Work Context and Industrial Composition Determine the Epidemiological Responses in a Multi-Group SIR Model

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Abstract Key economic indicators such as gross domestic product and unemployment rates provide a useful backdrop for assessing the state of the economy. In addition to more traditional uses, economic statistics can also be used to inform decision makers on how shifts in economic activity affect the progression of COVID-19. In this paper, we extend the domain of relevance for economic statistics by developing a multi-group SIR model that accounts for differences in work context and industrial composition. We show the model is useful for assessing how different economic scenarios affect the dynamics of COVID-19. Our model highlights how statistics on industry contact rates and the composition of economic output inform the dynamics of COVID-19 under different economic scenarios. Our study illustrates the importance of economic statistics for the numerical analysis of COVID-19 and describes how to use them to analyze different economic scenarios.

Keywords SIR, COVID–19, industrial composition, work context, national accounting

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1. Introduction

Economic statistics are essential for guiding local, state, and federal authorities on strategies for balancing economic losses with the social costs of the COVID-19 pandemic. Authorities tend to focus mainly on regional and national gross domestic product (GDP), but other regional, industry, and national statistics can also be utilized to improve our understanding of how economic activity influences COVID-19 dynamics. In this paper, we extend the domain of relevance for national economic statistics by studying how differences in work context and industrial composition determine the epidemiological responses to scenarios aimed at restoring economic activity. We consider differences in work contact and capacity to telework to characterize risk variation across industries. We introduce this risk variation into a multi-group susceptible-infected-recovered (SIR) model to capture the dynamics of contagion across different industries. We then offer an aggregation result that links the population-level contact rate of our SIR model with parameters that govern the recovery of the economy.

With the model, we compare outcomes under two different economic scenarios: (i) a fiscal stimulus package and (ii) the complete reopening of locked down industries. The economic scenarios in this paper are stylized and do not represent analysis of current economic conditions. Instead, we consider these scenarios as they are representative of and motivated by our main theoretical results. Under fiscal stimulus, resources are injected in the economy and labor expands in industries that serve the economy under lockdown. The risk profile across industries remains the same as in lockdown, but the population contact rate increases as more people are hired back into the economy. In contrast, reopening returns workers back to their initial industries, altering the risk profile relative to lockdown. As the composition of employment in the economy adjusts from reopening, the population contact rate can adjust upward or downward depending on the nature of the composition change. However, we find currently locked down industries have higher contact rates in the absence of complementary mitigation strategies. Consequently, reopening these industries shifts the composition of employed workers toward industries with higher contact rates, increasing the population level contact rate. We find this effect is strongest for food service and drinking places, for clothing and clothing accessories stores, and for amusement, gambling, and recreation industries.

The main insight of the paper is that the population contact rate, and thus the dynamics of COVID-19, is determined in part by work context and industrial composition. Under our stylized economic scenarios, adjustments in the composition of economic output can lead to an acceleration of the virus when industries with higher contact rates increase their share of total output.

For both scenarios, we calculate the number of new infections relative to the number of employed workers in the economy. New infections quickly increase relative to the case of lockdown, but a fiscal stimulus package generates fewer infections compared to the reopening of certain locked down industries. We find a fiscal stimulus package leads to fewer new infections when food service and drinking places, clothing and clothing accessories stores, and the amusement, gambling, and recreation industries remain under lockdown. We find reopening these industries leads to a larger shift in the population contact rate than under a fiscal stimulus scenario, where the same number of workers are added back to the post-lockdown industrial mix of economic activity.

Our multi-group SIR model is related to the models in Acemoglu et al. (2020), Baqaee et al. (2020), Çakmaklı et al. (2020), and Favero et al. (2020). The multi-group SIR model extends the canonical single group model of Kermack and McKendrick (1927) to account for heterogeneous risks across multiple groups. Çakmaklı et al. (2020) construct a similar multi-group SIR model that accounts for heterogeneity in physical contact at work, but they do not link their model with economic parameters that describe aggregate economic activity. Complementing their study, we illustrate how the population SIR model can be represented as disaggregated industry-specific SIR models. Acemoglu et al. (2020) provide a similar aggregation result in their model, where groups correspond to different age classifications. After aggregating the industry SIR models to the population-level, we show the population-level contact rate used in the standard SIR model is determined by industry-specific contact rates, industry composition, and spending levels in the economy.

Some recent papers deal with optimal policy responses to COVID-19 under different economic and epidemiological settings (Alvarez et al. 2020; Jones et al. 2020; Eichenbaum et al. 2020; Farboodi et al. 2020; Piguillem and Shi 2020; Gonzalez-Eiras and Niepelt 2020). Given the large uncertainties surrounding the current epidemic, we intentionally abstain from optimal policy analysis and instead focus on the trade-offs inherent in stylized economic scenarios. We choose this approach for several reasons. First, we do not consider complementary mitigation strategies, such as social distancing, mask mandates, or required testing. Recent research in this area shows that a bundled mitigation approach can limit virus transmission (Wang et al. 2020). With these complementary strategies in place, reopening high contact industries, such as food service and drinking places, may have a less profound impact on COVID-19 dynamics than our model would suggest.

Second, our simulation exercises do not account for consumer avoidance behavior, for example, voluntarily avoiding large public gatherings during a virus outbreak (Yoo et al. 2010; Alfaro et al. 2020; Gupta et al. 2020). While some early evidence suggests reopening increases mobility (Nguyen et al. 2020), consumer perception of virus risk may reduce, or hold constant, the transmission risk posed by reopening certain industries. Since our analysis does not consider this a possibility, our estimates may overstate the impacts of reopening on virus contagion.

Lastly, we stress that our model is best viewed as a method for calibrating macroeconomic models to account for feedback loops between industrial structure and virus dynamics. By now, there is a large literature on the macroeconomic impact of the COVID-19 pandemic. Of this literature, several papers, including but not limited to Eichenbaum et al. (2020), Jones et al. (2020), Farboodi et al. (2020), Garibaldi et al. (2020), and Krueger et al. (2020), study how behavioral responses to epidemics influence virus dynamics by changing key underlying parameters of epidemiological models. We complement these studies by focusing on how the population contact rate in the standard SIR model is affected by varying key economic parameters. This allows us to keep the focus on how changes in the economic landscape during the pandemic could potentially alter the dynamics of the COVID-19 pandemic.

The paper is organized as follows. In section 2, we present the multi-group SIR model used in the analysis. We illustrate how fiscal stimulus and reopening affect the population level contact rate. Importantly, we also show how the composition of economic activity and differences in industry-specific contact rates can be incorporated directly into a standard SIR model. Section 3 provides the details of the model's calibration. We discuss the data and methods used to estimate industry-specific contact rates, potential contacts, industrial composition in the post-lockdown period, and the multi-group SIR model.[2] We present the main results of our analysis in section 4. In this section, we compare the epidemiological outcomes under the fiscal stimulus and reopening scenarios. Section 5 discusses important caveats with respect to the interpretation of our results. We offer our conclusions and suggestions for future research in Section 6.

2. In this section, we present simulated estimates for GDP in 2020 Q2. We note here and in presentation of the result that these estimates *are not* official forecasts from the Bureau of Economic Analysis (BEA). The estimates presented in the paper are solely for the purposes defined in our study.

2. The Multi-Group SIR Model

We use a multi-group SIR model to capture how heterogeneous working environments and industrial composition affect the spread of COVID-19 among the population. We assume a population of individuals of size P can be divided into $N + 1$ groups, where N corresponds to the number of operational industries, and the final group consists of the "at-home" population. We define the "at-work" population as employees that cannot work from home, while the "at-home" population corresponds to children, retired, or unemployed individuals plus those teleworking. We show how the model integrates changes in economic activity with the virus dynamics in an aggregate population level SIR model.

2.1 Model Setup

In the canonical SIR model, at any given time, the population is divided into three groups: a susceptible group of individuals who have not yet contracted the virus, a group of infected individuals, and a group of recovered individuals who previously contracted the virus but are no longer contagious. The multi-group SIR model implemented in this paper consists of a collection of dynamic processes that represent the dynamics of infection and spread within and between groups. The model accounts for heterogeneity in contact rates and susceptible populations and is given by the following system of differential equations

$$\frac{d\mathbf{S}}{dt} = -\mathrm{diag}\,(\mathbf{S})\,\mathbf{BI}$$
$$\frac{d\mathbf{I}}{dt} = \mathrm{diag}\,(\mathbf{S})\,\mathbf{BI} - \gamma\mathbf{I}$$
$$\frac{d\mathbf{R}}{dt} = \gamma\mathbf{I}$$

where $\mathbf{S}$ is an $N + 1 \times 1$ vector containing the number of susceptible individuals S_{jt} in each industry j and time period t. The transmission of the virus is governed by an $N + 1 \times N + 1$ matrix of transmission coefficients $\mathbf{B}$. The element β_{jk} is the contact rate between group j and k. The number of infected individuals in each industry and time step, I_{jt}, is contained in the $N + 1 \times 1$ vector $\mathbf{I}$. Similarly, the number of recovered individuals in each industry and time step is given by the $N + 1 \times 1$ vector $\mathbf{R}$. Individuals recover at the rates given by the matrix γ, where the diagonal elements γ_j correspond to the recovery rate of group j and off-diagonal elements are zero.

We assume the row entries in **B** are constant within an industry, so that $\beta_{j,1} = \beta_{j,2} = \ldots = \beta_{j,N+1}$ for each industry j. Furthermore, we assume the recovery rates in γ are identical for all groups. Under these assumptions, the virus dynamics within a particular group can be written as follows

$$\frac{dS_{jt}}{dt} = -\beta_j S_{jt} \sum_{j=1}^{N+1} I_{jt}$$

$$\frac{dI_{jt}}{dt} = -\beta_j S_{jt} \sum_{j=1}^{N+1} I_{jt} - \gamma I_{jt}$$

$$\frac{dR_{jt}}{dt} = \gamma I_{jt}$$

Heterogeneity in risks comes from differences in contact rates at work across industries. For each of the N industries in the economy, we define the contact rate of the industry, β_j to be a combination of the at-home rate β and the industry contact index ρ_j. The industry contact rate $\rho_j\beta$ reflects the contact rates of workers in industry j who must be physically present at their jobs. Formally, the at-work contact rate is given by $\beta_j = (h_j + \omega_j\rho_j)\beta$. In this formulation, we use h_j to denote the amount of hours a worker is at home and w_j to account for the amount of hours spent at work, where $h_j = 1 - \omega_j$ to reflect the idea that a worker's time is spent either at work or at home. With these definitions and assumptions in mind, we can write the dynamics of the virus at the population level as

$$\frac{dS_t}{dt} = \sum_{j=1}^{N+1} \frac{dS_{jt}}{dt} = -\tilde{\beta}_t S_t I_t$$

$$\frac{dI_t}{dt} = \sum_{j=1}^{N+1} \frac{dI_{jt}}{dt} = -\tilde{\beta}_t S_t I_t - \gamma I_t$$

$$\frac{dR_t}{dt} = \sum_{j=1}^{N+1} \frac{dR_{jt}}{dt} = \gamma I_t$$

After aggregating to the population level, the dynamics of the multi-group SIR model resemble the dynamics of a standard SIR model, but with one important difference. In the population version of the multi-group SIR model, the effective population-level contact rate $\tilde{\beta}$ is a weighted sum of the group-level contact rate and it is proportional to the at-home contact rate β. Specifically, the population contact rate is given by the following expression

$$\tilde{\beta}_t = \left[\sum_{j=1}^{N+1} (h_j + \omega_j\rho_j) \frac{S_{jt}}{S_t} \right] \beta$$

This expression illustrates how both the transmission coefficients for each group, $(h_j + \omega_j \rho_j)\,\beta$, and the composition of susceptible individuals across the $N+1$ groups, S_{jt}/S_t, influences the contact rate in the economy. Intuitively, this expression dictates that when a higher fraction of susceptible individuals is in high contact industries, the overall contact rate of the economy increases, and thus the progression of the virus accelerates in the population.

2.2 Connecting the Model to the Economy

In this section, we connect the multi-group SIR model with parameters that describe the state of the economy. We illustrate how variations in these parameters influence the population-level contact rate, changing the contagion dynamics of the virus. We then link variations in these parameters with different economic scenarios during the COVID-19 pandemic.

We assume the initial susceptible population within an industry is proportional to the non-teleworking labor force in the industry, thus

$$S_{j0} = (1 - \tau_j)\, L_{j0}$$

where τ_j corresponds to the fraction of workers in an industry that are capable of teleworking and L_{j0} represents post-lockdown employment in industry j. The initial number of susceptible individuals in the at-home population is given by

$$H_0 = P - \sum_{j=1}^{N} (1 - \tau_j)\, L_{j0} = P - \bar{L}_0$$

where $\bar{L}_0$ is the total number of employed, non-teleworking workers in the economy. We rewrite each industry's initial labor force as a function of economic parameters as follows

$$\begin{aligned} L_{j0} &= \frac{1}{w_{j0}} \left(\frac{w_{j0} L_{j0}}{X_{j0}} \right) \left(\frac{X_{j0}}{C_0} \right) C_0 \\ &= \frac{\gamma_{j0} \delta_{j0}}{w_{j0}}\, C_0 \end{aligned}$$

where γ_{j0} is the labor cost share in industry j, X_{j0} is nominal gross output, δ_{j0} is the Domar weight of industry j, w_{j0} are averages wages in the industry, and C_0 is GDP.

Throughout the remainder of the paper, we assume industry average wages w_{j0} and industry labor shares γ_{j0} remain constant at the baseline value. The former is meant to reflect wage rigidity, and the latter assumes the industry production function remains unchanged over the time horizon of study. In contrast, we treat δ_j and C as economic objects that are affected by our scenarios. With this in mind, we drop the time subscripts on the economic parameters for cleanliness of notation. Substituting this into the expression for the initial susceptible population in the at-home group implies

$$H_0 = P - C \sum_{j=1}^{N} (1 - \tau_j) \frac{\gamma_j \delta_j}{w_j}$$

Substituting these expressions into the initial value of the population-level contact rate, we connect the population SIR model to economic activity as follows

$$\widetilde{\beta}_0 = \frac{1}{S_0} \left[H_0 + \sum_{j=1}^{N} (h_j + \omega_j \rho_j)(1 - \tau_j) \frac{\gamma_j \delta_j}{w_j} C \right] \beta$$

Using this expression, we introduce two effects to explain how the population-level contact rate $\widetilde{\beta}$ adjusts in response to new economic conditions. While we present these results as separate theoretical effects, the distinction is primarily for the purpose of parsimonious presentation. In practice, these effects are likely to occur simultaneously.

The Composition Effect

We define the composition effect as the change in the population-level contact rate caused by a shift in consumer spending patterns while holding income constant. Formally, a change in the composition of the economy affects the initial population contact rate as follows

$$d\widetilde{\beta}_0 = \frac{\beta}{S_0} \sum_{j=1}^{N} \omega_j \, (\rho_j - 1) \, (1 - \tau_j) \, L_j \, \frac{dXj}{Xj} \tag{1}$$

This effect arises when industries previously closed due to lockdowns, such as restaurants, gyms, and salons, are reopened. As consumers reallocate spending to these industries, producers in these industries hire back unemployed workers, thereby increasing the total number of potential interactions. Consequently, the contact rate in the population adjusts due to a change in the mixture of interactions in the economy.

The Stimulus Effect

The stimulus effect is defined as the change in the population contact rate caused by an increase in consumer spending. Formally, the stimulus effect adjusts the population-level contact rate in the following way.

$$d\widetilde{\beta}_0 = \frac{\beta}{S_0} \sum_{j=1}^{N} \omega_j \left(\rho_j - 1\right) \left(1 - \tau_j\right) L_j \; \frac{dC}{C} \tag{2}$$

In contrast to the reopening effect, the stimulus effect does not result in a change in the composition of spending but rather the scale of spending, as we assume the fiscal stimulus package is implemented without lifting any current lockdowns.[3] Instead, the fiscal stimulus increases overall spending, driving up employment under the post-lockdown industry composition.[4] In this scenario, higher employment increases the total number of potential contacts at work, which raises the population-level contact rate holding constant the post-lockdown composition.

These effects underpin the main differences across the economic scenarios we explore in this paper. The first scenario we examine is reopening the economy. In the model, the reopening scenario alters the composition of spending in the economy, and the change in composition adjusts the weights on each industry's contact rate, leading to an overall adjustment in the population-level contact rate. The second scenario we examine is a fiscal stimulus designed to increase consumer spending in the economy. The stimulus effect reflects how the population-level contact rate adjusts from the implementation of such a measure. While we examine these scenarios discretely, we expect some combination of these scenarios to be implemented simultaneously in practice.

3. Our analysis implicitly assumes the economic scenarios occur over short time horizons to avoid changes in composition arising from non-homothetic preferences. We thank Brian Sliker at BEA for pointing this out.

4. In the analysis, we remain agnostic on the spending levels required to raise employment to pre-lockdown conditions, especially since households may have enhanced precautionary savings motives during the lockdown period. Consequently, spending levels would need to be much higher than our economic model suggests. However, in any case, the same number of workers will return to work under the post-lockdown composition.

3. Model Calibration

This section presents our methodology for calibrating the multi-group SIR model and the economic parameters required for our analysis. We begin by presenting the data and methods behind our estimates for industry-specific contact rates. We follow this presentation with a brief overview of the method used to simulate the economic response to COVID-19 and subsequent lockdown measures. We conclude the section with a discussion of the parameters and assumptions within the multi-group SIR model.

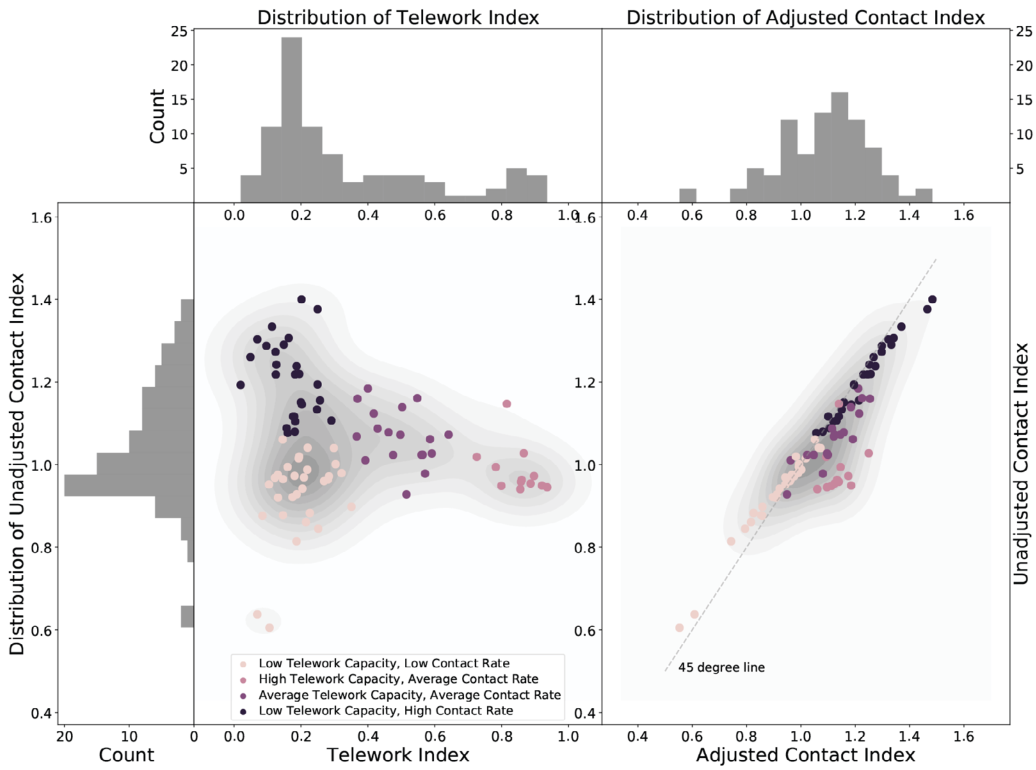
3.1 Industry Contact Rates

The industry-specific contact rates, β_j, dictate the behavior of the population-level contact rate when fiscal stimulus and reopening are introduced. To calibrate these parameters, we rely on attributes of an occupation's work context to capture the ability of a worker to social distance while still performing key job-related functions.

We use a combination of data sources for the calibration. First, we construct an *unadjusted physical contact index* using work context characteristics from the Occupational Network (ONET) database. From the ONET database, we identify three relevant work context elements that are relevant for this ranking: (i) face-to-face discussions, (ii) contact with others, and (iii) physical proximity. For each of these elements, ONET reports an importance score between 1–5, where 5 represents the highest level of contact. We compute the product of the importance scores to yield a value for each occupation, where the minimum possible value is 1 and the largest possible value is 125. We then compute the median of this series and use the median to rescale each occupation's unadjusted contact index, where the median index value is equal to one. This computation yields the physical contact index for an occupation, denoted as ρ_o. Occupations with higher values in the index are more likely to engage in face-to-face discussions, contact with others, or work in close physical proximity with co-workers. We report the results of this computation in tables 4-11 in Appendix B.

Lockdowns encourage telework capable employees to work from home. Hence, our second step is to construct the *adjusted* physical contact index, ρ_j, that reflects the contact rates of workers in industry j who must be physically present at their jobs. To make this adjustment, we use data on telework capable occupations from Dingel and Neiman (2020) and remove these occupations from our calculation. This data allows us to compute τ_j for each industry. We pair our occupational contact data with the Bureau of Labor Statistics' Occupational Employment Statistics to compute occupational employment shares for each industry. We then use these shares to construct the adjusted physical contact index at the 3-digit North American Industry Classification System (NAICS) level to match the level of detail in our underlying industry data. In what follows, when we reference an industry's contact index, we are referring to the adjusted contact index unless otherwise stated.

Figure 1: The Unadjusted Contact Index, Telework Index, and Adjusted Contact Index



Source: Occupational telework data come from Dingel and Neiman (2020), occupational shares are computed using the 2018 Occupational Employment Statistics, occupational contact data is collected from the Occupational Network Database, and the contact and telework indexes are computed using the author's calculations.

We display the physical contact indices in figure 1. In the first panel, we show the relationship between an industry's unadjusted contact index and teleworking capacity, including the distributions for each index. We cluster the industries into four categories using a simple k-means clustering routine. We note these clusters have no bearing on the subsequent analysis but help us during the presentation and analysis of our results. The first cluster includes industries with low telework capacity and a low unadjusted physical contact index. This cluster tends to include manufacturing and construction industries, where teleworking is not generally possible and contact with others tends to remain low. The second cluster includes industries with low teleworking capacity and high unadjusted physical contact indexes. These industries include many retail and health service industries. Hospitals (NAICS 621) and nursing facilities (NAICS 622) are the most salient examples, exhibiting the highest unadjusted physical contact indexes. This cluster also includes industries affected by the lockdown, such as food service and drinking places (NAICS 722). The third cluster includes industries with an average telework capacity, that is, $\tau_j = 0.5$, and average physical contact index. The composition of industries in this cluster is less clear, spanning from oil and gas extraction (NAICS 211) to electronics and appliance retailers (NAICS 443). The final cluster includes industries with high teleworking capabilities and average contact rates. A typical industry in this cluster are financial service industries, such as central banks (NAICS 524) but includes one outlying high telework capacity and high contact industry, educational services (NAICS 611).

In the second panel to the right, we show the relationship between the unadjusted and adjusted contact index for each industry. This figure illustrates how removing teleworkers from the at-work pool of employees changes the contact index for the industry. Industries below the 45-degree line experience an increase in their contact index, meaning the typical worker is more likely to come into physical contact with others. In effect, by removing teleworkers, workers who must be physically present to perform their duties are generally more susceptible to contracting and transmitting the virus since they are more likely to come into contact with others. However, at the same time, the pool of at-risk workers is lower so the net change in total infections is ambiguous. This is particularly prevalent in high contact, low telework industries, such as restaurants and hospitals. By sending teleworkers home, the average contact index is higher. This can be seen when comparing the distribution of the unadjusted contact index (mean = 1.0) and the adjusted contact index (mean = 1.2).

3.2 Industrial composition under lockdown

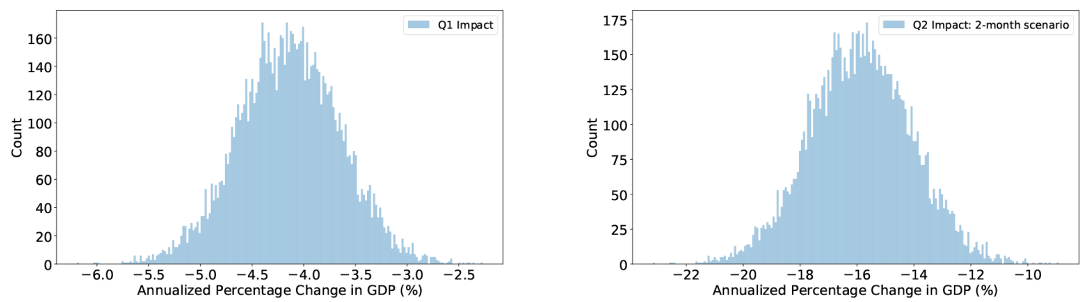
We take lockdown as our starting point and calibrate our model accordingly. Our calibration of the economic parameters in the model uses the standard demand-driven input-output model framework (Leontief 1936; Miller and Blair 2009) along with detailed industry data from the Bureau of Economic Analysis (BEA) to estimate industry output, employment, and aggregate value added in the lockdown period. This section provides the general details of the approach along with some of the main results from the calibration and simulation of economic activity. We list the data sources for calibrating the model's parameters in table 1, and we relegate the details of the simulation to Appendix A.

Table 1: Calibrated Parameters of the Model

Parameter	Description	Source
	Households and producers	
γ	Labor cost shares	2018 BEA Industry Account
$\mathbf{M}$	Leontief inverse	2018 BEA Detailed Use Table
$\boldsymbol{a}$	Expenditure shares	2018 BEA Detailed Use Table
	Reopening parameters	
θt	Final demand impacts	Dunn et al. (2020)

In our simulation we made several important assumptions. For instance, the model holds capital fixed and abstracts away from exports, imports, and changes in inventories. Furthermore, we do not consider how virus dynamics affect economic output and assume all economic impacts are the result of the lockdown.

Figure 2: Simulated Percentage Change in Quarterly GDP

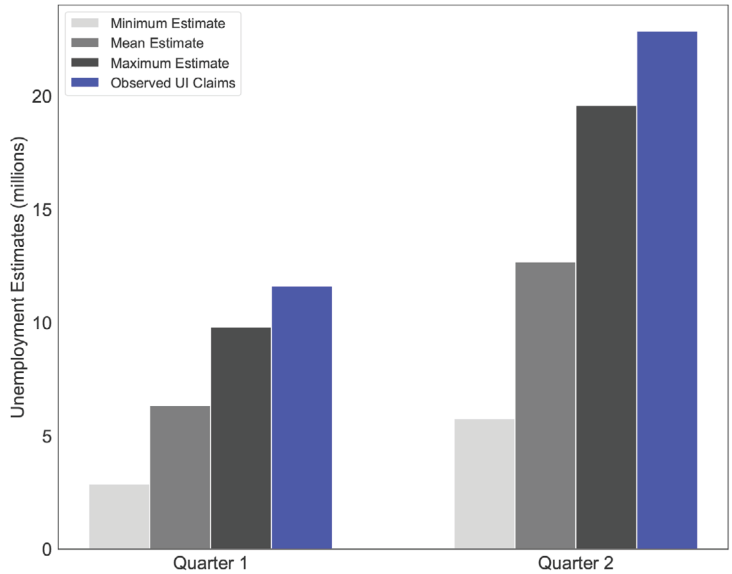


(a) First Quarter **(b)** Second Quarter

Source: These estimates are derived from the numerical simulations conducted by the authors.

Figure 2 presents our estimated impacts of lockdowns on quarterly GDP. To produce the range of estimates, we use the estimated 95 percent confidence intervals for the impacts of lockdowns on final demand spending from Dunn et al. (2020) and conduct 10,000 simulations using independent draws from their implied distributions. In the first quarter, our estimates range from –2.5 percent to –6.0 percent, where the average estimate is –15.8 percent. According to revised estimates from BEA, GDP in the first quarter contracted at an annualized rate of –5.0 percent. For the second quarter estimates, we conduct the simulation exercise under the assumption that lockdowns are lifted on June 1st, and economic activity recovers to the pre-lockdown levels immediately. The range of estimates for second quarter GDP are more pessimistic, reflecting the longer shutdown period. The range of estimates span from –8.9 percent to –23.1 percent, and the average estimate is 15.8 percent. We note these estimates are not official forecasts from the BEA. Instead, these are simulations used to only inform the key parameters in the multi-group SIR model, and, therefore, developed only for the purposes of this paper.

Figure 3: Unemployment Estimates versus Observed Unemployment Insurance Claims



Source: Observed UI Claims are sourced from the Department of Labor's UI Claims database. The minimum, mean, and maximum estimate are derived from the numerical simulations conducted by the authors.

Next, we simulate the employment impacts of the lockdown scenario. Figure 3 presents the results of our unemployment estimates. We select the minimum, average, and maximum estimate (in absolute value) from our GDP simulations and compute the number of unemployed workers in each quarter. The gray shaded bars correspond to our estimates, while the blue bar corresponds to actual unemployment insurance (UI) claims. At the time we were writing this paper, continued weekly UI claims totaled 34.5 million following the start of lockdown in the United States. Evaluated at the maximum impact, our model estimates a total of 26.8 million unemployed workers in the first and second quarter of 2020. Since the maximum impacts better reflect reality, we use these estimates to calibrate the multi-group SIR model.

Table 2: Actual versus Estimated Unemployment by Industry (Thousands of jobs)

Industry	February employment	April employment	Actual losses	Estimated losses	Difference
Clothing and accessories stores (448)	1,289	530	759	589	-170
Transit and ground transportation (485)	508	318	190	174	-16
Performing arts, spectator sports, related (711)	511	279	232	140	-92
Museums, historical sites, similar (712)	175	129	45	97	52
Amusement, gambling, and recreation (713)	1,785	715	1,070	940	-130
Accommodations (721)	2,091	1,206	885	989	104
Food service and drinking places (722)	12,303	6,384	5,919	4,255	-1,664

Source: Monthly employment and actual job losses are collected from the BLS. Estimated losses are derived from the numerical simulations conducted by the authors.

We present the results of our employment calibration in table 2 for selected industries. We will be focusing on these industries in our analysis below to showcase the logic of our argument. This table also shows one of the primary inputs for the simulation. First, we can see large variation in employment across industries. Food service and drinking places (722) employed more than 12 million people in February while museums, historical sites, and similar (712) employed only 172 thousand people. The table also shows that employment losses were not uniform in April. While museums, historical sites, and similar (712) lost 25 percent of employment, food service and drinking places (722) lost 48 percent and amusement, gambling, and recreation (713) lost almost 60 percent of workers. Our discussions below amount to reinstating lost jobs back into the economy. As such, we will be recovering our predicted losses and not the real losses suffered in the economy.

3.3 Potential Contacts

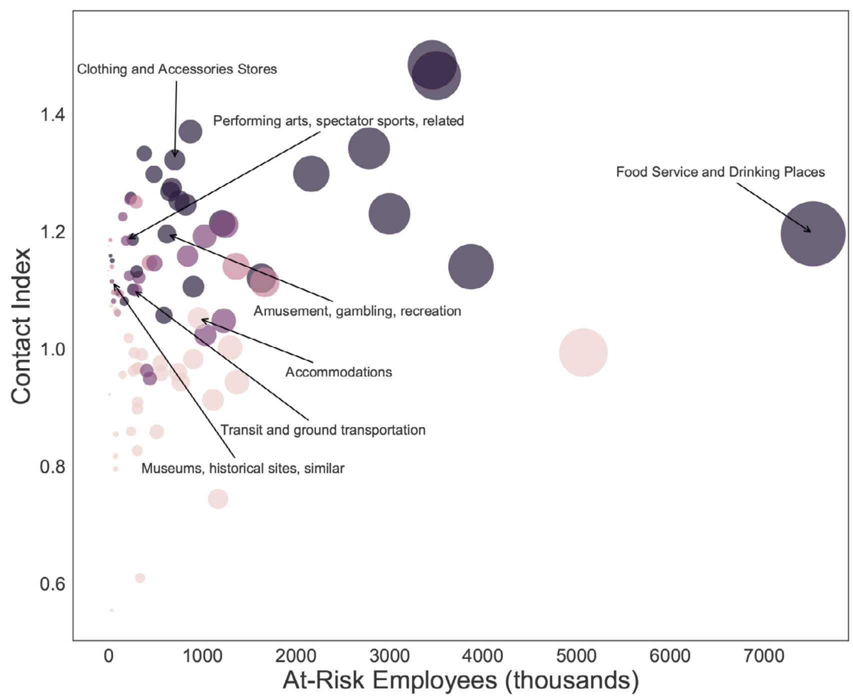
Industry composition and work context interact to determine the population-level contact rate. In section 2, we show how industry-specific contact indexes, ρ_j, interact with at-work employment levels, $(1 - \tau_j)\, L_j$, across industries to influence the population-level contact rate. We refer to the term $\rho_j\,(1 - \tau_j)\, L_j$ as the *potential contacts* in an industry to reflect the idea that industry-specific contact rates and employment levels dictate the number of possible interactions between individuals. In the analysis, we assume $h_j = 2/3$ and $\omega_j = 1/3$ across each industry to reflect the idea that only 8 hours of a day are spent at work. From this assumption, a combination of a high contact rate with a large number of non-teleworking workers, that is, a high number of potential contacts, increases the risk of virus contagion in both the industry and population.

Figure 4 displays the relationship between industry-specific contact rates, at-risk employment, and potential contacts. We use the term "at-risk" employees to denote non-teleworking employees. The colors match those we presented in figure 1, while the size of the circle captures the product between the physical contact rate and the employment size during the lockdown period. We label the industries that will be the focus of this analysis in our simulations below. This figure shows that risk is not only determined by the physical contact index within an industry; instead, the number of at-risk employees also determines overall risk posed to the population by an industry. For example, food services and drinking places, by employing the most people, also has the largest number of potential contacts that leads to the highest level of risk for virus contagion. Comparatively, the amusement, gambling, and recreation industry has a similar contact index as food service and drinking places but employs substantially less people. Consequently, this industry poses less risk to the overall population in our model since the potential contacts within the industry are lower than in food service and drinking places.

3.4 The Multi-group SIR model

To calibrate our multi-group SIR model, we start by using data on the cumulative infections in the United States. At the time this paper was written, approximately 1.485 million people in the United States have contracted the virus. Although these figures likely underestimate the actual number of cases, we calibrate the initial susceptible and recovered population to these numbers. We normalize population to one, such that $S_0 = 0.995$ and $R_0 = 0.0035$. In line with the literature, we set $\gamma = 1/18$ implying 18 days of recovery time on average. Using this value, we calibrate the initial number of infected individuals as $I_0 = 1 - S_0 - R_0 = 0.0015$, which pins down the average number of new daily infections for the past 18 days at 27,500. Unfortunately, we do not have detailed data on susceptible populations by industry. Thus, for our calibration, we assume the fraction of susceptible individuals, S_0, to weight each industry's estimated lockdown employment. Hence, we calibrate $S_{j0} = S_0(1 - \tau_j)\hat{L}_j$ for each industry, where we use the hat to emphasize this quantity is estimated from data.

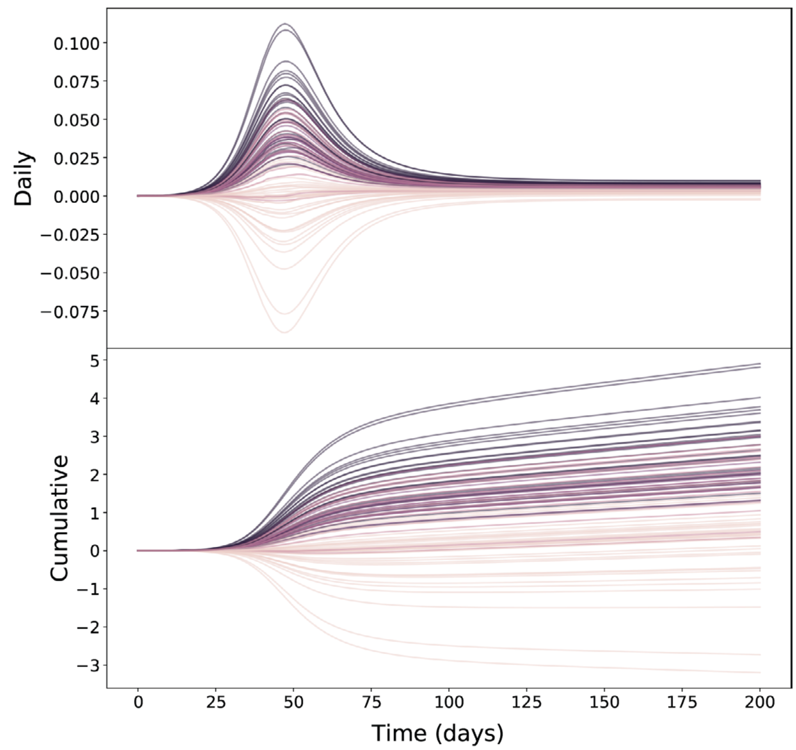
Figure 4: Industry Contact Rates, Employment, and Potential Contacts



Source: Author's calculations. All values are derived from simulation the calibrated multi-group SIR model.

We set $\tilde{\beta}_0 = 0.2$ to reflect an $R0 = 3.6$. The value of $\tilde{\beta}_0$ is highly uncertain and estimates of $R0$ range from 2–3 (Atkeson 2020). We elect to set $\tilde{\beta}_0 = 0.2$ to align with the simple calibration in Acemoglu et al. (2020), although our main conclusions are robust to this choice. We use the population-level contact rate to calibrate the at-home contact rate of β. Using our estimates for ρ_j, S_{j0} and H_0, we calibrate the at-home population's contact rate to be $\beta = 0.15$, only slightly lower than the average population contact rate.

Figure 5: New Infections per Worker



Source: Author's calculations. All values are derived from simulation the calibrated multi-group SIR model.

Figure 5 illustrates the mechanics of the calibrated multi-group SIR model. To construct this figure, we artificially remove one person from the at-home group and place them at work in any given industry and then simulate the additional infections caused by this movement. The colors match the industry clusters we identified in figure 1. The top panel in the figure depicts the change in daily infections, and the bottom panel shows the change in cumulative infections. Sending a single worker from home to hospitals, a high contact industry, increases daily infections by approximately 0.1 at the peak and generates 5 new infections after 200 days. In contrast, sending the same person to work in forestry and logging, a very low contact industry, will actually lead to fewer infections per day and around 4 fewer infections after 200 days. As the figure indicates, darker color industries, corresponding to high contact industries, add more infections over time, whereas lighter color industries, with lower contact rates, reduce infections over time.

The intuition behind this result is that a worker moving from the at-home group to work in a high contact industry will increase the population contact rate since $\beta_j > \beta$ for these industries, and vice versa. As a consequence, the number of infections increases because the population contact rate increases from this movement. In figure 5, we show the change in infections is highly correlated with the contact rate within an industry. We discuss the impact of this movement on the population contact rate in more detail in section 4.3.

4. Results

We analyze two, potentially complementary, approaches that aim to stabilize the economy during the pandemic. Reopenings, as their name indicates, return currently at home, unemployed workers to work in the industries that employed them before the lockdown. In contrast, fiscal stimulus aims to stabilize or increase aggregate demand via direct resource injections into the economy. In our scenario, we consider fiscal stimulus that directs payments directly to households, allowing consumers to purchase goods and services under the post-lockdown industrial mix. While the results are presented separately and contrasted, we emphasize these economic scenarios are likely to occur within a broader landscape of economic conditions that we do not consider. Moreover, we do not analyze situations where the two scenarios are combined.

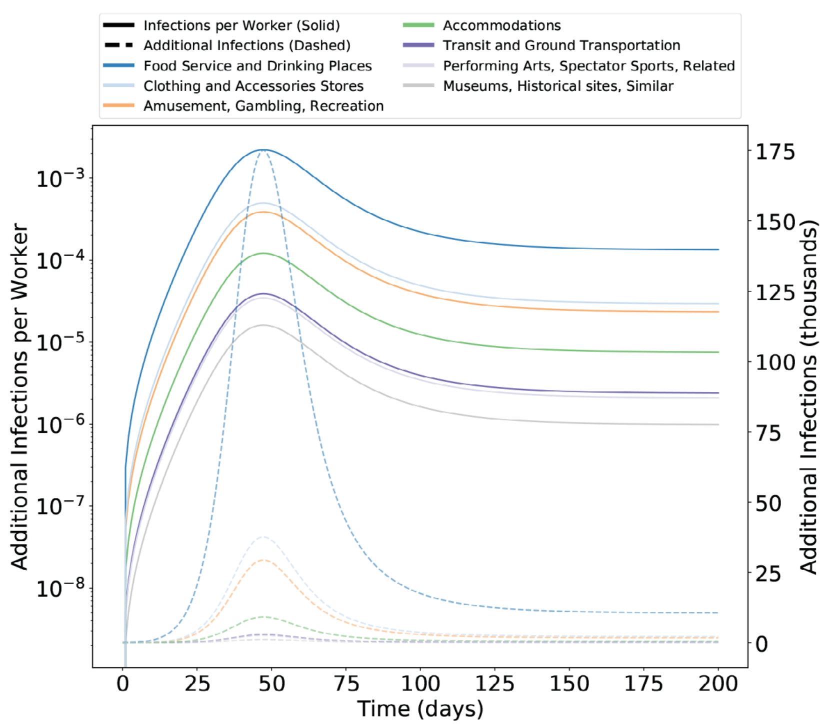
In our simulations, we consider the reopening of seven industries where producers face either capacity restrictions, forced closure under lockdown, or reduced demand from social distancing. The industries we consider are: food service and drinking places (NAICS 722); clothing and clothing accessories stores (NAICS 448); amusement, gambling, and recreation (NAICS 713); accommodations (NAICS 721); transit and ground transportation (NAICS 485); performing arts, spectator sports, and related (NAICS 711); and museums, historical sites, and similar (NAICS 712). Throughout the paper, we have illustrated how these industries vary in contact rates, potential contacts, and unemployment rates following the lockdown. Variation in these quantities will be useful for highlighting the main results of our analysis.

4.1 Reopening Scenario

When an industry reopens, three quantities will determine how the population-level contact rate changes after reopening. First, the physical contact rate of the reopened industry will directly affect the population contacted rate since the industry's contact rate reflects the probability of interacting with someone who is potentially infected. When this probability increases, workers are more likely to contract the virus and expose others, increasing overall infections. We illustrate the importance of industry contact rates in figure 5. Second, the number of at-risk employees in reopened industries has an important bearing on the population-level contact rate because more at-risk employees increase the number of interactions an additional worker can have per day. For the same industry contact rate, having more at-risk employees implies more infections occur in the population since more potential contacts would occur. Finally, we need to consider the change in industry revenues following reopening. As revenues increase, employers will hire back workers from the unemployed, at-home population. When an industry hires back more workers, the population contact rate will shift toward this industry's contact rate, potentially leading to an increase in the population contact rate. When an industry's contact rate is higher than the at-home contact rate, hiring workers back into this industry will increase infections.

The interaction of these three quantities determines the level of risk to the population when we reopen the economy. We present the results of the simulation in figure 6. On the primary (left) y-axis, we present the cumulative number of *additional* infections per employed worker to illustrate the trade-offs between reopening and total infections. We plot the additional cumulative infections caused by reopening on the secondary (right) y-axis. The figure reveals the important trade-offs between strategies for jump starting the economy and the dynamics of COVID-19. First, the figure shows adding workers back to the economy will generate new infections relative to the lockdown baseline under any reopening scenario. Second, the number of infections generated per employee continues to increase until peak infections are reached. This behavior of the model has important implications for managing the trade-offs between economic activity and the social costs of the virus. As cumulative infections increase over time, the economic benefits of adding workers to the economy will decline relative to the social costs of managing the virus and, at some point, reach a minimum. Finally, adding workers back to the economy leads to a peak number of additional, cumulative infections, suggesting peak infections occur sooner when economic activity increases. This final result suggests adding workers to the economy changes the population contact rate, a result we discuss in further detail below.

Figure 6: Epidemiological Responses to Re-opening Select Industries



Source: Author's calculations. All values are derived from simulation the calibrated multi-group SIR model.

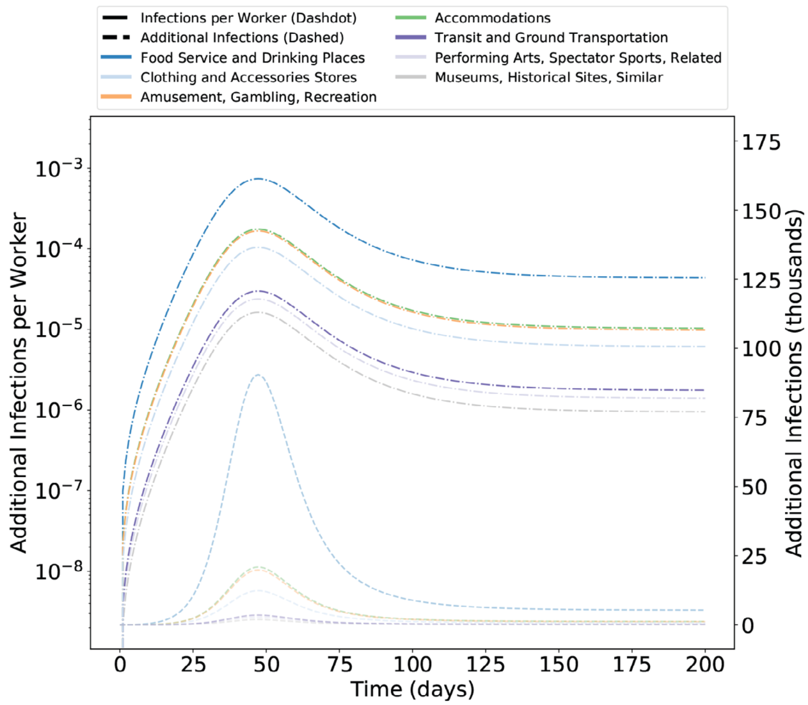
Consider the impact on infections when the food service and drinking places industry is reopened. We illustrate this impact in dark blue in figure 6. Before lockdown, the food service and drinking places industry employed around 12 million people and continues to employee over 6 million people during the lockdown. As shown in figure 4 the physical contact index is around 1.2, or 20 percent higher than the at-home contact index. Reopening the food service and drinking places industry in our simulation removes 4 million people from their at-home environment and locates them in their work environments. The food service and drinking places industry is a high-contact industry, with a large number of employees currently at work, receiving a large number of people back into their jobs. As indicated in 6, reopening the food service and drinking places industry adds an additional 175,000 cumulative infections to the economy up to when the peak difference occurs in the figure. This is equivalent to 22 new infections per 10,000 workers.

Next, let's consider the number of new infections generated by reopening the museums, historical sites, and similar industry. The museums, historical sites, and similar industry employed around 175,000 people before the pandemic and lost 45,000 people following the implementation of lockdowns (see table 2). The average contact rate in the industry is around 10 percent higher than the at-home contact rate, which is lower than food service and drinking places. Reopening the museums, historical sites, and similar industry adds a relatively small number of people to an industry currently employing relatively few, at-risk workers. As a result, the number of additional cumulative infections up to the peak difference only reaches 1,200, implying only 0.162 new infections per 10,000 workers.

4.2 Fiscal Stimulus

In our economic model, fiscal solutions stimulate aggregate demand in the economy. When fiscal stimulus increases aggregate demand, consumers purchase goods and services under the post-lockdown industrial mix. As business revenues increase, unemployed workers are hired back into the economy. Unlike the reopening scenario, these workers go back to industries serving the economy under lockdown conditions. That is, the composition of the economy does not change from the post-lockdown mix of activity. To compare the results with the reopenings, we simulate a fiscal stimulus scenario that results in the addition of the same number of workers as if we were reopening the same industries. For example, under the food service and drinking places fiscal stimulus, the stimulus results in the employment of around 4 million unemployed workers. We do not add workers directly into the food service and drinking places industry, but instead in a combination of industries that maintain the same industrial composition of the economy under lockdown.

Figure 7: Epidemiological Responses to Fiscal Stimulus



Source: Author's calculations. All values are derived from simulation the calibrated multi-group SIR model.

We present the results of this exercise in figure 7. Many of the conclusions we discussed in the previous section remain true for the fiscal stimulus scenario. In particular, we find restoring economic activity increases total infections, generates an upward trajectory for infections per worker, and leads to an earlier peak infection time frame. However, the implications for virus dynamics differ from the reopening scenario. For example, under the food service and drinking places fiscal stimulus, the addition of more workers to the pool of at-risk employees increases the risk profile of the economy, adding up to 90,000 cumulative infections at peak, corresponding to 7 infections per 10,000 workers. By comparison, if fiscal stimulus was instead crafted to hire back unemployed workers from the museums, gambling, and recreation industry, the addition of these unemployed workers into the post-lockdown industrial mix would result in 2,000 cumulative infections at peak, corresponding to 0.162 infections per 10,000 workers. In the next section, we compare the epidemiological outcomes from each scenario and discuss the mechanics driving these outcomes.

4.3 Discussion

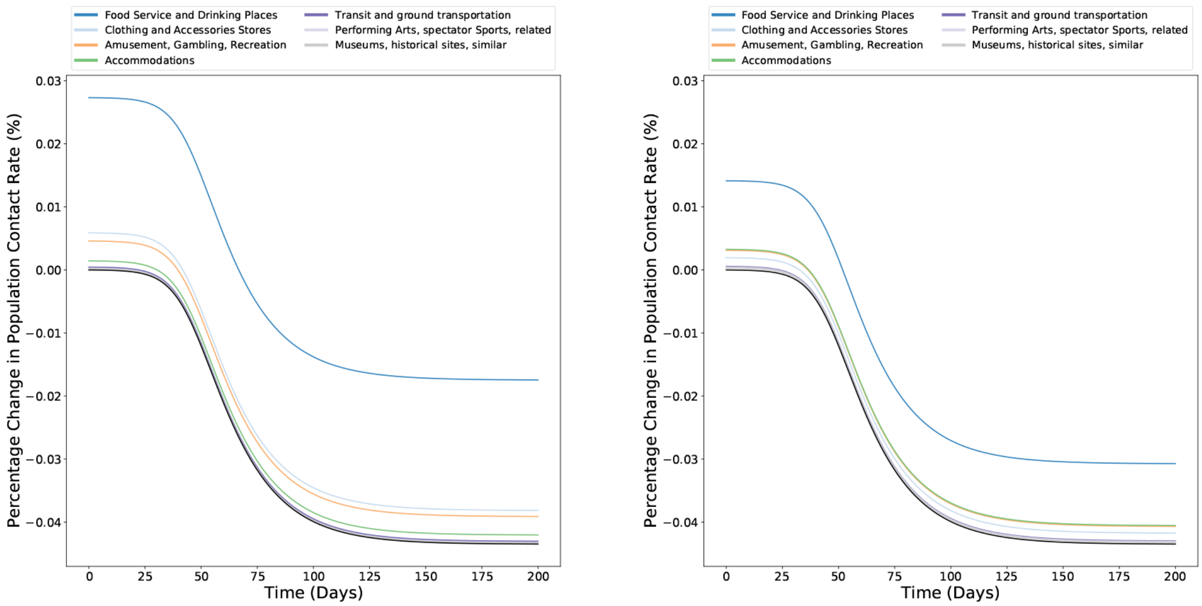
Comparing the results in figures 6 and 7 reveals important insights. We summarize these results in terms of total additional infections at the peak in table 3. Our results indicate the fiscal stimulus approach results in fewer infections than reopening in several key industries. First, we find that by adding back lost jobs in the Food Service and Drinking Places industry under the lockdown, industrial composition leads to fewer infections over time. This implies that for each worker added back to the economy, these workers infect fewer people than if added directly to the food service and drinking places industry. The same is true for clothing and accessories stores, and amusement, gambling and recreation; however, this is not always the case. For other industries, adding the same amount of workers via fiscal stimulus would result in a higher number of infections. The main reason for this is these industries present lower risk to the population than the average industry under lockdown. As we illustrated before, transit and ground transportation; museums, historical sites, and similar; performing arts, spectator sports, and related; and accommodations employ very few people and have a relatively low contact index, compared to other industries under lockdown, such as food service and drinking places, and clothing and clothing accessories stores. Consequently, these industries also have fewer potential contacts who can spread the infection. Thus, adding workers to industries with lower potential contacts can result in fewer infections than increasing employment in proportion to lockdown composition.

Table 3: Peak Infections under Alternative Scenarios

Industry	Peak infections		Difference
	Reopening	Fiscal stimulus	Reopening less fiscal stimulus
Clothing and accessories stores (448)	37,646	12,384	25,261
Transit and ground transportation (485)	2,926	3,547	-621
Performing arts, spectator sports, related (711)	2,599	2,829	-230
Museums, historical sites, similar (712)	1,216	1,923	-707
Amusement, gambling, and recreation (713)	29,430	19,868	9,562
Accommodations (721)	9,218	20,903	-11,685
Food service and drinking places (722)	175,218	90,502	84,716

Source: Author's calculations. All estimates are derived from the calibrated multi-group SIR model.

Figure 8: Population Contact Rate under Different Scenarios

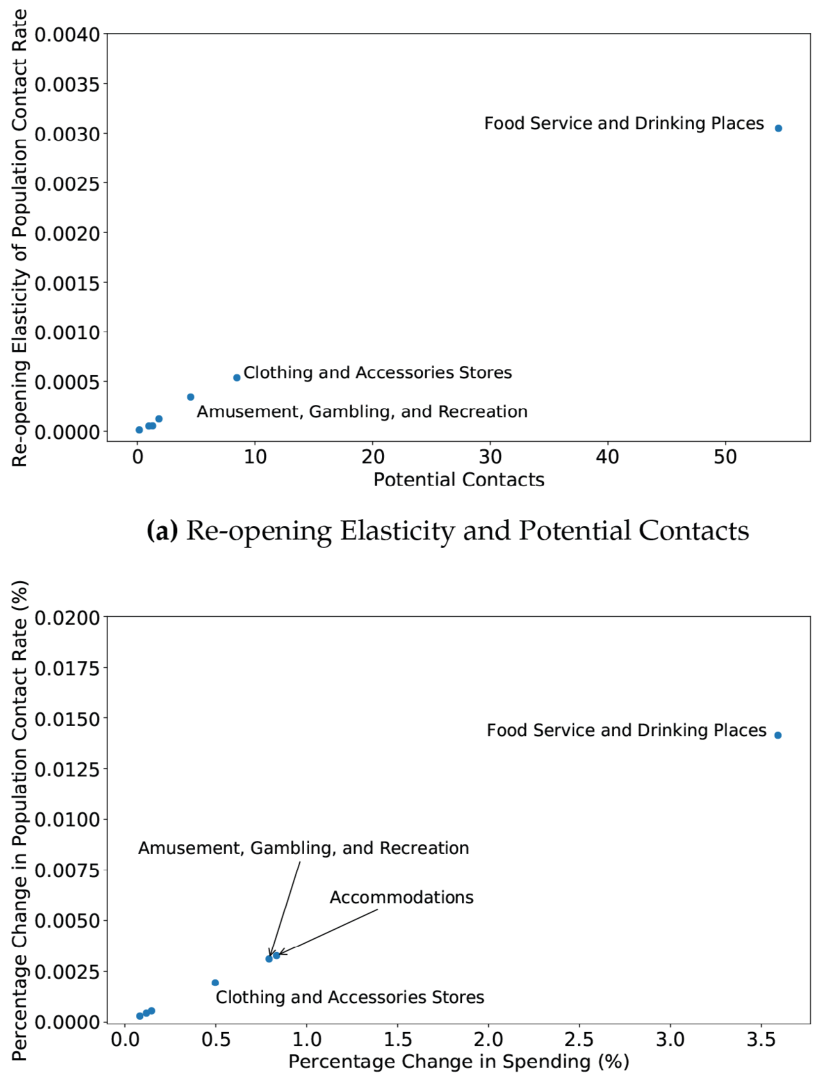


(a) Re-opening **(b)** Fiscal Stimulus

Source: Author's calculations. All values are derived from simulation the calibrated multi-group SIR model.

Variation in potential contacts changes the risk profile of the economy over time because they affect the population contact rate differently under our two scenarios. In figure 8, we illustrate how reopening and fiscal stimulus affect the population contact rate. When we add workers to the economy, initially we see an increase in the contact rate and it eventually decreases and becomes negative as the virus moves through the population at a faster pace, reducing susceptible populations and placing them in the recovered population. Panel (8a) shows how reopenings affect the population contact rate under different opening scenarios. In our simulations, reopening food service and drinking places leads to the largest increase in the population contact rate, followed by clothing and accessories stores, and amusement, gambling, and recreation. Comparing the outcomes in (8a) with those in (8b) illustrate how regaining employment losses with either reopening or fiscal stimulus affects the population contact rate.

Figure 9: Relation between population contact rate and economic scenarios



(a) Re-opening Elasticity and Potential Contacts

(b) Fiscal Stimulus and the Change in Population Contact Rate

Source: Author's calculations. All values are derived from simulation the calibrated multi-group SIR model.

We break down the driving forces behind the differences presented in figure 8 by using our theoretical prediction from section 2. We show the core theoretical relationships in figure 9, where we have labeled select industries. We show the reopening scenario in panel 9a. On the y-axis, we present the reopening elasticity of the population contact rate, which gives the percentage change in the population contact rate relative to the percentage change in revenues in reopened industries. We choose this normalization to highlight how potential contacts dictate changes in the population contact rate under reopening. Aligned with the theoretical predictions in section 2, the figure shows a positive correlation between the contact rate elasticity and the industry's potential contacts. For the same percentage change in gross output, reopening an industry with higher potential contacts will lead to a larger shift in the population contact rate. This occurs because workers are either being added to a larger pool of at-risk employees or to an industry with a higher contact rate. Adding workers to industries with more potential contacts raises the risk to the overall population by increasing the population contact rate by a larger magnitude.

In panel 9b, we present the results from the fiscal stimulus scenario. In contrast to panel 9a, we present the percentage change in the population contact rate on the y-axis and the percentage change in spending on the x-axis. The percentage change in spending reflects the size of the fiscal stimulus package necessary to recover lost employment in our model. The panel shows the size of the fiscal stimulus package correlates strongly with the percentage change in the population contact rate. The positive correlation aligns with the predictions from our theoretical model, where the composition of economic activity is fixed. In this case, the magnitude of reemployment, captured by the size of the stimulus package, is the source of variation in the population contact rate.

These two panels illustrate our theoretical predictions from section 2. For reopening, variation in potential contacts (including the percentage change in gross output), will dictate how much the population contact rate increases. However, for the same percentage change in gross output, the only factor influencing the population contact rate is the potential contacts of the industry when we reopen certain industries. For fiscal stimulus, the population contact rate is only affected by the size of the fiscal stimulus package, which proxies the number of employees added back to the economy, since the composition of hiring across industries remains unchanged.

5. Limitations

In this section, we summarize the key assumptions underlying our theoretical model and simulation. Our objective for this section is to convey the key assumptions of our analysis and relate them to our findings in order to bound the interpretation of our results. In section 3, we introduce an extension of the canonical susceptible-infected-recovered (SIR) model, which accounts for heterogeneity in contact rates within occupations and the composition of output across industries. For analytical tractability, we make some simplifying assumptions in the model framework. First, we make a simplifying assumption that the transmission coefficients for group j are equivalent across each group. This assumption simplifies the presentation of the main theoretical results, but it is done without loss of generality. Furthermore, this assumption is in accord with our calibration strategy, where data on inter-group transmission coefficients are unavailable.

Second, we assume certain parameters of the model are not affected by the economic scenarios we analyze. That is, our theoretical results do not account for how variations in economic activity, either through stimulus or reopening, affect the underlying parameters governing industry contact rates or hours spent at work. This assumption is not only for analytical convenience. Instead, we choose to not take a stand on how contact rates adjust following changes in the economic environment since we are analyzing stylized scenarios. Our theoretical framework, however, can be used to assess how variations in these parameters might impact COVID-19 dynamics alongside concomitant changes in the economic environment.

Section 4 introduces the calibration strategy used for simulation. There are a few important caveats to consider. First, industry-contact rates are computed using the most recent data from the ONET Work Context database. However, the industry-specific contact rates are static in the simulation and, therefore, do not adjust in our stylized economic scenarios. The static nature of these parameters implies our model does not capture the full impacts of the economic scenarios under investigation, and the total effect on infections would necessarily require data on how contact rates adjust within these different economic environments. Nevertheless, the model still provides insight on how COVID-19 dynamics are conditioned by the current economic environment.

Second, our approach for calibrating the multi-group SIR model is somewhat rigid. We calibrated the model using the best available data at the time the paper was written. However, new data is available daily and one is faced with a plethora of options for calibrating initial conditions. Because of this, we calibrate the model using a single set of initial conditions, including a single choice for the reproduction rate. This allows us to focus on the underlying mechanical details of the multi-group SIR model. With this approach, we find our simulation results accord with our theoretical predictions. When the composition of the economy adjusts toward high contact industries, the population-level contact rate rises more than a shift in economy activity toward low contact industries. Moreover, we find more infections occur when activity jumpstarts in industries with high contact rates and high employment.

6. Conclusions

In this paper, we introduce a multi-group SIR model that accounts for heterogeneity in physical contact across industries and industrial composition. We use the model to illustrate a new application of economic statistics to the COVID-19 pandemic. On the theoretical side, we show how a disaggregated multi-group SIR model can be reduced to a population SIR model and link the population-level contact rate with key economic parameters used to maintain and restore economic activity. We show fiscal stimulus influences the population-level contact rates by increasing the number of workers who must be physically present at work. In contrast, we find reopening scenarios both increases the number of physically present workers but also adjusts the distribution of economic activity toward higher contact industries.

On the numerical side, we calibrate the parameters of the multi-group SIR model using a combination of novel data sources and economic statistics. First, we construct a physical contact index for each industry that reflects variation in contact and telework capacity across occupations in the industry. We highlight that certain locked down industries, such as food service and drinking places, are usually high contact industries with low capacity to perform operations remotely. Second, we use detailed industry data from BEA to simulate economic conditions after lockdown orders were enacted. Our simulations predict a precipitous drop in the U.S. GDP in the first and second quarters of 2020. The drop in GDP is accompanied by substantial employment losses, amounting to more than 20 million workers across a host of industries.

Using our calibrated model, we simulate the epidemiological responses to different economic scenarios during the lockdown period. In this paper, we focus on fiscal stimulus and reopening scenarios. We find fiscal stimulus scenarios result in fewer infections than the reopening scenarios with high-contact, low telework capacity, and high employment industries. We find reopening these industries leads to a larger increase in the population-level contact rate than an equivalent stimulus scenario, since allocating workers to reopened industries leads to a new industrial mix of activity in the economy.

Our results should be interpreted with caution because our analysis does not account for several important features that might affect virus dynamics. First, we do not consider what happens when teleworkers also return to work. Instead, we assume teleworkers are allowed to remain at home for the foreseeable future. We illustrate that the contact index within most industries increases as a result of removing teleworkers from the pool of at-risk employees. Adding teleworkers to the mix of at-risk employees may increase infections, but the net effect is unclear. Second, we do not consider the implications for the at-home group when certain industries are allowed to reopen. For example, large event venues are likely to be a major transmission pathway for the virus, but our analysis does not account for this possibility. Third, we do not account for the supply chain impacts from reopening certain industries. Reopening food service and drinking places would likely have an impact on employment in the agriculture sector, but these employment impacts are not accounted for in our analysis. Finally, our analysis does not consider additional investments and/or precautions taken by businesses to minimize contact between customers at their locations.

With these caveats, the main qualitative conclusions of the analysis support extending the use of economic statistics into novel domains to inform relevant stakeholders during the COVID-19 pandemic. Future work can build upon the data and methods presented in this paper and can further extend this research. For example, we do not consider any feedback effects between virus dynamics and economic activity. As more workers are infected with the virus, they are also not likely to be able to perform work-related functions. Because of this, the virus may also lead to supply-side effects that further influence virus dynamics. Our research sets the stage for using economic statistics as a comprehensive input to numerical models that estimate the impacts of the COVID-19 pandemic.

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Appendix A. Model Setup for Economic Simulation

The model starts with the typical market clearing conditions for goods and services. In equilibrium, each industry *i*'s (gross) output, X_i in value terms is distributed as an intermediate input to other industries, denoted as z_{ij}, or as a final good to the household, denoted as f_i. The equilibrium market clearing conditions of the model are summarized by the following system of equations for all N industries

$$X_i = \sum_{j=1}^{N} z_{ij} + f_i$$

The standard approach to demand-driven input-output models is to rewrite the goods market clearing condition using the technical coefficients, $a_{ij} = \bar{z}_{ij} / \bar{X}_j$, where we use the bar to symbolize that the technical coefficients are calibrated to base period data and held constant in the analysis. To calibrate the technical coefficients, we use the unpublished, highly detailed 2018 Use Table from the Bureau of Economic Analysis (BEA). We aggregate the table to the 3-digit North American Industry Classification System (NAICS) level to match the industry detail of our contact index.

Rewriting the market clearing conditions using the technical coefficients yields

$$X_i = \sum_{j=1}^{N} a_{ij} X_j + f_i$$

This is the standard setup for demand-driven input-output analysis. In this setup, there are N equations for gross output by industry, and each industry's gross output depends on gross output in each downstream industry and own final uses.

Solving the system of equations for equilibrium output yields the familiar equation (in matrix notation)

$$\mathrm{X} = [\mathrm{I} - \mathrm{A}]^{-1} \mathrm{f} \tag{3}$$

where the quantity $\mathrm{L} = [\mathrm{I} - \mathrm{A}]^{-1}$ is the Leontief inverse. The Leontief inverse accounts for all direct and indirect interactions between industries in the economy's input-output network. Equation (3) captures how variations in an industry's final demand transmit upstream through the economy's supply chain to affect output in other industries.

A.1 Impact of COVID-19 on Final Demand Spending

We adjust the standard model in the following way. Let $\bar{a}_i$ be the share of industry i in the household's consumption bundle. We assume these share parameters are stationary in the model and that they compute the final demand share $\bar{a}_i$ using the 2018 Use Table. Using these shares, we rewrite equilibrium industry output as

$$X_i = \bar{C} \sum_{j=1}^{N} l_{ij}\bar{a}_j \tag{4}$$

where l_{ij} corresponds to the $(i, j) - th$ element of the Leontief inverse, and $\bar{C}$ is base period GDP. We calibrate $\bar{C}$ using 2019 Q4 GDP estimates from BEA. Adjusting the model in this way allows us to apply final demand shocks to industry that emerge in the model as change in the composition of spending while holding income in the economy constant. Based on this setup, *estimated* final demand spending in a shocked industry is given by the following

$$\hat{f}_i = \hat{\theta}_i \bar{a}_i \bar{C}$$

where we use hats to denote estimated values. The parameter $\hat{\theta}_i$ corresponds to the estimated impact of lockdowns on final demand. To calibrate this parameter, we use the estimates from Dunn, Hood, and Driessen (2020). Incorporating this relationship into the model for gross output yields an estimate for gross output at the industry-level

$$\hat{X}_i = \bar{C} \sum_{j=1}^{N} l_{ij}\hat{\theta}_j\bar{a}_j$$

It should be noted that overall income in the economy $\bar{C}$ has not adjusted from the containment policy shock in this estimate. This is to reflect the reality that income did not adjust immediately following the introduction of social containment. Instead, lockdowns immediately affected the composition of consumer spending, and the change in spending patterns instantiated a subsequent drop in income. Using the estimate for industry gross output, we estimate employment at the industry-level using the following

$$\hat{L}_i = \frac{\bar{\gamma}_i}{\bar{w}_i}\hat{X}_i$$

where γ_i is the labor cost share of industry i. We calibrate this parameter from the BEA 2018 Use Table. In the analysis, we hold wages and salaries fixed. Industry wages and salaries, $\bar{w}_i$, are computed using the 2019 Occupational Employment Statistics. Hence, by rearranging this expression, we estimate GDP as follows

$$\hat{C} = \sum_{i=1}^{N} \bar{w}_i \hat{L}_i$$

Appendix B. Contact by Occupation

Table B1: Top 25 Occupations for Face-to-Face Discussions

Title	Data value
Internists, general	5.0
Recreational therapists	5.0
Hospitalists	5.0
Neurologists	5.0
Locomotive firers	5.0
Ophthalmologists	5.0
Special education teachers, preschool	5.0
Nuclear power reactor operators	5.0
Urologists	5.0
Healthcare social workers	5.0
Physician assistants	5.0
Biomass power plant managers	5.0
Dentists, general	5.0
Physical therapists	5.0
Quality control systems managers	5.0
Patternmakers, metal and plastic	5.0
Nurse anesthetists	5.0
Orthotists and prosthetists	5.0
Electromechanical engineering technologists	5.0
Nuclear equipment operation technicians	5.0
Genetic counselors	5.0
Counter and rental clerks	5.0
Counseling psychologists	5.0
Prosthodontists	5.0
Chemical plant and system operators	4.99

Table B2: Last 25 Occupations in Face-to-Face Discussions

Title	Data value
Tire builders	2.55
Poets, lyricists and creative writers	2.56
Cutters and trimmers, hand	2.89
Animal breeders	3.14
Telephone operators	3.18
Fine artists, including painters, sculptors...	3.23
Models	3.40
Hunters and trappers	3.45
Refuse and recyclable material collectors	3.47
Conveyor operators and tenders	3.48
Dishwashers	3.48
Shoe machine operators and tenders	3.48
Rock splitters, quarry	3.48
Sewing machine operators	3.52
Insurance claims clerks	3.53
Textile knitting and weaving machine setters...	3.54
Craft artists	3.56
Musicians, instrumental	3.57
Meter readers, tilities	3.58
Cooks, private household	3.58
Potters, manufacturing	3.60
Music composers and arrangers	3.64
Transportation attendants, except flight attendants...	3.65
Coin, vending, and amusement machine servicers...	3.66
Outdoor power equipment and other small engine...	3.67

Table B3: Top 25 Occupations for Contact with Others

Title	Data value
Orthoptists	5.00
Physical therapist assistants	5.00
Spa managers	5.00
Ophthalmologists	5.00
Chiropractors	5.00
Dental hygienists	5.00
Respiratory therapy technicians	4.99
Speech-language pathology assistants	4.99
Telemarketers	4.99
Reservation and transportation ticket agents...	4.99
Medical secretaries	4.99
Education administrators, preschool and childc...	4.98
Receptionists and information clerks	4.98
Obstetricians and gynecologists	4.98
Physical therapists	4.98
Allergists and immunologists	4.98
Dermatologists	4.98
Special education teachers, preschool	4.98
Airline pilots, copilots, and flight engineers	4.97
Gaming cage workers	4.97
Loan interviewers and clerks	4.97
Radiation therapists	4.97
First-line supervisors of personal service...	4.97
Radio operators	4.96
Credit checkers	4.96

Table B4: Last 25 Occupations in Contact with Others

Title	Data value
Mathematical technicians	2.00
Farmworkers and laborers, crop	2.58
Poets, lyricists and creative writers	2.74
Painters, transportation equipment	2.83
Fallers	2.84
Meat, poultry, and fish cutters and trimmers	2.85
Pourers and casters, metal	2.89
Geological sample test technicians	2.90
Potters, manufacturing	2.97
Music composers and arrangers	2.98
Shoe machine operators and tenders	2.99
Sewers, hand	3.04
Fine artists, including painters, sculptors...	3.04
Craft artists	3.12
Welding, soldering, and brazing machine setter...	3.13
Textile knitting and weaving machine setters...	3.13
Lathe and turning machine tool setters, operat...	3.17
Rock splitters, quarry	3.18
Landscaping and groundskeeping workers	3.19
Separating, filtering, clarifying, precipitati...	3.21
Laundry and dry-cleaning workers	3.23
Hunters and trappers	3.23
Photonics technicians	3.24
Refuse and recyclable material collectors	3.24
Glass blowers, molders, benders, and finishers	3.27

Table B5: Top 25 Occupations for Physical Proximity to Others

Title	Data value
Sports medicine physicians	5.00
Choreographers	5.00
Physical therapists	4.99
Dental hygienists	4.99
Urologists	4.97
Dentists, general	4.97
Oral and maxillofacial surgeons	4.96
Surgical technologists	4.95
Skincare specialists	4.95
Dental assistants	4.94
Respiratory therapy technicians	4.93
Radiation therapists	4.92
Dermatologists	4.92
Dancers	4.91
Prosthodontists	4.91
Surgeons	4.89
Nurse midwives	4.89
Obstetricians and gynecologists	4.88
Cardiovascular technologists and technicians	4.88
Surgical assistants	4.87
Emergency medical technicians and paramedics	4.86
Orderlies	4.86
Radiologic technicians	4.84
Chiropractors	4.84
Flight attendants	4.82

Table B6: Last 25 Occupations in Physical Proximity to Others

Title	Data value
Fallers	1.29
Fine artists, including painters, sculptors...	1.37
Logging equipment operators	1.55
Poets, lyricists and creative writers	1.56
Hunters and trappers	1.68
Wellhead pumpers	1.74
Cooks, private household	1.83
Farmworkers and laborers, crop	1.94
Dredge operators	2.09
Bridge and lock tenders	2.10
Pesticide handlers, sprayers, and applicators...	2.14
Environmental economists	2.14
Petroleum engineers	2.20
Refuse and recyclable material collectors	2.22
Political scientists	2.23
Astronomers	2.25
Music composers and arrangers	2.26
Forestry and conservation science teachers...	2.26
First-line supervisors of logging workers	2.28
Compensation and benefits managers	2.29
Pathologists	2.29
Compensation, benefits, and job analysis...	2.29
Cleaning, washing, and metal pickling equipment...	2.29
Computer and information research scientists	2.30
Animal breeders	2.30

Table B7: Top 25 Occupations for Physical Contact Index

Title	Contact index
Physical therapists	1.87
Sports medicine physicians	1.85
Dental hygienists	1.83
Obstetricians and gynecologists	1.83
Chiropractors	1.82
Respiratory therapy technicians	1.80
Oral and maxillofacial surgeons	1.79
Dermatologists	1.79
Dentists, general	1.78
Urologists	1.77
Physical therapist aides	1.76
Nurse midwives	1.76
Ophthalmologists	1.76
Radiation therapists	1.74
Acute care nurses	1.73
Occupational therapists	1.73
Cardiovascular technologists and technicians	1.72
Prosthodontists	1.72
Orthodontists	1.72
Athletic trainers	1.72
Surgeons	1.72
Orthoptists	1.71
Respiratory therapists	1.70
Dental assistants	1.70
Anesthesiologists	1.69

Table B8: Last 25 Occupations in Physical Contact Index

Title	Contact index
Poets, lyricists and creative writers	0.16
Fine artists, including painters, sculptors...	0.20
Fallers	0.21
Hunters and trappers	0.28
Farmworkers and laborers, crop	0.34
Cooks, private household	0.35
Cutters and trimmers, hand	0.35
Animal breeders	0.36
Music composers and arrangers	0.37
Refuse and recyclable material collectors	0.38
Craft artists	0.40
Logging equipment operators	0.43
Conveyor operators and tenders	0.45
Sewers, hand	0.45
Rock splitters, quarry	0.45
Potters, manufacturing	0.45
Tire builders	0.46
Textile knitting and weaving machine setters...	0.46
Wellhead pumpers	0.47
Environmental economists	0.47
Pesticide handlers, sprayers, and applicators...	0.49
Meter readers, utilities	0.50
Geological sample test technicians	0.50
Astronomers	0.51
Pressers, textile, garment, and related materials	0.51