Job Amenity Shocks and Labor Reallocation*

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Abstract

We introduce aggregate shocks to the value of job amenities in a frictional equilibrium model of the labor market with on-the-job search, where the job creation cost is sunk and quits create vacancies. We examine how key labor market indicators respond to this shock: when the valuation of the amenity is heterogeneous in the population, labor reallocation ensues. A calibrated version of the model can quantitatively account for many peculiar traits of the post-pandemic labor market recovery through three aggregate shocks: a temporary fall in productivity to account for the short, but sharp, downturn; a rise in the opportunity cost of work; and, crucially, a persistent increase in the value that workers put on job amenities. Cross-sectoral patterns of vacancies, quit rates, and job-filling rates where sectors are ranked by the share of teleworkable jobs offer support to the view that they key amenity in question is the ability to work remotely.

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1 Introduction

The notion that jobs offer both wage and non-wage amenities for workers originates from Adam Smith's book "The Wealth of Nations," published in 1776. Smith asserts that workers preferences for jobs are not solely dictated by the wage, but rather by the *overall advantages and disadvantages* associated with a job. Before the 20th century, employers primarily focused on providing safe and healthy working environments as non-wage amenities. As labor markets evolved over time, jobs started to incorporate benefits such as health insurance and retirement plans. More recently, job amenities have expanded to provide better work-life balance, remote work options, flexible work hours, shift choices, access to gym and cafeteria facilities, etc.

While the canonical search models focus on wages as the sole determinant of desirability of a job, considering job amenities breaks the one-to-one mapping between offered wages and attractiveness of a job. Since workers are likely to value job amenities differently, their job choices are informed not only by the wage offered but also by the value they place on the non-wage amenities. A number of papers in the search and matching literature have studied the significance of job amenities in influencing various labor market outcomes, such as wage dispersion, job search behavior, worker flows from high to low-paid jobs, gender wage gap, and the sorting between workers and firms.[1]

We build on this growing literature and examine the effects of an aggregate shock to the value of amenities on the labor market. In particular, we aim to study how the labor market responds to a broad-based shift in workers' valuation of specific job amenities. This requires building an equilibrium model of job search with several ingredients: (i) heterogeneity in non-pecuniary amenities of jobs; (ii) heterogeneity in workers' valuation of these amenities; (iii) on-the-job search; and (iv) job vacancies created by quits. While our framework is applicable to examining other changes in workers' preferences (such as news about adverse health effects of certain occupations), our focus is the shift in worker preferences after the onset of the COVID-19 pandemic, and its labor market consequences.

The post-pandemic labor market has exhibited peculiar characteristics, deviating from typical recovery patterns, suggesting that an unconventional shock has impacted the economy. Three unprecedented developments in the labor market were observed during the post-pandemic economic recovery. First, the so-called *Great Resignation*: the quit rate for employed workers reached 3% in 2021 almost 50% higher than in 2019. We docu-

[1] See for example, Rosen (1986), Hwang et al. (1998), Nosal and Rupert (2007), Bonhomme and Jolivet (2009), Hall and Mueller (2018), Sorkin (2018), Albrecht et al. (2018), Lamadon et al. (2021), Le Barbanchon et al. (2021).

ment that this increase in quits coincided with challenges in filling job openings for firms and a deterioration of matching efficiency. Second, the Beveridge curve exhibited a wide loop and a vertical shift unlike its commonly observed horizontal movements, and the vacancy rate jumped to historically high levels. Finally, the behavior of wages during the recovery from the pandemic recession also deviated from previous patterns. While high-wage workers typically experience faster wage growth during recoveries, leading to an increase in the wage gap between high- and low-wage workers' compensation, the opposite occurred after the pandemic leading to a sizable wave of *wage compression.*

Our hypothesis is that shifts in worker preferences in favor of job amenities, mainly remote work, led to a persistent labor reallocation. which can explain the distinctive post-pandemic labor market dynamics.

Evidence from several recent surveys lends support for our hypothesis. A number of different indicators are consistent with the view of a persistent reallocation occurring (Barrero et al., 2021). The Real-Time Population Survey (RPS), which was designed and fielded by Bick and Blandin (2021) during the pandemic, estimates that 31.5% of workers switched jobs between February 2020 to October 2022 and 21% of these job switchers moved from on-site jobs to fully remote or hybrid jobs. Put differently, 1 in 5 of recent job switches involved a shift to fully or partially remote work arrangements. Based on the Survey of Working Arrangements and Attitudes, Barrero, Bloom, and Davis (2023) find that workers who value work from home (WFH) were willing to accept pay cuts of 10% on average in exchange for 2 workdays a week of WFH. Applications data compiled from LinkedIn job posts in February 2022 suggest that remote job openings were more attractive for job seekers. Specifically, job listings for remote work represented just 19.4% of all paid job posts but attracted 50.1% of all applications and 45.1% of all posting views. We view these observations as supporting evidence for a shift in worker preferences that led to a persistent labor reallocation, and use them to discipline our theoretical model which we summarize next.

The first building block of our theoretical framework is the canonical matching model of the labor market in the tradition of Mortensen and Pissarides (1994) where random meetings are determined through an aggregate matching function. Once workers and firms meet, an idiosyncratic match value (the constant output on the job) is observed and a decision to form the match is taken.

To this structure, we add on-the-job search through the well-established sequential auction framework (Postel-Vinay and Robin, 2002; Lise and Robin, 2017). Upon meeting an unemployed worker, the firm makes a take-or-leave offer to the unemployed. When an employed worker meets another firm, the current employer and the potential poaching employer engage in Bertrand competition. Such auction can lead to the worker being retained (with or without a wage rise) or to a quit, depending on the relative match value in the two firms. Once the wage is set, it will be renegotiated again only under mutual consent, i.e. when one of the two parties in the match has a credible threat (a binding outside option, e.g. coming from an external offer).

We further extend the model along two dimensions, both crucial to confront the data. First, we allow jobs to be created with or without a non-pecuniary amenity, a fixed characteristic of the job. As in Rosen (1986), the model delivers a theory of compensating wage differentials. Workers are heterogeneous in how much they value the amenity (e.g., some like working from home, others do not care). The heterogeneity in workers' preferences and job characteristics leads to sorting, as in the classical paper by Roy (1951).

The second extension pertains the way we model job creation. We do not deviate from free entry, but we assume that the job creation cost is sunk after the initial investment, as in Diamond (1982). As a consequence of 'Diamond-entry', not all vacancies at a point in time are newly created ones as in standard search-matching models. Because idle positions have positive value in equilibrium, some existing ones in the vacancy pool will be unfilled vacancies originally posted in the past, and others will be quit-induced vacancies for which the employer is looking to replace the old worker with a new one. In particular, the model features vacancy chains.[2]

These two extensions move the model closer to reality. There are many non-pecuniary characteristics of a job that enter job acceptance or mobility decisions. Our general formulation encompasses many possible amenities, such as location, work-environment, flexibility of work schedule, commuting, etc. In the context of the historical episode we consider, we will think of this amenity mostly in terms of teleworkability of the job, i.e. whether the job can be performed remotely or not. The sunk entry-cost extension captures the idea that jobs outlast matches. For example, creating an additional job at a call center requires purchasing a chair, a desk, and the necessary equipment. Hiring the first worker might entail recruiting and training costs, but once that first worker leaves the firm and that match is dissolved, rehiring a new worker does not require making the initial investment again. That investment is sunk and the job is ready to be filled again. This feature allows the model to generate a rise in vacancies caused by a spike in quits, a dynamic that

[2]This Diamond-entry approach to job creation –which is the way entry is modelled in the whole firm dynamics literature, e.g. (Hopenhayn, 1992)– is rare in search models, but other examples exist (e.g. Fujita and Ramey, 2007; Hornstein et al., 2007; Coles and Kelishomi, 2018; Qiu, 2022).

helps explaining the data.

We introduce three aggregate shocks into the model: (i) a temporary negative fall in productivity to account for the short, but sharp, downturn; (ii) a rise in the value of unemployment (i.e., a negative labor supply shock) consistent with the generous expansion in unemployment insurance benefits and fiscal transfers to low-income households which took place over the period under examination; and (iii) a persistent rise in the value that workers put on job amenities.

The impulse response of the economy to a job amenity shock induces a wave of persistent labor reallocation. After the shock, workers who care about the amenity and are employed on jobs without it are mismatched. As they quit to better jobs, they create a spike in vacancies which are undesirable for much of the population, and hence harder to fill. This process leads to a decline in aggregate match efficiency. Because of compensating differentials, wage growth in jobs endowed with the amenity is lower than in jobs without it —a force that contributes to moderating overall real wage growth.

We use the fully nonlinear impulse response functions of the model to infer the realizations of these three shocks that best explain several dimension of the post-COVID labor market dynamics: (i) unemployment, (ii) vacancies, (iii) job finding rate, (iv) match efficiency, (v) job-filling rate, (vi) job-to-job transitions, (vii) wages, and (viii) output. Once we feed the estimated shock paths in the model, we match all these time series quite well over the three years starting from the onset of the pandemic. A shock decomposition shows that the estimated rise in the value of job amenities is in line with the evidence we discussed, and is crucial to account for the rise in quits and vacancies, the fall in match efficiency and the decline in real wages. As in the data, the model implies stronger wage growth in low-amenity sectors.

A cross-sectoral version of the model also lines up with the data, once industries are ranked by the share of teleworkable jobs. As predicted by the model, sectors where the amenity is less prevalent had the largest rise in job-to-job transitions and vacancies, and the biggest drop in job filling rates.

The rest of the paper is organized as follows. Section 2 introduces the different data sources we use in the paper and illustrates the key stylized facts of the post-Covid labor market recovery. Section 3 illustrates the theoretical framework and formally defines the equilibrium. Section 4 describes the model's parameterization. Section 5 presents the impulse response functions of these shocks, and Section 6 shows the model's fit of the data and the shock decomposition. Section 7 concludes the paper.

2 The Post-pandemic Labor Market in the U.S.

The U.S. labor market dynamics after the pandemic shock have been puzzling especially when compared with previous recoveries. In this section, we document several key comparisons with earlier business cycles. We start with unemployment and vacancies, document the behavior of quits, matching efficiency as well as wage growth. Our analysis pertains to significant recent labor market phenomena, such as the *Great Resignation,* the shift in the *Beveridge curve*, and *Wage Compression.*

2.1 Unemployment and Vacancies

The COVID-19 pandemic caused a significant disruption in the U.S. labor market. The abrupt decline in employment and significant increase in the unemployment rate at the onset of the COVID-19 pandemic were unparalleled: payroll employment decreased by 13.6%, and the unemployment rate rose by 11.2 percentage points from March to April in 2020. Despite the significant contraction in economic activity during lockdowns, the labor market exhibited a remarkably quick recovery compared to previous recessions. The unemployment rate retreated from its post-war high of 14.7% to its lowest post-war level of 3.5% within two years. Job openings quickly recovered and reached its highest levels in the last 20 years. This rapid recovery contrasts sharply with earlier recessions, particularly the Great Recession period, when the unemployment rate remained above 5% for almost a decade.

An important feature of the pandemic is the record high number of workers who were on temporary layoffs. This group of workers referred to as *the unemployed with jobs* by Hall and Kudlyak (2022) expanded substantially in April 2020, accounting for an important part of the surge in unemployment. The resulting temporary-layoff unemployment mostly dissipated by the end of 2020 and the peak of the jobless unemployment rate was only 4.9% in November 2020.[3] Motivated by these observations, we exclude unemployed workers on temporary layoffs from the unemployment stock and calculate an alternative unemployment rate throughout the paper since our focus is mostly on the recovery period.[4] Another notable labor market development was the brisk pick-up in labor demand. While there was a decline in vacancies in 2020 from their pre-pandemic level of around 7 million to 4.7 million in April 2020, vacancies quickly recovered back to their

[3] Hall and Kudlyak (2022) and Forsythe, Kahn, Lange, and Wiczer (2022)

[4] See Figure A3 for a comparison of unemployment rates with and without temporary layoffs.

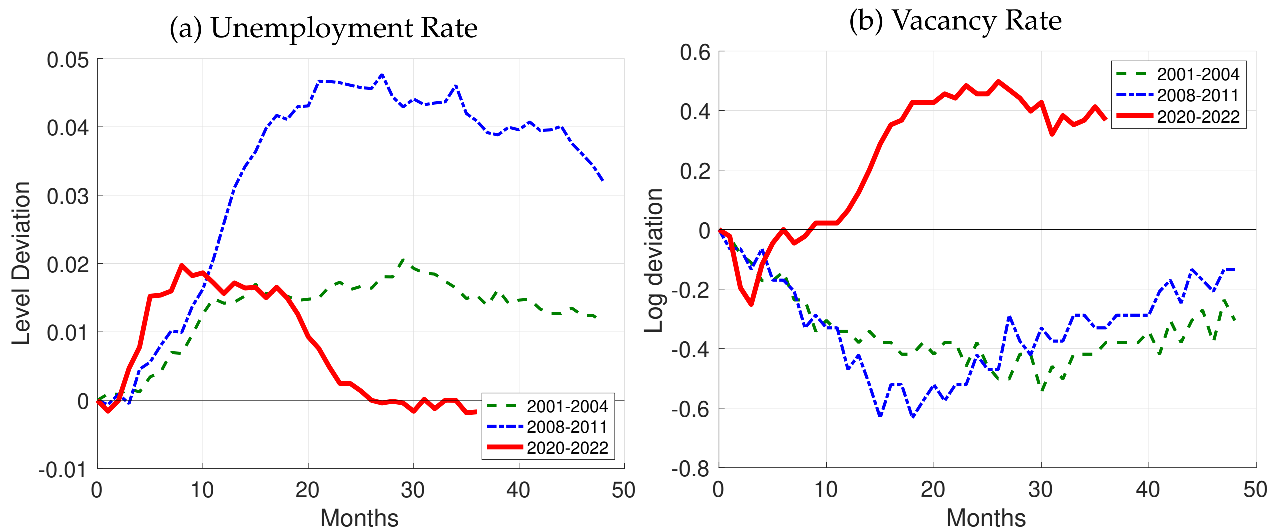


Figure 1: Level deviation in the unemployment rate (left) and log deviation in the vacancy rate (right) for 2001-2004, 2008-2011, and 2020-2022 periods.

Notes: CPS, JOLTS, and authors' calculations. The values are normalized to zero for January 2001, 2008, and 2020.

pre-recession level by January 2021 and continued to increase; peaking at 12 million in March 2022.

To provide a historical comparison with earlier recessions, Figure 1 compares the evolution of the unemployment rate and the vacancy rate normalized to zero at the beginning of the corresponding recession for the last three recessions. The pandemic recession stands out in its briefness. Not only the unemployment rate peaked earlier in the recent cycle but it also dropped precipitously. The unemployment rate peaked after 2.5 years following the 2001 recession while it was already back to its pre-recession level following the pandemic recession. The behavior of vacancies has also been very different. Vacancy rate reversed its drop quickly and reached to levels more than 50 percent higher than its pre-pandemic level.

Figure 2 shows how traditional measure of labor market tightness, the vacancy-to-unemployment ratio, evolved during the pandemic recession relative to earlier business cycles. Labor market conditions quickly became more favorable to jobseekers unlike the earlier recoveries when labor market conditions remained slack persistently. The right panel of Figure 2 shows the relative behavior of unemployment and vacancy rates in the context of the Beveridge curve. The recent vertical shift in the Beveridge curve stands in stark contrast to the horizontal shift of the curve which was arguably the most puzzling

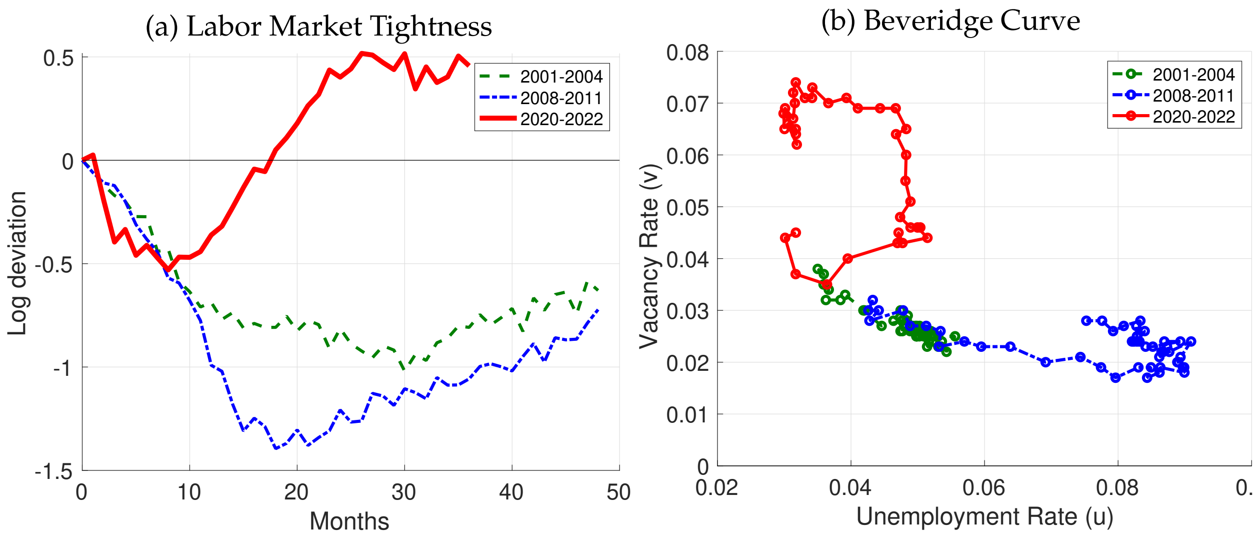


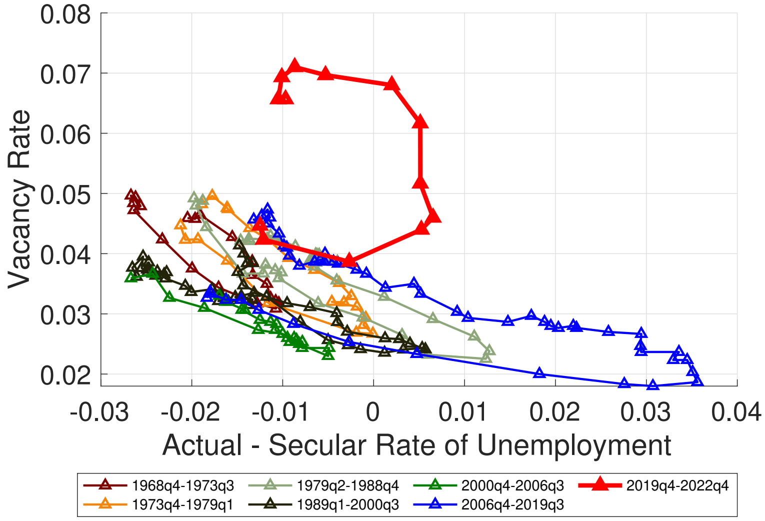
Figure 2: Vacancy-to-unemployment ratio (left) and the Beveridge Curve (right).

Notes: CPS, JOLTS, and authors' calculations. The values are normalized to zero for January 2001, 2008, and 2020. Labor market tightness is defined as vacancies/unemployed

feature of the labor market after the Great recession. While the literature analyzed the role of mismatch, unemployment insurance benefits, recruiting intensity, separations and workers' search effort in accounting for the horizontal shift in the Beveridge curve, the vertical shift observed after the pandemic remains unexplained.[5]

The nature of vacancies shifts after the pandemic remains unprecedented even when we focus on the last 50 years. Since the JOLTS started in 2000, we use the vacancy series constructed by Barnichon (2010) and Petrosky-Nadeau and Zhang (2021). We also take into account secular trends in the unemployment rate and compare the vacancy rate with the deviation of unemployment rate from its secular trend. Figure 3 plots the vacancy rate against the deviations of actual and secular rates of unemployment estimated in Crump et al. (2019). From 1968 to 2019, there was a clear negative correlation between the vacancy rate and unemployment: when the actual unemployment rate exceeded its secular trend, the vacancy rate was lower. This robust negative relationship broke down during the Pandemic recession when vacancies experienced a stark vertical jump.

[5]See for example, Daly, Hobijn, Şahin, and Valletta (2012), Davis, Faberman, and Haltiwanger (2013), Hall and Schulhofer-Wohl (2018), Şahin, Song, Topa, and Violante (2014), Gavazza, Mongey, and Violante (2018), Mukoyama, Patterson, and Şahin (2018), for the analysis of factors that shifted the Beveridge curve during the Great recession.



Source: CPS, JOLTS, and authors' calculations.

Figure 3: Vacancy rate and deviation of actual and secular rates of unemployment.

2.2 Quits, Job-finding and Job-filling Rates, and Matching Efficiency

Our examination of unemployment and vacancies have revealed that after the pandemic, the U.S. labor market has rapidly tightened with vacancy-to-unemployment ratio reaching 2 in 2022. However, only considering unemployed workers as job seekers is misleading as the extensive literature on job-to-job transitions has argued (Eeckhout and Lindenlaub (2019), Abraham, Haltiwanger, and Rendell (2020), Fujita, Moscarini, and Postel-Vinay (2023)). Abstracting from employed job searchers is likely to be even more important in the post-pandemic period due to the historically high quits rates that prevailed in 2021 and 2022. Following the end of the acute phase of the pandemic, quits rate rebounded briskly and reached its highest levels in the JOLTS series as shown in Figure 4. This significant surge in the quits rate has been coined as *the Great Resignation.* While the job-to-job transitions rate did not increase as much, its evolution has also been different than the earlier expansions.

Figure 5 plots the quits rate against the deviations of actual and secular rates of unemployment and shows that while both the previous recoveries exhibited a strong negative relationship between quits and unemployment rate deviations, the *Great Resignation* following the pandemic saw a breakdown of this relationship and a vertical jump in quits.

Given the increased importance of employed searchers, we incorporate them into our calculations for the job-finding and job-filling rates. In particular, we define searchers as the weighted average of unemployed and employed workers as $u_t + se_t$ where s is the

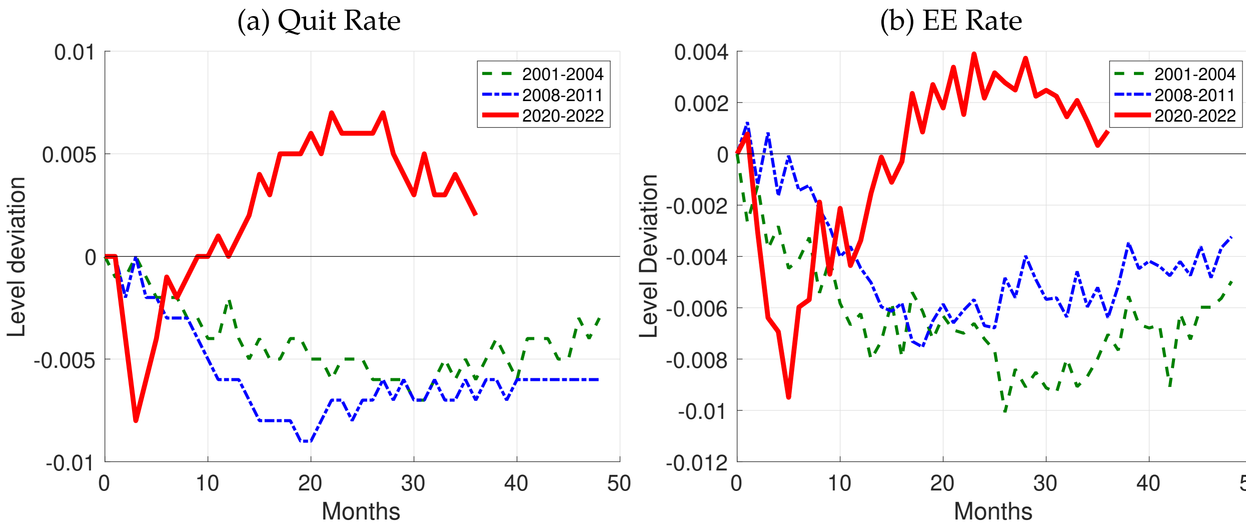
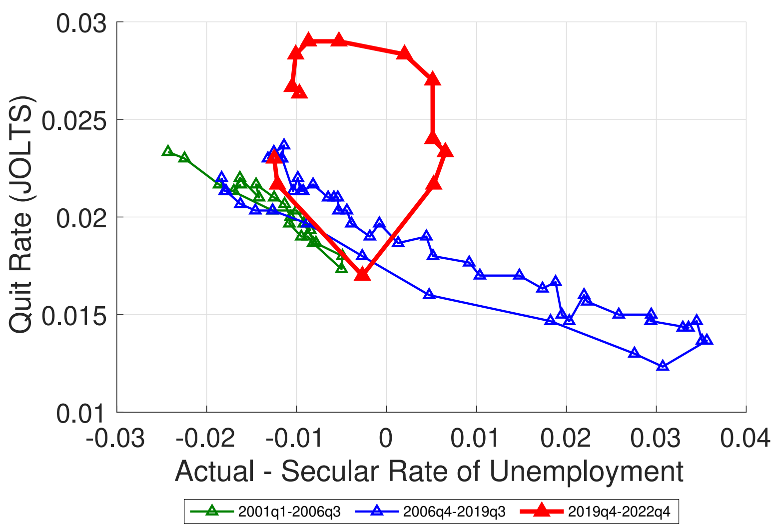


Figure 4: Quits and Job-to-job transitions

Notes: CPS, JOLTS, and authors' calculations. The values are normalized to zero for January 2001, 2008, and 2020. EE rate is expressed as EE hires as fraction of all employed. EE hires have been adjusted for JOLTS cyclicality and CPS levels as described in Appendix A.



Source: CPS, JOLTS, and authors' calculations.

Figure 5: Quits rate and deviation of actual and secular rates of unemployment.

relative search effort of the employed and v_t denotes vacancies. Total hires (h_t) is the sum of hires from unemployment (h_t^u) and employment (h_t^e). Therefore job-finding and filling rates are defined as $(h_t^u + h_t^e)/(u_t + se_t)$ and $(h_t^u + h_t^e)/v_t$, respectively. We use a relative search weight of 0.6 for employed workers consistent with our parametrization of the model in section 4. Our measure of total hires comes from the CPS and adjusts for

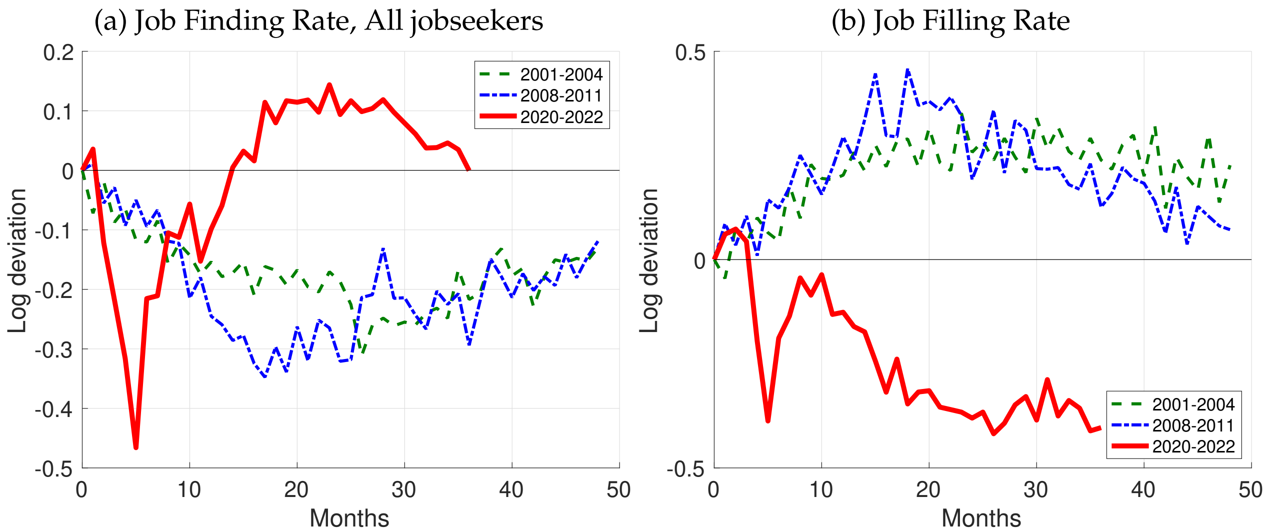


Figure 6: Job-finding (left) and job-filling rates (right).

Notes: CPS, JOLTS, and authors' calculations. The values are normalized to zero for January 2001, 2008, and 2020. Job finding and filling rates can be defined as total hires from employment and unemployment, expressed as a fraction of all jobseekers and vacancies, respectively. Total hires have been adjusted for JOLTS cyclicality and CPS levels as described in Appendix A.

JOLTS cyclicality, described in Appendix A. Throughout our analysis we abstract from hires from non-participants.

Figure 6 shows the job-finding rate of all job seekers and job-filling rate for job openings using these measures. The behavior of job-finding and job-filling rates have followed paths that are substantially different compared to earlier recessions. The job-finding rate experienced a robust increase, whereas the job-filling rate which typically exhibits sustained high levels after recessions, has remained subdued.[6] The shortfall in job-filling rate suggests a deterioration in matching efficiency in the labor market.[7]

A summary measure that is often used to capture the efficiency of the search and

[6]We also find that post-pandemic quit rate is highly predictive of the vacancy rate at the industry-level data. Tables A1 and A2 show the regression of vacancy and job filling rates on various worker separation margins from the JOLTS. We find that controlling for layoffs and other separations, quits correlated positively with vacancy rate in the aftermath of the pandemic recession. This was not true after the Great Recession which was a period in which the correlation between vacancies and quits was insignificant. Furthermore, Table A2 shows that post-pandemic quit rate varied negatively with the job-filling rate. In other words, industries with higher quits posted more vacancies but did not end up filling more vacancies. In contrast, there was no significant correlation between quits and job filling rate after the Great Recession or in the full sample of the JOLTS.

[7]Note that we use measures of hires from the CPS adjusted for the cyclicality of JOLTS measures throughout the paper. Appendix A provides details of calculations of these measures.

matching process in the labor market is the *aggregate matching efficiency*.[8] We next develop a generalized measure of matching efficiency which incorporates employed job-seekers starting with a matching function that characterizes the technology that firms and workers match with each other building on the Diamond-Mortensen-Pissarides framework. The inputs to the matching function are the vacancies (v_t) posted by firms looking to hire and unemployed (u_t) and employed (e_t) workers looking for jobs. Total hires which is the sum of hires from unemployment and employment are:

$$h_t = h_t^u + h_t^e = A_t v_t^{\alpha} \left(u_t + se_t\right)^{1-\alpha} \tag{1}$$

where A_t is the aggregate matching efficiency parameter, $\alpha \in (0, 1)$ is the vacancy share. Market tightness is defined as $v_t/(u_t + se_t)$. We can then define the matching efficiency for the unemployed and employed workers using their corresponding job-finding rates as

$$A_t^u = \frac{UE_t}{\left(\frac{v_t}{u_t+se_t}\right)^{\alpha}} \qquad \text{and} \qquad A_t^e = \frac{EE_t}{s\left(\frac{v_t}{u_t+se_t}\right)^{\alpha}} \tag{2}$$

where UE_t is the job-finding rate of the unemployed and EE_t is the job-finding rate of the employed workers. The aggregate matching efficiency is the weighted average of matching efficiency of the unemployed and employed workers where the weights correspond to their relative search input:

$$A_t = \left(\frac{u_t}{u_t + se_t}\right) A_t^u + \left(\frac{se_t}{u_t + se_t}\right) A_t^e. \tag{3}$$

We set $\alpha = 0.5$ following Petrongolo and Pissarides (2001). The relative search effort of the employed, s is set to 0.6 as before. Following Faberman et al. (2022)) to reflect their finding that while all unemployed workers search by definition, about 20% of employed actively engage in job search every month. We then compute the matching efficiency for both unemployed and employed job-seekers in Figure 7. The matching efficiency has declined more for both unemployed and employed searchers during the pandemic. Interestingly, there was no decline for employed workers' search efficiency during the Great recession and the declining matching efficiency had only affected the unemployed.

[8] Increases in mismatch, changes job search and recruiting intensities, workers' reservation wages are all determinants of matching efficiency in the labor market.

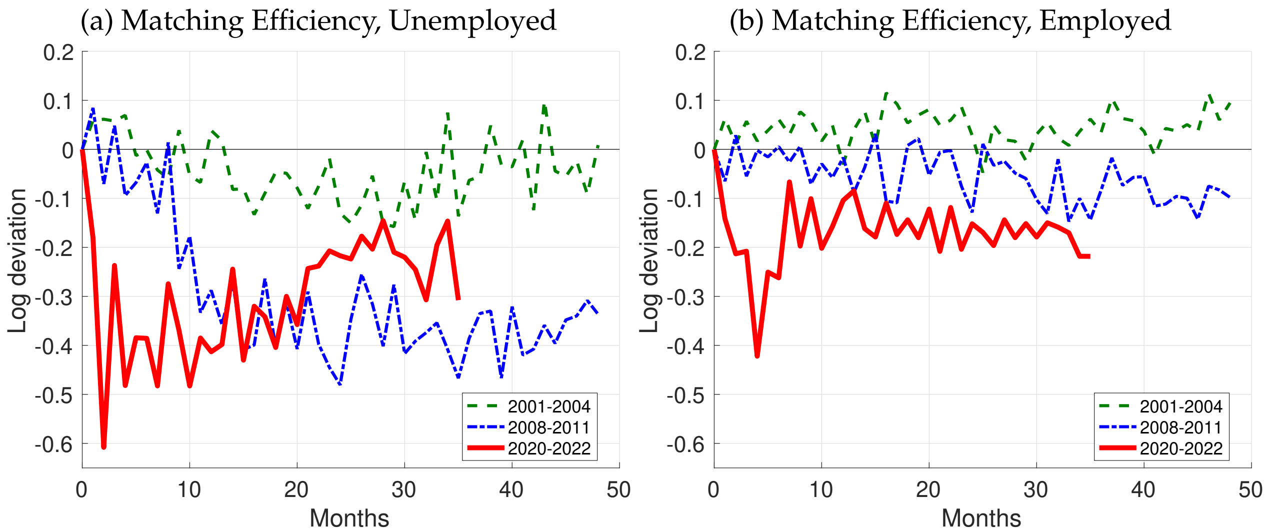


Figure 7: Matching efficiency of the unemployed (left) and employed (right) searchers.

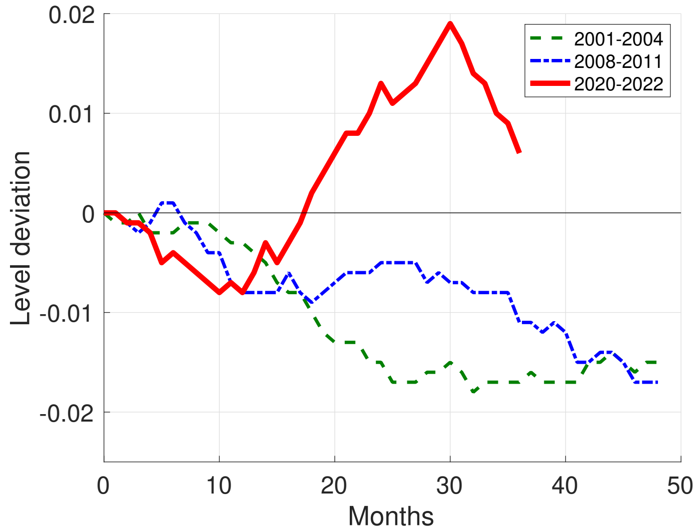
Notes: CPS, JOLTS, and authors' calculations. The values are normalized to zero for January 2001, 2008, and 2020. The matching efficiency of the unemployed and employed are derived in Equation 2. Hires from unemployment and employment adjust for JOLTS cyclicality and CPS levels as described in Appendix A.

2.3 Wage Compression

Finally, wage growth followed a different pattern after the pandemic recession. Typically, high wage workers experience faster wage growth during recoveries which increases the wage gap between high and low wage workers' compensation. Again, the pandemic recession was different. Nominal wage growth in the first quartile of wages relative to the fourth quartile has been high as shown in Figure 18. This observations has been referred to as *wage compression* by Autor, Dube, and McGrew (2023).

2.4 Availability of Remote Work and Worker Preferences

Our observations in the previous section suggest that labor market dynamics have been different during and after the pandemic recession. There are various factors that have been discussed to account for these differences. Yet, the most commonly discussed change in the labor market has been the rise of remote work arrangements. The COVID-19 pandemic brought on a drastic change in the nature of work. While the infrastructure and technology that made work from home were available, only one out of seventy jobs offered work from home option in March 2020. As stated by the McKinsey report ("What's next for remote work", 2022), the virus has broken through cultural and technological



Source: CPS and authors' calculations.

Figure 8: Nominal wage growth in the first quartile of wages relative to the fourth quartile.

barriers that prevented remote work in the past, setting in motion a structural shift in where work takes place, at least for some people. The quick shift to remote work during the lockdowns and and in the pre-vaccine period has been persistent with one out of five jobs offering remote work opportunities as of March 2022.

We argue that the unique labor market dynamics after the pandemic recession can be explained by changes in worker preferences, favoring remote work. The shift in worker preferences, combined with the quick recovery in the economy, resulted in higher quits as workers searched for better opportunities. Additionally, certain vacant positions that did not offer remote work arrangements became less desirable and harder to fill. This shift in workers' preferences, was gradually accommodated by firms creating a transition period when some jobs had become undesirable, thereby reducing job-filling rates.

While some tasks are impossible to perform remotely, Dingel and Neiman (2020) estimate that work from home (WFH) is feasible for 37% of workers.[9] In our view, the possibility of remote work introduced an additional dimension for workers to consider when evaluating job opportunities. For example, Barrero, Bloom, and Davis (2023) find that SWAA (Survey of Working Arrangements and Attitudes) respondents who value WFH were willing to accept pay cuts of 10% on average in exchange for 2 workdays a

[9]They also find substantial cross-industry variation. For example, while in the technology and information sector nearly 50% of jobs can be done remotely, in Retail, Construction, Accommodation, only 2% of jobs are consistent with WFH arrangements.

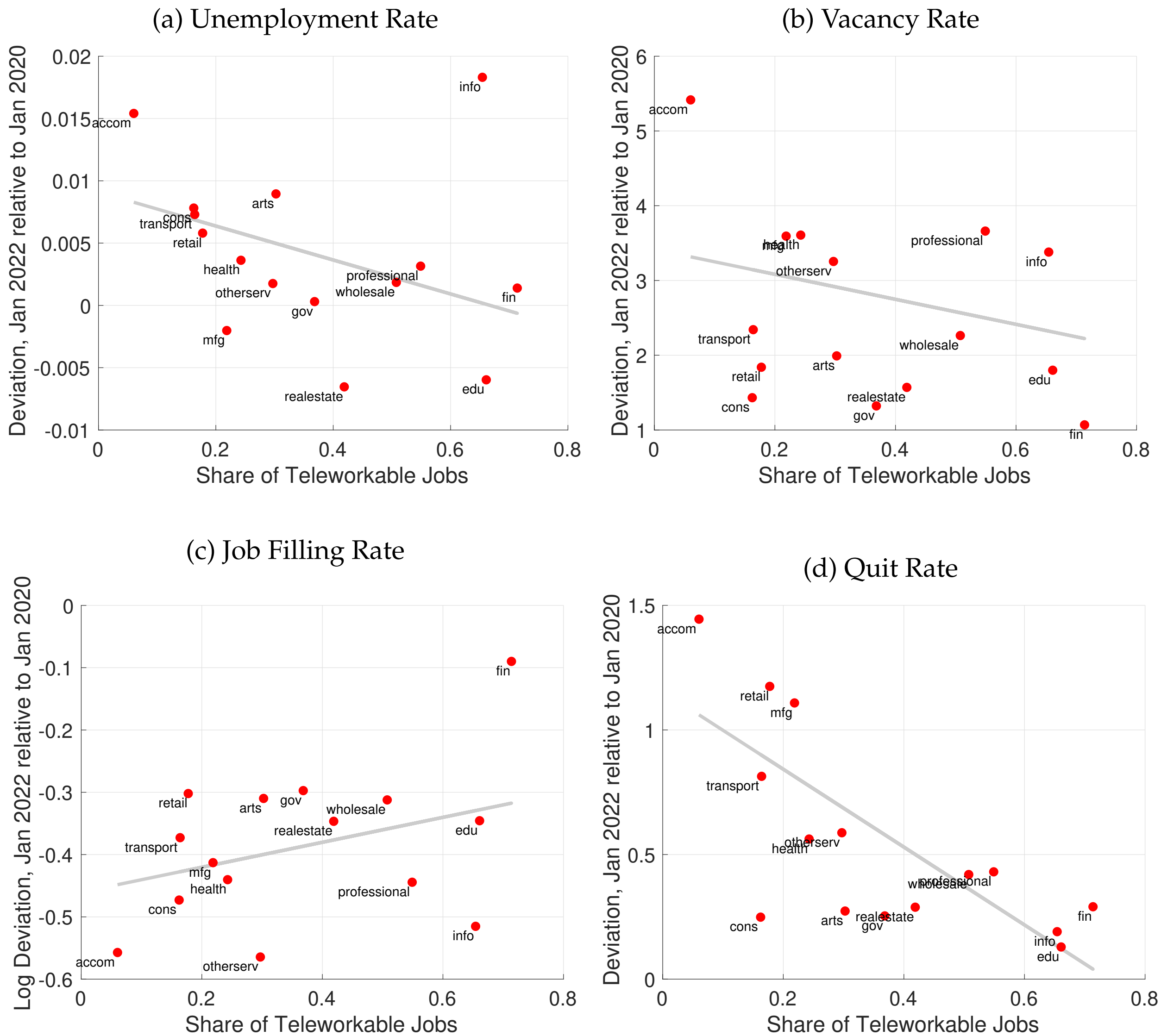


Figure 9: Labor Market Outcomes and Teleworkability of industries

Notes: CPS, JOLTS and authors' calculations. The x-axis plots the share of teleworkable jobs from Dingel and Neiman (2020). The y-axis plots the deviation of the outcome in January 2022 from January 2020. The fitted line is weighted by vacancy share of sectors in January 2020.

week of WFH. One potential reason is jobs with remote work arrangements enable workers to have greater flexibility and more time for home production and leisure activities. According to the same survey, when employees work from home, they save an average 65 minutes per day by not commuting and taking less time to get ready for work.

The Real-Time Population Survey (RPS) also provides support for this channel. Using retrospective questions, the survey estimates that 31.5% of workers switched jobs between February 2020 to October 2022.[10] 21% of these job switchers moved from on-site jobs to fully remote or hybrid jobs. Put differently, 1 in 5 of the job switches involved a shift to fully or partially remote work arrangements.

Differences in the teleworkability among various industries are also relevant for examining the role of remote work. Figure 9 shows that the deviation from pre-pandemic labor market trends was larger in sectors with the lowest share of teleworkable jobs. The unemployment and vacancy rates saw more significant increases in contact intensive sectors, leading to a more substantial rise in their labor market tightness. These sectors also experienced the most significant decline in filling rates. The *great resignation* was driven by contact-intensive sectors, whereas the sectors with more teleworkable jobs did not see a change in their quit rates relative to January 2020. The correlations indicate that workers were more inclined to quit from contact-intensive jobs, and these specific jobs likely experienced increased difficulty in filling positions after the pandemic.

3 Model

3.1 Environment

The model is a version of Lise and Robin (2017) with three key extensions: (i) match specific productivity, (ii) a distribution of job amenities and heterogeneous valuation of amenities among workers, and (iii) Diamond entry and vacancies as a stock. The last two features are crucial for the question we want to address. In taking the model to the data, we will think of job amenity mostly as how contact-intensive the job tasks are, and how easy it is to perform them remotely.

Time and shocks. The model is written in continuous time, as if the economy is following deterministic transitional dynamics determined by unforeseen 'MIT shocks'. We allow for three sources of aggregate shocks: a shock to the preference for job amenities, a shock to productivity, and a labor supply shock to the value of unemployment.

Demographics and preferences. The economy is populated by a continuum of infinitely-lived individual workers of measure one who can be either employed or unemployed.

[10]For details of the survey see https://sites.google.com/view/covid-rps.

Workers discount the future at rate r and have linear utility over consumption c_t. Consumption is equal to income. Employed individuals also obtain utility from a job amenity a. Let x denote the individual taste for (i.e., how much they value) the job amenity. The distribution of x across workers is exogenous, and denoted by $\ell(x)$. We assume that there exist two worker types with $x \in \{0, \bar{x}\}$, respectively. The variable Z_t^x is an aggregate shifter of the value of amenities. A worker of type x, employed in a job with amenity a at time t receives a utility flow equal to $Z_t^x xa$. Besides this dimension of heterogeneity, workers are equally productive ex-ante.

Production technology and income payments It takes one worker and one job to produce. A firm-worker pair produces an idiosyncratic output level y drawn from a distribution f, which we assume to be a discretized log-normal distribution with mean 1 and dispersion parameter σ. This idiosyncratic output level remains constant for the duration of the match and is rescaled by aggregate productivity Z_t^y. Let $y_t = Z_t^y y$ denote the combination of individual-level and aggregate productivity.

Worker-firm matches are destroyed exogenously at rate δ. When an unexpected aggregate shock hits the economy, some matches may be endogenously dissolved.

Employed workers receive a flow wage payment w. Section 3.4 describes the wage determination in detail. Unemployed workers receive a flow utility $b_t = Z_t^b b$, which we interpret as the combination of unemployment benefits and flow value of leisure. Z_t^b is an aggregate shifter of the flow value of unemployment.

Meeting technology At time t, a measure $u_t(x)$ of workers of type x is unemployed, and a measure $e_t(x, y, a)$ of workers of type x is employed on matches of type (y, a). The following consistency condition must hold for each type x.

$$u_t(x) + \sum_{y,a} e_t(x, y, a) = \ell(x). \tag{4}$$

The search intensity of the unemployed is normalized to 1. Let s denote the relative search effort of employed workers. The total number of job seekers s_t is then

$$\mathrm{s}_t = \sum_x u_t(x) + s \sum_{x,y,a} e_t(x, y, a) = \mathrm{u}_t + s\mathrm{e}_t \tag{5}$$

Let $v_t(a)$ denote the vacancies of type a. The total number of vacancies is

$$\mathtt{v}_t = \sum_a v_t(a) \tag{6}$$

Job seekers and vacancies meet at random. The total number of random meetings occurring at date t is given by the aggregate meeting technology

$$\mathtt{m}_t = m(\mathtt{v}_t, \mathtt{s}_t), \tag{7}$$

where m is a CRS meeting function. Let $p_t = \mathtt{m}_t/\mathtt{s}_t$ be the aggregate meeting rate for workers and $q_t = \mathtt{m}_t/\mathtt{v}_t$ the aggregate meeting rate per vacancy.

The draw of idiosyncratic match productivity y occurs right after a meeting is formed. Not all meetings transform into productive matches. In Section 3.2, we describe the match formation decision.

Job creation. We model job creation through 'Diamond entry'. There is an infinite supply of potential entrants. To become an incumbent, a potential entrant must pay an entry cost κ. Once the vacant job is created, but before it starts searching for a worker, it might be endowed with the amenity. This happens at random with an exogenous probability of $\zeta \in [0,1]$. As a result, in the economy there is always a share ζ of jobs endowed with the amenity and a share $1-\zeta$ without it. This modelling choice captures the idea that whether a job is endowed with the amenity (e.g., teleworkability) is a technological constraint of the economy.

The ex-ante value of entry is thus given by

$$\Omega_t = \zeta \Omega_t(\bar{a}) + (1-\zeta)\Omega_t(\underline{a})$$

and, with free entry, the number of jobs created i_t is always such that

$$\Omega_t = \kappa \tag{8}$$

Vacancies as a stock and vacancy chains. Because of Diamond entry, the entry cost cost is sunk for an incumbent and thus the value of an incumbent vacancy is weakly positive. As a result, entrant vacancies that do not immediately get filled stick around and contribute the the pool of idle jobs ready to hire.

In this model, vacancies are not a jump variable, as in standard search-matching models. At any time t, the stock of vacancies is a backward looking variable that depends on the past stock, the inflow and the outflow. The outflow has two components. First, vacancies exit exogenously at rate δ_v. Second, some vacancies get filled by job seekers. Likewise, the inflow has two components. First, the newly created job opportunities. In addition, we assume that upon a quit or an exogenous separation (occurring at rate δ), the vacant job enters a 'dormant state' in which the firm is not actively recruiting. Dormant vacancies re-enter the pool of actively searching vacancies stochastically at Poisson rate μ.[11] This is the second component of the vacancy inflow.

Note that the model features 'replacement hires', i.e. situations where a worker quits their job, the job becomes vacant, and a new worker is hired on the same job to replace the previous employee.

Wage setting. We assume the sequential auction contract renegotiation protocol of Postel-Vinay and Robin (2002). Wages can only be renegotiated under *mutual consent*, i.e. when either side has a credible threat. A *credible threat* occurs when one of the parties is better off taking their outside option than staying in the match (i.e,. one of the two participation constraints is violated). Upon renegotiation (or upon meeting between a vacancy and an unemployed worker), we assume that the firm makes a take-it-or-leave-it offer to the worker.

The events that can trigger renegotiation occur when a suitable outside offer is made to the worker, or when an aggregate shock changes the value of the surplus sufficiently.

3.2 Surplus and Value Functions

Surplus. Let the gross surplus of a match of type (x, y, a) at date t be

$$S_t(x, y, a) = J_t(w_t, x, y, a) + W_t(w_t, x, y, a) - U_t(x) \tag{9}$$

where J is the value of a match for the firm and W for the worker, and U is the value of unemployment. Note that this 'gross' surplus definition does not include the outside

[11] We include this dormant state primarily for numerical stability. Without it, separations that occur in a particular state immediately raise the number of vacancies, which discontinuously lowers the value of a vacancy for new entrants. This introduces numerical instability in the solution algorithm, which relies on a fixed point of this value. The dormant state ensures that vacancy inflows from separations are spread out over time, which in practice helps with the convergence of the solution algorithm.

option for the firm.

A key property of this economy, stemming from the wage protocol described above, is bilateral (or joint) efficiency which implies that hiring and separation decisions are obtained by comparing surpluses associated with the alternative options. It is possible to show that the surplus can be written independently of the wage as

$$(r+\delta)S_t(x,y,a) = Z_t^y y + Z_t^x xa - Z_t^b b + \partial_t S_t(x,y,a) \tag{10}$$

with the boundary condition $S_t(x,y,a) \geq \tilde{\Omega}_t(a)$ where $\tilde{\Omega}_t(a)$ denotes the value of a dormant vacancy with amenity a (see below). In the rest of this section, we describe all other value functions for firms and workers. All equations refer to the case where boundary conditions are non-binding.

Value of active and dormant vacancies As explained, vacancies enter the vacancy pool and at some rate meet a worker of type x. Upon drawing the idiosyncratic value y, it is determined whether the match is viable and a match of type (x,y,a) starts producing. If the vacant position does not meet a viable worker, it remains vacant. A vacant job is destroyed exogenously at rate δ_v. The value of an actively recruiting vacancy $\Omega_t(a)$ is given by

$$\begin{aligned}(r+q_t+\delta_v)\,\Omega_t(a) =& q_t \sum_{x,y}\Bigg[\mathbb{I}_{\{x\in\mathcal{H}_t(y,a)\}} J_t\left(\phi_t^u,x,y,a\right)\left(\frac{u_t(x)}{\mathrm{s}_t}\right) \\ &+ \mathbb{I}_{\{x\notin\mathcal{H}_t(y,a)\}}\Omega_t(a)\left(\frac{u_t(x)}{\mathrm{s}_t}\right) \\ &+ \sum_{y',a'}\mathbb{I}_{\{(x,y',a')\in\mathcal{P}_t(y,a)\}} J_t\left(\phi_t^q,x,y,a\right)\left(\frac{s\cdot e_t(x,y',a')}{\mathrm{s}_t}\right) \\ &+ \sum_{y',a'}\mathbb{I}_{\{(x,y',a')\notin\mathcal{P}_t(y,a)\}}\Omega_t(a)\left(\frac{s\cdot e_t(x,y',a')}{\mathrm{s}_t}\right)\Bigg] f(y) \\ &+ \partial_t\Omega_t(a)\end{aligned} \tag{11}$$

The sets $\mathcal{H}_t(y,a)$ and $\mathcal{P}_t(y,a)$ correspond to the hiring and poaching sets for a firm of type (y,a) at date t:

$$\mathcal{H}_t(y,a) = \{x : S_t(x,y,a) > \Omega_t(a)\} \tag{12}$$

$$\mathcal{P}_t(y,a) = \left\{\left(x,y',a'\right) : S_t(x,y,a) - \Omega_t(a) > S_t\left(x,y',a'\right) - \tilde{\Omega}_t\left(a'\right)\right\} \tag{13}$$

where $S_t(x, y, a) - \Omega_t(a)$ is the net surplus of the vacant job and $S_t(x, y', a') - \tilde{\Omega}_t(a')$ is the net surplus of the competing firm. [12] The value of a dormant vacancy of type a, $\tilde{\Omega}_t(a)$, is simply given by

$$(r + \delta_v + \mu)\tilde{\Omega}_t(a) = \mu\Omega_t(a) + \partial_t\tilde{\Omega}_t(a) \tag{14}$$

Match. The firm's value of a match between a worker of type x and a job of type a which produces output y where the worker is paid a wage w is given by

$$\begin{aligned}
(r + \delta + sp_t)J_t(w, x, y, a) \quad = \quad & Z_t^y y - w + \delta\tilde{\Omega}_t(a) \\
& + sp_t \underbrace{\sum_{(a',y') \in \mathcal{Q}_t(x,y,a)} \tilde{\Omega}_t(a) \cdot f(y') \cdot \left(\frac{v_t(a')}{\mathrm{v}_t}\right)}_{\text{worker quits to better job}} \\
& + sp_t \underbrace{\sum_{(a',y') \in \mathcal{R}_t(x,y,a)} J_t(\phi_t^r, x, y, a) \cdot f(y') \cdot \left(\frac{v_t(a')}{\mathrm{v}_t}\right)}_{\text{worker is retained with higher wage}} \\
& + sp_t \underbrace{\sum_{(a',y') \in \mathcal{N}_t(x,y,a)} J_t(w, x, y, a) \cdot f(y') \cdot \left(\frac{v_t(a')}{\mathrm{v}_t}\right)}_{\text{worker meets worse firm}} \\
& + \partial_t J_t
\end{aligned} \tag{15}$$

where

$$\mathcal{Q}_t(x, y, a) = \left\{ (y', a') : S_t(x, y', a') - \Omega_t(a') > S_t(x, y, a) - \tilde{\Omega}_t(a) \right\} \tag{16}$$

and

$$\mathcal{R}_t(x, y, a) = \left\{ (y', a') : W_t(w, x, y, a) - U_t(x) < S_t(x, y', a') - \Omega_t(a') \leq S_t(x, y, a) - \tilde{\Omega}_t(a) \right\} \tag{17}$$

are sets of the draws of job offers $(y'a')$ which trigger respectively a quit and a renegotiation. The set

$$\mathcal{N}_t(x, y, a) = \left\{ (y', a') : S_t(x, y, a) - \tilde{\Omega}_t(a) > W_t(w, x, y, a) - U_t(x) \geq S_t(x, y', a') - \Omega_t(a') \right\} \tag{18}$$

[12] The term "net surplus" here refers to the surplus net of the firm's outside option value.

is the set of firms that attempt to poach but are so low-productivity that no renegotiation is triggered.

Unemployed and Employed Worker. The value of unemployment for a worker of type x is

$$\begin{aligned}(r+p_t)U_t(x) &= Z_t^b b + p_t \sum_{a,y} \Bigg[\underbrace{\mathbb{I}_{\{x\in\mathcal{H}_t(y,a)\}} W_t(\phi^u, x, y, a)}_{\text{successful contacts}} \\ & \qquad \underbrace{+\mathbb{I}_{\{x\notin\mathcal{H}_t(y,a)\}} U_t(x)}_{\text{failed contacts}} \Bigg] \left(\frac{v_t(a)}{\mathrm{v}_t}\right) f(y) + \partial_t U_t\end{aligned}$$

Using the ToL wage protocol $W_t(\phi_t^u, x, y, a) = U_t(x)$, we can rewrite the value of unemployment as:

$$rU_t(x) = Z_t^b b + \partial_t U_t \tag{19}$$

The value of a worker of type x employed paid w on a job of type (y, a) is:

$$\begin{aligned}(r+\delta+sp_t) W_t(w,x,y,a) &= w + Z_t^x xa + \underbrace{\delta U_t(x)}_{\text{exogenous layoff}} \\ &\quad + sp_t \sum_{y',a'} \Bigg[\underbrace{\mathbb{I}_{\{(y',a')\in\mathcal{Q}_t(x,y,a)\}} W_t\left(\phi_t^q, x, y', a'\right)}_{\text{worker quits to better job}} \\ &\quad + \underbrace{\mathbb{I}_{\{(y',a')\in\mathcal{R}_t(x,y,a)\}} W_t(\phi_t^r, x, y, a)}_{\text{worker is retained with higher wage}} \\ &\quad + \underbrace{\mathbb{I}_{\{(y',a')\in\mathcal{N}_t(x,y,a)\}} W_t(w_t, x, y, a)}_{\text{worker meets worse job}} \Bigg] \left(\frac{v_t(a')}{\mathrm{v}_t}\right) f(y') \\ &\quad + \partial_t W_t\end{aligned} \tag{20}$$

3.3 Labor market flows

It is useful to write explicitly the dynamic equations for unemployment, employment, and vacancies. The law of motion for the unemployed is

$$du_t(x) = \underbrace{\delta \sum_{a,y} \mathbb{I}_{\left\{S_t(x,y,a) \geq \tilde{\Omega}(a)\right\}} e_t(x,y,a)\, dt}_{\text{exogenous separations}} + \underbrace{\sum_{a,y} \mathbb{I}_{\left\{S_t(x,y,a) < \tilde{\Omega}(a)\right\}} e_t(x,y,a)}_{\text{endogenous separations}} \tag{21}$$
$$\underbrace{-p_t u_t(x) \sum_{y,a} \mathbb{I}_{\{x \in \mathcal{H}_t(y,a)\}} \left(\frac{v_t(a)}{\mathrm{v}_t}\right) f(y)\, dt}_{\text{hires from unemployment}}$$

For the employed,

$$de_t(x,y,a) = \underbrace{-\delta \mathbb{I}_{\left\{S_t(x,y,a) \geq \tilde{\Omega}_t(a)\right\}} e_t(x,y,a)\, dt}_{\text{exogenous EU}} - \underbrace{\mathbb{I}_{\left\{S_t(x,y,a) < \tilde{\Omega}_t(a)\right\}} e_t(x,y,a)}_{\text{endogenous EU}} \tag{22}$$
$$\underbrace{-s p_t e_t(x,y,a) \left[\sum_{y',a'} \mathbb{I}_{\{(y',a') \in \mathcal{Q}_t(x,y,a)\}} \left(\frac{v_t(a')}{\mathrm{v}_t}\right) g(y')\right] dt}_{\text{EE-}}$$
$$\underbrace{+s p_t \sum_{y',a'} e(x,y',a')\, \mathbb{I}_{\{(x,y',a') \in \mathcal{P}_t(y,a)\}} \left(\frac{v_t(a)}{\mathrm{v}_t}\right) f(y)\, dt}_{\text{EE+}}$$
$$\underbrace{+p_t u_t(x) \mathbb{I}_{\{x \in \mathcal{H}_t(y,a)\}} \left(\frac{v_t(a)}{\mathrm{v}_t}\right) f(y)\, dt}_{\text{UE hires}}$$

For active vacancies,

$$dv_t(a) = -\underbrace{\delta_v v_t(a)\, dt}_{\text{vac. destruction}} + \underbrace{i_t(a)\, dt}_{\text{vac. creation}} + \underbrace{\mu \tilde{v}(a) dt}_{\text{entry from dormant}} \tag{23}$$
$$-q_t v_t(a) \sum_{x,y} \left[\underbrace{\mathbb{I}_{\{x \in \mathcal{H}_t(y,a)\}} \left(\frac{u_t(x)}{\mathrm{s}_t}\right)}_{\text{vacancies filled from } u}\right.$$
$$\left.\underbrace{\sum_{a',y'} \mathbb{I}_{\{(x,y',a') \in \mathcal{P}_t(y,a)\}} \left(\frac{s \cdot e_t(x,y',a')}{\mathrm{s}_t}\right)}_{\text{vacancies filled from } e}\right] f(y)\, dt$$

For dormant vacancies,

$$
\begin{aligned}
d\tilde{v}_t(a) \;=\; & -\underbrace{\delta_v \tilde{v}_t(a)\,dt}_{\text{vac. destruction}} - \underbrace{\mu \tilde{v}_t(a)\,dt}_{\text{activation}} \\
& + \sum_{x,y} \Bigg[\underbrace{\delta \mathbb{I}_{\left\{S_t(x,y,a) \geq \tilde{\Omega}_t(a)\right\}} e_t(x,y,a)\,dt}_{\text{exogenous EU}} + \underbrace{\mathbb{I}_{\left\{S_t(x,y,a) < \tilde{\Omega}_t(a)\right\}} e_t(x,y,a)}_{\text{endogenous EU}} \\
& \underbrace{+ s p_t e_t(x,y,a) \sum_{y',a'} \mathbb{I}_{\{(y',a') \in \mathcal{Q}_t(x,y,a)\}} \left(\frac{v_t(a')}{\mathrm{v}_t}\right) f(y')\,dt \Bigg]}_{\text{EE-}}
\end{aligned} \tag{24}
$$

Finally, note that match efficiency in our model is endogenous. Match efficiency is given by the ratio of hires to contact. This ratio depends on contact rates and match formation decisions. Let A_t^u and A_t^e denote match efficiency for the employed and the unemployed. It is easy to derive that, in our model:

$$
A_t^u = \sum_{x,y,a} \mathbb{I}_{\{x \in \mathcal{H}_t(y,a)\}} \left(\frac{u_t(x)}{u_t}\right) \left(\frac{v_t(a)}{\mathrm{v}_t}\right) f(y) \tag{25}
$$

$$
A_t^e = \sum_{x,y,a} \left[\sum_{y',a'} \mathbb{I}_{\{(x,y',a') \in \mathcal{P}_t(y,a)\}} \frac{e_t(x,y',a')}{e_t} \right] \left(\frac{v_t(a)}{\mathrm{v}_t}\right) f(y) \tag{26}
$$

Aggregate match efficiency is given by the average between the two weighted by the share of unemployed and employed job seekers, respectively.

$$
A_t = A_t^u \frac{u_t}{u_t + s e_t} + A_t^e \frac{s e_t}{u_t + s e_t} \tag{27}
$$

3.4 Wage determination

To describe how wages are determined in our model, we have six different cases to consider:

1. When an unemployed worker of type x meets a vacancy of type a, and the match value y is observed, the match is created if $J_t(\phi^u, x, y, a) > \Omega_t(a)$ and the wage is

set to the value $\phi^u(x,y,a)$ that solves

$$W_t(\phi_t^u, x, y, a) = U_t(x). \tag{28}$$

Because $S_t(x,y,a) = J_t(\phi^u, x, y, a) + W_t(\phi_t^u, x_t, y_t, a) - U_t(x)$, the value of a firm can be expressed as

$$J_t(\phi^u, x, y, a) = S_t(x, y, a), \tag{29}$$

i.e. because of the take-leave protocol, upon hiring a worker from unemployment, initially the firm gets all the surplus from the relationship.

2. When an employed worker of type x on a job (y,a) meets a firm $(y'a')$ and $S_t(x,y',a') - \Omega_t(a') > S_t(x,y,a) - \tilde{\Omega}_t(a)$, the worker moves to the new firm (y',a') because the poaching firm can always pay more than the current one can match. At the time of the transition, the worker's outside option is to extract the whole surplus at the previous match. At the new match, the worker therefore receives value

$$W_t(\phi^q, x, y', a') - U_t(x) = S_t(x,y,a) - \tilde{\Omega}_t(a) \tag{30}$$

This equation determines the wage $\phi^q(x,y,a,y',a')$ upon the job-to-job transition. As a result, the poaching firm value becomes

$$J_t(\phi^q, x, y', a') = S_t(x, y', a') - \left[S_t(x,y,a) - \tilde{\Omega}_t(a)\right] \tag{31}$$

3. When an employed worker of type x on firm (y,a) meets a firm $(y'a')$ and $W_t(w,a,x_t,y_t) - U_t(x) < S_t(x,y',a') - \Omega_t(a') \leq S_t(a,x_t,y_t) - \tilde{\Omega}_t(a)$, the worker stays with her current employer, but can use this outside offer to improve their position within the current firm. In this case, the incumbent firm makes a take-leave offer to the worker which is just enough to make them indifferent between staying and quitting and thus retains the worker:

$$W_t(\phi^r(y',a'), x, y, a) - U_t(x) = S_t(x,y',a') - \Omega_t(a') \tag{32}$$

This also determines the new retention wage $\phi^r(x,y,a,y',a')$. In this case, the current firm value drops to

$$J_t\left(\phi^r, x, y, a\right) = S_t(x, y, a) - \left[S_t(x, y', a') - \Omega_t\left(a'\right)\right]. \tag{33}$$

4. Whenever an employed worker of type x on firm (y, a) meets a firm of type (y', a') and $S_t(a, x_t, y_t) - \tilde{\Omega}_t(a) > W_t(w, a, x_t, y_t) - U_t(x) \geq S_t(a, x_t, y_t) - \Omega_t(a')$, the worker has nothing to gain from the outside offer. The worker does not move and their wage remains the same.

5. Even though we consider only MIT shocks + transition dynamics, such an unexpected aggregate shock can also lead to renegotiation at or during the transition. If, at any point under the old contract w,

$$W_t(w, x, y) - U_t(x) < 0 \text{ but } S_t(x, y, a) - \tilde{\Omega}_t(a) \geq 0$$

then the wage is raised to ϕ^+ just enough to avoid quitting, i.e.

$$W_t\left(\phi^+, x, y, a\right) - U_t(x) = 0 \tag{34}$$

and the firm value drops to

$$J_t\left(\phi^+, x, y, a\right) = S_t(x, y, a) \tag{35}$$

6. The reverse situation is when, along the transition, the wage is too high and it is the firm that threatens to fire the worker, i.e.

$$J_t(w, x, y, a) < \tilde{\Omega}_t(a), \text{but } S_t(x, y, a) \geq \tilde{\Omega}_t(a)$$

Since $J_t(w, x, y, a) = S_t(a, x, y) - [W_t(w, x, y, a) - U_t(x)]$,the value of the firm will be raised just enough to avoid a layoff

$$J_t\left(\phi^-, x, y, a\right) = \tilde{\Omega}_t(a) \tag{36}$$

and the new wage ϕ^- will satisfy

$$W_t\left(\phi^-, x, y, a\right) - U_t(x) = S_t(x, y, a) - \tilde{\Omega}_t(a) \tag{37}$$

3.5 Equilibrium

Given initial distributions $u_0(x), e_0(x, y, a), v_0(a), \tilde{v}_0(a)$ and paths for the aggregate shocks $\{Z_t^x, Z_t^y, Z_t^b\}_{t\geq 0}$, an equilibrium in this economy is

1. A list of value functions $\{S_t(x, y, a), \Omega_t(a), \tilde{\Omega}_t(a), J_t(w, x, y, a), U_t(x), W_t(w, x, y, a), \}_{t\geq 0}$ that satisfy equations (10), (11) (14), (15), (19), and (20),

2. Hiring, and poaching sets $\{\mathcal{H}_t(y, a), \mathcal{P}_t(y, a)\}_{t\geq 0}$, and quit, retention and neutral sets, $\{\mathcal{Q}_t(x, y, a), \mathcal{R}_t(x, y, a), \mathcal{N}_t(x, y, a)\}_{t\geq 0}$, that satisfy equations (12), (13), (16), (17), and (18)

3. Distributions $\{u_t(x), e_t(x, y, a), v_t(a), \tilde{v}_t(a)\}_{t\geq 0}$ that satisfy the laws of motion in equations (21), (22), (23), and (24), and implied meetings $\mathtt{m}_t = m(\mathtt{v}_t, \mathtt{s}_t)$

4. Hiring, poaching and retention wage functions $\{\phi_t^u(x, y, a), \phi_t^q(x, y, y', a, a'), \phi_t^r(x, y, y', a, a')\}_{t\geq 0}$ defined in equations (28), (30), and (32)

5. Boundary wage functions $\{\phi_t^+(x, y, a), \phi_t^-(x, y, a)\}_{t\geq 0}$ defined in equations (34) and (36)

6. A measure of entrants $i_t(a)$ that satisfies the entry condition in equation (8)

4 Parameterization

We parameterize the model in two blocks. Parameters in the first block are set externally and based on existing literature. Parameters in the second block are set to match moments from the data. Table 1 summarizes the parameter values and the targeted moments.

The first parameter block consists of the meeting function elasticity α, the discount rate r, the probability of drawing a high amenity ζ, and the share of high x workers. We set the elasticity of the meeting function α to 0.5 and the discount rate r to 5% annually. We set the probability of drawing a high amenity job to $\zeta = 0.25$ to approximate the overall share of teleworkable employment in the economy, 37% as found in Dingel and Neiman (2020). We then set the share of high x workers to 0.5, consistent with evidence from Barrero, Bloom, and Davis (2023), who find that about half of workers in the population would be willing to accept positive wage cuts in exchange for the ability to work from home.

Turning to the second block, the distance between $\underline{a}$ and $\bar{a}$ is normalized to one and we choose the two values in order to set the mean amenity value equal to zero. $\bar{x}$ is chosen to

Parameter		Value	Target to match	Target value
Elasticity of meeting function	α	0.5	*External*	
Discount rate	r	0.05/12	*External*	
Prob. of re-entering pool of active v	μ	1	*External*	
Share of $\bar{a}$ vacancies	ζ	0.25	*Dingel and Neiman (2020)*	
Share of pop. with $x = \bar{x}$	$\ell(\bar{x})$	0.5	*Barrero et al. (2022)*	
Amenity	$\underline{a}, \bar{a}$	$-0.39, 0.61$	Mean amenity	0
Utility flow from amenity	$\bar{x}$	0.048	Compensating differential	5%
Entry cost	κ	2.08	Encounter rate	1.5
Opportunity cost of work	b	1.01	UE rate	0.3
Log-productivity dispersion	σ	0.041	Δ log UR, 7% prod. shock	0.5
Separation rate	δ	0.015	EU rate	0.015
Vacancy destruction rate	δ_v	0.33	Share of replacement hires	0.5
Search effort of employed	s	0.58	EE rate / UE rate	0.07

Table 1: Parameters and corresponding targets

generate a small initial compensating differential (defined as the expected value of $\frac{\bar{x}(\bar{a}-\underline{a})}{w}$ in the population of high x workers) of 0.05. We choose the separation rate δ to match an EU rate of 0.015, consistent with a long-run average from CPS data. We set b and κ to jointly generate a monthly encounter rate of 1.5 (Faberman et al., 2022) and a monthly UE rate of 0.3 (a long-run average in the CPS). We choose the relative search intensity of the employed, s, to match an EE/UE ratio equal to 0.07. The productivity dispersion σ governs the sensitivity of our model to shocks. We choose it in order to generate an initial response of the unemployment rate of 0.5 log points to a 7% productivity shock, consistent with the initial dynamics of the COVID recession in which output per worker initially decreased by 7% and unemployment rose by about 0.5 log points. Finally, we set the vacancy destruction rate δ_v in order to match a share of vacated vacancies (i.e. vacancies created through a quit) of 0.5, a number consistent with evidence presented in Acharya and Wee (2020) and Qiu (2022).

5 Impulse response functions

We now illustrate how the model responds to each of our three aggregate shocks.

Figure 10 displays the impulse response to a negative productivity shock. The resulting dynamics are much like those that a standard model would deliver: As productivity falls, the incentive to post vacancies decreases and vacancies rapidly decline as entry dries

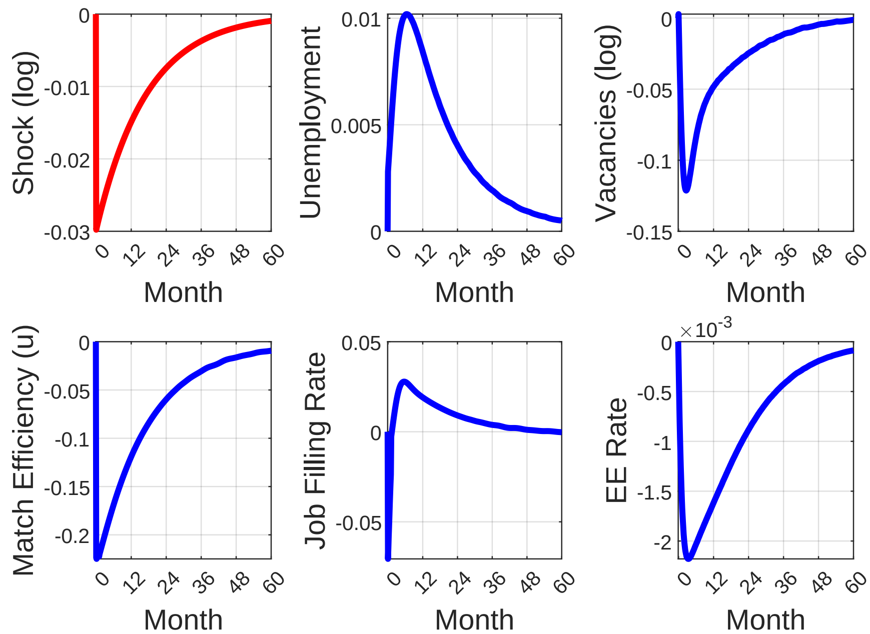


Figure 10: Impulse response functions to a productivity (y) shock

up. Falling vacancies reduce the job finding rate, which results in an increase of the unemployment rate. Mechanically, it becomes less likely that a worker and a firm obtain a productivity draw necessary for a viable match, and thus match efficiency decreases. Since match efficiency is a jump variable but vacancies are a stock, the job filling rate briefly falls before the drop in vacancies more than offsets the decline in the match efficiency and the reduced congestion leads the job filling rate to rise. Finally, the EE rate falls, because match efficiency falls (i.e., fewer contacts become matches) and the stock of vacancies decreases.

The impulse responses to a negative labor supply shock, a rise in the opportunity cost of work b, depicted in Figure 11, deliver a similar picture. This is not surprising: since allocations in our model depend solely on the surplus, and y and b enter the surplus additively, there is an equivalence between shocks to b and shocks to y.[13] The impulse responses of a positive shock to b are therefore similar to the impulse responses to a negative shock to y and many of the same mechanisms are at play. Match efficiency is reduced mechanically and unemployed workers become harder to hire, reducing the vacancy positing incentive. This decreases vacancies and thus the job finding rate. Consequently, the

[13]The equivalence is not one-to-one in our case, since Z_t^y enters multiplicatively and therefore affects the dispersion of y in the population

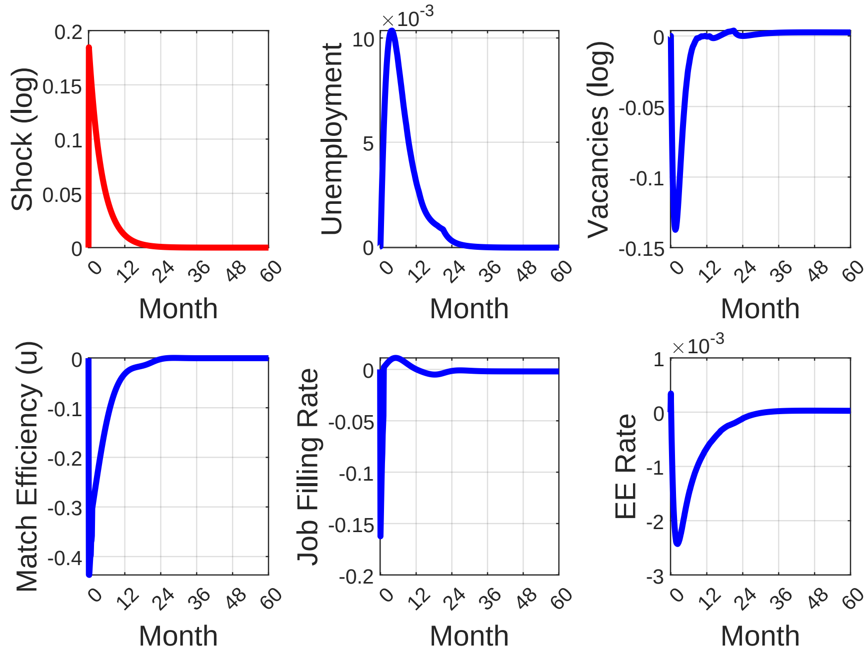


Figure 11: Impulse response functions to the opportunity cost of work (b) shock

unemployment rate goes up and vacancies become easier to fill. The simultaneous drop in match efficiency and vacancies exerts downward pressure on the EE rate.

Wages, however, respond differently to productivity and labor supply shocks. A negative productivity shock first raises average wages because of selection: surviving matches are better on average. Over time though the lower productivity pushes wages below trend. In contrast, a rise in b strengthens workers' outside option and leads to a sustained rise in average wages.

Labor market dynamics following a shock to the taste for the amenity x are displayed in Figure 13. We assume this shock to be permanent. For workers with $x = \bar{x}$, the shock increases the value of being in a high amenity job ($a = \bar{a}$) and decreases the value of being in a low amenity job ($a = \underline{a}$). Thus, some high x workers in the most unproductive low-amenity jobs immediately quit to unemployment. Others in slightly more productive matches stay employed and wait for an opportunity to quit into another job and leave their low amenity employer behind. These workers who quit both into employment and unemployment vacate their jobs, and the affected firms start searching for a replacement. However, these idle positions are predominantly low-amenity jobs that are hard to fill in the post-shock environment, because they are less likely to be accepted by high x workers. A surge in low-amenity vacancies thus drives the increase in the overall stock of vacan-

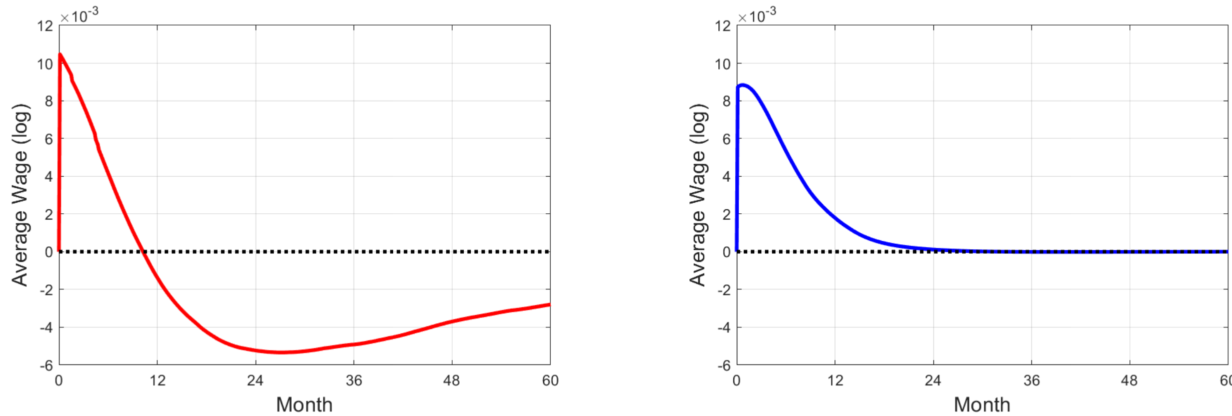


Figure 12: Response of wages to productivity shock (left panel) and shock to the opportunity cost of work (right panel)

cies. Since most vacancies are hard to fill, the overall job filling rate decreases and so does match efficiency. Slowly, as low amenity vacancies get filled mostly by low-x workers and disappear from the vacancy pool, the balance shifts back to an environment with more high amenity vacancies. As a result, match efficiency recovers but the large number of vacancies keeps the job filling rate low. The increased propensity of high-x workers in low-a jobs to reallocate to a new job pushes up the EE-rate in the early aftermath of the shock. The surge in reallocation eventually subsides but vacancies stay elevated, and thus the EE rate settles at a higher level.

6 Accounting for the post-COVID labor market dynamics

We now explore whether, and how, our model can quantitatively explain the peculiar dynamics of the post-COVID labor market we discussed in Section 2. We first describe how we filter the realizations of the aggregate shocks from the data, using the impulse response functions described above. Next, we present the fit of the model, and decompose it into the role played by the three aggregate shocks.

6.1 Estimation of aggregate shocks

Our aim is to estimate the realized path of the three aggregate shocks to productivity, opportunity cost of work, and the value of job amenities using data for the US labor market over the period 2020:1–2022:12.

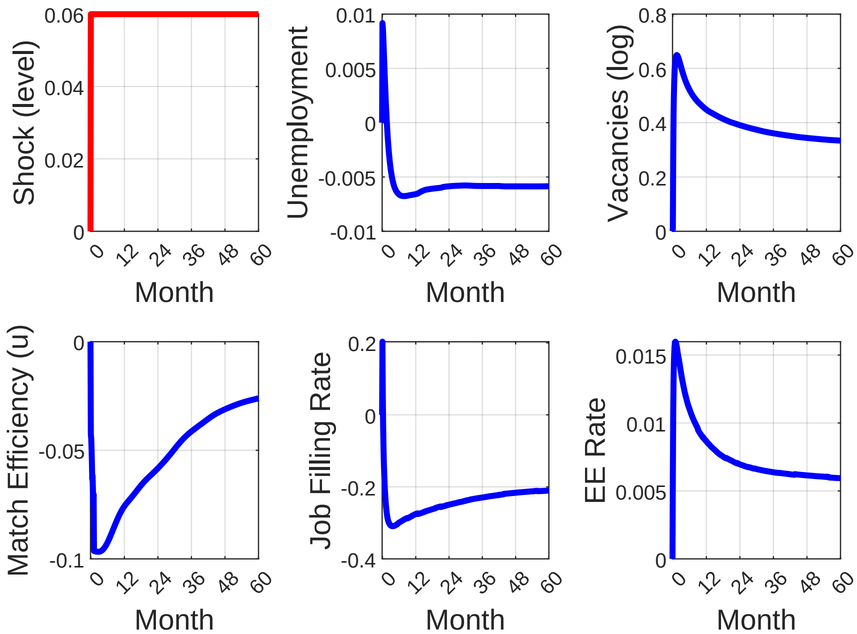


Figure 13: Impulse response functions to an amenity valuation (x) shock

The model implies a relationship between a series of shock realizations $\{\varepsilon_{s,t}\}_{t=0}^{T}$, where s denotes one of the three shocks, and the resulting data series $\{\hat{d}_{k,t}\}_{t=0}^{T}$, where k denotes a particular time series, and the hat symbol denotes log deviations. We use this implied relationship to invert the model and obtain the best fit for the underlying shock series. This procedure allows us to obtain the series of realized shocks that, through the lens of the model, is most consistent with the observed data. The implied shock series minimize the distance between a number of model-implied and empirically observed data series. Specifically, we match simultaneously eight time series: (i) unemployment rate, (ii) vacancies, (iii) the job filling rate, (iv) match efficiency of the unemployed, (v) the UE rate, (vi) the EE rate, (vii) total output, and (viii) real wages.[14]

Consistently with the way we solve the model, we assume that all shocks occur unexpectedly but trigger perfectly foreseen adjustment dynamics. Concretely, we assume that, for any shock s that unexpectedly occurs at t_0, the corresponding series Z_t^s follows

$$\log Z_t^s = \varepsilon_{t_0}^s e^{-\rho_s t}, \quad t = 0, ..., T$$

where we assume $\rho_y = 0.0578$ (which corresponds to a half-life of one year), $\rho_b = 0.231$

[14] Because three shocks are used to fit eight time series, one should not expect a perfect match.

(which corresponds to a half-life of three months) and $\rho_x = 0$ (meaning that amenity valuation shocks are permanent).

To solve for the underlying series of shocks, a key assumption that allows us to make progress is that the response of the system can be written as a sum of past shocks. Formally, for any history of shocks $\{\varepsilon_{s,t}\}_{t=0}^{T}$ and some data series $\{\hat{d}_k\}_{t=0}^{T}$, we assume that each realization $\hat{d}_{k,t}$ can be written as

$$\hat{d}_{k,t} = \sum_{s} \sum_{j=0}^{t} h_{s,j}^{k}(\varepsilon_{s,t-j})$$

for some function $h_{s,j}^{k}$ implied by the model. This formulation allows for shock responses to be *size- and sign-dependent*.[15] Allowing for such size- and sign-dependence is crucial because many impulse responses turn out to be highly non-linear in the size of the shock and asymmetric in our setting. To obtain an approximation of $h_{s,j}^{k}$, we first compute the monthly impulse responses to each aggregate shock, $\varepsilon_t^y, \varepsilon_t^b$ and ε_t^x at different horizons and for different magnitudes $\{\bar{\varepsilon}_i^s\}_{i=1}^{N_s}$ indexed by i. This set of impulse responses allows us to compute $h_{s,j}^{k}$ for any horizon j evaluated at this set of shock sizes, i.e. $\{h_{s,j}^{k}(\bar{\varepsilon}_i^s)\}_{i=1}^{N_s}$. Finally, we obtain $h_{s,j}^{k}$ for a given horizon j by interpolating the function between these values.

To estimate $\{\varepsilon_{s,t}\}_{t=0}^{T}$, we first obtain the relevant empirical counterparts of all series $\hat{d}_{k,t}$ from the data. Denote these data series by $\mathfrak{d}_{k,t}$. Then, with $h_{s,j}^{k}$ in hand, we numerically solve

$$\min_{\{\varepsilon_{s,t}\}_{t=0}^{T}} \underbrace{\sum_{k,t} \omega_k \left(\mathfrak{d}_{k,t} - \sum_{s} \sum_{j=0}^{t} h_{s,j}^{k}(\varepsilon_{s,t-j}) \right)^2}_{\text{Series fitting}} + \underbrace{\vartheta \sum_{s,t} (\Delta \varepsilon_{s,t})^2}_{\text{Smoothing}}$$

which yields the underlying shock series $\{\varepsilon_{s,t}\}_{t=0}^{\infty}$. Two variables of this object are worthy of further discussion: First, there is a vector of series-specific weights ω_k. For most variables, we choose ω_k to equal the inverse variance of the respective data series.[16] As our focus is particularly on unemployment and vacancies, and on their joint dynamics, the beceridge curve, we assign a higher weight to these series, i.e. 5 times their respec-

[15]For example, a large shock might trigger different responses than two shocks that are half the size. Likewise, a positive and a negative shock might trigger asymmetric responses.

[16]This ensures that variables with large fluctuations around the steady state do not dominate the fitting procedure.

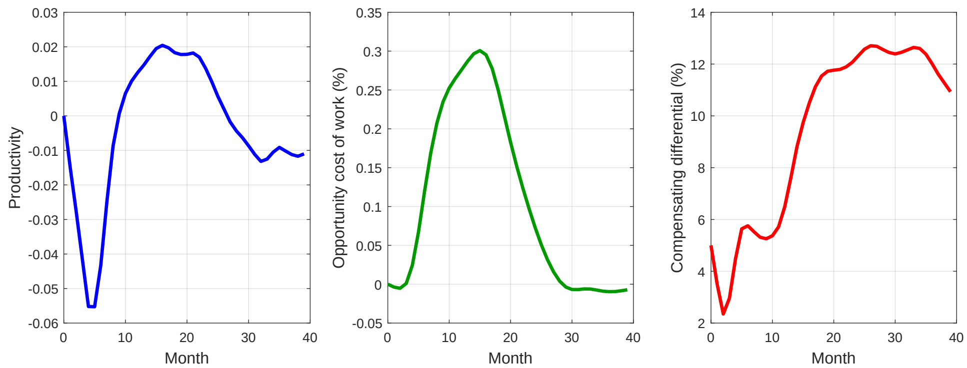


Figure 14: Estimated productivity, opportunity cost of work, and amenity shocks. The amenity shock is expressed in terms of compensating wage differential.

tive inverse series variances. Second, in addition to minimizing the distance between predicted and data series, we include a smoothing term in our objective function. The purpose of this term is to prevent estimates that imply alternating and large positive and negative shocks in quick succession. We find that $\vartheta = 2000$ produces a good balance of smoothness and goodness-of-fit.

Figure 14 reports the estimated shocks. The productivity shock displays a sharp, but short-lived, fall of around 5% which roughly corresponds to the period of lockdowns and restrictions of social and economic activity, followed by a quick rebound and a return to trend.

The labor supply shock indicates that the opportunity cost of working increased up to 30 percent over the first year following the shock, and then it completely subsumed in the second year. This shock is a catch-all for three factors which played a major role during this recovery: (i) the expansion in size and eligibility of UI benefits; (ii) the generous fiscal transfers to low-income households; (iii) the deteriorating health conditions of part of the workforce.

The estimated shocks to the value of job amenities display a gradual build-up which reaches a peak two years after the onset of the pandemic, after which the shock starts to regress. We express the size of the shock as the wage differential that an average worker who cares about the amenity would be willing to pay in order to obtain the amenity in their job. Quantitatively, the model tell us that the average value of job amenities in the population more than doubled, from an initial compensating wage differential of 5% to a peak of 12%.

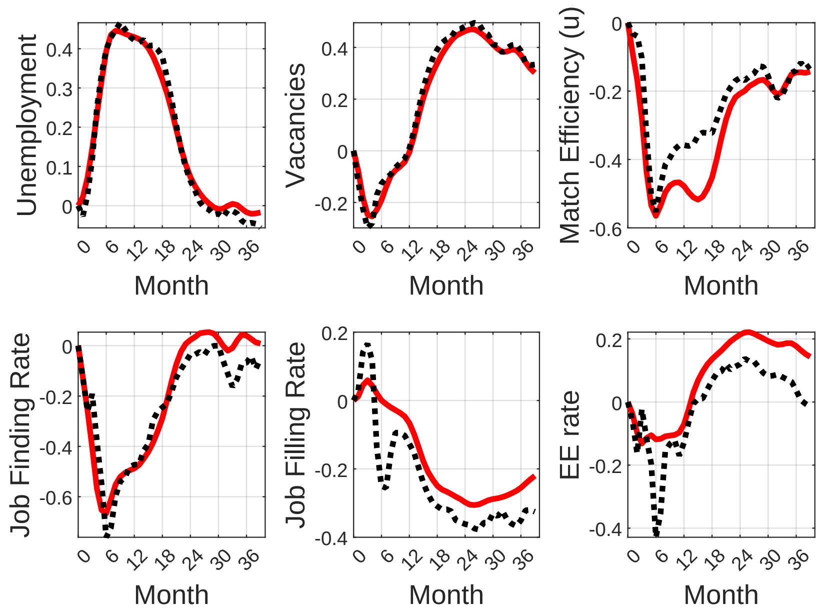


Figure 15: Model simulation fit of the data. Data in dashed line and model in solid line.

6.2 Model fit

Figure 15 plots the model's fit of the time series we use in the estimation. Overall, the model fits the data well in spite of the model being overidentified.

Because of the higher weight in the estimation, the path for unemployment and vacancies are matched very closely by the model. Match efficiency of the unemployed, the job finding and filling rates, as well as the EE rate are all closely replicated by the model.

Which aggregate shock is responsible for the dynamics of these various dimensions of the US labor market? Figure 19 plots model counterfactuals where we add one shock at the time.[17]

The productivity shock plays a dominant role in explaining the initial dynamics, in particular the quick rise in the unemployment rate, as well as the dip of vacancies, match efficiency and the job finding rate in the first few months. Soon after productivity starts recovering, the shock to the opportunity cost of work starts accounting for many of the observed dynamics, namely unemployment, match efficiency and the job finding rate. However, the role of these two shocks in explaining the other series is limited. For example, they do not account for the rise in vacancies and the EE rate. They also cannot

[17]In the figure, we start with the productivity shock, followed by b, and by amenity, but the order does not matter because of the additivity assumption.

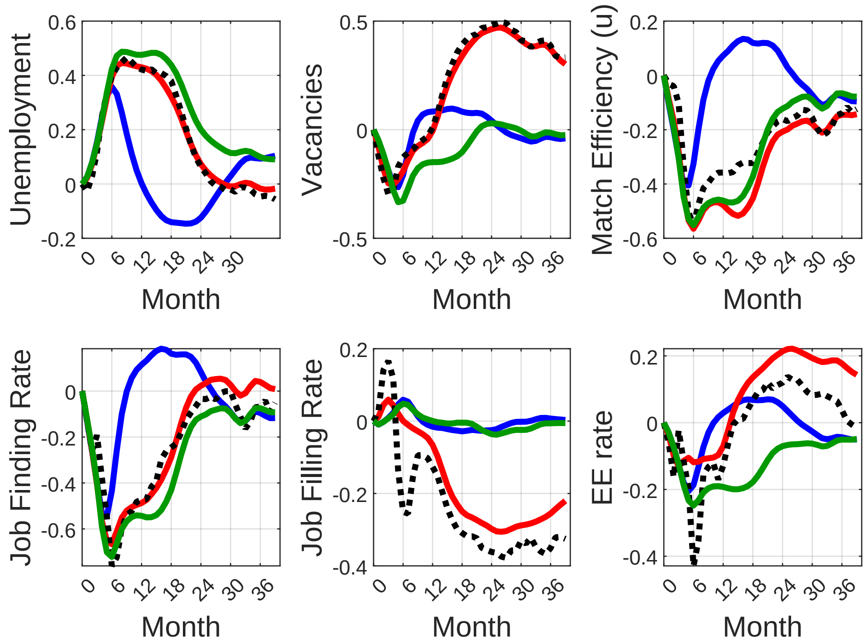


Figure 16: Decomposition of model's fit of the data (black dotted line) into productivity shock (blue), productivity + opportunity cost shock (green) and productivity+ opportunity cost + amenity shock (red).

generate the large drop in the job filling rate.

The rise in the value of job amenities turns out to be a powerful shock in our environment. It explains virtually the entirety of the rise in vacancies. Early on, the growth in vacancies is quit induced, as high-x workers leave low-amenity jobs. As time goes by and new vacancies are created, the vacancy composition keeps worsening as the newly created low-amenity jobs take much longer to fill than the high-amenity ones, and vacancies keep increasing. This growth in low-quality vacancies continues to depress match efficiency. As a result of these forces, the job filling rate tanks and remains persistently below trend: the entire decline in the job filling rate in the data is explained by the changing composition of the vacancy pool. These forces also set in motion a persistent labor reallocation process of workers: high-x workers move toward high amenity jobs, whereas low-x workers are willing to take the low amenity ones which, as we will see, pay a wage premium.

Figure 17 plots the Beveridge curve implied by the model. The model is able to generate the very wide Beveridge loop observed in the data. In particular, it features a quasi-vertical section of the Beveridge curve where vacancies rise without any meaning-

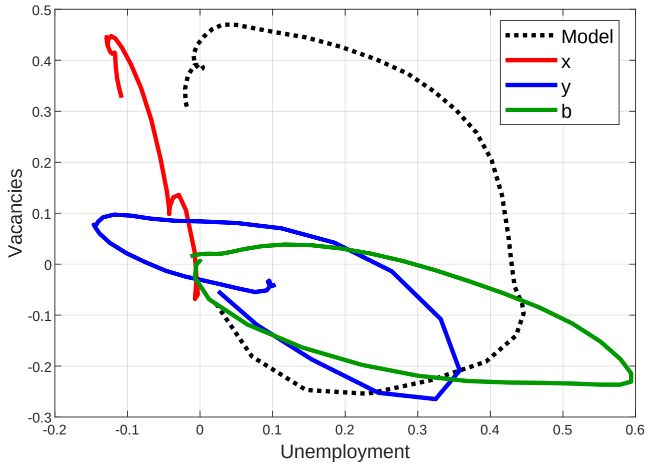


Figure 17: Model's Beveridge curve (dotted black line). Dynamics induced by shocks to productivity (blue line), opportunity cost of work (green line), and amenity value (red line).

ful change in unemployment. The figure also contains the decomposition into the three shocks. It is clear that, the productivity shock alone would have led to a narrow and flat loop, as in the previous recessions (recall Figure 1). Instead, the amenity shock sets in motion a process of quits-induced vacancies and persistent worker reallocation that induces a steep movement of the curve.

The left panel of Figure 18 plots the shock decomposition for deviations of output from its trend. Unsurprisingly, the productivity shock drives most of output dynamics, but the shock of opportunity cost of work also plays a sizable role in 2021, by reducing labor supply and production.

We now consider the time series for wages implied by the model. The top-right panel of Figure 18 displays the data and the model decomposition. The productivity shock has only a small impact on wages, whereas the labor supply shock can explain the sustained rise in wage growth for the first two years after the pandemic. It is, however, the amenity shock that accounts for the negative wage growth of the last twelve months. The bottom-right panel of the figure demonstrates that the rising attractiveness of high amenity jobs exerts strong downward pressure on wages because new hires are compensated by the non-pecuniary amenity. This finding mirrors Barrero, Bloom, Davis, Meyer, and Mihaylov (2022), who empirically investigate and quantify this mechanism.

We now illustrate the importance of the amenity shock in a slightly different way. Figure 19 shows the results from the model's estimation without amenity shock, where

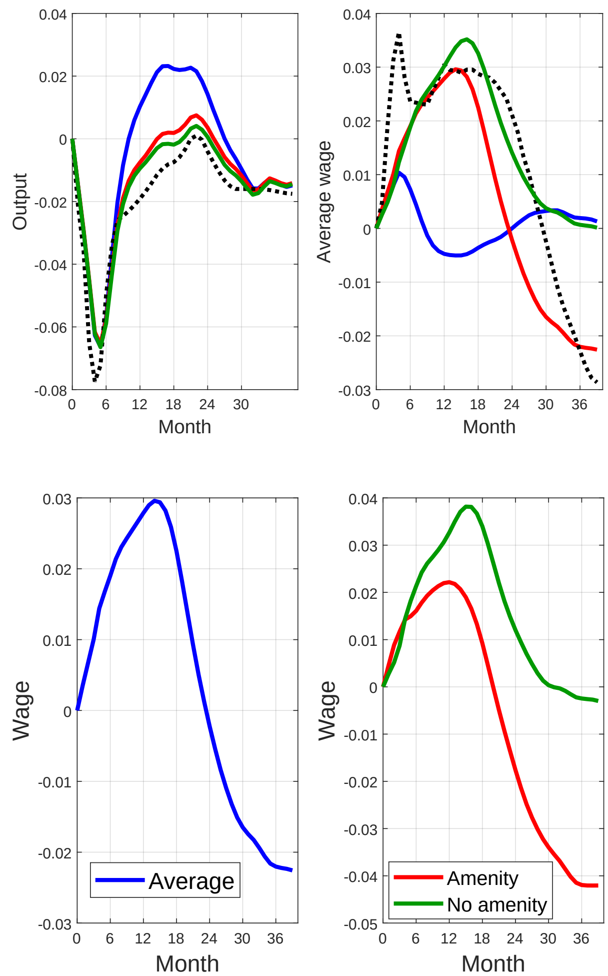


Figure 18: Top row. Decomposition of model's fit of the data on output and wages (black dotted line) into productivity shock (blue), productivity + opportunity cost shock (green) and productivity + opportunity cost + amenity shock (red). Bottom row. Average wage in the model in different types of jobs. Red: Low amenity. Green: High amenity. Blue: Both

we let the productivity and UI shock explain as much of the data as they can. Clearly, the model calls for an additional source of variation that can account for the joint dynamics of vacancies, job filling rate, and EE rate.

Cross-sectional implications. We conclude this section by confronting the cross-sectoral evidence presented in Section 2, where we showed that over the two years from January 2020 to January 2022, the rise in unemployment, vacancies and quits and the fall in the job filling rate are much more pronounced in sectors with low share of teleworkable jobs.

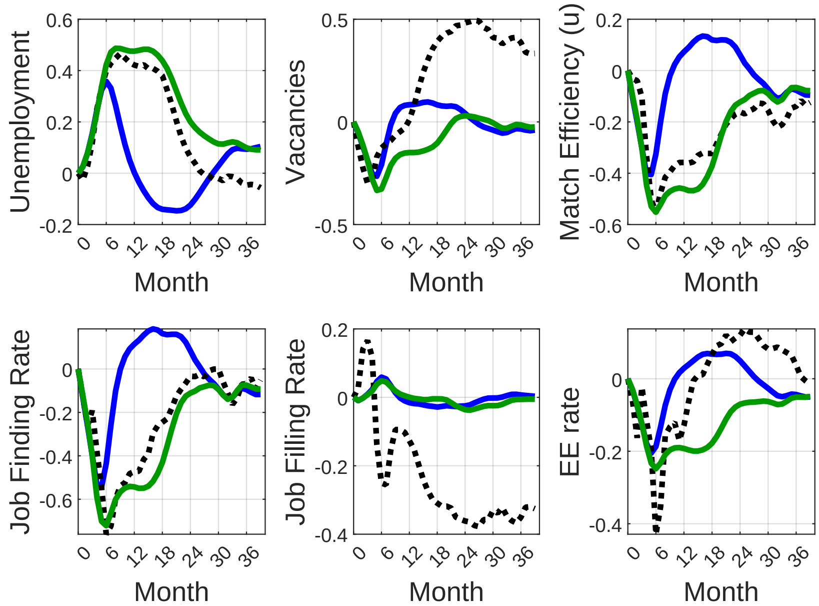


Figure 19: Model's simulation with shocks to productivity and opportunity cost of work only

We did not explicitly model different sectors. However, within our model one can think of sectors with different shares of teleworkable jobs as random collections of jobs with different proportions of jobs endowed with the amenity. When we define sectors this way, Figure 20 shows that the model is able to generate the empirical patterns.

7 Conclusions

How do frictional labor markets respond to aggregate shocks that shift the valuation of non-pecuniary job amenities? To answer this question, we have developed an equilibrium modelthat combines several building blocks of modern macro-labor: random matching á la Mortensen-Pissarides, on-the-job search and wage stetting á la Postel-Vinay-Robin, Diamond entry, and non-wage amenities á la Rosen.

A shock that shifts the preference for job amenity across workers who are heterogeneous in the extent to which they care about it induces a persistent labor reallocation. We argue that such shock is crucial in accounting for the post-pandemic labor market dynamics in the US, where we interpret the amenity as work from home.

As we keep updating the paper, we will refine our analysis in at least two directions.

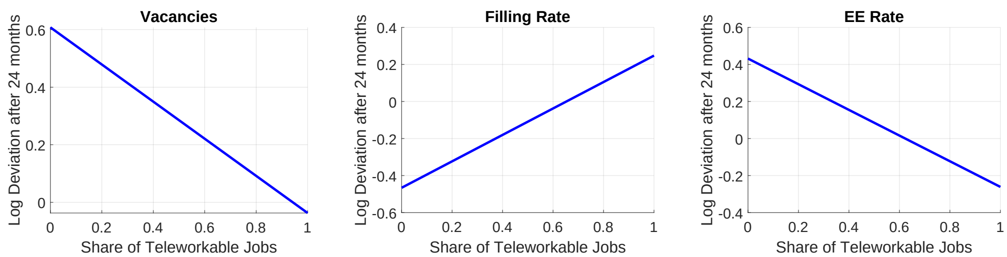


Figure 20: Model's equivalent of the cross-sectoral evidence of Figure 9.

Our view of the post-pandemic labor market is that the pandemic induced a rise in the demand for remote work. An alternative, complementary, interpretation of the events is that firms discovered cheaper ways of offering the remote-work option. A shock to ζ, the share of jobs that can be created with the amenity, would capture this idea in our model. A preliminary analysis of this shock within the model suggests that this shock can also fit labor market aggregates quite well, but it has different implications for wages.

An additional form of reallocation which has occurred during the pandemic is represented by the relative demand shift from contact-intensive services to goods producing sectors. We plan to analyze empirically the extent to which the data support this view vis-a-vis reallocation across different type of jobs within sectors. Again, we think that relative wage dynamics across sectors could be informative.

The pandemic was a global shock. Going forward, it would be valuable to put the US experience into an international context. The unprecedented surge in vacancies and quits seem, at least qualitatively, a common fixture of this recovery across countries (Causa et al., 2022). Similarly, Aksoy et al. (2022) document that there is, everywhere, a transition towards remote work. They also demonstrate, however, some degree of heterogeneity in preferences for remote work and uptake rates across countries. In addition, the way government responded to the outfall from the pandemic was quite different outside the US, where policy interventions, instead of directing support to jobless and low-income households, focused on the retention of ongoing employment relationships. The framework we developed can be used to model and interpret similarities and divergences between the US labor market dynamics and those of other countries.

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Appendix

A Adjusting the CPS and JOLTS hires in levels and cyclicality

The Current Population Survey (CPS) and Job Openings and Labor Turnover Survey (JOLTS) provide us with monthly measures of hires from the worker and firm side, respectively. In the CPS, hires in month t are defined as the sum of all workers who make flows into employment in month t from the state of employment in a different firm, unemployment (including temporary layoffs), or non-participation in month $t-1$. In the JOLTS, hires are defined as "any addition to an establishment's payroll, including newly hired and rehired employees.". In principle, both data sources capture total hires and should provide us with comparable measures. In practice, there is a discrepancy between these measures in levels and cyclicality. Figure A1 plots the CPS and JOLTS hires and shows that CPS hires are less cyclical and higher in levels compared to JOLTS hires. (The difference in levels between CPS and JOLTS has also been pointed out by Fujita et al. (2023) (focus on separations) and Hershbein (2017).

Throughout the paper, we adjust the total hires to match the JOLTS cyclicality and CPS levels. We re-scale all sources of hires in the CPS by adjusting for them for the cyclicality and levels factors defined below:

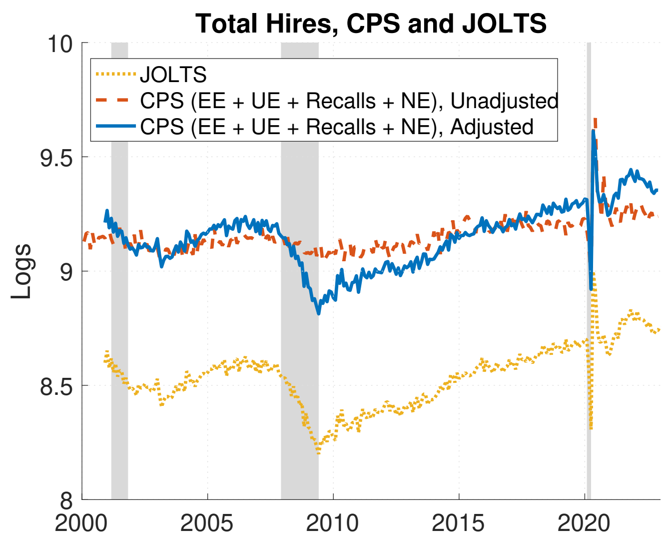
$$\text{Hires Cyclicality Factor}_t = \frac{Hires_t^{JOLTS}}{UE_t^{CPS} + NE_t^{CPS} + EE_t^{CPS} + Recalls_t^{CPS}}$$

$$\text{Hires Level Factor} = \frac{\overline{UE}^{CPS} + \overline{NE}^{CPS} + \overline{EE}^{CPS} + \overline{Recalls}^{CPS}}{\overline{Hires}^{JOLTS}}$$

We adjust the flow of UE hires, EE hires, and stock of the unemployed by expressing them as products of the hires cyclicality and level factors.

B Variable Definitions

- Unemployment Rate: Number of unemployed (excluding those on temporary layoffs) expressed as a fraction of the sum of employed and unemployed (excluding those on temporary layoffs).
- Vacancy Rate: Number of job openings expressed as a fraction of the sum of employees and job openings. Obtained from the JOLTS.
- Labor Market Tightness: Vacancies/Unemployed (excluding those on temporary layoffs)
- Beveridge Curve: Vacancy Rate plotted against Unemployment Rate
- Job Finding Rate: (UE hires + EE hires)/Job seekers $(U + s * E)$ where s = 0.58.
- Job Filling Rate: (UE hires + EE hires)/Vacancies
- Quit Rate: Quits/Employed. Obtained from the JOLTS.



Source: CPS, JOLTS, and authors' calculations.

Figure A1: Total Hires from the CPS and JOLTS. The CPS hires have been adjusted for JOLTS cyclicality and CPS levels.

- EE Rate: EE hires/Employed.
- UE Rate: UE hires/Unemployed (excluding those on temporary layoffs)

C Vacancy Posting, Job Filling, and Quits

Tables A1 and A2 show regressions of log vacancy rate and log job filling rates on log quit rate, controlling for layoffs and other separations. The quit rate correlates positively with and is highly predictive of the vacancy rate. This is especially true in a tight labor market, such as one after the Pandemic (Table A1, column 9), but not so after the Great Recession (column 6). Post-pandemic, industries with higher quits posted more vacancies but did not end up filling more vacancies. This is shown by the negative correlation between quits and job-filling rates, which was observed after the pandemic (Table A2, column 9) but not after the Great Recession (column 6) or for the full sample (column 3).

D Figures

	Dependent Variable: Log Vacancy Rate								
	Full Sample			2009:7-2011:7			2020:5-2022:5		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Log Quit Rate	0.352***	0.483***	0.136***	0.290***	0.494***	0.153	0.535***	0.596***	0.530***
	(0.00727)	(0.0109)	(0.0217)	(0.0323)	(0.0367)	(0.0958)	(0.0284)	(0.0379)	(0.0957)
Log Layoff Rate		-0.166***	-0.0654***		-0.335***	-0.372***		-0.124***	-0.289***
		(0.0103)	(0.0137)		(0.0322)	(0.0694)		(0.0278)	(0.0450)
Log Other Separations Rate		-0.0131	-0.0476***		0.00860	-0.0259		0.0334	-0.00780
		(0.00961)	(0.00844)		(0.0338)	(0.0311)		(0.0278)	(0.0266)
Time FE	Y	Y	Y	N	N	N	N	N	N
Sector FE	N	N	Y	N	N	Y	N	N	Y
N	4522	4470	4470	425	420	420	425	420	420
R^2	0.658	0.687	0.835	0.122	0.335	0.557	0.485	0.529	0.711

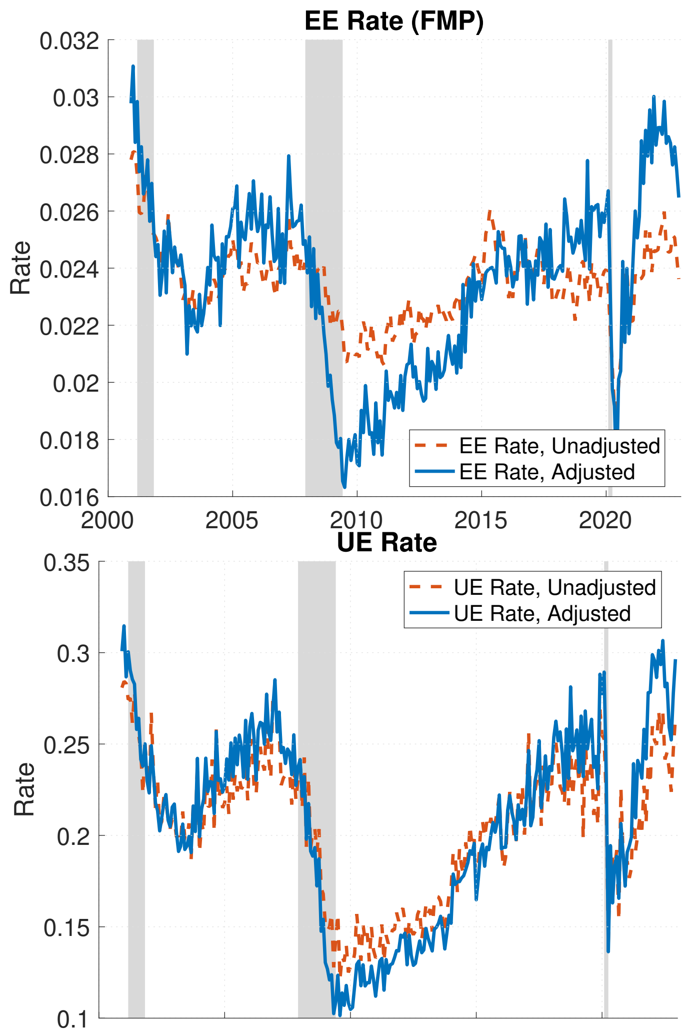
Table A1: Regressions: Vacancies and Quits

Notes: JOLTS, 2000:12-2023:1. Time FE include calendar month fixed effects and Sector FE include 17 two-digit NAICS industry fixed effects. Robust standard errors in parenthesis. * p<0.10, ** p<0.05, *** p<0.01.

	Dependent Variable: Log Job Filling Rate								
	Full Sample			2009:7-2011:7			2020:5-2022:5		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Log Quit Rate	0.473***	0.0544***	0.177***	0.453***	-0.0107	0.0801	0.142***	-0.0938**	-0.601***
	(0.00923)	(0.0114)	(0.0234)	(0.0417)	(0.0386)	(0.0974)	(0.0476)	(0.0375)	(0.117)
Log Layoff Rate		0.530***	0.245***		0.768***	0.496***		0.486***	0.334***
		(0.0113)	(0.0141)		(0.0348)	(0.0619)		(0.0275)	(0.0534)
Log Other Separations Rate		0.0392***	0.0760***		0.0329	0.0545*		-0.0673**	0.0344
		(0.0101)	(0.00888)		(0.0360)	(0.0295)		(0.0300)	(0.0307)
Time FE	Y	Y	Y	N	N	N	N	N	N
Sector FE	N	N	Y	N	N	Y	N	N	Y
N	4522	4470	4470	425	420	420	425	420	420
R^2	0.489	0.716	0.852	0.143	0.660	0.808	0.0263	0.493	0.695

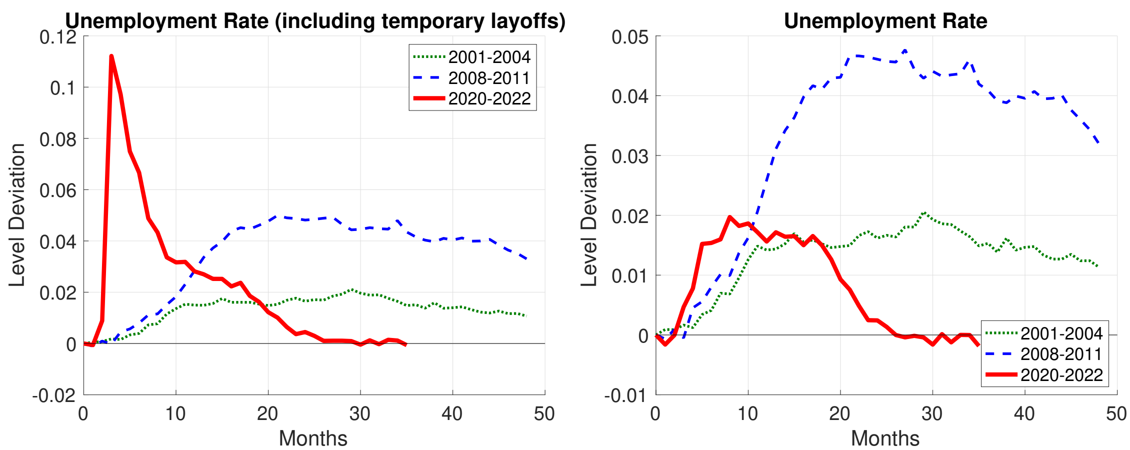
Table A2: Regressions: Job Filling and Quits

Notes: JOLTS, 2000:12-2023:1. Job Filling Rate = Hires/Vacancies. Time FE include calendar month fixed effects and Sector FE include 17 two-digit NAICS industry fixed effects. Robust standard errors in parenthesis. * p<0.10, ** p<0.05, *** p<0.01.



Source: CPS, JOLTS, and authors' calculations.

Figure A2: UE rate and Fujita et al. (2023)-based EE rate. Adjusted for JOLTS cyclicality and CPS levels.



Source: CPS, and authors' calculations.

Figure A3: Level deviation in the unemployment rate excluding and including workers on temporary layoffs in 2001-2004, 2008-2011, and 2020-2022 periods. The values are normalized to 0 for January 2001, 2008, and 2020.