Working from a Distance: Productivity Dispersion and Labor Reallocation*

Jingping Gu Dongya Koh Andrew Liu
University of Arkansas

September 30, 2020

Abstract

Following the shocks of the COVID-19 pandemic, the economy may be significantly changed relative to the pre-pandemic world. One critical shift induced by the COVID-19 pandemic is a need for physical distance (at least 6 feet apart) between workers and customers. In this study, we examine the impacts of social distancing in the workplace on employment and productivity across industries. Using our constructed measure of adaptability to social distancing, we empirically find that industries that are more adaptive to social distancing had less decline in employment and productivity during the pandemic. Using this empirical evidence, our model predicts that employment and productivity dispersion would induce labor reallocation across sectors, while imperfect labor mobility may result in a long road to economic recovery.

Keywords: COVID-19, social distancing, productivity, labor reallocation, economic recovery

JEL Codes: E24, E27, J24, J64

*We would like to thank Raul Santaeulalia-Llopis, Javier Birchenall and Kieran Walsh for valuable comments. We have also benefited from the seminar and conference participants at the Sam M. Walton College of Business at the University of Arkansas, ESCoE Conference on Economic Measurement 2020, and UCSB Macro Group.

1 Introduction

Despite a gradual reopening of the economy after a few weeks of business closures, our economy after the recent COVID-19 shock may look completely different from the pre-pandemic world. One critical change due to COVID-19 is a need for physical distance (at least 6 feet apart) between workers. Although recent technologies have aided our transition to a new, socially distanced working environment, the efficiency of this new working style may vary across types of businesses. Some industries can more easily implement social distancing[1] (such as consulting, IT related works, data analysis, and education services). On the other hand, some industries suffer a productivity drop after adopting social distancing among workers (such as construction sites, food processing sites, hospitals, dental clinics, and some elements of the media industry).

This study sheds light on the effects of social distancing on productivity dispersion as it differs across industries and the consequential effects on labor reallocation. We construct measures of how easily an industry can adopt social distancing in their workplace using the American Community Survey (ACS). We find that there is a positive relationship between the adaptability to social distancing and employment and productivity changes; that is, more adaptive industries had less decline in employment and productivity because of the pandemic. Correspondingly, we find that less adaptive industries experienced a larger dispersion in employment and productivity responses due to COVID-19.

Publicly available data allows us to empirically document only the immediate responses of the U.S. economy to the pandemic shock.[2,3] However, the post-pandemic projection of economic recovery is of more interest to the public. Therefore, we calibrate a multisector model of labor reallocation and predict the persistent effects of a pandemic shock on labor reallocation across industries and on economic recovery. The calibrated model predicts that productivity dispersion across industries induces labor reallocation from less adaptive industries to more adaptive industries, while imperfect labor mobility across sectors slows down progress toward economic recovery.

Our prediction of economic recovery from the pandemic shock may depend on the productivity adjustment of less adaptive industries. If less adaptive industries were to implement

[1]We define social distancing in a broader sense, not only keeping 6-feet distance among workers and customers but also working remotely or encompassing all the preventive actions taken by firms and industries after COVID-19.

[2]At the time of this writing, the latest public data available was July 2020 monthly data from the Bureau of Labor Statistics (BLS) or the second quarter data of 2020 in the Bureau of Economic Analysis (BEA).

[3]The pandemic shock can be interpreted as not just an exogenous outbreak of COVID-19 but also nationwide lockdown and social distancing policies implemented by the U.S. government.

a technological shift resulting in increasing productivity back to the pre-pandemic level, then the aggregate economy may recovery more rapidly. On the contrary, if less adaptive industries fail to adjust to a new environment and therefore persistently suffer inefficient productivity, the economic recovery may be slow. These scenarios are two extremes, and the most likely outcome will fall somewhere in between.

2 Related Literature

In contrast with recent slowdowns associated with an economy under lockdown, COVID-19-related research has been vigorously produced at a rapid pace. One topic of interest in the literature measures the effect of social distancing on working conditions during the COVID-19, as exemplified in a study by Dingel and Neiman (2020) that combines Occupational Information Network (O*NET) surveys and some information from the U.S. Bureau of Labor Statistics (BLS) to investigate which occupations may be conducted remotely in different industries, cities, and countries. This paper examines various countries and finds that lower-income economies have a lower percentage of jobs that can be performed at home. Brynjolfsson et al. (2020) conducted their own online survey for the U.S. to explore who continued commuting to the office or working from home during COVID-19. Mongey et al. (2020) further examined two different measures: the likelihood that jobs could be performed from home and the personal proximity in the workplace.

Another avenue of research that are closely related to our work examines the effect of the pandemic shock on particular markets. For example, Cowan (2020) uses the Current Population Survey (CPS) data from February to April 2020 to examine the short-run effects of COVID-19 on the U.S. labor market and a particular population's working status. One of the most closely related research is Gregory et al. (2020) where they calibrate a search-theoretic model using Longitudinal Employer and Household Dynamics (LEHD) and the Survey of Income and Program Participation (SIPP) from 1997-2014 to forecast the U.S. labor market recovery after the pandemic. Despite the similarity of their prediction on a slow recovery to our results, the source of their recovery in the model is mainly driven by worker productivity and a corresponding job finding rate. In contrast, our focus herein is on the decline of the firm's productivity and, therefore, labor demand due to the required social distancing among workers.

3 Empirical Evidence

In this section, we empirically examine how social distancing in the workplace affects productivity across various industries. The dispersion of productivity across industries critically hinges on the differences in adaptability to social distancing, or how easily industries can implement social distancing in their workplace. First, we construct measures of adaptability to social distancing. Second, we empirically show that those industries that are more flexible to practicing social distancing or work from home tend to have less decline in employment and productivity, according to the data from the second quarter of 2020, which captures the immediate response to unexpected COVID-19 shocks.

3.1 Measuring the Adaptability to Social Distancing

Some industries (e.g., IT, consulting, banking, etc.) easily leveraged recent technological advances, such as high home internet bandwidth and secure video call features, to implement social distancing in the workplace and enable workers to work from home with only minor disruptions to workflow. Conversely, some industries (e.g., construction, nail salons, dental clinics, etc.) simply require a physical presence, and have been unable to adopt social distancing in the workplace. Such sectoral differences in adaptability to social distancing may create productivity dispersion across industries after the outbreak of COVID-19. To examine the link between the adaptability to social distancing and productivity across industries, we construct a measure of how easily industry can adopt social distancing in their workplace.

For this, we use the American Community Survey (ACS) of the U.S. Census. ACS is an annual survey that asks about occupations, education, commuting to work, and housing of U.S. citizens to better understand people's life patterns and determine the distribution of federal and state funds. We use the latest 2018 ACS 1-year Public Use Microdata Sample, with data collected from Jan. 1. 2018 to Dec. 31, 2018, for a variety of geographic areas with more than 65,000 respondents. For the measure of adaptability to social distancing, we use one survey question in ACS that asks about "transportation to work." The survey provides information on how many workers in the 2-6 digit 2017 NAICS code commute to their workplace by "car/truck/van" "taxi/cab," "motorcycle," "bicycle," "walked," "worked at home," etc. Using this 2018 survey information, we compute the share of workers who worked at home in an industry i. This pre-pandemic survey informs us of the degree of the physical presence of workers at a workplace in each industry at baseline. This information can be used as a proxy for how adaptive an industry would be to transitioning to remote work after COVID-19.

Table 1 shows the share of workers who worked at home by a 2-digit industry. An industry with the highest adaptability to social distancing is "professional, scientific, and technical services" with 15% of workers in that industry worked at home prior to the pandemic (excluding missing responses). They are mostly professional workers (e.g., lawyers, engineers, computer programmers, researchers, and consultants) who provide specialized services to their customers online. In contrast, the lowest fraction working from home was workers in "accommodation and food services" with only 1.7% of workers working at home. Overall, tertiary and quaternary sectors (e.g., services, information, finance, and insurance) tend to have a higher share of workers working from home. In contrast, primary and secondary sectors (e.g., mining, manufacturing, and utilities) tend to have a lower share of workers working at home.

Notable exceptions are agriculture and education services. The share of workers working from home is the second highest in the agriculture sector, with 13% of agricultural workers working from home, mainly because farming is usually performed on a farm adjacent to the farmer's house. In contrast, education services only have 3.3% of workers providing services from home because the provision of online courses was limited in public education systems prior to COVID-19. However, this has now clearly changed among the educational sector. This result suggests that the share of workers working at home prior to the pandemic may not be a perfect measure for the "potential" adaptability to social distancing. Nonetheless, the measure is informative of the adaptability to working from home as there might be less adjustment cost for industries where larger fractions of workers are already remotely working. Also, one advantage of using this measure as a proxy for the adaptability to social distancing is that the measure is classified into 274 detailed levels of sub-industries.[4]

It is important to note that our measure of adaptability to social distancing is interpreted as the fraction of jobs in industry i that can be performed from home. When an industry consists of job types that are less restricted by the physical location, the industry may exhibit higher share of workers working at home and greater adaptability to social distancing. Indeed, in the paper by Dingel and Neiman (2020), feasibility to work from home was constructed from occupational characteristics and classified by industry level according to the occupational composition within each industry. In our Online Appendix, we show that our measure is positively correlated with the measure from this prior paper. Further, we confirm that our empirical findings are robust with their measure.

[4] Dingel and Neiman (2020)'s measure of feasibility of working at home that we discuss in our Online Appendix is aggregated into the classification of 108 sub-industries, while another measure constructed from the American Time Use Survery is classified into 19 industries.

3.2 Employment and Productivity Responses to COVID-19

Immediately after the COVID-19 outbreak, the unemployment rate in the U.S. increased from 3.5% (February) to 4.4% (March) before skyrocketing to 14.7% in April. The temporary suspension of economic activities and nationwide lockdown were the leading cause of this unemployment surge.

Employment Responses. We use monthly employment data by industry, available from BLS, and relate it to our measure of adaptability to see if the drop in employment in each industry is affected by the adaptability to social distancing. Panel (a) of Figure 1 demonstrates the employment decline between the fourth quarter of 2019 and the second quarter of 2020, as it relates to the share of workers who worked at home prior to the pandemic by industry.[5] As expected, industries with a higher pre-pandemic share of workers working at home experienced a less-severe drop in employment. For example, "professional, scientific, and technical services," which had the highest share of workers who worked at home, experienced a minor 2.3% drop in employment due to the pandemic. In contrast, "accommodations and food services," which had only 1.7% of workers who worked from home prior to the pandemic, experienced a 23.8% employment decrease following the COVID-19 shock. A log-linear line weighted by the employment share of industry in the figure shows a positive relationship between adaptability to social distancing and employment responses to COVID-19.

From the figure, it is apparent that the dispersion of employment growth also varied by the adaptability to social distancing. For instance, for industries in the range of 0 to 5% share of workers who worked at home prior to the pandemic, the employment growth ranged from a 33.9% decline ("Amusements, gambling, and recreation industries," a sub-industry in " Arts, entertainment, and recreation") to 0.6% decline ("Utilities" industry). However, for industries in the range of 10 to 20% of workers who worked at home, the employment growth ranged from 4.6% employment decline ("Real estate and rental and leasing" industry) to 1.6% employment decline ("Computer systems design and related services," a sub-industry in the "Professional, scientific, and technical services" industry). In sum, less adaptive industries experienced a greater decline in employment, on average, as well as a larger dispersion of employment responses to the pandemic.

Productivity Responses. Firms and institutions have had to focus attention on ensuring the health and well-being of their employees and customers during the COVID-19 pandemic.

[5] The employment growth in monthly frequency from January of 2020 to April, May, June, or July of 2020 shows the similar positive relationship.

To prevent the spread of infection, social distancing and face mask regulations have been implemented in most of the areas in the U.S. Additionally, for example, some grocery stores have replaced cashier checkout counters with all self-checkouts. Most restaurants offer curb-side pickup and have reduced the number of tables for dining. These adjustments either under-utilize installed capital or replace current employees with new capital, both of which result in decreased number of workers, as shown in panel (a) of Figure 1. This implies that the productivity or efficiency of production should also be affected by the pandemic shock in a manner that varies by the adaptability to a new business style.

We compute the productivity changes after COVID-19 by industry using the data before the pandemic (the fourth quarter of 2019) and right after the pandemic outbreak (the second quarter of 2020). Our objective is to examine if adaptability to social distancing is associated with changes in productivity. We assume that the production function of real value-added of an industry i in period t takes a Cobb-Douglas form:[6]

$$Y_{i,t} = A_{i,t} K_{i,t}^{\alpha_i} L_{i,t}^{1-\alpha_i} \tag{1}$$

where K indicates real net stock of capital, L indicates the number of employees, α indicates the capital income share, and A indicates total-factor productivity (TFP). By taking logs on this production function, we compute the industry-specific TFP, $A_{i,t}$, as the residual.

For this calculation, we use "Real Gross Value Added" from GDP-by-Industry accounts in BEA for $Y_{i,t}$, Employment by industry from BLS current employment statistics for $L_{i,t}$,[7] "Real Net Stock of Capital" from BEA Fixed Asset Table 3.2ESI for $K_{i,t}$, and "Components of Value Added by Industry" from GDP-by-Industry accounts in BEA to construct capital income share in industry i, α_i.

Of these public data series, the BLS monthly employment data is available for the most recent month (e.g., July 2020 at the time of this writing). BEA real value-added is quarterly data, and the latest available are from the second quarter of 2020. The rest of the BEA data are all annual data, available up to 2019. Due to the unavailability of some data, we have to impose an assumption that the capital income share across industries (α_i) and the real net

[6] To check the sensitivity of the functional form, we compare our accounting calculation of industry-specific productivity with a nonparametric estimation of technology efficiency in our Online Appendix. One advantage of nonparametric analysis is that the model allows more flexible functional form, and therefore, the Cobb-Douglass production function is no longer needed to estimate industry productivity.

[7] We confirm that the empirical results remain unchanged with the annual "Hours Worked by Full-Time and Part-Time Employees by Industry" from BEA NIPA Table 6.9D. In this study, we prefer to use the BLS monthly employment data over total hours of work from BEA for a direct comparison to the employment responses shown in panel (a) of Figure 1.

stock of capital across industries ($K_{i,t}$) remain stable before and after the shock. This assumption is not critical for the dynamics of productivity because the real net stock of capital and capital income share are far less responsive to an aggregate shock than employment and output in the short run.[8] Thus, we compute the recent productivity at a quarterly frequency before and after the pandemic outbreak by taking 2019 data for the capital income share and the real stock of capital.

Taking a log difference of two data points, 2019Q4 and 2020Q2, we can identify the immediate response of industry productivity to the pandemic shock.[9] Panel (b) of Figure 1 shows the productivity growth from 2019Q4 to 2020Q2 for 2-4 digit industries, sorted by the adaptability measure that we constructed in the previous section. Though weaker than the employment, the productivity responses also exhibit a positive relationship with adaptability to social distancing. Three sub-industries with relatively large employment share that experience a large drop in productivity are "Air transportation" (72.3% drop), "amusement, gambling, and recreation" (16.5% drop), "Transportation and warehousing" (11.3% drop). These industries are unable to provide their service remotely.

Analogous to the employment growth, the productivity responses to the pandemic shock are also dispersed across industries. Even though the dispersion of productivity over the share of workers working at home is not as evident as the dispersion of employment, for the industries with the share of workers working at home ranging from 0 to 5%, the productivity growth ranges from a 72.3% decline ("Air transportation") to 0.9% growth ("Broadcasting and telecommunications"). On the other hand, for the industries with the larger share of workers working at home, ranging from 10 to 20%, the productivity growth ranges from a 2.4% decline ("Professional, scientific, and technical services") to 1.6% decline ("Computer systems design and related services").

Statistical Significance. Using the employment and productivity data constructed above, we test the statistical significance of the effect of social distancing implemented in each industry after the pandemic spread of COVID-19 on the employment and productivity decline. We regress the employment growth and productivity growth before (2019Q4) and right after

[8]Assuming that real net stock of capital and capital income share remain unchanged is more valid with a two-quarter change in 2019Q4-2020Q2 than a one-year change in 2019Q2-2020Q2. Even though the aggregate capital income share is known to be procyclical to aggregate shocks, the cyclicality of sectoral capital share is not well known.

[9]The assumption on the 2019 net stock of capital and capital income share implies that our calculated productivity growth is almost identical to the growth rate of labor productivity. With more data being available soon, we will be able to observe the one-year change of TFP $A_{i,t}$ in each industry with time-varying capital and capital income share.

COVID-19 (2020Q2) on the log of the adaptability measure. The estimating equation is

$$\Delta \log R_i = \alpha + \beta \; \log(WFH_i) + \varepsilon_i \tag{2}$$

where $\Delta \log R_i$ takes either a log difference of employment or productivity of an industry i from pre-pandemic t to post-pandemic $t+1$; and $\log(WFH_i)$ indicates a pre-pandemic measure of adaptability to social distancing of industry i in log. Our conjecture that industries with higher flexibility to social distancing tend to experience less decline in employment and productivity from COVID-19 predicts $\beta > 0$.

The results from this estimation are shown in Table 2. We take different measures of adaptability to social distancing for the estimation.[10] For our measures of adaptability to social distancing and Dingel and Neiman (2020)'s measure, the positive effect on the employment growth and productivity growth are statistically significant. More specifically, as the ACS share of workers working at home increases by 1%, the employment decline mitigates by 7.6%. Similarly, when Dingel and Neiman (2020)'s measure of feasibility to work from home increases by 1%, the employment decline is reduced by 6.4%.

The productivity responses also exhibit a statistically significant, positive relationship with adaptability to social distancing. For instance, when ACS measure increases by 1%, the productivity grows by 3.9%. Similarly, productivity growth rises by 3.2% when Dingel and Neiman (2020)'s measure increases by 1%. These results support the notion that industries that were less able to adapt to remote work and social distancing suffered greater impacts on employment and productivity in the wake of the pandemic.[11]

4 A Multisector Model of Labor Reallocation

Empirical evidence shows the immediate responses of employment and productivity to COVID-19 shock. However, the projection of economic recovery after the shock is a more timely question to examine than the immediate responses. Unfortunately, data at the time of this writing cannot answer this question. Instead, we exploit a model to predict the short-run and medium-run responses of the economy after the shock. In this section, we use a multi-sector search model by Chodorow-Reich and Wieland (2020) to examine labor reallocation across industries, given the sectoral productivity responses to an aggregate pandemic shock.

[10] The construction of alternative measures is described in detail in our Online Appendix.

[11] We also checked the responses of real wage to the pandemic shock in our Online Appendix. We find that the average wage responses to the shock are negligible, while the wage growth becomes more dispersed after the shock.

4.1 Model

Time is discrete. Let there be $\mathcal{I}$ industries in the economy. Each sector i produces a homogeneous good $y_{i,t}$. Labor is the only factor input in the good production. Equivalently, one can assume that capital is fixed and cannot be reallocated across sectors:

$$y_{i,t} = A_i(\nu_t)e_{i,t}. \tag{3}$$

$A_i(\nu_t)$ is a sector-specific productivity responding to an aggregate social-distancing restriction ν_t. From our empirical evidence, we assume that the sector-specific productivity depends only on the economy-wide social distancing restriction. The functional form could differ by sectors as the social distancing restriction affects each sector differently. While we do not restrict the functional form, it is sensible to assume that at least after some level $\overline{\nu}$, A_i is weakly decreasing in ν_t. We also assume that the firms can only hire from a sector-specific labor market. In the directed search literature, the assumption means that each sector is also a sub-market (Moen, 1997; Delacroix and Shi, 2006; Shi, 2009).

Workers and firms match according to a sector-specific matching function $Mv_{i,t}^{1-\eta}x_{i,t}^{\eta}$ where M indicates a matching efficiency, η indicates a bargaining power of workers, $v_{i,t}$ is the measure of vacancy, and $x_{i,t}$ is the measure of job searchers. Because there are multiple sectors, and we assume that not everyone in a sector can be reallocated within a period, the measure of job searchers is not proportional to the measure of unemployed workers. Let $\theta_{i,t}$ denote the market tightness in sector i which is defined as $v_{i,t}/x_{i,t}$.

Employed workers are separated exogenously at a rate δ. After the realization of the separation shock, the workers receive a reallocation shock at an exogenous rate λ every period. In line with recent literature on semi-directed search (see e.g., Pilossoph (2014); Kennan and Walker (2011); Chodorow-Reich and Wieland (2020)), the workers who receive the reallocation shock draws a vector of idiosyncratic taste shock $\{\varepsilon_{i,t}\}_{i=1}^{\mathcal{I}}$ across sectors. The taste shock is additive to the worker's value function, which allows workers flowing from low-productivity sectors to high-productivity sectors and vice versa. The taste shock $\varepsilon_{i,t}$ follows a Type I extreme-value distribution with parameters $(-\rho\gamma, \rho)$. With the distributional assumption of the taste shock, the conditional choice probabilities have a multinominal logit form (McFadden, 1973, 1981).

Firm in sector i receives the real marginal revenue product $p_{i,t}$ by selling the intermediate good and pays the real wage cost $w_{i,t}$ to workers. Firms post vacancy $v_{i,t}$ at a cost κ. Assuming a free entry condition, the expected value of vacancy becomes zero. Bellman equations for filled job and vacancy posting are illustrated as

$$J_{i,t} = p_{i,t} - w_{i,t} + \beta(1-\delta)J_{i,t+1} \tag{4}$$

$$\kappa = q(\theta_{i,t})J_{i,t} \tag{5}$$

where β is a discount factor, and δ is an exogenous job separation rate.

Employed workers receive the sector-specific wage $w_{i,t}$. When receiving the separation shock, the worker enters the unemployment pool immediately and search for jobs. When receiving the reallocation shock, the worker chooses to switch to the sector that has the highest expected continuation value, augmented by the taste shocks. Unemployed workers receive unemployment benefit z which is common across sectors. Denote the value function of the employed worker in sector i at period t by $W_{i,t}$. The value function of unemployed worker searching a job in sector i at period t is denoted as $U_{i,t}$. Then, the worker's recursive Bellmen equations are specified as

$$\begin{aligned} W_{i,t} = w_{i,t} + \beta\{[(1-\delta) + \delta(1-\lambda)f(\theta_{i,t+1})]W_{i,t+1} + \delta(1-\lambda)(1-f(\theta_{i,t+1}))U_{i,t+1}\} \\ + \beta\delta\lambda\left[\mathbb{E}_\varepsilon \max_j\{(1-f(\theta_{j,t+1}))U_{j,t+1} + f(\theta_{j,t+1})W_{j,t+1} + \varepsilon_{j,t}\}\right] \end{aligned} \tag{6}$$

$$\begin{aligned} U_{i,t} = z + \beta\{(1-\delta\lambda)[f(\theta_{i,t+1}))W_{i,t+1} + (1-f(\theta_{i,t+1}))U_{i,t+1}]\} \\ + \beta\delta\lambda\left[\mathbb{E}_\varepsilon \max_j\{(1-f(\theta_{j,t+1}))U_{j,t+1} + f(\theta_{j,t+1})W_{j,t+1} + \varepsilon_{j,t}\}\right] \end{aligned} \tag{7}$$

where $\mathbb{E}_\varepsilon$ takes an expectation over the idiosyncratic taste shocks $\{\varepsilon_{i,t}\}_{i=1}^{\mathcal{I}}$. The discrete choices $\mathbb{E}_\varepsilon \max_j\{(1-f(\theta_{j,t+1}))U_{j,t+1} + f(\theta_{j,t+1})W_{j,t+1} + \varepsilon_{j,t}\}$ with Type I extreme value taste shocks ε_j can be written as $\rho \log \sum_j \exp\{(1-f(\theta_i'))U_j' + f(\theta_i')W_j'\}/\rho$.

We characterize three laws of motion for employment $e_{i,t}$, unemployment $u_{i,t}$, and job searcher $x_{i,t}$ over time:

$$x_{i,t+1} = \delta(1-\lambda)e_{i,t} + (1-\delta\lambda)u_{i,t} + \pi_i\delta\lambda\sum_j^I(e_{j,t} + u_{j,t}) \tag{8}$$

$$e_{i,t+1} = (1-\delta)e_{i,t} + f(\theta_{i,t+1})x_{i,t+1} \tag{9}$$

$$u_{i,t+1} = (1-f(\theta_{i,t+1}))x_{i,t+1} \tag{10}$$

where π_i denotes the transition probability to sector i conditional on receiving a reallocation shock. The laws of motion show that both the reallocation shock and the social-distancing shock are important for the measure of job searchers and hence the employment and the unemployment. In particular, the social-distancing shock affects $x_{i,t}$ by changing the probability that the workers switch to sector i.

Finally, we assume that the market wage is determined by the Nash bargaining scheme between firms and workers, w_i^*, but is constrained by the downward nominal wage rigidity:

$$w_i = \max\{w_i^*, (1-\chi)w_{i,t-1}/\Pi_{i,t}\}. \tag{11}$$

Denote Π_i the gross producer price index, and the nominal wage cannot fall by χ percent.

4.2 Calibration

To examine the effect of productivity dispersion across sectors and differential speed of sectoral adjustment to pandemic shocks on the aggregate recovery, we calibrate the model with two sectors, $\mathcal{I} = 2$. As demonstrated in the empirical evidence of productivity dispersion associated with adaptability to social distancing, we assume two sectors in which, without loss of generality, sector 1 is less adaptive to social distancing and thereby receiving a larger productivity drop followed by a slow adjustment of their production efficiency. In contrast, sector 2 is more adaptive to social distancing and hence recovering the productivity fairly quickly after having a mild productivity decline. The rest of the model parameters are taken from Chodorow-Reich and Wieland (2020). Cost of vacancy (κ) and matching efficiency (M) are calibrated to match job finding rate $f(\theta) = 0.5$ and job filling rate $q(\theta) = 0.75$. The calibrated model parameters are shown in our Online Appendix.

4.3 Quantitative Analysis of Pandemic Shocks

We simulate the model with two sectors in which the productivity of two sectors declines and recovers at a different rate specified as $A_{i,t+1} = (1-\alpha_i)\bar{A} + \alpha_i A_{i,t} + \sigma_i \nu_t$ given an aggregate pandemic shock (ν_t) at period 0. Two sectors' productivity in the steady state is normalized to $\bar{A} = 1$ for simplicity. Receiving a one unit of negative aggregate shock at period 0, we assume that sector 1 exhibits $\sigma_1 = 0.1$ of productivity decline and $\alpha_1 = 0.9$ of persistence of the shock over time, whereas sector 2 exhibits $\sigma_2 = 0.05$ and $\alpha_2 = 0.1$. The simulated paths of productivity are shown in panel (a) of Figure 2. We numerically solve and demonstrate the impulse responses of aggregate unemployment as well as sectoral variables to one-time pandemic shock at t=0.

Panel (b) of Figure 2 shows the impulse response of market tightness for each sector. The steady-state market tightness for both sectors is 0.666. After the aggregate shock at time 0, the market tightness for sector 1 drops by 91% while it only drops by 14.8% for sector 2. The larger decline for sector 1 attributes to a constant decrease in job search after the shock (panel (c)) and to job vacancy plummeting without a subsequent rise afterward (panel (d)). On the other hand, a tiny and temporary drop in productivity in sector 2 results in a small drop of vacancy followed by a rapid increase, which is also offset by a rapid increase in the job search.

Unemployment of workers previously working in sector 1 starts falling after a one-time 2% jump at time 1 (panel (e)). The fall is due to a large drop in market tightness, which results in a decline in job-finding rate in sector 1, leading to a mild decline in job search. Intuitively, workers in sector 1 are shifting to more adaptive and relatively more productive sector 2. Conversely, the inflow of workers from sector 1 overcrowds sector 2 and, as a consequence, the unemployment in sector 2 rises rapidly. An aggregated effect of pandemic shock with the reallocation of workers is shown in panel (f) of Figure 2. The unemployment rate rises by almost 2.42 percentage points in two periods after the shock. The economy recovers to 0.05 percentage point in 6 periods as more workers in sector 1 transition to sector 2. This simple scenario—without considering the second and third waves of COVID-19— informs us that even though some industries' productivity suffers from adopting social distancing, workers are reallocated to more adaptive and productive industries. Therefore, the economy can exhibit an optimistic quick recovery from the pandemic shock. We now experiment with some changes in critical factors of the economy to explore changes in the projection of economic recovery.[12]

Adaptability to Pandemic Shocks Because of its work characteristics, some industries are more flexible to implement social distancing in their working environment than other industries. Our empirical evidence in the previous section demonstrates that the industry-level work-from-home index as a proxy for the adaptability to social distancing nonlinearly relates to the employment and productivity growth after the pandemic shock. This evidence implies that some industries are more vulnerable to pandemic shock, suffering productivity drops after adopting social distancing in the working environment. Therefore, we experiment with how the adaptability of each sector to pandemic shocks may affect economic recovery.

We consider a case where the persistence of the productivity in sector 1 changes while holding the persistence of sector 2 constant. The results are shown in panel (a) of Figure 3.

[12] Note that in our model simulation, we do not take into account the second and third waves of pandemic shocks. Therefore, our simulation results exhibit an optimistic view of the recovery from the one-time pandemic shock.

When sector 1 adjusts their productivity fairly quickly with $\alpha_1 = 0.5$, the labor reallocation across sectors almost disappears. Although the immediate response of productivity of sector 1 to the aggregate shock is still twice as large as that of sector 2, the productivity of sector 1 returns to the original level in 7 periods. A quick recovery of the productivity in sector one reduces the decline of market tightness to almost half of the benchmark case. This reduction is mainly driven by the reduction of worker reallocation from sector 1 to sector 2. Given the perfect foresight of this productivity projection, an outflow of workers in sector 1 to sector 2 disappears, and therefore, the rise of unemployment in both sectors remain minor as the productivity recovers in a short period of time. Likewise, the rise of aggregate unemployment due to the shock is only a third of the benchmark case and returns to the original level in 6 periods. If the productivity of sector 1 takes an even shorter period of adjustment ($\alpha_1 = 0.1$), the fall of market tightness becomes even smaller. The unemployment in sector 1 becomes almost negligible immediately after the shock. The impact on aggregate unemployment is also negligible that the peak is only 25% of the peak in the benchmark case.[13]

Reallocation of Labor across Sectors We can explore the effect of the reallocation friction (λ) on sectoral variables and aggregate unemployment along the transition path. Panel (b) of Figure 3 shows the impact of labor reallocation on the labor market under the productivity dispersion across sectors. The steady-state market tightness for both sectors does not change by the reallocation friction. However, when there is no labor reallocation across sectors ($\lambda = 0$), each sector is on its own. Therefore, the job search rate in sector 1 mildly rises, while there is no rise in job search in sector 2. This implies that the rise of the unemployment rate in sector 2 is negligible, while the unemployment becomes larger in sector 1. In aggregate, the unemployment rate is 0.54 percentage point higher than the benchmark case.

In contrast, as we assume perfect labor mobility across sectors ($\lambda = 1$), more job search occurs in sector 2 with a faster decline of search in sector 1. As more reallocation to sector 2 takes place along the transition path, more job search concentrating in a productive sector drives a higher unemployment rate in sector 2, whereas the unemployment rate in a less productive sector falls even more than the benchmark case. In aggregate, the unemployment rate is 0.25 percentage points lower than the benchmark case. This finding informs us that the higher reallocation friction across sectors obstructs an economic recovery from the pandemic shock.

[13]We only show impulse responses of sectoral and aggregate unemployment to save space of this paper. All the simulated impulse responses are shown in our Online Appendix.

Downward Nominal Wage Rigidity Finally, we experiment the effect of downward nominal wage rigidity (DNWR). We explore how the economic recovery might change by the presence of DNWR.Given the aggregate adverse shock in the economy, the productivity of both sectors falls. Under the flexible wage, the market wage falls accordingly as the productivity declines to optimize the allocation of labor. However, the downward adjustment of market wage is constrained by the DNWR imposed on both markets. As a result, the wage rigidity engenders more fluctuations in employment and labor mobility across sectors.

More fluctuations under DNWR is shown in panel (c) of Figure 3. The market tightness plummets at period 0 in sector 1 under a strong rigidity ($\chi = 0.0035$), while the drop is mild under the weaker rigidity ($\chi = 0.1$). This is because market wage falls under the flexible wage system to respond to the productivity decline, and hence a sudden drop of vacancy after the shock in sector 1 vanishes. However, under DNWR the wage fails to reflect the productivity decline which induces a large drop of vacancy in sector 1. Had the wage be flexibly adjusted to the productivity decline, more workers in sector 1 would remain in the sector with a lower wage, which would have resulted in less unemployment in sector 1. In aggregate, the unemployment under the flexible wage would have been almost 6% of unemployment in the benchmark case. In other words, the wage rigidity may disrupt an adjustment to the pandemic shock and, as a consequence, excessively slows down the economic recovery.

5 Conclusion

Recent evidence confirms that the shock of COVID-19 induced changes in employment and productivity that varied across industries. Some industries with higher adaptability to social distancing were less vulnerable to the changes necessitated by the pandemic. While the dispersion of employment and productivity may be expected to lead to the reallocation of labor across industries, imperfect labor mobility obstructs that reallocation. Our model prediction of labor reallocation due to the dispersion of productivity shows that the economic disruption may depend on the degree of labor mobility and the speed of adjustment to social distancing, especially in less adaptive industries. The extent of recovery from the pandemic may also depend on these factors.

References

Brynjolfsson, E., Horton, J. J., Ozimek, A., Rock, D., Sharma, G., and TuYe, H.-Y. (2020). COVID-19 and Remote Work: An Early Look at US Data. NBER Workign Paper Series 27344.

Chodorow-Reich, G. and Wieland, J. (2020). Secular labor reallocation and business cycles. Journal of Political Economy, 128(6):2245–2287.

Cowan, B. (2020). Short-run Effects of COVID-19 on U.S. Worker Transitions. NBER Workign Paper Series 27315.

Delacroix, A. and Shi, S. (2006). Directed search on the job and the wage ladder. International Economic Review, 47:327–399.

Dingel, J. and Neiman, B. (2020). How Many Jobs Can be Done at Home? Journal of Public Economics, 189.

Gregory, V., Menzio, G., and Wiczer, D. (2020). Pandemic Recession: L- or V-Shaped? Quarterly Review.

Kennan, J. and Walker, J. R. (2011). The effect of expected income on individual migration decisions. Econometrica, 79(1):211–251.

McFadden, D. (1973). Conditional logit analysis of qualitative choice behavior. In Zarembka, P., editor, Frontiers of Econometrics. Academic Press, New York.

McFadden, D. (1981). Econometric models of probabilistic choice. In Manski, C. and McFadden, D., editors, Structural Analysis of Discrete Data with Econometric Applications, pages 198–272. MIT Press, Cambridge.

Moen, E. R. (1997). Competitive search equilibrium. The Journal of Political Economy, 105(2):385–411.

Mongey, S., Pilossoph, L., and Weinberg, A. (2020). Which Workers Bear the Burden of Social Distancing Policies? NBER Workign Paper Series 27085.

Pilossoph, L. (2014). Sectoral shocks and move unemployment. Unpublished Manuscript.

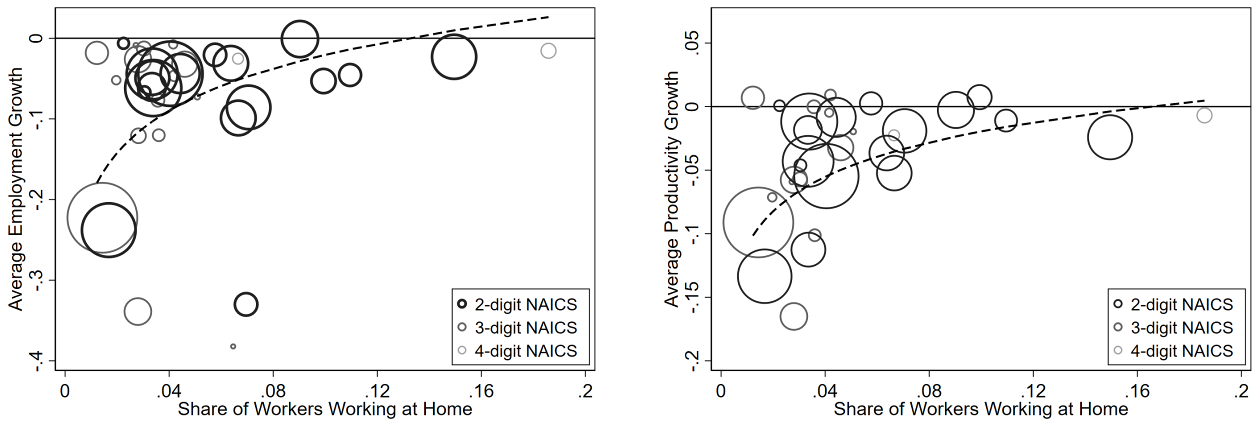
Shi, S. (2009). Directed search for equilibrium with wage-tenure contracts. Econometrica, 77:561–584.

Table 1: The Share of Workers Worked at Home by 2-digit Industry

Industry (2-digit)	Share
Professional, Scientific, and Technical Services	.150
Agriculture, Forestry, Fishing, and Hunting	.130
Real Estate and Rental and Leasing	.110
Information	.099
Finance and Insurance	.090
Administrative and support and waste management services	.071
Arts, Entertainment, and Recreation	.070
Other Services, Except Public Administration	.067
Wholesale Trade	.064
Management Of Companies And Enterprises	.058
Construction	.044
Health Care and Social Assistance	.040
Retail Trade	.034
Transportation and Warehousing	.034
Manufacturing	.033
Educational Services	.033
Mining, Quarrying, and Oil and Gas Extraction	.031
Public Administration	.025
Utilities	.022
Accommodation and Food Services	.017

Figure 1: Employment/Productivity Decline by the Adaptability to Social Distancing

(a) Employment Responses (b) Productivity Responses



Notes: Panel (a) and (b) shows the relationship between the share of workers working at home in 2018 and the average employment growth and productivity growth from 2019Q4 to 2020Q2, respectively. The size of each circle indicates the share of employment in each (sub-)industry. The dashed line indicates a log-linear line of the scatterplots. Note that sub-industries with more than 20% drop in productivity are not shown in panel (b).

Table 2: Effects of Social Distancing on Employment and Productivity Growth

	Employment Growth			Productivity Growth		
	(1)	(2)	(3)	(1)	(2)	(3)
log(ACS WFH)	0.0756***			0.0391**		
	(0.0180)			(0.0158)		
log(ATUS WFH)		0.0667**			0.0349	
		(0.0257)			(0.0200)	
log(DN WFH)			0.0635***			0.0323***
			(0.0101)			(0.0101)
Constant	0.153**	0.0552	0.000489	0.0704	0.0195	-0.0132
	(0.0582)	(0.0528)	(0.0157)	(0.0510)	(0.0411)	(0.0156)
Observation	35	17	64	35	17	64

Note: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. ACS WFH indicates our work-from-home (WFH) measure from American Community Survey. ATUS WFH and DN WFH are alternative measures from American Time Use Survey and Dingel and Neiman (2020), respectively, that we describe in our Online Appendix.

Figure 2: Impulse Responses of Labor Market to a Pandemic Shock

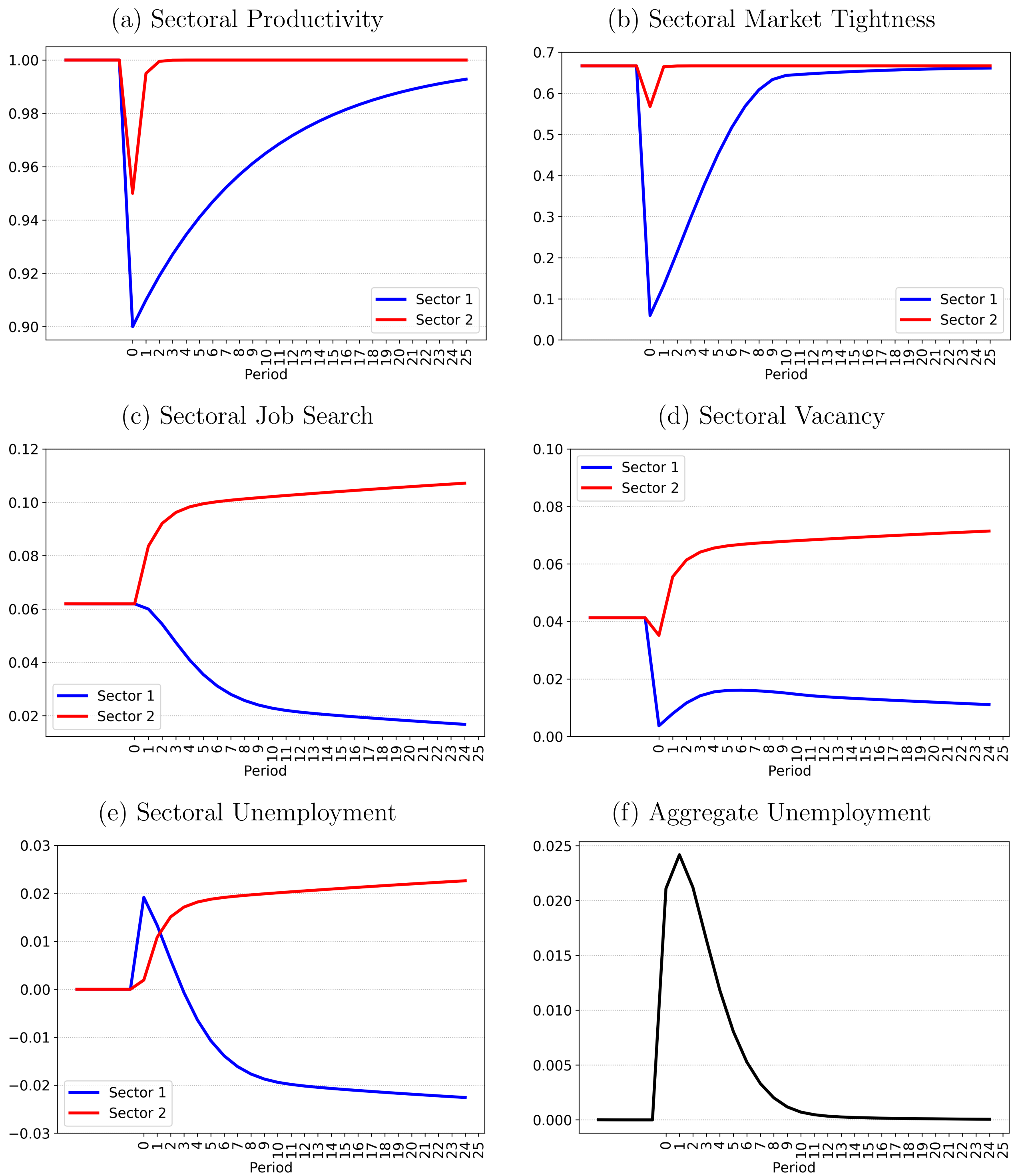
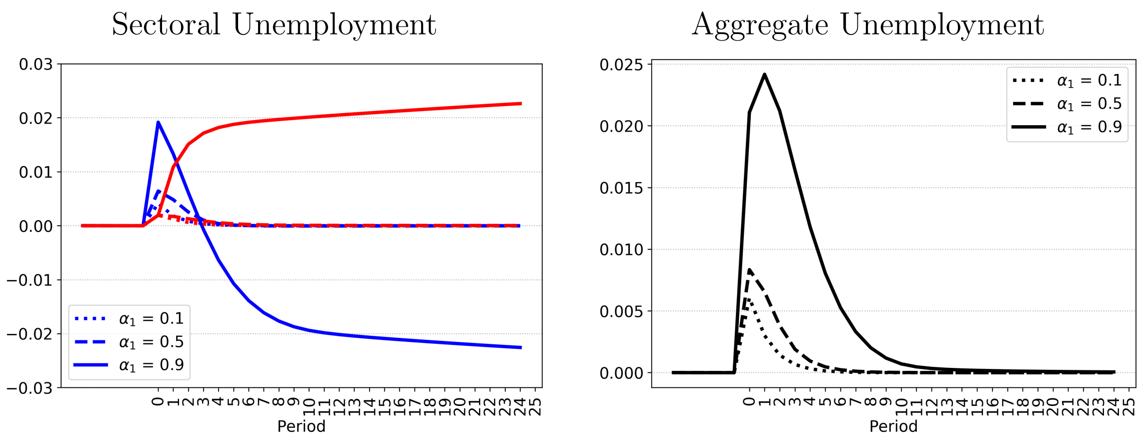
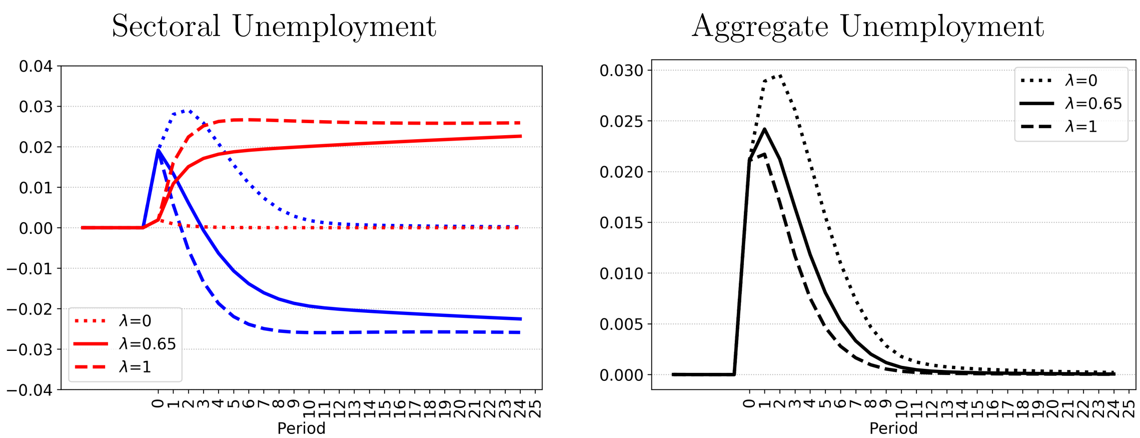


Figure 3: Counterfactual Impulse Responses of Labor Market

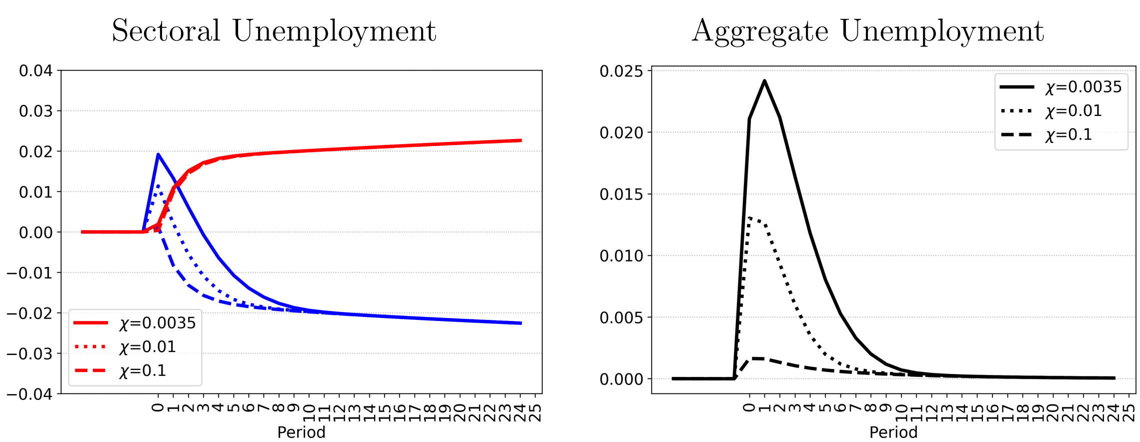
(a) Persistence of Shocks in Sector 1



(b) Reallocation of Labor



(c) Nominal Wage Rigidity



Notes: Panel (a) shows the impulse response of sectoral unemployment and aggregate unemployment with the various persistence levels of productivity in sector 1 after the pandemic shock at period 0. Panel (b) shows the impulse response of sectoral unemployment and aggregate unemployment with the various levels of reallocation friction (λ). Panel (c) shows the impulse response of sectoral unemployment and aggregate unemployment with the various nominal wage rigidity (χ).