Worker heterogeneity, selection, and unemployment dynamics in a pandemic*

Federico Ravenna† and Carl E. Walsh‡

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Abstract

We employ a new Keynesian model with random search in the labor market and endogenous selection among heterogeneous workers to investigate the impact of a pandemic-induced recession on the distribution of unemployment across workers. In such a recession, workers whose unemployment spells in normal times are inefficiently frequent and long are disproportionately affected. This remains true even when the pandemic initially causes mass layoffs that affect workers broadly or if many separations represent temporary layoffs. Monetary policy that responds to labor market variables affects unemployment for all workers but does relatively little for the distribution of unemployment across the workers.

Keywords: Unemployment, heterogeneity, selection, COVID-19, monetary policy

JEL classification: E24, E32, E52.

The COVID-19 pandemic of 2020 generated a severe economic contraction in the global economy, and its impact on unemployment was unlike anything seen in previous recessions. The unemployment rate in the U.S. jumped from 3.5% in February 2020 to 14.8% in April. In contrast, the Great Recession following the global financial crisis resulted in a peak U.S. unemployment rate of 10% in October 2009, which, in turn, was the highest level seen over the previous quarter of a century.[1] Using a heterogeneous worker new Keynesian model with search and matching frictions in the labor market in which firm-worker matches that end are

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†Head of Research, Danmarks Nationalbank, University of Copenhagen, HEC Montreal and CEPR. Email: fera@nationalbanken.dk.

‡Distinguished Professor of Economics Emeritus, University of California, Santa Cruz. Email: walshc@ucsc.edu.

[1] In June 1983, the unemployment rate was 10.1%.

not simply chosen randomly from among existing matches and firms selectively screen job seekers before making hires, we show how a pandemic recession disproportionately affects those workers who, in normal times, experience longer and more frequent spells of unemployment. In addition, endogenous separations and hiring decisions are inefficient in the competitive market equilibrium; workers with higher average unemployment rates experience more unemployment than is socially efficient; workers with lower average unemployment rates experience less unemployment than is socially efficient. Endogenous selection matters even in a COVID-19 pandemic scenario in which there is a surge in mass layoffs that initially affects all workers non-selectively. Workers with lower average unemployment rates benefit if separations in a pandemic take the form of temporary layoffs, as layoffs initially did in the COVID-19 recession, but this benefit is not shared by workers with higher average unemployment rates.

The paper makes four primary contributions. First, we identify a new externality when selection arises from labor heterogeneity. Individual firms in the market equilibrium ignore the effects their separation and hiring decisions have on the size and the composition of the pool of unemployed workers. The first effect on the size of the unemployment pool is well-known and gives rise to the Hosios condition for search efficiency. The second effect on the average quality of the unemployment pool distorts the distribution of unemployment across worker types. Second, we model the pandemic as a negative preference shock that reduces market consumption and a spike in mass layoffs and show how the latter ends up having a disproportional effect on the workers with higher average rates of unemployment. Third, we show that if layoffs in a pandemic are predominately temporary, the recession still induces a rise in endogenous separations, and the employment benefits of temporary layoffs accrue primarily to the workers with lower average unemployment rates. Fourth, we find that if the central bank responds to labor market variables, it can limit the volatility of unemployment, but the ability of monetary policy to affect the distribution of unemployment across worker types is limited.

The COVID-19 recession has been the result of a variety of underlying shocks that do not easily map into the parsimonious number of shocks typically included in a macro model, and the recent literature has employed different strategies for modelling the causes of the recession. Combinations of supply and demand shocks are employed by Baqaee and Farhi (2020), Fornaro and Wolf (2020), and Kocherlakota (2020). The nature of the supply shock has been treated differently in the literature. Kocherlakota (2020) models it as restrictions on labor supply, while Gregory et al. (2020) assume a temporary decline in worker productivity, and Bernstein et al. (2020) employ a large and persistent job separation shock. Models based on infection shocks include Kapicka and Rupert (2020), Jackson and Ortego-Marti (2020) who combine an infection shock with a skill loss shock that hits the unemployed, and Eichenbaum et al. (2020) and Lepetit and Fuentes-Albero (2021) who imbed an infection shock into a NK framework.

While it is clear that there is not yet a consensus on how to fully replicate the shocks that generated the COVID-19 recession, we choose to combine a preference shock that shifts demand away from market goods and towards leisure and home production with a shock to exogenous separations that affects all workers as a means of capturing many aspects observed in the pandemic.[2] To produce the COVID-19 scenario, we build a hypothetical scenario based on forecasts for observable variables, specifically total separations and output, that were produced at the beginning of the COVID-19 recession. That is, rather than simulate the model's response to exogenous shocks, as in a standard impulse response exercise, we let the model back out the preference and separation shocks that drive the dynamics, conditional on the forecasts.

A preference shock is a standard means of generating an aggregate demand shock in NK models, while a separation shock helps capture the sharp rise in layoffs during the initial stages of the pandemic when stay-at-home measures caused a collapse in demand while lockdowns forced businesses to temporarily close. The result was a surge in unemployment across the entire economy.[3] In contrast to Bernstein et al. (2020) in which all separations are exogenous, we emphasize endogenous separations that amplify the effects of a shock to exogenous separations. We stress how endogenous separations differentially affect those workers who take longer to find new jobs, thus helping to account for the persistence of the rise in unemployment.[4]

[2] Our choice of a separation shock is discussed further in section 3.

[3] Aum et al. (2020) estimate that up to half of job losses in the U.S. and UK may have been due to lockdowns., and the evidence in Kahn et al. (2020) suggests employment losses in April 2020 as measured by unemployment insurance claims were common across U.S. industries and occupations, whether the industry was considered essential or work-from-home capable.

[4] Cheng et al. (2020) finds that "the groups that had the highest unemployment rates in April also tended to have the lowest reemployment rates, potentially making churn harmful to people and groups with more and/or longer job losses." And Gregory et al. (2020) conclude that "...the lockdown instituted to prevent the spread of the novel coronavirus is shown to have long-lasting negative effects on unemployment. This is so because the lockdown disproportionately disrupts the employment of workers who need years to find stable jobs."

We focus on heterogeneity across workers rather than other dimensions of heterogeneity such as differential effects across sectors or industries. This is motivated in part by recent discussions by policymakers who have displayed interest in the labor market and distributional consequences across workers of monetary policy. For example, Federal Reserve Chair Powell has stressed the gains to those who may benefit from a strong labor market (Powell 2020).[5] Our framework allows us to explore some of the consequences of monetary policy for differences in labor market experiences across workers.

Our paper is related to three areas of the literature: research on worker and match heterogeneity, search and matching models with nominal rigidities, and recent work on the macroeconomic effects of COVID-19.

Worker and match heterogeneity play a key role in several models in the search and matching literature and in models with job-to-job transitions (e.g., Guerrieri (2007), Nagypal (2007), Nagypal and Mortensen (2007), Bils et al. (2012), Hall and Schulhofer-Wohl (2018)). Workers differ along many dimensions, and some, such as educational level, specific job skills or experience, age, and gender may be easily observable. The heterogeneity we focus on arises from *ex ante* unobservable differences among workers.[6] Workers with certain characteristics (young, low-schooling, etc.) experience higher increases in joblessness during a downturn, and several authors (see Grigsby 2020; Baley 2020) find that these workers also differ in unobservable characteristics; ceteris paribus, they have lower productivity. Using CPS data Grigsby (2020) estimates that selectivity in separations and hiring during the Great Recession led to the efficiency of production workers rising by 50%, and to a 10% rise in the aggregate mean human capital of employed workers economy-wide. Positive selection in the employment pool is mirrored by negative selection into the unemployment pool during recessions. In our model this selection effect alters the quality composition of the unemployment and leads to inefficiency in the allocation and excess volatility of unemployment, relative to an environment not

[5] Bergman et al. (2021) use a model of unobserved-heterogeneity across workers to study the effects of monetary policy shock. They show that tight labor markets benefit low-skill workers disproportionally.

[6] Mincer-wage regressions that condition on observable characteristics of workers exhibit large unexplained residual variation in wages across workers (see Lemieux (2006), and Hornstein et al. (2011)). Other aspects of labor market outcomes are also difficult to explain based on observable worker characteristics. For example, Dickens and Triest (2012) estimate a model of involuntary separation transition probabilities; controlling for age, education, race, and gender, their estimated equation has an R-squared of 0.129, suggesting heterogeneity of worker experiences within groups classified based on standard observable characteristics is important.

accounting for selection.

In a model with heterogeneous skills and exogenous separation rates, Pries (2008) shows that the composition effect has a large impact on the cyclical value of vacancies and thus on the behavior of employment flows. Ahn and Hamilton (2019) emphasize unobserved differences across workers in (exogenous) unemployment exit probabilities, consistent with the idea that heterogeneity among the workers flowing into unemployment can account for differences in future outflow rates. Kospentaris (2020) argues that unobserved heterogeneity has a large impact on job-finding rates and finds it can explain more than two thirds of total duration dependence in unemployment. This heterogeneity hypothesis (see Davis 1996 and Baker 1992) is central to our approach.

Ravn and Sterk (2017) also develop a model with worker heterogeneity, but they focus on differences in search efficiency rather than productivity differences, and they assume separation probabilities are the same all workers – only job finding rates differ. We allow both separation rates and job finding rates to vary endogenously and to differ across worker types.

While the framework we propose is closely related to this previous work on labor heterogeneity in a search and matching environment, we provide a model with nominal rigidities that allows the role of monetary policy to be analyzed. Our modeling framework is thus part of the literature that combines search and matching labor markets with nominal frictions. Earlier contributors to this area include, among others, Walsh (2003, 2005), Trigari (2009), Sala et al. (2008), Thomas (2008), Gertler et al. (2008), and Ravenna and Walsh (2008). These contributions, all assume homogenous workers. We show how layoffs in the competitive equilibrium can be inefficient when labor is heterogeneous, a result that is consistent with that of Berger et al. (2019), who argued for monetary policy to target the layoff rate in a model with countercyclical layoffs.

Finally, a growing number of papers have modelled the macroeconomic implications of COVID-19. Guerrieri et al. (2020) focus on sectorial heterogeneity in a two-sector model to show how job destruction in one sector can create a demand-driven recession in the other sector. Kapicka and Rupert (2020) focus on employment adjustments caused by a pandemic within a search and matching framework which distinguishes between workers by health status. Gregory et al. (2020) study the effects of COVID-19 in a search model with worker and sector heterogeneity. They assume transition probabilities between states are partly exogenous, depending on the worker type. Our focus is on how selection affects those probabilities through the impact of shocks on optimal labor market choices. We also incorporate nominal rigidities and endogenous variation in the discount rate, the latter a factor emphasized by Hall (2017) and found by Leduc and Liu (2020) to be important in explaining labor market fluctuations. Consistent with our results and those of Hall (2015) and Ravn and Sterk (2017), the low job-finding rate of some workers plays a crucial role in the behavior of unemployment during recoveries.[7]

The paper is organized as follows. In section 1, the basic theoretical model of Ravenna and Walsh (2012) on which we build is briefly reviewed. We then show, in section 2, that even when prices are flexible and the Hosios condition for search efficiency is satisfied, worker heterogeneity results in inefficient job separations and hiring decisions. In section 3 we use the model to simulate a COVID-19 recession caused by social distancing and lockdown requirements that result in mass layoffs and a drop in aggregate demand. We then extend the model in section 4 to include temporary layoffs. In section 5 we investigate whether monetary policy responses to labor market variables can both reduce unemployment in a pandemic and reduce inequality in the distribution of unemployment across workers; we also assess the inflation consequences of such policies. Conclusions are summarized in section 6.

1 The model of productivity heterogeneity

In this section, we describe the basic model of worker heterogeneity and explain how selectivity in hiring and retention decisions affects employment dynamics. The model deviates from a standard NK model with search and matching model with endogenous separations such as Walsh (2005) by adopting the simple model of worker heterogeneity developed in Ravenna and Walsh (2012).[8] As such, we focus here on the key elements that differentiate the model from a basic NK model; details on the complete model can be found in the online appendix. We

[7] In analysing recovery after the Great Recession, Hall (2015) concludes that "The return to normal has been slower than in previous postrecession episodes because the crisis shifted the composition of job seekers toward those with low job-finding rates and low exit rates from unemployment." (p. 121)

[8] Our model is as close as possible to a baseline new Keynesian model of the business cycle with search and matching in the labor market. See Ravenna and Walsh (2012) for more details and for an analysis of the effects of selection on the dynamic impact of productivity shocks.

discuss the baseline selection mechanism assuming only two states for workers - employed or searching for employment; in section 4 we extend the model to allow some unemployed workers to be on temporary layoff and not actively searching for a job.

The model consists of households, wholesale and retail firms, and a monetary policy authority. The representative household purchases consumption goods, holds bonds, and supplies labor to wholesale firms. Wholesale firms hire labor in a market characterized by search and matching frictions and produce a homogeneous good that is sold in a competitive market to retail firms. Retail firms transform the wholesale good into differentiated final goods which are sold to households for consumption and to wholesale firms to use in posting job vacancies. Prices of retail goods are sticky ala Calvo.

1.1 Worker types and productivity

We assume workers are of two types that differ in their average productivity and its variability: we refer to these types as low-efficiency workers and high-efficiency workers. While an unemployed worker's type is unobserved ex ante, we assume a firm that is hiring engages in a process of interviewing, or screening, during which the firm is able to observe the productivity of a job applicant. Firms can also observe the productivity of their existing employees.[9] Firms employ an (optimal) cutoff productivity strategy; any job applicant whose productivity exceeds the cutoff is hired; any existing worker whose productivity is below the cutoff is fired. This cutoff productivity threshold is endogenous; in a recession it rises so that some unemployed workers who would be hired in normal times are not hired, and some existing employed workers who would be retained in normal times are not retained.

A fraction $\bar{\gamma}$ of workers are of low (l) average efficiency, while the remaining $1-\bar{\gamma}$ are of high (h) average efficiency.[10] The worker's efficiency type, h or l, is permanently assigned. If L^j denotes the labor force of type j, $j = h, l$, we normalize the total labor force such that $L^h + L^l = L = 1$. Total employment is $N_t = N_t^l + N_t^h$, where N^j is the number of type j workers who are employed. Define $\xi_t \equiv N_t^l/N_t$ as the fraction of employed workers who are of

[9] By assuming *ex ante unobservable heterogeneity,* the effects we emphasize would still operate within each submarket if labor markets were segmented by observable characteristics.

[10] Ahn and Hamilton (2019) show that the average duration of US unemployment can be matched if the labor force consists of just two types of workers who differ in their job finding probabilities, as will be the case endogenously in our model.

type l. The productivity of a type h worker is constant and equal to ϕ^h, while the productivity for a type l worker is stochastic and equal to $a^l_{i,t}\phi^l$, where $a^l_{i,t}$ is an idiosyncratic, stochastic productivity shock to worker i of type l. We assume $a^l_{i,t}$ is serially uncorrelated and uniformly distributed between zero and one; its cumulative distribution function is denoted by $F(.)$.[11] A low-efficiency worker is less productive than an high-efficiency worker on average, but not always. For high realizations of the idiosyncratic productivity shock, $a^l_{i,t}\phi^l$ can exceed ϕ^h. The productivity volatility of low-efficiency workers could arise because they experience highs and lows, extremely productive at times, unproductive other times, or they may be workers with unstable or chaotic lives outside of work or health issues that get reflected in variation in their job performance. Whatever the source, employers may have difficulty discerning these characteristics of workers without interviewing them or actually observing them as an employee.

1.2 Households, labor flows, and vacancies

The household consists of a continuum of workers. The representative household maximizes

$$\mathrm{E}_t \sum_{i=0}^{\infty} \beta^i \left\{ D_t \frac{\mathcal{C}_{t+i}^{1-\sigma}}{1-\sigma} - \left[v(h^h_{t+i})(1-\xi_{t+i})N_{t+i} + \xi_{t+i}N_{t+i} \int_{\bar{a}_t}^{1} v(h^l_{i,t+i}) f(a) da \right] \right\}, \tag{1}$$

where $\sigma > 0$ is the coefficient of relative risk aversion, D_t is an aggregate preference shock, $\mathcal{C}_t$ is the sum of a market-purchased composite consumption good C_t and home-produced consumption by unemployed workers $C^u_t = (1 - N_t)w^u$. In (1),

$$v(h^h_{t+i})(1-\xi_{t+i})N_{t+i} + \xi_{t+i}N_{t+i} \int_{\bar{a}_t}^{1} v(h^l_{i,t+i}) f(a^l) da^l$$

is the disutility to the household of having N_t members working. Hours worked by a type l will depends on the worker's idiosyncratic productivity shock, while because all type h workers are equally productive, they all supply the same number of hours. We assume $v(h_{t+i}) = \ell h_{t+i}^{1+\chi}/(1+\chi)$.

A firm can observe the productivity of its existing employees. However, firms must interview

[11] This assumption is for simplicity as it will imply that endogenous separations and interviews that do not lead to hires only involve low skilled workers. In section 2, we discuss the inefficiency of the allocation and the online appendix shows that the efficiency results extend to the case in which both types are treated symmetrically in experiencing idiosyncratic, stochastic fluctuations in productivity and endogenous separations.

unemployed job applicants to determine a job seeker's current productivity level and efficiency type. The aggregate number of interviews per period is determined through random matching, and all job seekers have identical interview-finding probability, regardless of type. At the interview, the job applicant's productivity level and type is revealed. We assume the (non-stochastic) productivity of an h worker is sufficiently high to guarantee a positive surplus in all states. Thus, if the efficiency type is revealed to be h, the worker is hired and produces with probability equal to one. If an interview reveals the job seeker is a type l, firms hire only type l workers whose productivity is sufficient to generate a positive surplus. Because currently employed type l workers also receive new idiosyncratic productivity realizations, only those who continue to generate a positive surplus are retained.

At the start of each period, there is an exogenous, stochastic separation realization ρ_t^x that affects all employed workers, regardless of type. We treat the mass layoffs associated with social distancing requirements and lockdowns at the onset of COVID-19 as, in part, an exogenous spike in this separation hazard.

The number of job seekers, denoted by S_t, equals those unmatched at the start of the period plus those who do not survive the exogenous separation hazard, or $S_t = 1 - (1 - \rho_t^x) N_{t-1}$. We define the end-of-period number of unemployed workers as $U_t = 1 - N_t$.[12] Let S_t^j be the number of type j workers who are seeking jobs (so $S_t = S_t^h + S_t^l$) and denote the share of job seekers of type l by $\gamma_t \equiv S_t^l / S_t$. After exogenous separations occur, all other aggregate shocks realizations are observed and wholesale firms determine a productivity cutoff $\bar{a}_t^l$ that determines whether a type l worker will generate a positive surplus. The time t idiosyncratic productivity shocks associated with employed low-efficiency workers and with job seekers who are interviewed are observed. With probability $\rho_t^n \equiv F(\bar{a}_t^l)$, a low-efficiency worker's productivity draw will be less than $\bar{a}_t^l$. An unemployed low-efficiency worker with $a_{i,t}^l < \bar{a}_t^l$ who is interviewed is not hired. Absent any direct hiring or firing costs, $\bar{a}_t^l$ is also the cutoff value that determines whether an existing employee is retained.

Three key equations are important for understanding why selection affects unemployment

[12] The two measures of unemployment can differ as some exogeneously separated workers find employment (and produce) during the period. In search models based on a monthly period of observation, it is more common to assume workers hired in period t do not produce until period $t+1$. Because we base our model on a quarterly frequency, we allow for some exogenously separated workers to find jobs and produce within the same period.

dynamics and the employment experiences of the two types of workers. The first key equation defines the cutoff value of productivity that determines whether a type l work is hired if interviewed and retained if employed. The second key equation relates matching efficiency to vacancies, the number of searching workers, and the quality-composition of the pool of unemployed workers. And the third key equation is the job posting condition that links vacancies to the composition of the unemployment pool. We discuss each in turn.

Cutoff productivity

Labor is used by wholesale firms to produce a homogenous output that is sold in a competitive market at price P_t^w. Let P_t be the final goods price index and define $\mu_t = P_t/P_t^w$ as the retail-price markup. Wholesale firms post vacancies V_t, interview and screen applicants, and make retention decisions. The optimization problem of the firm can be written in terms of a key variable, the surplus generated by worker-firm matches, and a critical role is played by the match surplus of a low-efficiency worker. This surplus is equal to

$$s_{i,t}^l = \left(\frac{a_{i,t}^l \phi^l h_{i,t}^l}{\mu_t}\right) - \frac{v(h_{i,t}^l)}{\lambda_t} + q_t^l - w_t^{u,l}, \tag{2}$$

where $h_{i,t}^l$ denotes the hours worked by an employed low-efficiency worker (such a worker produces $a_{i,t}^l \phi^l h_t^l$ of the wholesale good whose real value in terms of retail goods is $a_{i,t}^l \phi^l h_t^l/\mu_t$), $v(h_t^l)$ is the disutility of hours worked, $\lambda_t = D_t \mathcal{C}_t^{-\sigma}$ is Lagrangian multiplier on the household's budget constraint, q_t^l is the expected continuation value of a match with a low-efficiency worker, and $w_t^{u,l}$ is the value of an unmatched type l worker's outside opportunity.[13] Hours are chosen to maximize the surplus and thus will vary with a type l worker's idiosyncratic productivity realization. The cutoff value $\bar{a}_t^l$ of a worker's idiosyncratic productivity realization at which $s_{i,t}^l = 0$ is

$$\bar{a}_t^l = \left(\frac{\mu_t}{\phi^l \bar{h}_{i,t}^l}\right)\left(\frac{v(\bar{h}_{i,t}^l)}{\lambda_t} - q_t^l + w_t^{u,l}\right), \tag{3}$$

where $\bar{h}_t^l$ maximizes the joint surplus for a worker with $a_{i,t}^l = \bar{a}_t^l$.[14] Given household preferences

[13] We assume unmatched workers produce a home consumption good. Details of the surplus derivations are provided in the online appendix.

[14] If we had included an aggregate producitivity shock z_t, then the denominator of (3) would become $z_t \phi^l \bar{h}_t^l$ and an increase in z_t would decrease $\bar{a}_t$, increasing hires and retentions. See Ravenna and Walsh (2012).

(1), optimal hours satisfies $v'(h^l_{i,t})/\lambda_t = a^l_{i,t}\phi^h/\mu_t$.[15] Equation (3) implies that $\bar{a}^l_t$ is the same for all firms considering the retention or hire of a low–efficiency worker. An increase in the retail price markup μ_t reduces the value of intermediate firms' output, and the worker productivity level necessary to generate a positive match surplus rises. This increases $\bar{a}^l_t$, reduces the fraction of low-efficiency job seekers who receive job offers, and increases the endogenous separation rate of already employed low-efficiency workers. This leads to an increase in the share of low-efficiency workers in the unemployed pool (i.e., γ_t rises).

Efficiency of the matching function

The number of vacancies posted by wholesale firms V_t, together with the number of job seekers S_t, determines the number of interviews I_t via a standard CRS matching function:

$$I_t = \psi V_t^{1-a} S_t^a; \qquad 0 < \alpha < 1,\, \psi > 0. \tag{4}$$

A job seeker gets an interview with probability $k^w_t \equiv I_t/S_t = \psi\theta_t^{1-a}$, where $\theta_t \equiv V_t/S_t$. The job finding probability is identical to the interview rate for high-efficiency workers, while for low-efficiency workers it is lower, and equal to $k^{w,l}_t = (1-\rho^n_t)\, k^w_t < k^w_t$. Because the probability a worker drawn from the pool of unemployed job seekers is low-efficiency is γ_t, the overall job finding probability is

$$k^{w,job}_t = (1-\gamma_t)k^w_t + \gamma_t k^{w,l}_t = (1-\gamma_t\rho^n_t)\, k^w_t. \tag{5}$$

New hires H_t are given by the number of interviewees who are of high-efficiency, all of whom are hired, plus the number of interviewees who are of low-efficiency times the fraction of these with productivity levels that exceed $\bar{a}^l_t$:

$$H_t = (1-\gamma_t)k^w_t S_t + \gamma_t\,(1-\rho^n_t)\, k^w_t S_t = (1-\gamma_t\rho^n_t)\, k^w_t S_t. \tag{6}$$

Screening implies that fewer workers are hired than are interviewed: $H_t < k^w_t S_t$. The number of new hires depends on the endogenous average quality of the pool of unemployed workers as

[15] For type h workers, the condition for optimal hours is $v'(h^h_t)/\lambda_t = \phi^h/\mu_t$, implying h^h_t is the same for all such workers.

measured by γ_t and on the endogenous separation rate ρ_t^n. The latter depends on $\bar{a}_t^l$ which, from (3), depends on the retail-price markup. The effective aggregate matching function linking vacancies, job seekers and new hires can be expressed as

$$H_t = (1 - \gamma_t \rho_t^n)\, k_t^w S_t = \psi_t V_t^{1-a} S_t^a, \tag{7}$$

where $\psi_t \equiv (1 - \gamma_t \rho_t^n)\, \psi < \psi$. Matching efficiency is measured by ψ_t. In a recession, both the endogenous separations rate ρ_t^n and the share of type l workers among the pool of job seekers γ_t rise, resulting in a fall in ψ_t. In a boom, both ρ_t^n and γ_t fall. Thus, matching efficiency is endogenous and procyclical.

Vacancy posting

We assume Nash bargaining with firms receiving a share $1 - \eta$ of the joint surplus from a match. The job posting condition takes the form

$$k_t^f (1 - \eta) \left[(1 - \gamma_t) s_t^h + \gamma_t (1 - \rho_t^n) \mathrm{E}_t (s_{i,t}^l | hiring) \right] = \kappa, \tag{8}$$

where κ is the cost of posting a vacancy, expressed in terms of final goods. The left side of (8) is the probability the firm conducts an interview $k_t^f = \psi \theta_t^{-a}$ times the firm's share of the expected surplus, since with probability $(1 - \gamma_t)$ the firm interviews (and hires) a high-efficiency worker and with probability γ_t, it interviews a low-efficiency worker which results in a hire with probability $1 - \rho_t^n$. Because the expected surplus from a high-efficiency worker is greater than the expected surplus obtained from entering into an interview with a low-efficiency worker, the incentive to post vacancies falls when a rise in γ_t reduces the average quality of the unemployment pool.

1.3 Implications of selection and the transmission of monetary policy

Equations (3) for $\bar{a}_t^l$, (7) for hires, and (8) for job posting are central to understanding the model's key implications that will come into play during a pandemic recession. Consider a negative demand shock that causes a rise in the retail price markup as wholesale prices, which are flexible, fall relative to sticky retail prices. From (3), a rise in the retail price markup μ_t

increases $\bar{a}_t^l$, the critical productivity cutoff for hiring a type l worker or retaining an existing type l employee. This rise in a_t^l increases the endogenous separation rate and generates an inflow into unemployment of type l workers. It also reduces the outflow of type l workers from unemployment as more are screened out in interviews. With the share of low-efficiency workers in the pool of unemployed workers γ_t higher, firms posting vacancies are more likely to interview a type l workers and less likely to make a successful hire. From (7), effective hiring efficiency falls and, from (8) the incentive to create vacancies falls. This reduces the job finding probability of type l workers but also of type h workers. Unemployment duration for high-efficiency workers rises, while duration for low-efficiency workers rises both because the probability of getting interviewed has fallen but also because the probability of being hired, conditional on being interviewed, has fallen. These endogenous developments amplify the rise of unemployment during a recession and slow the subsequent recovery of employment.

A persistent shock to the exogenous separation rate ρ_t^x increases unemployment of both worker types. By reducing the expected duration of matches, the continuation value of a match falls, and, from (3), $\bar{a}_t^l$ rises. This increases endogenous separations, amplifying the rise in unemployment among type l workers. The rise in ρ_t^n due to the rise in $\bar{a}_t^l$, and the rise in γ_t as the composition of the job seekers shifts towards low-efficiency workers, reduces the efficiency of the matching process – measured by ψ_t – as selection leads to fewer interviews translating into hires. This also dampens the rise in the job filling rate that occurs as the number of job seekers rises, which, together with the decline in the expected productivity of job applications as a result of the rise in γ_t, acts to reduce the incentive for firms to post new vacancies.

1.4 Retail firms, monetary policy, and market clearing

The rest of the model follows the standard specification in new Keynesian models. The assumption that retail firms adjust their price ala Calvo leads to a basic new Keynesian Phillips curve in which the driver for inflation, real marginal cost, is the price of the wholesale good P_t^w, the input of the retail firms, relative to the price of final output P_t. Thus, real marginal cost is the inverse of the markup of retail over wholesale goods.

The representative household's first order conditions imply the following intertemporal optimality condition must hold in equilibrium:

$$\lambda_t = \beta(1+i_t)\mathrm{E}_t\left(\frac{P_t}{P_{t+1}}\right)\lambda_{t+1}, \tag{9}$$

where λ_t is the marginal utility of income, $D_t\mathcal{C}_t^{-\sigma}$, and i_t is the nominal rate of interest.

Monetary policy is represented through a simple instrument rule. Our benchmark rule takes the simple form

$$\ln(1+i_t) = -\ln\beta + \omega_\pi\pi_t. \tag{10}$$

In section 5 we investigate how dynamics are affected if monetary policy also responds to developments in the labor market.

Finally, goods market clearing requires that the household consumption of market-produced goods plus final goods purchased by wholesale firms to cover the costs of posting job vacancies equals the output of the retail sector, or

$$Y_t = \Delta_t\left(C_t + \kappa V_t\right), \tag{11}$$

where $\Delta_t \geq 0$ is a measure of relative price dispersion.[16]

2 Inefficient screening and separations

Before carrying out our quantitative exercises of heterogeneity-driven selectivity in hiring and separations in a pandemic-induced recession, we address the implications of worker heterogeneity for the efficiency of the competitive equilibrium. We show that selection leads to a new source of inefficiency; in the competitive equilibrium, individual firms ignore the effects their vacancy posting and separation decisions have on the average quality-composition of the pool of unemployed. Relative to the efficient equilibrium, low-efficiency workers experience spells of unemployment that are inefficiently frequent and average unemployment duration that is inefficiently long. This inefficiency remains even when the Hosios condition is imposed, prices are flexible, and a subsidy to firms offsets the steady-state distortion due to imperfect com-

[16]The complete set of equilibrium conditions are given in the online appendix.

petition. The efficient equilibrium provides a benchmark for interpreting the distributional consequences across workers of the COVID-19 recession that we analyze in section 3.

In a basic new Keynesian model with search and matching frictions but a homogeneous labor force, Ravenna and Walsh (2011) identify four distortions that arise in the competitive equilibrium with Nash bargaining over wages: (1) a non-zero steady-state markup due to monopolistic competition generates a level of output that is inefficiently low; (2) price rigidity generates inefficient relative price dispersion due to fluctuations in the markup; (3) fluctuations in the markup distort hours from their efficient level; and (4) the vacancy posting condition is inefficient if the Hosios condition is not satisfied. These four distortions would be eliminated if (a) a subsidy to firms is used to raise steady-state output to its efficient level; (b) the markup is constant (i.e., prices are stable); and (c) the Hosios condition holds.

The existence of time-varying worker heterogeneity generates a fifth distortion. When firms separate from low-efficiency employees or screen out such workers at the interview stage, they also jointly determine the average efficiency level of the pool of searching workers from which all new matches are formed. However, firms ignore the impact of their decisions on the size of the unemployment pool and on its quality. The first effect – the externality arising from the impact on the size of the pool of unemployed workers – is eliminated when the Hosios condition is satisfied. The second effect – on the quality of the pool – is not eliminated. The resulting *selection distortion* remains even when prices are flexible and the Hosios condition is met.

This distortion generates a wedge between the value of matches in the market equilibrium and in the social planner's problem of maximizing household utility given by (1), subject to the economy's technology and resource constraints and the search and matching process characterizing the labor market. Let s_t^h and $\bar{s}_t^h$ ($s_{i,t}^l(a_{i,t}^l)$ and $\bar{s}_{i,t}^l(a_{i,t}^l)$) denote the joint surplus for a match with a high-efficiency (low-efficiency) worker in the market equilibrium and the social planner's allocation, respectively. For matches with a low-efficiency worker, the surpluses will depend on the workers idiosyncratic productivity level $a_{i,t}^l$. Define $\mathcal{S}_t^h \equiv \bar{s}_t^h - s_t^h$ and $\mathcal{S}_{i,t}^l(a_{i,t}^l) \equiv \bar{s}_{i,t}^l(a_{i,t}^l) - s_{i,t}^l(a_{i,t}^l)$. Evaluated at the efficient equilibrium, the online appendix shows that

$$\mathcal{S}_t^h = \beta \mathrm{E}_t \left(\frac{\lambda_{t+1}}{\lambda_t} \right) \left(1 - \rho_{t+1}^x\right) \left(1 - \alpha k_{t+1}^w\right) \mathcal{S}_{t+1}^h - \beta \mathrm{E}_t \left(\frac{\lambda_{t+1}}{\lambda_t} \right) \gamma_{t+1} X_{t+1} \qquad (12)$$

and

$$\mathcal{S}^l_{i,t}(a^l_{i,t}) = \beta \mathrm{E}_t \left(\frac{\lambda_{t+1}}{\lambda_t}\right)\left(1-\rho^x_{t+1}\right)\left(1-\alpha k^w_{t+1}\right)\left(1-\rho^n_{t+1}\right)\mathcal{S}^l_{i,t+1}(a^l_{t+1})$$
$$+\beta \mathrm{E}_t \left(\frac{\lambda_{t+1}}{\lambda_t}\right)\left(1-\gamma_{t+1}\right)X_{t+1}, \tag{13}$$

where

$$X_{t+1} \equiv (1-\alpha)\left(1-\rho^x_{t+1}\right)k^w_{t+1}\left[\bar{s}^h_{t+1}-\left(1-\rho^n_{t+1}\right)\bar{s}^l_{i,t+1}(a^l_{t+1})\right]. \tag{14}$$

The sign of X_{t+1} depends on the expected value of $\bar{s}^h_{t+1}-\left(1-\rho^n_{t+1}\right)\bar{s}^l_{t+1}(a^l_{t+1})$, the average surplus at $t+1$ of a high-efficiency worker, conditional on surviving the exogenous separation hazard, minus the average surplus at $t+1$ of a low-efficiency worker, conditional on that worker surviving the exogenous separation hazard and being retained.[17]

The market equilibrium is efficient if and only if $\mathcal{S}^h_t = \mathcal{S}^l_{i,t}(a^l_{i,t}) = 0$ for all i and t. For example, if labor is homogeneous and all workers are high-efficiency, only (12) is relevant, $\gamma_{t+1} = 0$ (there are no low-efficiency workers among the unemployed), and $\gamma_{t+1}X_{t+1} = 0$. In this case, (12) becomes $\mathcal{S}^h_t = \beta \mathrm{E}_t \Lambda_{t+1}\mathcal{S}^h_{t+1}$ which is satisfied if $\mathcal{S}^h_t = 0$ for all t. Similarly, if all workers are low-efficiency, $\gamma_{t+1} = 1$ and $\mathcal{S}^l_{i,t}(a^l_{i,t}) = 0$.

When the efficiency of labor types differ, $0 < \gamma_t < 1$ and $X_{t+1} \neq 0$. In this case, both $\mathcal{S}^h_t$ and $\mathcal{S}^l_{i,t}(a^l_{i,t})$ also differ from zero. The terms involving X_{t+1} appear because the social planner accounts for the effect of worker type on the composition of the unemployment pool, an effect ignored by firms in the competitive equilibrium. Consider first the case of a type h worker. The social planner internalizes the effect the employment of an additional high-efficiency worker has in lowering the average productivity of the pool of job seekers, making it more likely that a new hire would be a low-efficiency worker. This "cost" is measured by the last term in (12) and implies $\mathcal{S}^h_t = \bar{s}^h_t - s^h_t < 0$; it reduces the surplus of a type h worker from the perspective of the social planner relative to the firm's valuation.

Hiring a type l worker improves the average productivity of the remaining pool of unemployed workers, and, from the perspective of the social planner, this increases the valuation of matching with a type l worker, as measured by the last term in (13). The social planner

[17] X_{t+1} does not depends on i because $s^l_{i,t}$ is i.i.d. X_{t+1} is a function of the two labor types but not on the idiosyncratic realizations of $a^l_{i,t+1}$.

places a higher valuation on a match with such a worker relative to the firm's valuation so $\mathcal{S}^l_{i,t}(a^l_{i,t}) \equiv \bar{s}^l_{i,t}(a^l_{i,t}) - s^l_{i,t}(a^l_{i,t}) > 0$.

Thus, in the market equilibrium, firms over value high-efficiency workers and under value low-efficiency workers relative to the social planner. The lower valuation placed on a match with a low-efficiency worker implies that the cutoff productivity level for hiring and retaining workers in the market equilibrium is too high. Some low-efficiency workers who experience endogenous separation and become unemployed in the competitive equilibrium would remain employed by the social planner. Similarly, some low-efficiency workers who obtain interviews but are screened out in the competitive equilibrium would be hired by the social planner. As a result, low-efficiency workers face unemployment spells that are too frequent and too long.

This also translates into a higher share of low-efficiency workers among the unemployed and a lower expected benefit to posting vacancies in the market equilibrium. Reduced job posting implies high-efficiency workers also experience a lower job finding rate and longer average duration of unemployment. Ceteris paribus, endogenous separations are too high in the competitive equilibrium, average unemployment is also too high, and average unemployment duration is inefficiently long.[18]

In the next section, we use the efficient allocation as a benchmark for studying the market response to a COVID-19 recession.

3 A COVID-19 recession and the role of worker heterogeneity

We use the model of worker heterogeneity to investigate the impact of a COVID-19 recession and discuss the key propagation mechanisms that cause the pandemic to have differential effects across worker-types. In this section we assume that firms can only recruit from the unemployment pool and workers can only be employed or searching for work. Our baseline model captures the recession and recovery path in an economy with permanent separations and where labor separations require that firm-worker matches be re-established through a costly matching process. In section 4 we allow for some workers to be on temporary layoff and therefore unemployed but not actively searching for work.

[18] The appendix shows that this result can be extended to the case in which both worker types experience individual-specific i.i.d. productivity shocks and endogenous separations.

To begin, we discuss the parameterization and the shocks we employ to capture the COVID-19 recession. We then explore the responses implied by the market equilibrium and compare these to the efficient responses. Our main results are: (1) low-efficiency workers are disproportionately affected in a pandemic recession even though the initial spike in job loss affects both worker types; and (2) responses in the market equilibrium are inefficient, and the labor market experiences of those workers who generally experience poorer labor market outcomes worsen significantly more, relative to the efficient equilibrium, as compared to high efficiency workers.

3.1 Parameterization

Six parameters are key to determining the impact of labor-productivity heterogeneity on the model economy. These parameter are the value of home production w^u, the coefficient ℓ scaling the disutility of labor hours, the cost of vacancy posting κ, the productivity of the matching technology ψ, the relative steady-state productivity of high- to low-efficiency workers $\phi^h / \left(\phi^l \int_0^1 a_i^l dF(a_i^l) \right)$ and the labor force share of low-efficiency workers $\bar{\gamma}$. Values for these parameters are selected by jointly targeting six steady-state values: the steady-state aggregate unemployment rate U_{ss} and the unemployment rates U_{ss}^l and U_{ss}^h for each worker type, average hours per worker h_{ss}^{av}, vacancy posting costs κV_{ss} as a share of output, and the probability k_{ss}^f of a vacancy match with a job application. The target steady state values and the implied parameters are reported in Table 1.

U_{ss} is set to the average U.S. civilian unemployment rate over 1948:Q4 to 2019:Q4. Neither U_{ss}^l nor U_{ss}^h are directly observable, so our baseline parameterization follows Gregory et al. (2021) who use the Longitudinal Employer and Household Dynamics (LEHD) data from 1997 to 2014 to estimate the labor market shares and unemployment rates for three separate worker types that differ by employment duration. We map these estimates into our model with two types of workers, implying a share of low-efficiency workers in the labor force of 38% with an average unemployment rate of 9.87%, and a share of high-efficiency workers of 62%, with an average unemployment rate of 2.97%.

This baseline parameterization implies an unemployment rate ratio U_{ss}^l/U_{ss}^h equal to 3.3. Given that U_{ss}^h and U_{ss}^l are not observable, for robustness we considered alternatives that resulted in a higher value of 4.2 and a lower value of 2.5 for this ratio, keeping U_{ss} constant at 5.6%. The higher value of U_{ss}^l/U_{ss}^h comes from an alternative mapping of the three labor types in Gregory et al. (2021) into our model with two labor types that implies $\bar{\gamma} = 20\%$, $U_{ss}^h = 2.1\%$ and $U_{ss}^l = 14.4\%$. The lower value of U_{ss}^l/U_{ss}^h is based on the observed difference in average unemployment rate for workers aged 16 to 24 (4.4%) and over-24 (11.6%). Our general conclusions are robust to these alternative parameterizations and results are reported in the online appendix.

The other targeted moments reported in Table 1 include steady-state hours per worker h_{ss}^{av}, the steady-state aggregate separation rate ρ_{ss} and the probability of a match between an applicant and a vacancy k_{ss}^f. These values are parameterized to standard values in U.S. business cycle literature. The share of output devoted to hiring activities is in line with empirical evidence reported in Ravenna and Walsh (2008). For parameters standard to new Keynesian models, we adopt values common in the literature, and for the benchmark monetary policy rule, we use a standard value of 1.5 for the response coefficient on inflation. We assume the i.i.d. productivity shock $a_{i,t}^l$ has a uniform distribution with support $(0, 1]$.

Table 1 summarizes the key parameter and steady-state values. In our parameterization, the share of type l workers in the total labor force is 38%. Because the separation rate for these workers is about 40% larger than the average separation rate, their share in the steady-state pool of job seekers γ_{ss} is 52%, while their share ξ_{ss} in steady-state employment is only 36%.[19] Thus, low-efficiency workers are over-represented in the pool of unemployed, and this pool has a lower average productivity than the pool of employed workers, as reported in table 1. When matched for an interview with a firm, high-efficiency workers are expected to have an hourly productivity 16% higher than low-efficiency workers. The productivity ratio between employed and unemployed workers is smaller and equal to 1.04, since only relatively highly productivity type l workers are retained in employment. The extent of selection at hiring is small; firms screen out only about 2.55% of the workers they interview and just 4.9% of the type l workers who are interviewed. However, as (7) showed, the screening-out rate increases in a recession as γ_t, the share of low-efficiency workers among the unemployed increases and $\bar{a}_t^l$, the minimum

[19] The value for the excess-separation rate of type l workers, ρ_n^{ss}, is the consequence of a parameterization requiring both a high ratio between the unemployment rates of type l and h workers and a high quarterly probability of an interview $k_{ss}^f = 0.9$.

productivity for a match to generate a positive value, increases.

In the simulations, we follow the standard approach in NK models of assuming the existence of a tax/subsidy system that ensures the steady-state allocations in the planner's problem and the market allocation coincide. This requires that the Hosios condition holds and that the study-state distortions due to imperfect competition and the selection distortion are eliminated.

3.2 Shocks

Figure 1 provides some macroeconomic evidence on the distinctive character of the COVID-19 recession. It illustrates the behavior of the employment-to-population ratio, layoffs and discharges, the private saving rate, and inflation over the 12 months after the onset of the COVID-19 recession and, for comparison, the first 12 months of the Great Recession following the global financial crisis.[20] All values are scaled to unity at the start of the recession. The spike in layoffs and discharges measured by JOLTS data during COVID-19 contrasts sharply with their behavior in the Great Recession, during which the initial rise in layoffs is barely discernible and where layoffs then rose gradually over the first year of the recession. In the COVID-19 recession, shelter-in-place orders, social distancing requirements and breakdowns in supply chains reduced the economy's ability to produce and, as such, were associated with a small rise in inflation.

While sectorial redistributional effects were important, the rise in the saving rate and the subsequent fall in inflation shown in the figure suggest the pandemic also featured an overall drop in spending, as would be generated by a negative aggregate demand shock.

To describe the COVID-19 recession, therefore, we assume that the economy is hit by both a positive shock to exogenous separations and a preference shock that reduces demand. Based on CPS data, Cortes and Forsythe (2020b) report that over 80% of the pandemic-induced fall in employment in April 2020 resulted from individuals exiting employment, while reduced hiring accounted for the rest. The public heath responses to COVID-19, including business closures, lockdowns and social distancing requirements, resulted in the destruction of job matches and had features common to a negative supply shock in that it reduced the economy's ability to

[20] The NBER Business Cycle Dating Committee has judged that the COVID-19 recession lasted just two months, with the economy's peak occuring in February 2020 and the trough reached in April 2020.

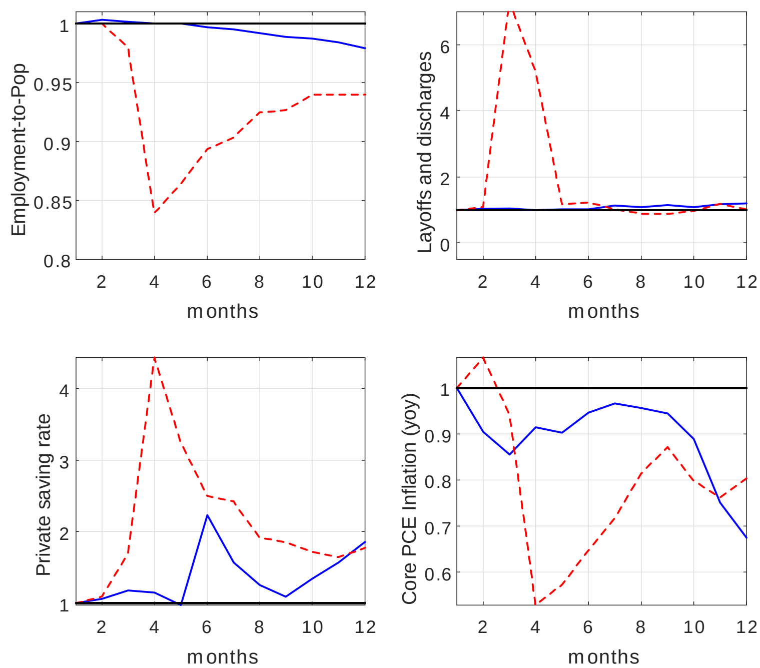

Figure 1: Macro developments during 2020 in the U.S. The time scale denotes months since December 2007 (solid lines) for the Great Recession and January 2020 (dashed lines) for the COVID recession.

produce without generating a corresponding drop in demand. The separation shock captures some of the supply side aspects of COVID-19 in a manner that adversely affects all workers, regardless of type. Guerrieri et al. (2020) model COVID-19 as a shock that destroys jobs, much as our separation shock does. Gregory et al. (2020) models the decline in employment as a negative aggregate TFP shock. Such a shock would be expected to lead to an increase in separations, a fall in hiring, and a decline in wages for workers who remain employed. However, Cortes and Forsythe (2020a) find that the decline in aggregate employment, rather than a decline in average wages accounts, for the observed decline in labor earnings.We then capture the accompanying fall in aggregate demand through a negative preference shock, representing a shift in households' preferences away from current consumption and towards home-production and leisure. Both shocks will generate further responses in total separations as endogenous separations adjust.

To produce the COVID-19 scenario, we condition on forecast paths for output and total separation produced at the beginning of the COVID-19 recession. The model uses the forecasts to endogenously allocate the path of total separations and output across an exogenous, unexpected shock to ρ_t^x and an exogenous preference shock D_t. We then produce conditional forecasts for labor market variables and other aggregate variables which are not supplied to the model.

This means our simulations are hypothetical paths in the absence of the effects of the vast income support measures (the CARES act) and expansionary monetary policies (discretionary cuts in the federal funds rate, forward guidance, and quantitative easing measures) which are outside our model and that affected the actual path of the economy within the first months of the pandemic. Our target output path is based on the 2020Q2 vintage of the Survey of Professional Forecasters (SPF) for GDP growth, relative to a potential growth path of 2% per year. The SPF predicts GDP growth only up to 5 quarters ahead. For the subsequent 5 quarters, we assume the economy recovers at the same rate as over the forecast horizon, with the shortfall in output dissipating at an estimated quarter-over-quarter rate of 67.4%. The SPF does not provide a forecast for total separations, so our target path for separations is obtained by measuring the 2020Q2 increase in the cumulated CPS transition rate from employment to non-employment over each month, as a share of the previous month employment stock, relative to the transition rate averaged over the 2018-2019 period.[21] The path for total separations then assumes the initial rise reverts back to steady state at the same rate as the SPF output forecast.[22]

Both shocks are essential to discuss a pandemic-induced recession. The exogenous separation shocks act as a supply shock; the value of each existing or potential match falls, ceteris paribus, since the cost per vacancy is fixed but its return in terms of match-lifetime production is lower, given that the match is expected to have a shorter duration. By itself, the separation shock is not sufficient to lower demand in line with the SPF forecast for the U.S. economy as it pushes firms to quickly rehire a large share of the separating workers. The preference shock acts as a demand shock that allows the model to match the output loss for a given separation path. The demand shock lowers output and the demand for labor but cannot, by itself, reasonably account for all of the surge in total separations. Together, the two shocks

[21] Considering the ratio of total transitions over a quarter relative to the average number employed over the quarter returns a similar increase in transition rates for 2020Q2.

[22] The SPF provides a forecast for unemployment. Using as target variables the 2020Q2 vintage of unemployment and output, the model-implied paths for the ρ_t^x and D_t shocks that are similar to the our baseline and has limited impact on the results. We prefer our specifications, which allows the model to produce a conditional forecast for unemployment – which turns out to be very close to the SPF forecast.

capture important aspects of the 2020 recession.

3.3 Mass layoffs and the distribution of unemployment across worker types

Our first set of results explains why selection changes the dynamics of the economy in the COVID-19 recession and reallocates the burden of the recession across worker types. On the workers' side, we find that low-efficiency workers are disproportionately affected even though the initial spike in job loss affects both worker types. We also find that selection worsens labor market conditions for *all* worker types. On the firms' side, we show that the wedge between the interview probability and the job-filling probability increases - firms become more 'picky'. An econometrician not accounting for time-varying selection would measure a fall in the efficiency of matching during the pandemic recession and a negative TFP shock affecting the pool of unemployed workers.

The behavior of unemployment implied by the model is shown in Figure 2, which plots the aggregate unemployment rate and the unemployment rates of high-efficiency and low-efficiency workers in the left panel. Because the steady-state value of U^l is much higher than that of U^h, each series is shown as a deviation from its own steady-state value. The right panel shows the share of the aggregate unemployment rate response that consists of each worker type. The outer envelope of the shared regions in the right panel is the total unemployment rate and corresponds to the bold line in the left panel. For type h workers, their unemployment rate rises by less than 3 percentage point above its steady-state value. In contrast, that of type l workers jumps by almost 15 percentage points, from its steady-state value of just under 10% to almost 25%. Thus, the unemployment rate of type l workers rises more and from a higher steady-state base than the total unemployment rate or the rate for type h workers. And after 6 quarters, the unemployment rate among high-efficiency workers is less than 1 percentage point above its steady-state value, while for low-efficiency workers it is still 4.6 percentage points above steady state. The right panel of the figure shows the composition of total unemployment among worker types. Even though type l workers are less than 40% of the labor force, they account for the bulk of the pandemic-induced higher aggregate unemployment rate.

To understand the reasons for the poor labor market experiences of low-efficiency workers, consider first a non-pandemic recession. Firms reduce their workforce by becoming more

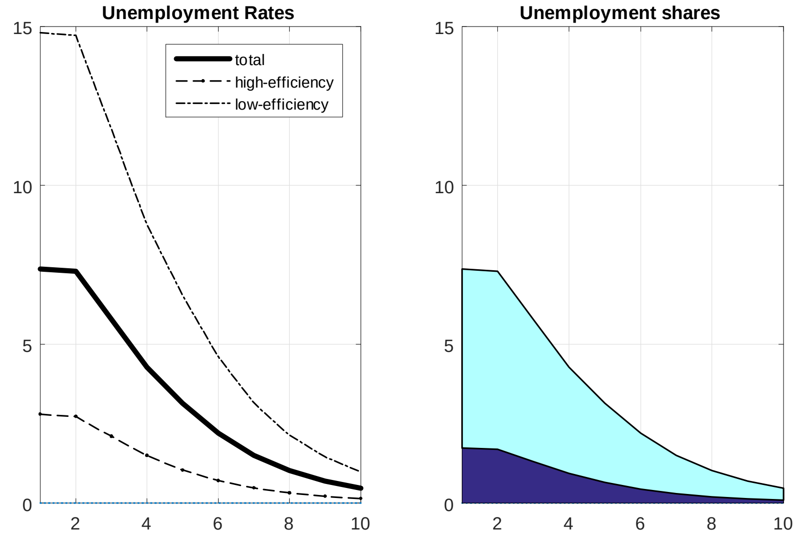

Figure 2: COVID scenario unemployment responses. The left panel shows the responses of U, U^h, and U^l, with each expressed in terms of percentage point deviation from their steady-state values. The right panel shows the total aggregate unemployment rate response and the share accounted for by each worker type: type l (in light) and type h (in dark).

selective, retaining fewer low-efficiency workers and screening out more such workers in the interview process. This leads to a rise in γ_t, the share of low-efficiency workers in the pool of job seekers which, in turn, reduces the incentive for firms to post job vacancies. In a pandemic scenario, however, social distancing and lockdowns leads to mass layoffs that affect both worker types. Because most workers are high-efficiency types, more type h workers initially flow into the unemployment pool and γ_t initially falls, as shown in the top left panel of Figure 3. But the fall in γ_t is quickly reversed and then remains persistently above its steady-state value. This reversal reflects greater selectivity by firms; the productivity cutoff value $\bar{a}_t^l$ rises as shown in the top right panel of the figure. Firms become more selective for two reasons. First, the drop in demand for the wholesale good results in a fall in its price relative to the index of sticky retail goods prices; that is, the retail price markup μ_t rises, as the bottom left panel of the figure shows. The marginal revenue product of a type l worker with idiosyncratic productivity $a_{i,t}^l$ is $a_{i,t}^l \phi^l / \mu_t$. When μ_t rises, the value of $a_{i,t}^l$ necessary to generate a positive match surplus rises. Second, the value of $\bar{a}_t^l$ also depends on the continuation value of a match. With a persistent rise in ρ_t^x the expected duration of a match and its continuation value falls, implying only very productive type l workers generate a positive surplus. The rise in $\bar{a}_t^l$ increases the

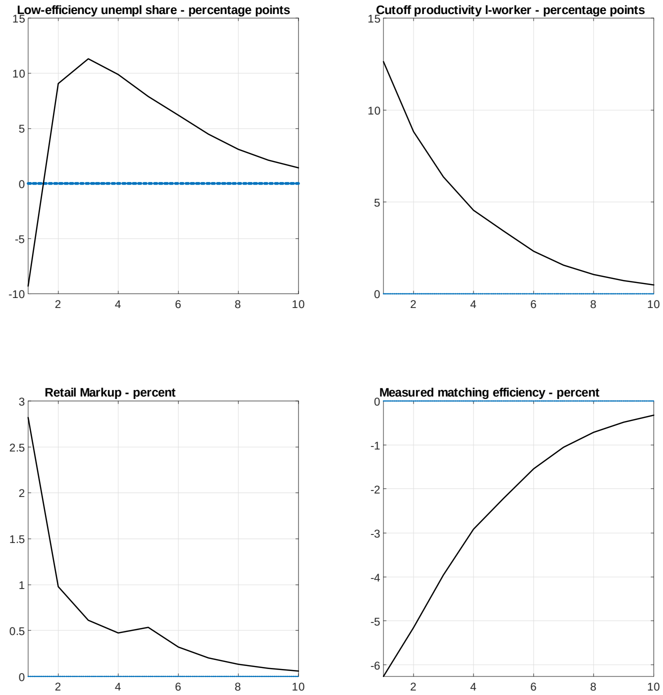

Figure 3: COVID-19 scenario: Responses of γ_t (upper left), $\bar{a}_t^l$ (upper right), μ_t (lower left) and $1-\gamma_t\rho_t^n$ (lower right) to the COVID-19 shocks. Upper panels are percentage point deviations from steady state; lower panels are percent deviations from steady state.

endogenous separation rate, and this further reduces the expected duration of a match. The rate at which type l workers enter the pool of unemployment rises and their exit rate falls, causing γ_t to rise above its steady-state value. As both γ_t and $\bar{a}_t^l$ increase, the efficiency of the aggregate matching function as defined by $1-\gamma_t\rho_t^n$ in (7) falls (see bottom right panel).

The responses of job finding rates, vacancy filling rates, vacancies per job seeker, and the average productivity of the pool of unemployed are shown in Figure 4. As the upper left panel shows, the job finding probability falls significantly for type l workers, reflecting the fall in vacancies per job seeker shown in the lower left panel, which reduces the probability a worker gets an interview, and the fall in the probability a type l worker is hired, conditional on getting an interview. From the perspective of firms, the fall in vacancies per job seeker increases the chances a firm will interview a worker (see dashed line in upper right panel), but the probability of actually successfully hiring rises much less (the solid line in the upper right panel) as firms screen out more of the workers who are interviewed.

Normally, a mass exogenous destruction of job matches would lead firms to quickly post vacancies to rebuild employment. The recovery of employment is muted in the case of pandemic-induced mass layoffs for two reasons. First, the pandemic involves a negative preference shock that reduces the demand for market goods as well as a shock to separation, and this reduces aggregate labor demand. Second, as γ_t rises, the average productivity of job seekers falls, as shown in the lower right panel of the figure. This reduces the expected surplus the firm can expect if it posts a new vacancy. It is more likely to interview a low-efficiency worker, and the rise in $\bar{a}_t^l$ means any type l worker the firm does interviews is less likely to be sufficiently productive to generate a positive surplus.

While our discussion has focused on low-efficiency workers as they are the most affected, high-efficiency workers are also adversely affected. The mass layoff due to the separation shock leads to more type h workers in the pool of unemployed. Vacancies per job seeker falls, but once the average productivity of the unemployed begins to fall, this further reduces vacancy creation. Both developments cause a fall in the probability a type h worker is interviewed. As a result, the job finding rate for these workers declines (see upper left panel). It declines much less than the job finding rate of type l workers, but type h workers do experience longer spells of unemployment as their exit rate declines. The effects of the pandemic shock are exacerbated by the way selection slows the rate at which *all* workers exit unemployment.

3.4 Results on efficiency

Our second major result is that the endogenous responses to the pandemic shock are inefficient and that the resulting inefficiencies disproportionately affects those workers whose average labor market outcomes involve more frequent and longer unemployment spells. The reason is that, as shown in section 2, the surplus generated by such workers in the competitive equilibrium is undervalued relative to its valuation by the social planner. The reverse holds for type h workers.

To assess the effects of the market distortions, we integrate the wedge between the market and efficient outcomes over the first 10 quarters of the pandemic scenario. Applied to unemployments rates, for example, this would provide a measure of the cumulative excess unemployment after the shocks due to market distortions. These measures of excess unemployment for each worker type are shown in the left panel of Figure 5. Both unemployment rates in-

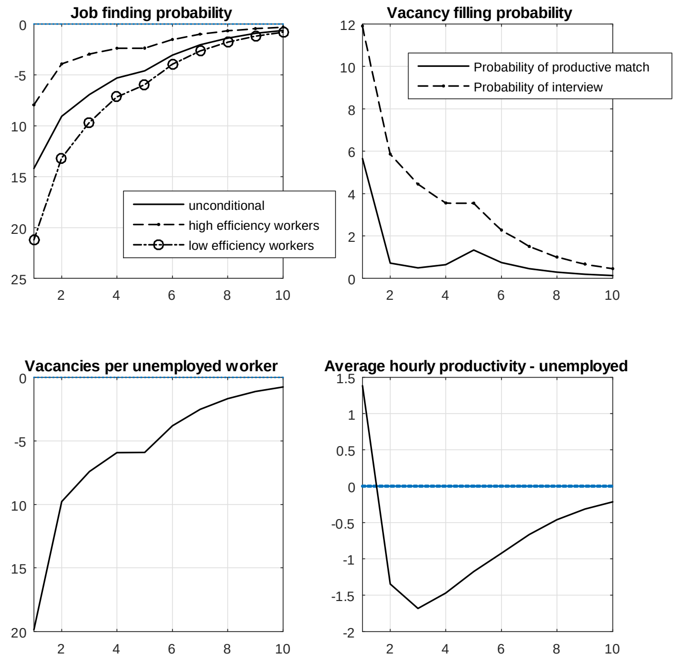

Figure 4: COVID-19 scenario: Responses of job finding probabilities (upper left), vacancy filling probabilities (upper right), vacancies per job seeker (lower left) and average productivity of the unemployed (lower right) to the COVID-19 shocks. Each variable is expressed as a deviation from its steady-state value.

crease more in the market equilibrium than in the social planner's allocation, but the impact is particularly pronounced for type l workers. After 5 quarters, type l workers have suffered a cumulative efficiency wedge equal to 100% of their steady-state unemployment rate. Since the latter is roughly 10%, they experience an additional 10 percentage points of unemployment over this period that is socially inefficient. In contrast, type h workers, while also experiencing inefficiently high unemployment, suffer cumulative excess unemployment of less than 20% of their steady-state rate of 3%, or approximately an additional 0.6 percentage points of excess unemployment. Thus, the consequences of the pandemic shocks fall disproportionately on type l workers.

With unemployment rates higher and employment lower in the market equilibrium, aggregate output is also inefficiently low in response to the shocks. The cumulative loss in output due to the inefficiency wedge is shown in the right panel of figure 5. After 10 quarters, this efficiency loss totals 4.75% of steady-state output.

To understand the mechanisms generating these efficiency wedges, recall that we have followed the common practice of eliminating steady-state distortions and we have imposed the

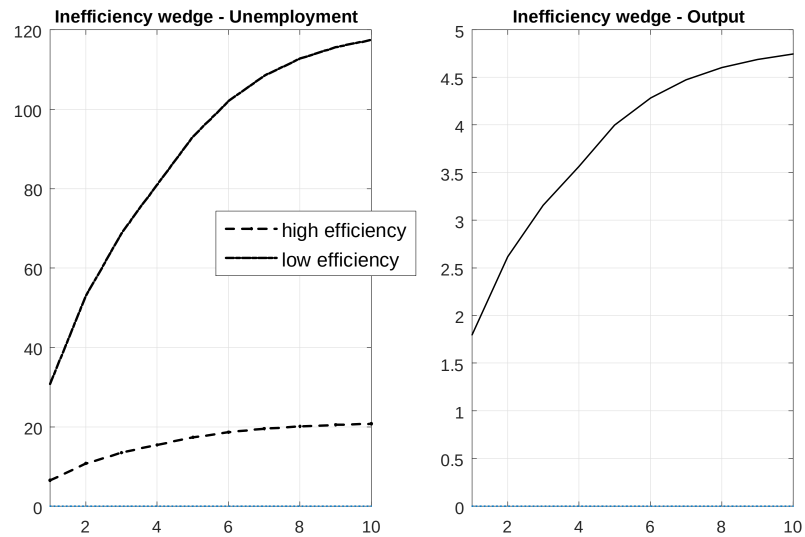

Figure 5: COVID-19 scenario unemployment and output cumulative efficiency losses. The cumulative gap between the market outcome and the efficient allocation in response to the COVID-19 shocks for unemployment rates by worker type (left panel) and for output (right panel) measured as a percent of steady-state values.

Hosios condition. Therefore, the only remaining distortions arise from price stickiness and the selection distortion. The efficient equilibrium ensures price stability, so the markup is constant and $\mu_t = 1$. In the market equilibrium, price stickiness leads to a rise in the markup. This rise in μ_t was one of the channels generating a rise in $\bar{a}_t^l$ and an increase in selectivity. Thus, $\bar{a}_t^l$ increases more in the market equilibrium than it would in the efficient allocation due to both price stickiness and the selection distortion, and this inefficiency wedge is shown in the top panel of Figure 6. The higher value of $\bar{a}_t^l$ in the market equilibrium implies greater selectivity and a higher endogenous separation rate for low-efficiency workers than would be efficient. Hence, the share of type l workers in the pool of unemployed is also inefficiently high (see middle panel) through both an inefficiently high exit rate from employment and inefficiently low exit rate from unemployment.

The consequences of inefficiently high values of $\bar{a}_t^l$ and γ_t affect the job finding probabilities for both worker types. The composition effect lowers the average productivity of the pool of job seekers, firms have less of an incentive to post vacancies, and the efficiency of the matching function is lower. These developments lead to inefficiently lower job finding rates for type l workers *and* for type h workers, as shown in the lower left panel of figure 6.

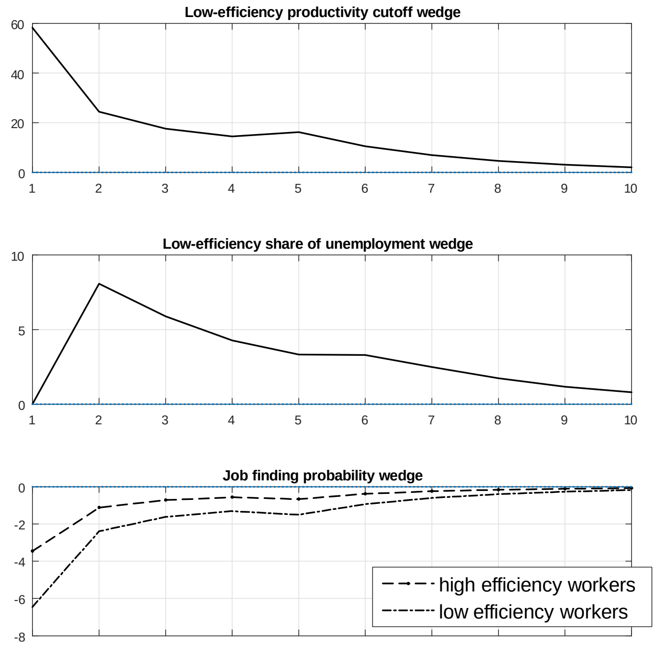

Figure 6: COVID-19 scenario efficiency losses. The difference between market and efficient responses to the COVID-19 shocks for $\bar{a}_t^l$ (upper panel), γ_t^l (middle right), and job finding rates k_t^w and $k_t^{w,l}$ (lower left) measured as a percent of steady-state values.

4 Temporary layoffs

Our baseline model assumes that all exogenous separations are permanent separations. Workers flowing into unemployment directly enter the pool of searching workers. However, in the initial phase of the COVID-19 recessions, a large fraction of separations consisted of temporary layoffs, as Barrero et al. (2020) and Kudlyak and Wolcott (2020) have emphasized. The top panel of Figure 7 shows the atypical behavior of temporary layoffs in early 2020. According to the BLS household survey, the share of job losers on temporary layoff averaged 12.4% between January 2000 and December 2019 before spiking at 77.9% in April 2020. The bottom panel of the figure focuses in on the period from December 2019 to March 2021. After peaking in April, temporary layoffs declined steadily until November before rising slightly in December as COVID-19 cases again spiked in the U.S. Based on previous recessions, Barrero et al. (2020) estimated that 42% of recent layoffs would result in permanent job losses. It is therefore important to see how dynamics are affected when a large share of layoffs are, at least initially, temporary. If these workers are recalled to their former jobs as the economy begins to reopen,

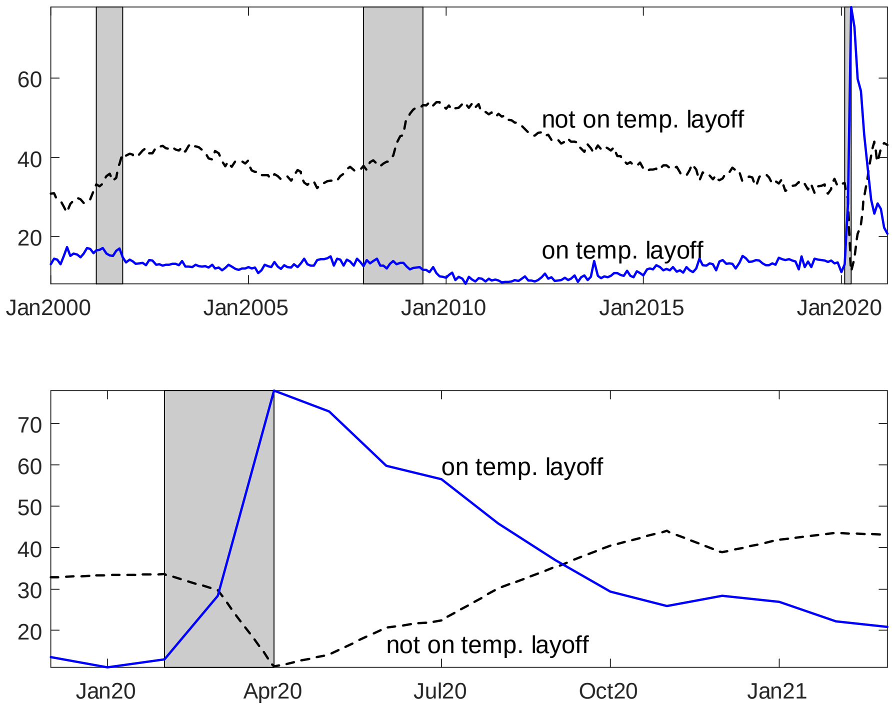

Figure 7: Share of job lossers on temporary layoffs and not on temporary layoffs. Source: CPS series LNS13023654 and LNS13026511. Business cycle recessions shown by shaded regions (NBER dating). Top panel: Jan. 2000-Mar. 2021. Bottom panel: Dec. 2019-Mar 2021.

the speed at which employment recovers may be much faster than predicted by models that ignore temporary layoffs. In this section, therefore, we extend our model to include both permanent and temporary layoffs.

It is useful to note first how unusual the COVID-19 behavior of temporary layoffs was. Over the 420 months between January 1985 and December 2019, a period that includes the Great Moderation, the Global Financial Crisis, and the post-financial crisis recovery, the covariance between the share of temporary layoffs and the unemployment rate was -1.63, indicating that the share of workers on temporary layoff was procyclical. Adding the twelve months January to December 2020 to the sample causes this covariance to flip to a positive 2.09.[23] The COVID-19 surge in both unemployment and in the share of those on temporary layoff was unprecedented.

To allow for temporary separations, we assume a fraction $0 \leq \Gamma_t \leq 1$ of exogenous separations at time t are temporary. Workers on temporary layoff are assumed to be recalled at a constant rate $0 < r \leq 1$. All recalled workers of type h are rehired. However, type l workers

[23]The correlation coefficients are -0.61 and 0.21 for the two periods.

receive idiosyncratic productivity realizations, and consequently, the productivity of a type l worker when recalled at $t+i$ may fail to exceed $\bar{a}_{t+i}^{l}$. Thus, only a share $\left(1-\rho_{t+i}^{n}\right)$ of type l workers who are recalled at time $t+i$ are actually rehired. We assume those who are screened out after recall enter the pool of permanently separated job seekers.

If Γ_t were constant, our model would predict that the share of unemployed on temporary layoff would fall in a recession, consistent with the pre-pandemic evidence, as total separations include both exogenous and endogenous separations and the latter rise during a recession. To capture the positive co-movement seen during the pandemic, we assume that the positive shock to total exogenous separations is accompanied by a positive shock to Γ_t.

The stock of workers of each type that are on temporary layoff evolves according to

$$T_t^j = (1-r)\left(T_{t-1}^j + \Gamma_t \rho_t^x N_{t-1}^j\right), \tag{15}$$

for $j = h,\ j$, where T_t^j is equal to the number of type j workers on temporary layoff. Note we assume that some workers put on temporary layoff in the current quarter may be recalled within the quarter.

The number of job seekers, S_t, equals the total number of workers unmatched at the start of the period, $1-N_{t-1}$, plus those who do not survive the exogenous separation hazard, $\rho_t^x N_{t-1}$, minus those previously separated workers put on temporary layoff awaiting recall to their previous job. Letting $T_t = T_t^h + T_t^l$,

$$S_t = 1 - (1-\rho_t^x) N_{t-1} - T_t.$$

Total new matches equal new hires plus recall hires, or

$$H_t = (1-\gamma_t\rho_t^n) k_t^w S_t + r\left[T_{t-1}^h + \rho_t^x \Gamma_t N_{t-1}^h + (1-\rho_t^n)\left(T_{t-1}^l + \rho_t^x \Gamma_t N_{t-1}^l\right)\right].$$

Employment in period t consists of surviving matches plus new matches:

$$\begin{aligned} N_t &= (1-\rho_t^x)\left[\left(1-\xi_{t-1}\right) + (1-\rho_t^n)\,\xi_{t-1}\right] N_{t-1} + (1-\gamma_t\rho_t^n) k_t^w S_t \\ &\quad + r\left[T_t^h + \rho_t^x \Gamma_t \left(1-\xi_{t-1}\right) N_{t-1}\right] + r\left(1-\rho_t^{n,l}\right)\left(T_t^l + \rho_t^x \Gamma_t \xi_{t-1} N_{t-1}\right). \end{aligned} \tag{16}$$

Finally, the share ξ_t of type l workers among the employed is given by:

$$\xi_t = (1-\rho_t^n)\left[\frac{\xi_{t-1}(1-\rho_t^x)N_{t-1} + \gamma_t k_t^w S_t + r\left(T_{t-1}^l + \rho_t^x \Gamma_t \xi_{t-1} N_{t-1}\right)}{N_t}\right],$$

where the last two terms in the numerator consist of those type l who are interviewed and not screened out, $(1-\rho_t^n)\gamma_t k_t^w S_t$, as well as those type l who are recalled but not screened out, $(1-\rho_t^n) r \left(T_{t-1}^l + \rho_t^x \Gamma_t \xi_{t-1} N_{t-1}\right)$.

4.1 Calibration

Our model of temporary layoffs adds two new parameters to the model: the steady-state value Γ and the recall rate r. To allow the introduction of temporary separations to have the strongest possible impact on the dynamics of the model, we assume that all workers flowing into the pool of temporary layoffs eventually get recalled for a job interview without the need for a vacancy being posted, and that the probability of a recall interview within four quarters of the initial separation is 95%. This implies a quarterly recall hazard r of 53%. In steady-state, over 99% of recalled workers enter into a productive match, while the recall share of workers finding a match endogenously falls after the start of the COVID-19 recession since selected separations increase sharply.

We parameterize the steady-state share of workers in temporary unemployment relative to the total stock of unemployed to 13%, a value in line with the share reported in Kudlyak and Wolcott (2020) for the 1985-2019 sample. This share, together with the quarterly recall rate, implies that the steady-state share of exogenous separations flowing into the pool of temporary unemployment is equal to 6.44%.

Next we parameterize the shock Γ_t to target the path for the share of workers on temporary unemployment relative to the total stock of unemployed T_t/U_t reported from the BLS for the first four quarters following the onset of the COVID-19 recession. In the first quarter the targeted share is equal to 70%, approximately equal to the average of the targeted temporary unemployment share over the months of March, April, May 2020. The temporary unemployment share declines in the second, third and fourth quarter of the recession to 46.5%, 27.9% and 23.4%..

4.2 A COVID-19 recession with temporary layoffs

We now discuss how temporary layoffs affect the dynamic adjustment of unemployment and its distribution across worker types relative to the model of section 3 in which all separations were permanent. Our main result is that the use of temporary layoffs primarily benefits high-efficiency workers. Such workers are more likely to return directly to employment without participating in the search and matching process, and they experience less overall unemployment. Even though the recall rate is the same for both worker types, some recalled type l workers are screened out and not rehired. This leads to a larger rise in the share of low-efficiency workers among the pool of job seekers relative to the benchmark case with only permanent layoffs. Because firms can rebuild matches through recalls, fewer vacancies are posted and firms become more selective.

These implications of allowing for temporary layoffs are shown in Figure 8. All panels show differences in the dynamics of a variable relative to the case discussed in section 3 where layoffs were permanent. The upper left panel shows that the number of searching workers falls relative to the benchmark permanent layoff model as some non-matched workers are on temporary layoff awaiting recall and are not searching. This affects type h workers primarily; type l workers see a smaller reduction in active job searchers as employed workers with sufficiently low productivity outcomes endogenously separate permanently and will not end up in the temporary layoff pool. Aggregate unemployment, shown in the upper right panel, is almost 1.5 percentage points lower in the temporary layoff model than when all layoffs are permanent as some workers on temporary layoff can be recalled within the same quarter. Figure 2 showed that almost all the rise in unemployment in the permanent layoff model consistent of low-efficiency workers, but Figure 8 shows that almost all the reduction in U_t from temporary layoffs comes from lower unemployment among type h workers as some low-efficiency workers are recalled but not rehired.

Vacancies per job seeker fall with temporary layoffs, but as the lower left panel shows, labor market tightness θ falls more when firms employ temporary layoffs. Because firms now have access to recalled workers as employment recovers, there is a reduced need to hire in the search market. When firms do post a vacancy, they are also more likely to hire a low-efficiency

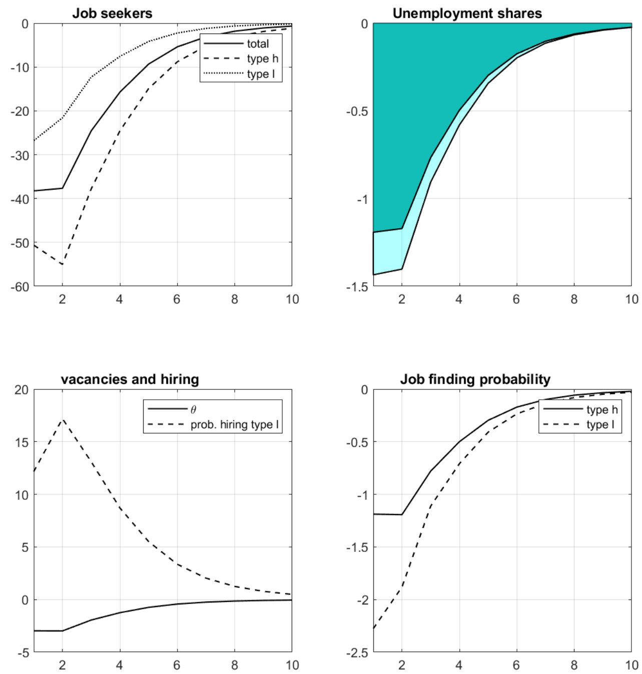

Figure 8: Temporary layoff model: Each panel shows the difference between the selected variable in the model with temporary layoffs and in the benchmark model in which all layoffs are permament. Panel 2 shows the total fall in unemployment in percentage points divided into the share accounted for by each worker type shown as the difference between the temporary layoff model and the permanent layoff model: type l (light), type h (dark). Other panels expressed as percent of steady state.

worker, an outcome that also dampens the incentive to post vacancies. Finally, the probability of finding a job in the search and matching market falls for both high- and low-efficiency workers, but the lower right panel of the figure shows that this probability falls more in the presences of temporary layoffs, and it falls more for low-efficiency workers.

The composition of the pool of job searchers measured by γ_t and the cutoff productivity level $\bar{a}_t^l$ are again key to understanding the effects on the different worker types. After the initial spike in layoffs that affects both worker types, the share of type l workers in the unemployment pool is higher in the temporary layoff model as more type h workers are able to move directly from temporary layoff to employment through recall. The greater increase in γ_t with temporary layoffs accounts for the increased probability a firm with a vacancy will fill it would a type l workers (see lower left panel of figure 8). Firms interview more type l workers but they also become more selective, as $\bar{a}_t^l$ rises, reflecting the larger increase in the markup that occurs with temporary layoffs. The markup rises relative to the permanent layoff model because, with unemployment lower in the temporary layoff model, employment is higher, wholesale output is higher, and the price of the wholesale good falls more relative to the sticky retail price index.[24]

Finally, the introduction of temporary layoffs lowers the unemployment rate for both worker types. However, when a large fraction of the jobs lost as a result of mass layoffs take the form of temporary layoffs, as they did in the early days of the COVID-19 recession, the composition of unemployment is strongly skewed towards low-efficiency workers. One way to measure this skewness is to calculate the ratio of U^l to U^h. With only permanent layoffs, the ratio U^l/U^h is equal to 3.25 on impact, 3.6 after one year, and 4.03 after two years. Allowing for temporary layoffs, this ratio rises to 9.78, 7.3 and 5.7 at the same three horizons. In this sense, temporary layoffs skew the burden of the recession towards low-efficiency workers.

5 Monetary policy

In this section, we use our temporary layoff model to investigate how different worker types and the aggregate economy are affected by alternative monetary policy rules in the face of the COVID-19 shock. The model provides a framework to discuss the impact of policies on inequality across workers and the implications of using policies explicitly aimed at being more inclusive in supporting workers across the productivity and wage distribution. We first discuss the trade-offs faced by the monetary authority.

Our COVID-19 shock is a combination of an aggregate preference shock and shocks to separations and temporary layoffs. In standard new Keynesian models with sticky prices but flexible wages, aggregate demand shocks do not present policy trade-offs and, except at the zero lower bound, can be completely offset by monetary policy, while any supply shock that generates inefficiencies, such as a shock to the markup, will force policy trade-offs. In the face of such supply shocks, reducing the real output impact of the shock exacerbates the inflationary consequences of the shock. As shown in section 2, labor market adjustments in the heterogeneous labor model are inefficient, so the separation shock in our model generates a trade-off that is like a standard cost shock in a basic NK model.

[24] Wholesale output rises because employment rises but also because the increase in $\bar{a}_t^l$ means the average productivity of type l workers who are retained or hired is higher.

The aggregate preference shock affects the demand for market-produced goods, an effect that could be neutralized by monetary policy, but it also affects labor market outcomes and therefore generates policy trade-offs in the heterogeneous labor model since it impacts the inefficiency wedge independently from movements in the markup. To understand why, consider the household's utility maximization problem in section 1 in which the Lagrangian multiplier on the household's budget constraint, that is, the marginal utility of income, is equal to $\lambda_t = D_t \mathcal{C}_t^{-\sigma}$.

Stabilizing consumption would require that λ_t move in proportion to the shock D_t. However, λ_t affects workers' marginal rate of substitution between leisure and income, reducing directly the optimal choice of hours and the value of a match surplus. In addition, if D_t follows a stationary AR process, a negative realization of D_t would cause a fall in λ_t and a smaller fall in λ_{t+1}. From the household's Euler condition, $\lambda_t = \mathrm{E}_t\,(1 + r_t)\,\lambda_{t+1}$, where r_t is the real interest rate. Thus, r_t would fall. Because the expected duration of an employment match is several periods, the fall in the real interest rate necessary to stabilize consumption would increase the expected present discounted value of a worker-firm match surplus.[25] Thus, optimal hours, the expected value of the match surplus from both the worker's and the firm's perspectives, vacancy posting decisions by firms, as well as the cutoff productivity level that triggers endogenous separations and the rate at which type l workers are screened out when interviewed are all affected. These labor market effects of the preference shock result in inefficient employment adjustments.

If policy instead stabilizes λ_t, then $\mathcal{C}_t^{-\sigma}$ rises in the face of a negative preference shock and consumption demand falls. Monetary policy cannot maintain goods clearing without cutting interest rates. Reducing the real interest rate raises the continuation value of matches and thus the value of a worker-firm match. This sets off inefficient labor market adjustments. Thus, the preference shock drives a wedge between the marginal utility of consumption $\mathcal{C}_t^{-\sigma}$ and the

[25] The online appendix shows that, for a type h worker, the joint surplus of a match is given by

$$s_t^h = \left(\frac{\phi^h h_t^h}{\mu_t}\right) - \frac{v(h_t^h)}{\lambda_t} - w^u + \beta \mathrm{E}_t \left(\frac{\lambda_{t+1}}{\lambda_t}\right)(1 - \rho_{t+1}^x)\,(1 - \eta k_{t+1}^w)\,s_{t+1}^h,$$

and the optimal choice of hours satisfies $v_h(h_t^h) = \lambda_t \left(\phi^h/\mu_t\right)$, illustrating how λ_t affects the choice of hours, the discount rate applied to future surpluses, and the overall value of s_t^h. A similar expression, incorporating idiosyncratic productivity shocks and endogenous separations holds for a match with a type l worker. See the online appendix for details.

marginal utility of income λ_t and has both demand effects and supply effects on the economy. Policy cannot simultaneously neutralize both effects, and a policy that stabilized prices and let output adjust would not be optimal due to the inefficient separations and screening that result.

In previous sections, our baseline policy rule given in (10) assumed the nominal interest rate reacted only to inflation. We now consider modifications to this rule that are designed to more directly target labor market developments. Specifically, we consider an unemployment rate version of a basic Taylor (1993) rule of the form

$$\ln(1 + i_t) = -\ln\beta + \omega_\pi \pi_t + \omega_U U_t, \tag{17}$$

where U_t is aggregate unemployment. We focus on how the value of ω_U, measuring the aggressiveness with which policy responds to unemployment, affects the economy's response in our COVID-19 scenario. We illustrate the role of ω_U by discussing the results for three different values: $\omega_U = 0$ corresponding to our benchmark rule (10); a rule with $\omega_U = -0.4$, which succeeds in reducing the impact of the pandemic on aggregate unemployment relative to the benchmark rule by 25%; and a rule with $\omega_U = -0.8$ to capture a stronger response to unemployment. For reference, the Taylor rule discussed in the 2021 Monetary Policy Report (MRP) of the Federal Reserve (p. 44) puts a coefficient of one on the unemployment rate gap. Since the MRP rule expresses interest rates and inflation at annual rates, while our framework is based on a quarterly frequency, the MRP value of one would imply a value $\omega_U = -0.25$ in (17), while the MRP's balanced-approached rule implies a value of $\omega_U = -0.5$. Thus our choice of $\omega_U = -0.4$ is bracketed by the values in the MRP, while $\omega_U = -0.8$ represents a much stronger response to unemployment. For all three rules, we maintain $\omega_\pi = 1.5$ as in the benchmark rule.

We also consider two additional policy rules. One rule simply maintains inflation at zero. This provides a useful baseline to assess the employment consequences of ignoring unemployment and simply maintaining price stability. It also provides a baseline for assessing the inflationary consequences of policies that aim to stabilize unemployment. Finally, to investigate the implications of responding to an alternative measure of labor market activity, we consider a rule that includes inflation but replaces the unemployment rate with the total employment separation rate ρ_t. Berger et al. (2019), for example, examined rules targeting the layoff rate, and found that they approximate well the behavior of the Federal Reserve and produced good macroeconomic outcomes. We calibrate the coefficient on ρ_t so that the reduction in the initial level of unemployment at the start of the pandemic is the same as under the aggressive unemployment rule with $\omega_U = -0.8$.

We use five metrics to evaluate these alternative policies. The first is the output loss, measured as the cumulative loss in output, expressed as a percentage of steady-state output, over the first two years of the pandemic. The second metric we call the 'type l unemployment loss'. This is defined as the cumulative excess percentage points of total unemployment U_t accounted for by l-workers over the same two-year horizon.[26] We also calculate the corresponding type h unemployment loss. Our fourth metric is a measure of the distribution of excess unemployment across the two worker types. We label this the *inequality ratio* and define it simply as the ratio of the type l unemployment loss to the type h unemployment loss. A smaller value of this ratio implies that a policy results in less dispersion in the behavior of unemployment across the two worker types. In the context of the COVID-19 recession, which affects disproportionately type l workers, a lower inequality ratio implies a rebalancing of the burden of the recession towards a more equal distribution across worker groups.

Finally, we assess the inflation costs of more expansionary policies that aim to limit the unemployment cost of a pandemic. To do so, we compute a *sacrifice ratio* defined as the cumulative deviation of inflation from price stability divided by the cumulative reduction in unemployment relative to the policy of price stability over the first two years of the pandemic. Letting $U_{t,\pi=0}$ denote unemployment in period t under the $\pi = 0$ policy, the sacrifice ratio is

$$Sacrifice\ Ratio_T \equiv \sum_{t=1}^{T=8} \pi_t / \sum_{t=1}^{T=8} (U_{t,\pi=0} - U_t) = (p_T - p_0) \,/ \sum_{t=1}^{T=8} (U_{t,\pi=0} - U_t).$$

This ratio provides an assessment of the cost in terms of inflation for each percentage point reduction in cumulative aggregate unemployment relative to unemployment conditional on

[26] At each t the excess $l-$unemployment rate is computed as $\alpha U_t^l - U_{ss}$ where $\alpha = (N_t^l - N_{ss}^l)/(N_t - N_{ss})$.Scaling the number of unemployment workers by the total number of unemployed allows us to compare the unemployment losses across workers types.

a policy of price stability.[27] The cumulative inflation measure in the numerator is just the percent rise in the price level over the two years. As we show below, the benchmark policy performs worst than the zero inflation policy. We thus use the policy consistent with price stability as our baseline for calculating the sacrifice ratio.

5.1 Comparing alternative rules

The implications of the alternative rules are reported in Table 2. Column (1) provides results for the policy that maintains price stability, column (2) contains results for our benchmark rule used in previous sections that incorporates a policy response only to inflation. Columns (3) and (4) give evidence on the consequences of responding to aggregate unemployment as well as to inflation. Finally, column (5) replaces unemployment with the total separation rate as an alternative measure of labor market activity.

Comparing columns (1) and (2) shows that the benchmark rule given by (10) is inefficient and is dominated in terms of both unemployment volatility and inflation volatility by a policy that ensures price stability. That is, strict inflation targeting yields a smaller output loss as well as smaller unemployment losses for both worker types than when policy responds by moving the nominal interest rate by 1.5 times the movements in inflation. The reason is that the benchmark policy (10) fails to prevent prices from falling, as can be seen in the upper left panel of figure 9 which shows responses of macroeconomic variables in the COVID-19 scenario under alternative policies. The dotted lines correspond to the benchmark policy. The policy of price stability is shown by the solid lines. By preventing inflation from falling, maintaining $\pi_t = 0$ results in a more expansionary policy than the benchmark policy and succeeds in dampening the fall in output and the rise in the unemployment loss for both worker types. Policies (1) and (2) both involve significant reductions in the nominal interest rate, as seen in the lower left panel of the figure, suggesting that the effective lower bound on nominal rates would limit their feasibility.

The smaller output loss under price stability benefits both worker types, as measured by the worker-specific unemployment losses. Price stability also reduces the inequality ratio; that

[27] Typically, a sacrifice ratio measures the unemployment cost of reducing inflation. Because our focus on the inflation cost of different policies designed to limit the pandemic impact on unemployment, we define it as the inflation cost of limiting the rise in unemployment.

is, type l workers benefit relative to type h workers under a policy that keeps inflation at zero. As is common in new-Keynesian models with forward-looking price setting, the policymaker's commitment to a price level target affects firms' expectations - and in our model also the surpluses' continuation values - leading to more favorable outcomes, relative to our benchmark rule that allows inflation to fall.

Columns (3) and (4) offer a comparison of the price stability and the benchmark policies with rules that react to aggregate unemployment as well as to inflation. The weight on U_t, $\omega_U = -0.4$, in column (3) is calibrated to achieve a 25% reduction in the initial unemployment rate experienced under the pandemic shocks as compared to the benchmark policy in column (2). This value also implies that the initial unemployment effect under the rule equals the rise in unemployment under the policy of price stability, as can be seen in the upper right panel of figure 9.

The rule calibrated to reduce the rise in U_t, not surprisingly, also reduces the output loss. It also is successful in reducing the unemployment loss for both worker types. Relative to the benchmark policy in column (2), type l workers benefit greatly when policy responds to aggregate unemployment, with their cumulated unemployment loss falling from 24.56% to 16.95%, a 31% reduction. In comparison to the benchmark policy, setting $\omega_U = -0.4$ succeeds in reducing the unemployment cost for type l workers relative to type h workers, as measured by the inequality ratio; this ratio falls from 8.07 to 6.85, a 14% decline. The comparison of column (3) with price stability in column (1) shows similar if more modest improvements; the type l unemployment loss falls by 11% (from 19.01 under price stability to 16.95), type h unemployment falls by 4% (from 2.56 to 2.47), and the inequality ratio decreases by 7.7%. Note that the declines in the inequality ratio are less than proportional to the falls in the unemployment loss for low-efficiency workers. This reflects the fact that the policy also reduces the unemployment loss for high-efficiency workers. By benefiting *all* workers, a policy responding to U_t has a more modest impact on how the burden of the recession is allocated across the two types of workers.

The policy in column (4) considers the effects of responding more aggressively to aggregate unemployment, in this case by doubling the response coefficient ω_U from -0.4 to -0.8. Not surprisingly, this policy succeeds in producing a smaller output loss and smaller unemployment

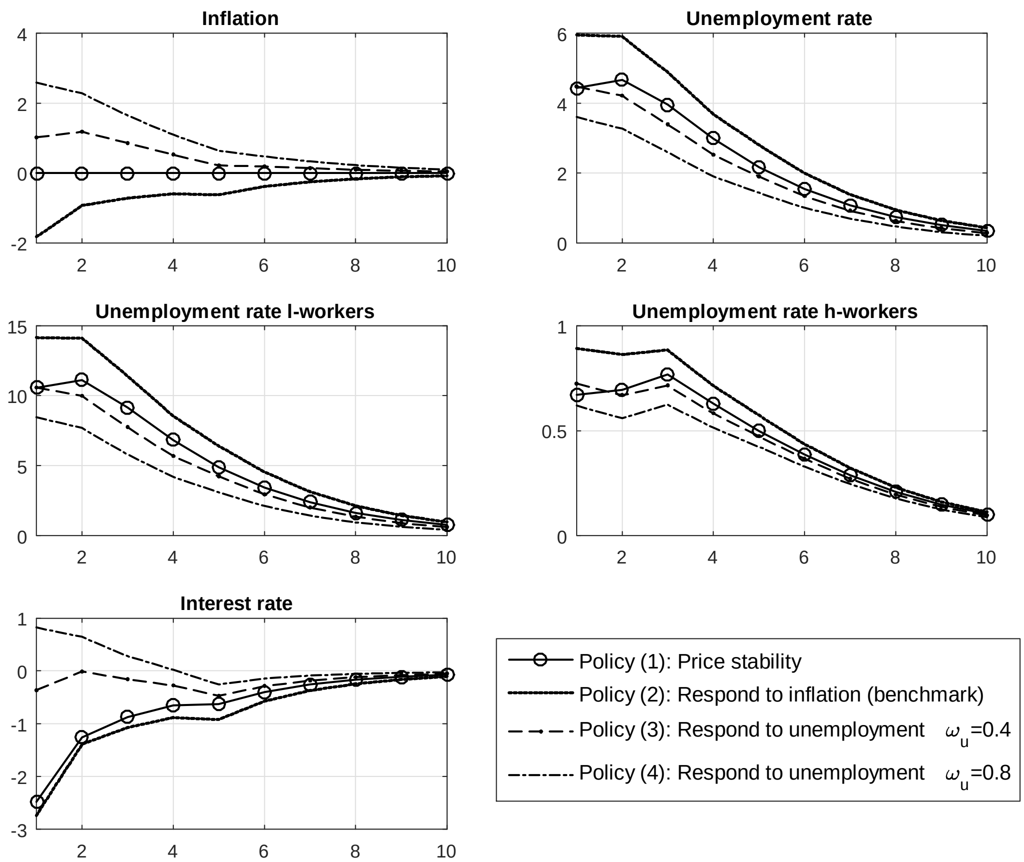

Figure 9: Impulse resonses to the COVID-19 shock under alternative policy rules. Inflation and interest rate are shown at quarterly rates.

losses for both worker types. Output loss and type h unemployment loss both decline by 13 to 14%, while type l unemployment loss falls by 24% relative to the less aggressive policy where $\omega_U = -0.4$. The column (4) policy also achieves the lowest value of the inequality ratio among the policies reported in the table. Thus, the more aggressive responses to unemployment has a disproportionately positive impact on unemployment among the workers who experience more frequent and longer spells of unemployment.

The bottom row of table 2 offers some insight into the inflation costs associated with policies that more aggressively target unemployment. Moving from a policy of price stability to one that follows the unemployment policy rule with $\omega_U = -0.4$ produces a path of aggregate unemployment that generates, in total, 2.14 fewer percentage points of unemployment while leaving the price level 4.24% higher after two years. That is, the policy in column (3) leaves the price level 1.97% higher after two-years per percentage point reduction in excess unemployment. Reacting more aggressively to unemployment by increasing the absolute value of ω_U from 0.4 to 0.8 as in the column (4) policy leads to a much larger unemployment improvement relative to price stability, with a cumulative reduction of unemployment equal to 6.56 percentage points. This more expansionary policy also generates significantly more inflation, with the price level 9.31% higher after two years relative to the baseline of price stability. The sacrifice ratio, however, at 1.41, is actually lower than under the column (3) policy, implying the price rise per percentage point reduction in unemployment is lower.

Column (5) in Table 2 reports the results if monetary policy responds to total separations ρ_t by following the policy rule

$$\ln(1 + i_t) = -\ln \beta + \omega_\pi \pi_t + \omega_\rho \rho_t, \tag{18}$$

where ω_ρ is calibrated to target the same reduction in the initial impact of the pandemic recession on aggregate unemployment as achieved by the policy with $\omega_U = -0.8$ reported in column (4). This implies a value for ω_ρ of -0.021; ω_π is maintained equal to 1.5. By construction, endogenous separations fall on type l workers, so a monetary policy that reacts directly to separations might offer the potential to benefit specifically type l workers. However, a comparison of columns 4 and 5 shows that this is not the case. The output loss and type-specific unemployment losses are all larger under the ρ_t policy rule. Furthermore, the inequality ratio is higher as well.[28]

The result can be traced back to the causes of the increase in the unemployment stock during the recession. The initial unemployment increase is driven by the sharp increase in exogenous layoffs, while as the recession progresses the fall in job finding probability becomes the main driver of the persistence in unemployment. Therefore the unemployment rate falls much more slowly than layoffs, which return relatively quickly to their steady-state level. Conditional on the policy (5) responding to total separations, after 5 quarters the unemployment rate has fallen by about 50% relative to its initial level, while the separation rate has fallen by 75%. A policy responding to the layoff rate ends up cutting support to the economy too early relative to a policy responding to the unemployment rate.

The comparison of policy rules has been conducted using the model that includes temporary layoffs. Such layoffs, by introducing the possibility of recall to employment directly from being on temporary layoff, serves to benefit high-efficiency workers more than low-efficiency workers. Firms can expand employment through recall, reducing the need to post vacancies. With firms posting fewer vacancies relative to outcomes without temporary layoffs, l workers, who are over-represented in the unemployment pool, experience a lower exit rate from unemployment. Their share in the unemployment pool increases above what would be observed in the model with only permanent unemployment. This in turn lowers even more the incentive of firms to post vacancies, and, with access to high-efficiency workers via recalls, firms become more selective, that is, $\bar{a}_t^l$ rises. In equilibrium, the possibility of recalling workers from temporary unemployment reduces total unemployment, but unemployment for l workers is only marginally lower. Policy therefore needs to be more aggressive to succeed in lowering their unemployment rate significantly relative to a model to the case without recall.

Policies that react to labor market variables do have some effect in reallocating the impact from a pandemic shock across worker types, and thus reducing the inequality of the recession burden, at least relative to either price stability policy in column (1) or the benchmark policy in column (2), but the effects are modest. The similarity of the l-unemployment loss and h-unemployment losses under the U_t and ρ_t rules indicates the measures of unemployment loss

[28] To aovid clutter in figure 9, the impulse responses under the ρ_t policy are provided in the online appendix.

move roughly in line with the aggregate economy, regardless of the specific variable added to the policy rule.

Overall the separation rate policy delivers a cumulative reduction of unemployment equal to 4.42%, which is greater that the column (3) policy but less than the column (4) policy. Similarly, the resulting rise in the price level after two years under the separation rate policy of 5.77% is greater than the column (3) policy but less than the column (5) policy. Expressed in terms of the price level rise per percentage reduction in unemployment, its sacrifice ratio, at 1.31, is the lowest of the three policies that respond to labor market variables. The policy in column (5) is very expansionary at the beginning at the pandemic, when the unemployment increase is driven by the rise in layoffs. However, it is not as expansionary latter periods when the layoff rate declines but unemployment remains high because hiring take longer to recover. Because inflation is a forward looking variable in the model, a policy that promises to be less expansionary in the future acts to dampen the inflationary impact of COVID-19.

The general explanation for these results is that monetary policy affects the aggregate economy but cannot ensure that expansionary policy designed to dampen the adverse impacts of the pandemic will propagate in a manner that helps those workers most affected by the recession. Focusing on the behavior of the markup helps understand why. Monetary policy is able to reduce unemployment by reducing interest rates and increasing aggregate demand. This increased demand for retail goods also boosts the demand for wholesale goods and the demand for labor. Under the benchmark policy, the retail price markup rises as the recessionary drop in demand causes wholesale prices to fall, as shown in the top panel of Figure 10. All the alternative policies are more expansionary at the onset of the pandemic. As such, they support aggregate demand and output. This limits the rise in the markup, and, as seen in the bottom panel, the rise in $\bar{a}_t^l$, helping to reduce the inflow of type l workers into unemployment and increase their exit rate from unemployment. However, the effect on the inequality ratio is limited because the markup affects the marginal revenue product of *both* worker types; the value of the output produced by a type h worker is ϕ^h/μ_t and that by a type l worker is $a_{i,t}^l\phi^l/\mu_t$. To the extent μ_t rises less, the match surpluses for low-efficiency workers *and* high-efficiency workers fall less. Both types benefit, but because both worker types benefit, the ability of monetary policy to have a significant and differential impact on the different worker

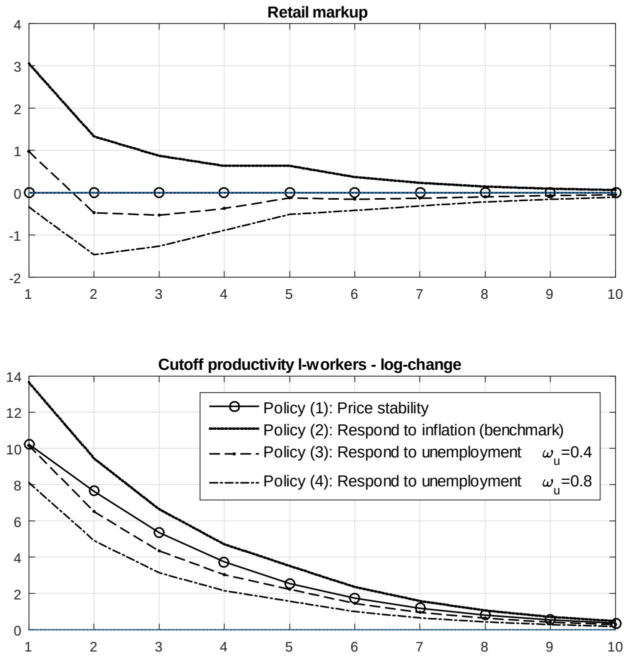

Figure 10: Temporary layoff model with alternative policies rules. Panels show the responses of μ_t (top) and $\bar{a}_t^l$ (bottom) to the pandemic shocks under four different rules; price stability (solid line), the baseline rule (dotted line), the $\omega_U = -0.4$ rule (dot-dashed line), and the $\omega_U = -0.8$ rule (dashed line)

groups is limited.

The inverse of μ_t is real marginal cost for retail firms. By limiting the rise in μ_t, the policies stabilizing U_t also stabilize inflation. This is also true of the ρ_t policy.[29] As row (5) of the table shows, the policies responding to U_t (col. 2) or ρ_t (col. 3) each has a lower sacrifice ratio than the baseline rule that responds only to inflation (col. 1).

Overall, our analysis finds that the monetary authority can reduce the impact of the COVID-19 shock on the aggregate economy and on the adverse employment outcomes of low-efficiency workers. However monetary policy is not very effective in reallocating the impact of a pandemic shock across worker types. Reducing the burden of the recession for the low-efficiency group of workers will necessarily lead to also supporting employment for high-efficiency workers. This does not imply that monetary policy is ineffective – rather, the monetary policy transmission channel is not adequate to target specific groups of workers affected by the pandemic. A policy of price stability prevents the deflation associated with the COVID-19 shocks

[29] See the impulse response figure in the online appendix.

under a simple inflation targeting policy, and is effective in reducing unemployment, albeit not as effective as the more employment ‘inclusive’ policies we consider.

6 Conclusions

We have used a calibrated new Keynesian model with labor heterogeneity and selection in a search and matching labor market to investigate the distribution of unemployment across workers in a pandemic recession such as that caused by COVID-19. We model the pandemic as resulting from two shocks; one shifts household preferences away from market produced consumption and toward leisure and home production, while the second causes a spike in mass layoffs. The model is then used to compare the market adjustment to a COVID-19 shock to the adjustment in the social planner’s allocation. We identify a new externality that arises when individual firms ignore the effects their separation and hiring decisions have on the composition of the pool of unemployed workers. During a pandemic-induced recession, the resulting distortion acts to disproportionately worsen the labor force outcomes for those workers who on average have more frequent and longer spells of unemployment. Inefficient selection in endogenous hiring and retention decisions adversely affects the quality of the unemployment pool, leading firms to post fewer vacancies. All workers end up experiencing poorer labor market outcomes. These results continue to hold even if a large fraction of the layoffs take the form of temporary layoffs, as they did early in the COVID-19 recession.

COVID-19 had heterogeneous effects across many economics dimensions, with disparate effect across sectors, industries, regions, and individuals. We have focused on heterogeneity across workers and their employment experiences because of the interest expressed by central banks, particularly in the U.S., over the distributional impact of monetary policy on workers who suffer high rates of unemployment. While our model suggests that by responding to labor market variables monetary policy can help stabilize unemployment in the face of recessionary shocks, thereby benefiting all workers, the ability to affect the distribution of unemployment across worker types is more limited. Monetary policy can reduce the inequality of the recessionary burden falling on workers with different productivity levels by responding to aggregate unemployment or separations, but only at a considerable cost in terms of inflation. Because the markup plays a central role in determining the value of job matches and therefore the endogenous separation rate, a policy of price stability that stabilizes the markup does surprisingly well and outperformed our benchmark rule which failed to prevent deflation. To significantly affect the disproportionate unemployment burden that falls on some workers, our results suggest tools other than monetary policy, such as taxes and/or subsidies, may be more effective instruments for dealing with cyclical variations in impact of unemployment across workers.

References

Ahn, H. J. and J. D. Hamilton (2019). Heterogeneity and unemployment dynamics. *Journal of Business and Economic Statistics*, 1–16.

Aum, S., S. Y. Kee, and Y. Shin (2020). COVID-19 Doesn't Need Lockdown to Destroy Job: The Effect of Local Outbreaks in Korea. *NBER Working Paper No. 27264*.

Baker, M. (1992). Unemployment duration: compositional effects and cyclical variability. *American Econmic Review 82*, 315–321.

Baley, I., A. Figueiredo, and R. Ulbricht (2020). Mismatch Cycles. *Working Paper*.

Baqaee, D. R. and E. Farhi (2020). Supply and Demand in Disaggregated Keynesian Economies with an Application to the Covid-19 Crisis. *NBER Working Paper No. 27152*.

Barrero, J. M., N. Bloom, and S. J. Davis (2020). COVID-19 is also a reallocation shock. *NBER Working Paper No. 27137*.

Berger, D., I. Dew-Becker, L. D. W. Schmidt, and Y. Takahashi (2019). Layoff Risk, the Welfare Cost of Business Cycles, and Monetary Policy. *Working Paper*.

Bergman, N., D. A. Matsa, and M. Weber (2021). Heterogeneous Labor Market Effects of Monetary Policy. *Chicago Booth Research Paper No. 21-02*.

Bernstein, J., A. W. Richter, and N. A. Throckmorton (2020). COVID-19: A View from the Labor Market. *Federal Reserve Bank of Dallas, Working Paper No. 2010*.

Bils, M., Y. Chang, and S.-B. Kim (2012). Comparative advantage and unemployment. *Journal of Monetary Economics 59*(2), 150–165.

Cheng, W., P. Carlin, J. Carroll, S. Gupta, F. L. Rojas, L. Montenovo, T. D. Nguyen, I. M. Schmutte, O. Scrivner, K. I. Simon, C. Wing, and B. Weinberg (2020). Back to Business and (Re)Employing Workers? Labor Market Activity During State COVID-19 Reopenings. *NBER Working Paper No. 27419*.

Cortes, G. M. and E. Forsythe (2020a). Impacts of the Covid-19 Pandemic and the CARES Act on Earnings and Inequality. *IZA DP No. 13643*, 1–42.

Cortes, G. M. and E. Forsythe (2020b). The Heterogeneous Labor Market Impacts of the Covid-19 Pandemic. *Upjohn Institute Working Paper 20-327*.

Davis, S. J., J. C. Haltiwanger, and S. Schuh (1996). *Job Creation and Job Destruction.* Cambridge, MA: The MIT Press.

Dickens, W. T. and R. K. Triest (2012, jan). Potential Effects of the Great Recession on the U.S. Labor Market. *The B.E. Journal of Macroeconomics 12*(3).

Eichenbaum, M. S., S. Rebelo, and M. Trabandt (2020). Epidemics in the Neoclassical and New Keynesian Models. *NBER Working Paper No. 27130*.

Fornaro, L. and M. Wolf (2020). Covid-19 Coronavirus and Macroeconomic Policy: Some Analytical Notes. *Working Paper* (March), 1–8.

Gertler, M., L. Sala, and A. Trigari (2008). An estimated monetary DSGE model with unemployment and staggered Nash wage bargaining. *Journal of Money, Credit and Banking 40*(8), 1713–1764.

Gregory, V., G. Menzio, and D. Wiczer (2020). Pandemic Recessions: L- or V-Shaped. *FRB Minneapolis Quarterly Review* (May).

Gregory, V., G. Menzio, and D. G. Wiczer (2021). The Alpha Beta Gamma of the Labor Market. *NBER Working Paper No. 28663*.

Grigsby, J. (2020). Skill Heterogeneity and Aggregate Labor Market. *Working paper*.

Guerrieri, V. (2007). Heterogeneity and unemployment volatility. *Scandinavian Journal of Economics 109*(4), 6667–693.

Guerrieri, V., G. Lorenzoni, L. Straub, and I. Werning (2020). Macroeconomic Implications of COVID-19: Can Negative Supply Shocks Cause Demand Shortages? *NBER Working Paper No. 26918*.

Hall, R. E. (2015). Quantifying the Lasting Harm to the U. S. Economy from the Financial Crisis. In J. A. Parker and M. Woodford (Eds.), *NBER Macroeconomics Annual 2014*, Volume 29, pp. 71–128. University of Chicago Press.

Hall, R. E. (2017). High discounts and high unemployment. *American Economic Review 107*(2), 305–330.

Hall, R. E. and S. Schulhofer-Wohl (2018). Measuring job-finding rates and matching efficiency with heterogeneous job-seekers. *American Economic Journal: Macroeconomics 10*(1), 1–32.

Hornstein, A., P. Krusell, and G. L. Violante (2011). Frictional Wage Dispersion in Search Models: A Quantitative Assessment. *American Economic Review 101*(7), 2873–2898.

Jackson, P. and V. Ortego-Marti (2020). Skill Loss during Unemployment and the Scarring Effects of the COVID-19 Pandemic. *UC Riverside Working Papers 202020*.

Kahn, L. B., F. Lange, and D. G. Wiczer (2020). Labor Demand in the Time of COVID-19: Evidence from Vacancy Postings and UI Claims. *NBER Working Papers No. 27061*.

Kapicka, M. and P. Rupert (2020). Labor Markets during Pandemics. *Working Paper*.

Kocherlakota, N. R. (2020). 21st century macro. *NBER Working Paper No. 26791*.

Kospentaris, I. (2020). Unobserved Heterogeneity and Skill Loss in a Structural Model of Duration Dependence. *Review of Economic Dynamics 39*, 280–303.

Kudlyak, M. and E. Wolcott (2020). Pandemic Layoffs. *Working Paper* (May).

Leduc, S. and Z. Liu (2020). The weak job recovery in a macro model of search and recruiting intensity. *American Economic Journal: Macroeconomics 12*(1), 310–343.

Lemieux, T. (2006). Increasing residual wage inequality: composition effects, noisy data or rising demand for skills? *American Economic Review 96*(3), 461–498.

Lepetit, A. and C. Fuentes-Albero (2021). The Limited Power of Monetary Policy in a Pandemic. *Working Paper* (January).

Nagypal, E. (2007). Learning-by-doing versus learning about match quality. *Review of Economic Studies 74*(2), 537–566.

Nagypal, E. and D. T. Mortensen (2007). Labor-market volatility in matching models with endogenous separations. *Scandinavian Journal of Economics 109*(4), 645–665.

Powell, J. H. (2020). New economic challenges and the Fed's monetary policy review. *FRB Kansas City Jackson Hole Symposium*.

Pries, M. J. (2008). Worker heterogeneity and labor market volatility in matching models. *Review of Economic Dynamics 11*, 644–687.

Ravenna, F. and C. E. Walsh (2008). Vacancies, unemployment, and the Phillips curve. *European Economic Review 52*(8), 1494–1521.

Ravenna, F. and C. E. Walsh (2011). Welfare-Based Optimal Monetary Policy with Unemployment and Sticky Prices: a Linear-Quadratic Framework. *American Economic Journal: Macroeconomics 3*(April), 130–162.

Ravenna, F. and C. E. Walsh (2012). Screening and Labor Market Flows in a Model with Heterogeneous Workers. *Journal of Money, Credit and Banking 44*(2), 31–71.

Ravn, M. O. and V. Sterk (2017). Job uncertainty and deep recessions. *Journal of Monetary Economics 90*, 125–141.

Sala, L., U. Söderstrom, and A. Trigari (2008, jul). Monetary Policy under Uncertainty in an Estimated Model with Labor Market Frictions. *Journal of Monetary Economics 55*(5), 983–1006.

Taylor, J. B. (1993). Discretion versus policy rules in practice. *Carnegie Rochester Conference Series on Public Policy 39*(1), 195–214.

Thomas, C. (2008). Search and Matching Frictions and Optimal Monetary Policy. *Journal of Monetary Economics 55*, 936–956.

Trigari, A. (2009, feb). Equilibrium Unemployment, Job Flows, and Inflation Dynamics. *Journal of Money, Credit and Banking 41*(1), 1–33.

Walsh, C. E. (2003). Labor Market Search and Monetary Shocks. In S. AltuÄİ, J. Chadha, and C. Nolan (Eds.), *Elements of Dynamic Macroeconomic Analysis*, pp. 451–486. Cambridge, U.K.: Cambridge Univeristy Press.

Walsh, C. E. (2005). Labor Market Search, Sticky Prices, and Interest Rate Policies. *Review of Economic Dynamics 8*(4), 829–849.

Table 1: Parameters and Steady State Values		
Targeted Steady State Values		
Unemployment rate	u_{ss}	5.6%
Unemployment rate: $l-efficiency$ labor	u_{ss}^{l}	9.87%
Unemployment rate: $h-efficiency$ labor	u_{ss}^{h}	2.97%
Average hours per worker	h_{ss}^{av}	0.33
Vacancy posting cost share of output	$\frac{\kappa V_{ss}}{Y_{ss}}$	0.015
Probability of vacancy matched with applicant	k_{ss}^{f}	0.9
Implied Parameters and Steady State Values		
Labor force $l-efficiency$ workers share	$\overline{\gamma}$	0.38
Unemployment share $l-efficiency$	γ_{ss}	0.52
Employment share $l-efficiency$	ξ_{ss}	0.36
Relative productivity of high-/low-efficiency workers		1.16
Relative productivity of employed/unemployed workers		1.04
Interview matching function efficiency	ψ	0.743
Disutility of labor hours	ℓ	8.5
Value of home production	w^{u}	0.057
Vacancy posting cost	κ	0.036
Inverse of labor hours supply elasticity	χ	1
Relative risk aversion	σ	1
Unemployment elasticity of matching function	α	0.6
Workers' share of surplus	η	0.6
Steady-state separation rate	ρ_{ss}	7.45%
Exogenous separation rate	ρ^{x}	5.8%
Endogenous separation/screening rate	ρ_{ss}^{n}	4.9%
AR(1) parameter for exogenous shocks	ρ_{z}	0.7
Price elasticity of retail goods demand	ε	11
Discount factor	β	0.99
Average retail price duration (quarters)	$\frac{1}{1-\omega}$	4

Table 1: Baseline Parameterization. Average productivity of high- and low-efficiency worker-hours is given by ϕ^{h} and $\phi^{l}\int_{0}^{1} a_{i}^{l} dF(a_{i}^{l})$. U.S. unemployment rate for low- and high-efficiency workers from the classification of workers based on employment spell duration from LEHD data taken from Gregory, et. al. (2021). See the Appendix for details.

Table 2: Outcome for Alternative Policies					
	Alternative policies				
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Variables in policy rule		$\boldsymbol{\pi}$	π, U	π, U	π, ρ
Response coefficients ω_π and ω_U		**1.5, 0**	**1.5, −0.4**	**1.5, −0.8**	**1.5, −0.021**
Target reduction	$\boldsymbol{\pi = 0}$		**25% (U)**		
1) Output loss	**27.09%**	**32.78%**	**26.02%**	**22.31%**	**23.63%**
2) l**-unemployment loss**	**19.01%**	**24.56%**	**16.95%**	**12.85%**	**14.88%**
3) h**-unemployment loss**	**2.56%**	**3.04%**	**2.47%**	**2.16%**	**2.27%**
4) Inequality ratio	**7.42**	**8.07**	**6.85**	**5.95**	**6.55**
5) Sacrifice Ratio	–	–	**1.97**	**1.41**	**1.31**

Table 2: Policies: column 1 – price stability; column 2 benchmark policy given by (10); column 3 given by (17) with $\omega_U = -0.4$, parameterized to reduce the rise in unemployment in the first period of the COVID shock by 25%. relative to column 2; column 4 given by (17) with $\omega_U = -0.8$. Output and unemployment losses by worker-types, the unemployment inequality ratio, and the sacrifice ratio are defined in the text.