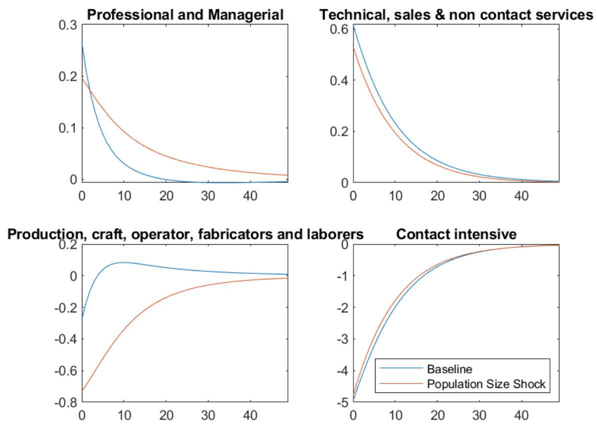


Figure 10: Impulse responses of the Gini coefficient to different recession types at quarterly frequency comparing the baseline model with an alternative shocks specification that combines a decrease in the population size with a sector specific demand shock.

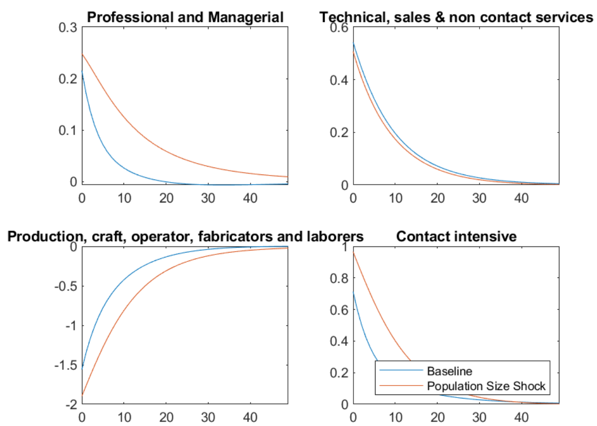
are high frequency data. The data is from New York state, which publishes an industry breakdown of new unemployment insurance claims unlike most states.

Unfortunately, the sector classifications reported by New York state differ slightly from 2-digit NAICS and do not contain more detailed breakdowns, so it's not possible to reclassify the sector data using our modified classifications. However, some patterns appear consistent with our model. Consistent with the shocks we feed in to represent the current crisis, Accommodation, transportation, and arts and entertainment, are all in the half of sectors with the biggest rise in claims from the year before. As our model predicts, manufacturing has also been hit hard (due to second-round demand effects according to our model's prediction.)[13] Low income-elasticity sectors like mining and agriculture saw a much smaller rise in unemployment claims than most other industries.

[13]Our model abstracts from the ability to work from home, which might be another reason manufacturing has been hit hard since it is difficult to perform manufacturing labor at home. For a detailed discussion of this aspect of the crisis, see Dingel & Neiman (2020).



(a) COVID-19



(b) Standard Recession

Figure 11: Impulse responses of relative income by occupation comparing the baseline model with an alternative shocks specification that combines population size and sector specific demand shock.

7 Policy Experiments

In future versions we will explore policy experiments similar to those being proposed and/or implemented already in the U.S. These include tax rebates based on past income, which can be modelled by changing government transfers in the model, interest rate policy of the central bank, and government purchases. From these experiments we would mainly like to know the effects of different policies on income inequality and the depth of the recession. Outside the model are several other policies explored by Faria-e Castro (2020) such as changes to unemployment benefits and financial interventions like liquidity assistance to services firms.

Industry	YOY %Δ in claims	% of tot. claims
Other services	7626	5.9
Unclassified	6823	3.9
Accommodation and food	4846	16.7
Retail trade	4134	14.1
Health care and social asst.	3289	11.1
Transportation	2939	4.1
Educational services	2881	2.3
Arts, entertainment, recreation	2784	3.4
Wholesale trade	2337	3.5
Manufacturing	2131	5.4
Construction/utilities	1895	11.8
Profession, scientific, technical services	1661	3.6
Real estate	1584	1.5
Admin. and support	1538	8.6
Mining	1363	0.1
Management	1326	0.3
Information	1077	2.5
Agriculture, forestry, etc.	576	0.1
Finance and Insurance	407	0.7
Public administration	343	0.4
Total	2580	100

Table 6: New unemployment insurance claims by sector of employment in New York state, week of April 4-11, 2020. Source: New York Department of Labor, Division of Research and Statistics (2020).

8 Conclusion

We provide a model of how income effects may influence the effect of coronavirus on different sectors and occupations in the U.S. In doing so, we abstract from some issues such as the ability to work from home, endogenous occupational choice, supply side factors, and focus on the way households consumption bundles are likely to change.

We show that income inequality is likely to rise by more than 50% more than it has in past recessions. First, we show that contact intensive occupation workers most affected by social distancing measures have the lowest average wages of any occupation group. Second, they are highly concentrated in a few sectors of the economy that have a high income elasticity and have little means to insure themselves with work in different sectors when consumers cut back on consumption of those sectors. This is distinct from manufacturing workers who are usually most effected by downturns. These workers' tend to be employed intensively across many sectors of the economy.

However, in aggregate, our model predicts the evolution of total output will be fairly similar to past recessions: contact intensive service workers are a relatively small fraction of total employment and the drop in their income has little effect on amplification or persistence of the recession.

References

Aguiar, M., & Bils, M. (2015). Has consumption inequality mirrored income inequality? *American Economic Review*, *105*(9), 2725–2756.

Ahn, S. H., Kaplan, G., Moll, B., Winberry, T., & Wolf, C. (2018). When inequality matters for macro and macro matters for inequality. *NBER Macroeconomics Annual*, *32*(1), 1–75.

Alon, T., Doepke, M., Olmstead-Rumsey, J., & Tertilt, M. (2020). The impact of COVID-19 on Gender Equality. (March), 141–171.

Auclert, A., & Rognlie, M. (2020). Inequality and aggregate demand. (January), 33–42.

Baker, S. R., Steffen, R. A. F., Meyer, S., Pagel, M., & Yannelis, C. (2020). How Does Household Spending Respond to an Epidemic? Consumption During the 2020 COVID-19 Pandemic. (March).

Berger, D., Herkenhoff, K., & Mongey, S. (2020). An SEIR Infectious Disease Model with Testing and Conditional Quarantine.

Buera, F. J., Kaboski, J. P., Rogerson, R., & Vizcaino, J. I. (2018). Skill-Biased Structural Change. (pp. 1–45).

Comin, D., Lashkari, D., & Mestieri, M. (2019). Structural Change with Long-run Income and Price Effects.
URL `http://www.nber.org/papers/w21595%5Cnhttp://www.nber.org/papers/w21595.pdf`

Coskun, S., & Dalgic, H. (2020). The Emergence of Procyclical Fertility: The Role of Gender Differences in Employment Risk. *CRC TR Discussion Paper Series*, (224).

Danieli, A. (2020). Expenditure Elasticity and Inequality Over the Business Cycle. (pp. 1–77).

Debortoli, D., & Galí, J. (2018). Monetary Policy with Heterogeneous Agents: Insights from TANK Models. *Unpublished Manuscript*, *649396*, 1–38.

Dingel, J., & Neiman, B. (2020). How Many Jobs Can be Done at Home? (March).

Eichenbaum, M., Rebelo, S., & Trabandt, M. (2020). The Macroeconomics of Epidemics.

Erceg, C. J., Henderson, D. W., & Levin, A. T. (2000). Optimal monetary policy with staggered wage and price contracts. *Journal of Monetary Economics*, *46*(2), 281–313.

Faria-e Castro, M. (2020). Fiscal Policy during a Pandemic. (March), 1–35.

Glover, A., Heathcote, J., Krueger, D., & Rios-Rull, J.-V. (2020). Health versus Wealth: On the Distributional Effects of Controlling a Pandemic.

Gormsen, N. J., & Koijen, R. S. J. (2020). Coronavirus: Impact on Stock Prices and Growth Expectations. (pp. 1–27).

Heathcote, J., Perri, F., & Violante, G. L. (2010). Unequal we stand: An empirical analysis of economic inequality in the United States, 1967-2006. *Review of Economic Dynamics*, *13*(1), 15–51.

Jaimovich, N., Rebelo, S., & Wong, A. (2019). Trading down and the business cycle. *Journal of Monetary Economics*, *102*(October), 96–121.

Kaplan, G., Moll, B., & Violante, G. L. (2020). Pandemics According to HANK.

Kreamer, J. (2019). Sectoral Heterogeneity and Monetary Policy.

Leibovici, F., Santacreu, A. M., & Famiglietti, M. (2020). Social Distancing and Contact-Intensive Occupations. *On the Economy, St. Louis Fed*, (March), 1–4.

Mongey, S., & Weinberg, A. (2020). Characteristics of workers in low work-from-home and high personal-proximity occupations. (March).

New York Department of Labor, Division of Research and Statistics (2020). Initial Claims Data, Week Ending 4/11/20. *Research Notes*, (pp. 1–16).

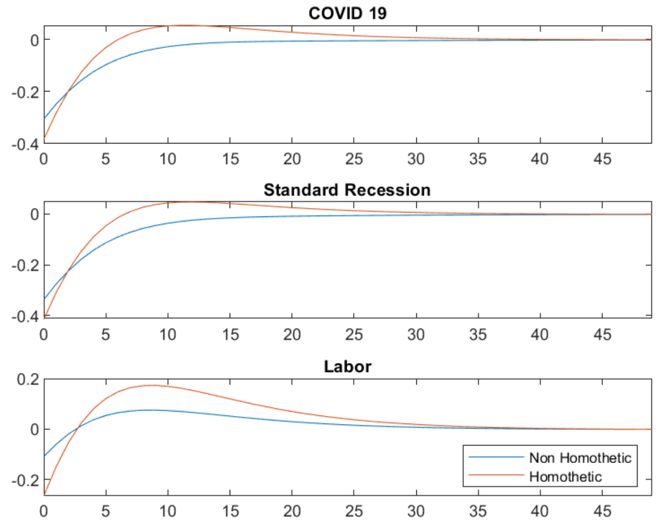
Patterson, C. (2019). The Matching Multiplier and the Amplification of Recessions.

A Aggregate Effect in the non-homothetic Model

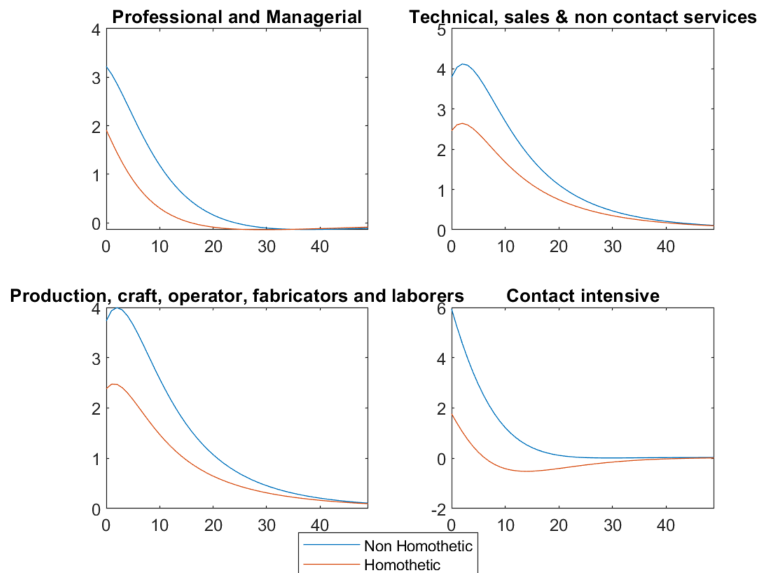
The key to the difference in the aggregate affect between the homothetic and non-homothetic model lies in the effect changes in C_t^k have on the price index P_t^k and $\bar{\epsilon}$. $\bar{\epsilon}$ decreases as C_t^k decreases since the household allocates more consumption to low elasticity sectors. The elasticity of the price index to the consumption aggregate is given in equation 16. This equation shows that the elasticity decreases when $\bar{\epsilon}_t^k$ decreases, meaning it decreases when C_t^k decreases as well.

$$\eta_{P_t^k, C_t^k} = \frac{\bar{\epsilon}_t^k}{1-\sigma} - 1 \tag{16}$$

This effect leads to a lower drop in the real interest rate and a higher increase in real wages as can be seen in figure (12). These effects push aggregate output in opposite directions, however the wage effect is stronger, leading to a smaller decline in output compared to the homothetic model.



(a) Real Interest Rate



(b) Real Wage

Figure 12: Impulse responses of the real interest rate and real wage with non-homothetic preferences vs. a homothetic benchmark model where all $\{\epsilon_j\}_{j\in J}$ are set to $1-\sigma$.

B Gini index including medical occupations

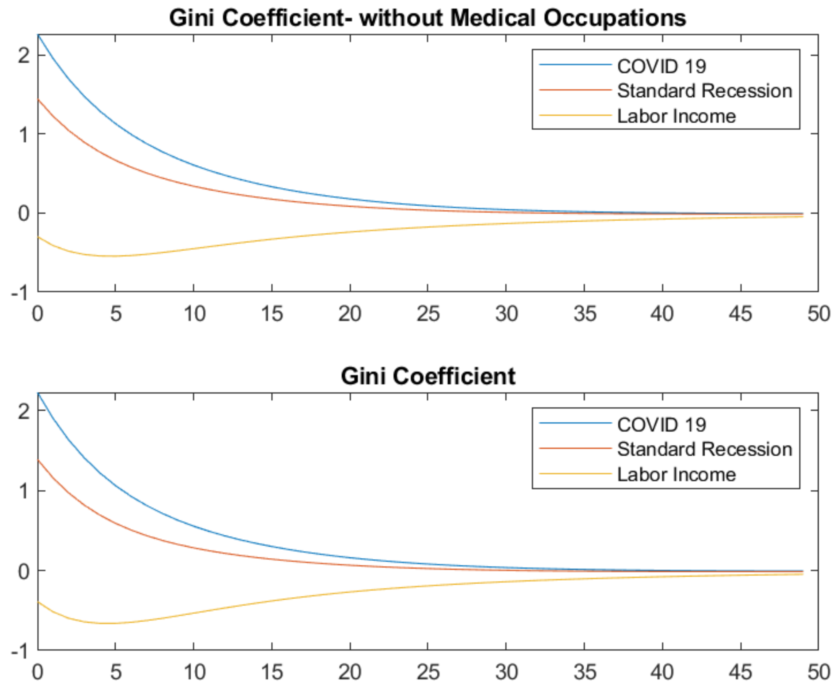


Figure 13: Impulse responses of Gini coefficient to different recession types at quarterly frequency with and without medical occupations in computation of the Gini.

C Sector Level IRF

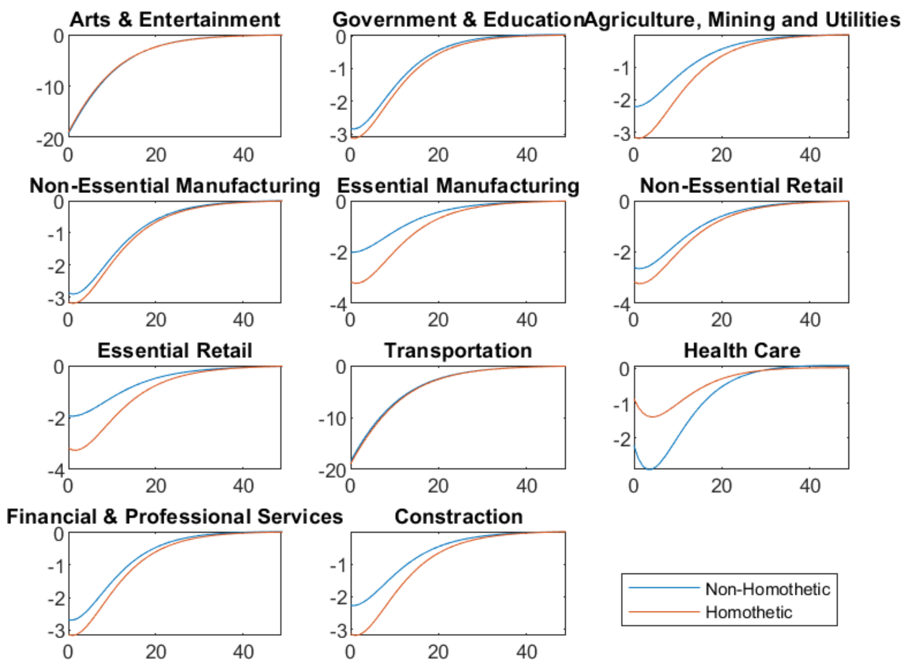


Figure 14: Impulse responses of sector levels at quarterly frequency with and without non-homothetic preferences.