

Job Amenity Shocks and Labor Reallocation*

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Abstract

We introduce aggregate shocks to workers' 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 trigger 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 decline in the willingness to work; and, crucially, a persistent increase in the value that workers put on job amenities. Cross-sectoral patterns of vacancies, quit rates, job-filling rates, and wages—where sectors are ranked by the share of teleworkable jobs—offer support to the view that the key amenity in question is the ability to work remotely.

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1 Introduction

The notion that both wage compensation and non-wage job amenities are salient for workers goes back at least to Adam Smith. In *The Wealth of Nations*, Smith asserts that workers' preferences for jobs are not dictated solely 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-pecuniary 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 further to provide employees with access to various facilities (e.g., cafeteria, break room, gym, day care), flexible work hours and shift choices, remote work options, and better work-life balance in general.

While canonical models of frictional labor markets still focus on wages as the sole determinant of desirability of a job, 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 gaps, and sorting between workers and firms.¹

In this paper, we combine this literature with business cycle theory, and examine the effects of an aggregate shift to the valuation of job amenities on the labor market. This analysis requires building an equilibrium model of job search with several ingredients: (i) heterogeneity in non-pecuniary job amenities; (ii) heterogeneity in workers' valuation of said amenities; (iii) on-the-job search; and (iv) job vacancies created by quits. While our framework is applicable to examining an array of events (such as news about adverse health effects of certain occupations, or changes in the cost of providing a particular amenity), our focus is the shift in worker preferences for remote work 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 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. Second, the so-called *Great Resignation*: the quit rate for employed workers reached 3% in 2021 almost 50% higher than in 2019.

¹See, 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. \(2021\)](#).

We document that this increase in quits coincided with challenges in filling job openings for firms and with a deterioration of matching efficiency. Finally, the behavior of wages during the recovery from the pandemic recession also deviated from previous patterns leading to a sizable *wage compression*.

Our hypothesis is that shifts in worker preferences in favor of job amenities, mainly the ability to work remotely, led to a persistent labor reallocation which can explain these 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 7% 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).

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 model thus features a two-dimensional job ladder, and workers disagree on the ranking of jobs as in [Lindenlaub and Postel-Vinay \(2023\)](#).

The second extension pertains the way we model job creation. 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 former employee with a new one. In particular, the model features vacancy chains.² Notably, the non-zero value of a vacancy breaks the block-recursivity exploited in [Lise and Robin \(2017\)](#) and makes the computation of aggregate dynamics more demanding.

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 helps explaining the data.

The response of the economy to a shock raising the value that workers put on job amenities 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

²This 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](#)).

amenity is lower than in jobs without it—a force that contributes to moderating overall real wage growth.

In our quantitative analysis, we add two additional aggregate shocks to the model: (i) a temporary negative fall in productivity to account for the short, but sharp, downturn of 2020; (ii) a rise in the opportunity cost of work (i.e., a negative labor supply shock) consistent with the fear of the virus, the generous expansion in unemployment insurance benefits, and the generous fiscal transfers to low-income households which took place over the period under examination.

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-pandemic 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. The model also calls for a negative productivity shock to explain the short but deep recession associated to the lockdown, followed by a quick rebound. It also calls for a sizable negative labor supply shock to fully account for unemployment and wage dynamics.

A cross-sectoral version of the model 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 vacancies, quits and wages, 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 presents the theoretical framework. 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 make several 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 14.3%, and the unemployment rate rose by 11.2 percentage points from February 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 14.8% 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 treat them as non-participants. For consistency, we also exclude recalls from hires and temporary layoffs from separations.⁴

Another notable labor market development was the brisk turnaround in vacancies. While there was a decline in vacancies in 2020 from their pre-pandemic level of around

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

⁴See [Figure D1](#) for a comparison of unemployment rates with and without temporary layoffs.

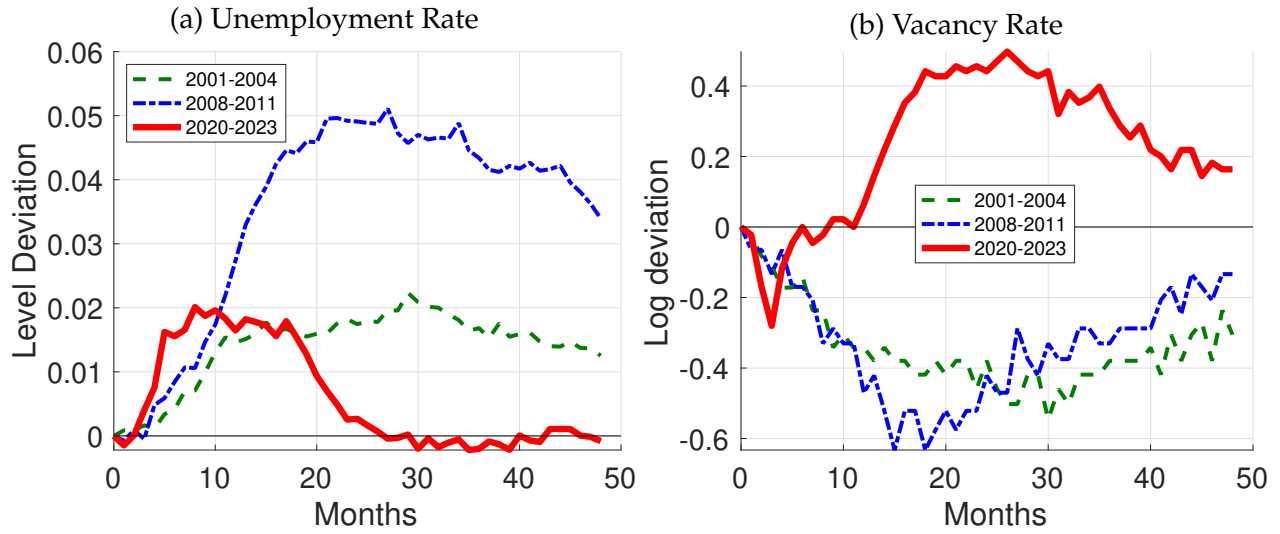


Figure 1: Level deviation in the unemployment rate (left) and log deviation in the vacancy rate (right) for 2001-2004, 2008-2011, and 2020-2023 periods.

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

7 million to 4.7 million in April 2020, vacancies quickly recovered back to their pre-recession level by January 2021 and continued to increase; peaking at around 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.⁵

The left 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

⁵Figure D2 in the Appendix shows how the 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.

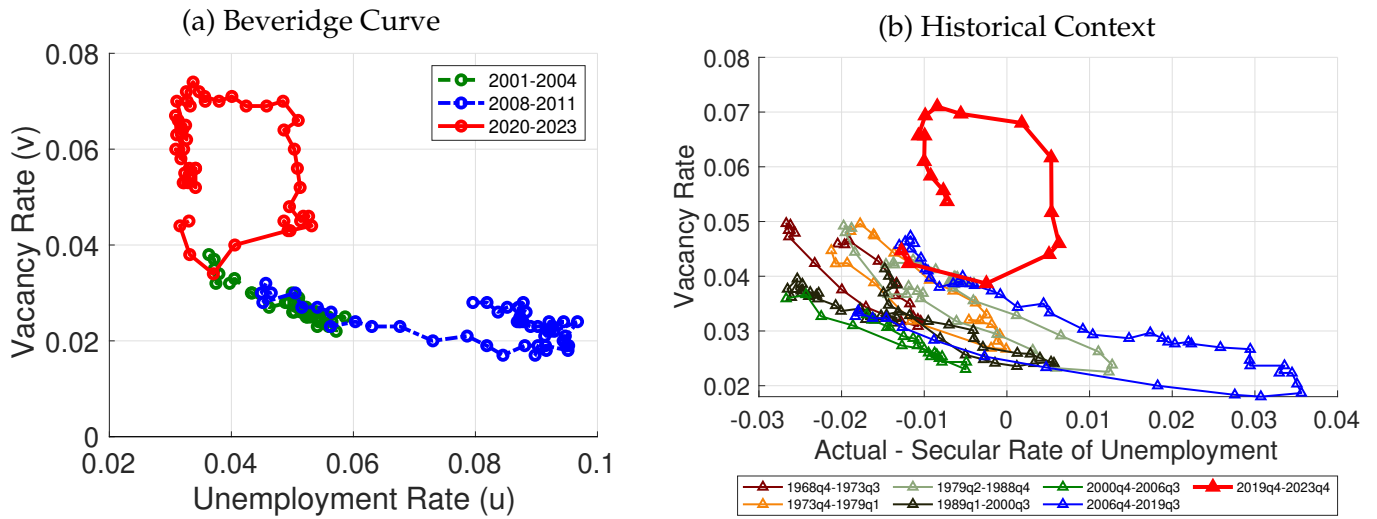


Figure 2: Beveridge Curve over the last three cycles (left) and in historical context (right).

Notes: CPS, JOLTS, and authors' calculations based on [Barnichon \(2010\)](#) and [Petrosky-Nadeau and Zhang \(2021\)](#).

puzzling 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.⁶

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. The right-panel of Figure 2 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.

⁶See 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.

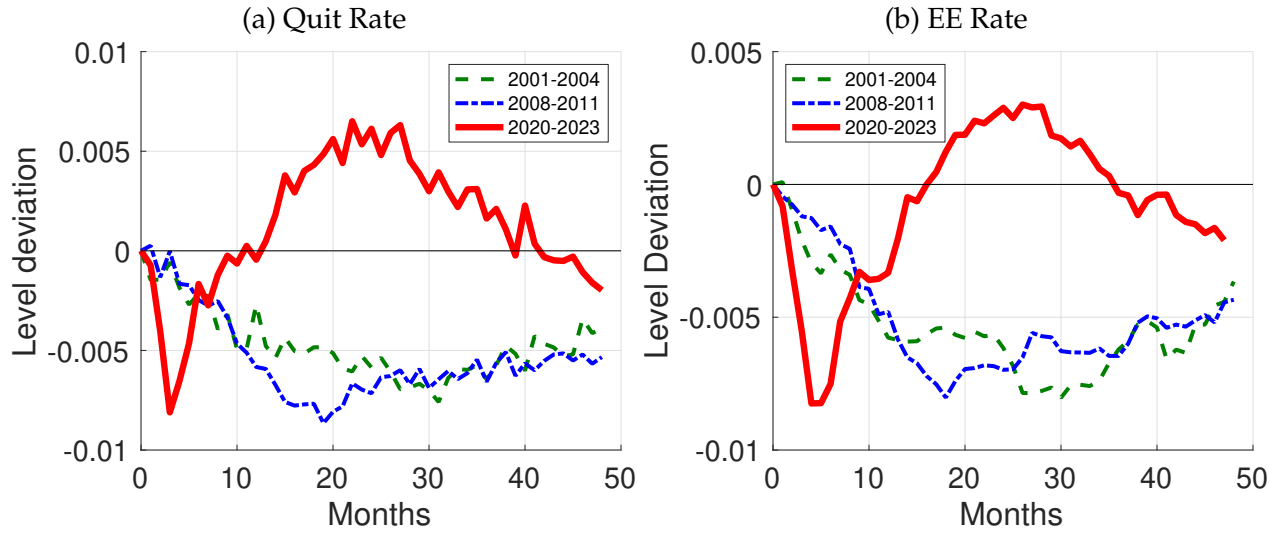


Figure 3: Quits and Job-to-job transitions

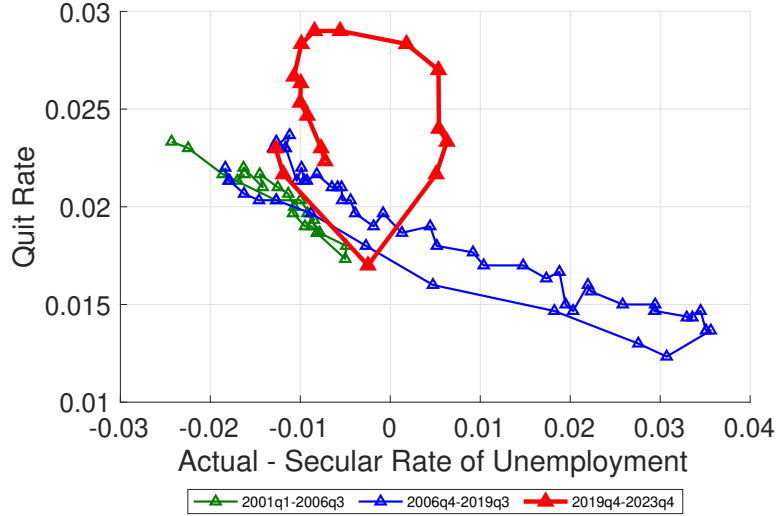
Notes: CPS, JOLTS, and authors' calculations. The values are normalized to zero for January 2001, 2008, and 2020. EE rate is expressed as EE hires as fraction of all employed. EE hires have been adjusted for JOLTS cyclical and CPS levels as described in Appendix A.

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 3. 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 4 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



Source: CPS, JOLTS, and authors' calculations.

Figure 4: Quits rate and deviation of actual and secular rates of unemployment.

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

Figure 5 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.⁷ The shortfall in job-filling

⁷We also find that post-pandemic quit rate is highly predictive of the vacancy rate at the industry-level data. Tables C1 and C2 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 C2 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.

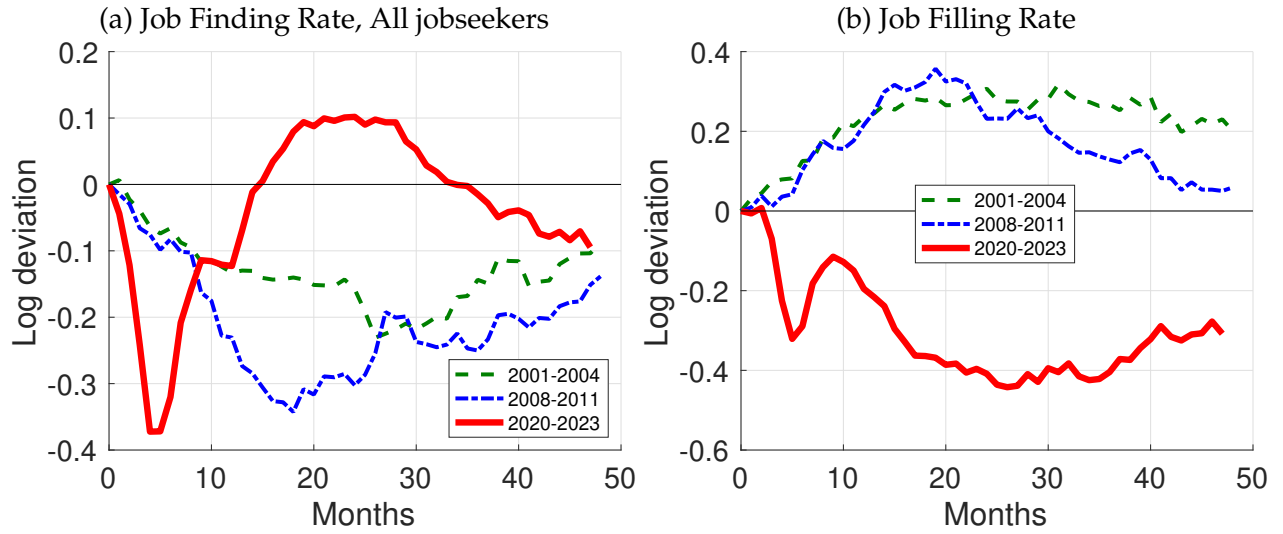


Figure 5: Job-finding (left) and job-filling rates (right).

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 cyclicity and CPS levels as described in Appendix A. Job filling rate expressed as a 3-month centered moving average.

rate suggests a deterioration in matching efficiency in the labor market.⁸

A summary measure that is often used to capture the efficiency of the search and matching process in the labor market is the *aggregate matching efficiency*.⁹ 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:

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

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

⁸Note that we use measures of hires from the CPS adjusted for the cyclicity of JOLTS measures throughout the paper. Appendix A provides details of calculations of these measures.

⁹Increases in mismatch, changes job search and recruiting intensities, workers' reservation wages are all determinants of matching efficiency in the labor market.

for the unemployed and employed workers using their corresponding job-finding rates as

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

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:

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

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 6](#). 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.

2.3 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 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 in the pre-vaccine period has declined after the re-opening of the economy and the introduction of vaccines. But, it has stabilized at a much higher rate than its pre-pandemic level



Figure 6: 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 and expressed in terms of 3-month centered moving averages. Hires from unemployment and employment adjust for JOLTS cyclical and CPS levels as described in Appendix A.

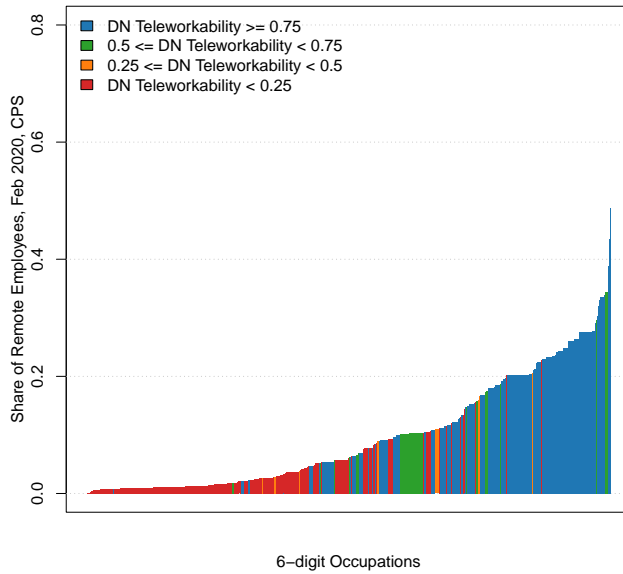
with around 30% of work days spent working from home according to [Barrero, Bloom, and Davis \(2023\)](#).

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.

At the onset of the pandemic, [Dingel and Neiman \(2020\)](#) analyzed the feasibility of working at home for detailed occupational categories. By merging this classification with occupational employment counts, they estimated that work from home (WFH) was feasible for 37% of workers. They also found 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.

It is useful to compare the feasibility of remote work as identified at the occupation level by [Dingel and Neiman \(2020\)](#) with the prevalence of remote work before the pan-

(a) Remote Occupations, Feb 2020



(b) Remote Occupations, Oct 2022-Dec 2023

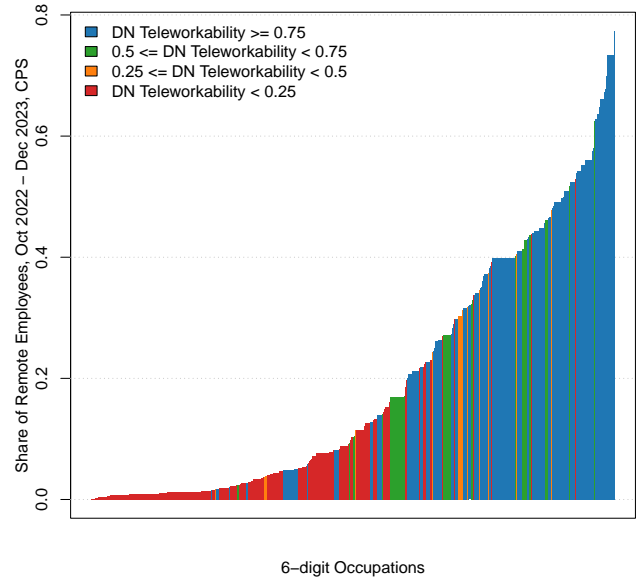


Figure 7: Feasibility of teleworkability and share of remote work across occupations.

Notes: CPS, and authors' calculations. The x-axis ranks 422 occupations at the SOC 2010 6-digit level by their share of weekly hours teleworked shown on the y-axis from the CPS Telework supplement (October 2022-December 2023). Width of the bars indicate employment share of occupations. The different colors indicate the share of teleworkable jobs in an occupation based on tasks performed from [Dingel and Neiman \(2020\)](#).

demic and in 2022-2023. The BLS added new questions to the Current Population Survey (CPS) starting in October 2022 that focus on telework or work at home for pay. These questions ask whether people had teleworked or worked at home for pay in the survey reference week. The employed respondents were also asked if they had teleworked in February 2020. In Figure 7, we plot the share of remote employees against the feasibility of remote work as estimated by [Dingel and Neiman \(2020\)](#), with the width of the bars reflecting the employment share of respective occupations, for February 2020 (panel a) and October 2022-December 2023 period (panel b). The figure shows that there was widespread adoption of remote work in occupations where teleworkability is feasible. In certain occupations, such as computer programmers, the percentage of remote workers exceeded 75 percent in 2022-2023.

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 around 7% on average in



Figure 8: Labor Market Outcomes and Teleworkability of industries

Notes: CES, CPS, JOLTS and authors' calculations. The x-axis plots the share of teleworkable jobs using Dingel and Neiman (2020) classification aggregated to sectoral level. The y-axis plots the deviation of the centered-moving average of the outcome in January 2022 from January 2020. The fitted line is weighted by the centered-moving average of vacancy shares of sectors in January 2020.

exchange for 2 workdays a 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

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

shift to fully or partially remote work arrangements.

Differences in feasibility of teleworkability among various industries are also informative in assessing the role of remote work in post-pandemic labor market dynamics. Figure 8 shows the log deviation of various labor market indicators in January 2022 relative to January 2020 for different sectors as a function of teleworkability of the sector estimated using Dingel and Neiman (2020) classification. The vacancy rates increased more in sectors where remote work was less feasible and these sectors also experienced the most significant decline in their job filling rates as panels (a) and (b) of Figure 8 show. Sectors with a higher share of teleworkable jobs did not experience a deviation in their quit rates relative to January 2020, while excess quits in contact-intensive sectors were the main drivers of the *Great resignation* (panel d). Finally, growth rate of average hourly earnings has been higher in sectors with a low share of teleworkable jobs.

3 Model

Our empirical analysis identified some key deviations in labor market dynamics following the onset of the pandemic. Most notably, we have documented that the behavior of vacancies, quits, job-filling rate, matching efficiency and prevalence of remote work all deviated from historical patterns. Informed by these observations, we set up a search and matching model with crucial extensions for a quantitative assessment of importance of these factors.

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 since they allow us to connect to the data on quits and vacancies. In taking the model to the data, we will think of job amenity mostly as how the ability to perform job tasks 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. The shock to value of unemployment is intended to capture the expansion of UI benefits, the generous fiscal transfers and the deteriorating health conditions due to the pandemic.

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. Workers discount the future at rate r and have linear utility over consumption c_t which equals their income.

Unemployed workers receive a flow utility $b_t = Z_t^b b$, which we interpret as the combination of consumption (unemployment benefits) and the flow value of leisure. Z_t^b is an aggregate shifter of the flow value of unemployment.

Employed workers receive a flow wage payment w_t . Appendix E.1 describes the wage determination in detail. 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 an additional utility flow equal to $Z_t^x xa$. Besides this dimension of heterogeneity, workers are equally productive ex-ante.

We can write the flow utility of a worker with amenity valuation x as

$$\mathcal{U}_t = \begin{cases} w_t + Z_t^x xa & \text{if employed in a job with amenity } a \text{ at wage } w_t \\ Z_t^b b & \text{if unemployed} \end{cases}$$

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.

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 .

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

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

$$s_t = \sum_x u_t(x) + s \sum_{x,y,a} e_t(x,y,a) = u_t + s e_t \quad (5)$$

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

$$v_t = \sum_a v_t(a) \quad (6)$$

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

$$m_t = m(v_t, s_t), \quad (7)$$

where m is a CRS meeting function. Let $p_t = m_t/s_t$ be the meeting rate for the unemployed, $p_t s$ the one for the employed, and $q_t = m_t/v_t$ the one for vacancies.

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 a sufficiently large supply H of potential entrants. To become an incumbent, a potential entrant must draw an entry cost $\kappa \sim G$ where $G(\kappa^*) := \text{Prob}(\kappa \leq \kappa^*) = (\gamma \kappa^*)^\xi$ for $\kappa^* \in [0, 1/\gamma]$ and $\xi > 0$. Given an ex-ante value of entering $\bar{\Omega}_t$, the mass of newly entering vacancies is given by

$$i_t = H \cdot G(\bar{\Omega}_t) = H \cdot (\gamma \bar{\Omega}_t)^\xi$$

where we assume H to be large enough such that $0 < \bar{\Omega}_t < 1/\gamma$ for all $t \geq 0$ (for any given value of $H\gamma^\xi$). Thus, ξ captures the elasticity of job creation with respect to the value of a

job. This elasticity can in principle be chosen to be finite (see [Coles and Kelishomi, 2018](#)). However, the model also nests the limiting case $\zeta \rightarrow \infty$, which corresponds to free entry.

Once the vacant job is created, but before it starts searching for a worker, it draws a value of a from a Bernoulli distribution with support $\{\underline{a}, \bar{a}\}$. With probability $\zeta \in [0, 1]$, $a = \bar{a}$ and the job is endowed with the amenity. As a result, among jobs that newly enter 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: some jobs feature essential tasks that need to be performed on site, while others do not and are teleworkable.

The ex-ante value of entry is thus given by $\zeta\Omega_t(\bar{a}) + (1 - \zeta)\Omega_t(\underline{a})$ and, the number of jobs created i_t equals

$$i_t = H\gamma^\zeta [\zeta\Omega_t(\bar{a}) + (1 - \zeta)\Omega_t(\underline{a})]^\zeta \quad (8)$$

Vacancies as a stock and vacancy chains. Because of Diamond entry, the entry 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 to 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 into the stock and the outflow from the stock. 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. Second, the jobs vacated by quits. 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

Note that the model features ‘vacancy chains’ and ‘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.

¹¹We 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.

3.2 Surplus Determination and Rent Splitting

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

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

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 option for the firm¹².

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 ToL 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. The details of our wage setting protocol are collected in [Appendix E.1](#).

Surplus dynamics. 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. Another implication of our wage setting protocol is that the surplus becomes independent of the wage (see [Lise and Robin, 2017](#), for details). As a result, all allocations can be calculated without knowledge of the wages. In [Appendix E.3](#), we show that the surplus can be written as

$$(r + \delta)S_t(x, y, a) = Z_t^y y + Z_t^x x a - Z_t^b b + \delta \tilde{\Omega}_t(a) + \partial_t S_t(x, y, a) \quad (10)$$

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).

This concludes the description of the model. Since some equations are lengthy but

¹²Depending on whether a job is filled or vacant, the outside option of the firm can be either the value of an active or a dormant vacancy. For this reason, it is more convenient to define the ‘gross’ surplus, which does not include this outside option.

Parameter		Value	Target to match	Target value
Elasticity of meeting function	α	0.5	<i>External</i>	
Discount rate	r	0.05/12	<i>External</i>	
Prob. of re-entering pool of active v	μ	1	<i>External</i>	
Elasticity of entry	ζ	∞	<i>External</i>	
Share of \bar{a} vacancies	ζ	0.25	<i>Dingel and Neiman (2020)</i>	
Share of pop. with $x = \bar{x}$	$\ell(\bar{x})$	0.5	<i>Barrero et al. (2022)</i>	
Amenity	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	Meeting rate of unempl.	1.5
Opportunity cost of work	b	1.01	UE rate	0.3
Log-productivity dispersion	σ	0.041	$\Delta \log u$, -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

all derivations are fairly standard, we relegate the characterization of the value functions and laws of motion to Appendix E, where we also formally define an equilibrium of the model in the usual way.

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 internally 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 entry elasticity ζ , 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. ζ governs the sensitivity of vacancies to changes in the value of a job. We find that, with finite ζ , the model tends to undershoot the empirically observed variance of vacancies in response to productivity shocks. For this reason, we focus on the limiting case $\zeta \rightarrow \infty$ which corresponds to a model in which the entry cost κ is deterministic and $\bar{\Omega}_t \leq \kappa$ and $i_t \geq 0$ hold with complementary slackness.¹³ Next, we set the probability of

¹³For the numerical solution algorithm we approximate free entry with a large but finite value of ζ .

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 \(2020\)](#). Lastly, we set the share of high x workers to 0.5, consistent with evidence from [Barrero, Bloom, and Davis \(2021\)](#) and [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 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 Z^s , $s = y, b, x$. A shock of size ε_0^s that hits at time $t = 0$ follows a path given by

$$Z_t^s = \varepsilon_0^s e^{-\rho_s t}, \quad \text{for } t \geq 0 \quad (11)$$

We assume that the b shock reverts very quickly, with $\rho_b = -0.23$, implying that it takes about two years to fade out completely. This fast mean reversion reflects the observation that UI benefits extensions during recessions are, typically, short-lived.¹⁴ For the productivity shock, we set $\rho_z = -0.057$, corresponding to a half-life of one year, and about 5

¹⁴With the exception of the Great Recession, in all the downturns since 1970 –including the pandemic— UI extensions lasted around two years.

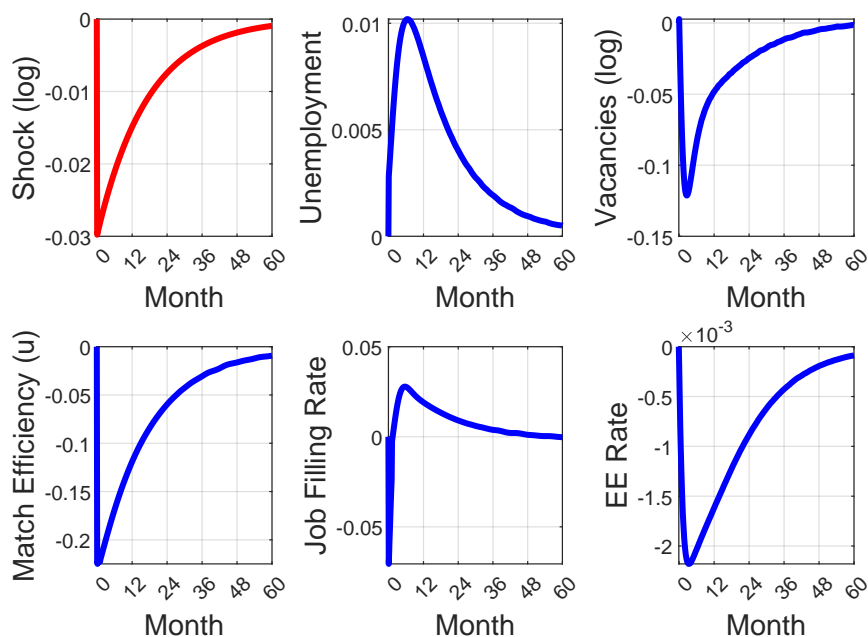


Figure 9: Impulse response functions to a productivity (y) shock

years until the shock dissipates entirely. We assume that the amenity shock is permanent ($\rho_x = 0$), i.e. it generates a long-lasting shift in preferences.

Figure 9 displays the impulse response to a negative productivity shock that pushes unemployment up by 1 percentage point.¹⁵ 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 up. Falling vacancies reduce the job finding rate, which results in an increase of the unemployment rate. Because aggregate productivity is lower, it becomes less likely that a worker and a firm obtain an idiosyncratic productivity draw necessary for a viable match, and thus match efficiency decreases. Since match efficiency is a jump variable but vacancies are sluggish, the job filling rate falls at impact. Then, 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 the stock of vacancies decreases (i.e., jobseekers make fewer contacts) and match efficiency falls (i.e., fewer contacts become matches).

The impulse responses to a negative labor supply shock (a rise in the opportunity cost of work b) depicted in Figure 10, deliver similar dynamics. This is not surprising: since

¹⁵The size of all three shocks in Figures 9, 10, and 12 has been normalized to produce the same increase in the unemployment rate.

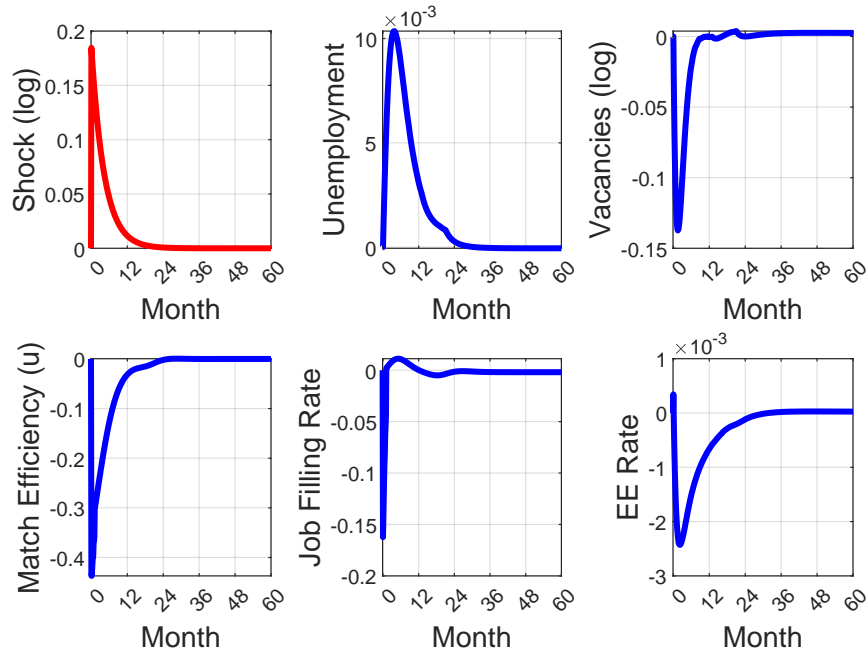


Figure 10: Impulse response functions to the opportunity cost of work (b) shock

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 of the opposite sign.¹⁶ Many of the same mechanisms are at play. Match efficiency is reduced because the workers' outside option of unemployment is more desirable now. Unemployed workers become harder to hire, reducing vacancy posting incentives. This channel decreases vacancies and the job finding rate. Consequently, the 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. As illustrated in Figure 11, 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 household valuation of the amenity x are displayed in Figure 12. 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 ($a = \underline{a}$).

¹⁶The equivalence is not an isomorphism since Z_i^y enters multiplicatively and therefore affects the dispersion of y in the population

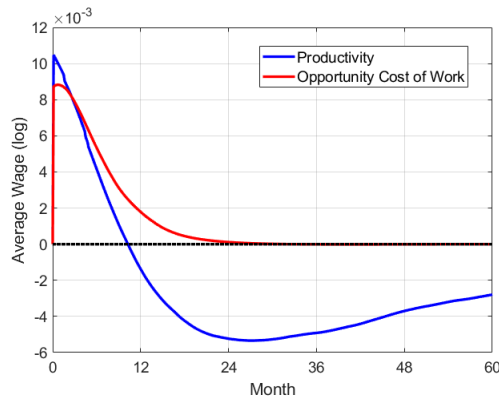


Figure 11: Response of average wages to a negative productivity shock (blue) and to a positive shock to the opportunity cost of work (red).

Thus, some high x workers in the most unproductive low-amenity jobs immediately quit to unemployment, and in fact unemployment jumps at impact. Workers in slightly more productive matches stay employed and wait for an opportunity to quit into another job in order to 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 vacancies. 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 persistently 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.

5.1 Estimation of Aggregate Shocks

The model's impulse response functions (IRFs) imply a unique relationship between a sequence $\{Z_t^s\}_{t=0}^T$ of shock realizations and a time path $\{d_t^k\}_{t=0}^T$ of a model aggregate variable k . Our aim is to leverage these IRFs to estimate the realized path of the three aggregate shocks from observed time series data for the US labor market. To obtain the series of realized shocks that, through the lens of the model, is most consistent with the data, we minimize the distance between a number of model-implied time series and their empirical counterparts.

Consistently with the way we compute IRFs, we assume that stochastic innovations

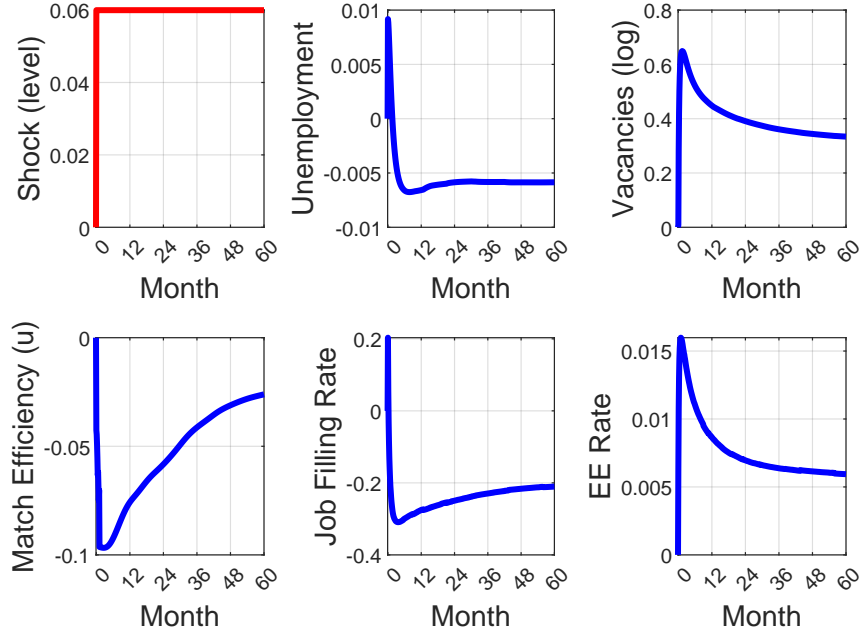


Figure 12: Impulse response functions to an amenity valuation (x) shock

are unanticipated (i.e., MIT shocks) and trigger a perfectly foreseen transition for the shocks given by (11), and for the aggregate variables d^k given by the model's deterministic equilibrium dynamics. In addition, a key assumption that allows us to make progress is that the response of the system can be written as a sum of past (possibly nonlinear) functions of the innovations. Formally, for any history of innovations $\{\varepsilon_t^s\}_{t=0}^T$ and some model series $\{d_t^k\}_{t=0}^T$, we assume that each realization d_t^k can be written as

$$d_t^k = \sum_s \sum_{j=0}^t h_{s,j}^k(\varepsilon_{t-j}^s)$$

where the function $h_{s,j}^k$ is implied by the model. This formulation allows for shock responses to be *size- and sign-dependent*.¹⁷ 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 impulse responses to each aggregate shock, ε_t^y , ε_t^b and ε_t^x at different horizons and for different shock magnitudes,

¹⁷For 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.

both positive and negative. This set of impulse responses allows us to compute $h_{s,j}^k$ for any horizon j evaluated at this set of shock values. Finally, we obtain $h_{s,j}^k$ for any arbitrary horizon j and shock size by interpolating the function.

To estimate $\{\varepsilon_t^s\}_{t=0}^T$, we first obtain the relevant empirical counterparts \hat{d}_t^k of all series from the data. Then, we numerically solve

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

which yields the underlying shock series $\{\varepsilon_t^s\}_{t=0}^T$.

Two objects of this minimand are worthy of further discussion. First, there is a vector of series-specific weights ω_k . Second, we include a smoothing term in our objective function, with parameter ϑ . The purpose of this term is to prevent estimates that imply alternating and large positive and negative shocks in quick succession.¹⁸

6 Accounting for the Post-Pandemic Labor Market

We now explore whether, and how, our model can quantitatively explain the peculiar dynamics of the post-pandemic labor market we discussed in Section 2. We first report the estimated shocks. Next, we present the fit of the model, and decompose it into the role played by the three aggregate shocks.

6.1 Realized Shocks

To estimate the series of realized shocks we use eight time series for the period 2020:01-2023:09: (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) aggregate output, and (viii) average wages. Because three shocks are used to match eight time series one should not expect a perfect fit.¹⁹ For most variables, we choose a weight ω_k to equal the inverse vari-

¹⁸In practice, we find that $\vartheta = 2000$ produces a good balance of smoothness and goodness-of-fit.

¹⁹To be precise, the UE rate can be obtained from unemployment, vacancies and match efficiency for the unemployed, all targeted time series as well.

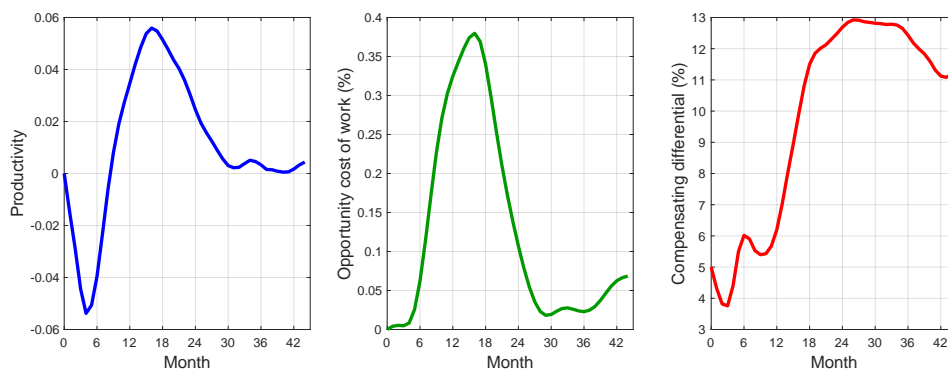


Figure 13: Estimated productivity, opportunity cost of work, and amenity shocks. The amenity shock is expressed in terms of compensating wage differential for workers with $x > 0$.

ance of the respective data series.²⁰ As our focus is particularly on unemployment and vacancies, and on their joint dynamics, the Beveridge curve, we assign a higher weight to these series, i.e. five times their respective inverse series variances.

Figure 13 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 by over 35 percent over the first year following the shock, and then it completely subsided 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 tells us that the average value of job amenities, among those who care, more than doubled from an initial compensating wage differential of 5% to a peak of 12%. Since for half of the population $x = 0$, the model estimates an average compensating differential in the population of around 6-7% at the peak, a value in line

²⁰This ensures that variables with large fluctuations around the steady state do not dominate the fitting procedure.

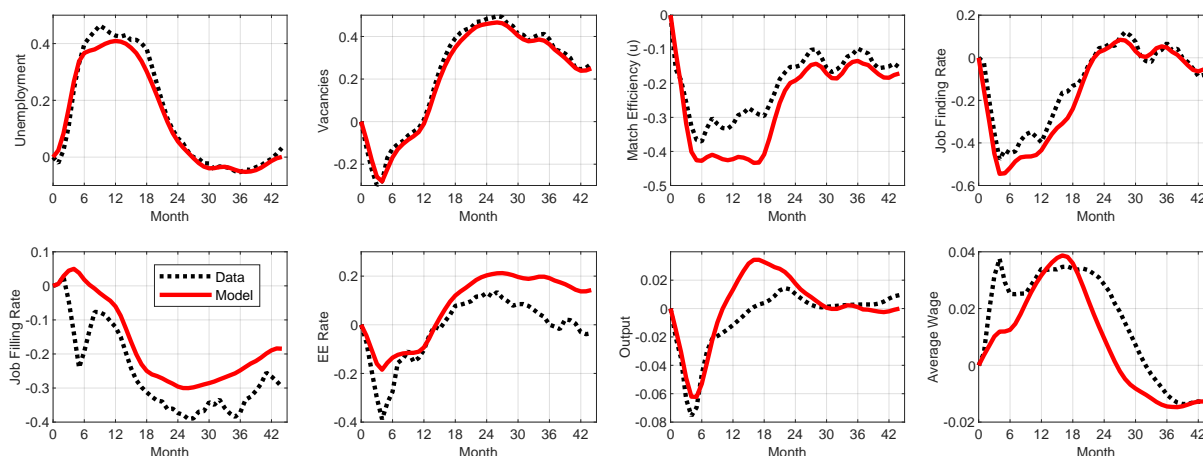


Figure 14: Model simulation fit of the data. Data in black dashed line and model in solid red line. Each panel depicts log-deviations from steady-state.

with the data. Results from a survey fielded after the pandemic by [Barrero et al. \(2022\)](#) suggest that respondents are willing to accept pay cuts of 7 percent, on average, for the option to work from home two or three days per week.

6.2 Model Fit and Shock Decomposition

Figure 14 plots the model’s fit of the time series we use in the estimation. Overall, the fit is quite good, in spite of the model being significantly overidentified. Because of the higher weight in the estimation, the path for unemployment and vacancies are matched very closely by the model at the cost of a less close fit for some of the other series. The model somewhat overestimates the drop in match efficiency, the rise in EE transitions, and the rebound in output after the recession, whereas it slightly underestimates the drop in the job filling rate. Even for these time series, however, the model is remarkably close to the data.

Which one of the aggregate shocks is responsible for the dynamics of these various dimensions of the US labor market? Figure 15 plots model counterfactuals where we add one shock at the time.²¹

The v-shaped productivity shock (blue line in Figure 15) plays a dominant role in explaining the dynamics of the economy over the first 6 months, in particular the quick rise

²¹In the text, we start with the productivity shock, followed by b , and by amenity, but the order does not matter because of the additive separability.

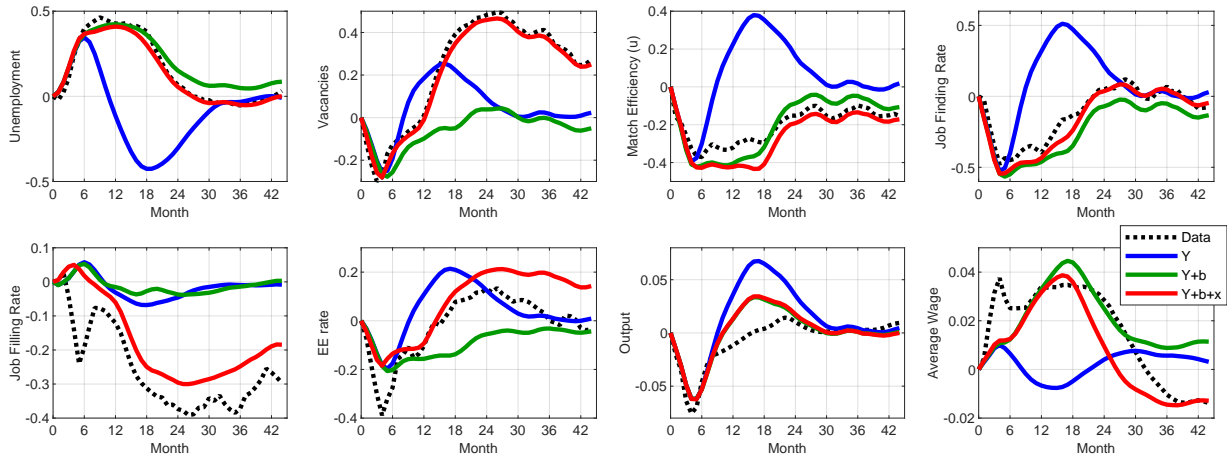


Figure 15: Decomposition of model's fit of the data (black dotted line) into productivity shock (blue), productivity + opportunity cost shocks (green) and productivity + opportunity cost + amenity shocks (red).

in the unemployment rate, as well as the dip of vacancies, match efficiency, job finding rate and output. However, the sharp rebound in productivity which follows the initial short-lived, but deep, recession generates counterfactual dynamics for many model series: an excessive drop in unemployment and average wage (due to negative selection into employment), and an exaggerated increase in match efficiency, job finding rate, job filling rate and output.

The negative labor supply shock (a rise in b) more than offsets the rebound in productivity in the second year of the recovery. As a result, the sum of these two shocks (green line in Figure 15) accounts well for the rise in unemployment and the average wage, as well as the drop in match efficiency and UE rate observed over this period. Also the fit for output is improved, since a larger b reduces employment. At the same time, though, this shock is so powerful that it substantially depresses vacancy creation. As a consequence, the model is still far from matching the fall in the job filling rate, and counterfactually implies a decline in the EE rate. Interestingly, the labor supply shock can explain the sustained rise in real wage growth for the first two years after the pandemic, and part of its decline.

The rise in the value of job amenities plays a key role in explaining the data because it accounts for virtually the entirety of the rise in vacancies and the fall in the job filling rate. This force also sets in motion a labor reallocation process that leads to a persistent rise in job-to-job transitions. Another important feature of the amenity shock is that it con-

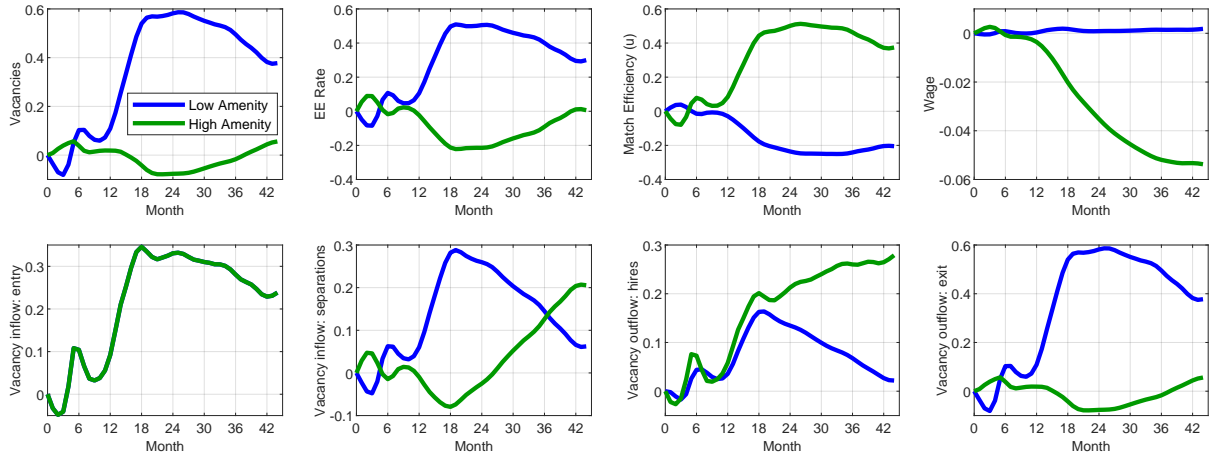


Figure 16: Dynamics of various aggregate variables induced by the x shock plotted separately for low amenity jobs (blue) and high amenity jobs (green) jobs. Log-deviations from initial steady-state.

tributes to the protracted reduction in average real wages observed in the data, especially in the last 12 months.

Figure 16, which plots a number of variables by amenity type (low vs high), sheds some light on the transmission mechanism of the x shock. The top-left panel shows that the surge in vacancies in the first two years of the recovery is entirely explained by the low amenity types. The bottom row splits the change in the stock into all its flows. What explains the different dynamics of the two types of vacancies is the inflow due to separations which surges for the low-amenity type, which becomes less attractive, and falls for the high-amenity type which becomes relatively more desirable. The mirror image of these sharp rise in unattractive vacated idle jobs is the increase in EE transitions originating from low-amenity jobs and the decline in match efficiency of this class of vacancies. The top-right panel of Figure 16 demonstrates that the rising attractiveness of high amenity jobs, due to the shift in \bar{x} , exerts strong downward pressure on wages because new hires are compensated by the non-pecuniary amenity. The model implication mirrors the findings in [Barrero, Bloom, Davis, Meyer, and Mihaylov \(2022\)](#), who empirically investigate this mechanism.

The rise in the value of the job amenity induces a wave of labor reallocation that corrects the misallocation of worker types on job types that emerges after the shock: high- x workers move toward high amenity jobs, whereas low- x workers are willing to take the low amenity ones which now pay a larger wage premium to compensate for their lost

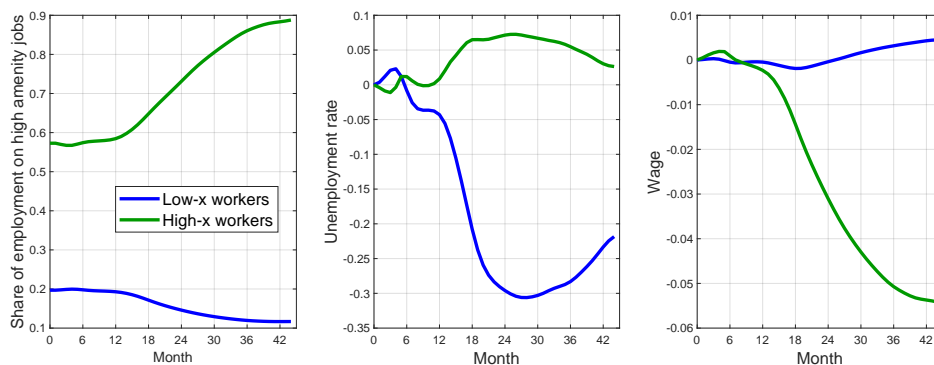


Figure 17: Share of employment on high amenity jobs, unemployment rate, and average wage dynamics induced by the job amenity shock plotted separately for low x workers (blue) and high x workers (green) jobs. Log-deviations from initial steady-state.

appeal. The left panel of Figure 17 illustrates this mechanism. The relative scarcity of low- x workers, from the perspective of low-amenity employers, reduces their unemployment rate and even slightly increases their wage in real terms. At the same time, average wages of high- x workers falls as they trade-off monetary compensation for the, now more valuable, job amenity.

Figure 18 plots the Beveridge curve implied by the model and its decomposition into the three shocks. The model is able to generate the wide Beveridge loop observed in the data. In particular, the two quasi-vertical sections of the Beveridge curve (one in 2021 and one in 2023) where vacancies rise and fall without virtually any change in unemployment.

From the decomposition, it is clear that the productivity and labor supply shocks alone would have led to a narrow and flatter loop, as in all previous recessions (recall Figure 1). Instead, the amenity shock leads to a process of quits-induced vacancies and persistent worker reallocation that generates a step movement of the curve.

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

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 19 shows that the model is able to generate the empirical patterns.

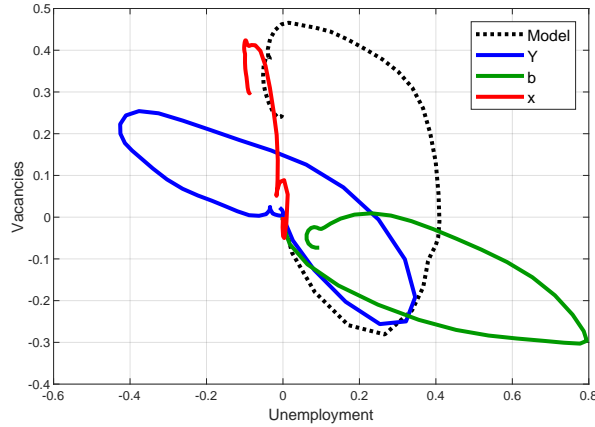


Figure 18: Model’s Beveridge curve (dotted black line). Dynamics induced by shocks to productivity (blue), opportunity cost of work (green), and amenity value (red).

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 model that combines several building blocks of modern macro-labor: random matching à la Mortensen-Pissarides, on-the-job search and wage setting à la Postel-Vinay-Robin, Diamond entry, and non-wage amenities à 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 necessary 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.

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 suggests that this shock can also fit labor market aggregates quite well, but it has cross-sectoral implications that are less consistent with the data. In particular, this shock leads to a stronger rise in vacancies in sectors where teleworkability is more prevalent, whereas the data feature the opposite pattern.

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

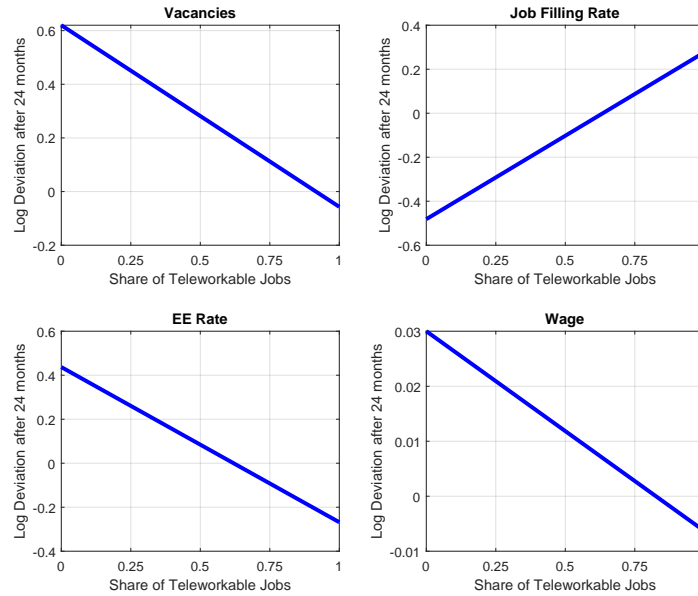


Figure 19: Model’s counterpart of the cross-sectoral evidence of Figure 8.

vis-a-vis reallocation across different type of jobs within sectors. 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 seems, 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: policy interventions, instead of directing support to jobless and low-income households, focused on the retention of ongoing employment relationships.²² 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.

²²See Cai and Heathcote (2023) for an analysis of the optimal design of labor market policy in the presence of a wave of job quits, with an application to the US pandemic.

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Appendix

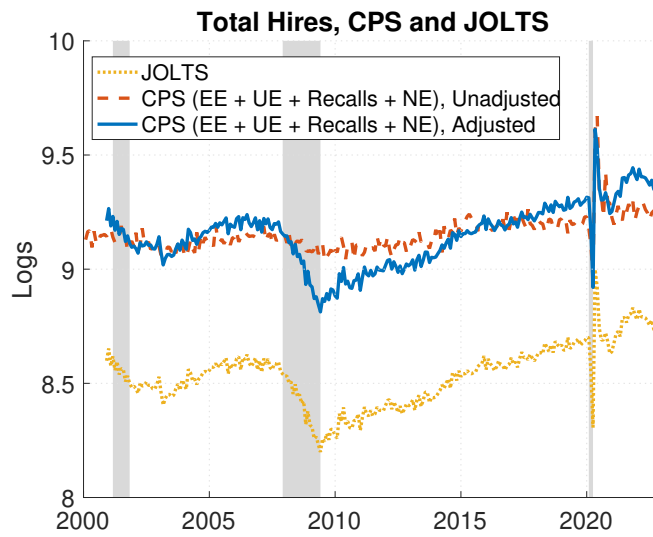
A Adjusting the CPS and JOLTS hires in levels and cyclicity

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 cyclicity. 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 cyclicity and CPS levels. We re-scale all sources of hires in the CPS by adjusting for them for the cyclicity and levels factors defined below:

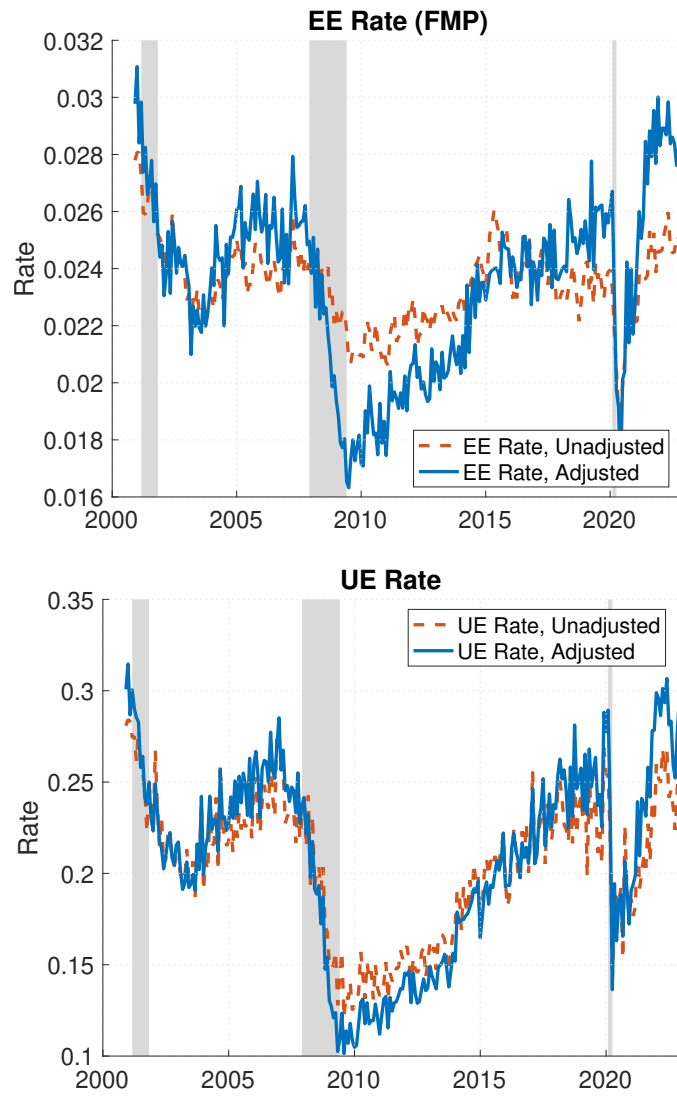
$$\text{Hires Cyclicity Factor}_t = \frac{Hires_t^{JOLTS}}{UE_t^{CPS} + NE_t^{CPS} + EE_t^{CPS} + Recalls_t^{CPS}}$$
$$\text{Hires Level Factor} = \frac{\overline{UE}^{CPS} + \overline{NE}^{CPS} + \overline{EE}^{CPS} + \overline{Recalls}^{CPS}}{\overline{Hires}^{JOLTS}}$$

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



Source: CPS, JOLTS, and authors' calculations.

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



Source: CPS, JOLTS, and authors' calculations.

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

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: $(UE \text{ hires} + EE \text{ hires}) / \text{Job seekers}$ ($U + s * E$) where $s = 0.58$.
- Job Filling Rate: $(UE \text{ hires} + EE \text{ hires}) / \text{Vacancies}$
- Quit Rate: Quits/Employed. Obtained from the JOLTS.
- EE Rate: EE hires/Employed.
- UE Rate: UE hires/Unemployed (excluding those on temporary layoffs)

C Vacancy Posting, Job Filling, and Quits

The JOLTS allow us to examine the relationship between quits, vacancies and job-filling rates at the industry level for the last three recoveries. Specifically, we consider three time periods that match the plots in the main text: 2001-2004, 2008-2011 and 2020-2023. Tables C1 and C2 report regressions of log vacancy rate and log job filling rates on log quit rate, controlling for layoffs and other separations. The quit rate exhibits a positive correlation in the 2020-2023 period (Table C1, column 9), which is weaker in the earlier recoveries (columns 3 and 6). Table C2 shows that the relationship between the quits rate and job filling rate was different in the 2020-2023 period: industries with higher quits, despite posting more vacancies, experienced lower job filling rates (column 9). In contrast, during the recoveries following 2001 and 2007-09 recessions, the quits rate correlated positively with the job filling rate (columns 3 and 6).

	Dependent Variable: Log Vacancy Rate								
	2001m1-2004m1			2008m1-2011m1			2020m1-2023m1		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Log Quit Rate	0.370*** (0.020)	0.557*** (0.027)	0.105 (0.072)	0.302*** (0.025)	0.483*** (0.029)	0.054 (0.061)	0.405*** (0.035)	0.427*** (0.044)	0.161*** (0.058)
Log Layoff Rate		-0.233*** (0.027)	-0.057 (0.040)		-0.315*** (0.030)	-0.162*** (0.045)		-0.034** (0.017)	-0.106*** (0.017)
Log Other Separations Rate		-0.115*** (0.029)	-0.076*** (0.024)		-0.003 (0.028)	-0.050** (0.023)		0.045** (0.022)	-0.001 (0.019)
Sector FE			Y			Y			Y
N	629	617	617	629	616	616	629	617	617
R ²	0.304	0.411	0.779	0.320	0.455	0.695	0.621	0.627	0.802

Table C1: Regressions: Vacancies and Quits

Notes: JOLTS, 2001m1-2023m1, seasonally adjusted. All columns include year fixed effects. Columns (3), (6) and (9) include 2-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								
	2001m1-2004m1			2008m1-2011m1			2020m1-2023m1		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Log Quit Rate	0.456*** (0.026)	-0.002 (0.027)	0.166** (0.065)	0.435*** (0.031)	0.032 (0.031)	0.157** (0.062)	0.297*** (0.039)	0.174*** (0.035)	-0.159** (0.069)
Log Layoff Rate		0.582*** (0.028)	0.260*** (0.037)		0.705*** (0.032)	0.253*** (0.044)		0.201*** (0.025)	0.002 (0.025)
Log Other Separations Rate		0.149*** (0.029)	0.094*** (0.024)		0.017 (0.030)	0.059** (0.024)		-0.106*** (0.023)	0.016 (0.023)
Sector FE			Y			Y			Y
N	629	617	617	629	616	616	629	617	617
R ²	0.242	0.609	0.847	0.217	0.635	0.816	0.393	0.525	0.745

Table C2: Regressions: Job Filling and Quits

Notes: JOLTS, 2001m1-2023m1, seasonally adjusted. Job Filling Rate = Hires/Vacancies. All columns include year fixed effects. Columns (3), (6) and (9) include 2-digit NAICS industry fixed effects. Robust standard errors in parenthesis. * p<0.10, ** p<0.05, *** p<0.01.

D Figures

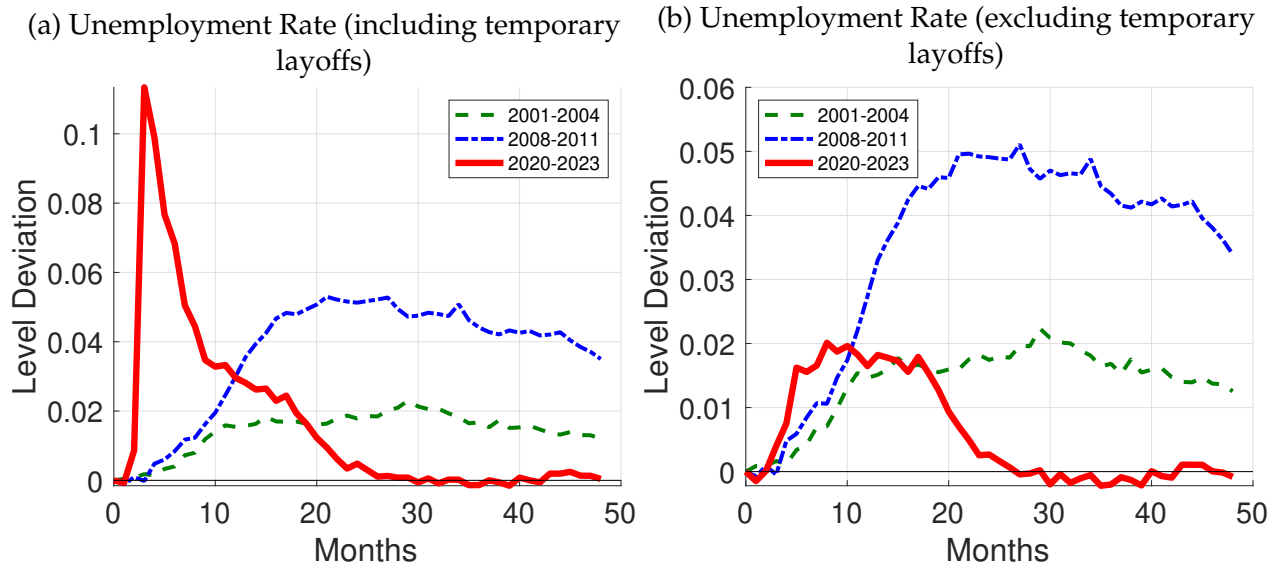


Figure D1: Unemployment rate with and without temporary layoffs

Notes: CPS, and authors' calculations. Level deviation in the unemployment rate excluding and including workers on temporary layoffs in 2001-2004, 2008-2011, and 2020-2023 periods. The values are normalized to 0 for January 2001, 2008, and 2020.

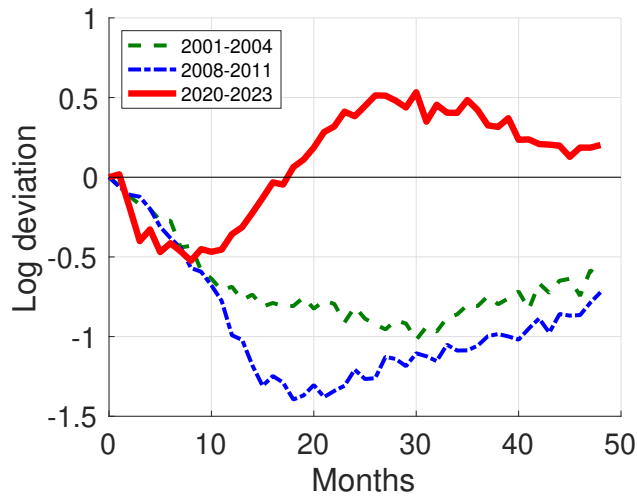


Figure D2: Vacancy-to-unemployment ratio

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

E Derivations and solution method

In this appendix, we describe the wage setting protocol in detail, derive all relevant value functions for firms and workers, and derive the surplus equation. We then define an equilibrium and sketch a solution algorithm for the model. All equations refer to the case where boundary conditions are non-binding.

Sections E.1 and E.2 discuss the wage setting assumptions and derive the Bellman equations for the firm and worker. Building on these assumptions and equations, E.3 shows that the surplus equation can be written as in equation (10).

E.1 Wage Determination

Let ϕ_t denote the wage paid to the worker as a function of the relevant individual state variables. 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

$$W_t(\phi_t^u, x, y, a) = U_t(x). \quad (12)$$

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

$$J_t(\phi_t^u, x, y, a) = S_t(x, y, a), \quad (13)$$

i.e. because of the ToL protocol, upon hiring a worker from unemployment, the firm initially receives 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

$$W_t(\phi^q, x, y', a') - U_t(x) = S_t(x, y, a) - \tilde{\Omega}_t(a) \quad (14)$$

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

$$J_t(\phi^q, x, y', a') = S_t(x, y', a') - [S_t(x, y, a) - \tilde{\Omega}_t(a)] \quad (15)$$

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 ToL offer to the worker which is just enough to make them indifferent between staying and quitting and thus retains the worker:

$$W_t(\phi^r, x, y, a) - U_t(x) = S_t(x, y', a') - \Omega_t(a') \quad (16)$$

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

$$J_t(\phi^r, x, y, a) = S_t(x, y, a) - [S_t(x, y', a') - \Omega_t(a')] . \quad (17)$$

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.

$$W_t(\phi^+, x, y, a) - U_t(x) = 0 \quad (18)$$

and the firm value drops to

$$J_t(\phi^+, x, y, a) = S_t(x, y, a) \quad (19)$$

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

$$J_t(\phi^-, x, y, a) = \tilde{\Omega}_t(a) \quad (20)$$

and the new wage ϕ^- will satisfy

$$W_t(\phi^-, x, y, a) - U_t(x) = S_t(x, y, a) - \tilde{\Omega}_t(a) \quad (21)$$

E.2 Match Value

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

$$\begin{aligned}
(r + \delta + sp_t)J_t(w, x, y, a) &= Z_t^y y - w + \delta \tilde{\Omega}_t(a) & (22) \\
&+ sp_t \underbrace{\sum_{(a', y') \in \mathcal{Q}_t(x, y, a)} \tilde{\Omega}_t(a) \cdot f(y') \cdot \left(\frac{v_t(a')}{v_t}\right)}_{\text{worker quits to better job}} \\
&+ sp_t \underbrace{\sum_{(a', y') \in \mathcal{R}_t(x, y, a)} J_t(\phi_t^r, x, y, a) \cdot f(y') \cdot \left(\frac{v_t(a')}{v_t}\right)}_{\text{worker is retained with higher wage}} \\
&+ sp_t \underbrace{\sum_{(a', y') \in \mathcal{N}_t(x, y, a)} J_t(w, x, y, a) \cdot f(y') \cdot \left(\frac{v_t(a')}{v_t}\right)}_{\text{worker meets worse firm}} \\
&+ \partial_t J_t
\end{aligned}$$

where

$$\mathcal{Q}_t(x, y, a) = \{(y', a') : S_t(x, y', a') - \Omega_t(a') > S_t(x, y, a) - \tilde{\Omega}_t(a)\} \quad (23)$$

and

$$\mathcal{R}_t(x, y, a) = \{(y', a') : W_t(w, x, y, a) - U_t(x) < S_t(x, y', a') - \Omega_t(a') \leq S_t(x, y, a) - \tilde{\Omega}_t(a)\} \quad (24)$$

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

$$\mathcal{N}_t(x, y, a) = \{(y', a') : S_t(x, y, a) - \tilde{\Omega}_t(a) > W_t(w, x, y, a) - U_t(x) \geq S_t(x, y', a') - \Omega_t(a')\} \quad (25)$$

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

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

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

$$rU_t(x) = Z_t^b b + \partial_t U_t \quad (26)$$

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

$$\begin{aligned}
(r + \delta + sp_t) W_t(w, x, y, a) &= w + Z_t^x xa + \underbrace{\delta U_t(x)}_{\text{exogenous layoff}} \\
&+ sp_t \sum_{y', a'} \left[\underbrace{\mathbb{I}_{\{(y', a') \in \mathcal{Q}_t(x, y, a)\}} W_t(\phi_t^q, x, y', a')}_{\text{worker quits to better job}} \right. \\
&+ \underbrace{\mathbb{I}_{\{(y', a') \in \mathcal{R}_t(x, y, a)\}} W_t(\phi_t^r, x, y, a)}_{\text{worker is retained with higher wage}} \\
&+ \left. \underbrace{\mathbb{I}_{\{(y', a') \in \mathcal{N}_t(x, y, a)\}} W_t(w_t, x, y, a)}_{\text{worker meets worse job}} \right] \left(\frac{v_t(a')}{v_t} \right) f(y') \\
&+ \partial_t W_t
\end{aligned} \tag{27}$$

E.3 Surplus Representation

The wage setting protocol, described in the previous section, implies the following relationships between ϕ^q , ϕ^r , and the value functions:

$$\begin{aligned}
W_t(\phi^q, x, y', a') &= S_t(x, y, a) - \tilde{\Omega}_t(a) + U_t(x) \\
W_t(\phi^r, x, y, a) - U_t(x) &= S_t(x, y', a') - \Omega_t(a') + U_t(x) \\
J_t(\phi^r, x, y, a) &= S_t(x, y, a) - [S_t(x, y', a') - \Omega_t(a')]
\end{aligned}$$

We can use these relationships to rewrite the Bellman equations for the worker and the firm as follows:

$$\begin{aligned}
(r + \delta + sp_t) W_t(w, x, y, a) &= w + Z_t^x xa + \delta U_t(x) \\
&+ sp_t \sum_{(y', a') \in \mathcal{Q}_t(x, y, a)} [S_t(x, y, a) - \tilde{\Omega}_t(a) + U_t(x)] f(y') \left(\frac{v_t(a')}{v_t} \right) \\
&+ sp_t \sum_{(y', a') \in \mathcal{R}_t(x, y, a)} [S_t(x, y', a') - \Omega_t(a') + U_t(x)] f(y') \left(\frac{v_t(a')}{v_t} \right) \\
&+ sp_t \sum_{(a', y') \in \mathcal{N}_t(x, y, a)} W_t(w, x, y, a) \left(\frac{v_t(a')}{v_t} \right) f(y') \\
&+ \partial_t W_t
\end{aligned}$$

$$\begin{aligned}
(r + \delta + sp_t)J_t &= y_t - w + \delta \tilde{\Omega}_t(a) \\
&+ sp_t \sum_{(a', y') \in \mathcal{Q}_t(x, y, a)} \tilde{\Omega}_t(a) \cdot f(y') \left(\frac{v_t(a')}{v_t} \right) \\
&+ sp_t \sum_{(a', y') \in \mathcal{R}_t(x, y, a)} [S_t(x, y, a) - S_t(x, y', a') + \Omega_t(a')] f(y') \left(\frac{v_t(a')}{v_t} \right) \\
&+ sp_t \sum_{(a', y') \in \mathcal{N}_t(x, y, a)} J_t(w, x, y, a) f(y') \left(\frac{v_t(a')}{v_t} \right) \\
&+ \partial_t J_t
\end{aligned}$$

Summing up these two equations, we get

$$\begin{aligned}
(r + \delta + sp_t)(J_t + W_t) &= y_t + Z_t^x xa + \delta [U_t(x) + \tilde{\Omega}_t(a)] \\
&+ sp_t \sum_{(y', a') \in \mathcal{Q}_t(x, y, a)} [S_t(x, y, a) + U_t(x)] f(y') \left(\frac{v_t(a')}{v_t} \right) \\
&+ sp_t \sum_{(a', y') \in \mathcal{R}_t(x, y, a)} [S_t(x, y, a) + U_t(x)] f(y') \left(\frac{v_t(a')}{v_t} \right) \\
&+ sp_t \sum_{(a', y') \in \mathcal{N}_t(x, y, a)} [S_t(x, y, a) + U_t(x)] f(y') \left(\frac{v_t(a')}{v_t} \right) \\
&+ \partial_t (J_t + W_t)
\end{aligned}$$

The value of unemployment is

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

Using the wage definitions, we can rewrite the value of unemployment as:

$$rU_t(x) = Z_t^b b + \partial_t U_t \quad (28)$$

Subtracting the value of unemployment (28) from both sides and simplifying yields the final expression for the surplus

$$\begin{aligned}
(r + \delta + sp_t)(J_t + W_t - U_t) &= Z_t^y y + Z_t^x xa - Z_t^b b + \delta [U_t(x) + \tilde{\Omega}_t(a)] - \delta U_t(x) \\
&+ sp_t \sum_{(y', a') \in \mathcal{Q}_t(x, y, a)} [S_t(x, y, a)] f(y') \left(\frac{v_t(a')}{v_t} \right) \\
&+ sp_t \sum_{(a', y') \in \mathcal{R}_t(x, y, a)} [S_t(x, y, a)] f(y') \left(\frac{v_t(a')}{v_t} \right) \\
&+ sp_t \sum_{(a', y') \in \mathcal{N}_t(x, y, a)} [S_t(x, y, a)] f(y') \left(\frac{v_t(a')}{v_t} \right) \\
&+ \partial_t (J_t + W_t - U_t)
\end{aligned}$$

and thus

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

subject to the boundary condition $S_t \geq \tilde{\Omega}_t(a)$. Conditional on $\tilde{\Omega}_t$, one can thus solve for the surplus independently of the distributions. To solve the model, we only need to find two scalars $(\Omega_t(\underline{a}), \Omega_t(\bar{a}))$ as a function of time.

E.4 Value of Active and Dormant Vacancies

As outlined in the main text, 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

$$\begin{aligned}
(r + q_t + \delta_v) \Omega_t(a) &= q_t \sum_{x, y} \left[\mathbb{I}_{\{x \in \mathcal{H}_t(y, a)\}} J_t(\phi_t^u, x, y, a) \left(\frac{u_t(x)}{s_t} \right) \right. \\
&+ \mathbb{I}_{\{x \notin \mathcal{H}_t(y, a)\}} \Omega_t(a) \left(\frac{u_t(x)}{s_t} \right) \\
&+ \sum_{y', a'} \mathbb{I}_{\{(x, y', a') \in \mathcal{P}_t(y, a)\}} J_t(\phi_t^q, x, y, a) \left(\frac{s \cdot e_t(x, y', a')}{s_t} \right) \\
&+ \left. \sum_{y', a'} \mathbb{I}_{\{(x, y', a') \notin \mathcal{P}_t(y, a)\}} \Omega_t(a) \left(\frac{s \cdot e_t(x, y', a')}{s_t} \right) \right] f(y) \\
&+ \partial_t \Omega_t(a)
\end{aligned} \tag{29}$$

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 :

$$\mathcal{H}_t(y, a) = \{x : S_t(x, y, a) > \Omega_t(a)\} \tag{30}$$

$$\mathcal{P}_t(y, a) = \{(x, y', a') : S_t(x, y, a) - \Omega_t(a) > S_t(x, y', a') - \tilde{\Omega}_t(a')\} \tag{31}$$

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.

To solve the model, it is useful to simplify this expression further, such that it does not depend on wage terms. To do so, we can substitute in $J_t(\phi_t^u, x, y, a) = S_t(x, y, a)$ and $J_t(\phi_t^q, x, y, a) = S_t(x, y, a) - S_t(x, y', a') + \tilde{\Omega}_t(a')$. This yields

$$\begin{aligned}
(r + q_t + \delta_v) \Omega_t(a) &= q_t \sum_{x,y} \left[\mathbb{I}_{\{x \in \mathcal{H}_t(y,a)\}} S_t(x, y, a) \left(\frac{u_t(x)}{s_t} \right) \right. \\
&\quad + \mathbb{I}_{\{x \notin \mathcal{H}_t(y,a)\}} \Omega_t(a) \left(\frac{u_t(x)}{s_t} \right) \\
&\quad + \sum_{y',a'} \mathbb{I}_{\{(x,y',a') \in \mathcal{P}_t(y,a)\}} [S_t(x, y, a) - S_t(x, y', a') + \tilde{\Omega}_t(a')] \left(\frac{s \cdot e_t(x, y', a')}{s_t} \right) \\
&\quad \left. + \sum_{y',a'} \mathbb{I}_{\{(x,y',a') \notin \mathcal{P}_t(y,a)\}} \Omega_t(a) \left(\frac{s \cdot e_t(x, y', a')}{s_t} \right) \right] f(y) \\
&\quad + \partial_t \Omega_t(a)
\end{aligned}$$

which, using the set definitions from above, corresponds to the following equation:

$$\begin{aligned}
(r + \delta_v + q_t) \Omega_t(a) &= q_t \sum_{x,y} f(y) \cdot \left[\left(\max\{\Omega_t(a), S_t(x, y, a)\} \cdot \frac{u_t(x)}{s_t} \right) \right. \\
&\quad \left. + \left(\sum_{x',y'} \max\{\Omega(a), S_t(x, y, a) - S_t(x, y', a') + \tilde{\Omega}_t(a')\} \cdot \frac{s_e \cdot e_t(x, y', a')}{s_t} \right) \right] + \partial_t \Omega_t(a) \quad (32)
\end{aligned}$$

Finally, the value of a dormant vacancy of type a , $\tilde{\Omega}_t(a)$, is simply given by

$$(r + \delta_v + \mu) \tilde{\Omega}_t(a) = \mu \Omega_t(a) + \partial_t \tilde{\Omega}_t(a) \quad (33)$$

E.5 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

$$\begin{aligned}
du_t(x) &= \underbrace{\delta \sum_{a,y} \mathbb{I}_{\{S_t(x,y,a) \geq \tilde{\Omega}(a)\}} e_t(x, y, a) dt}_{\text{exogenous separations}} + \underbrace{\sum_{a,y} \mathbb{I}_{\{S_t(x,y,a) < \tilde{\Omega}(a)\}} e_t(x, y, a)}_{\text{endogenous separations}} \\
&\quad - \underbrace{p_t u_t(x) \sum_{y,a} \mathbb{I}_{\{x \in \mathcal{H}_t(y,a)\}} \left(\frac{v_t(a)}{v_t} \right) f(y) dt}_{\text{hires from unemployment}} \quad (34)
\end{aligned}$$

For the employed,

$$\begin{aligned}
de_t(x, y, a) = & \underbrace{-\delta \mathbb{I}_{\{S_t(x, y, a) \geq \bar{\Omega}_t(a)\}} e_t(x, y, a) dt}_{\text{exogenous EU}} - \underbrace{\mathbb{I}_{\{S_t(x, y, a) < \bar{\Omega}_t(a)\}} e_t(x, y, a)}_{\text{endogenous EU}} \\
& \underbrace{-sp_t e_t(x, y, a) \left[\sum_{y', a'} \mathbb{I}_{\{(y', a') \in \mathcal{Q}_t(x, y, a)\}} \left(\frac{v_t(a')}{\mathbf{v}_t} \right) f(y') \right] dt}_{\text{EE-}} \\
& \underbrace{+sp_t \sum_{y', a'} e(x, y', a') \mathbb{I}_{\{(x, y', a') \in \mathcal{P}_t(y, a)\}} \left(\frac{v_t(a)}{\mathbf{v}_t} \right) f(y) dt}_{\text{EE+}} \\
& \underbrace{+p_t u_t(x) \mathbb{I}_{\{x \in \mathcal{H}_t(y, a)\}} \left(\frac{v_t(a)}{\mathbf{v}_t} \right) f(y) dt}_{\text{UE hires}}
\end{aligned} \tag{35}$$

For active vacancies,

$$\begin{aligned}
dv_t(a) = & \underbrace{-\delta_v v_t(a) dt}_{\text{vac. destruction}} + \underbrace{i_t(a) dt}_{\text{vac. creation}} + \underbrace{\mu \tilde{v}(a) dt}_{\text{entry from dormant}} \\
& -q_t v_t(a) \sum_{x, y} \left[\underbrace{\mathbb{I}_{\{x \in \mathcal{H}_t(y, a)\}} \left(\frac{u_t(x)}{\mathbf{s}_t} \right)}_{\text{vacancies filled from } u} \right. \\
& \left. + \underbrace{\sum_{a', y'} \mathbb{I}_{\{(x, y', a') \in \mathcal{P}_t(y, a)\}} \left(\frac{s \cdot e_t(x, y', a')}{\mathbf{s}_t} \right)}_{\text{vacancies filled from } e} \right] f(y) dt
\end{aligned} \tag{36}$$

For dormant vacancies,

$$\begin{aligned}
d\tilde{v}_t(a) = & \underbrace{-\delta_v \tilde{v}_t(a) dt}_{\text{vac. destruction}} - \underbrace{\mu \tilde{v}_t(a) dt}_{\text{activation}} \\
& + \sum_{x, y} \left[\underbrace{\delta \mathbb{I}_{\{S_t(x, y, a) \geq \bar{\Omega}_t(a)\}} e_t(x, y, a) dt}_{\text{exogenous EU}} + \underbrace{\mathbb{I}_{\{S_t(x, y, a) < \bar{\Omega}_t(a)\}} e_t(x, y, a)}_{\text{endogenous EU}} \right. \\
& \left. + sp_t e_t(x, y, a) \sum_{y', a'} \mathbb{I}_{\{(y', a') \in \mathcal{Q}_t(x, y, a)\}} \left(\frac{v_t(a')}{\mathbf{v}_t} \right) f(y') dt \right] \\
& \underbrace{\hspace{10em}}_{\text{EE-}}
\end{aligned} \tag{37}$$

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^e and A_t^u denote match efficiency for the employed and the unemployed. It is easy to derive that,

in our model:

$$A_t^u = \sum_{x,y,a} \mathbb{I}_{\{x \in \mathcal{H}_t(y,a)\}} \left(\frac{u_t(x)}{u_t} \right) \left(\frac{v_t(a)}{v_t} \right) f(y) \quad (38)$$

$$A_t^e = \sum_{x,y,a} \left[\sum_{y',a'} \mathbb{I}_{\{(x,y',a') \in \mathcal{P}_t(y,a)\}} \frac{e_t(x,y',a')}{e_t} \right] \left(\frac{v_t(a)}{v_t} \right) f(y) \quad (39)$$

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

$$A_t = A_t^u \frac{u_t}{u_t + se_t} + A_t^e \frac{se_t}{u_t + se_t} \quad (40)$$

E.6 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), (22), (27), (28), (29), and (33)
2. Quit, retention and neutral sets, $\{Q_t(x, y, a), \mathcal{R}_t(x, y, a), \mathcal{N}_t(x, y, a)\}_{t \geq 0}$, and hiring and poaching sets $\{\mathcal{H}_t(y, a), \mathcal{P}_t(y, a)\}_{t \geq 0}$, and that satisfy equations (23), (24), (25), (30), and (31)
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 (34), (35), (36), and (37), and implied meetings $m_t = m(v_t, s_t)$
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 (12), (14), and (16)
5. Boundary wage functions $\{\phi_t^+(x, y, a), \phi_t^-(x, y, a)\}_{t \geq 0}$ defined in equations (18) and (20)
6. A measure of entrants $i_t(a)$ that satisfies the entry condition in equation (8)

E.7 Solving the Model

Taking stock, we can now construct a simple solution algorithm for the model, using the equations in the previous subsections:

1. Guess $\Omega_t(a)$.
2. Compute S_t and $\tilde{\Omega}_t$ conditional on Ω_t , using equations (10) and (33).
3. Compute all distributions $u_t(x), e_t(x, y, a)$ conditional on $\Omega_t, \tilde{\Omega}_t, S_t$, using the laws of motion (34), (35), (36), and (37).
4. Update $\Omega_t(a)$ to reduce the error in equation (32).
5. Iterate until equation (32) holds.