Skill Loss during Unemployment and the Scarring Effects of the COVID-19 Pandemic[*]

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Abstract

We integrate the SIR epidemiology model into a search and matching framework with skill loss during unemployment. As infections spread, fewer jobs are created, skills deteriorate and TFP declines. The equilibrium is not efficient due to infection and skill composition externalities. Job creation increases infections due to increased interactions among workers. However, lower job creation decreases TFP due to skill loss. A three-month lockdown causes a 0.56% decline in TFP, i.e. nearly 50% of productivity losses in past recessions. We study the efficient allocation given the trade-off between both externalities and show that quantitatively the skill composition externality is sizable.

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"Moreover, the longer the downturn lasts, the greater the potential for longer-term damage from permanent job loss and business closures. Long periods of unemployment can erode workers' skills and hurt their future job prospects." – Jerome H. Powell before the US Senate on June 16, 2020

1 Introduction

As of January 2021, it has been ten months since the World Health Organization declared COVID-19 a pandemic. The cost in terms of lives lost has been substantial, as nearly 2 million people have died. The economic costs have also been extraordinary. In the period between March-April 2020, nearly twenty million jobs were lost in the US and the unemployment rate reached levels not observed since the Great Depression. As the number of infections continues to grow and workers remain displaced from their jobs, there is potential for the pandemic to cause long-lasting economic costs, effectively scarring the economy for years to come. As seen in the above statement from Federal Reserve Chairman Jerome H. Powell, policymakers were concerned about this possibility within a few months of the onset of the pandemic, as it is well documented that workers lose human capital during long periods of unemployment. When workers lose skills during unemployment, longer and more frequent unemployment spells worsen the skill composition of the work force, which in turn decreases TFP.

We integrate the canonical SIR framework (Kermack and McKendrick, 1927) with a search and matching model in which workers lose human capital while unemployed to study the effects of the COVID-19 pandemic on unemployment, TFP and health outcomes. Our integration of the SIR framework with a search and matching model follows Kapička and Rupert (2020) by assuming that employed workers are more likely to become infected than unemployed workers. When employed workers become infected, they are not productive and face the possibility of dying. As a pandemic evolves, firms create fewer jobs due to the increased risk that their employee becomes infected and the match no longer produces output. We extend this framework by assuming workers are exposed to skill loss shocks when they are either unemployed or are employed and not working due to being infected.

Through the addition of skill loss shocks, our model allows us to study the dynamics of the skill composition of workers and TFP following the outbreak of a pandemic. As infections rise and fewer jobs are created, the probability of finding a job decreases, and the unemployment rate increases. As workers face longer unemployment durations, they are more likely to lose skills and the skill composition of the labor force deteriorates over the course of the pandemic. Following the worsening of the skill composition, average labor productivity, and hence TFP decrease.

The decentralized equilibrium is not efficient due to two externalities. First, as emphasized by Kapička and Rupert (2020), there is an infection externality whereby workers and firms do not internalize that by forming a match, they increase the spread of the virus. Second, firms do not internalize that by creating a vacancy, they reduce unemployment durations of workers and reduce their exposure to skill loss, thereby improving the skill composition of the unemployed (Laureys, 2020). Thus, the addition of skill loss during unemployment introduces novel normative implications when considering optimal job creation throughout a pandemic. A planner who reduces job creation in an effort to limit infections and deaths also increases unemployment durations, worsens the skill composition of the unemployed, and reduces TFP.

We calibrate the model to quantify the effect of the COVID-19 pandemic on unemployment, the skill composition of the unemployed and TFP through skill loss during unemployment. Additionally, we use the calibrated model to study the optimal job creation when a social planner faces a tradeoff between reducing infections and deaths against decreases in productivity through skill loss during unemployment. In our baseline exercise without any policy intervention, the unemployment rate increases by nearly 3.8 percentage points, the skill composition of unemployed workers worsens, and TFP decreases by 0.44%. Given that the typical decline in TFP during recessions is 1.13%, the baseline results generate a decline in TFP close to 39% of the typical productivity losses seen in past recessions. Moreover, the effects of the pandemic on TFP are long lasting: TFP reaches its lowest point only 55 weeks after the onset of the pandemic and remains far below its pre-pandemic value even 100 weeks after the pandemic started.

To study the effect of a lockdown, we increase the job separation probability for three months at the onset of the pandemic. By increasing job separations, fewer firms create jobs, fewer workers are employed and infections drop. We find that this policy saves nearly 65,000 lives. However, there is a substantial cost in terms of increased unemployment. The increased separations combined with reduced job creation increases the unemployment rate by nearly 7.6 percentage points in a period of three months. There is also a long-term economic cost associated with the lockdown; as the increased unemployment rate causes more workers to be exposed to human capital depreciation, further worsening the skill composition of job seekers. We find that, sixty-two weeks after the pandemic began, TFP reaches its lowest point and has decreased by 0.56%. Conducting the same calculation as with our baseline results, a 0.56% decline in TFP due to loss of skill during unemployment corresponds to nearly 50% of the productivity losses in previous recessions, indicating that the COVID-19 pandemic and the recession it has caused will leave significant scarring effects on the economy for years to come.

Finally, we compute the constrained-efficient allocation. In the absence of a pandemic, the economy is inefficient due to the skill composition externality even when the Hosios-Mortensen-Pissarides condition holds, a result similar to Laureys (2020). Job creation is higher in the pre-pandemic steady-state, as the planner creates more jobs to improve the skill composition of the unemployed. After the onset of the pandemic, job creation in the constrained-efficient allocation declines sharply to limit the spread of the virus. We find that the increase in unemployment relative to the pre-pandemic steady-state in the constrained-efficient allocation is higher than the baseline economy, but lower than the three-month lockdown, showing that the planner does limit job creation to reduce infections and deaths, but not to the extent caused by a three-month lockdown, as the planner also wants to limit the decline in TFP through loss of skill during unemployment.

Related literature. There is a burgeoning economic literature on the COVID-19 pandemic. Here, we briefly review the most related literature. Our paper is most closely related to Kapička and Rupert (2020) who integrate the SIR framework of Kermack and McKendrick (1927) into the Diamond-Mortensen-Pissarides (DMP) model of equilibrium unemployment (Pissarides (1985), Mortensen and Pissarides (1994)). They assume employed workers have more interactions than unemployed workers, and hence have a higher probability of becoming infected. The model is used to study the dynamics of wages and the unemployment rate throughout the pandemic and optimal quarantine policies. We employ a similar framework, but also add loss of skill during unemployment. Our framework allows us to study the effects of a pandemic and lockdowns on unemployment, the skill composition of the unemployed and TFP, and to characterize optimal job creation during a pandemic when the economy exhibits both infection and skill composition externalities. In contrast with their results, according to which the planner significantly lowers job creation to limit the infection externality, we find that quantitatively the planner's efficient allocation features significantly more job creation to counter the skill composition externality, which highlights the quantitative importance of the skill composition externality. In addition, skill loss improves the performance of the DMP model in response to shocks (Ortego-Marti, 2017a).

Other studies discussing the impact of COVID-19 on the labor market include Gregory et al. (2020), who develop a framework with both permanent and temporary layoffs to forecast labor market dynamics following a lockdown shock. Their framework does not model the pandemic and does not study loss of skill during unemployment. Petrosky-Nadeau and Valletta (2020) and Sahin et al. (2020) forecast unemployment dynamics following the initial spike in unemployment following the onset of the COVID-19 pandemic, while Coibion et al. (2020) document large flows into non-participation and that initial job losses were larger than implied by initial unemployment insurance claims.

Many other papers have introduced the SIR framework of Kermack and McKendrick (1927) into economic models and applied them to the COVID-19 pandemic. Atkeson (2020) provided an early introduction into SIR models and how they could be applied to the current pandemic while Fernández-Villaverde and Jones (2020) developed an SIRD model to forecast the COVID-19 pandemic under lockdowns and changes to social distancing behaviour. Eichenbaum et al. (2020) extended the SIR framework to study the relationship between economic decisions and epidemics and optimal containment policies. Garibaldi et al. (2020) extended the SIR framework to include search frictions and explicitly model interactions between agents. In addition, many papers have characterized optimal policy responses to the COVID-19 pandemic. Hall et al. (2020) develop a framework to study the optimal tradeoff between consumption and deaths while Alvarez et al. (2020) study optimal lockdown policies. Berger et al. (2020) develop a SEIR framework to study optimal quarantine and testing. Guerrieri et al. (2020) demonstrate how the initial supply shock associated with the COVID-19 pandemic can lead to a subsequent aggregate demand shock and optimal fiscal and monetary policy response. Both Bethune and Korinek (2020) and Farboodi et al. (2020) study in detail the externalities present in an economic environment with a pandemic and characterize optimal policy responses. While the above papers study optimal policy during a pandemic, none of them consider an environment with both a SIR epidemiological model and skill loss during unemployment. We contribute to this literature by characterizing the constrained-efficient allocation of a planner who faces a tradeoff between reducing infections/deaths and long-lasting declines to TFP through loss of skill during unemployment.

Finally, our paper is closely related to previous work on skill loss during unemployment. Two seminal papers in this literature are Pissarides (1992) and Ljungqvist and Sargent (1998). Pissarides (1992) shows that unemployment is more persistent when unemployed workers suffer skill decay during unemployment, whereas Ljungqvist and Sargent (1998) provide a rationale for the high unemployment in Europe relative to the US due to the generous UI benefits in Europe. Ortego-Marti (2017c, 2020) show how loss of skill during unemployment impacts TFP while Doppelt (2019) focuses on the classical debate over the long-run relationship between growth and unemployment. Laureys (2020) discusses the externalities caused by loss of skill during unemployment, an externality also present in our environment, and the implications for optimal policy. Our project is also related to Ortego-Marti (2016) who studies wage dispersion in the presence of skill loss, and to Heathcote et al. (2020) who study how loss of skill during unemployment can increase inequality in the long-run. However, none of these papers consider an epidemiological SIR model to study the effect of a pandemic. We contribute to this literature by developing a framework which can be used to model the effect of a pandemic on TFP through loss of skill during unemployment, and by providing quantitative results regarding the long-run effect of the COVID-19 pandemic on both unemployment and TFP in the US.

2 Environment

Time, agents, and preferences. Time is discrete and indexed by $t \in \mathbb{N}_0$. There are two types of agents: a large measure of firms and workers whose initial population is normalized to one. All agents are risk-neutral and have a discount factor $\beta \in (0, 1)$. Workers are categorized by their employment status (employed or unemployed), skill level (high or low skill), and health status (susceptible, infected, or recovered). In each period, a measure μ of workers enter the labor force as unemployed who are highly skilled and susceptible.

Health statuses. Workers can be susceptible to the infection but not yet infected (S), infected but not yet recovered or deceased (I), or recovered and immune from further infection (R). The probability that a susceptible person becomes infected depends on their employment status. Employed workers become infected with probability $\pi_t^{EI} = \pi^E I_t$, where I_t is the stock of infected workers at time t. Unemployed workers become infected with probability $\pi_t^{UI} = \pi^U I_t$. Following Kapička and Rupert (2020), we assume that employed workers have more interactions than the unemployed and hence have more opportunities to become infected, i.e. $\pi^E > \pi^U$. Infected workers recover with probability π_R and die from the infection with probability π_D.

Skills and technology. Workers are heterogenous in their skill due to skill loss during unemployment. For tractability purposes, there are two levels of skill indexed by $\chi \in \{L, H\}$: low (L) and high (H). Employed high skill workers produce y units of output per period, while low skill workers produce δy with $\delta \in (0, 1)$. We use the terminology of low and high skill to simplify the exposition, but this skill level should not be confused with other determinants of human capital such as educational attainment, occupation or experience. If a susceptible employed worker becomes infected, they remain employed and do not produce output. Skill loss occurs as follows. In each period, high skill workers who are either unemployed or employed and infected permanently become low skilled with probability σ. As we discuss later, the assumption that skill losses are permanent is well supported empirically. Unemployed workers receive utility b while unemployed, representing the value of leisure, home-production, and unemployment benefits.

The labor market. Workers search for jobs while firms search for applicants in a frictional labor market. Unemployed infected workers can not look for a job and remain unemployed until either they recover or die. Firms with a vacancy incur a vacancy posting cost $k > 0$ each period. The labor market is unsegmented, i.e. firms posting a vacancy can meet unemployed workers of either skill level. The number of meetings between firms and workers, M_t, is given by the aggregate meeting function $M_t = m(U_t, V_t)$, where U_t is the stock of unemployed workers who are not infected at the beginning of period t and V_t is the stock of vacancies. The meeting function exhibits constant returns to scale, and is increasing and concave in both of its arguments. Workers meet firms with probability $f(\theta_t) = m(U_t, V_t)/U_t$, where $\theta_t \equiv V_t/U_t$ is labor market tightness. The meeting probability $f(\theta)$ is strictly increasing in θ, with $\lim_{\theta\to 0} f(\theta) = 0$ and $\lim_{\theta\to\infty} f(\theta) = 1$. Firms meet workers with probability $q(\theta_t) = m(U_t, V_t)/V_t$, where $q(\theta)$ is strictly decreasing in θ, $\lim_{\theta\to 0} q(\theta) = 1$, and $\lim_{\theta\to\infty} q(\theta) = 0$. An unemployed worker's skill level and health status are observable upon meeting the firm. Filled jobs are destroyed with an exogenous probability s.

Timing. At the beginning of each period, firms post vacancies and hire workers. After hiring takes place, high skill workers who remain unemployed or employed and infected then experience skill loss shocks. Workers then experience infection, recovery, and death shocks. A fraction μ of the remaining workers then leave the labor force. Finally, all remaining filled jobs are hit with separation shocks.

3 Accounting

In this section, we characterize the flows of workers across employment statuses, skill levels, and health statuses. Let $N_t^{\chi S}$, $N_t^{\chi I}$, and $N_t^{\chi R}$ be the measure of unemployed workers at time t of skill level χ and respective health status. Further, let $E_t^{\chi S}$, $E_t^{\chi I}$, and $E_t^{\chi R}$ denote the respective measures of employed workers. The aggregate measure of unemployed and employed workers of each respective skill type is given by

$$N_t^\chi = N_t^{\chi S} + N_t^{\chi I} + N_t^{\chi R},\ E_t^\chi = E_t^{\chi S} + E_t^{\chi I} + E_t^{\chi R},$$

while the aggregate stocks of unemployed and employed workers across health statuses are given by

$$N_t^S = N_t^{LS} + N_t^{HS},\ E_t^S = E_t^{LS} + E_t^{HS},$$

$$N_t^I = N_t^{LI} + N_t^{HI},\ E_t^S = E_t^{LI} + E_t^{HI},$$

$$N_t^R = N_t^{LR} + N_t^{HR},\ E_t^S = E_t^{LR} + E_t^{HR},$$

where the aggregate measure of unemployed and employed workers are given by $N_t = N_t^L + N_t^H = N_t^S + N_t^I + N_t^R$ and $E_t = E_t^L + E_t^H = E_t^S + E_t^I + E_t^R$. The measures of workers of skill level χ who are susceptible (S_t^χ), infected (I_t^χ), and recovered (R_t^χ) are given by

$$S_t^\chi = N_t^{\chi S} + E_t^{\chi S},$$

$$I_t^\chi = N_t^{\chi I} + E_t^{\chi I},$$

$$R_t^\chi = N_t^{\chi R} + E_t^{\chi R}.$$

The aggregate measures of susceptible, infected, and recovered workers are given by $S_t = S_t^L + S_t^H$, $I_t = I_t^L + I_t^H$, and $R_t = R_t^L + R_t^H$, respectively. The population at time t, Pop_t, is given by

$$Pop_t = N_t + E_t = S_t + I_t + R_t.$$

With these identities in hand, we characterize the laws of motion for unemployment and employment. Beginning with unemployment among low skill workers, we have

$$N_{t+1}^{LS} = (1-\mu)\big[(1-f(\theta_t))(1-\pi_t^{UI})[N_t^{LS} + \sigma N_t^{HS}] + s(1-\pi_t^{EI})E_t^{LS}\big], \tag{1}$$

$$N_{t+1}^{LI} = (1-\mu)\big[(1-\pi_R-\pi_D)[N_t^{LI} + sE_t^{LI} + \sigma N_t^{HI} + \sigma s E_t^{HI}] + \pi_t^{UI}[N_t^{LS} + \sigma N_t^{HS}] + s\pi_t^{EI}E_t^{LS}\big], \tag{2}$$

$$N_{t+1}^{LR} = (1-\mu)\big[(1-f(\theta_t))[N_t^{LR} + \sigma N_t^{HR}] + \pi_R[N_t^{LI} + sE_t^{LI} + \sigma N_t^{HI} + \sigma s E_t^{HI}] + sE_t^{LR}\big], \tag{3}$$

$$\begin{aligned} N_{t+1}^{L} = (1-\mu)\big[&(1-f(\theta_t)(1-\pi_t^{UI}))[N_t^{LS} + \sigma N_t^{HS}] + (1-f(\theta_t))[N_t^{LR} + \sigma N_t^{HR}] \\ &+ (1-\pi_D)[N_t^{LI} + \sigma N_t^{HI}] + s[E_t^L - \pi_D E_t^{LI} + \sigma E_t^{HI}(1-\pi_D)]\big]. \end{aligned} \tag{4}$$

As seen in (1), the stock of susceptible unemployed low skill workers will contain a fraction $(1 - f(\theta_t))(1-\pi_t^{UI})$ of those susceptible low skill workers who did not find a job or become infected, a fraction $(1-f(\theta_t))(1-\pi_t^{UI})\sigma$ of the susceptible high skill workers who remain unemployed, susceptible, and became low skilled. Additionally, the stock of susceptible unemployed low skill workers contains a fraction $s(1-\pi_t^{EI})$ of the low skill susceptible workers who were employed, lost their job, and did not get infected. Equation (2) shows that next period's stock of infected low skill unemployed workers is composed of a fraction $(1-\pi_R-\pi_D)$ of those who began the period infected and remain infected, a fraction π_t^{UI} of susceptible unemployed workers who become infected, and a fraction $s\pi_t^{EI}$ of employed susceptible workers who lose their job and become infected. From equation (3), the stock of low skill unemployed workers who are recovered contains a fraction $1-f(\theta_t)$ of unemployed recovered workers who did not find a job, a fraction π_R of infected workers who recover and are unemployed, and a fraction s of recovered workers who are employed that lose their job. Finally, equation (4) aggregates across health statuses to describe the evolution of the aggregate stock of unemployed low skill workers.

The flows of unemployed high skill workers are given by

$$N_{t+1}^{HS}=\mu+(1-\mu)\big[(1-\sigma)(1-f(\theta_t))(1-\pi_t^{UI})N_t^{HS}+s(1-\pi_t^{EI})E_t^{HS}\big], \tag{5}$$

$$N_{t+1}^{HI}=(1-\mu)\big[(1-\pi_R-\pi_D)(1-\sigma)[N_t^{HI}+sE_t^{HI}]+\pi_t^{UI}(1-\sigma)N_t^{HS}+s\pi_t^{EI}E_t^{HS}\big], \tag{6}$$

$$N_{t+1}^{HR}=(1-\mu)\big[(1-\sigma)[(1-f(\theta_t))N_t^{HR}+\pi_R N_t^{HI}+\pi_R sE_t^{HI}]+sE_t^{HR}\big], \tag{7}$$

$$\begin{aligned}N_{t+1}^{H}=\mu+(1-\mu)\big[&(1-\sigma)[(1-f(\theta_t)(1-\pi_t^{UI}))N_t^{HS}+(1-f(\theta_t))N_t^{HR}\\&+(1-\pi_D)N_t^{HI}]+s[E_t^H-(\pi_D+\sigma(1-\pi_D))E_t^{HI}]\big].\end{aligned} \tag{8}$$

Equations (5)-(8) have a similar interpretation to (1)-(3) with a few notable differences. First, as seen in (5), there is an additional flow into the stock of unemployed high skill susceptible workers, μ, from new workers entering the labor force. Additionally, the stocks of unemployed high skill workers account for the possibility of skill loss among high skill workers who are either unemployed or employed and infected. From (4) and (8), aggregating across skill levels gives the aggregate flows of unemployed workers

$$N_{t+1}=\mu+(1-\mu)\big[(1-f(\theta_t)(1-\pi_t^{UI}))N_t^S+(1-f(\theta_t))N_t^R+(1-\pi_D)N_t^I+s[E_t-\pi_D E_t^I]\big]. \tag{9}$$

Next, we focus on the flows of employed workers. The flows of low skill employed workers are given by

$$E_{t+1}^{LS} = (1-\mu)\big[(1-\pi_t^{EI})(1-s)E_t^{LS} + f(\theta_t)(1-\pi_t^{UI})N_t^{LS}\big], \tag{10}$$

$$E_{t+1}^{LI} = (1-\mu)(1-s)\big[(1-\pi_R-\pi_D)[E_t^{LI} + \sigma E_t^{HI}] + \pi_t^{EI}E_t^{LS}\big], \tag{11}$$

$$E_{t+1}^{LR} = (1-\mu)\big[(1-s)[E_t^{LR} + \pi_R E_t^{LI} + \sigma\pi_R E_t^{HI}] + f(\theta_t)N_t^{LR}\big], \tag{12}$$

$$E_{t+1}^{L} = (1-\mu)\big[(1-s)[E_t^{L} - \pi_D E_t^{LI} + \sigma E_t^{HI}(1-\pi_D)] + f(\theta_t)[(1-\pi_t^{UI})N_t^{LS} + N_t^{LR}]\big]. \tag{13}$$

Equation (10) illustrates that the stock of employed susceptible workers contains a fraction $(1-\pi_t^{EI})(1-s)$ of the employed susceptible workers who did not become infected and did not lose their job and a fraction $f(\theta_t)(1-\pi_t^{UI})$ of the unemployed susceptible workers who found a job and did not become infected. From (11), workers will remain infected and employed with probability $(1-\pi_R-\pi_D)(1-s)$ and susceptible employed workers enter next period's stock of employed infected workers with probability π_t^{EI}. Equation (12) shows that next period's stock of employed recovered workers contains a fraction $1-s$ of the employed workers who have recovered and did not lose their job and a fraction $f(\theta_t)$ of the unemployed recovered workers who find a job. Equation (13) aggregates across health statuses to illustrate the aggregate flows of employment among low skill workers.

The flow equations for employment among high skill workers are given by

$$E_{t+1}^{HS} = (1-\mu)\big[(1-\pi_t^{EI})(1-s)E_t^{HS} + f(\theta_t)(1-\pi_t^{UI})N_t^{HS}\big], \tag{14}$$

$$E_{t+1}^{HI} = (1-\mu)(1-s)\big[(1-\sigma)(1-\pi_R-\pi_D)E_t^{HI} + \pi_t^{EI}E_t^{HS}\big], \tag{15}$$

$$E_{t+1}^{HR} = (1-\mu)\big[(1-s)[E_t^{HR} + (1-\sigma)\pi_R E_t^{HI}] + f(\theta_t)N_t^{HR}\big], \tag{16}$$

$$E_{t+1}^{H} = (1-\mu)\big[(1-s)[E_t^{H} - (\sigma(1-\pi_D)+\pi_D)E_t^{HI}] + f(\theta_t)[(1-\pi_t^{UI})N_t^{HS} + N_t^{HR}]\big], \tag{17}$$

where the main difference to equations (10)-(13) is that high skill workers can experience skill loss while they are employed and infected. From (13) and (17), the aggregate flows of employment are given by

$$E_{t+1} = (1-\mu)\big[(1-s)[E_t - \pi_D E_t^{I}] + f(\theta_t)[(1-\pi_t^{UI})N_t^{I} + N_t^{R}]\big]. \tag{18}$$

Using $S_{t+1}^{\chi} = N_{t+1}^{\chi S} + E_{t+1}^{\chi S}$, the flows of susceptible workers by skill level and in aggregate are given by

$$S_{t+1}^{L} = (1-\mu)\big[(1-\pi_t^{UI})N_t^{LS} + (1-\pi_t^{EI})E_t^{LS} + \sigma(1-f(\theta_t))(1-\pi_t^{UI})N_t^{HS}\big], \tag{19}$$

$$S_{t+1}^{H} = \mu + (1-\mu)\big[(1-\pi_t^{UI})N_t^{HS} + (1-\pi_t^{EI})E_t^{HS} - \sigma(1-f(\theta_t))(1-\pi_t^{HS})N_t^{HS}\big], \tag{20}$$

$$S_{t+1} = \mu + (1-\mu)\big[(1-\pi_t^{UI})S_t - (\pi_t^{EI} - \pi_t^{UI})E_t^{S}\big], \tag{21}$$

while the dynamics for infections are given by

$$I_{t+1}^{L} = (1-\mu)\big[(1-\pi_R-\pi_D)[I_t^L + \sigma I_t^H] + \pi_t^{UI}[N_t^{LS} + \sigma N_t^{HS}] + \pi_t^{EI}E_t^{LS}\big], \tag{22}$$

$$I_{t+1}^{H} = (1-\mu)\big[(1-\sigma)[(1-\pi_R-\pi_D)I_t^H + \pi_t^{UI}N_t^{HS}] + \pi_t^{EI}E_t^{HS}\big], \tag{23}$$

$$I_{t+1} = (1-\mu)\big[(1-\pi_R-\pi_D)I_t + \pi_t^{UI}S_t + (\pi_t^{EI} - \pi_t^{UI})E_t^{S}\big], \tag{24}$$

and the dynamics for recoveries are given by

$$R_{t+1}^{L} = (1-\mu)\big[R_t^L + \pi_R I_t^L + \sigma[(1-f(\theta_t))N_t^{HR} + \pi_R N_t^{HI} + \pi_R s E_t^{HI}]\big], \tag{25}$$

$$R_{t+1}^{H} = (1-\mu)\big[R_t^H + \pi_R I_t^H - \sigma[(1-f(\theta_t))N_t^{HR} + \pi_R N_t^{HI} + \pi_R s E_t^{HI}]\big], \tag{26}$$

$$R_{t+1} = (1-\mu)\big[R_t + \pi_R I_t\big]. \tag{27}$$

Letting D_t denote the total number of deaths from the pandemic at time t, it follows that

$$D_{t+1} = D_t + \pi_D I_t. \tag{28}$$

Finally, the population evolves according to

$$Pop_{t+1} = Pop_t - (D_{t+1} - D_t). \tag{29}$$

4 Equilibrium

We begin this section by describing the Bellman equations for workers and firms. We then derive the pre-pandemic equilibrium and discuss how job creation depends on the skill distribution. Intuitively, when unemployment is high and many workers lose skills, aggregate productivity drops and firms' profits shrink, so firms respond by creating fewer jobs. We then derive the equilibrium during a pandemic. During a pandemic, firms take into account not only the distribution of workers across skills, but also across health statuses. As infections rise, it becomes more difficult to hire a susceptible worker, and susceptible employed workers are more likely to become infected and unproductive. As a result, firms create fewer jobs as infections ramp up.

Let $U_t^{\chi S}$, $U_t^{\chi I}$, and $U_t^{\chi R}$ denote the lifetime discounted utility of an unemployed worker with skill level χ who is susceptible, infected, and recovered. Further, let $W_t^{\chi S}$, $W_t^{\chi I}$, and $W_t^{\chi R}$ denote the lifetime discounted utility of an employed worker with skill level χ and respective health status. We normalize the value of death to 0. The value functions for low skill unemployed workers satisfy the following Bellman Equations

$$U_t^{LS} = b + \bar{\beta}\{f(\theta_t)(1-\pi_t^{UI})W_{t+1}^{LS} + \pi_t^{UI}U_{t+1}^{LI} + (1-f(\theta_t))(1-\pi_t^{UI})U_{t+1}^{LS}\}, \tag{30}$$

$$U_t^{LI} = b + \bar{\beta}\{(1-\pi_R-\pi_D)U_{t+1}^{LI} + \pi_R U_{t+1}^{LR}\}, \tag{31}$$

$$U_t^{LR} = b + \bar{\beta}\{f(\theta_t)W_{t+1}^{LR} + (1-f(\theta_t))U_{t+1}^{LR}\}, \tag{32}$$

where $\bar{\beta} \equiv \beta(1-\mu)$ is the effective discount factor. From (30), unemployed low skill workers who are susceptible enjoy utility b. With probability $f(\theta_t)(1-\pi_t^{UI})$ they find a job and do not become infected. They become infected and remain unemployed with probability π_t^{UI}. With probability $(1-f(\theta_t))(1-\pi_t^{UI})$ they remain unemployed and susceptible. Equation (31) shows that a low skill unemployed worker who is infected has utility b. With probability $(1-\pi_R-\pi_D)$ they remain infected and recover with probability π_R. Recall that infected workers can not search for jobs, so they remain unemployed even if they recover. As for recovered workers, (32) shows that they face a standard labor search problem where they either find a job with probability $f(\theta_t)$ or do not with probability $1-f(\theta_t)$. Recovered workers do not face the probability of infection as they have gained immunity.

The value functions of high skill unemployed workers are given by

$$\begin{aligned} U_t^{HS} = b + \bar{\beta}\{f(\theta_t)(1-\pi_t^{UI})W_{t+1}^{HS} + \sigma[\pi_t^{UI}U_{t+1}^{LI} + (1-f(\theta_t))(1-\pi_t^{UI})U_{t+1}^{LS}] + \\ (1-\sigma)[\pi_t^{UI}U_{t+1}^{HI} + (1-f(\theta_t))(1-\pi_t^{UI})U_{t+1}^{HS}]\}, \end{aligned} \tag{33}$$

$$U_t^{HI} = b + \bar{\beta}\{\sigma[(1-\pi_R-\pi_D)U_{t+1}^{LI} + \pi_R U_{t+1}^{LR}] + (1-\sigma)[(1-\pi_R-\pi_D)U_{t+1}^{HI} + \pi_R U_{t+1}^{HR}]\}, \tag{34}$$

$$U_t^{HR} = b + \bar{\beta}\{f(\theta_t)W_{t+1}^{HR} + (1-f(\theta_t))[\sigma U_{t+1}^{LR} + (1-\sigma)U_{t+1}^{HR}]\}. \tag{35}$$

Equations (33)-(35) have a very similar interpretation as (30)-(32) in terms of the transitions between health statuses and employment statuses. However, an important difference is the possibility of skill loss. Equation (33) shows that if the high skill worker does not find a job, then with probability σ they become low skilled and face the possibility of becoming infected. Equations (34) and (35) illustrate that unemployed high skill workers who are infected or recovered continue to face the possibility of skill loss.

Turning to the value functions for employed low skill workers, they are given by

$$W_t^{LS} = w_t^{LS} + \bar{\beta}\big\{\pi_t^{EI}[(1-s)W_{t+1}^{LI} + sU_{t+1}^{LI}] + (1-\pi_t^{EI})[(1-s)W_{t+1}^{LS} + sU_{t+1}^{LS}]\big\}, \tag{36}$$

$$W_t^{LI} = w_t^{LI} + \bar{\beta}\big\{(1-\pi_R-\pi_D)[(1-s)W_{t+1}^{LI} + sU_{t+1}^{LI}] + \pi_R[(1-s)W_{t+1}^{LR} + sU_{t+1}^{LR}]\big\}, \tag{37}$$

$$W_t^{LR} = w_t^{LR} + \bar{\beta}\big\{sU_{t+1}^{LR} + (1-s)W_{t+1}^{LR}\big\}. \tag{38}$$

Equation (36) details that employed low skill workers who are susceptible earn a wage w_t^{LS} and with probability π_t^{EI} become infected while working. Conditional on becoming infected, they remain employed with probability $1-s$. If the worker does not become infected, they still face the possibility of losing their job and transitioning to unemployment. From (37), employed low skill workers earn their wage, w_t^{LI}. The worker remains infected with probability $(1-\pi_R-\pi_D)$ and recovers with probability π_R. Conditional on surviving, they remain employed with probability $1-s$. Equation (38) shows that recovered workers face a standard problem, as they only face the possibility of losing their job.

The value functions for high skill employed workers are given by

$$W_t^{HS} = w_t^{HS} + \bar{\beta}\big\{\pi_t^{EI}[(1-s)W_{t+1}^{HI} + sU_{t+1}^{HI}] + (1-\pi_t^{EI})[(1-s)W_{t+1}^{HS} + sU_{t+1}^{HS}]\big\}, \tag{39}$$

$$\begin{aligned} W_t^{HI} = w_t^{HI} + \bar{\beta}\big\{&\sigma\big[(1-\pi_R-\pi_D)[(1-s)W_{t+1}^{LI} + sU_{t+1}^{LI}] + \pi_R[(1-s)W_{t+1}^{LR} + sU_{t+1}^{LR}]\big] \\ &+ (1-\sigma)\big[(1-\pi_R-\pi_D)[(1-s)W_{t+1}^{HI} + sU_{t+1}^{HI}] + \pi_R[(1-s)W_{t+1}^{HR} + sU_{t+1}^{HR}]\big]\big\}, \end{aligned} \tag{40}$$

$$W_t^{HR} = w_t^{HR} + \bar{\beta}\big\{(1-s)W_{t+1}^{HR} + sU_{t+1}^{HR}\big\}. \tag{41}$$

Equations (39)-(41) have the same interpretation as (36)-(38) except that high skill workers face the risk of skill loss while they are employed and infected.

We now shift our attention to the firms' value functions. Let V_t denote the value of a vacancy and $J_t^{\chi S}$, $J_t^{\chi I}$, and $J_t^{\chi R}$ the value a filled job with a worker of skill level χ and respective health status. Additionally, we introduce some notation to describe the composition of job seekers. Let φ_t denote the share of job seekers with low skills and ϕ_t^{χ} the share of job seekers with skill level χ who are susceptible. The value of a vacancy satisfies

$$\begin{aligned} V_t = -k + \bar{\beta}\big\{&q(\theta_t)\big[\varphi_t[\phi_t^L(1-\pi_t^{UI})J_{t+1}^{LS} + (1-\phi_t^L)J_{t+1}^{LR}] + (1-\varphi_t)[\phi_t^H(1-\pi_t^{UI})J_{t+1}^{HS} + (1-\phi_t^H)J_{t+1}^{HR}]\big] \\ &+ \big(1-q(\theta_t)[\varphi_t(1-\phi_t^L\pi_t^{UI}) + (1-\varphi_t)(1-\phi_t^H\pi_t^{UI})]\big)V_{t+1}\big\} + \beta\mu V_{t+1}. \end{aligned} \tag{42}$$

Equation (42) shows that vacant firms incur the vacancy posting cost k and meet a worker with probability $q(\theta_t)$. Conditional on meeting a worker, the firm meets a low skill worker with probability φ_t and high skill worker with probability $1-\varphi_t$. Among meetings with a worker of skill type χ, firms match with a susceptible worker with probability $\phi_t^{\chi}(1-\pi_t^{UI})$, which accounts for the risk that a susceptible worker they meet becomes infected, and a recovered worker with probability $1-\phi_t^{\chi}$. The firm continues to have a vacancy either if it does not meet a worker or met a worker who became infected in the same time period.

The value functions for filled jobs with low skill workers are given by

$$J_t^{LS} = \delta y - w_t^{LS} + \bar{\beta}\big\{\pi_t^{EI}(1-s)J_{t+1}^{LI} + (1-\pi_t^{EI})(1-s)J_{t+1}^{LS} + sV_{t+1}\big\} + \beta\mu V_{t+1}, \tag{43}$$

$$J_t^{LI} = -w_t^{LI} + \bar{\beta}\big\{(1-\pi_R-\pi_D)(1-s)J_{t+1}^{LI} + \pi_R(1-s)J_{t+1}^{LR} + (\pi_D + s(1-\pi_D))V_{t+1}\big\} + \beta\mu V_{t+1}, \tag{44}$$

$$J_t^{LR} = \delta y - w_t^{LR} + \bar{\beta}\big\{(1-s)J_{t+1}^{LR} + sV_{t+1}\big\} + \beta\mu V_{t+1}. \tag{45}$$

From (43), a filled job with a low skill susceptible worker generates a profit of output net of the worker's wage, $\delta y - w_t^{LS}$. The worker becomes infected and the job is not destroyed with probability $\pi_t^{EI}(1-s)$. The probability that the worker remains susceptible and the job is not destroyed is given by $(1-\pi_t^{EI})(1-s)$. Equation (44) illustrates that employed workers who are infected do not generate output and earn a wage w_t^{LI}. If the job is not destroyed, the worker remains infected with probability $1-\pi_R-\pi_D$ or recovers with probability π_R and the match continues with probability $1-s$. With probability $\pi_D + s(1-\pi_D)$, either the infected worker dies or the worker survives and the job is destroyed. In either case, the firm returns to having a vacancy. Finally, (45) represents that a filled job with a recovered worker is standard, as the worker's health status no longer changes.

The value functions for filled jobs with high skill workers are given by

$$J_t^{HS} = y - w_t^{HS} + \bar{\beta}\big\{\pi_t^{EI}(1-s)J_{t+1}^{HI} + (1-\pi_t^{EI})(1-s)J_{t+1}^{HS} + sV_{t+1}\big\} + \beta\mu V_{t+1}, \tag{46}$$

$$\begin{aligned} J_t^{HI} = & -w_t^{HI} + \bar{\beta}\big\{\sigma[(1-\pi_R-\pi_D)(1-s)J_{t+1}^{LI} + \pi_R(1-s)J_{t+1}^{LR}] + \\ & (1-\sigma)[(1-\pi_R-\pi_D)(1-s)J_{t+1}^{HI} + \pi_R(1-s)J_{t+1}^{HR}] + (\pi_D + s(1-\pi_D))V_{t+1}\big\} + \beta\mu V_{t+1}, \end{aligned} \tag{47}$$

$$J_t^{HR} = y - w_t^{HR} + \bar{\beta}\big\{(1-s)J_{t+1}^{HR} + sV_{t+1}\big\} + \beta\mu V_{t+1}. \tag{48}$$

Equations (46)-(48) are the same as (43)-(45) with the exception of the possibility of high skill workers suffering a loss of skill while they are employed and infected.

4.1 Pre-pandemic Steady-State

In this section we study the steady-state equilibrium in the labor market before the onset of the pandemic. We start by introducing the free-entry condition for vacancy creation, wage determination, and the steady-state distribution of workers. The equilibrium is then defined and characterized.

There is free entry of firms, which drives the value of a vacancy to zero in equilibrium. As is standard in the literature, wages are determined by Nash bargaining. Denoting $\eta \in [0,1]$ as the worker's bargaining power, wages solve:

$$w^{\chi} = \arg\max \left[W^{\chi} - U^{\chi}\right]^{\eta}\left[J^{\chi}\right]^{1-\eta}. \tag{49}$$

Letting $F^{\chi} = J^{\chi} + W^{\chi} - U^{\chi}$ denote the total surplus of a match between a firm and a worker of skill level χ, the solution to (49) gives the following surplus sharing rules

$$W^{\chi} - U^{\chi} = \eta F^{\chi};\ J^{\chi} = (1-\eta)F^{\chi}. \tag{50}$$

Using the Bellman equations, surplus sharing rules, and letting $\Delta^{H,L} \equiv U^H - U^L$ denote the cost of skill loss, we have

$$F^L = \frac{\delta y - b}{1 - \bar{\beta}(1 - s - \eta f(\theta))}, \tag{51}$$

$$F^H = \frac{y - b + \bar{\beta}(1 - f(\theta))\sigma\Delta^{H,L}}{1 - \bar{\beta}(1 - s - \eta f(\theta))}. \tag{52}$$

From (52), the surplus in a match with a high skill worker is increasing in the probability of skill loss σ, as the cost of skill loss $\Delta^{H,L}$ reduces the worker's reservation wage. Substituting (51)-(52) into (50) and solving for wages gives

$$w^L = \frac{\eta\delta y[1 - \bar{\beta}(1 - s - f(\theta))] + (1-\eta)b[1 - \bar{\beta}(1-s)]}{1 - \bar{\beta}(1 - s - \eta f(\theta))}, \tag{53}$$

$$w^H = \frac{\eta y[1 - \bar{\beta}(1 - s - f(\theta))] + (1-\eta)[b - \bar{\beta}\sigma(1 - f(\theta))\Delta^{H,L}][1 - \bar{\beta}(1-s)]}{1 - \bar{\beta}(1 - s - \eta f(\theta))}. \tag{54}$$

Using the free entry condition, $V = 0$, and substituting (50)-(52) into the Bellman for vacancies, (42), we have the job creation condition

$$\frac{k}{q(\theta)} = \frac{\bar{\beta}(1-\eta)\left[\varphi(\delta y - b) + (1-\varphi)\left(y - b + \bar{\beta}\sigma(1-f)\Delta^{H,L}\right)\right]}{1 - \bar{\beta}(1 - s - \eta f(\theta))}, \tag{55}$$

which illustrates that firms create jobs until the expected cost from posting a vacancy, the left hand side of (55), equals the expected value of filling a vacancy, the right hand side of (55). In the pre-pandemic steady-state, the expected value of a filled job captures the heterogenous skills among unemployed workers.

From the flow equations in Section 3, the fraction of unemployed workers who are less-skilled, φ, is given by

$$\varphi = \frac{\sigma(1-\mu)(1-f(\theta))[1-(1-\mu)(1-s)]}{\mu(1-\mu)f(\theta) + [\mu + (1-\mu)(1-f(\theta))\sigma][1-(1-\mu)(1-s)]}. \tag{56}$$

From (56), φ is increasing in the probability of skill loss σ, as an increase in the risk of skill loss increases the flow of high skill unemployed workers to low skill unemployed workers. The composition φ is also increasing in the separation probability s, as having more workers entering unemployment from employment exposes more high skill workers to the risk of skill loss. Also, φ is decreasing in market tightness, θ. If firms create more jobs, then high skill workers are more likely to exit unemployment and avoid skill loss. The opposite is also true: if there is a downturn and less jobs are created, then high skill workers face more opportunities for skill loss, leading to a higher fraction among the pool of unemployed who are less-skilled.

We close the model with the steady-state unemployment rate:

$$u = \frac{\mu + (1-\mu)s}{\mu + (1-\mu)(s + f(\theta))}. \tag{57}$$

Definition 1. A steady-state equilibrium is a tuple $\{\theta, \varphi, u\}$ such that market tightness, θ, satisfies (55), the fraction of unemployed workers who are less-skilled, φ, is given by (56), and the unemployment rate, u, is given by (57).

Proposition 1. *Assume that $\delta y > b$ and*

$$k < \frac{\bar{\beta}(1-\eta)\big[\sigma(1-\mu)(\delta y - b) + \mu(y-b)\big]}{[1-\bar{\beta}(1-s)][\mu + (1-\mu)\sigma]}. \tag{58}$$

There exists an active steady-state equilibrium with $\theta > 0$.

As in Pissarides (1992), the equilibrium with loss of skill during unemployment may not be unique. This is due to the fact that as firms create more jobs, the skill composition of the unemployed improves, which means the right hand side of the job creation condition can be upward sloping. This occurs, quantitatively, only under extreme and unrealistic parameter values. With a characterization of the pre-pandemic economy in hand, we turn to the equilibrium during a pandemic.

4.2 Equilibrium during a Pandemic

In this section, we describe the equilibrium in the labor market after the onset of a pandemic. As before, wages are determined through Nash bargaining and renegotiated each period. Letting $\Omega \in \{LS, LI, LR, HS, HI, HR\}$ denote the worker's skill and health status, wages solve

$$w_t^{\Omega} = \arg\max \left[W_t^{\Omega} - U_t^{\Omega}\right]^{\eta} \left[J_t^{\Omega}\right]^{1-\eta}. \tag{59}$$

The solution to (59) gives the surplus sharing rules

$$W_t^{\Omega} - U_t^{\Omega} = \eta F_t^{\Omega};\ J_t^{\Omega} = (1-\eta) F_t^{\Omega}, \tag{60}$$

where $F_t^{\Omega} = J_t^{\Omega} + W_t^{\Omega} - U_t^{\Omega}$ is the total surplus of a match. To characterize the entry of firms, it will be useful to describe the evolution of match surpluses over time. Combining the surplus sharing rules with the Bellman equations, we can write the law of motions for the total surpluses of each match:

$$F_t^{LS} = \delta y - b + \bar{\beta}\big\{\pi_t^{EI}(1-s)F_{t+1}^{LI} + [(1-s)(1-\pi_t^{EI}) - \eta f(\theta_t)(1-\pi_t^{UI})]F_{t+1}^{LS} \\ + (\pi_t^{EI} - \pi_t^{UI})\Delta_{t+1}^{LI,LS}\big\}, \tag{61}$$

$$F_t^{HS} = y - b + \bar{\beta}\big\{\pi_t^{EI}(1-s)F_{t+1}^{HI} + [(1-s)(1-\pi_t^{EI}) - \eta f(\theta_t)(1-\pi_t^{UI})]F_{t+1}^{HS} \\ + (\pi_t^{EI} - \pi_t^{UI})\Delta_{t+1}^{HI,HS} + \sigma\big[\pi_t^{UI}\Delta_{t+1}^{HI,LI} + (1-\pi_t^{UI})(1-f(\theta_t))\Delta_{t+1}^{HS,LS}\big]\big\}, \tag{62}$$

$$F_t^{LI} = -b + \bar{\beta}(1-s)\big\{(1-\pi_R-\pi_D)F_{t+1}^{LI} + \pi_R F_{t+1}^{LR}\big\}, \tag{63}$$

$$F_t^{HI} = -b + \bar{\beta}(1-s)\big\{\sigma\big[(1-\pi_R-\pi_D)F_{t+1}^{LI} + \pi_R F_{t+1}^{LR}\big] + (1-\sigma)\big[(1-\pi_R-\pi_D)F_{t+1}^{HI} + \pi_R F_{t+1}^{HR}\big]\big\}, \tag{64}$$

$$F_t^{LR} = \delta y - b + \bar{\beta}\big[1 - s - \eta f(\theta_t)\big]F_{t+1}^{LR}, \tag{65}$$

$$F_t^{HR} = y - b + \bar{\beta}\big\{(1 - s - \eta f(\theta_t))F_{t+1}^{HR} + \sigma(1-f(\theta_t))\Delta_{t+1}^{HR,LR}\big\}, \tag{66}$$

where $\Delta_t^{\Omega',\Omega} \equiv U_t^{\Omega'} - U_t^{\Omega}$ represents the difference in lifetime utility between state Ω' and state Ω. From the Bellman equations, they satisfy

$$\Delta_t^{HS,LS} = \bar{\beta}\big\{\eta f(\theta_t)(1-\pi_t^{UI})\big[F_{t+1}^{HS} - F_{t+1}^{LS}\big] + (1-\sigma)\pi_t^{UI}\Delta_{t+1}^{HI,LI} + \\ (1-\pi_t^{UI})\big[1-(1-f(\theta_t))\sigma\big]\Delta_{t+1}^{HS,LS}\big\}, \tag{67}$$

$$\Delta_t^{LI,LS} = \bar{\beta}\big\{(1-\pi_t^{UI})\big(\Delta_{t+1}^{LI,LS} - \eta f(\theta_t)F_{t+1}^{LS}\big) + \pi_R\Delta_{t+1}^{LR,LI} - \pi_D U_{t+1}^{LI}\big\}, \tag{68}$$

$$\Delta_t^{HI,HS} = \bar{\beta}\big\{(1-\pi_t^{UI})\big(\Delta_{t+1}^{HI,HS} - \eta f(\theta_t)F_{t+1}^{HS}\big) + \pi_R\Delta_{t+1}^{HR,HI} - \pi_D U_{t+1}^{HI} \\ + \sigma\big[\pi_R\Delta_{t+1}^{LR,HR} + (1-f(\theta_t))(1-\pi_t^{UI})\Delta_{t+1}^{HS,LS} + (1-\pi_t^{UI}-\pi_R-\pi_D)\Delta_{t+1}^{LI,HI}\big]\big\}, \tag{69}$$

$$\Delta_t^{HI,LI} = \bar{\beta}(1-\sigma)\big\{(1-\pi_R-\pi_D)\Delta_{t+1}^{HI,LI} + \pi_R\Delta_{t+1}^{HR,LR}\big\}, \tag{70}$$

$$\Delta_t^{LR,LI} = \bar{\beta}\big\{\eta f(\theta_t)F_{t+1}^{LR} + (1-\pi_R)\Delta_{t+1}^{LR,LI} + \pi_D U_{t+1}^{LI}\big\}, \tag{71}$$

$$\Delta_t^{HR,HI} = \bar{\beta}\big\{\eta f(\theta_t)F_{t+1}^{HR} + (1-\pi_R)\Delta_{t+1}^{HR,HI} + \pi_D U_{t+1}^{HI} + \\ + \sigma\big[(1-f(\theta_t)-\pi_R)\Delta_{t+1}^{LR,HR} - (1-\pi_R-\pi_D)\Delta_{t+1}^{LI,HI}\big]\big\}, \tag{72}$$

$$\Delta_t^{HR,LR} = \bar{\beta}\big\{\eta f(\theta_t)\big[F_{t+1}^{HR} - F_{t+1}^{LR}\big] + (1-\sigma(1-f(\theta_t)))\Delta_{t+1}^{HR,LR}\big\}. \tag{73}$$

The last step before arriving at the job creation condition is to describe the composition of job seekers by skill level and health status. The skill composition of job seekers is given by

$$\varphi_t = \frac{N_t^{LS} + N_t^{LR}}{N_t^S + N_t^R};\ 1 - \varphi_t = \frac{N_t^{HS} + N_t^{HR}}{N_t^S + N_t^R}, \tag{74}$$

where $N_t^S + N_t^R$ is the total measure of job seekers as infected workers do not search. The fraction of job seekers of skill level χ who are susceptible is given by

$$\phi_t^\chi = \frac{N_t^{\chi S}}{N_t^{\chi S} + N_t^{\chi R}}. \tag{75}$$

Under the free-entry condition, the value of a vacancy is zero at all time periods, i.e. $V_t = 0$, $\forall t \in \mathbb{N}_0$. This gives the following job creation condition to relate the expected cost of a vacancy to the expected surplus of a filled job:

$$\frac{k}{q(\theta_t)} = \bar{\beta}(1-\eta)\{\varphi_t[\phi_t^L(1-\pi_t^{UI})F_{t+1}^{LS} + (1-\phi_t^L)F_{t+1}^{LR}] + (1-\varphi_t)[\phi_t^H(1-\pi_t^{UI})F_{t+1}^{HS} + (1-\phi_t^H)F_{t+1}^{HR}]\}. \tag{76}$$

From (76), firms do not only consider the skill composition of unemployed workers, but also the composition of health statuses and the probability a susceptible worker they meet becomes infected.

Definition 2. An equilibrium is a sequence of worker allocations across labor market and health statuses $\{N_t^\Omega, E_t^\Omega, N_t^\chi, E_t^\chi, N_t, E_t, S_t^\chi, I_t^\chi, R_t^\chi, S_t, I_t, R_t, D_t\}_{t=0}^\infty$, composition of job seekers $\{\varphi_t, \phi_t^\chi\}_{t=0}^\infty$, match surpluses $\{F_t^\Omega\}_{t=0}^\infty$, and market tightness $\{\theta_t\}_{t=0}^\infty$ for $\chi \in \{L, H\}$ and $\Omega \in \{LS, LI, LR, HS, HI, HR\}$ such that the allocation of workers across labor market statuses evolve according to (1)-(18), the allocation of workers across health statuses evolves according to (19)-(28), the composition of job seekers is given by (74)-(75), match surpluses satisfy (61)-(66), and market tightness satisfies (76).

We assume the labor market is initially in the pre-pandemic steady-state, where market tightness solves (55), the composition of skills is given by (56), and the unemployment rate is given by (57). To introduce a pandemic, the initial allocation across health statuses is given by $\{N_0^{\chi S}, E_0^{\chi S}, N_0^{\chi I}, E_0^{\chi I}\}$ and $\{N^{\chi R}, E^{\chi R}\} = \{0, 0\}$ for $\chi \in \{L, H\}$ where the initial number of infected, $\sum_\chi \left[N_0^{\chi I} + E_0^{\chi I}\right]$, is a small fraction of the population.

5 Planner's problem

In addition to the typical search externalities (Hosios, 1990), there are two inefficiencies in the economy. The first, emphasized by Kapička and Rupert (2020), is an infection externality. Workers and firms do not internalize that forming matches propagates the spread of the virus because employed workers have a higher probability of becoming infected, and therefore infecting others. Second, firms do not internalize the effect of job creation on the skill composition of the unemployed. By creating more jobs, firms reduce unemployment and unemployment duration, which raise aggregate productivity and TFP by improving the skill composition, a result similar to Laureys (2020). We call this the skill composition externality. Because of these two additional externalities, the equilibrium is inefficient even when the Hosios-Mortensen-Pissarides condition holds. In addition, the social planner faces a trade-off. On one hand, reducing job creation curtails infections and deaths. On the other, fewer jobs increases unemployment durations and skill loss, worsening the skill composition of the unemployed and decreasing productivity.

To study the efficient allocation in light of these inefficiencies, we consider the problem of a social planner who chooses the amount of vacancies to create and matches to form in order to maximize the present-discounted value of net output subject to the matching frictions present in the decentralized economy. Additionally, we consider a planner who can not destroy matches, takes the separation probability as given, and knows the workers' skill level. The planner's problem is given by

$$\max_{\{\theta_t\}_{t=0}^{\infty}} \sum_{t=0}^{\infty} \beta^t \big[\delta y\big(E_t^{LS} + E_t^{LR}\big) + y\big(E_t^{HS} + E_t^{HR}\big) + b\big(N_t^{LS} + N_t^{LI} + N_t^{LR} + N_t^{HS} + N_t^{HI} + N_t^{HR}\big) - k\theta_t\big(N_t^{LS} + N_t^{LR} + N_t^{HS} + N_t^{HR}\big)\big], \quad (77)$$

subject to the constraints:

$$N_{t+1}^{LS} = (1-\mu)\big[(1-f(\theta_t))(1-\pi_t^{UI})[N_t^{LS}+\sigma N_t^{HS}] + s(1-\pi_t^{EI})E_t^{LS}\big], \tag{78}$$

$$N_{t+1}^{LI} = (1-\mu)\big[(1-\pi_R-\pi_D)[N_t^{LI}+sE_t^{LI}+\sigma N_t^{HI}+\sigma sE_t^{HI}] + \pi_t^{UI}[N_t^{LS}+\sigma N_t^{HS}] + s\pi_t^{EI}E_t^{LS}\big], \tag{79}$$

$$N_{t+1}^{LR} = (1-\mu)\big[(1-f(\theta_t))[N_t^{LR}+\sigma N_t^{HR}] + \pi_R[N_t^{LI}+sE_t^{LI}+\sigma N_t^{HI}+\sigma sE_t^{HI}] + sE_t^{LR}\big], \tag{80}$$

$$E_{t+1}^{LS} = (1-\mu)\big[(1-\pi_t^{EI})(1-s)E_t^{LS} + f(\theta_t)(1-\pi_t^{UI})N_t^{LS}\big], \tag{81}$$

$$E_{t+1}^{LI} = (1-\mu)(1-s)\big[(1-\pi_R-\pi_D)[E_t^{LI}+\sigma E_t^{HI}] + \pi_t^{EI}E_t^{LS}\big], \tag{82}$$

$$E_{t+1}^{LR} = (1-\mu)\big[(1-s)[E_t^{LR}+\pi_R E_t^{LI}+\sigma\pi_R E_t^{HI}] + f(\theta_t)N_t^{LR}\big], \tag{83}$$

$$N_{t+1}^{HS} = \mu + (1-\mu)\big[(1-\sigma)(1-f(\theta_t))(1-\pi_t^{UI})N_t^{HS} + s(1-\pi_t^{EI})E_t^{HS}\big], \tag{84}$$

$$N_{t+1}^{HI} = (1-\mu)\big[(1-\pi_R-\pi_D)(1-\sigma)[N_t^{HI}+sE_t^{HI}] + \pi_t^{UI}(1-\sigma)N_t^{HS} + s\pi_t^{EI}E_t^{HS}\big], \tag{85}$$

$$N_{t+1}^{HR} = (1-\mu)\big[(1-\sigma)[(1-f(\theta_t))N_t^{HR} + \pi_R N_t^{HI} + \pi_R sE_t^{HI}] + sE_t^{HR}\big], \tag{86}$$

$$E_{t+1}^{HS} = (1-\mu)\big[(1-\pi_t^{EI})(1-s)E_t^{HS} + f(\theta_t)(1-\pi_t^{UI})N_t^{HS}\big], \tag{87}$$

$$E_{t+1}^{HI} = (1-\mu)(1-s)\big[(1-\sigma)(1-\pi_R-\pi_D)E_t^{HI} + \pi_t^{EI}E_t^{HS}\big], \tag{88}$$

$$E_{t+1}^{HR} = (1-\mu)\big[(1-s)[E_t^{HR}+(1-\sigma)\pi_R E_t^{HI}] + f(\theta_t)N_t^{HR}\big], \tag{89}$$

$$\pi_t^{UI} = \pi^U\big(N_t^{LI}+E_t^{LI}+N_t^{HI}+E_t^{HI}\big), \tag{90}$$

$$\pi_t^{EI} = \pi^E\big(N_t^{LI}+E_t^{LI}+N_t^{HI}+E_t^{HI}\big). \tag{91}$$

Denoting λ_t^Ω as the Lagrange multipliers on the N_t^Ω constraints and Λ_t^Ω as the multipliers on the E_t^Ω constraints, the planner's optimal choice for market tightness satisfies

$$\frac{k}{q(\theta_t)} = \bar{\beta}(1-\zeta)\big\{\varphi_t\big[\phi_t^L(1-\pi_t^{UI})\Gamma_{t+1}^{LS} + (1-\phi_t^L)\Gamma_{t+1}^{LR}\big] +$$
$$(1-\varphi_t)\big[\phi_t^H(1-\pi_t^{UI})[\Gamma_{t+1}^{HS}+\sigma(\lambda_{t+1}^{HS}-\lambda_{t+1}^{LS})] + (1-\phi_t^H)[\Gamma_{t+1}^{HR}+\sigma(\lambda_{t+1}^{HR}-\lambda_{t+1}^{LR})]\big]\big\}, \tag{92}$$

where $\zeta \equiv \frac{-\theta q'(\theta)}{q(\theta)}$ is the elasticity of the meeting function with respect to job seekers. The multipliers, λ_t^Ω and Λ_t^Ω, represent the social value of an unemployed and employed worker of type Ω, respectively, and $\Gamma_t^\Omega \equiv \Lambda_t^\Omega - \lambda_t^\Omega$.

We derive the social values of unemployment and employment for each type of worker by taking the first order conditions of (77) with respective to the relevant stocks. Beginning with unemployed, low skill workers, the first order conditions with respect to N_t^{LS}, N_t^{LI}, and N_t^{LR} are given by

$$\lambda_t^{LS} = b - k\theta_t + \bar{\beta}\{f(\theta_t)(1-\pi_t^{UI})\Lambda_{t+1}^{LS} + \pi_t^{UI}\lambda_{t+1}^{LI} + (1-f(\theta_t))(1-\pi_t^{UI})\lambda_{t+1}^{LS}\}, \tag{93}$$

$$\lambda_t^{LI} = b + \bar{\beta}\{(1-\pi_R-\pi_D)\lambda_{t+1}^{LI} + \pi_R\lambda_{t+1}^{LR}\} - \bar{\beta}\Psi_t, \tag{94}$$

$$\lambda_t^{LR} = b - k\theta_t + \bar{\beta}\{f(\theta_t)\Lambda_{t+1}^{LR} + (1-f(\theta_t))\lambda_{t+1}^{LR}\}. \tag{95}$$

Equations (93)-(95) are similar to the Bellmans for unemployed, low skill workers (equations (30)-(32)). A key difference can be seen by comparing equations (94) and (31), where Ψ_t in (94) captures the infection externality and is given by

$$\begin{aligned}\Psi_t = \pi^U N_t^{LS}\big[\lambda_{t+1}^{LS} - \lambda_{t+1}^{LI} + f(\theta_t)(\Lambda_{t+1}^{LS} - \lambda_{t+1}^{LS})\big] + \pi^E s E_t^{LS}(\lambda_{t+1}^{LS} - \lambda_{t+1}^{LI}) + \pi^E(1-s)E_t^{LS}(\Lambda_{t+1}^{LS} - \Lambda_{t+1}^{LI}) \\ + \pi^U N_t^{HS}\big[\lambda_{t+1}^{HS} - \lambda_{t+1}^{HI} + f(\theta_t)(\Lambda_{t+1}^{HS} - \lambda_{t+1}^{HS})\big] + \pi^E s E_t^{HS}(\lambda_{t+1}^{HS} - \lambda_{t+1}^{HI}) + \\ \pi^E(1-s)E_t^{HS}(\Lambda_{t+1}^{HS} - \Lambda_{t+1}^{HI}) + \pi^U\sigma N_t^{HS}\big[\lambda_{t+1}^{HI} - \lambda_{t+1}^{LI} - (1-f(\theta_t))(\lambda_{t+1}^{HS} - \lambda_{t+1}^{LS})\big].\end{aligned} \tag{96}$$

The first term in (96) captures the effect of an infected worker on low skill susceptible unemployed workers, who lose the value of unemployment, $\lambda_{t+1}^{LS} - \lambda_{t+1}^{LI}$, and a fraction, $f(\theta_t)$, who found a job and lose the value of employment, $\Lambda_{t+1}^{LS} - \lambda_{t+1}^{LS}$. The second term captures the effect on employed workers whose job was destroyed and lose the value of unemployment, $\lambda_{t+1}^{LS} - \lambda_{t+1}^{LI}$, while the third term captures the impact on employed workers who did not lose their job, but lose the value of being employed and susceptible, $\Lambda_{t+1}^{LS} - \Lambda_{t+1}^{LI}$. The next three terms are the same as the first three, except they capture the respective impacts on high skill workers. The last term captures an additional impact on high skill, unemployed workers. As some high skill workers who become infected are also exposed to skill loss, a fraction σ of them have the additional loss of the value of unemployment while being high skilled and infected, $\lambda_{t+1}^{HI} - \lambda_{t+1}^{LI}$. This is net of the typical effect of skill loss, which occurs for a fraction $1 - f(\theta_t)$ of workers who do not find a job and lose the value of unemployment while being high skilled and susceptible, $\lambda_{t+1}^{HS} - \lambda_{t+1}^{LS}$. Thus, one difference in the infection externality in our model relative to Kapička and Rupert (2020) is that an additional infection reduces the job-finding probability of high skill susceptible workers, which further exposes them to skill loss.

Next, we proceed to derive the social value of employed, low skill workers by taking the first order conditions with respect to E_t^{LS}, E_t^{LI}, and E_t^{LR}:

$$\Lambda_t^{LS} = \delta y + \bar{\beta}\{\pi_t^{EI}[(1-s)\Lambda_{t+1}^{LI} + s\lambda_{t+1}^{LI}] + (1-\pi_t^{EI})[(1-s)\Lambda_{t+1}^{LS} + s\lambda_{t+1}^{LS}]\}, \tag{97}$$

$$\Lambda_t^{LI} = \bar{\beta}\{(1-\pi_R-\pi_D)[(1-s)\Lambda_{t+1}^{LI} + s\lambda_{t+1}^{LI}] + \pi_R[(1-s)\Lambda_{t+1}^{LR} + s\lambda_{t+1}^{LR}]\} - \bar{\beta}\Psi_t, \tag{98}$$

$$\Lambda_t^{LR} = \delta y + \bar{\beta}\{s\lambda_{t+1}^{LR} + (1-s)\Lambda_{t+1}^{LR}\}, \tag{99}$$

which are analogous to the Bellmans for low skill, employed workers shown in equations (36)-(38). Again, the key difference is that equation (98) accounts for the infection externalities, whereas (37) does not.

Continuing now with high skill workers, the first order conditions with respect to N_t^{HS}, N_t^{HI}, and N_t^{HR} are given by

$$\lambda_t^{HS} = b - k\theta_t + \bar{\beta}\{f(\theta_t)(1-\pi_t^{UI})\Lambda_{t+1}^{HS} + \sigma[\pi_t^{UI}\lambda_{t+1}^{LI} + (1-f(\theta_t))(1-\pi_t^{UI})\lambda_{t+1}^{LS}] + (1-\sigma)[\pi_t^{UI}\lambda_{t+1}^{HI} + (1-f(\theta_t))(1-\pi_t^{UI})\lambda_{t+1}^{HS}]\}, \tag{100}$$

$$\lambda_t^{HI} = b + \bar{\beta}\{\sigma[(1-\pi_R-\pi_D)\lambda_{t+1}^{LI} + \pi_R\lambda_{t+1}^{LR}] + (1-\sigma)[(1-\pi_R-\pi_D)\lambda_{t+1}^{HI} + \pi_R\lambda_{t+1}^{HR}]\} - \bar{\beta}\Psi_t, \tag{101}$$

$$\lambda_t^{HR} = b - k\theta_t + \bar{\beta}\{f(\theta_t)\Lambda_{t+1}^{HR} + (1-f(\theta_t))[\sigma\lambda_{t+1}^{LR} + (1-\sigma)\lambda_{t+1}^{HR}]\}, \tag{102}$$

which are comparable to the Bellmans given by equations (33)-(35). Lastly, the first order conditions with respect to E_t^{HS}, E_t^{HI}, and E_t^{HR} are given by

$$\Lambda_t^{HS} = y + \bar{\beta}\{\pi_t^{EI}[(1-s)\Lambda_{t+1}^{HI} + s\lambda_{t+1}^{HI}] + (1-\pi_t^{EI})[(1-s)\Lambda_{t+1}^{HS} + s\lambda_{t+1}^{HS}]\}, \tag{103}$$

$$\Lambda_t^{HI} = \bar{\beta}\{\sigma\big[(1-\pi_R-\pi_D)[(1-s)\Lambda_{t+1}^{LI} + s\lambda_{t+1}^{LI}] + \pi_R[(1-s)\Lambda_{t+1}^{LR} + s\lambda_{t+1}^{LR}]\big] + (1-\sigma)\big[(1-\pi_R-\pi_D)[(1-s)\Lambda_{t+1}^{HI} + s\lambda_{t+1}^{HI}] + \pi_R[(1-s)\Lambda_{t+1}^{HR} + s\lambda_{t+1}^{HR}]\big]\} - \bar{\beta}\Psi_t, \tag{104}$$

$$\Lambda_t^{HR} = y + \bar{\beta}\{s\lambda_{t+1}^{HR} + (1-s)\Lambda_{t+1}^{HR}\}, \tag{105}$$

which are comparable to (39)-(41), the Bellman equations for high skill employed workers.

Definition 3. A constrained-efficient allocation is a sequence of worker allocations across labor market and health statuses $\{N_t^{\Omega}, E_t^{\Omega}, N_t^{\chi}, E_t^{\chi}, N_t, E_t, S_t^{\chi}, I_t^{\chi}, R_t^{\chi}, S_t, I_t, R_t, D_t\}_{t=0}^{\infty}$, composition of job seekers $\{\varphi_t, \phi_t^{\chi}\}_{t=0}^{\infty}$, match surpluses $\{\Gamma_t^{\Omega}\}_{t=0}^{\infty}$, formation of matches with type Ω workers, and market tightness $\{\theta_t\}_{t=0}^{\infty}$ for $\chi \in \{L, H\}$ and $\Omega \in \{LS, LI, LR, HS, HI, HR\}$ such that the allocation of workers across labor market statuses evolve according to (1)-(18), the allocation of workers across health statuses evolves according to (19)-(28), the composition of job seekers is given by (74)-(75), match surpluses are given by $\Gamma_t^{\Omega} = \Lambda_t^{\Omega} - \lambda_t^{\Omega}$ where Λ_t^{Ω} and λ_t^{Ω} satisfy (93)-(105), matches with low skill workers are formed if $\Gamma_t^{L\omega} \geq 0$, matches with high skill workers are formed if $\Gamma_t^{H\omega} + \sigma(\lambda_t^{H\omega} - \lambda_t^{L\omega}) \geq 0$ for $\omega \in \{S, R\}$, and market tightness satisfies (92).

Before turning to the quantitative analysis, we briefly discuss the skill composition externality.[1] To do so, we first note that the social value of forming a match with a high skill worker, as seen in equation (92), can be written as $\Lambda_t^{H\omega} - [\sigma\lambda_t^{L\omega} + (1-\sigma)\lambda_t^{H\omega}]$. So the planner uses the high

[1]See Laureys (2020) for a formal analysis of the skill composition externality.

skill worker's expected value of unemployment, $\sigma\lambda_t^{L\omega} + (1-\sigma)\lambda_t^{H\omega}$, as the worker's social value of remaining unemployed. This is because the planner internalizes that forming a match with a high skill worker prevents them from losing their skills. To further illustrate the skill composition externality, we compute the social value of forming a match with a high skill worker in the pre-pandemic steady-state:

$$\Lambda^H - [\sigma\lambda^L + (1-\sigma)\lambda^H] = \frac{y - b + k\theta + \sigma(1+\bar{\beta}s)(\lambda^H - \lambda^L)}{1 - \bar{\beta}(1 - s - f(\theta))}. \tag{106}$$

Equation (106) is directly comparable to the decentralized surplus of forming a match with a high skill worker, given by equation (52). There are several differences between equations (52) and (106). We emphasize the terms multiplied by $\lambda^H - \lambda^L$ in (106) and $\Delta^{H,L}$ in (52). What we see in (106) is the planner takes into account that if there is a separation next period, which occurs with probability s, there will be a high skill worker entering the pool of unemployed workers, rather than a low skill worker, as evidenced by $\lambda^H - \lambda^L$ being multiplied by $\bar{\beta}s$. Section 6 will show that, among other results, typically the planner creates more jobs as the social value of forming a match with high skill workers is higher than in the decentralized economy for the reasons outlined above.

6 Quantitative Analysis

We begin this section with a description of the findings from the literature on skill loss during unemployment. A salient feature is that skill losses are both large and persistent. We then quantify the effect of a pandemic on the economy. Next, we study the impact of a pandemic when the economy also faces a lockdown to try to control the pandemic. Finally, we discuss the social planner's problem to quantitatively assess the relative importance of the infection and skill composition externalities. We find that, although the social planner reduces job creation more aggressively than in the baseline economy to prevent the spread of infections, the desire to counter the skill composition externality dominates. The planner's optimal allocation features more job creation than both the baseline and the lockdown economies.

6.1 Evidence of skill loss during unemployment

Our calibration of skill loss during unemployment draws from Ortego-Marti (2016, 2017b,c), which estimate skill loss during unemployment using the 1968-1997 waves of the Panel Study of Income Dynamics (PSID), a large panel of US workers. The panel structure is important to control for workers's unobserved characteristics that may affect their productivity, as less productive workers earn lower wages and tend to be unemployed more often. In addition, the panel structure provides estimates of how wage losses depend on unemployment duration.

Ortego-Marti (2016, 2017c) find that an additional month of unemployment is associated with a 1.22% wage loss. These findings are in line with findings in the job displacement literature, which exploit the exogeneity of plant closings to estimate the causal effect of job loss on wages.[2] Except for a few studies, most estimates from the literature are not directly comparable because they lack information on unemployment duration. The most closely related findings include Schmieder et al. (2016), who estimate the causal effect of unemployment duration on wages using German administrative data. When the authors impose no restrictions on workers' prior experience in their estimation (see their Table 4, column 4), their causal estimate is 1.3%, remarkably close to the estimate of 1.22% in Ortego-Marti (2016, 2017c). Other comparable findings on the effect of unemployment duration on reemployment wages include Neal (1995), who reports a monthly depreciation of 1.59%, and Addison and Portugal (1989) who find a monthly rate of 1.44%. Both papers use the DWS supplement of the CPS, which lacks a panel structure. To the extent that displaced workers earn lower wages than their non-displaced peers, the larger estimates in Neal (1995) and Addison and Portugal (1989) may be due to the fact that they are unable to control for workers' unobserved characteristics.

The findings in the job displacement literature tend to be even larger. Jacobson et al. (1993) use administrative data from the state of Pennsylvania and find losses of around 50% at the time of separation. Earnings of displaced workers still remain 30% below the earnings of non-separated workers 5 years after separation. Davis and von Wachter (2011) use longitudinal Social Security records of US workers from 1974 to 2008 to study the effect of mass-layoffs and find average losses of around 30% upon separation. Workers see some earnings recovery, but after 20 years earnings still remain 15-20% below the control group. Using German administrative data, Jarosch (2015) finds that earnings drop by 35% upon separation and are still around 10% lower 20 years after separation. The pattern is similar for wages. Workers' wages drop by about 20% after separation, and remain around 10% lower 20 years later. Both Davis and von Wachter (2011) and Jarosch (2015) find that losses flatten after 10 years. In addition, Jarosch (2015) finds a very small difference in earnings losses between all separators and workers separated at mass-layoffs 20 years after separation, and similarly for wages, which suggests a limited effect of signaling on wage losses. These losses are all much larger than the ones implied by a 1.22% loss, which implies a 13.7% wage loss *if a worker remains unemployed for a full year*.[3] Overall, we view our choice of a 1.22% monthly skill depreciation rate as a lower bound.

More direct evidence of skill loss during unemployment are reported in Edin and Gustavsson (2008), who find that one full year of non-employment is associated with a loss of the equivalent of 0.7 years of schooling using Swedish data on test scores assessing respondents' quantitative and analytical skills. Respondents in this study are mostly low skill workers, which highlights the prevalence of skill atrophy among all workers. Further evidence of skill decay during employment breaks

[2]Fallick (1996) and Kletzer (1998) provide a review of the early findings from this literature, see Schmieder et al. (2016) and the references therein for more recent findings. Some notable papers in this literature include Couch and Placzek (2010), Davis and von Wachter (2011), Jacobson et al. (1993), Jarosch (2015), Schmieder et al. (2016) and von Wachter et al. (2009), which use administrative data; Ortego-Marti (2016), Ruhm (1991) and Stevens (1997), which use the PSID; Addison and Portugal (1989), Carrington (1993), Farber (1997), Neal (1995) and Topel (1990) which use the Displaced Worker Survey (DWS) supplement of the Current Population Survey (CPS).

[3]The average duration for workers experiencing an unemployment spell is around 2 months in the PSID.

is found in experimental data. Skill loss due to breaks in production are found in the provision of health services—David and Brachet (2011), Hockenberry et al. (2008) and Hockenberry and Helmchen (2014)—, and in jobs involving routine tasks such as data entry—Globerson et al. (1989)—, mechanical assembly—Bailey (1989)—and car radio production—Shafer et al. (2001). This literature also finds that productivity depreciation increases with the duration of the interruption between tasks. Evidence of skill loss is also found in papers studying the effects of motherhood on women's earnings, based on early papers by Mincer and Polachek (1974) and Mincer and Ofek (1982) (see (Beblo et al., 2008) and (Gangl and Ziefle, 2009) and the references therein); and in the educational literature on summer learning loss or *summer glide* among students, which also studies the large learning loss due to COVID-19 related school closures and distance learning, see Hanushek and Woessmann (2020) and the references therein.

Skill losses due to unemployment are also extremely persistent. Ortego-Marti (2016) decomposes the effect of unemployment between recent spells and spells that occurred more than 5 years prior to the survey year. Recent unemployment spells have a strong effect on wages. A month of unemployment accumulated in the previous 5 years lowers wages by 1.61%. However, a month of unemployment experienced more than 5 years prior still lowers workers' wages by 1.04%. The results are similar when one uses a cut-off of 7 years instead of 5 years. Along with the findings in Davis and von Wachter (2011) and Jarosch (2015) described above, who find that wage losses follow workers for more than 20 years, this supports our assumption of long-lasting effects of unemployment on human capital. The results on skill loss are also not driven by the life-cycle. Ortego-Marti (2017c) shows that human capital depreciation is similar across age groups, consistent with findings on the effect of job displacement for young workers (Kletzer and Fairlie, 2003). Finally, the evidence in both Ortego-Marti (2017c) and Schmieder et al. (2016) supports that wage losses depend on unemployment duration and are not simply sunk at separation.

6.2 Calibration Strategy

The unit of time is one week. The discount factor is $\beta = 0.99^{1/52}$. The weekly separation probability is set to $s = 0.035/(52/12)$. The probability of leaving the labor force is $\mu = 1/2080$, which means workers are in the labor force on average for 40 years. The output produced by high skill workers is normalized to $y = 1$. Following Hall and Milgrom (2008), the value of unemployment, b, is set so that the ratio of b to average wages is equal to 0.71. With this strategy, we find $b = 0.5203$. The meeting function is Cobb-Douglas

$$M_t = AU_t^{\alpha}V_t^{1-\alpha}, \tag{107}$$

where the matching efficiency, A, is set to target a weekly job-finding probability of $0.45/(52/12)$. Combined with normalizing steady-state market tightness to one as in Shimer (2005), we have $A = 0.1038$ and $k = 0.3047$. Based on Petrongolo and Pissarides (2001) and Pissarides (2009), the elasticity of the meeting function, α, is set to 0.5 and we subsequently assume $\eta = 0.5$ to implement the Hosios-Mortensen-Pissarides condition (Hosios, 1990).

The remaining labor market parameters are the probability of skill loss, σ, and the output produced by low skill workers, δ. We calibrate these parameters to match the empirical evidence on the effect of unemployment duration on wages. However, as discussed in Laureys (2020), this empirical evidence can not be used to choose a unique value of both σ and δ. Thus, we set $\sigma = 1/13$, which corresponds to skill loss taking 3 months on average and is well supported by the empirical evidence on how quickly skill loss occurs.[4] We then choose δ to match the estimated effects of unemployment duration on wages. That is, we choose a value of δ, and given the pre-pandemic steady-state wages across skill levels and transition probabilities between employment and unemployment, we simulate 10,000 employment histories and estimate the following regression:

$$\ln(wage) = \beta_0 + \beta_1 \times Unhis + \epsilon, \tag{108}$$

where $Unhis$ is the length of the unemployment spell in months and $\ln(wage)$ are log wages. For each simulated employment histories, we compute β_1 and repeat this process 100 times where we then have an average estimate of β_1. We vary δ and repeat this exercise until our average estimate of β_1 is -0.012, based on empirical estimates of the effect of unemployment history on wages discussed in the previous section (Ortego-Marti, 2016; Schmieder et al., 2016).[5] Through this procedure, we find $\delta = 0.725$.

There are four health parameters to calibrate. We follow Eichenbaum et al. (2020) and set the recovery probability as $\pi_R = 0.3850$ and the death probability to be $\pi_D = 0.0039$. Finally, we follow Kapička and Rupert (2020) and set $\pi^U = 0.1953$ and $\pi^E = 0.6783$ who calibrate the ratio π^U/π^E to match data on the relative amount of social interactions unemployed and employed workers have and to target a steady-state value of infected and recovered to be two-thirds.[6] Table 1 summarizes the parameter values.

6.3 Baseline Results

We assume the economy is in the pre-pandemic steady-state and the population is normalized to one. We then introduce the onset of a pandemic by assuming 0.001% of the population becomes infected.[7]

Figure 1(a) demonstrates the spread of the infection by showing the fraction of the population that is infected in each week. Infections peak in weeks 27-28 where 8.72% of the population is

[4]See Ortego-Marti (2016, 2017b,c) for evidence from the PSID regarding how quickly human capital depreciates during unemployment and how losses vary across occupations and sectors. In the Appendix, we recalibrate the model for the case where it takes an average of 6 months for loss of skill to occur. We perform the same quantitative exercises under this alternative calibrations and show the quantitative results are robust to the choice of σ.

[5]As we discuss in the previous section, our target of $\beta_1 = -0.012$ is conservative and may be viewed as a lower bound on skill loss. Given how job losses between March and April 2020 were distributed across different industries, and how skill loss differs across industries (Ortego-Marti, 2017b), the average β_1 is in fact closer to -0.013.

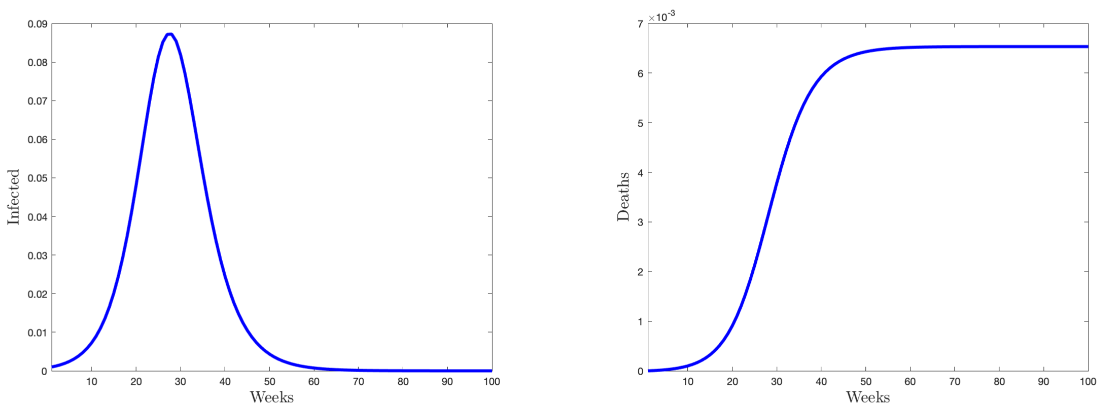
[6]The data on number of social interactions across unemployed and employed workers is based on a Gallup survey after the onset of the COVID-19 pandemic to take into account social distancing. See Kapička and Rupert (2020) for more details.

[7]See the Appendix for details on the computation procedure.

Parameter	Definition	Value
β	Discount factor	0.9998
y	Productivity of high skill workers	1.0000
s	Separation probability	0.0081
μ	Probability of exiting the labor force	4.8×10^{-4}
A	Matching efficiency	0.1038
α	Elasticity of the matching function	0.5000
η	Worker's bargaining power	0.5000
σ	Probability of skill loss	0.0769
δ	Productivity of low skill workers	0.7250
k	Vacancy posting cost	0.3047
b	Value of unemployment	0.5203
π_D	Probability of death from infection	0.0039
π_R	Probability of recovery	0.3850
π^U	Infection exposure of unemployed workers	0.1953
π^E	Infection exposure of employed workers	0.6783

Table 1: Parameter values

infected. After one year, the fraction of the population infected is well below 1% and approaches 0% thereafter. Figure 1(b) illustrates the cumulative amount of deaths throughout the pandemic. The amount of deaths levels off after one year, at 0.65% of the population.



(a) Fraction infected

(b) Total deaths

Figure 1: Total infections and deaths

Next, Figure 2 shows the connection between the pandemic and the labor market by presenting the infection probabilities across employment statuses. It is not surprising, given that $\pi^E > \pi^U$, the probability of becoming infected is larger for employed workers than those who are unemployed. At the peak of the pandemic, the probability of becoming infected for employed workers is 5.92%, whereas it is 1.70% for unemployed workers.

Figure 3(a) demonstrates the dynamics of market tightness. As employed workers have a higher

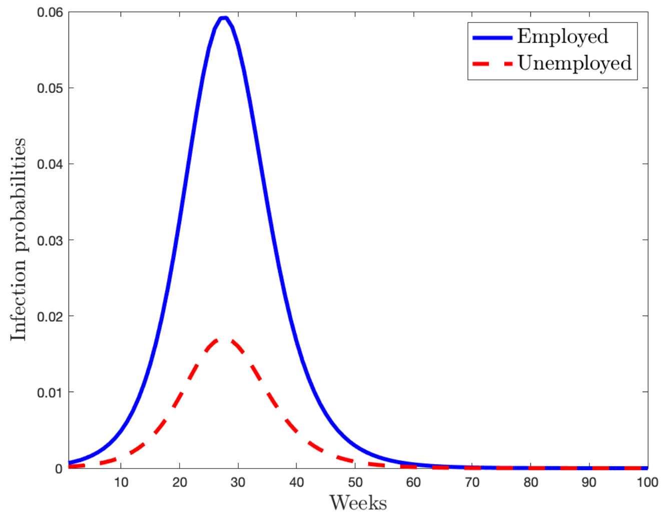
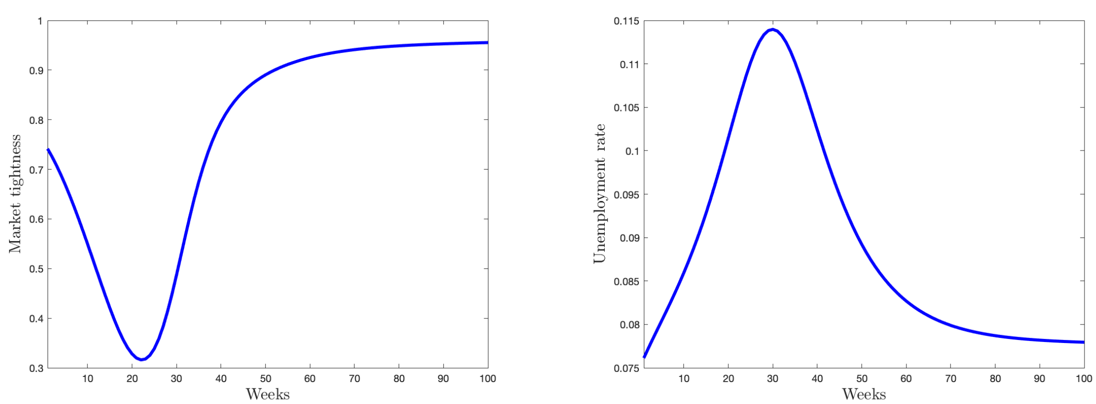


Figure 2: Infection probabilities

chance of becoming infected, and not producing output while infected, market tightness immediately declines at the onset of the pandemic from 1 to 0.7416. As the pandemic worsens and infections increase, market tightness further decreases until it reaches its lowest value of 0.3161 after 22 weeks. As the pandemic starts to recede and the number of infections decreases, job creation slowly recovers. Figure 3(b) presents the corresponding dynamics of unemployment. Given the effect of the pandemic on market tightness, the job-finding probability decreases and unemployment increases. The unemployment rate peaks at 11.4% after 30 weeks and slowly declines thereafter.

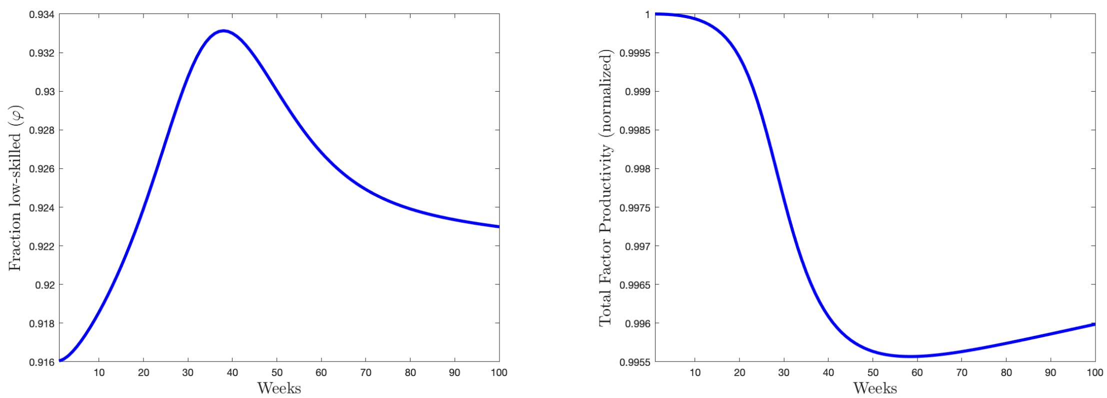


(a) Market tightness

(b) Unemployment rate

Figure 3: Market tightness and unemployment

From Figure 3 there are long-lasting effects of the pandemic on market tightness and unemployment for many months even after the number of infections is essentially zero. Figure 4 examines this in further detail by studying the effect of the pandemic on the fraction of the unemployed who are low skill (φ). As seen in Figure 4(a), the composition deteriorates over the course of the pandemic until the fraction of unemployed workers who are low skilled peaks after 39 weeks. Moreover, the composition is very slow to recover and remains at an elevated level 100 weeks after the onset of the pandemic.



(a) Composition of unemployed workers

(b) Total Factor Productivity

Figure 4: Composition of the unemployed and TFP

We conclude our baseline results by showing the effect of the pandemic on TFP, which we define as average labor productivity among workers who are productive.[8] That is,

$$\text{TFP} = \frac{y[\delta(E^{LS} + E^{LR}) + (E^{HS} + E^{HR})]}{E^{LS} + E^{LR} + E^{HS} + E^{HR}}. \tag{109}$$

As the skill level of the unemployed worsens over the pandemic, as seen in Figure 4(a), the composition of employed workers shifts to more low skill workers whose productivity is δy, causing TFP to decrease. Figure 4(b) illustrates the economic scarring effects of a pandemic. We see that TFP slowly declines through the pandemic and closely follows the dynamics of the composition of unemployed. TFP reaches its lowest value after 55 weeks, where it is 0.44% below the pre-pandemic steady-state value. We also see that TFP is slow to recover, as it is still 0.4% below the pre-pandemic steady-state value after 100 weeks.

How does a 0.44% decline in TFP compare with previous recessions? To investigate, we calculate the average decline in TFP in US recessions between 1954-2017 and find that TFP typically decreases by 1.13%.[9] Thus, our baseline results generate a decline in TFP that is nearly 39% of the typical productivity losses seen in past recessions.

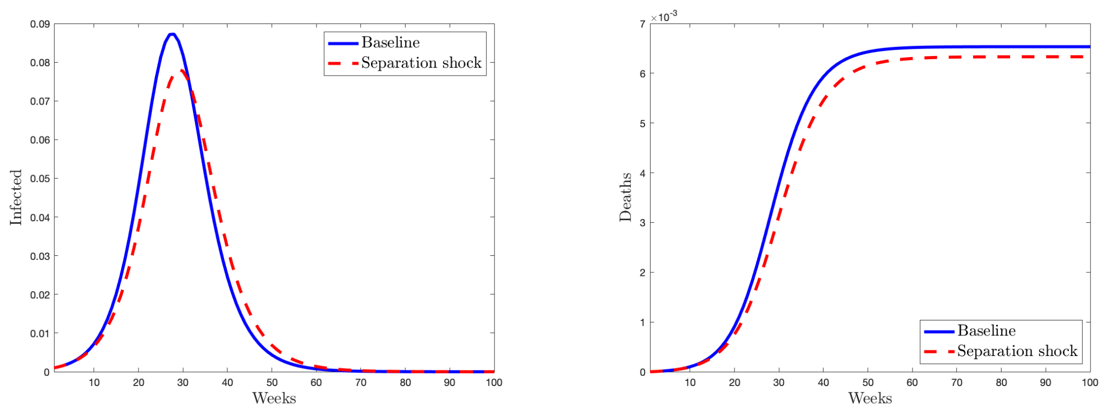
[8] Our measure of TFP does not include employed workers who are infected. In the Appendix, we present results for the response of TFP when including infected workers in the calculation of average labor productivity.

[9] We use the series "Total Factor Productivity at Constant National Prices for United States" developed by Feenstra et al. (2015) and downloadable at https://fred.stlouisfed.org/series/RTFPNAUSA632NRUG. We de-trend the series with a linear time trend and then calculate the average percentage deviations from the trend in NBER recession years.

6.4 Separation shock

To simulate a lockdown, we increase the separation probability from $s = 0.0081$ to $s = 0.0173$ (a monthly separation probability of 0.075) at the onset of the pandemic.[10] We study a three month lockdown by assuming the separation probability remains at the elevated level for three months before returning to $s = 0.0081$.

Figures 5-6 illustrate the effect of imposing a three month lockdown on the evolution of the pandemic. Beginning with Figure 5(a), increasing job separations "flattens the curve" as the fraction of the population that is infected peaks at 7.82% in week 29, as opposed to a peak of 8.72% a few weeks earlier in the baseline results. Figure 5(b) shows that lower infections reduces deaths, as the cumulative death rate decreases from 0.65% to 0.63%, saving 65,640 lives. From Figure 6, the lockdown reduces the peak infection probability among employed workers from 5.92% to 5.30%, while the peak infection probability among unemployed workers decreases from 1.7% to 1.53%.



(a) Fraction infected

(b) Total deaths

Figure 5: Total infections and deaths

Figure 7 demonstrates the impact of the separation shock on market tightness and the unemployment rate. Starting with Figure 7(a), the initial decline in market tightness is slightly larger with the lockdown. As the pandemic evolves, however, the rate of decline in market tightness is slower than the baseline results. This is due to the fact that the lockdown slows down the onset of the pandemic and employed workers have a lower probability of becoming infected. After the lockdown ends, market tightness declines further as infections increase more rapidly. It is in week 23 that market tightness reaches its lowest value of 0.2930 and begins to slowly recover.

Figure 7(b) shows the corresponding dynamics of the unemployment rate. As expected, the imposition of a lockdown through increased separations causes the unemployment rate to rapidly increase. The unemployment rate peaks at 15.23% in week 13, directly after the lockdown ends.

[10] According to the Job Openings and Labor Turnover Survey, the average monthly separation probability between March and May 2020 was 6.8%. As discussed by Coibion et al. (2020), initial job losses were likely undercounted, hence we impose a slightly larger monthly separation probability of 7.5%.

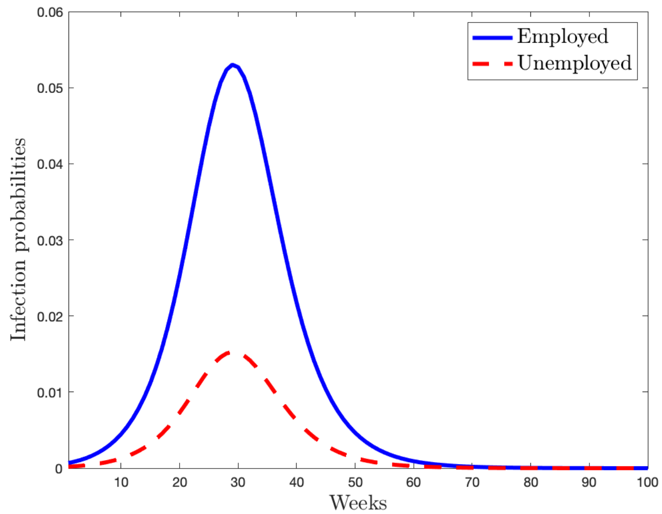
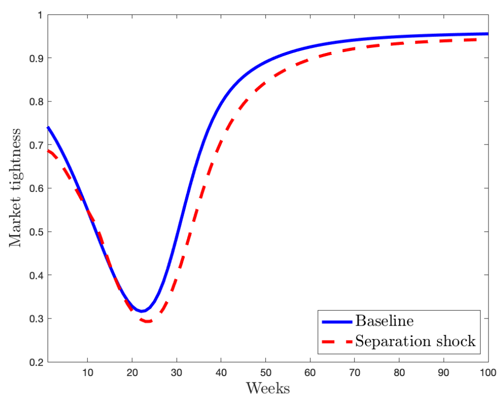
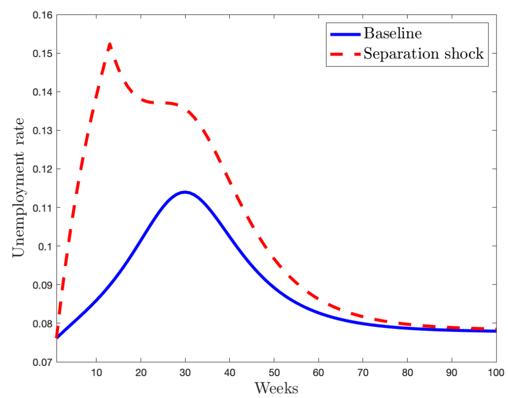


Figure 6: Infection probabilities



(a) Market tightness

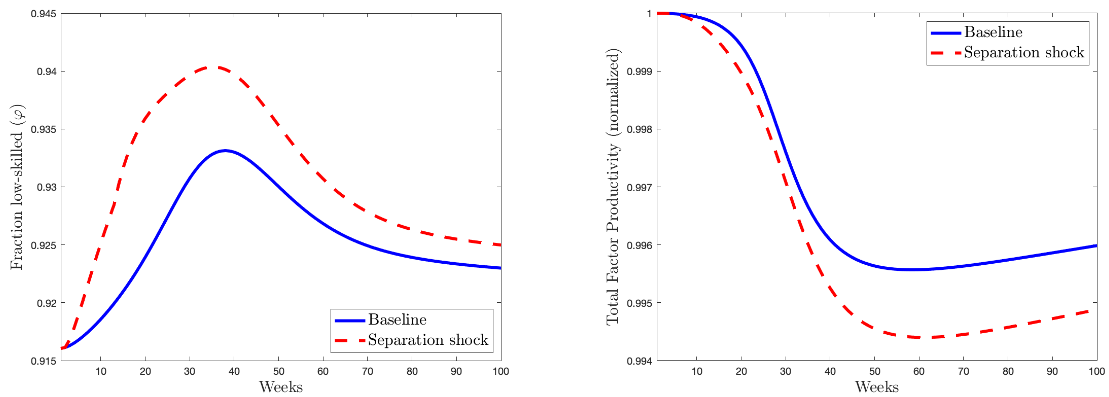


(b) Unemployment rate

Figure 7: Market tightness and unemployment

As the separation rate returns to its pre-pandemic level, the unemployment rate initially declines at a fast pace. However, as the pandemic and number of infections worsens and market tightness continues to decrease, the recovery in unemployment slows down. Between weeks 13-20, the unemployment rate decreases from 15.23% to 13.8%, or 1.43 percentage points. However, in the next twelve weeks, the unemployment rate declines by 0.80 percentage points. It is only after the number of infections substantially declines that we observe a recovery in market tightness, and thus the unemployment rate speeds up and approaches the pre-pandemic unemployment rate.

Finally, Figure 8 illustrates the long-term consequences of the separation shock on the composition of unemployed workers and TFP. Figure 8(b) shows that the average skill level among unemployed workers deteriorates at a faster pace under the lockdown. Moreover, as the amount of job creation decreases further after the lockdown ends, the composition of unemployed further worsens after the lockdown ends. Under the separation shock, the fraction of unemployed who are low skill peaks at 94.04%, whereas the composition peaks at 93.31% in the baseline results. Additionally, the fraction of unemployed who are low skill remains higher relative to the baseline results even after 100 weeks.



(a) Composition of unemployed workers

(b) Total Factor Productivity

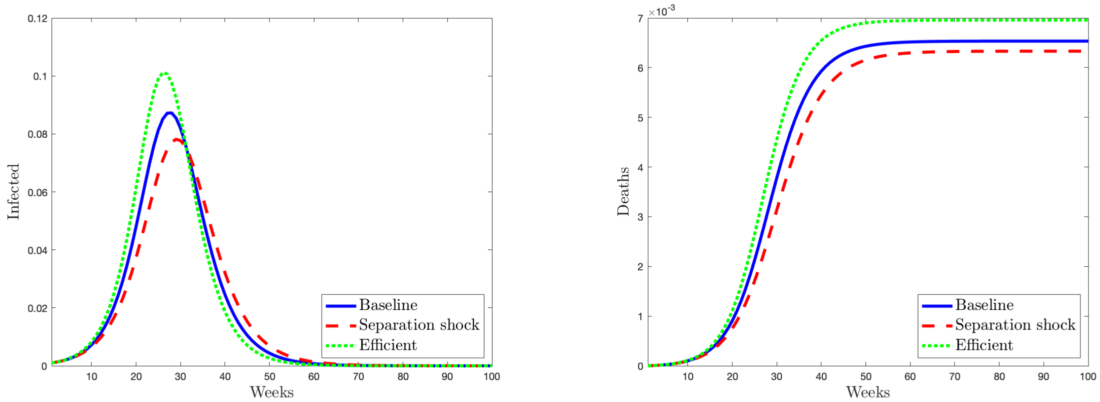
Figure 8: Composition of the unemployed and TFP

Figure 8(b) demonstrates the effect of the lockdown on TFP. Given that the skill composition of the unemployed is worse with the lockdown, it is not surprising that TFP declines even further. TFP reaches its lowest value of 0.9944 after 62 weeks, which is 0.12% lower than the lowest point in the baseline results. Given that TFP typically declines by 1.13% in recessions, the decline under the three month lockdown accounts for nearly 50% of the usual productivity losses in recessions. Further, the decline in TFP relative to the baseline scenario does not close between weeks 60-100, illustrating the additional decline in productivity due to the lockdown persists for many months after the pandemic has ended.

6.5 Efficient allocations

In this section we present the solution to the planner's problem introduced in Section 5. Beginning with Figure 9, we have the evolution of infections and deaths. As seen in Figure 9(a), infections are higher than in the baseline simulation and separation shock. Figure 9(b) shows that the amount of deaths in the planner's solution are higher than the baseline simulation: there are nearly 164,000 more deaths in the efficient allocation than the baseline allocation.

Figure 10 presents the planner's choice of market tightness. Job creation is consistently higher in the efficient allocation than the baseline allocation and separation shock. This illustrates the planner internalizing the effect creating a job has on the skill composition of the unemployed, as they create more jobs to slow down the process of skill loss among the unemployed. The results show that quantitatively the skill composition externality is significant. The optimal response with



(a) Fraction infected

(b) Total deaths

Figure 9: Total infections and deaths

skill loss is in sharp contrast with Kapička and Rupert (2020). In their environment, job creation collapses and in some cases fully shuts down when the economy is only subjected to the infection externality. However, the infection externality in our environment is also sizable. The decline in market tightness is very sharp relative to both the baseline and lockdown economies.

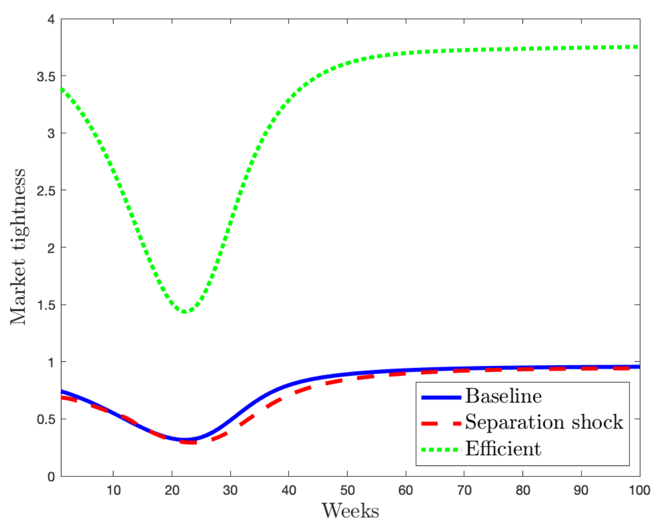
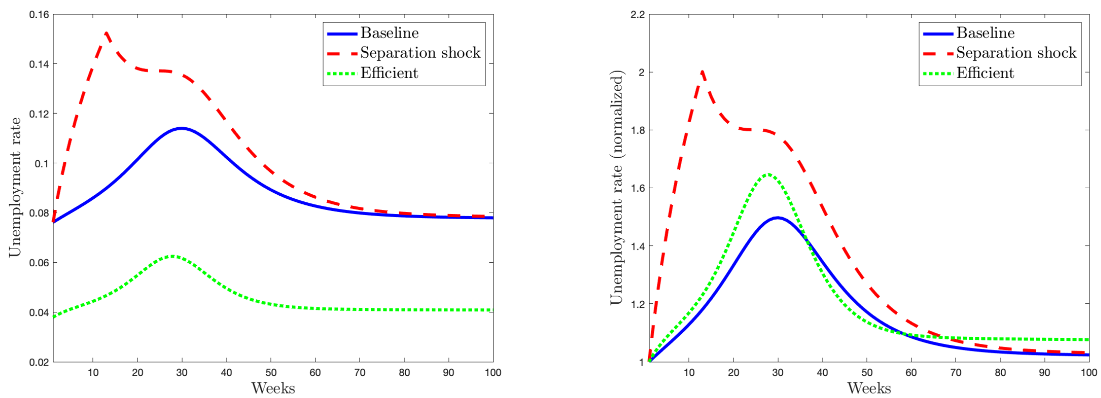


Figure 10: Market tightness

Figure 11 shows the corresponding unemployment dynamics. Beginning with Figure 11(a), the unemployment rate in the efficient allocation begins at a lower steady-state value of 3.79% as the planner creates more jobs pre-pandemic. As the planner reduces job creation, the aggregate unemployment rate increases and peaks at 6.25%. While this increase in unemployment may seem modest, it is important to consider where the unemployment rate begins pre-pandemic. Figure 11(b) shows the unemployment rate across the three allocations, each normalized to 1 at the beginning of the pandemic. We see that the relative increase in unemployment in the efficient allocation is larger than the baseline allocation, reflecting that the planner internalizes the infection externalities. However, the increase in unemployment in the efficient allocation is not as extreme as the separation shock, which caused the unemployment rate to nearly double.

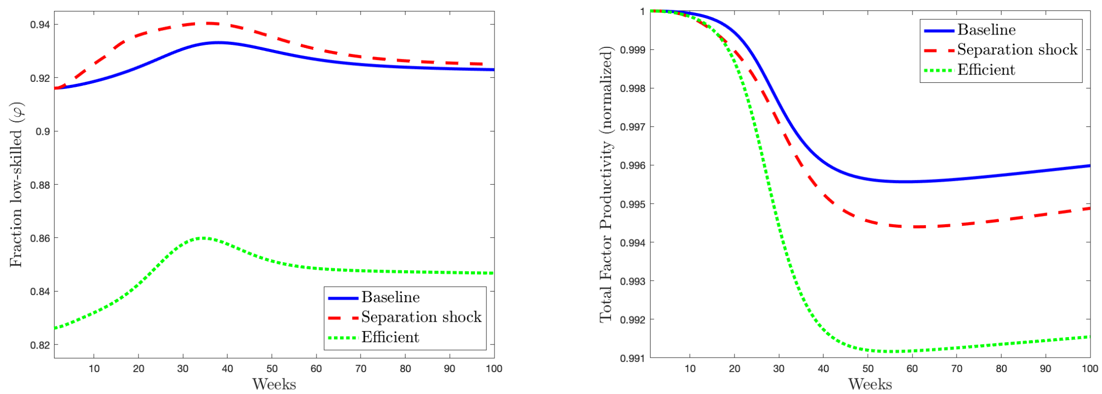


(a) Unemployment

(b) Unemployment (normalized)

Figure 11: Optimal unemployment

Lastly, Figure 12 presents the composition of the unemployed and TFP under the efficient allocation. Beginning with Figure 12(a), the skill composition under the efficient allocation begins with a lower proportion of low skill workers. This is because the planner creates more jobs in the pre-pandemic steady-state, thereby reducing high skill workers' exposure to skill loss. As the pandemic begins and worsens, the skill composition deteriorates. As infections decrease and more vacancies are created, the skill composition in the efficient allocation recovers as job creation in the efficient allocation is higher. Figure 12(b) shows that TFP declines considerably in the efficient allocation, reaching its lowest value 63 weeks after the pandemic began with a decline of 0.88%. It is important to note that while TFP exhibits its largest percentage decrease under the efficient allocation, the level of TFP is consistently higher in the efficient allocation than in the baseline and separation shock, as seen in Figure 13.



(a) Composition of unemployed workers

(b) Total Factor Productivity

Figure 12: Composition of the unemployed and TFP

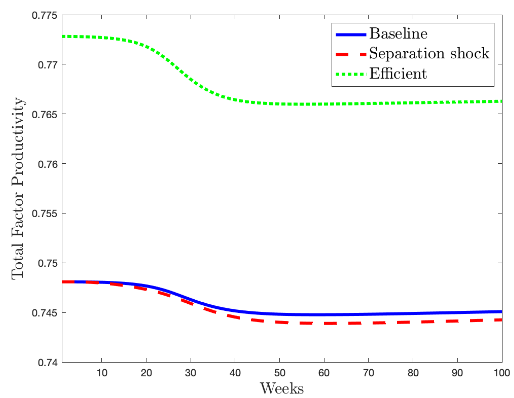


Figure 13: Non-normalized levels of TFP

7 Conclusion

The health and economic costs caused by the COVID-19 pandemic have been substantial. Given that workers lose skills during unemployment, the economic costs of the pandemic are likely to be long-lasting, potentially scarring the economy for years to come. To study this, we have integrated a frictional labor market with skill loss during unemployment with the Kermack and McKendrick (1927) SIR framework. The model shows that the onset of a pandemic reduces job creation, which in turn exposes unemployed workers to skill loss. As the skill composition of unemployed workers worsens over the pandemic, average labor productivity and TFP decrease. Our model suggests that the scarring effects of the COVID-19 pandemic on the economy through skill loss during unemployment will be substantial, as the decline in TFP following a three month lockdown accounts for nearly 50% of the productivity losses typically observed in recessions.

The decentralized equilibrium is not efficient due to the infection and skill composition externalities. These externalities also present a tradeoff to a social planner: reducing job creation lessens infections and deaths while also worsening the skill composition of the unemployed and productivity. Our quantitative results show that the planner creates more jobs throughout the pandemic to limit skill loss among the unemployed. The planner, however, does reduce job creation more relative to the pre-pandemic steady-state than the baseline allocation to account for the infection externalities.

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Appendix

Proof of Proposition 1

We begin by deriving the closed-form job creation condition. From the Bellman equations for unemployed workers, it is simple to show

$$U^H - U^L = \frac{\bar{\beta}\eta f(\theta)[F^H - F^L]}{1-\bar{\beta}(1-(1-f(\theta))\sigma)}. \tag{110}$$

Substituting (110) into (52), we have that F^H satisfies

$$F^H = y - b + \bar{\beta}\left\{(1-s-\eta f(\theta))F^H + \bar{\beta}(1-f(\theta))\sigma\eta f(\theta)\frac{F^H - F^L}{1-\bar{\beta}(1-(1-f(\theta))\sigma)}\right\}. \tag{111}$$

Substituting for F^L using (51) and solving for F^H yields

$$F^H = \frac{(y-b)[1-\bar{\beta}(1-(1-f(\theta))\sigma)][1-\bar{\beta}(1-s-\eta f(\theta))] - \bar{\beta}^2(1-f(\theta))\sigma\eta f(\theta)(\delta y - b)}{[1-\bar{\beta}(1-(1-f(\theta))\sigma)][1-\bar{\beta}(1-s-\eta f(\theta))]^2 - \bar{\beta}^2(1-f(\theta))\sigma\eta f(\theta)[1-\bar{\beta}(1-s-\eta f(\theta))]}. \tag{112}$$

With equations (51) and (112), we can write the job creation condition as

$$\frac{k[1-\bar{\beta}(1-s-\eta f(\theta))]}{\bar{\beta}(1-\eta)q(\theta)} = \varphi(\delta y - b) +$$

$$(1-\varphi)\frac{(y-b)[1-\bar{\beta}(1-(1-f(\theta))\sigma)][1-\bar{\beta}(1-s-\eta f(\theta))] - \bar{\beta}^2(1-f(\theta))\sigma\eta f(\theta)(\delta y - b)}{[1-\bar{\beta}(1-(1-f(\theta))\sigma)][1-\bar{\beta}(1-s-\eta f(\theta))] - \bar{\beta}^2(1-f(\theta))\sigma\eta f(\theta)}, \tag{113}$$

where φ is given by (56). A sufficient condition for an equilibrium to exist will ensure that the left hand side and right hand side of (113) cross at least once. It is easy to verify that as $\theta \to \infty$, the left hand side approaches ∞ while the right hand side converges to $y - b$. Thus, a sufficient condition for at least one crossing is that the value of the left hand side is below that of the right hand side at $\theta = 0$. It is straitforward to verify that this is true when (58) holds. ■

Computation Procedure

We assume that the economy has reached its post-pandemic steady-steady at a date, T, that is sufficiently far into the future and compute the equilibrium as follows.

1. Guess a sequence $\{\theta_t\}_{t=0}^{T-1}$.
2. Given the sequence of market tightness and initial values, I_0 and Pop_0, compute $\{I_t, \varphi_t, \phi_t^{\chi}\}_{t=0}^{T-1}$.
3. Using output from step 2, iterate backwards from T to compute the sequence $\{F_t^{LS}, F_t^{LR}, F_t^{HS}, F_t^{HR}\}_{t=0}^{T-1}$.
4. Using output from both steps 2 and 3, compute a new sequence $\{\theta_t^*\}_{t=0}^{T-1}$ using the job creation condition.

5. Adjust the initial guess in step 1 using a gradient-based method until the sum of squared differences between $\{\theta_t\}_{t=0}^{T-1}$ and $\{\theta_t^*\}_{t=0}^{T-1}$ is arbitrarily small.

Alternative Calibrations

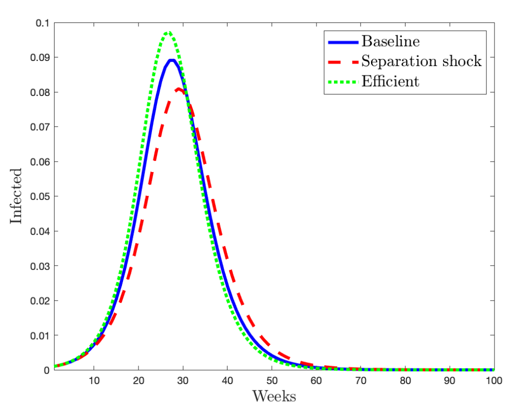
In the baseline calibration, we take the assumption that it takes workers on average 3 months to experience loss of skill during unemployment. We then chose δ to match the empirical evidence on the effect of length of unemployment duration on wages. Here, we present on the alternative calibration that it takes on average six months for workers' human capital to depreciate. Table 2 shows how the alternative strategies change the calibrated parameters.[11]

Parameter	Definition	Baseline	6 month skill loss
σ	Probability of skill loss	0.0769	0.0385
δ	Productivity of low skill workers	0.7250	0.7475
k	Vacancy posting cost	0.3047	0.3796
b	Value of unemployment	0.5203	0.5474

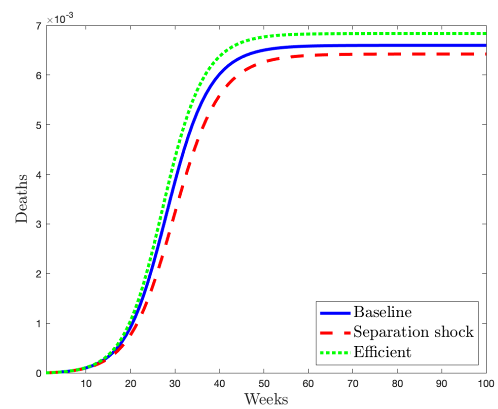
Table 2: Parameter values under alternative values of σ

Quantitative Results: Skill Loss in 6 Months

We also simulate the effect of a pandemic under the calibration where skill loss occurs on average in 6 months. Figures 14-16 present the results.



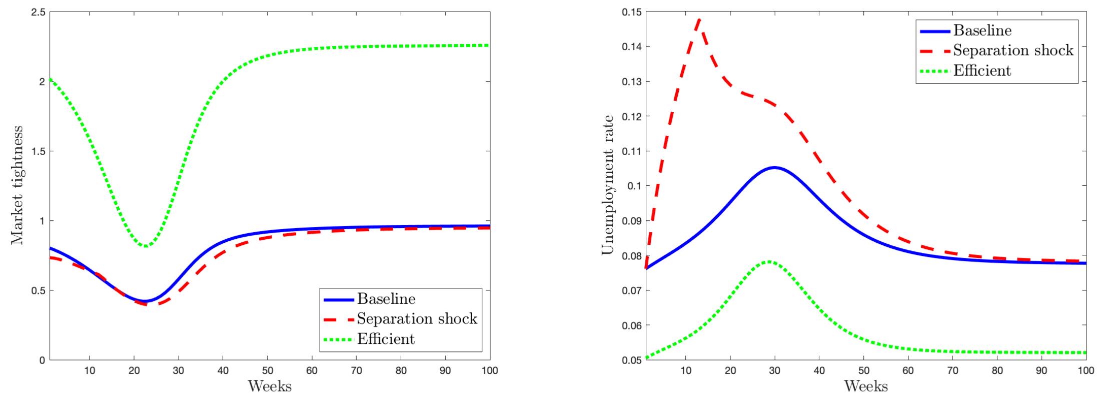
(a) Fraction infected



(b) Total deaths

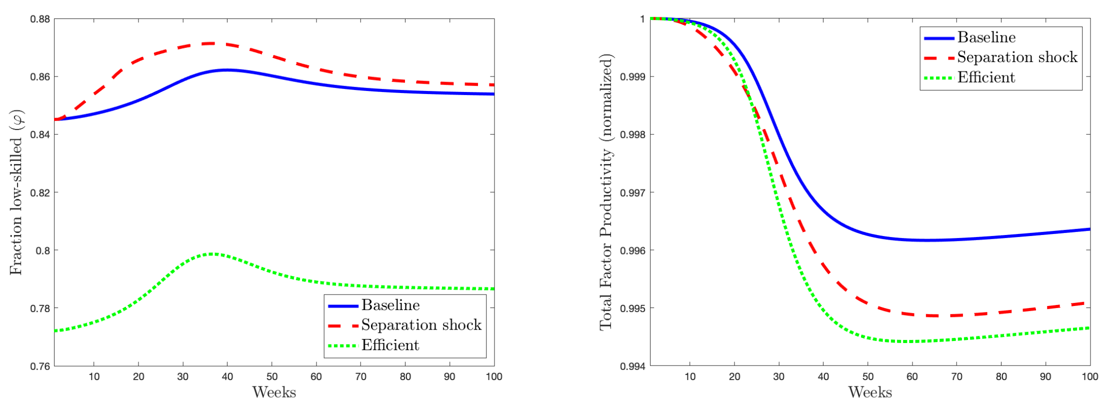
Figure 14: Total infections and deaths - Skill loss in 6 months

[11] Parameters not listed in Table 2 take the same values as in Table 1.



(a) Market tightness (b) Unemployment rate

Figure 15: Market tightness and unemployment - Skill loss in 6 months



(a) Composition of unemployed workers (b) Total Factor Productivity

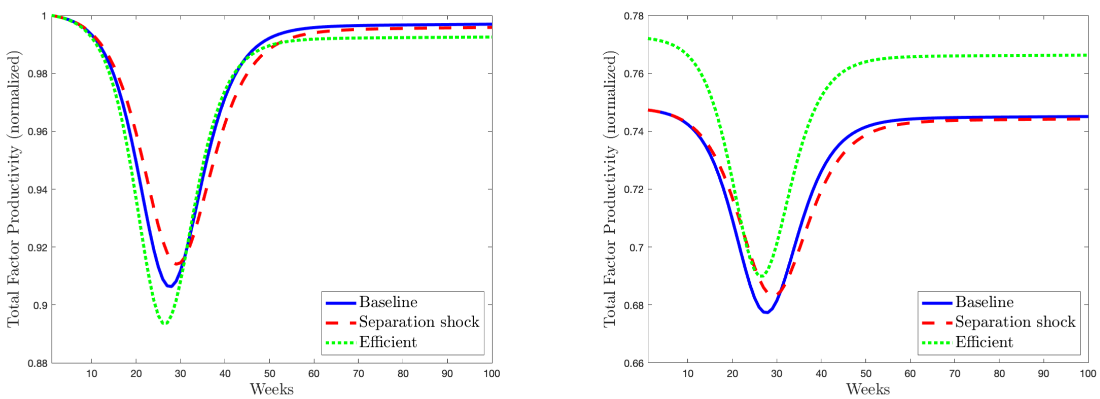
Figure 16: Composition of the unemployed and TFP - Skill loss in 6 months

TFP including infected workers

In the main text, our calculation of TFP, as seen in equation (109), does not include infected workers. In this section, we present an alternative measure of TFP that does include these workers and present quantitative results under this definition. This alternative measure of TFP is given by:

$$\text{TFP} = \frac{y[\delta(E^{LS} + E^{LR}) + (E^{HS} + E^{HR})]}{E^{LS} + E^{LI} + E^{LR} + E^{HS} + E^{HI} + E^{HR}}, \tag{114}$$

where the only difference relative to (109) is we include infected workers, $E^{\chi I}$ for $\chi \in \{L, H\}$. Note in equation (114) that infected workers do not show up in the numerator as they do not produce any output while infected. Figure 17 presents the corresponding dynamics of our alternative measure of TFP for the three analyses presented in Sections 6.3-6.5. Clearly, the productivity losses are much larger under this measure, approximately 9%, as a large fraction of the workforce produces zero output when infection rates are high.



(a) Normalized (b) Levels

Figure 17: TFP when including infected, employed workers