Vacant Jobs*

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Abstract

Vacancies are the key equilibrium margin in canonical theories of unemployment, describing employers' job creation. The point of this paper is that vacancies can also arise from a labor supply side force—workers exiting the labor force hence vacating their positions. I document empirical facts of the prevalence of such behavior. I develop a model of vacating that quantitatively replicates properties of labor market flows. Recognizing vacating resolves the challenge in the business cycle theory of unemployment when the opportunity cost of employment is procyclical. Procyclical employment-to-nonparticipation quits contribute to vacancy fluctuations due to the vacating channel, accounting for about one-third of unemployment fluctuations. Understanding the source of vacancies also has important policy implications: While creating a new job as an investment activity is responsive to the interest rate, reposting a vacated position is not. This sheds new light on the possibility of a "soft landing"—raising interest rates without causing high unemployment—during the "Great Resignation," a period of elevated vacating.

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JEL Codes: E24, E32, J22, J63, J64

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1 Introduction

The workhorse theory of unemployment, the Diamond-Mortensen-Pissarides (DMP) model, recognizes vacancies as the key variable for aggregate labor market dynamics: Vacancies drive unemployed workers' job-finding prospects and thereby unemployment fluctuations. Its equilibrium determination is a labor demand side force through *employers creating jobs* (i.e., the so-called "job creation condition"). The point of this paper is that aggregate vacancy fluctuations can also arise from a labor supply side force through *workers vacating jobs*. I show that it has important macroeconomic implications on the labor market, including unemployment fluctuations over the business cycle and responses to changes in the discount rate.

When a worker leaves the labor market for reasons that change her own labor force attachment but not the job's productivity, such as caregiving responsibilities for a child, the job remains profitable to the employer. Thus, the employer has the incentive to advertise the position to look for a replacement worker. In this case, a vacancy appears due to a drop in labor supply rather than a rise in labor demand. In this paper, "vacating" is defined as such behavior of workers exiting the labor force and vacating their positions.[1] The importance of vacating is especially evident in episodes of labor shortages, where large negative aggregate labor supply shocks are followed by spikes in vacancies (Figure 1). But even in normal times, worker exiting is a prevalent form of employment outflows and position vacating is a prevalent form of vacancy inflows (Figure 3).

Vacating is not only empirically relevant but also brings novel insights. Understanding labor market fluctuations has long ranked among the most important and difficult issues in macroeconomics. For instance, the challenge is often named the "Shimer (2005) puzzle" within the DMP paradigm and the challenge has recently been ramped up by the "Chodorow-Reich and Karabarbounis (2016) puzzle." It has by now been well understood that the quantitative performance of the model's response to productivity p crucially relies on a large opportunity cost of employment denoted z, or equivalently, a small surplus $p - z$ (Hagedorn and Manovskii, 2008), and since then there have been numerous attempts to resolve the Shimer puzzle, all similarly relying on a small "fundamental surplus" (Ljungqvist and Sargent, 2017). However, all these attempts have been questioned by Chodorow-Reich and Karabarbounis (2016) (hereafter, CRK), who argue that z is procyclical and estimate the elasticity of z with respective to p to be

[1] For clarity, I remark here on why the terminology emphasizes quits to nonparticipation, but not quits to another job or quits to unemployment. First, I discuss "vacating" from the perspective of the aggregate labor market, not an establishment. A job-to-job transition generates a vacant job at one establishment but at the same time fills another one somewhere else. In the aggregate, they cancel out each other. A worker exiting the labor market generates a vacant job without filling another one, which results in an extra vacancy in the aggregate. Second, theoretically, all quits to nonemployment would have the same qualitative implications as "vacating." But empirically, quits to unemployment have been minuscule according to the Current Population Survey. I thus focus on the much more prevalent form of quits to out of the labor force.

around 1. The intuition is that a procyclical z undoes the fluctuations in surplus and hence job creation incentives. CRK's finding seems discouraging and pessimists view such a procyclical z as the dead end of macro labor models.[2] I show that, however, once vacating is recognized, the CRK puzzle is resolved.

Why is that? First, a procyclical z means the value of staying at home is higher in good times. Moreover, as the labor market gets tighter in booms, the option value of staying out of the labor force is also higher. That is, workers are more comfortable with quitting the labor market when they have to, because they understand that it is easier to get back to the labor market once the shock reverts. As a result, the employment-to-nonparticipation rate is procyclical, a less-known but salient feature in the data.[3] This means that, in good times, not only employers create more jobs, but also workers vacate more jobs. Therefore, vacating amplifies vacancy fluctuations, and hence unemployment fluctuations in equilibrium. One may wonder why it is possible to escape the CRK critique, given that they have demonstrated the robustness of the challenge across a bunch of model specifications. The reason is that the CRK critique holds under the standard equilibrium determination of free entry, which is the basis of the elasticity derivations in Footnote 2. This paper's view of vacancies, however, deviates from the standard equilibrium determination that essentially treats vacancies as isomorphic to *recruiting efforts* (which are gone once paid), to an alternative that treats vacancies as *empty workstations* (which have embodied physical or organizational investment specific to the position), hence the title.[4]

To formalize this insight, I develop a parsimonious model to analyze the macroeconomic implications of vacating. I introduce two key elements into the textbook DMP structure for transparency. First, the model treats vacancies as empty workstations rather than only recruiting efforts. Advertising a vacancy incurs a flow recruiting cost, but creating a new job requires a investment to set up the position.[5] Potential entrants draw a stochastic position setup cost, which implies a finite elasticity of job creation, as opposed to the commonly as-

[2]To formally illustrate the problem, I present the steady state comparative statics, i.e., the elasticity of labor market tightness θ with respective to p, a useful device to gauge the model's business cycle property. In a standard DMP model when z is a constant, the elasticity is $\epsilon_{\theta,p} = \Gamma \frac{p}{p-z}$ where Γ can be bounded by reasonable parameters choices (Hagedorn and Manovskii, 2008). When z is allowed to vary with p, the elasticity becomes $\epsilon_{\theta,p} = \Gamma \frac{p-z\epsilon_{z,p}}{p-z}$ (Chodorow-Reich and Karabarbounis, 2016). Clearly, $\epsilon_{\theta,p} = 0$ when $\epsilon_{z,p} = 1$.

[3]It has been documented in, for example, Shimer (2012), Jung and Kuhn (2014), Elsby, Hobijn, and Şahin (2015), Krusell, Mukoyama, Rogerson, and Şahin (2017).

[4]This alters the dynamics of vacancies and leads to two additional equilibrium amplification mechanisms. First, vacancies are filled slower in good times because there are many of them but few unemployed workers. Second, vacancies are destroyed less frequently in good times, just like jobs are destroyed less frequently. Both are irrelevant to vacancy determination under the standard free entry job creation condition, because by assumption vacancies that are not filled are destroyed.

[5]The investment could be into either physical or organizational capital. For example, a job could be associated with an office or a machine. Alternatively, a job could be tied to a specific position in the organizational structure with an interdependent production process (Kuhn, Luo, Manovskii, and Qiu, 2022). In general, it captures any investment specific to the position in the sense that the value of the asset would decline if it were put to its best alternative use.

sumed infinite elasticity implied by the free entry condition. Technically, it renders vacancies a sluggish rather than jump variable. Second, I allow for empirically sensible labor force entry and exit behavior. On the exit side, the model introduces idiosyncratic preference shocks to workers' labor market attachment that induce workers' exits into nonmarket activities (in which case the worker leaves the labor force and the job becomes vacant), in addition to the usual assumption of idiosyncratic productivity shocks that endogenize job destruction (in which case the job is destroyed and the worker separates into unemployment). On the entry side, I propose a generalized matching function that replicates both the levels and volatility of the different job-finding rates of unemployed workers, nonparticipants, and employed workers.[6]

The model is calibrated to the US labor market over the business cycle. The idea of identification of the key new parameters is as follows. The investment cost distribution determines the elasticity of newly created jobs, and is hence identified by the relative volatility between created and vacated vacancies. The labor force attachment shock determines the relative importance of workers' idiosyncratic concerns vs. systematic economic considerations, and is hence identified by the volatility of the EN rate over the business cycle. The model replicates the means and standard deviations of not only flows between employment and unemployment (i.e., the separation and job-finding rates), but also flows into and out of the labor force. Consequently, the model reproduces cyclical properties of labor market stock variables as well, including the unemployment rate, employment-population ratio, and labor force participation rate. Besides these unconditional moments the existing literature typically focuses on, the model also matches untargeted conditional moments such as impulse response functions to productivity shocks and the realized path of the US labor market. It is worth noting that all these properties are achieved under a small (0.47) and procyclical (unit elasticity) z as advocated by Chodorow-Reich and Karabarbounis (2016).

First, I use the model to revisit the question of whether the labor force participation margin matters for unemployment fluctuations. Conventional wisdom ascribes a negligible role to the participation margin and the majority of the literature abstracts from the participation margin.[7] Specifically, I quantify the role of vacating in unemployment fluctuations. To do so, I consider a hypothetical economy where the procyclicality of the EN rate is shut down by taking the limit

[6] The model nests the textbook DMP model. The distributions of position setup costs and worker preference shocks nest the standard formulation of degenerate distributions at zero. The generalized matching function also nests the standard formulation of constant relative search intensity.

[7] There may be two reasons why this is the case. First, empirically, the LFPR itself has little variation, compared to the large variation in unemployment rate. But flows into and out of the labor force are both very large and volatile, and they have different implications on the labor market fluctuations. Second, theoretically, introducing a one-time labor supply shock into an otherwise standard DMP model does not have any effect. If the shock is persistent, the model would only predict the opposite to data: Expecting a rise in labor force exits increases employers' risk of losing a worker and decreases the value of posting a vacancy, so employers are discouraged from recruiting and vacancies are depressed.

of the standard deviation of the labor force attachment shock to infinity (while renormalizing the mean to keep the level of EN unchanged). I find that unemployment response to the same productivity shock is reduced by about one third. That is, procyclical EN accounts for about one-third of the business cycle variation in unemployment due to the vacating channel.[8]

Second, I revisit how labor markets respond to changes in discount or interest rates. Conventional wisdom suggests that a higher discount deters job creation and consequently increases unemployment (Hall, 2017). This paper highlights two different sources of vacancies that respond differently to interest rates. Creating new jobs involves an investment in setting up the position and is thus very responsive to interest rates, whereas reposting vacated jobs that have already embodied the sunk investment is much less responsive. The aggregate labor market response thus crucially depends on the dominant source of vacancies. This insight is especially relevant to the ongoing debate on the possibility of a "soft landing," i.e., hiking interest rates without causing high unemployment. If job creation were the primary source of vacancies, then a tightening monetary policy would reduce vacancies and increase unemployment (see, e.g., an analysis by Blanchard, Domash, and Summers, 2022, based on the postwar empirical regularities). The current labor market, however, features the so-called "Great Resignation"—we see a high vacancy rate not because employers are creating tons of new jobs but workers are vacating jobs more often than usual. Thus, the overall impact of raising interest rates is attenuated, and a soft landing is conceivable.

1.1 Related Literature

The paper makes several contributions to the literature. First, the paper makes an empirical contribution to facts on vacancies. Since the pioneering work by Abraham (1983), the number of vacancies has been an important indicator in aggregate labor market analyses.[9] However, despite the voluminous literature studying unemployment, relatively little is known about vacancies. Davis, Faberman, and Haltiwanger (2013) document facts on vacancy filling rates in the cross section of establishments and have spurred recent developments in theoretical models and

[8] Existing three-state flow variance decomposition of unemployment volatility performed by Jung and Kuhn (2014); Elsby, Hobijn, and Şahin (2015) finds an important role of the N margin through UN and NU, but little role of EN. Why do I reach a different conclusion? This is due to the distinction between a statistical decomposition and a structural analysis. Note that by construction, an EN transition does not even involve the unemployment state, so it is not surprising that by construction, it does not show up in a statistical decomposition of unemployment fluctuations. But this paper studies EN's structural role—in booms, more EN quits increase vacancies through the vacating channel, contributing to the improvement of unemployed workers' job-finding prospects. In fact, the simulated data of the model is still consistent with a statistical decomposition that suggests a dominant role of the UE rate and a small role of the EN rate.

[9] See Abraham and Katz (1986); Abraham and Wachter (1987); Blanchard and Diamond (1989) for early contributions and Shimer (2005) for a more recent contribution.

empirical measurements of employer heterogeneity in recruiting intensity and hiring practices.[10] An emerging empirical literature uses online vacancy posting data to gauge various aspects of labor demand.[11] This paper studies different sources of vacancies. I document the prevalence of position vacating, in addition to job creation, as a source of vacancies. Conceptually, a vacancy can arise due either to a rise in labor demand or a fall in labor supply.

Second, the paper makes a theoretical contribution to the equilibrium theory of frictional labor markets. The novel vacating channel arises from the interaction between the vacant jobs representation of vacancies (as opposed to the usual recruiting effort representation) and an operative labor force entry and exit margin (as opposed to the usual two-state abstraction). On the vacancy side, the model integrates two alternative vacancy creation processes. Reposting a vacated job involves only a flow recruiting cost as in standard models, whereas creating a new job involves a sunk investment cost that is analogous to Fujita (2004) and Fujita and Ramey (2007), and more recently Coles and Moghaddasi Kelishomi (2018).[12] On the labor supply side, the model is related to three-state models that incorporate labor force participation decisions into search-and-matching models.[13] This paper proposes a novel parsimonious formulation that quantitatively replicates the cyclical properties of all worker flow rates between employment states. At the establishment level, the vacating channel bears some resemblance to the "vacancy chains" story induced by workers' job-to-job transitions (Akerlof, Rose, and Yellen, 1988; Faberman and Nagypal, 2008; Mercan and Schoefer, 2020; Elsby, Gottfries, Michaels, and Ratner, 2021; Acharya and Wee, 2020), but at the aggregate level, they have different macroeconomic implications.

[10]See Kaas and Kircher (2015); Gavazza, Mongey, and Violante (2018) for related theoretical contributions and Mueller, Osterwalder, Zweimüller, and Kettemann (2018); Mongey and Violante (2019); Carrillo-Tudela, Gartner, and Kaas (2020); Lochner, Merkl, Stüber, and Gürtzgen (2021) for further empirical evidence. Kuhn, Manovskii, and Qiu (2021) document facts on vacancy filling rates in the cross section of locations and show that the geography of vacancy posting and filling is informative to distinguish alternative theories of spatial unemployment disparities.

[11]See Kuhn and Shen (2013), Hershbein and Kahn (2018), Deming and Kahn (2018), and Acemoglu, Autor, Hazell, and Restrepo (2020), among others.

[12]Although majority of the literature has converged to a free entry tradition, Coles and Moghaddasi Kelishomi (2018) point out that this alternative job creation process is similar to Diamond (1982) and call it Diamond entry. The Diamond entry has by now been adopted in Shao and Silos (2013); Leduc and Liu (2020); Haefke and Reiter (2020); Den Haan, Freund, and Rendahl (2021); Potter (2022). Similar entry processes have been adopted in other settings such as Melitz (2003) and Beaudry, Green, and Sand (2018).

[13]Early contributions including Tripier (2004); Haefke and Reiter (2011); Shimer (2013) are devised to account for cyclical movements of labor market stocks but do not aim at replicating gross worker flows. Krusell, Mukoyama, Rogerson, and Şahin (2017) introduce rich worker heterogeneity in a partial equilibrium search model where job finding rates are exogenous and vacancies are not considered. Veracierto (2008) and Krusell, Mukoyama, Rogerson, and Şahin (2020) study a three-state model in the Lucas and Prescott (1974) island economy and hence do not speak to vacancies. Cairó, Fujita, and Morales-Jiménez (2022) and Ferraro and Fiori (2022) match the volatility and cyclicality of all six gross worker flow rates. Hagedorn, Manovskii, and Mitman (2020) confront the theoretical implications of a three-state model with empirical evidence exploiting the unexpected elimination of federal unemployment benefit extensions.

Third, the paper contributes to understanding the sources of unemployment fluctuations over the business cycle. As an empirically relevant quantitative model, the paper not only resolves the unemployment volatility puzzle (Shimer, 2005). Moreover, the vacant-job framework further provides a novel resolution to the "augmented" unemployment volatility puzzle when the opportunity cost of employment is procyclical (Chodorow-Reich and Karabarbounis, 2016). Through the vacating channel, procyclical employment-to-nonparticipation quits cause vacancy fluctuations, which in turn lead to job finding rate fluctuations. Thus, the labor force participation margin structurally matters in the equilibrium theory of unemployment, while the model is still consistent with the accounting property that a larger share of unemployment fluctuations is attributed to the job finding rate in a variance decomposition.[14]

Fourth, by distinguishing created and vacated vacancies, the paper also contributes to understanding the labor market impact of changing interest/discount rates (Mukoyama, 2009; Hall, 2017; Kehoe, Midrigan, and Pastorino, 2019; Clymo, 2020; Leduc and Liu, 2020; Martellini, Menzio, and Visschers, 2021). The defining feature of created vacancies is that a sunk investment cost is required, as opposed to vacated vacancies. Although the creation channel, as an investment activity, is responsive to interest rates, the vacating channel is not. Thus, the overall labor market response depends on the relative importance of the two channels, providing a novel perspective for evaluating monetary policies.

Lastly, the vacating channel has broader implications for the impact of negative labor supply shocks, such as induced by immigration policies, retirement behavior, family care, disability or illness, and other idiosyncratic worker shortfalls. The vacating channel prompts a reevaluation of the lump of labor fallacy. Policymakers in several countries propose to encourage one group of workers to exit their jobs with the intention to reduce unemployment of another group. Such policies have been criticized by economists as a mistaken belief that there is a fixed amount of work available (e.g., Gruber and Wise, 2010). The vacating channel suggests that "lump of labor fallacy" is a fallacy only in the long run but not in the short run. The labor market can indeed adapt to changes in labor supply, but the adjustment takes time.

Road Map. The rest of the paper is organized as follows. In Section 2, I document the empirical facts about the vacating channel. In Section 3, I develop a framework where the vacating channel operates. Section 4 brings the model to the data and examines its cyclical

[14] The literature often ascribes a primary role to the job finding rate, a secondary role to the separation rate, and a negligible role to the labor force participation margin. The Shimer (2012) decomposition assigns a dominant role to the job finding rate, which motivates a large literature that abstracts from separation rate fluctuations and focuses solely on equilibrium responses of the job finding rate (e.g., Shimer, 2005; Hagedorn and Manovskii, 2008). Although the empirical analyses by Fujita and Ramey (2009) and Elsby, Michaels, and Solon (2009) agree that the job finding rate accounts for more unemployment fluctuations than the separation rate, they disagree with the exact magnitude. Thus, Fujita and Ramey (2012) quantitatively analyze a DMP model with endogenous separations that reproduces the volatility of both flows.

properties. Section 5 considers a couple of applications. Section 6 concludes.

2 Facts

This section documents three main facts. First, I provide evidence of vacating both in the aggregate and in the cross-section of establishments. Moreover, compared to newly created vacancies, vacated vacancies are both more prevalent in the labor market and more volatile over the business cycle. Second, I document reasons for workers' transitions from employment to nonparticipation. The findings point to labor supply side factors being the primary driver, such as caring for family, retirement, and education, rather than labor demand side factors. Third, most of the cyclical fluctuations in vacancies are accounted for by fluctuations in outflows and less so by inflows, emphasizing the importance of the stock representation of vacancies in aggregate labor market analyses. These facts are also robust in other economies to whose vacancy data I have access, in addition to the United States.

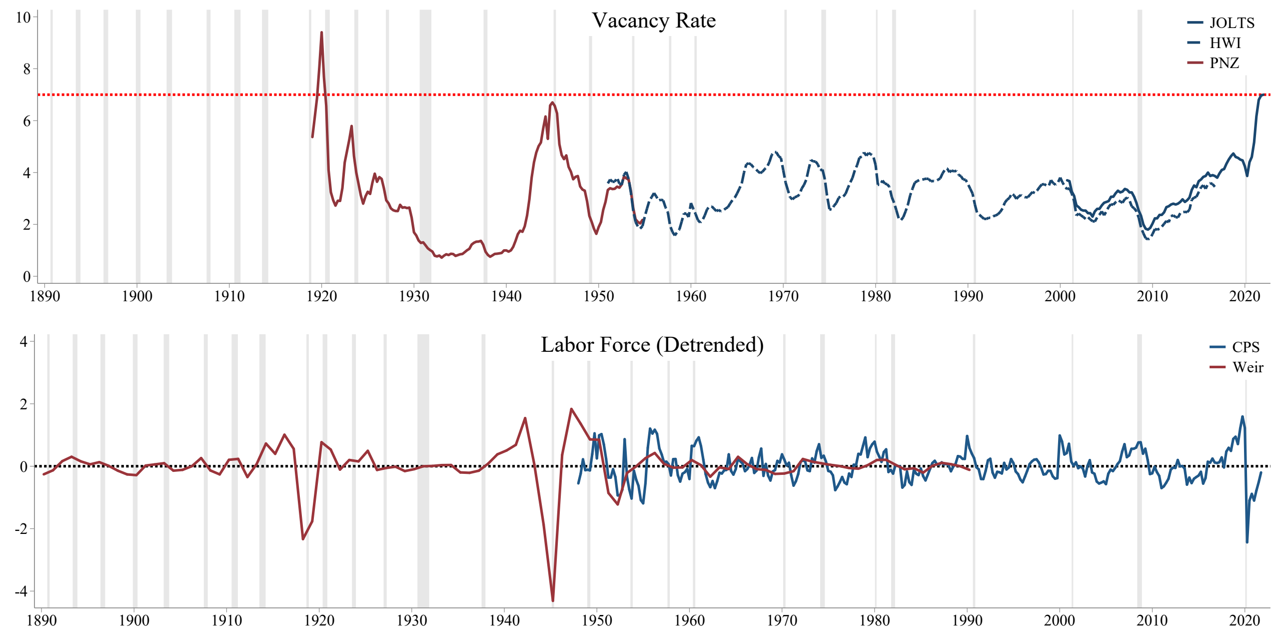
2.1 Empirical Evidence of the Vacating Channel

2.1.1 Historical Episodes of Aggregate Labor Shortages

We now live in an unusual labor market with help-wanted signs virtually everywhere. Unlike previous employment troughs that struggle with high unemployment rates, the post-pandemic labor market is concerned with a skyrocketing vacancy rate, after a large, negative aggregate labor supply shock induced by Covid. The vacancy rate of 7% reaches a record high since the introduction of the Job Openings and Labor Turnover Survey in 2000, and more than doubles the average since 1951 according to the Composite Help-Wanted Index. This is widely perceived as unprecedented in the context of the postwar US labor market data that researchers today are accustomed to.

The first empirical contribution of this paper is to go beyond the traditional focus on the postwar data in the macro labor literature. "History doesn't repeat itself, but it often rhymes"—digging into historical data unveils that such a great labor shortage is not without precedent. Figure 1 identifies two similar historical episodes in the past century. The first one happened around 1918, which coincided with the influenza pandemic hence akin to the labor market today (and it also coincided with World War I). The second one happened around 1943, which coincided with World War II when the US sent young workers overseas to serve in the military. In all these three episodes, the labor market experienced massive labor force outflows, as indicated by the bottom panel of Figure 1 (about 3%, 5%, and 3% drop in the size of the

Figure 1: Vacancies and Labor Force in A Century of the US Labor Market



Notes: The top panel plots the monthly time series of vacancy rate. The "JOLTS" series for December 2000 onward is obtained from the Job Openings and Labor Turnover Survey at the US Bureau of Labor Statistics. The "HWI" series for January 1951 to December 2016 is from the composite Help-Wanted Index constructed by Barnichon (2010). The "PNZ" series is obtained from Petrosky-Nadeau and Zhang (2021), which is in turn based on the Metropolitan Life Insurance company (MetLife) help-wanted advertising index for January 1919 to December 1950 from NBER macrohistory files. The bottom panel plots the time series of the labor force. The "CPS" series refers to the month labor force data for January 1948 onward obtained from the Current Population Survey at the US Bureau of Labor Statistics. The "Weir" series refers to the annual labor force data for 1890 to 1990 obtained from Weir (1992). Labor force data are first logged and then HP detrended with smoothing parameter 6.25 for annual series, 1,600 for quarterly series, and 129,600 for monthly series, following Ravn and Uhlig (2002).

labor force, respectively). Regardless of the underlying reason underlying these aggregate labor supply shocks, be it the disease or the war, they all lead to subsequent spikes in vacancies, as shown in the top panel of Figure 1, revealing the vacating channel. Data sources are explained in the notes of Figure 1.[15]

Of course, these episodes are special and it is not the focus of this paper to study the underlying sources of aggregate labor supply shocks. The point of Figure 1 is to visually illustrate the vacating channel, made especially evident by aggregate labor supply shocks. In addition, it is often challenging to make causal statements from aggregate time series data. To address these concerns, I provide establishment-level evidence in the next subsection that a increase in

[15]Vacancy data from different sources have been harmonized so that their overlapping periods yield the same level. For example, the MetLife index has been rescaled to match HWI in the first quarter of 1951, which has in turn been rescaled to match JOLTS in the first quarter of 2001. Nevertheless, it is still possible that levels are not perfectly comparable across data sources due to differences in sample frames. Figure 1, however, does not aim to construct a measure of consistent levels over time. Instead, it highlights the directions and timings of big changes in vacancies and labor force in historical episodes.

workers' voluntary quits leads to a subsequent rise in vacancies within an establishment, which corroborates the vacating channel with microdata. In the subsection after, I further show that workers' idiosyncratic labor supply shocks, hence the vacating channel, are important even in normal times without aggregate labor supply shocks.

It is worth noting that outside the three episodes of aggregate labor supply shocks, vacancies seem to comove positively with labor force. This is not surprising; it is well-documented that vacancies are strongly procyclical and labor force is weakly procyclical over the postwar, pre-pandemic business cycles. Section 4 shows that the model with the vacating channel is able to replicate qualitatively and quantitatively these properties as well in usual business cycle with aggregate productivity/labor demand shocks and without aggregate labor supply shocks.

2.1.2 Establishment-Level Evidence of Workers' Voluntary Quits

This section documents micro evidence of the vacating channel using employer vacancy surveys and find a robust pattern for a few economies including US, Germany, and Taiwan. The Job Openings and Labor Turnover Survey (JOLTS) program at the US Bureau of Labor Statistics is a monthly representative employer survey covering about 21,000 establishments that collects data on vacancies, hires (i.e., all additions to payroll during a month), and separations (i.e., all departures from payroll during a month). Separations are further classified into quits, which are voluntary separations initiated by employees, and layoffs, which are involuntary separations initiated by employers. To qualify as a vacancy, three conditions must be met: (1) a specific position exists and there is work available for that position; (2) the job could start within 30 days;[16] and (3) there is active recruiting for workers from outside the establishment.[17,18] These conditions mirror those that define unemployment. I also utilize another two similar establishment surveys to JOLTS that contain information on both quits and vacancies: German Job Vacancy Survey of the IAB and Taiwan Job Vacancy and Employment Status Survey.[19]

I estimate the effect of workers' quits at an establishment on its vacancies. The vacancy surveys in Taiwan and Germany are annual surveys, with a stratified random sample drawn

[16] The 30-day criterion removes both "phantom" postings that are no longer available (Cheron and Decreuse, 2017) and "planned" postings that correspond to actual positions in the future.

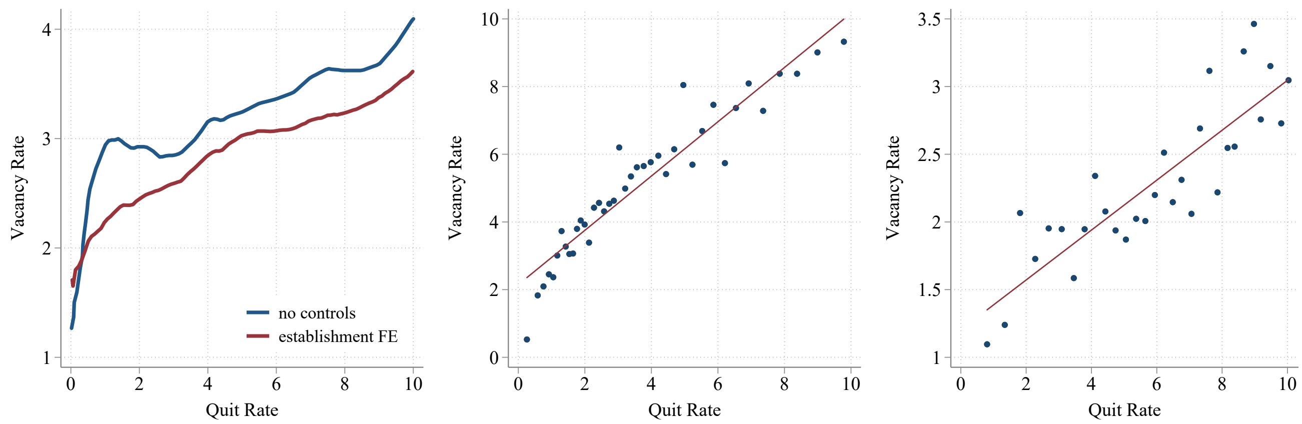
[17] According to the definition by BLS, the requirement for "active recruiting" is rather broad, and is met if the establishment is taking some steps to fill a position, such as advertising in newspapers, on television, or on radio; posting Internet notices; posting "help wanted" signs; networking with colleagues or making "word of mouth" announcements; accepting applications; interviewing candidates; contacting employment agencies; or soliciting employees at job fairs, state or local employment offices, or similar sources.

[18] The following positions do not count as a job opening in JOLTS: positions open only to internal transfers, promotions or demotions, or recall from layoffs; positions with start dates more than 30 days in the future; positions that have hired someone who has not yet reported for work; positions designed for employees of temporary help agencies, employee leasing companies, outside contractors, or consultants.

[19] Access to the German Job Vacancy Survey is provided by the IAB under project number 102312. Taiwan Job Vacancy and Employment Status Survey is accessed via the Survey Research Data Archive.

Figure 2: Establishment-Level Evidence of Vacated Vacancies

(a) United States (b) Germany (c) Taiwan



Notes: This figure plots the establishment-level vacancy rate and quit rate for the US, Germany, and Taiwan.

anew every year. Although the German vacancy survey does have a short panel dimension within a year, only information on vacancies is collected each quarter in the short surveys, but quits are only asked once in the long survey. Thus I am constrained to use repeated cross-sectional establishment data. Specifically, I estimate the following regression

$$y_{i,t} = \beta x_{i,t} + \gamma Z_{i,t} + \alpha_t + \varepsilon_{i,t},$$

where the dependent variable is the vacancy rate $y_{i,t} = \text{Vacancies}_{i,t}/\text{Employment}_{i,t}$, the independent variable is the quit rate $x_{i,t} = \text{Quits}_{i,t}/\text{Employment}_{i,t}$, and the vector of control variables $Z_{i,t}$ include industry fixed effects, firm size fixed effects, and year fixed effects. Note that y is a point-in-time measure of the number of vacancies at the end of a period, whereas x is a flow measure that counts all voluntary separations during the previous period. Thus, one should not expect a unit elasticity even if any quit leads to an immediate advertising of a vacancy. The estimated relationship between vacancy rate and quit rate within establishments is plotted in Figure 2. Panel (a) is estimated in JOLTS microdata, reproduced from Faberman and Nagypal (2008). Panels (b) and (c) are estimated in Germany and Taiwan vacancy survey microdata. All three results point to a robust finding that the employers tend to keep the positions open when workers voluntarily quit their jobs, corroborating the vacating channel at the micro level.

The micro-level evidence shown in Figure 2 survives after various aggregations. Figure A-1 documents a robust positive relationship between vacancies and quits in the time series, across sectors, and across space in the United States.

2.1.3 Prevalence of Worker Exiting and Position Vacating

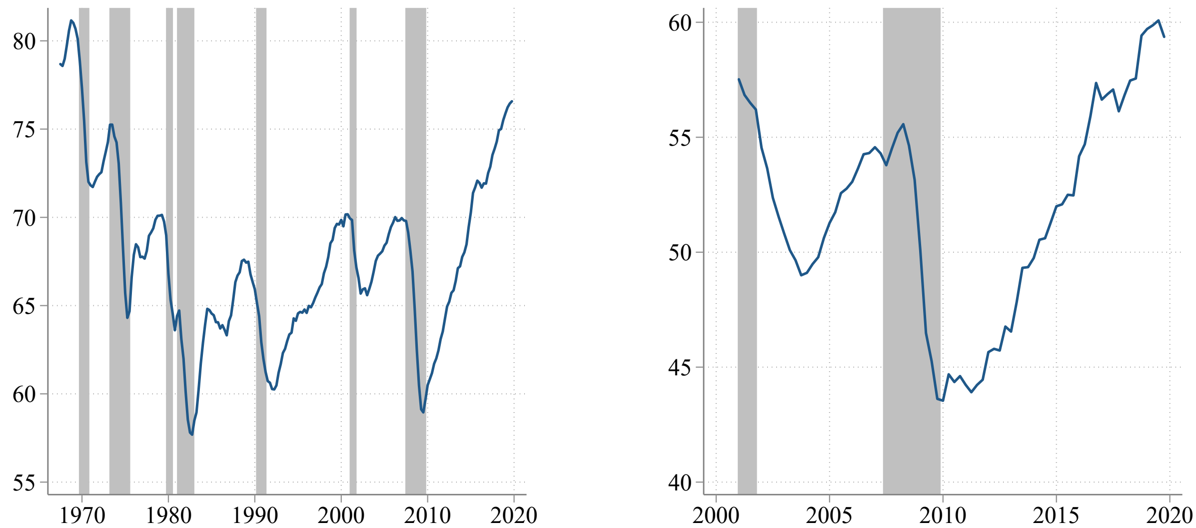
Canonical theories of frictional labor markets conceptualize employment outflows as job destruction and vacancy inflows as job creation. The previous result on the vacating channel highlights a different form of separation from job destruction: workers voluntarily exiting the labor market. It also highlights a different source of vacancies from newly created positions: existing positions vacated by workers quitting their jobs. That is, the vacating channel links employment outflows to vacancy inflows, the two pillars in thinking about equilibrium unemployment. Such distinction is not only a conceptual matter, but also empirically important as shown in Figure 3.

At any point in time, the population is classified into three labor force states: (1) employed workers who are working (denoted E), (2) unemployed workers who are not working but actively looking for a job within the last 4 weeks (denoted U), (3) nonparticipants out of the labor force who are not working and not searching (denoted N). I use the short-panel dimension of the Current Population Survey (CPS) design to measure month-to-month transitions in workers' labor force status (data extracted from IPUMS by Flood et al., 2022). For example, the probability that an employed worker leaves the labor force in a particular month (EN transition rate) can be calculated as the proportion of employed workers who report being out of the labor force in the following month. Figure A-9 plots the time series of all six gross worker flow rates, and Figure A-10 plots their cyclical components extracted by the HP filter with smoothing parameter $1,600$ for the quarterly series. To deal with the potential time-aggregation bias, I compute the continuous-time adjusted Poisson arrival rates, plotted as the dashed lines (see Appendix III.2 for the derivation of the time-aggregation correction).

Panel (a) of Figure 3 shows the prevalence of worker exiting. The monthly employment-to-nonparticipation (EN) transition rate is about 3%, as shown in Panel (e) of Figure A-9. In other words, every month, around 3% of employed workers become nonparticipants in the following month. The seemingly small rate in fact corresponds to large EN flows, given the big denominator of the total employed population. The large EN transition rate is not driven by a potential time aggregation bias that employed workers first go to unemployment and then go out of the labor force. The dashed line plotting the Poisson rates and the solid line plotting the monthly transition probability are almost on top of each other in Panel (e) of both Figure A-9 and A-10. Panel (a) of Figure A-9 shows that the monthly employment-to-unemployment (EU) transition rate is on average about 1.5%, and the time aggregation adjusted EU rate is about 2%, both of which are smaller than the EN rate. The result survives the classification error adjustments considered in Appendix III.3. The share of workers exiting labor force among employment outflows is then defined as the ratio of EN rate to employment outflow rate (i.e., the sum of EN and EU rate). On average, two thirds of employment outflows are exiting the

Figure 3: Prevalence of Worker Exiting and Position Vacating

(a) Worker Exiting Among Employment Outflows (b) Position Vacating Among Vacancy Inflows



Notes: This figure plots the share of employment-to-nonparticipation transitions among employment outflows in the left panel and the share of position vacating among vacancy inflows in the right panel.

labor force, while the standard analysis focuses on the remaining one third that are being laid off to unemployment.

Panel (b) of Figure 3 shows the prevalence of position vacating, using the JOLTS data. Quits are defined as separations initiated by employees, whereas layoffs and discharges are defined as separations initiated by employers. Since these variables in JOLTS are reported by employers, it is reasonable to interpret a quit as separation in a position that the employer wants to keep. This has also been confirmed in the establishment-level evidence in the previous subsection. Thus, the quit rate serves as a sensible proxy for position vacating rate, and I define the share of position vacating among vacancy inflows as the ratio of workers' voluntary quit rate to the overall vacancy inflow rate.[20] The remaining vacancy inflows are attributed to newly created positions. The details of measuring vacancy inflows are relegated to Appendix III.1. On average, more than half of the vacancy inflows are position vacating, while the standard analysis focuses on the remaining half that are job creation. Moreover, the share of position vacating is procyclical, indicating that position vacating are more volatile than job creation (given that both are procyclical).

[20]It is worth pointing out that quits as defined in JOLTS do not distinguish the destination of the worker. Thus, a quit could be moving to another job or exiting the labor market, and either can similarly generate a vacated vacancy from the employer's perspective. In the model laid out in Section 3, I allow for both types of quits to be consistent with the definition in the data. Given that EN rate is of similar magnitude to (slightly larger than) the job-to-job rate according to CPS, a back-of-the-envelope calculation would attribute slightly more than half of the vacated vacancies to arise from workers' exiting the labor market.

I further construct an alternative measure of the share of vacated vacancies among the vacancy stock. The key idea is to attribute replacement hires at an establishment as to fill vacated positions, which can be constructed using the Quarterly Workforce Indicators (QWI) data. See Appendix I.2 for details of the implementation. Moreover, I also check other vacancy surveys that directly ask employers for the reason why a vacancy arises. Figure A-2 plots these three series and finds a robust pattern of a large and procyclical share of vacated vacancies. For instance, 60% of the vacancies are vacated vacancies in the US according to the alternative QWI measure, 55% of the vacancies are vacated vacancies in Taiwan, and 75% of the vacancies are vacated vacancies in Poland. In all three cases, the share of vacated vacancies comoves negatively with the unemployment rate. See Appendix I.2 for more discussion. Lastly, I negotiated a proprietary dataset containing linked vacancy-personnel information that allows for tracking the life cycle of a position.

To summarize, this section shows that worker exiting the labor force is an empirically important source of employment outflows, and position vacating is an empirically important source of vacancy inflows.

2.2 Additional Facts

The previous section provides empirical evidence of the vacating channel and showcases the empirical prevalence of the vacating channel. This section provides additional facts that are instrumental to the development of a theory where the vacating channel operates. The canonical theory of a frictional labor market rests on two pillars: separations (i.e., employment outflows) and match formation between job seekers and vacancies. Section 2.2.1 discusses the nature of two different employment outflows to nonparticipation vs. unemployment. Section 2.2.2 discusses the nature of vacancy dynamics by quantifying the relative importance of the ins and outs of vacancies.

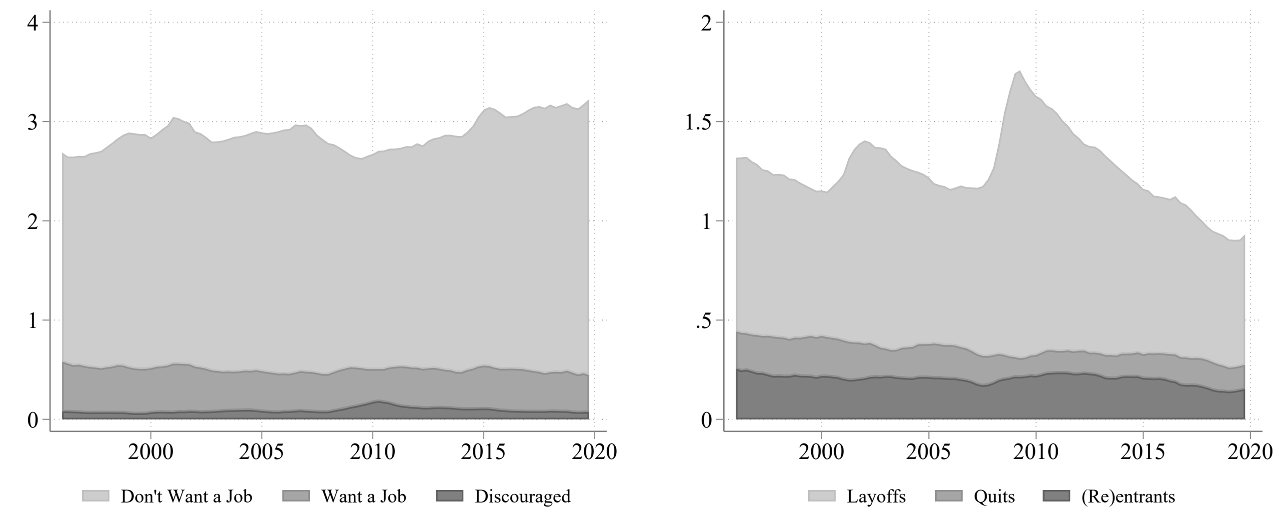
2.2.1 A Tale of Two Employment Outflows: to Nonparticipation vs. to Unemployment

In canonical theories of frictional labor markets, there is only one source of employment outflows, i.e., employment-to-unemployment transitions, which is conceptualized as job destruction, whereas the vacating channel studied in this paper emphasizes employment-to-nonparticipation transitions. How should we think of these two different worker flows?

First of all, the EN rate is procyclical, meaning that a larger fraction of employed workers moves to nonparticipation in good times (with low unemployment rates) than in bad times (with high unemployment rates). In contrast, the widely-studied EU rate is countercyclical. The opposite cyclicality of these two employment outflows already indicates the different nature

Figure 4: A Tale of Two Employment Outflows

(a) Employment to Nonparticipation (b) Employment to Unemployment



Notes: This figure plots two types of employment outflows by reason.

of these two phenomena. Furthermore, it is thus not surprising the share of EN rate among employment outflows is procyclical, as shown in Panel (a) of Figure 3.

Do workers exit employment to nonparticipation voluntarily? If so, why do employed workers quit to nonparticipation? I approach this question in two ways. First, I classify nonparticipants into three groups based on more detailed out-of-labor-force status. For respondents out of the labor force, the CPS asks "Do you currently want a job, either full time or part time?" I define those who answer "yes" to this question as nonparticipants who want a job. For these nonparticipants who want a job, the CPS asks "What is the main reason you were not looking for work during the last 4 weeks?" I define as discouraged workers those who report that (1) they believe no work available in area of expertise, (2) they could not find any work, (3) they lack necessary schooling/training, (4) employers think too young or too old, or (5) they are subject to other types of discrimination.[21]

Panel (a) of Figure 4 plots the composition of EN transitions into discouraged workers (dark gray), nonparticipants who want a job but do not participate in the labor market for reasons orthogonal to job prospects (medium gray), and other nonparticipants who do not even want a job (light gray). First, on average, only about 3 percent of all EN transitions are being discouraged. This suggests that depressed job prospects are a negligible reason for EN

[21]Other respondents report that they cannot arrange childcare, have family responsibilities, are enrolled in school or other training, suffer from ill-health or physical disability, have difficulties with transportation problems, or other reasons that are difficult to categorize. These respondents are excluded from discouraged workers. I also consider an alternative classification covering these reasons. See Appendix I.3 for details.

transitions. Among these nonparticipants who just leave employment, 83% of them say that they do not want a job. This shows that EN transitions happen primarily due to events at the worker side rather than the job side. Moreover, this number is only a conservative estimate—even among nonparticipants who do say that they want a job, many of them do not participate in the labor market because of non-market reasons such as the need to take care of the family.

In terms of the cyclical patterns, employment-to-discouragement transitions are countercyclical as expected. For example, the number of employed workers transitioning into being discouraged in the following month increased during the Great Recession. Thus, depressed job prospects cannot at all explain the procyclicality of EN transitions. Even if we extend the coverage, EN transitions that still want a job is acyclical. Thus, we conclude that the procyclicality, as well as the magnitude of EN transitions, is driven by changes to workers' own labor force attachment.

In the second classification, I look into the reason for being out of the labor force for workers making EN transitions. Appendix I.3 provide the details on the construction of this measure. Figure A-3 plots employment-to-nonparticipation transition rates by reason. On average, 29.0% of employment-to-nonparticipation transitions go to school, 26.7% take care of the family, 18.6% are retirement, 10.7% are due to disability or illness, 12.9% for other reasons, and 2.0% with missing answers. Retirement, disability, and "other", together account for about 40% of employment-to-nonparticipation transitions. These three components are barely cyclical. The procyclicality of the EN rate is mostly driven by needs for family care and school attendance. These two components account for close to the remaining 60% of employment-to-nonparticipation transitions. This classification corroborates the finding that both the procyclicality and the magnitude of EN transitions are driven by non-market reasons. This paper focuses on the aggregate labor market patterns consistent across demographic groups, although there are indeed differences by demographics (see Figure A-4 and discussion therein). The distributions of reasons among UN transitions and N stocks are reported in Figure A-6.

In contrast, the distribution of reasons for employment-to-unemployment transitions shown in Panel (b) of Figure 4 reveals that most EU transitions are involuntary separations. This constructed by looking into why respondents were unemployed for workers making EU transitions. I distinguish between (1) workers who had lost jobs (due to temporary layoff, involuntary job loss, or ending of a temporary job), (2) those who had quit jobs, and (3) those who were re-entering the labor force after an extended absence from the work force (including those who report to be new entrants). On average, 72% of EU transitions are layoffs and only 12% are quits. The remaining 16% of EU transitions have been through the nonparticipation state, indicating a potential time-aggregation issue in the raw data constructed from CPS panels. I solve the time-aggregation issue by adjusting the transition probability to Poisson rate in the data as explained in Appendix III.2 and by analyzing a continuous-time model accordingly as set up in Section 3.

In summary, this section shows that most EN transitions are workers' voluntary separations where most EU transitions are involuntary separations. This suggests that it is a reasonable representation to model EN transitions as triggered by shocks to workers and EU transitions as triggered by shocks to jobs. I sometimes refer to the shock to workers as the idiosyncratic preference shock and the shock to jobs as the idiosyncratic productivity shock for convenience.

2.2.2 The Ins and Outs of Vacancies

As with any other stock variable, vacancies reflect the race between its inflow and outflow. A high vacancy stock could be a result of either high vacancy inflow or low vacancy outflow. Thus, a vacancy can be seen as either desire to hire or failure to hire, two starkly different interpretations. In the textbook Mortensen and Pissarides (1994) paradigm with free entry, the vacancy stock is equivalent to the vacancy inflow and hence vacancies solely reflect a desire to hire. In contrast, in models with a fixed number of jobs such as Shimer and Smith (2000), vacancies only reflect a failure to hire. This section lays out a decomposition framework for understanding the ins and outs of vacancies.[22] It turns out that vacancy outflows account for the majority of vacancy fluctuations over the business cycle.

The law of motion for vacancies is

$$V_t = V_{t-1} - O_t + I_t, \tag{1}$$

where V_t is the end-of-period number of vacancies at time t, O_t and I_t the vacancy outflow and inflow during period t, respectively. Equation (1) is nothing but an accounting identity. Define vacancy outflow rate as $o_t = O_t/V_{t-1}$ and vacancy inflow rate as $i_t = I_t/E_{t-1}$, where E_t denotes the end-of-period number of filled jobs at time t. I then reach a rate representation of the law of motion:[23]

$$v_t = v_{t-1} \times (1 - o_t) + (1 - v_{t-1}) \times i_t. \tag{2}$$

The decomposition relies on a "steady state" approximation of vacancy rate when $v_t \approx v_{t-1}$.

[22] I paraphrase the titles of Darby, Haltiwanger, and Plant (1986), "The Ins and Outs of Unemployment: the Ins Win," and later on Shimer (2012), "Reassessing the Ins and Outs of Unemployment," on decomposing unemployment dynamics.

[23] To be precise, the rate representation relies on an approximation that $g_t := J_t/J_{t-1} = 1$, where J_t is the sum of vacant jobs and filled jobs. This approximation is in essence symmetric to the standard approximation of a constant labor force in the literature studying unemployment dynamics. In fact, this is an extremely tight approximation at the monthly frequency. For instance, in the US, g_t is tightly distributed around 1 with a maximum deviation of 0.5%, and the deviations are within 0.1% for 95% of the time. This is not surprising—it merely states that the total number of jobs does not fluctuate much between two consecutive months.

Table 1: Data Sources for Vacancy Dynamics

Country	Data Source
United States	Job Openings and Labor Turnover Survey (JOLTS)
Germany	Federal Employment Agency (Bundesagentur für Arbeit)
Netherlands	Centraal Bureau voor de Statistiek (CBS) Open Data StatLine
Austria	Labor Market Data (Arbeitsmarktdaten) Online
United Kingdom	Nomis at Office for National Statistics (ONS)

Notes: This table summarizes the data sources used in the cross-country analysis of vacancy dynamics.

I verify in the data that this is also a good approximation at the monthly frequency. In fact, the distribution of v_t/v_{t-1} is tightly around 1. I reach the following "steady state" approximation:[24]

$$v_t \approx \frac{i_t}{i_t + o_t} := v_t^{ss}, \qquad \text{or} \quad \frac{v_t}{1-v_t} \approx \frac{i_t}{o_t} := \frac{v_t^{ss}}{1-v_t^{ss}}.$$

To perform the decomposition formally, I introduce an approximation error term ε_t in the steady state approximation such that

$$\log \frac{v_t}{1-v_t} = \log i_t + (-\log o_t) + \varepsilon_t.$$

Consider the following variance decomposition

$$\text{var}_t\left(\log \frac{v_t}{1-v_t}\right) = \text{cov}_t\left(\log \frac{v_t}{1-v_t}, \log i_t\right) + \text{cov}_t\left(\log \frac{v_t}{1-v_t}, -\log o_t\right) + \text{cov}_t\left(\log \frac{v_t}{1-v_t}, \varepsilon_t\right),$$

where the variance and covariances are taken over time. It therefore allows to quantitatively evaluate the contributions of $\log i_t$, $\log o_t$, and ε_t, respectively, to the variation in the vacancy rate. Essentially, I adapt the decomposition framework in the literature on understanding unemployment dynamics such as Fujita and Ramey (2009), and Elsby, Michaels, and Solon (2009) to understanding vacancy dynamics. This has not been done before presumably because most of the existing models simplify vacancies as a jump variable and hence do not feature a law of motion for vacancy dynamics.

I obtain measures of vacancy inflow and outflow rates in the US labor market from JOLTS, with details provided in Appendix III.1. I HP-filter each log variable with smoothing parameter 1,600 and apply the variance decomposition to the cyclical components. The formal decomposition reveals that vacancy outflows account for 74.2% of the cyclical variation in vacancy rate,

[24] Note that the approximation does not require a constant vacancy rate; it only requires that the vacancy rates are close enough in two adjacent periods. In fact, both i_t and o_t (hence v_t^{ss}) are changing over time. This approximation is exact when two consecutive periods happen to have the same vacancy rate, and would be accurate when the vacancy rates do not differ much in two adjacent periods.

whereas vacancy inflows account for 26.3%, with a residual of -0.5%.[25]

In this section, I utilize vacancy data from several countries, each with own unique strength. In particular, these data provide direct measures on vacancy inflows and outflows. Although there may be discrepancies in definitions and sampling frames across different surveys, I do not seek to compare the levels across countries, but instead focus on the overall business cycle patterns within countries.

Data sources. Data for the United States are from the Job Openings and Labor Turnover Survey (JOLTS) program. Data for Germany are obtained from statistics of the Federal Employment Agency (Bundesagentur für Arbeit). Data for Netherlands are obtained via Statistics Netherlands (Centraal Bureau voor de Statistiek, CBS) Open Data StatLine. Data for Austria are obtained from Labor Market Data (Arbeitsmarktdaten) Online. Data for UK are obtained from Nomis labor market statistics provided by the Office for National Statistics (ONS). The data sources are summarized in Table 1 for reference.

This section visualizes the importance of inflows and outflows using the approach as in Shimer (2012). To do so, I construct another two counterfactual vacancy series, in addition to the steady-state approximation. The first one is obtained as the implied steady-state vacancy rate by using the actual outflow series o_t but fixing inflow at its average $\bar{i}$, i.e.,

$$v_t^o := \frac{\bar{i}}{\bar{i} + o_t}.$$

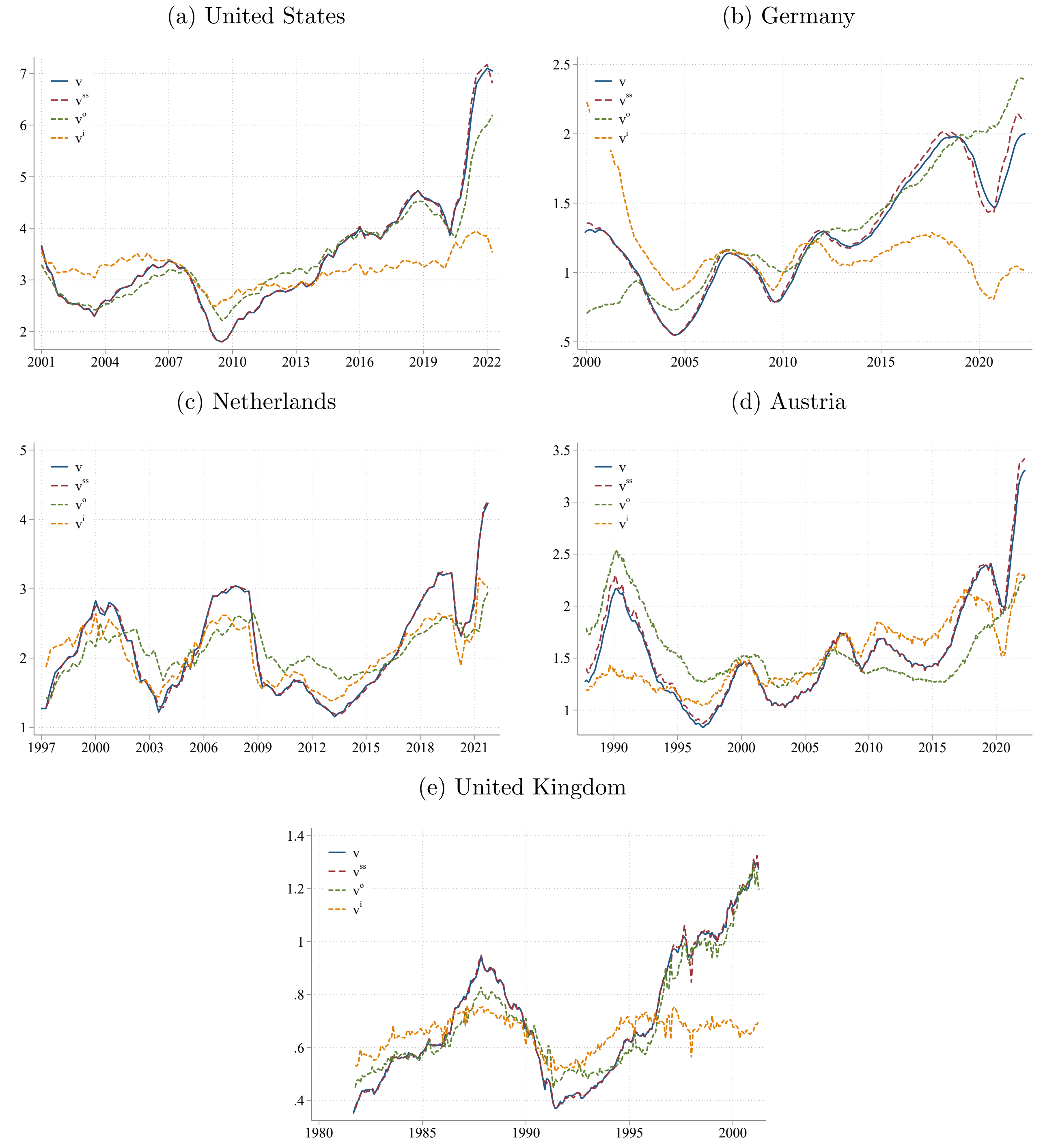
The second one is symmetrically obtained by using the actual inflow series i_t but fixing outflow at its average $\bar{o}$, i.e.,

$$v_t^i := \frac{i_t}{i_t + \bar{o}}.$$

Figure 5 plots the evolution of these two series for each country. First, in every panel, the blue solid line plotting the actual vacancy rate and the red dashed line plotting the steady-state approximation are almost on top of each other, suggesting that the steady-state approximation is a good one. For example, the correlation between the actual vacancy rate and the steady-state implied vacancy rate in the US is 99.87%. Second, the v^o series tracks the actual vacancy rate much more closely than the v^i series, indicating that keeping track of the outflow o_t alone can already replicate most of the variation in v_t, consistent with the formal variance decomposition derived in the previous section that outflow accounts for the majority of vacancy fluctuations.

[25] If one zooms in to the Great Labor Shortage by comparing Q4 2021 with Q1 2020, 75.5% of the increase in the vacancy rate can be accounted for by a drop in the vacancy outflow rate, and 28.1% by an increase in vacancy inflow rate, and -3.6% by a residual. Thus the Great Labor Shortage is, in an accounting sense, mostly due to failure to hire, rather than desire to hire.

Figure 5: The Inflow-Outflow Decomposition of Vacancies



Notes: This figure plots the actual vacancy rate v (blue solid line), the steady-state approximated vacancy rate v^{ss} (red dashed line), the counterfactual vacancy rate v^{o} by varying o only (green dashed line), and the counterfactual vacancy rate v^{i} by varying i only (orange dashed line).

2.3 Taking Stock

This section presents three empirical facts. Strikingly, all three facts are in sharp contrast with what is implied by the textbook model of frictional labor markets.

First, Section 2.1 documents the empirical evidence and prevalence of the vacating channel. Historical episodes of labor shortages reveal that, in the aggregate, massive labor force outflows led to skyrocketing vacancies. Micro employer vacancy survey data further corroborate that, within an establishment, workers' voluntary quits lead to an increase in vacancies. The fact is robust to various levels of aggregation, including across sectors, across local labor markets, and over time. Moreover, such vacated vacancies are an empirically prevalent form of vacancies in the labor market. Vacated vacancies are also more volatile than created vacancies over the business cycle. The same patterns hold in several economies whose vacancy surveys permit such measurement. In contrast, all vacancies in the textbook model are newly created jobs, and the job creation margin is the only equilibrium driving force. Employment-to-nonparticipation transitions are an empirically prevalent form of separations in the labor market. Every month, about 3% of employed workers leave the labor force. The magnitude dominates the number of employed workers who lose their jobs and become unemployed. In contrast, separations in the textbook model are all layoffs due to job destruction.

The second and third fact documented are not only empirically relevant on their own rights, but also generate interesting interactions as summarized by the vacating channel this paper focuses on. Section 2.2.1 shows that these workers quit to nonparticipation for reasons that are not systematically related to the productivity of their previous jobs or the state of the aggregate economy. However, the vacating channel is absent in standard models, even if one were to introduce employment-to-nonparticipation quits. The third fact points to the root of the problem. Section 2.2.2 shows that vacancies adhere to a law of motion, and vacancy outflows account for most of the vacancy fluctuations. However, the textbook model interprets vacancies as essentially recruiting effort that once it is paid, it is gone. Thus, vacancies are determined solely by the inflow, whereas the realized outflow has no bearing on the vacancy stock.[26] As a consequence, vacancies and labor market tightness are jump variables and can adjust immediately from one period to the next to any type of shock. The key for vacancy behavior to be consistent with these facts and for the vacating channel to be operative is to model vacancies as vacant jobs, therefore the vacating channel of vacancies arises, in addition to the standard job creation channel. Consequently, vacancy outflows into filling and destruction also arise. The vacant-job perspective brings new insights, which we now turn to based on

[26]The employers' belief of the vacancy filling rate does influence the value of a vacancy though and hence vacancy posting decisions. Under rational expectations, the model by construction does not allow for a meaningful distinction between realized and perceived outflows.

a formal framework. It also provides a cautionary note against the widespread practice of interpreting high vacancies as evidence of strong labor demand.

3 Framework

This section proposes a framework to study the aggregate labor market implications of the vacating channel, arising from the interaction between negative labor supply shocks and vacancies. The framework nests the DMP model to facilitate a clear demonstration of the novel mechanisms and a transparent comparison with the textbook benchmark.

3.1 Baseline Model

3.1.1 Environment

Time is continuous. Agents are forward-looking and discount the future at rate r.

Labor Market Status. Workers are in one of the three labor force states—employed workers who are working (e), unemployed workers who are not working but searching (u), and nonparticipants who are not working and not actively searching (n). Transitioning out of and into the nonparticipation state thus captures labor force entry and exit. On the firm side, entrepreneurs create and destroy jobs. Among active jobs, there are filled jobs that are producing (p) and vacant jobs that are not producing but recruiting (v). Jobs can be destroyed and exit the labor market (x).

Idiosyncratic Shocks. Jobs are facing idiosyncratic production shocks. With Poisson rate λ, a job draws a maintenance cost ε from a distribution F^{ε} that has to be paid in order to keep active and continue production. Workers are subject to idiosyncratic preference shocks. With Poisson rate ψ, a worker draws a cost ω from a distribution F^{ω} that has to be endured in order to stay in the labor force. Workers' idiosyncratic preference shocks serve as a means to rationalize the flow rates into out of the labor force for agents without ex-ante heterogeneity.[27,28]

Search and Matching. Labor market frictions are characterized by an aggregate matching function $M(\{U, E, N\}, V)$, where U, E, N, V are the measures of unemployed workers, em-

[27]This formulation could be viewed as a reduced-form representation of explicit worker heterogeneity as modeled by Krusell, Mukoyama, Rogerson, and Şahin (2017). The wording of preference or productivity is only semantic here; the key is whether the shock hits the worker or the job.

[28]A similar preference shock structure has been adopted into a partial equilibrium search model by Sorkin (2018) to rationalize job-to-job transitions with wage decreases and Arcidiacono, Gyetvai, Maurel, and Jardim (2022) to use conditional choice probabilities for identification and estimation, a multisector island model by Pilossoph (2012) to replicate gross intersectoral flows, and a directed search model by Krusell, Luo, and Ríos-Rull (2022) to estimate wage rigidity.

ployed workers, nonparticipants, vacant jobs, respectively.[29] Denote S the measure of total effective searchers, including unemployed workers who actively search (whose search intensity is taken as the unit and hence normalized to 1), nonparticipants who passively search, and employed workers who search on the job, such that the transformed matching function $M(S,V)$ is assumed to exhibit constant returns to scale. Thus the worker contact rate per search intensity is $p(\theta) = M/S$ and job contact rate $q(\theta) = M/V$, where $\theta := V/S$ defines the effective labor market tightness.[30]

Wage Determination. Wage is determined by Nash Bargaining, where the outside option is the value of unemployment for the worker and the value of being vacant for the employer. Firms' maintenance costs and workers' preference shocks are assumed to materialize after the bargaining, and become sunk for the next instant. Hence, realizations of these shocks do not impact the bargained wage. This is equivalent to assuming realizations of idiosyncratic shocks are private information and claiming an arbitrary realization is costless and unverifiable.[31] Workers have a bargaining power of β.

Entry and Exit. There is a flow rate m^j of potential entrants of job opportunities, each of which draws an entry cost c from a distribution $G(c)$. If the potential entrant decides to pay the cost and create the job, she can start recruiting by paying a flow cost κ (e.g., recruiting cost, maintenance cost, rents, etc.). An exiting job delivers a scrap value ς.

3.1.2 Value Functions

Denote V^s the value function of being at state s, where $s \in \{e,u,n,p,v,x\}$ for employed workers, unemployed workers, nonparticipants, producing jobs, vacant jobs, and exiting jobs, respectively. I start by presenting the Hamilton-Jacobi-Bellman (HJB) equations in the steady state, but will analyze both the dynamic stochastic general equilibrium and the transition dynamics in response to aggregate shocks later. Denote φ^{od} the Poisson transition rate between an origin state o and a destination state d.

[29] Note that although job-to-job and nonparticipation-to-employment rates are small relative to the job-finding rate of unemployed workers, these two flows are large in absolute terms. This means employed workers and nonparticipants fill a substantial fraction of vacancies. Therefore, a theory of realistic vacancy dynamics must include both employed and nonparticipant searchers, in addition to the commonly assumed unemployed searchers.

[30] Note that the usual measure of tightness defined as the vacancy-unemployment ratio $\tilde{\theta} := V/U$ differs from the effective tightness θ in this generalized model where unemployed workers are not the only searchers.

[31] The assumption is innocuous. The force at play is a cutoff property above which the realization of the shock leads to workers' labor force exit and below which it does not. Allowing the realization to affect wage bargaining changes the threshold and boils down to a recalibration of the distribution of the preference shock while preserving the targeted flow rates unchanged.

The HJB equation for an employed worker (e) is

$$rV^e = w + \varphi^{eu}\left(V^u - V^e\right) + \varphi^{ee'}\left(V^{e'} - V^e\right) + \psi\left(\int \max\left\{V^e - \omega, V^n\right\} \mathrm{d}F^\omega\left(\omega\right) - V^e\right).$$

The employed worker gets a flow wage of w. With the job destruction rate φ^{eu} (which is endogenously determined and will be explained in the following paragraph), the worker separates from employment into unemployment. With the arrival rate ψ, the worker draws a cost that needs to be paid in order to stay in the labor force, capturing various reasons why a worker may leave the labor force such as caring, disability, retirement. The worker then optimally decides to exit the labor force depending on the realization of the preference shock, based on a cutoff rule that $\omega > V^e - V^n$. This endogenously gives rise to the employment-to-nonparticipation transition rate $\varphi^{en} = \psi\left(1 - F^\omega\left(V^e - V^n\right)\right)$. On-the-job search is introduced in the simplest way as a "godfather" shock nicknamed in the literature, i.e., workers receive offers that they cannot refuse. With rate $\varphi^{ee'}\left(\theta\right)$ that depends on the equilibrium labor market tightness, the employed worker makes a job-to-job transition, but due to the assumption of representative jobs, no pecuniary gains in values are incurred, i.e., $V^{e'} - V^e = 0$.[32]

The HJB equation for a producing job (p) is

$$rV^p = y - w + \varphi^{pv}\left(V^v - V^p\right) + \lambda\left(\int \max\left\{V^p - \varepsilon, V^x\right\} \mathrm{d}F^\varepsilon\left(\varepsilon\right) - V^p\right).$$

The firm claims the residual profit of output y net wage w. With rate φ^{pv}, the job is vacated by worker quits.[33] The job vacation rate is endogenously determined by $\varphi^{pv} = \varphi^{ee'} + \varphi^{en}$, i.e., the sum of job-to-job quit rate and labor force quit rate of the employed worker. With rate λ, the job draws a maintenance cost that has to be paid in order to continue operation. If the realization of the cost is sufficiently large, the firm optimally decides to avoid the cost payment by destroying the job, thus endogenizing the job destruction rate $\varphi^{eu} = \varphi^{px} = \lambda\left(1 - F^\varepsilon\left(V^p - V^x\right)\right)$.

The HJB equation for an unemployed worker (u) is

$$rV^u = z^u + p\left(\theta\right)\left(V^e - V^u\right) + \psi\left(\int \max\left\{V^u - \omega, V^n\right\} \mathrm{d}F^\omega\left(\omega\right) - V^u\right).$$

The unemployed worker enjoys a flow utility of z^u. With rate $\varphi^{ue} = p\left(\theta\right)$, which is a function of the equilibrium labor market tightness, the unemployed worker finds a job and becomes

[32] This simple formulation is in fact consistent with explicitly modeling a job ladder in the sequential auction model à la Postel-Vinay and Robin (2002), where the new employer offers a wage that gives the worker exactly the same value as her previous job. The analytical convenience comes at the expense of abstracting away from the rich wage dynamics associated with workers' on-the-job search as in Postel-Vinay and Robin (2002).

[33] This is reminiscent of a sentence in the classic paper by Blanchard and Diamond (1989): "A quit is associated with the posting of a new vacancy; a job termination is not."

employed. Similar to an employed worker, the unemployed worker is also hit by a preference shock at rate ψ and makes the labor force exit decision based on the realization of the shock. The unemployment-to-nonpartipation transition rate is given by $\varphi^{un} = \psi\left(1 - F^{\omega}\left(V^{u} - V^{n}\right)\right)$.

The HJB equation for a vacant job (v) is

$$rV^{v} = -\kappa + q\left(\theta\right)\left(V^{p} - V^{v}\right) + \lambda\left(\int \max\left\{V^{v} - \varepsilon, V^{x}\right\} \mathrm{d}F^{\varepsilon}\left(\varepsilon\right) - V^{v}\right).$$

The owner of the vacant job pays a flow cost of κ. With rate $\varphi^{vp} = q\left(\theta\right)$, the vacant job is filled by a worker and turns into a producing job. Similar to a producing job, the vacant job is also hit by a maintenance cost shock at rate λ and makes the exit decision based on the realization of the shock. The vacancy destruction rate is given by $\varphi^{vx} = \lambda\left(1 - F^{\varepsilon}\left(V^{v} - V^{x}\right)\right)$.

The HJB equation for a nonparticipant (n) is

$$rV^{n} = z^{n} + \varphi^{ne}\left(\theta\right)\left(V^{e} - V^{n}\right) + \left(m^{w} - \varphi^{ne}\left(\theta\right)\right)\left(V^{u} - V^{n}\right).$$

A worker not in the labor force enjoys a flow utility of z^{n}. With rate m^{w}, the worker enters the labor force. With rate $\varphi^{ne}\left(\theta\right)$, the worker enters the labor force by directly becoming employed. The modeling cost of a constant labor force entry rate is motivated by the empirical observation that it is acyclical. As a consequence, the NU transition rate in the model is given by $\varphi^{nu} = m^{w} - \varphi^{ne}$.

An exiting job (x) obtains the scrap value. Thus, $V^{x} = \varsigma$.

3.1.3 Laws of Motion

I start with the law of motion of vacant jobs, which is one novel element of the model. There are four channels that affect the inflows and outflows of vacant jobs: (1) creation, (2) vacating, (3) filling, and (4) destruction. First, new jobs are created vacant. A potential entrant compares the value of a vacant job with the realized cost of implementing the idea she draws. In particular, a new job is created if $c \leq V^{v}$. Thus the aggregate inflow rate of newly created jobs can be written as $v^{n} = m^{j} G\left(V^{v}\right)$. Second, positions are vacated by workers quitting their jobs at rate φ^{pv}, endogenously determined by workers job-to-job transitions and employment-to-nonparticipation transitions. The vacated positions therefore add to the pool of job openings available for job seekers. Third, vacant jobs are filled at rate φ^{vp}, determined by labor market tightness through the aggregate matching function that summarizes labor market frictions. Lastly, a job can be destroyed when the maintenance cost exceeds the employer's profit from continuing operation. The rate at which a vacant job is destroyed is denoted φ^{vx}. All four channels of vacancy flows

Table 2: Worker Flows and Job Flows in the Model

(a) Worker Flow Rates

Worker Flow	Formula
EU φ^{eu}	$\lambda\left(1-F^{\varepsilon}\left(V^{p}-V^{x}\right)\right)$
EN φ^{en}	$\psi^{e}\left(1-F^{\omega^{e}}\left(V^{e}-V^{n}\right)\right)$
UN φ^{un}	$\psi^{u}\left(1-F^{\omega^{u}}\left(V^{u}-V^{n}\right)\right)$
UE φ^{ue}	$\varphi^{ue}\left(\theta\right)$
EE $\varphi^{ee'}$	$\varphi^{ee'}\left(\theta\right)$
NE φ^{ne}	$\varphi^{ne}\left(\theta\right)$
NU φ^{nu}	$m^{w}-\varphi^{ne}$

(b) Job Flow Rates

Job Flow	Formula
Active Jobs	
VP φ^{vp}	$q\left(\theta\right)$
PV φ^{pv}	$\varphi^{en}+\varphi^{ee'}$
Exit	
PX φ^{px}	$\lambda\left(1-F^{\varepsilon}\left(V^{p}-V^{x}\right)\right)$
VX φ^{vx}	$\lambda\left(1-F^{\varepsilon}\left(V^{v}-V^{x}\right)\right)$
Entry φ^{xv}	$G\left(V^{v}\right)$

Notes: This table summarizes the worker flow rates and job flow rates.

are endogenous. The law of motion of vacant jobs can be written as

$$\dot{V}=\underbrace{v^{n}}_{\text{creation}}+\underbrace{E\varphi^{pv}}_{\text{vacating}}-\underbrace{V\varphi^{vp}}_{\text{filling}}-\underbrace{V\varphi^{vx}}_{\text{destruction}},$$

where the first two channels, creation and vacating, are vacancy inflows, and the last two channels, filling and destruction, are vacancy outflows.

The laws of motion on the worker side are more standard. The law of motion for employment is $\dot{E}=N\varphi^{ne}+U\varphi^{ue}-E\left(\varphi^{eu}+\varphi^{en}\right)$, for unemployment $\dot{U}=N\varphi^{nu}+E\varphi^{eu}-U\left(\varphi^{ue}+\varphi^{un}\right)$, and for nonparticipation $\dot{N}=E\varphi^{en}+U\varphi^{un}-N\left(\varphi^{ne}+\varphi^{nu}\right)$. These equations can be summarized more succinctly in matrix form. Denote the distribution over labor force statuses into a vector $X=(E,U,N)'$. Collect the transition rates into a continuous-time transition matrix given by

$$\varphi=\begin{bmatrix}\bullet & \varphi^{ue} & \varphi^{ne}\\ \varphi^{eu} & \bullet & \varphi^{nu}\\ \varphi^{en} & \varphi^{un} & \bullet\end{bmatrix},$$

with each column summing up to 0, such that the law of motion is given by $\dot{X}=\varphi X$. The transition rates have already been derived in the previous section and are now summarized in Table 2.

Worker flows and job flows are interdependent. For example, either an unemployed worker's job finding (UE) or a nonparticipant's job finding (NE) is associated with a vacancy being filled (VP). An employed worker's job-to-job transition (EE) fills a vacancy but at the same time also vacates a position, hence in net having no direct impact on job flows. In contrast, an employed worker who quits to nonparticipation (EN) vacates her position (PV) without filling another vacancy somewhere else. EU transitions are layoffs associated with job destruction (PX). Transitions between the two non-employed states of workers (UN and NU) do not directly involve job flows. Likewise, transitions between the two non-producing states of jobs, vacancy destruction (VX) and new job creation (XV), do not directly involve worker flows.

3.1.4 Equilibrium

The paper uses three equilibrium notions. The previous section presents the model in its steady state for simplicity. I will study the dynamic stochastic equilibrium with aggregate shocks for business cycle analysis, and the transitional dynamics equilibrium in response to a deterministic aggregate shock to disentangle mechanisms and to study the "Great Resignation" in the quantitative application.

Steady State Equilibrium The steady state equilibrium is defined as a set of value functions $\{V^s\}$ for each state, a set of transition rate policies $\{\varphi^{od}\}$ for each origin and destination pair, a distribution of workers and jobs across labor market statuses U, E, N, V and the resulting labor market tightness θ, such that the HJB equations in Section 3.1.2 hold and the laws of motion in Section 3.1.3 balance inflows and outflows (i.e., give zero net flows).

Dynamic Stochastic Equilibrium Consider aggregate shocks to an aggregate variable A such that with an arrival rate Λ, the aggregate variable evolves according to a stochastic matrix $\Gamma(A'|A)$. In this case, the equilibrium is a set of value functions $\{V^s(\Omega)\}$ that are functions of the aggregate state variables $\Omega := \{A, U, N, V\}$.[34] The dynamic stochastic equilibrium is defined such that the modified HJB equations hold with the understanding that laws of motion hold. For instance, the modified HJB equation for a filled job is

$$\begin{aligned} rV^p(\Omega) &= y(\Omega) - w(\Omega) + \varphi^{pv}(\Omega)\left(V^v(\Omega) - V^p(\Omega)\right) \\ &\quad + \lambda\left(\int \max\left\{V^p(\Omega) - \varepsilon, V^x(\Omega)\right\} \mathrm{d}F^\varepsilon(\varepsilon) - V^p(\Omega)\right) \\ &\quad + \Lambda\left(V^p(A'; U, N, V) - V^p(\Omega)\right) \mathrm{d}\Gamma(A'|A) + \sum_{X \in \Omega \setminus A} \dot{X}(\Omega) \frac{\partial}{\partial X} V^p(\Omega). \end{aligned}$$

The remaining HJB equations are relegated to Appendix II.1.1.

[34] E is a redundant state variable because $U + N + E = 1$.

Transitional Dynamics Equilibrium Consider a deterministic path of a change to an aggregate variable $\{A_t\}_{t=0}^{T}$. In this case, the transitional dynamics equilibrium is a path of value functions indexed by t, $\{\{V_t^i\}\}_{t=0}^{T}$, such that the modified HJB equations hold with the understanding that laws of motion hold. For instance, the modified HJB equation for a filled job is

$$r_t V_t^p = y_t - w_t + \varphi_t^{pv}\left(V_t^v - V_t^p\right) + \lambda \left(\int \max\left\{V^p - \varepsilon, V^x\right\} \mathrm{d}F^{\varepsilon}(\varepsilon) - V^p\right) + \dot{V}_t^p.$$

The remaining HJB equations are relegated to Appendix II.1.2.

3.2 Discussions

3.2.1 Discussion on Limiting Economies

The objective of the model is to introduce minimal changes to the benchmark model so that the vacating channel operates. Thus, I strive for simplicity and stay as close as possible to the textbook DMP model (Pissarides, 2000), in order to transparently study the economic insights of the vacating channel.

The model builds on the textbook DMP model and introduces two novel elements. First, on the employer side, creating a job involves a sunk investment to set up the position in addition to the usual flow recruiting cost, and the position set-up cost is drawn from a distribution that implies a finite job creation elasticity with respect to the value of a vacant job (see Appendix II.2.2) as opposed to infinite job creation elasticity connoted in the usual free entry condition (see Appendix II.3). It collapses to the standard formulation if the entry cost distribution G is degenerate at 0. Second, on the worker side, preference shocks arrive that change workers' labor market attachment. It reduces to the standard formulation if the preference shock distribution F^{ω} is degenerate at 0 (alternatively, the arrival rate of the preference shock is 0). Thus, the textbook DMP model is nested as a limiting economy of this model where the entry cost distribution and the preference shock distribution are both degenerate at 0.

Of course, to carefully close the new model with additional features, the implementation involves a couple of further details. First, I propose a generalized matching function that nests the standard one, as described in Section 4.1. Second, I allow the idiosyncratic production cost to hit not only producing jobs but also vacant jobs, while endogenous vacancy destruction is irrelevant in standard models. As opposed to the first two elements that bring conceptual differences and novel economic insights, the latter two elements, both of which can also be easily shut down in the limiting economy, are primarily for completeness and empirical relevance.

3.2.2 Discussion on Worker Flows and Job Flows

The model features three states on the worker side: employed workers (e), unemployed workers (u), and nonparticipants (n), as well as three states on the job side: filled jobs (p), vacant jobs (v), and destroyed jobs (x). The equilibrium characterizes both gross worker flows among three states and job flows. The model thus provides a parsimonious framework that captures main economic insights emphasized by two classic theories of aggregate labor market fluctuations—the DMP paradigm and the RBC paradigm.

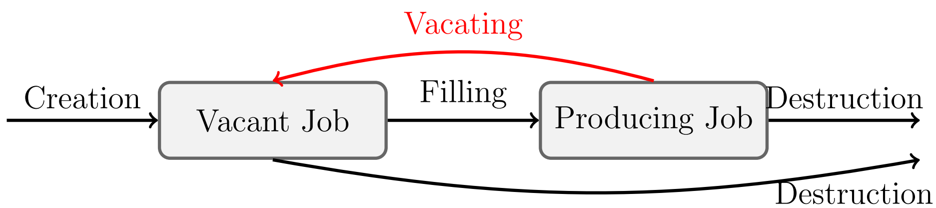
The DMP paradigm in the spirit of Mortensen and Pissarides (1994) emphasizes worker transitions between employment and unemployment. Job findings (UE) arise from the key equilibrating force—the vacancy posting margin (XV), and its subsequent match formation towards production (VP). Separations (EU) arise from job destruction (PX). It does not model vacancy destruction, as vacancies are effectively assumed to be destroyed at the end of each period if not filled. In that sense, vacancies are isomorphic to recruiting efforts. It does not model transitions between in and out of the labor force.

The RBC paradigm in the spirit of Lucas and Rapping (1969), on the other hand, emphasizes the labor supply margin, although it typically focuses on cyclical variations in the stocks of employment and nonemployment, rather than gross worker flows between employment and nonparticipation. In fact, the conventional wisdom extended from the RBC paradigm to flows is counterfactual: it suggests that workers are encouraged to enter the labor market in booms (hence procyclical entry) and leave the labor market in recessions (hence countercyclical exits). In the data, however, the overall labor force entry rate (i.e., NL rate) is acyclical, whereas EN (and UN) exit rates are procyclical. It features a competitive labor market so that there are no unemployed workers or vacant jobs by construction.

This is not the first paper to combine the two paradigms (see Footnote 13 for a discussion of related contributions and see Hagedorn, Manovskii, and Mitman (2020) for empirical evidence). What is novel is the resulting vacating channel—workers' employment-to-nonparticipation quits also generate vacancies, which is absent in previous studies. The vacating channel opens up interactions between workers' labor supply decision highlighted by the RBC paradigm and employers' vacancy posting decision highlighted by the DMP paradigm. Key for the vacating channel to operate is to distinguish between created vacancies and vacated vacancies, with the former requiring a sunk investment for establishing a position and the latter requiring merely a flow recruiting cost. In that sense, the model also incorporates the distinction between entrants and incumbents as emphasized by the industry dynamics paradigm, albeit in a simplistic manner.[35]

[35]For example, it does not feature an endogenous firm size distribution. Nevertheless, Figure A-8 shows that it is a reasonable approximation to abstract away from firm size when discussing aggregate vacancy fluctuation,

Figure 6: The Life Cycle of a Job



Notes: This figure summarizes the life cycle of job.

3.2.3 Discussion on Vacancy Dynamics

A vacancy is part of the life cycle of a job. Figure 6 summarizes the life cycle of job. A job is born vacant, when an entrepreneur creates it (the *creation* channel). A vacant job can also arise from an existing position being vacated by a worker who exits the labor market for reasons unrelated to the job (the *vacating* channel). They form the two sources of vacancy inflows: new jobs that are just created and existing jobs that are just vacated. In the presence of labor market frictions, it takes time for a vacant job to be filled (the *filling* channel). The job will stay vacant until it is filled, after which it starts production. Eventually, a job, either vacant or filled, can be destroyed due to negative shocks to the job (the *destruction* channel), completing the life cycle of the job. The latter two channels form vacancy outflows. Note that standard theories conceptualize vacancies as arising only from the creation channel as in the job creation equation of the canonical model, and conceptualize separations as induced by the destruction channel as in the job destruction equation. The vacant job perspective leads to rich vacancy dynamics featuring four vacancy channels: creation, filling, vacating, and destruction. That is,

$$\Delta\text{Vacancies} = \underbrace{\text{Creation} + \text{Vacating}}_{\text{Inflows}} \underbrace{-\text{Filling} - \text{Destruction}}_{\text{Outflows}}.$$

Creation. In the textbook Mortensen and Pissarides (1994) model and the majority of studies following the DMP paradigm with free entry, the only vacancy channel is the *creation* channel. All unfilled vacancies disappear at the end of each period and do not affect the vacancy stock in the following period (see Appendix II.3 for a detailed discussion).

Filling. The filling channel natural arises once the model deviates from the jump variable representation of vacancies rendered by the free-entry condition. Recent work by Coles and Moghaddasi Kelishomi (2018); Haefke and Reiter (2020) illustrate the cyclical implication of the filling channel that in recessions, a higher number of unemployed workers depletes the existing vacancy stock faster. The filling channel is also implicitly present in stock-flow matching models such as Coles and Smith (1998); Ebrahimy and Shimer (2010) and frictional sorting models such

most of which comes from the extensive rather than intensive margin.

as Shimer and Smith (2000); Hagedorn, Law, and Manovskii (2017); Huang and Qiu (2021).

Destruction. Although destruction of filled jobs is widely studied, destruction of vacant jobs is often overlooked. Vacancy destruction is conceptually similar to the destruction channel emphasized by Carrillo-Tudela, Clymo, and Coles (2021) when firms do not replace workers who quit. They show that it accounts for the slow recovery of unemployment.

Vacating. The key novelty of this paper is to study the vacating channel—when a worker leaves the labor force for nonmarket reasons, she vacates her job. For a particular establishment, both EN quits and job-to-job quits are associated with vacation of an existing position. Thus, at the micro level, the vacating channel this paper studies is similar to the "vacancy chains" mechanism (Akerlof, Rose, and Yellen, 1988; Faberman and Nagypal, 2008; Mercan and Schoefer, 2020; Elsby, Gottfries, Michaels, and Ratner, 2021; Acharya and Wee, 2020). But at the macro level, the vacating channel directly generates one vacancy whereas job-to-job transitions do not directly generate vacancies (as a job-to-job transition generates a vacated vacancy at one establishment but at the same time fills a vacancy at another establishment).

4 Business Cycles

4.1 Calibration Strategy and Identification

This section studies the business cycle version of the model with an aggregate productivity shock. I calibrate the model to match business cycle facts in the US labor market, including means of the gross worker flow rates and standard deviations of the cyclical components of the gross worker flow rates.

External Targets. I set the discount rate to the conventional value of $r = 0.0033$ that corresponds to an annual interest rate of 4%. I calibrate the worker bargaining power to micro estimates of rent-sharing elasticities that consistently point to around 0.103, as is reviewed by Card, Cardoso, Heining, and Kline (2018); Jäger, Schoefer, Young, and Zweimüller (2020).[36] I set z^u to 0.47 according to the estimate by Chodorow-Reich and Karabarbounis (2016), and increase it by 0.33, the estimated value of home productivity in Bridgman (2016), to set z^n. The aggregate productivity process is taken from Hagedorn and Manovskii (2008), who estimate an AR(1) process at the weekly frequency with an auto-correlation of 0.9895 and a standard deviation of the innovation of 0.0034. I set $z^u_t = z^u A_t$ and $z^n_t = z^n A_t$ in line with the empirical evidence in Chodorow-Reich and Karabarbounis (2016), and $\kappa_t = \kappa A_t$ consistent with Hagedorn and Manovskii (2008). Note that the procyclicality of z and κ induces further challenge

[36] See Figure A-7 for a summary of estimates from the rent-sharing literature.

for the model to produce large fluctuations. These parameters are summarized in the top panel of Table 3.

Note that I studiously deviate from the calibration of $z^u = 0.955$ proposed by Hagedorn and Manovskii (2008), which is a well-known calibration that replicates volatility of labor market fluctuations in the DMP model. Instead, I calibrate it to a much lower value of $z^u = 0.47$ as suggested by Chodorow-Reich and Karabarbounis (2016). Crucially, I set the elasticity of the z's with respect to productivity to be 1, in line with CRK's estimates. Their estimated low level and high procyclicality of the flow value of unemployment pose a substantial challenge to search and matching models in replicating empirically sensible labor market fluctuation. I show that the "augmented" unemployment volatility puzzle is resolved once the vacancy channels in this paper are considered.

External Estimation: The Matching Function. The matching function is parameterized to have a Cobb-Douglas form $M(S,V) = \alpha S^{\gamma} V^{1-\gamma}$, such that the worker contact rate per search intensity is $p(\theta) = \alpha\theta^{1-\gamma}$ and the job contact rate is $q(\theta) = \alpha\theta^{-\gamma}$. I propose a novel formulation for the measure of total effective searchers defined implicitly as

$$S = \phi_u p^{\xi_u - 1} U + \phi_e p^{\xi_e - 1} E + \phi_n p^{\xi_n - 1} N,$$

where $p := M/S = \alpha\theta^{1-\gamma}$ is the job-finding rate per search intensity and hence captures the extent of labor market tightness from the job searchers' perspective. The elasticity parameter ξ_s captures the responsiveness of job-finding behavior for an s-state worker in response to a change in the aggregate job-finding behavior, and the scale parameter ϕ_s captures the relative level of the search intensity. Normalize $\phi_u = 1$ and $\xi_u = 1$ so that the aggregate job-finding rate is defined from the perspective of the unemployed, i.e., $p = \varphi^{ue}$.

Standard formulations assume that unemployed workers search with a normalized intensity of 1, nonparticipants search with constant intensity ϕ^n (passive search), and employed workers search with constant intensity ϕ^e (on-the-job search). Thus the measure of effective searchers is $S := U + \phi^e E + \phi^n N$, where U, E, N are the measure of unemployed workers, employed workers, and nonparticipants, respectively. Our novel formulation nests the standard formulation that assumes a unit elasticity that is identical across labor force statuses, namely, $\xi_e = \xi_n = 1$. I instead flexibly estimate the value for ξ_e and ξ_n in the data. In particular, this generalized formulation of effective searchers implies that

$$\log \varphi^{ee'} = \log \phi_e + \xi_e \log \varphi^{ue}, \quad \log \varphi^{ne} = \log \phi_n + \xi_n \log \varphi^{ue}.$$

I empirically estimate this relationship in the data using the time series data on $\varphi^{ue}, \varphi^{ee'}, \varphi^{ne}$

Table 3: Calibrated Parameters

Param.	Value	Target	Param.	Value	Target
External Calibration					
r	0.0033	Annual interest rate	β	0.1030	Rent sharing elasticity
z^u	0.47	CR-K (2016)	z^n	0.80	Bridgman (2016)
ρ_A	0.9895	Hagedorn-Manovskii	σ_ε	0.0034	Hagedorn-Manovskii
External Estimation: Matching Function					
ξ_u	1	Normalization	ϕ_u	1	Normalization
ξ_e	0.2760	Regress $\log \varphi^{ee'}$ on $\log \varphi^{ue}$	ϕ_e	0.0339	$\varphi^{ee'} / (\varphi^{ue})^{\xi_e}$
ξ_n	0.2619	Regress $\log \varphi^{ne}$ on $\log \varphi^{ue}$	ϕ_n	0.0581	$\varphi^{ne} / (\varphi^{ue})^{\xi_n}$
γ	0.4029	Regress $\log \varphi^{ve}$ on $\log \theta$	α	0.7991	$\varphi^{ue}/\theta^{1-\gamma}$
Internal Estimation					
μ^{en}	-0.2341	Mean of EN rate	ν_{en}	0.131	Std of EN rate
μ^{un}	-0.1891	Mean of UN rate	ν_{un}	0.065	Std of UN rate
μ^x	2.2633	Mean of EU rate	ν_x	0.304	Std of EU rate
κ	0.172	Std of UE rate	ξ	10.7	Std Share of Vacated Vac.

Notes: This table reports parameters, calibrated values, and targets informative to identifying those parameters.

that are seasonally adjusted, quarterly averaged, logged, and HP-filter detrended, as is the common practice in the literature. The first regression gives an estimate of $\xi_e = 0.3481$ (with a standard error of 0.0247 and R-squared of 0.68) and the second regression gives an estimate of $\xi_n = 0.2619$ (with a standard error of 0.0119 and R-squared of 0.70). I then target the steady state levels of the job-to-job rate relative to the job-finding rate, and the nonparticipation-to-employment rate relative to the job-finding rate, which identifies $\phi_e = 0.0339$ and $\phi_n = 0.0581$, respectively.

Finally, I obtain γ by regressing the (log detrended) vacancy filling rate (see Appendix III.1 for details) on (log detrended) labor market tightness, where the tightness is measured directly as $\log \varphi^{ue} - \log \varphi^{ve}$. Consistency with the matching function thus implies a value of $\alpha = \varphi^{ue}/\theta^{1-\gamma}$. The 8 parameters of the matching function discussed in this subsection are summarized in the second panel of Table 3.

Internal Estimation: Inner Loop (Method of Moments). Given the parameters to be estimated in the outer loop (see below), I estimate three parameters—the means of the idiosyncratic shocks—by targeting the relevant steady state level of the corresponding worker flow rate. Specifically, the EU rate identifies the mean of the job destruction shock, and the EN and UN rates identify the mean of the preference shock that hits the employed and unemployed workers, respectively. Moving these parameters to an inner loop reduces the computational burden of estimating the outer loop, which is very costly.

Since I do not directly observe vacancy destruction in the data, I assume that the production shocks that hit vacant jobs follow the same process as those that hit producing jobs. Note also that the arrival rates are not separately identified from the mean of the shocks using only data on worker flows. The idea is that, for instance, a higher employment-to-nonparticipation rate could be consistent with either a higher value of the preference shock for staying at home, or a higher frequency that the shock hits. I thus normalize the arrival rates $(\lambda, \psi^{en}, \psi^{un})$ so that the transition realizes on average one out of five times that the shock arrives. The 3 parameters of the inner loop estimation are summarized in the third panel of Table 3.

Internal Estimation: Outer Loop (Simulated Method of Moments). The outer loop involves matching business cycle moments through the simulated method moments. Specially, for a given guess of parameters, I solve the business cycle version of the model. Using the solution, I then simulate 1000 time series of the aggregate labor market variables. For each simulated time series, I take logs, quarterly average, and HP-filter, and calculate the standard deviation of the detrended series, and average the statistics across the 1000 simulations for each guessed set of parameters. If the resulting simulated moments do not match the business cycle moments calculated in the data using a similar procedure, I pick another guess of parameters until the moments match. Note that it is a challenging estimation problem which involves solving the dynamic stochastic business cycle model and simulating thousands of paths of histories for each guess of parameters, and searching for many parameters jointly by matching the simulated business cycle moments to data.

I estimate three parameters—the standard deviations of the idiosyncratic shocks—by targeting the relevant business cycle second-order moments of the corresponding worker flow rate. Specifically, the standard deviation of the detrended EU rate identifies the standard deviation of the job destruction shock, and the standard deviations of the detrended EN and UN rates identify the standard deviations of the preference shock that hits the employed and unemployed workers, respectively. The volatility of job finding rate relies on the response of vacancies, hence providing information on κ conditional on other vacancy channels. Finally, the volatility of the replacement hiring over the business cycle identifies the job creation elasticity. The 4 parameters of the outer loop estimation are summarized in the bottom panel of Table 3.

In practice, I parameterize the distribution of idiosyncratic shocks as generalized logistic (the difference between two extreme value variables is distributed logistic). It has been a popular functional form assumption in the empirical micro literature due to its tractability (Appendix

II.2.1 derives useful propositions). Following Coles and Moghaddasi Kelishomi (2018), I parameterize the distribution of the sunk investment cost so that new job creation exhibits a constant elasticity ξ with respect to the value of a vacant job. I provide an explicit micro-foundation of a distribution that is consistent with the isoelastic job creation in Appendix II.2.2.

4.2 Model Validations

Table 4 reports the model fit in the first order moments and second order moments of worker flow rates. As shown in the table, the model not only matches the levels of all 7 worker flow rates in the steady state, but also matches the volatility of all 7 worker flow rates over the business cycle. The model is already impressive as it reproduces large fluctuations as in the data, and is hence capable of solving the Shimer (2005) puzzle and the Chodorow-Reich and Karabarbounis (2016) puzzle.[37] Nevertheless, these unconditional standard deviations are targeted moments after all. This section thus conducts several tests of the model to evaluate its performance along a few untargeted dimensions.

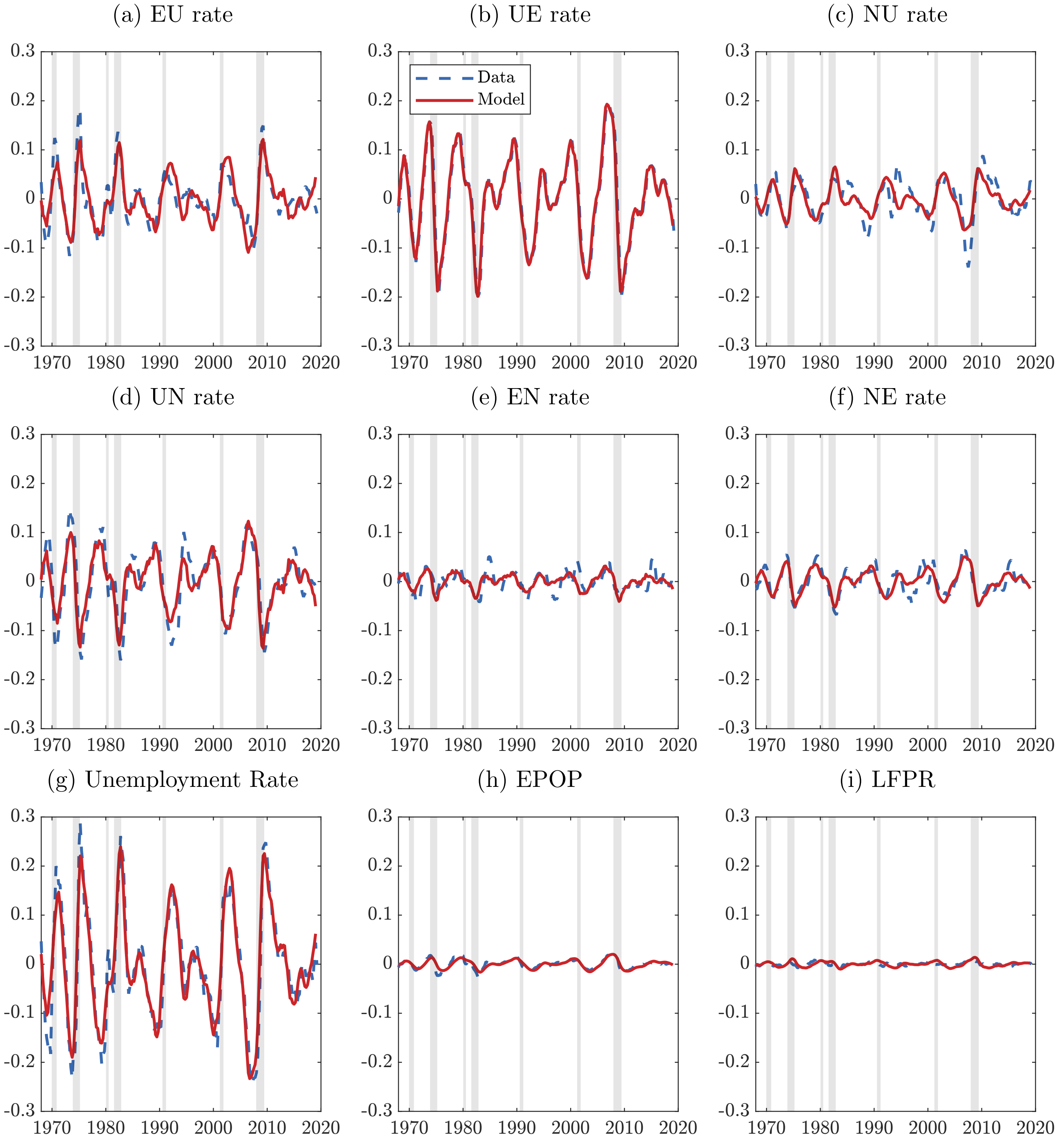
4.2.1 Labor Market History

First, I assess the model's ability to reproduce the US labor market history. To do so, I ask the model to match the history of the (log detrended) job finding rate, by selecting a path of realized aggregate productivity shocks. I then input the path of realized aggregate productivity shocks into the model to determine its predictions on other objects, including all gross worker flow rates and labor market stock variables such as unemployment rate, employment-population ratio, and labor force participation rate.

In Figure 7, red solid lines report the simulated history and blue dashed lines the actual history of the US labor market. Note that in Panel (b), the UE rate is matched exactly, as it is targeted when finding the path of realized aggregate productivity shocks. All other panels are untargeted, yet the model produces a very good match to the evolution of these variables, as the red lines and blue lines are almost on top of each other. Since the model matches all worker flow rates, it is thus not surprising that the model also matches the stocks well. Specifically, the model predicts both large volatility and countercyclicality of the unemployment rate, and the small volatility and procyclicality of the employment-population ratio and the labor force

[37] Shimer (2005) poses two puzzles that conventional search and matching models fail to address: first, under an empirically sensible productivity process, the model fails to reproduce the large labor market fluctuations as observed in the data; second, once countercyclical job destruction is introduced, the model predicts a counterfactual upward-sloping Beveridge curve. Chodorow-Reich and Karabarbounis (2016) shows that when the opportunity cost of employment is procyclical, the model has barely any fluctuations. The model proposed in this paper resolves all these "puzzles."

Figure 7: External Validation—Labor Market History



Notes: This figure plots the simulated and actual labor market history of the gross worker flow rates (EU, UE, NU, UN, EN, and NE rates) and stock variables (unemployment rate, employment-population ratio, and labor force participation rate). NBER dated recessions are shaded.

Table 4: Model Fit

	First Order Moments		Second Order Moments	
	Data	Model	Data	Model
EU rate	0.0195	0.0195	0.0534	0.0532
UE rate	0.3667	0.3667	0.0889	0.0865
NU rate	0.0358	0.0358	0.0400	0.0291
UN rate	0.3180	0.3180	0.0694	0.0676
EN rate	0.0294	0.0294	0.0209	0.0220
NE rate	0.0447	0.0447	0.0278	0.0226
EE rate	0.0239	0.0239	0.0300	0.0301

Notes: The first order moment refers to the average in the data and the steady state level in the model. The second order moment refers to the standard deviation of the series that is (seasonally adjusted in the data), quarterly averaged, logged, and HP-detrended.

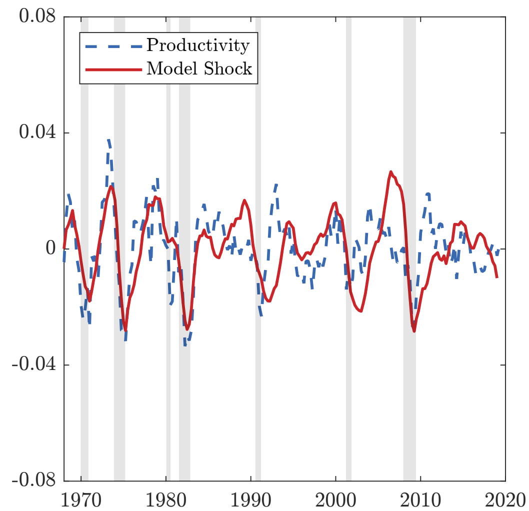
participation rate.

The business cycle model has only one aggregate shock, namely the aggregate productivity shock A_t. Figure 7 seems to suggest that the one-shock model is adequate to account for labor market fluctuations. Figure 8 explicitly compares the implied path of aggregate productivity in the model (red solid line) with the measured labor productivity in the data (blue dashed line), defined as value added per employment. The model can generate large fluctuations with a small productivity shock, as observed in the data. Prior to the 1990s, the model-implied productivity path and the data-measured productivity path are tightly overlapped, indicating a good fit of the model. After the 1990s, however, the model-implied productivity path lags the measured productivity path. This corresponds to the well-documented phenomenon of "jobless recoveries"—employment recovers much slower than productivity—witnessed in the US labor market after the 1990s. It is not the objective of this paper to provide a resolution to the "jobless recoveries." One potential solution could be unemployment benefit extensions as demonstrated in Mitman and Rabinovich (2019).

4.2.2 Impulse Response

In the calibration, I target *unconditional* moments such as standard deviations of the worker flow rates, following the tradition of the literature. Another test of the model is to examine its predictions on *conditional* moments, such as impulse response functions. In the model, the impulse responses of each variable are calculated by solving the transitional dynamics equilibrium with a deterministic path of geometrically decaying aggregate productivity. In the data, the

Figure 8: Model-Implied Shock vs. Labor Productivity Data

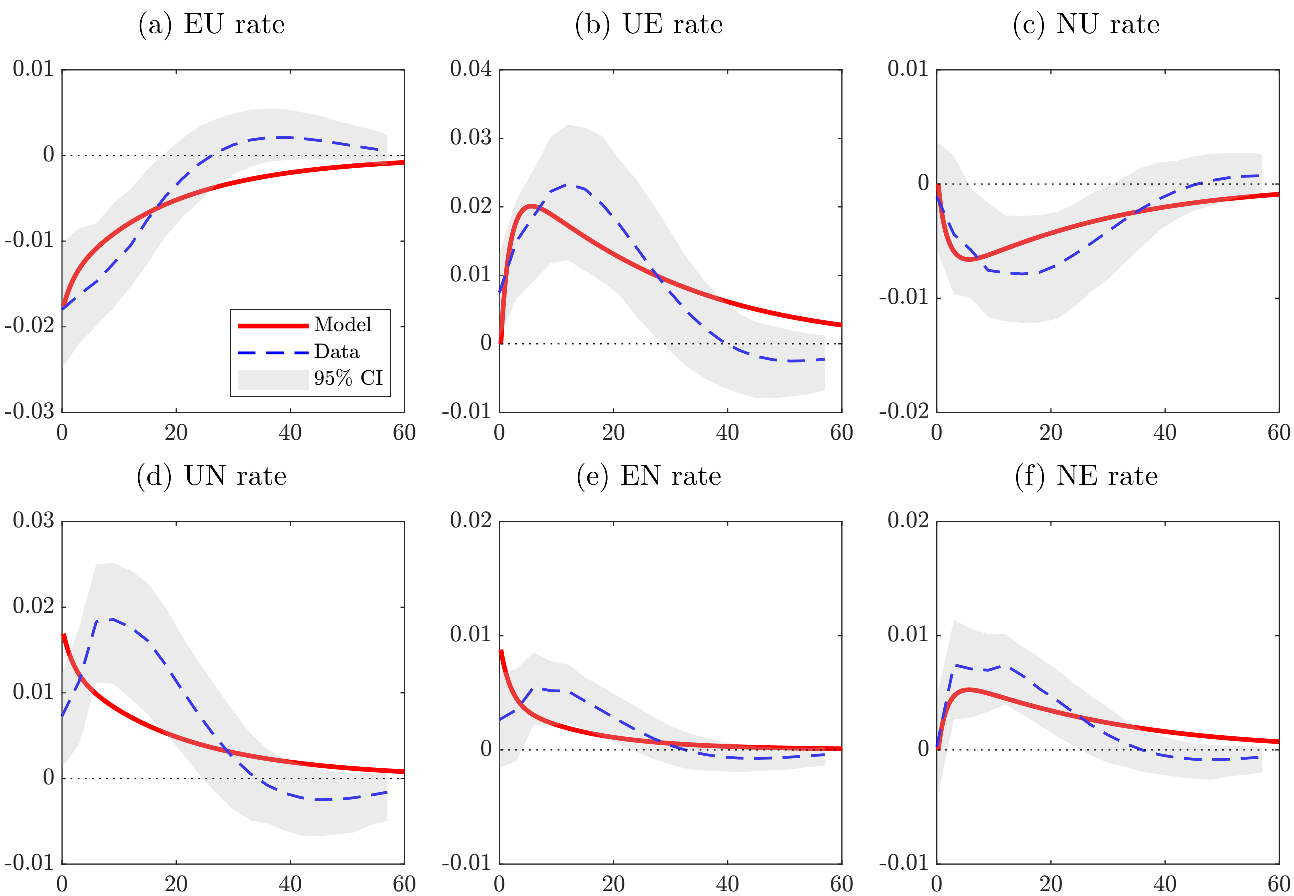


Notes: This figure plots the model-implied shock with labor productivity data. NBER dated recessions are shaded.

impulse responses of each variable are estimated by a vector auto-regression (VAR) model. The IRFs to an aggregate productivity shock are identified by the Cholesky decomposition where labor productivity is ordered first. Figure 9 plots the impulse response functions for each worker flow rates in response to a 1% drop in the aggregate productivity, both in the model (red solid lines) and in the data (blue dashed lines). Although these moments are completely untargeted, the model predicts plausible dynamics.

Suppose the aggregate productivity improves. Given that jobs are more productive now, employers are less likely to destroy them even when confronted with a relatively large production cost, which would otherwise induce job destruction. As a result, the threshold for job destruction increases and the EU rate falls. As unemployment decreases while vacancies increases, the labor market becomes tighter. Therefore, the UE job finding rate increases. Similarly, the NE job finding rate of nonparticipants also increases due to a tighter labor market. Constrained by the empirical property of the acyclical labor force entry rate, that is, the sum of NE and NU rate is roughly constant over the business cycle, it has to be that NU rate decreases in response to an increase in aggregate productivity. As the labor market gets tighter, the job finding prospects improve, and workers are less reluctant to exit the labor force. Consequently, the UN and EN rate increase, as they do in the data. The model is thus capable of reproducing the cyclical dynamics of all worker flow rates.

Figure 9: External Validation—Impulse Response Function of Worker Flow Rates



Notes: This figure plots the impulse response functions of the EU, UE, NU, UN, EN, and NE rate, in response to a one standard deviation in the aggregate productivity.

4.2.3 Flow Decompositions

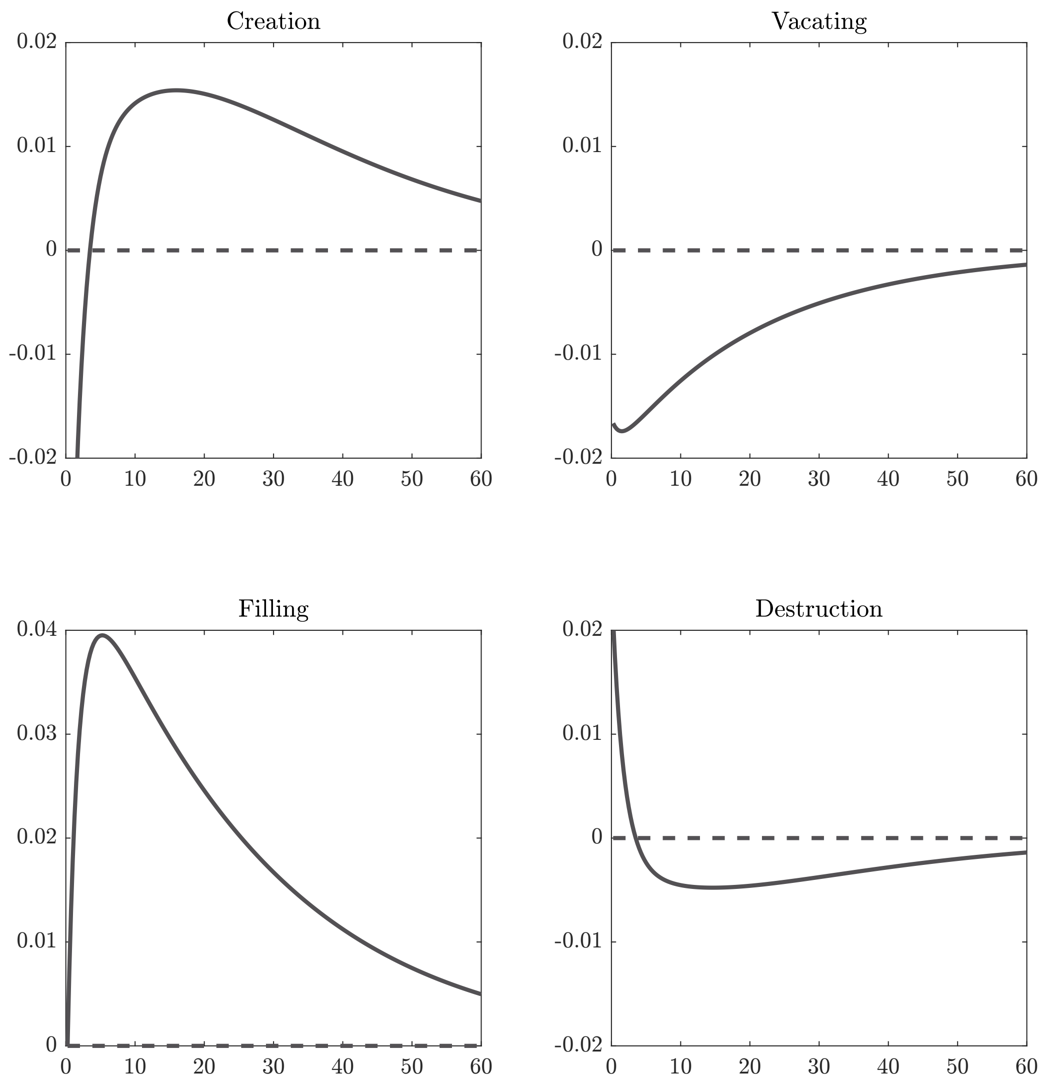
Figure 11 plots the unemployment (Panel a) and vacancy dynamics (Panel b) in the model in response to a 1% drop in the aggregate productivity. First, both unemployment and vacancies respond a lot to a small drop of aggregate productivity, resolving the first Shimer (2005) puzzle. Second, despite featuring countercyclical job destruction, the model still generates downward-sloping Beveridge curve as vacancies move in the opposite direction to unemployment, thus resolving the second Shimer (2005) puzzle.

Moreover, the inflow-outflow decomposition of unemployment and vacancy dynamics in Figure 11 are consistent with their empirical counterpart. It is well documented that job-finding rate (unemployment outflow rate) accounts for the majority of the unemployment fluctuations. I have provided the new finding in Section 2.2.2 that vacancy outflow accounts for the majority of the vacancy fluctuation over the business cycle.

4.3 Model Mechanisms

How does the model achieve desirable business cycle properties and get around the issue pointed out by Chodorow-Reich and Karabarbounis (2016)? It is instructive to zoom in into the four vacancy channels captured by the model. Vacancies arise when jobs are created and vacated, and disappear when filled or destroyed. Figure 10 plots the impulse response functions of the creation, vacating, filling, and destruction channel, in response to a 1% drop in the aggregate productivity.

Figure 10: Impulse Response Function of Vacancy Channels



Notes: This figure plots the impulse response functions of the creation, vacating, filling, and destruction channel, in response to a 1% drop in the aggregate productivity.

The *creation* channel first dips at the outset of a negative productivity shock, capturing that a drop in productivity discourages employers' job creation. This effect, however, is very temporary, and disappears immediately after a couple of months, reminiscent of the first Shimer

(2005) puzzle of the lack of job creation response. In fact, it even becomes slightly positive after a few months, illustrating the second Shimer (2005) puzzle of a counterfactual Beveridge curve. Note that the fact that the standard DMP with free entry predicts counterfactual Beveridge curve whereas the vacant jobs model restores it is reminiscent of the insight in Caballero and Hammour (1996) that the presence of specific investment restores the Beveridge curve by decoupling job creation and job destruction, albeit in a different framework.

The *filling* channel goes up. Note that the filling channel composes one of the outflows of vacancies, so an increasing filling channel implies a decreasing number of vacancies. This means when aggregate productivity drops, vacancies decrease because it is being filled at a faster speed. This channel has been at the center of the discussion in Coles and Moghaddasi Kelishomi (2018) and Haefke and Reiter (2020). In fact, this effect is both large and persistent, consistent with the empirical finding in Section 2.2.2 that vacancy outflow is an important aspect of vacancy dynamics.

The *vacating* channel leads to a decline in vacancies. This is due to procyclical job-to-job and EN quits. It is worth pointing out that EN quits have different aggregate impacts than job-to-job quits. A job-to-job quit generates a vacancy through the vacating channel, but at the same time, it also depletes a vacancy through the filling channel. In contrast, an EN quit generates a vacancy through the vacating channel, but it does not deplete a vacancy anywhere else until the nonparticipant finds a job, which on average will take a long time. Thus, EN quits become a potentially important source of the aggregate vacancy inflow through the vacating channel. The next subsection will quantify the magnitude of this mechanism.

Lastly, the *destruction* channel first spikes, reflecting vacancy destruction, a similar force to job destruction. To the extent that the negative productivity shock reduces the value of a job and hence a vacant job, employers are more likely to exit when facing idiosyncratic production cost. The logic holds for both filled and vacant jobs. However, this force dissipates rather quickly.

4.4 Does the Participation Margin Matter in the Theory of Unemployment?

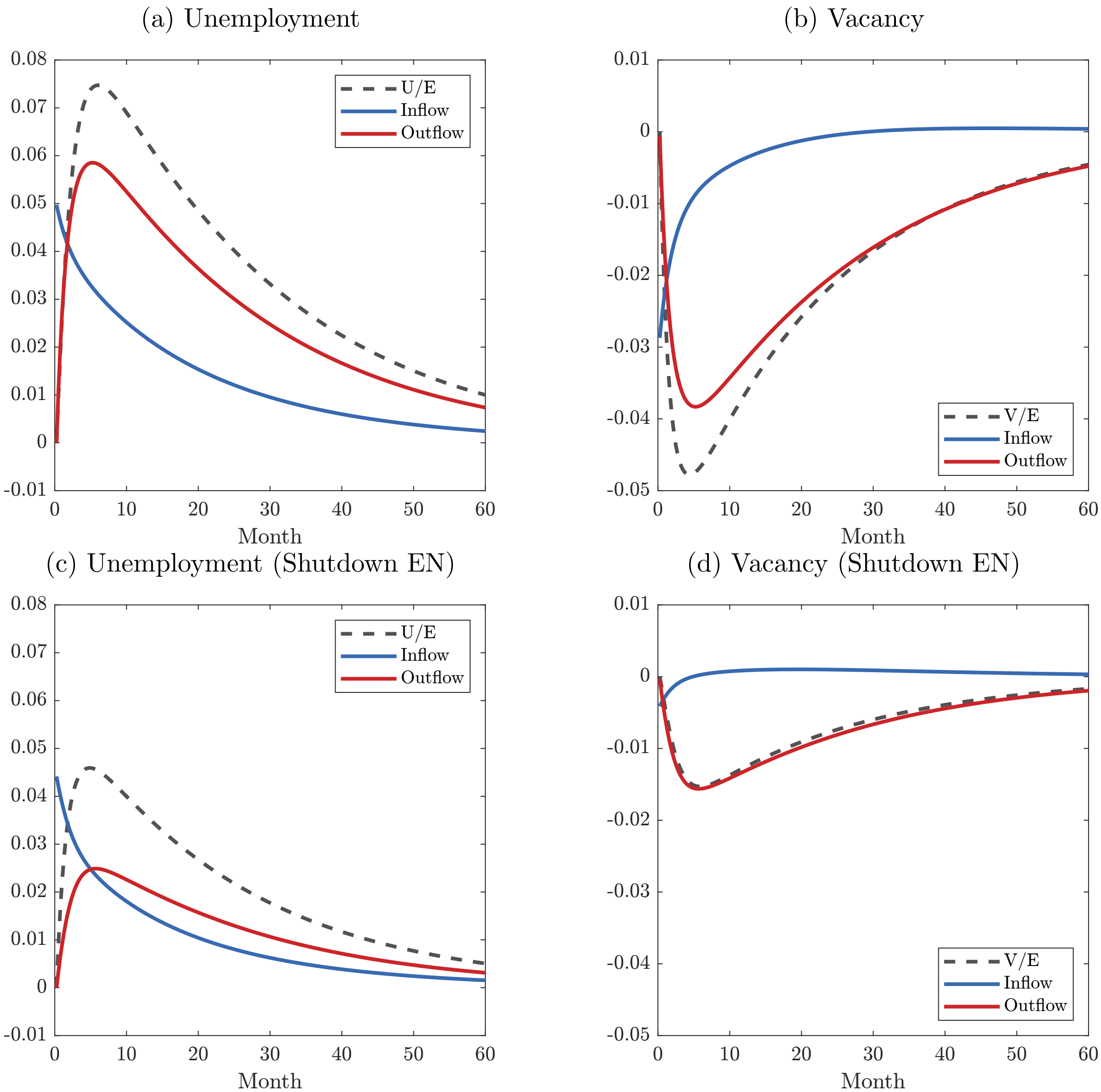
Does the participation margin matter in the business cycle theory of unemployment? The conventional wisdom is that it does not do much. That conclusion is based on the three-state inflow-outflow decomposition of unemployment. This accounting exercise typically reveals a minor role in the participation margin, whereas job finding is often revealed to play an important role in accounting. The previous analysis, however, hints at a potentially important role of EN quits in determining unemployment fluctuations because EN quits are an important source of vacancy fluctuations through the vacating channel, which in turn are an important source of unemployed workers' job finding fluctuations.

To formally quantify the importance of this channel, I consider a counterfactual economy where the employment-to-nonparticipation quit is acyclical. To achieve so, I set the standard deviation of the preference shock associated with the EN quit to be large, but I recalibrate the mean of the preference shock so that the steady-state level of the EN quit rate is unchanged. When the preference shock has a large variance, the aggregate flow rate does not capture the systematic difference between the value of the employment and nonparticipation state, but purely reflects the idiosyncratic preference shock. As a result, the EN quit rate is acyclical over the business cycle as long as the preference shock structure is stable. This provides a counterfactual economy where procyclical EN quit is shut down, whereas the rest of the economy is the same as the baseline economy.

Figure 11 plots the resulting response on unemployment (Panel c) and vacancies (Panel d) in response to the same 1% drop in the aggregate productivity, but in the counterfactual economy where the EN rate is acyclical. For the ease of comparison, I plot Panel (c) and (d) in the same scale as Panel (a) and (b). It is striking that shutting the procyclicality EN rate alone (while preserving its magnitude) dampens the job-finding rate fluctuation by more than half and the unemployment fluctuation by more than one-third. To see this, note that the standard deviation of the (logged, detrended) UE job finding rate in the baseline model is 0.0865, but only 0.0368 in the counterfactual economy with acyclical EN quits, dropping by 57%. Similarly, the maximal unemployment response is 7.5% in the baseline economy, but only 4.8% in the counterfactual economy, dropping by 36%.

Therefore, I conclude that the participation margin matters a lot in the business cycle theory of unemployment. In particular, the procyclical EN quit is responsible for more than half of the UE job finding volatility and for one-third of the unemployment fluctuation over the business cycle. Note that this finding is still consistent with an accounting decomposition that job-finding fluctuations account for most unemployment fluctuations. However, our analysis reveals that an important source of the job-finding fluctuations, which is an immediate result of vacancy fluctuations, is coming from the fluctuations in the EN quit rate through the vacating channel. Although the fluctuation in the EN quit rate appears small at first glance, it is economically large. The reason is that the denominator of the EN rate, namely, employment, is large. Thus, a small change in the EN rate in fact results in large fluctuations in vacancies through the vacating channel.

Figure 11: Inflow-Outflow Decomposition of Unemployment and Vacancy Dynamics



Notes: This figure plots the unemployment (left panel) and vacancy (right panel) dynamics in the model in response to a 1% drop in the aggregate productivity. The dashed black lines plot the impulse response function of U/E ratio and V/E ratio, respectively. The red and blue lines plot the outflows and inflows, respectively.

5 Other Applications

5.1 Labor Market Response to Interest Rate Changes

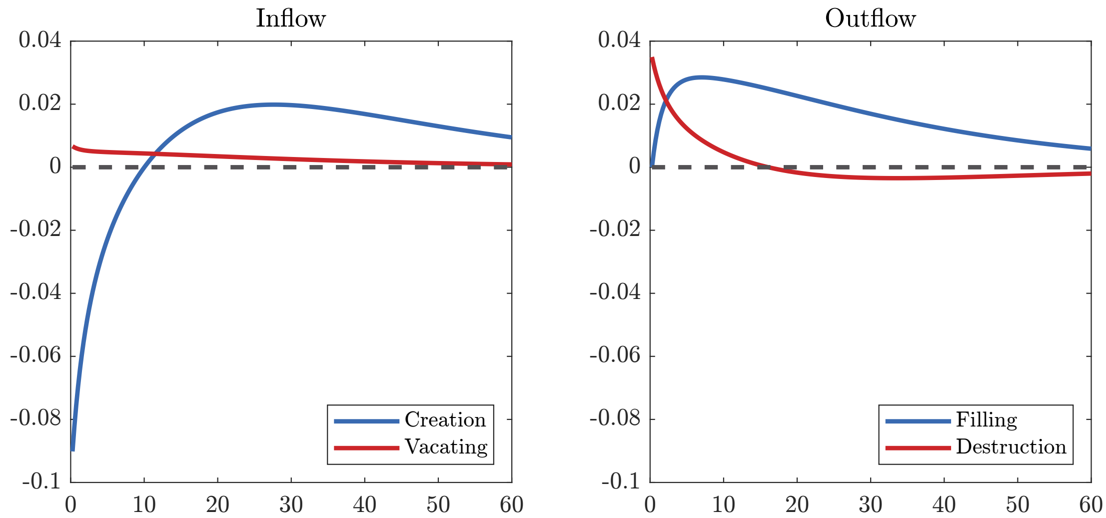
How does the labor market respond to changes in interest rates? A higher interest rate implies a lower present value of an asset and hence discourages investment activities. Thus, employers' incentive for creating new jobs, as any other types of investment, is depressed. According to the DMP view of the labor market, the number of vacancies tends to fall and unemployment tends to rise (Hall, 2017).

This paper highlights another source of vacancies—vacancies arise not only because employers create new jobs, but also because workers vacate existing jobs. The defining feature of an existing job is that it has already been put in place and has embodied the sunk investment in the position. New job creation, as an investment activity, is indeed very responsive to changes in interest rates. Reposting an existing job vacated by workers quitting the job, however, is not, as the employer has already paid the sunk investment of setting up the position. Thus, the overall labor market response crucially depends on the composition of these two sources of vacancies. The impact of interest rate on vacancies and unemployment would be attenuated when worker vacating dominates job creation. This insight provides a novel perspective in understanding monetary transmissions into the labor market and is particularly relevant to the current debate on the possibility of a "soft landing" in the post-pandemic labor market with the so-called "Great Resignation," which we will turn to in the next subsection. Prior to that, I first present the model mechanisms and the empirical evidence for this insight.

To formalize the above intuition, I conduct the following experiment to illustrate how different vacancy channels respond to interest rate shocks. Consider an interest rate shock of 1 percentage point (or, 25% deviation from the baseline value). Figure 12 reports the impulse response functions of different vacancy channels under the calibrated model discussed in Section 4. The left panel plots the response of the two inflow channels. In response to a 1 percentage point increase in the real interest rate, the creation channel is depressed by almost 10%. This is because job creation is an investment activity that pays the sunk cost today but only reaps the benefits in the future, consistent with the conventional wisdom that a higher interest rate discourages job creation. The vacating channel, in contrast, is barely changed. If anything, the vacating channel is even increased a little bit. This result formalizes the insight that the job creation channel of vacancies and the worker vacating channel of vacancies respond differently to a tightening monetary policy, and the aggregate impact depends on which channel dominates.

As for the outflow channels, both the vacancy filling channel and the vacancy destruction channel respond in the expected direction, but the effect is small compared to the response of

Figure 12: Impulse Response Function of Vacancy Channels

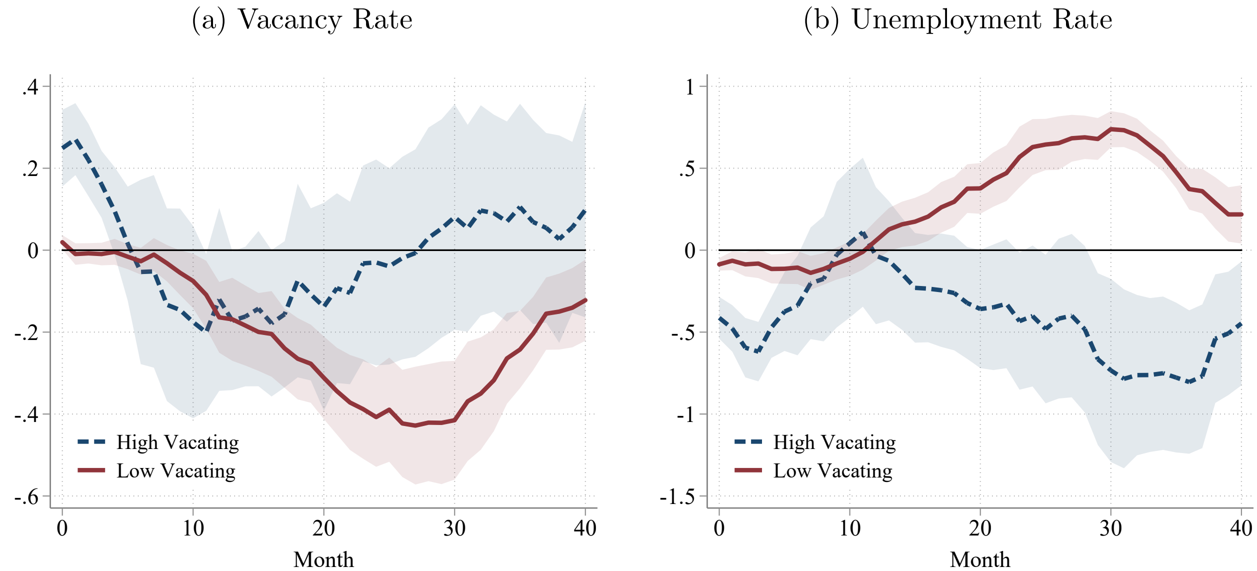


Notes: This figure plots the impulse response functions of the creation, vacating, filling, and destruction channel, in response to a 1 percentage point increase in the annual real interest rate.

the job creation channel. Moreover, the filling channel itself represents an equilibrium feedback effect because it depends on the changing labor market tightness that results from the responses of the inflow channels in the first place. The filling channel is persistent due to the stock nature of the aggregate vacancies. The vacancy destruction channel is reminiscent to the job destruction channel highlighted in Martellini, Menzio, and Visschers (2021), who show that in a model with endogenous separations, an increase in the real interest rate not only lowers the job finding rate, but also lowers the separation rate. Their mechanism is also featured in the model.

To empirically test such prediction in the data, I adopt the local projections method proposed by Jordà (2005) and its extension for instrumental variable estimates, known as "local projections-IV" (or LP-IV), as in Stock and Watson (2018). To identify how the labor market impact of interest rate changes depends on the prevalence of worker vacating, I include an interaction term between the interest rate and an indicator for high or low worker vacating. The local projections estimation technique is particularly suited here, as it flexibly allows heterogeneous effects by a current state, without placing any restrictions on the evolution of the state (see, e.g., Ramey and Zubairy, 2018). For a measure of exogenous monetary policy shocks, I use the narrative-based monetary policy shock series proposed by Romer and Romer (2004) and updated by Wieland and Yang (2020). Compared to other measures of monetary policy shocks, the primary benefit of the narrative identification is its coverage for a longer sample period, which permits enough variations in different levels of aggregate vacating. I use the Romer-Romer monetary policy shock (and its interaction with the indicator for high or low worker vacating) as the instrumental variable.

Figure 13: Impulse Responses of Vacancy and Unemployment Rate to Interest Rate Shock



Notes: This figure plots the impulse responses of the vacancy rate and unemployment rate to an interest rate shock by the aggregate state of high (blue dashed line) or low (red solid line) vacating, estimated from the LP-IV technique with the Romer-Romer shock as the instrument. Shaded areas are the 90 percent confidence intervals with the Newey-West standard errors.

Formally, I estimate the following specification:

$$y_{t+h} = \beta_{0,h} + \beta_{1,h}\Delta r_t + \beta_{2,h}\Delta r_t \times \mathbb{I}_t + \beta_{3,h}(L)'\mathbf{X}_t + \varepsilon_{t+h}$$

for $h \geq 0$, where the dependent variable y_{t+h} is the unemployment rate or vacancy rate at time $t+h$, Δr_t is the first difference of the federal funds rate, the interest rate at which depository institutions trade federal funds (balances held at Federal Reserve Banks) with each other overnight. To construct the indicator $\mathbb{I}_t$ that classifies the aggregate labor market state into high or low worker vacating, I HP-filter the employment-to-nonparticipation rate, and define $\mathbb{I}_t$ as 1 if the resulting cyclical component is positive and as 0 otherwise. Lag controls are included to strengthen the lead-lag exogeneity assumption for LP-IV identification as discussed in Stock and Watson (2018). This equation is instrumented by the Romer-Romer shock and its interaction with the vacating indicator.[38] Newey and West (1987) standard errors are computed to allow for heteroskedasticity and autocorrelation in the error structure.

Figure 13 plots the resulting impulse responses of the vacancy rate and unemployment rate

[38]The first stage of the LP-IV estimation is:

$$\Delta r_t = \gamma_{1,0} + \gamma_{1,1}\text{Shock}_t + \gamma_{1,2}\text{Shock}_t \times \mathbb{I}_t + \gamma_{1,3}(L)'\mathbf{X}_t + \eta_{1,t}$$
$$\Delta r_t \times \mathbb{I}_t = \gamma_{2,0} + \gamma_{2,1}\text{Shock}_t + \gamma_{2,2}\text{Shock}_t \times \mathbb{I}_t + \gamma_{2,3}(L)'\mathbf{X}_t + \eta_{2,t},$$

where Shock_t denotes the Romer and Romer (2004) shock.

to an interest rate shock by the aggregate state of high or low vacating. The red lines show that when the labor market exhibits low vacating, a higher interest rate depresses vacancies and elevates unemployment, consistent with Hall (2017) that takes the the conventional job creation view of vacancies. The blue lines, however, show that the labor market exhibits high vacating, an interest rate shock does not have a detectable impact on vacancies or unemployment. This provides empirical evidence for the theoretical prediction of the model that the impact of interest rate on vacancies and unemployment would be attenuated when worker vacating is important.

5.2 The Great Resignation and "Soft Landing"

Figure 14 summarizes the three key unique features in the post-pandemic labor market. First, Figure 14a plots the quit rate, i.e., the ratio of separations initiated by employees to employment. The quit rate is unprecedentedly high and hence dubbed as "the Great Resignation." The quit rate increases by 25% from 2.4 percentage points to 3 percentage points. Second, Figure 14b reveals a drop in the labor force participation rate of about 1.6% from 63.2 percentage points to 62.2 percentage points. Third, as previewed in the introduction, Figure 14c shows an increase of the vacancy rate by about 40% from 5 percentage points to 7 percentage points.

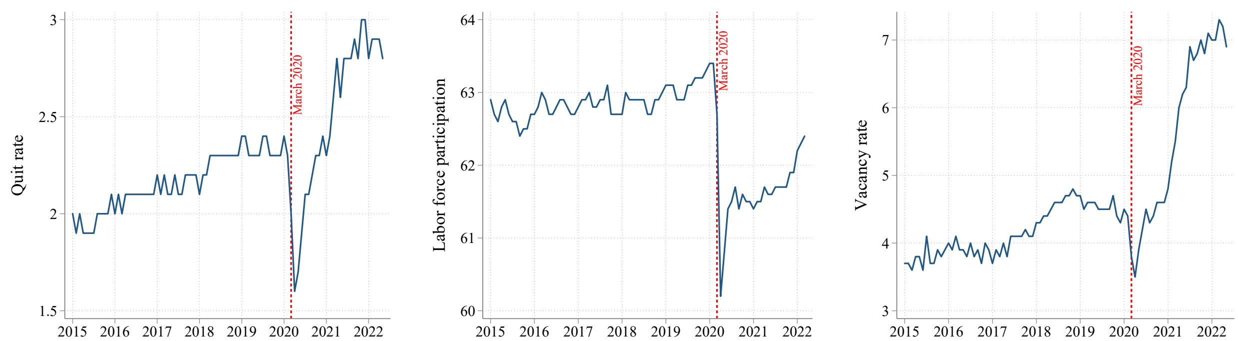
The "Great Resignation" highlights that vacated vacancies can be an important source of vacancies in the current labor market. To understand the impact of the "Great Resignation", I feed in a shock to the EN quit rate, so that the overall quit rate (i.e., the sum of job-to-job quit and EN quit) increases by 25% thus matching the spike in the quit rate in Figure 14a. Job-to-job quits increase endogenously in equilibrium as the labor market becomes tighter. I assume that the shock dissipates exponentially in 2 years. The resulting impulse responses of the labor force participation and vacancy rate are plotted in Figure 15. In the model, the labor force participation rate drops to an almost exact extent as it drops in the data. In the model, the vacancy rate increases by 20%, which is only about half of the vacancy increase that happens in the data. This means that the Great Resignation only contributes to half of the spike in vacancies in the post-pandemic labor market.

The post-pandemic labor market is featuring an extremely high vacancy rate—out of 100 jobs, 7 are vacant. At the same time, the US economy is also witnessing record high inflation over the past decades. Such high inflation calls for the attention of the policymakers at the Federal Reserve Bank to take action to reduce inflation. An ideal scenario would be to reduce inflation without inducing a spike in unemployment, the so-called "soft landing."

Is "soft landing" possible? There seem to be divided views among economists. Motivated by the unusually high vacancy rate, several Fed officials have suggested that "soft landing" is possible through a decrease in vacancies while going back to the point on the Beveridge curve

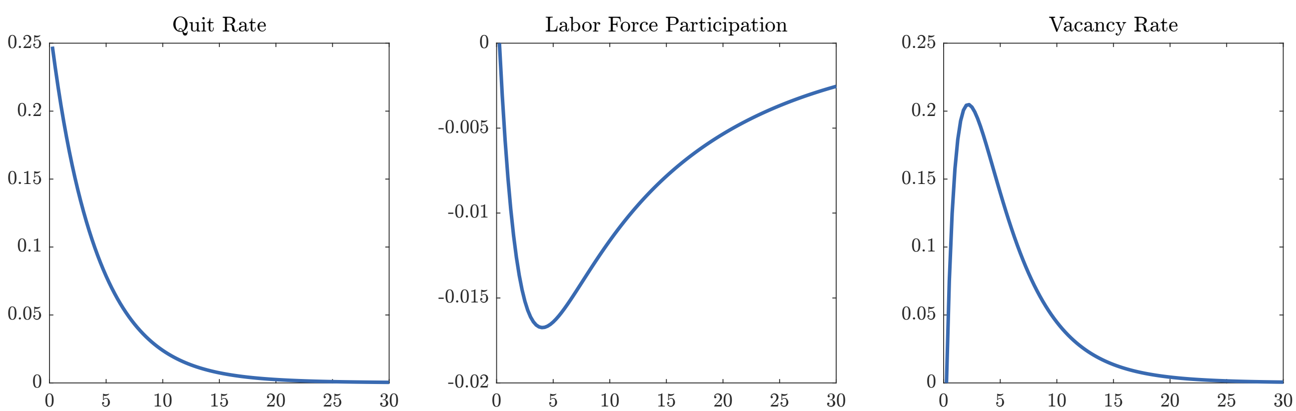
Figure 14: Great Labor Shortage in the Data

(a) Quit Rate (b) Labor Force Participation (c) Vacancy Rate



Notes: This figure plots the quit rate, the labor force participation rate, and the vacancy rate.

Figure 15: Great Labor Shortage in the Model



Notes: This figure plots the quit rate, the labor force participation rate, and the vacancy rate in the model.

in 2019, thus leaving unemployment unchanged. Such an optimistic view has been challenged by Blanchard, Domash, and Summers (2022). They analyze the historical relationship between vacancies and unemployment and find that it is implausible to decrease vacancies without increasing unemployment. The optimistic view loosely hints that vacancies today seem to be different from three years ago. The pessimistic view respects the empirical regularity of a robust negative association between vacancies and unemployment.

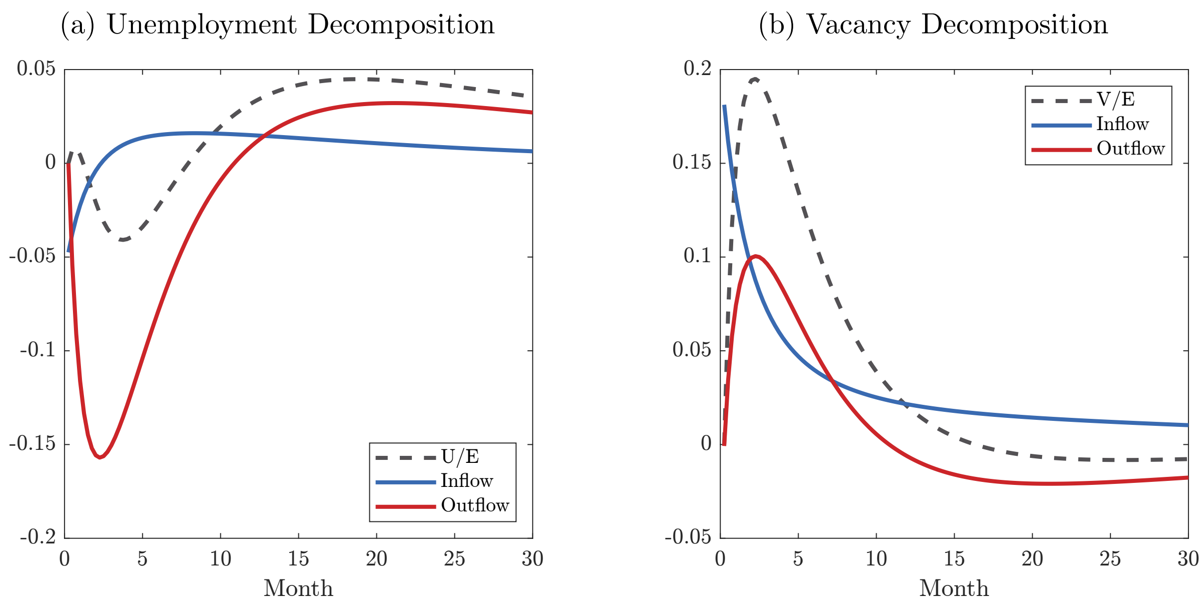
This paper provides a new perspective. In particular, the vacating channel, does not respond as much as the job creation channel. If, as in the conventional wisdom, job creation is the source of vacancies, then vacancies are depressed by a higher interest rate and hence unemployment is likely elevated as a consequence. If, however, the primary source of high vacancies in the post-pandemic labor market is not job creation, but the vacating channel, then soft landing is possible. In fact, as we will show below, the major source of the high vacancies in the post-pandemic labor market is indeed from the vacating channel, consistent with the "Great Resignation" narrative. That is, the reason we see a lot of vacancies in the labor market today, not because of a huge amount of job creation activity, but because of a spike in vacating due to worker quits.

Therefore, whether soft landing is possible depends on the dominant source of vacancies. If the high vacancies in the post-pandemic labor market are mainly a result of the elevated vacating channel, as opposed to the creation channel, then soft landing is possible. Section 5.2 has provided evidence that the vacating channel is indeed an important source of the high vacancies.

To quantify the possibility of a soft landing, I combine the Great Resignation shock in Section 5.2 and the interest rate shock considered in this Section, and study their resulting unemployment and vacancy dynamics. As expected, vacancies are still high, and are only depressed a little bit compared to Figure 17. This is because in the presence of the Great Resignation shock, the economy features lots of vacated vacancies, which are unresponsive to an interest rate shock. Given that vacancies decline little, unemployment therefore does not increase much. Thus, soft landing seems possible.

The paper makes a policy contribution to the understanding monetary transitions to the labor market. One prominent example is the post-pandemic labor market. Facing extremely high inflation and vacancy rate, policymakers are wondering about the possibility of a soft landing. The conventional wisdom suggests that it is not likely, as historically a decline in vacancy rate is always associated with a rise in unemployment. This paper provides a novel perspective that although the creation channel is responsive to interest rates, the vacating channel is not. To the extent that the post-pandemic labor shortage is mostly driven by the vacating channel (the so-called "Great Resignation"), it is indeed possible to achieve "soft

Figure 16: Is Soft Landing Possible



Notes: This figure plots the unemployment (left panel) and vacancy (right panel) dynamics in the model in response to a 1 percentage point increase in the real annual interest rate. The dashed black lines plot the impulse response function of U/E ratio and V/E ratio, respectively. The red and blue lines plot the outflows and inflows, respectively.

landing". Of course, this exercise itself does not constitute a policy recommendation, but provides a novel perspective in understanding the effect of monetary policy on the labor market. A careful policy evaluation with a full-fledged monetary model would be needed, but beyond the scope of this paper. It is acknowledged that an experiment of changing real interest rates is not necessarily equivalent to an experiment of changing monetary policy. Nevertheless, it provides useful information for evaluating monetary policy (see, e.g., Guerrieri, Lorenzoni, Straub, and Werning, 2022).[39]

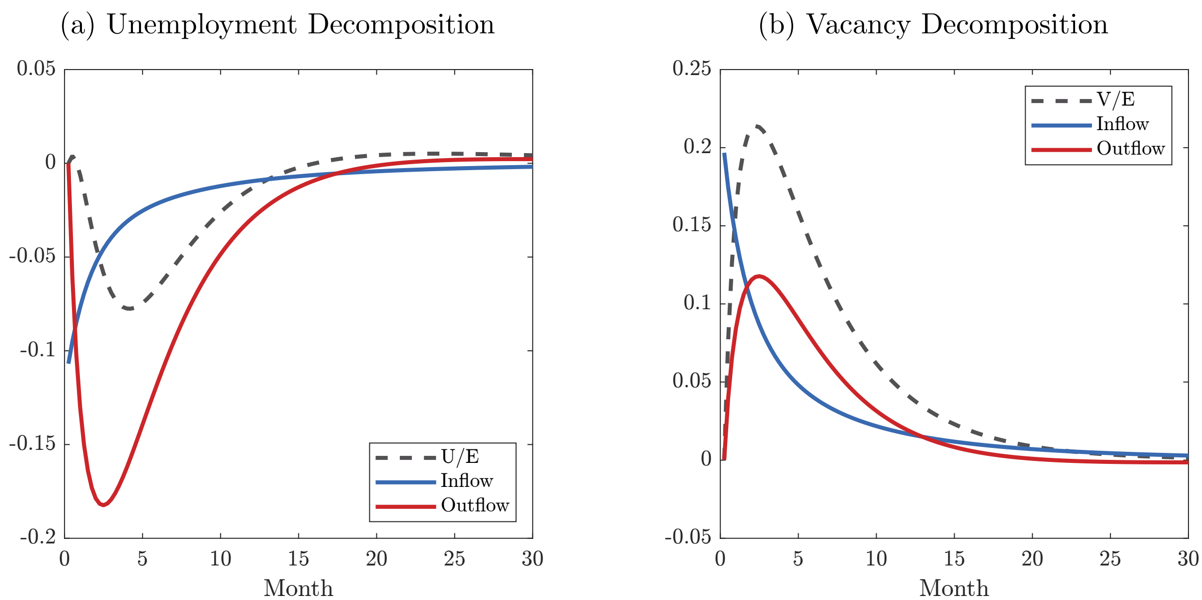
5.3 Is "Lump of Labor Fallacy" Really a Fallacy?

Figure 17 further plots the unemployment and vacancy dynamics under the previous experiment. It shows that a wave of quit vacates positions that are still productive. These vacated position now become open opportunities for unemployed workers, and hence increase their job finding prospects. As a result, unemployment decreases.

This idea is seemingly reminiscent of the so-called "lump-of-labor" fallacy. The key is to notice the distinction between the effect in transitional dynamics and the effect across steady

[39]The thought experiment is to consider a monetary economy with nominal rigidities in the background, where the interest rate is set by the monetary authority. In these models, it is usually useful to first study the flexible price allocation and the impact of the real interest rate. Then one can add those nominal rigidities and think about their implications.

Figure 17: Unemployment and Vacancy Response to Great Resignation Shock



Notes: This figure plots the unemployment (left panel) and vacancy (right panel) dynamics in the model in response to a 1 percentage point increase in the real annual interest rate. The dashed black lines plot the impulse response function of U/E ratio and V/E ratio, respectively. The red and blue lines plot the outflows and inflows, respectively.

states. Note that all curves in Figure 17 converge to their steady state level. Thus, temporarily encouraging one group of workers to quit to generate vacant jobs for unemployed searchers falls into the "lump-of-labor" fallacy. However, the effect is different over the transitional path as illustrated by Figure 17. To the extent that it takes time for the economy to transition to the steady state after an aggregate shock, there is indeed some notion of "lump-of-labor" during the transition path. But this is a temporary phenomenon. For instance, at the monthly frequency, vacated positions generated by workers' quits would be reposted and enhance unemployed searchers' job finding prospects. This is no longer true if one focuses on longer-run implications.

Without explicitly discussing it, several empirical studies under specific settings have in fact implicitly hinted at the vacating channel. For example, Dicarlo (2022) studies Italian firms' responses to negative labor supply shocks due to the removal of immigration restrictions between Italy and Switzerland. He documents evidence that firms replace workers they lost and hence provide new job opportunities for workers who do not migrate, supporting the vacating channel. Mohnen (2022) studies the impact of changing retirement behavior in the United States on the youth, and finds that in commuting zones where more workers retire due to the initial age structure, the share of younger workers in high-skill jobs rises, consistent with the vacating channel. Jäger and Heining (2019) use worker deaths as exogenous variations of unexpected worker shortfalls, and find that the hiring of new workers rises sharply following a worker death, once again confirming that the vacating channel operates.

6 Conclusion

Not all vacancies reflect new labor demand. A vacancy is an empty workstation (a vacant job). A job can become vacant if the worker quits the job for reasons unrelated to the productivity of the job. Conceptually, the vacating channel introduces a different source of vacancies, namely existing positions vacated by worker turnover, whereas the conventional theory conceptualizes vacancies as job creation, capturing employers' labor demand. The vacating channel also naturally distinguishes between two types of separations. The conventional theory conceptualizes separations as job destruction caused by negative productivity shocks to the jobs, in which case the jobs are destroyed and their employees are laid off and become unemployed. The vacating channel arises as workers' labor market attachment shifts due to preference shocks to the workers, in which case the jobs are not destroyed but become vacant.

This paper documents new empirical facts that support and highlight such an "empty workstation" perspective of vacancies. First, the paper provides both micro-level evidence that quits lead to vacancies within establishments and aggregate-level evidence that vacated vacancies are both more prevalent and more volatile than created vacancies, emphasizing the empirical relevance of the vacating channel. Second, in contrast to standard theories that model vacancies as a jump variable determined purely by the inflow, this paper shows that vacancies obey a law of motion where the outflow matters more for vacancy fluctuations over the business cycle. Both facts are robust in a number of economies with available vacancy flow data.

Recognizing this vacating channel brings novel insights. First, the paper shows that the participation margin in fact matters a lot in the business cycle theory of unemployment fluctuations. Procyclical employment-to-nonparticipation quits become an important source of vacancy fluctuation through the vacating channel, hence the job-finding fluctuation of unemployed workers. This resolves the Chodorow-Reich and Karabarbounis (2016) puzzle. Second, the paper shows that the aggregate labor market impact of changing real interest rates depends on the dominant vacancy channel. The creation channel, as an investment activity, responds a lot to interest rates, while the vacating channel does not. High vacancies in the post-pandemic labor market are primarily characterized by vacated vacancies due to the spike in worker quits, the so-called "Great Resignation," shedding light on the possibility of a softing landing in response to the tightening monetary policy.

The analysis so far points to several possible avenues for future research. First, although the current paper focuses on the business cycle frequency, it is an important direction to study the long-run growth implications of vacant jobs. For example, technological progress may be embodied in jobs as reflected in the sunk investment of creating a position this paper emphasizes. Through the lens of Schumpeterian creative destruction à la Aghion and Howitt (1992), vacant jobs may speed up the destruction of obsolete jobs and the creation of frontier jobs. As another example, prolonged vacant jobs caused by labor shortages may push employers to adopt labor-saving technologies as in theories of directed technological change (Acemoglu, 2007). Empirically, it seems feasible to leverage geographic and sectoral variation in the exposure to labor shortages to empirically investigate the impact on robot adoption. Theoretically, it is natural to combine the vacant-job framework in this paper with the task-based framework of automation as in Acemoglu and Restrepo (2018).

Second, although the current paper adopts a single-job representation following the search and matching tradition as a first step, it is a natural next step to understand richer implications of vacant jobs on firm dynamics and allow for explicit job ladders. Incorporating the vacating channel into a multi-worker firm environment adds to the emerging literature on joint characterization of firm and worker dynamics in frictional labor markets (Schaal, 2017; Bilal, Engbom, Mongey, and Violante, 2022; Elsby and Gottfries, 2022, among others). Moreover, it is an exciting direction to study the impact of vacant jobs on firm dynamics with an explicit organizational structure. For instance, one vacant job may lead to a large drop in team output due to disruptions in a coordinated production process (Kuhn, Luo, Manovskii, and Qiu, 2022) or the presence of critical positions in the production process (Bloesch, Larsen, and Taska, 2022).

Third, this paper draws implications for monetary transmissions to the labor market based on responses to changes in the real interest rate. To the extent that the monetary policy impacts the real interest rate due to frictions, this provides useful information conceptually. Nevertheless, a quantitative evaluation of monetary policies would require a full-fledged monetary block in a framework where a New Keynesian model meets search and matching (e.g., Christiano, Eichenbaum, and Trabandt, 2016) or a model where money search meets labor search (e.g., Berentsen, Menzio, and Wright, 2011).

Lastly, the model strives for simplicity and transparency vis-à-vis the textbook DMP benchmark. Despite being a useful first step to understand the vacating channel, Figure A-4 documents rich heterogeneity in workers' vacating behavior, e.g., by gender, by education, and over the life cycle. It is fruitful to study the aggregate implications of such micro heterogeneity.

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Online Appendix for "Vacant Jobs"

Xincheng Qiu

I Empirical Appendix

I.1 Vacancies and Quits

Figure A-1 shows the relationship between vacancy rate and quit rate over time, across sectors, and across space in the US labor market. Panel (a) plots the time-series relationship where each dot represents a month. In times with a high quit rate, the vacancy rate is also high. Panel (b) depicts the cross-sectional relationship between the vacancy rate and quit rate across sectors. Clearly, sectors with a higher quit rate also tend to have a higher vacancy rate. Panels (c) and (d) plot the spatial relationship between the vacancy rate and quit rate across 18 largest metropolitan statistical areas and across 51 states, respectively. Both demonstrate that in locations with higher quit rates, the vacancy rate also tends to be higher.

Figure 2 provides micro evidence at the establishment level that quits lead to vacancies. To what extent does the aggregate correlation between vacancies and quits, say, across states, reflect the vacating channel, rather than a reverse causality? To estimate the causal effect of quits on vacancies at the state level, I use state non-competes agreement regulation changes as an instrumental variable to quits. The assumption for the instrument to be valid is that non-competes regulations affect workers' quit behavior, but do not directly affect vacancies through other mechanisms. Column (4) reports the 2SLS estimates using state-level non-competes regulation changes.

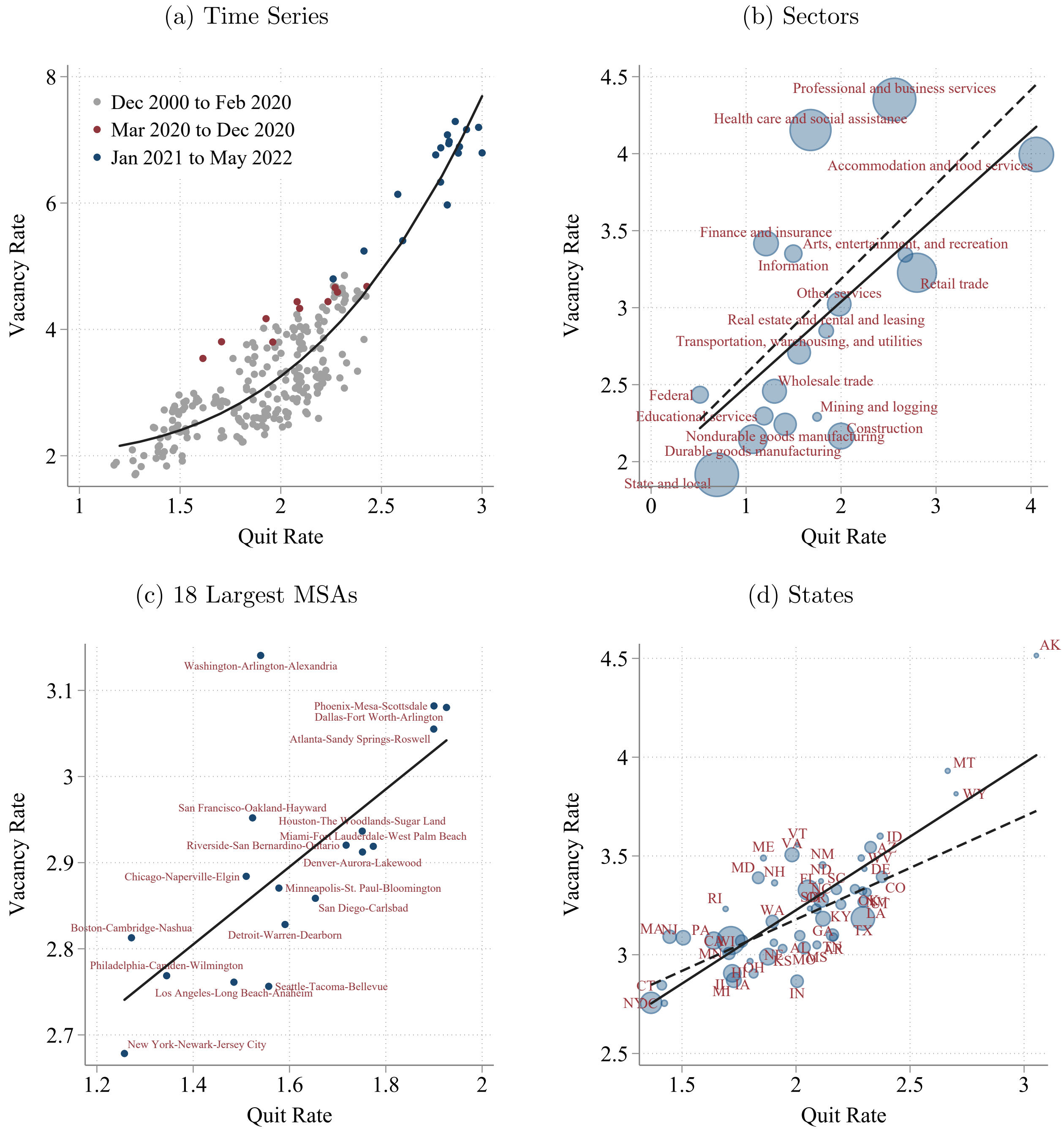
Table A-1: Vacancies and Quits

	(1)	(2)	(3)	(4)
Quits	0.927***	1.031***	0.447***	1.026***
	(0.042)	(0.031)	(0.028)	(0.277)
State FE	No	Yes	Yes	Yes
Time FE	No	No	Yes	Yes
NCA IV	No	No	No	Yes
Observations	5559	5559	5559	3221
R-squared	0.51	0.61	0.76	0.59

Clustered standard errors (at the state level), * p<0.10, ** p<0.05, *** p<0.01

Notes: This table reports the state-level regressions of vacancy rate on quit rate.

Figure A-1: Vacancies and Quits



Notes: This figure plots the relationship between vacancy rate and quit rate. Panel (a) shows their relationship in the time series, with each dot representing a monthly period. Panel (b) shows their relationship across sectors, with the size of the circle representing the size of the sector. Panel (c) and (d) show their relationship across space, specifically, across 18 largest MSAs and across states, respectively. Solid lines are fitted lines. Dashed lines are fitted lines with weighted regressions.

I.2 Vacated Vacancies

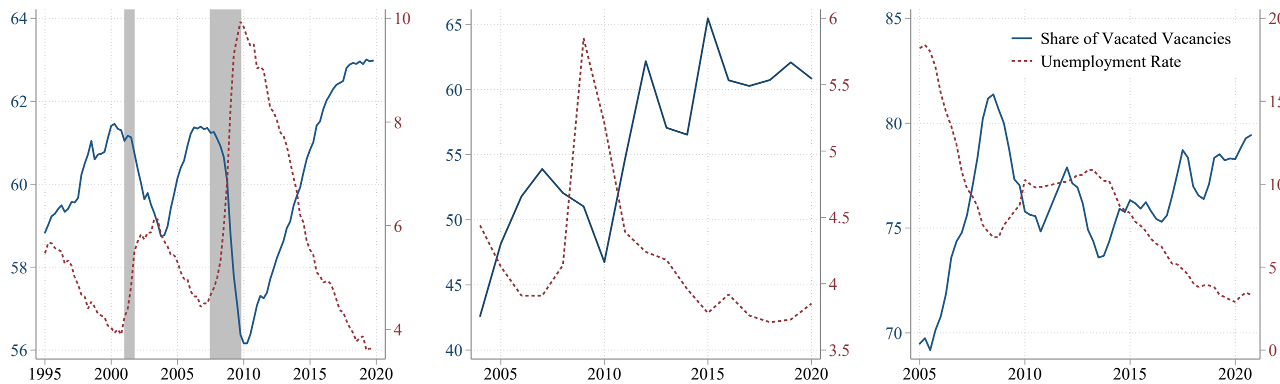
Separately measuring the number of vacated and created vacancies in the US labor market poses an empirical challenge. JOLTS, the official vacancy survey in the US, is not designed to elicit the reasons why employers have vacancies. Online job postings, another popular alternative data source for measuring vacancies, do not contain such information either, as employers almost never specify in the job description whether the position is a newly created one or an existing one seeking a replacement worker. I approach the empirical challenge in three ways. First, I construct novel measures for vacated vacancies among both vacancy inflows and outflows, leveraging the conceptual difference between vacated and created vacancies. Second, I check other vacancy surveys that directly ask employers for the reason why a vacancy arises including Taiwan and Poland, and find similar patterns.

I construct two measures for the share of vacated vacancies, one among vacancy inflows and the other among vacancy outflows. On the inflow side, I exploit the defining property of vacated vacancies, namely that they arise from quits. Thus, the inflow of vacated vacancies is imputed as the flow of workers voluntary quits, and the inflow of created vacancies as the remaining inflows. The result is shown in Panel (b) of Figure 3 in the main text. On the outflow side, I attribute replacement hires as to fill vacated vacancies and the remaining hires, if any, as to fill created vacancies. Replacement hires are defined as the smaller one between hires and separations at an establishment. For example, consider an establishment has 5 hires and 3 separations last month. The measurement would then attribute 3 out of the 5 hires as to replace the 3 workers who separate and fill 3 vacated vacancies, while the other 2 hires are to fill 2 newly created vacancies. Suppose, on the contrary, another establishment has 3 hires and 5 separations last month. This imputation would then attribute all 3 hires as to replace workers who separate, filling 3 vacated vacancies and none created vacancies. This measure is constructed using the Quarterly Workforce Indicators (QWI) data, an aggregate data product tabulated from the high-quality administrative Longitudinal Employer-Household Dynamics program at the Census. Moreover, if the speed of being filled is approximately independent to type of vacancies, then the share of vacated vacancies among vacancy fillings also resembles the share of vacated vacancies among vacancy stocks. In fact, this serves as a conservative estimate if one believes that newly created vacancies are filled faster than vacated vacancies, in line with the empirical evidence in Davis, Faberman, and Haltiwanger (2013) that fast-growing firms fill their vacancies faster. Panel (a) of Figure A-2 plot the share of vacated vacancies among outflows in the US. It shows that vacated vacancies are the more prevalent form of vacancies than created vacancies.

This pattern is similar in other vacancy surveys that specifically inquire about the cause of a vacancy. The Taiwan vacancy survey categorizes sources of vacancies as due to worker turnover,

Figure A-2: Share of Vacated Vacancies in the Aggregate

(a) United States (b) Taiwan (c) Poland



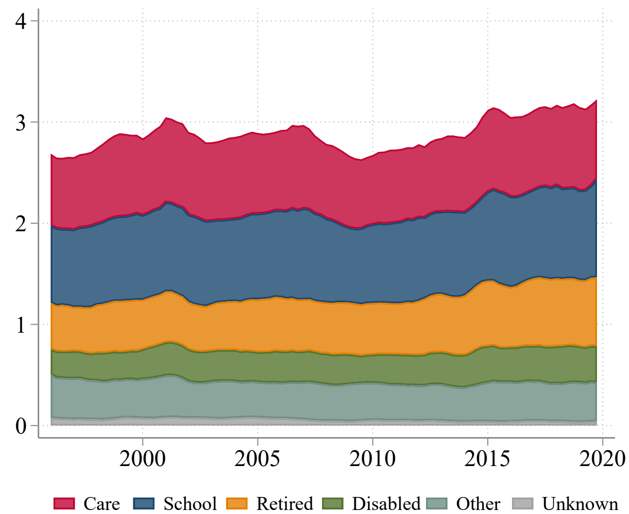
Notes: This figure plots the share of vacated vacancies in the aggregate over the business cycle. Panel (a) plot, for the United States, the share of vacated vacancies among vacancy outflows. Panel (b) and (c) plot the share of vacated vacancies among vacancy stock for Taiwan and Poland, respectively.

establishment expansion, seasonal demand, organization restructure, hard-to-fill positions, legal restrictions, and others. I define the share of vacated vacancies as the fraction of vacancies due to worker turnover among all vacancies. The Poland vacancy survey elicits whether a vacancy is a newly created job. I define the share of vacated vacancies as one minus the share of newly created vacancies. The two resulting series are plotted in Panel (b) and (c) of Figure A-2. Since the two economies experience different business cycles than the US, I also plot the unemployment rate to better visualize the cyclical nature of vacated vacancies. Consistent with what is found in the US data, the share of vacated vacancies is larger than 50% and is procyclical in the sense that it moves in the opposite direction of the unemployment rate. This implies that vacated vacancies are more prevalent and more volatile than created vacancies.

I.3 Reasons for Nonparticipation

CPS asks for the status of persons not in the labor force, and classifies them into three categories: (a) retired, (b) unable to work, and (c) others. For respondents who reported being not in the labor force, but did not give "unable to work" or "retired" as a reason, a follow-up question is asked about the major activity, with possible answers including (i) disabled, (ii) ill, (iii) in school, (iv) taking care of house or family, (v) something else. In the following analysis, I combine (b) unable to work, (i) disabled, (ii) ill into one group broadly called "disabled." By doing so, I reach a mutually exclusive classification of reasons for nonparticipation: (1) retirement, (2) disability, (3) family responsibilities, (4) in school, (5) other reasons, and (6) missing answers for reasons for nonparticipation. The distribution of reasons for employment-to-nonparticipation transitions over time is plotted in Figure A-3.

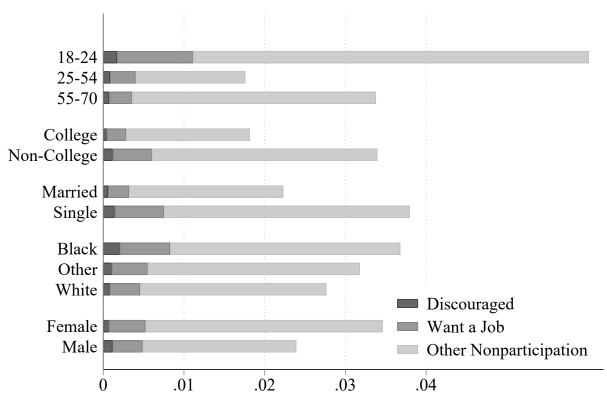
Figure A-3: Reason for Employment-to-Nonparticipation Transitions



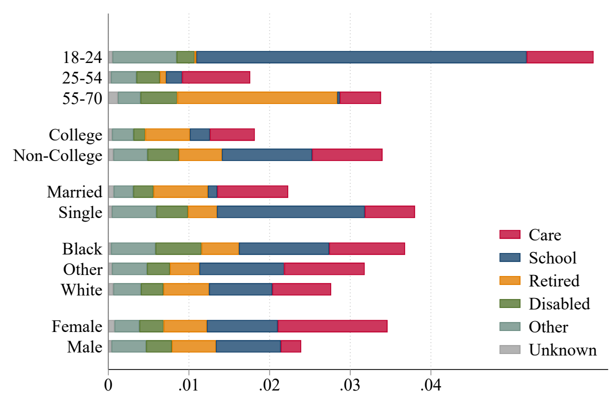
Notes: This figure plots the reasons for employment-to-nonparticipation transitions over the business cycle.

Figure A-4: Employment-to-Nonparticipation by Demographics

(a) Detailed Out-of-Labor-Force Status



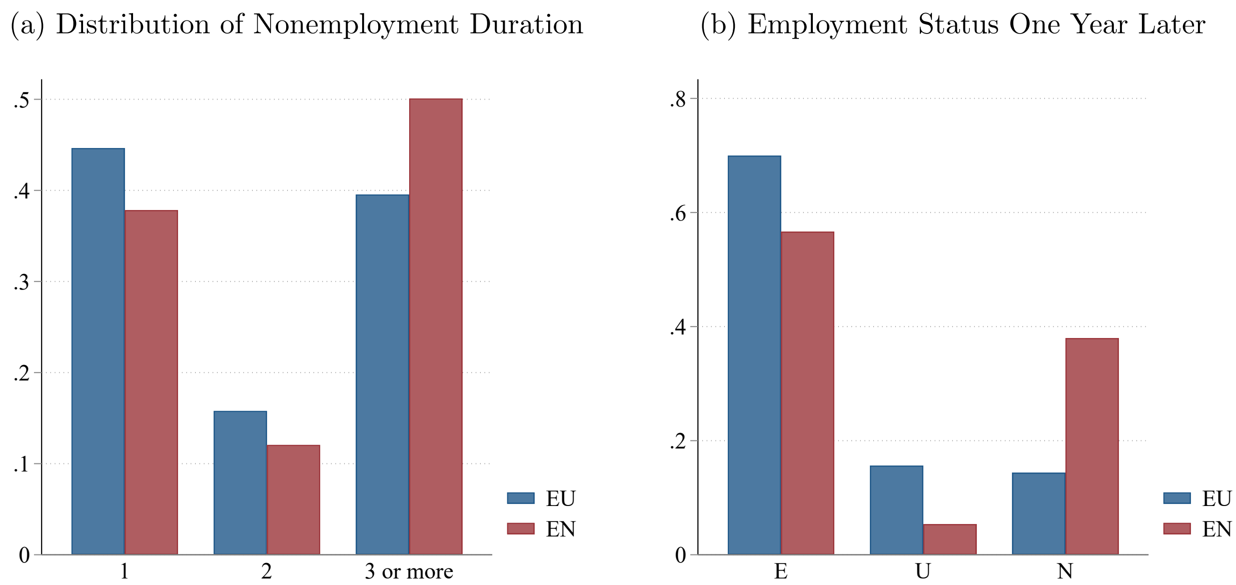
(b) Reason for Nonparticipation



Notes: This figure plots the reasons for employment-to-nonparticipation transitions by demographic groups.

The distribution of reasons for leaving employment to nonparticipation differs by demographic group, as shown in Figure A-4. For instance, female workers have a higher EN rate than male workers, predominantly because female workers are more likely to exit employment for family responsibilities. The reasons for employment-to-nonparticipation transitions reveal strong life cycle patterns: EN transitions among young workers below 25 years old are mostly going to school, among prime-age workers between 25 to 54 years old are mostly taking care of the family, among old workers more than 55 years old are mostly retirement. Compared to college workers, non-college workers are more likely to become nonparticipants, with the

Figure A-5: Persistence of EU vs. EN transitions



Notes: This figure plots the distribution of nonemployment duration (in months) for EU and EN transitions in the left panel, and the distribution of employment one year after the EU or EN transitions in the right panel.

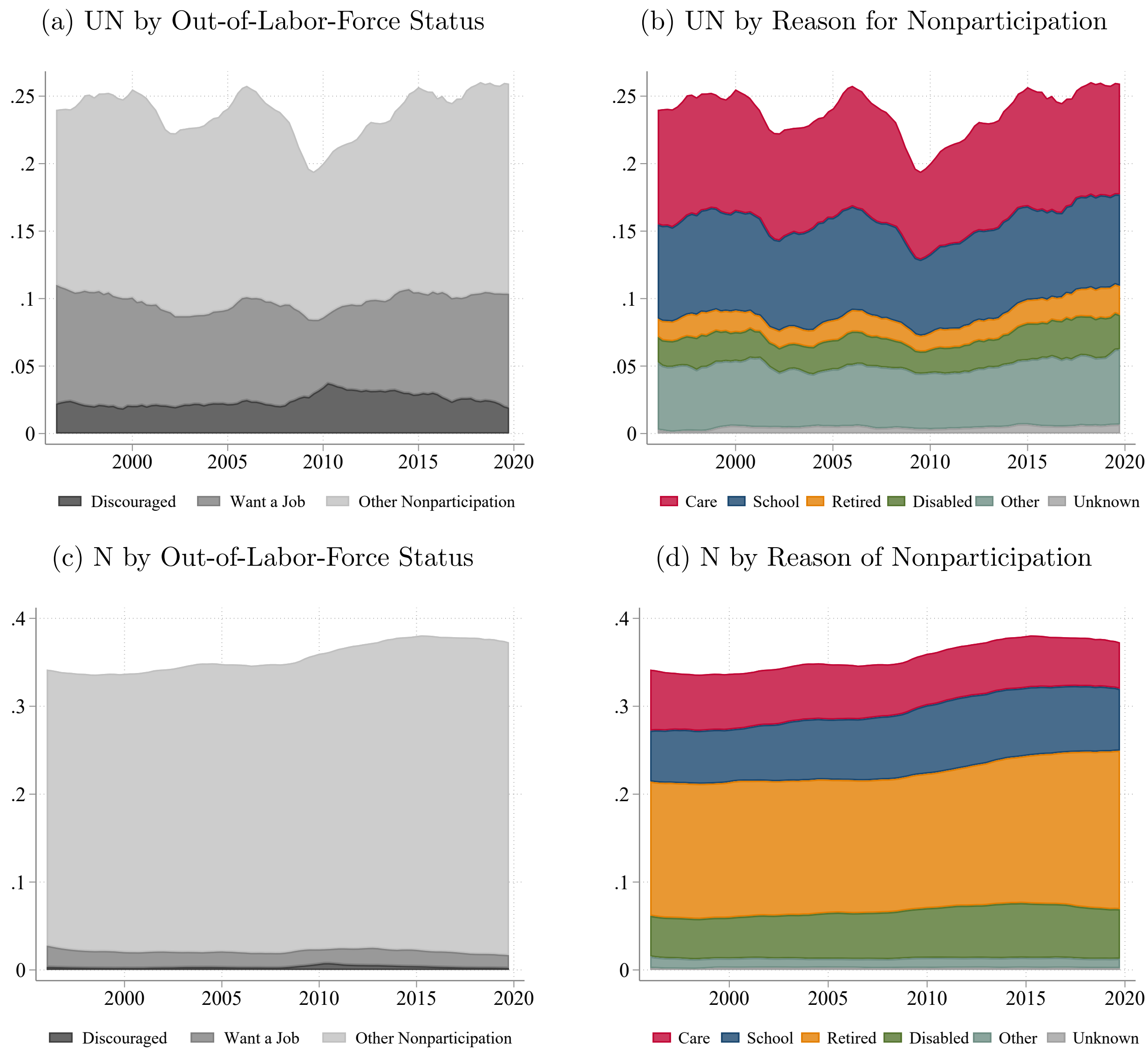
difference mainly driven by higher likelihood of non-college workers to go back to school or become disabled. Married workers are more likely to leave employment to take care of family than single workers, but the overall EN rate is much higher for single workers as they are more likely to be young and go back to school. There are no substantial differences among racial groups.

Panel (a) of Figure A-5 plots the distribution of nonemployment duration associated with EU or EN transitions. The CPS has a so-called 4-8-4 sampling scheme in the sense that respondents are tracked for 4 consecutive months, then out of the survey for 8 month, and finally return for another 4 consecutive months before exiting the sample permanently. I leverage the short-panel design of CPS by matching respondents longitudinally from the 1st to 4th month or the 5th to 8th month in survey (MIS). I calculate the nonemployment duration for EU and EN transitions that happen in the end of the 1st or 5th MIS in order to avoid right censoring. About 45% of workers making EU transitions return to employment in a month, while a smaller share at 38% of EN transitions return employment in a month. Nevertheless, it still suggests a nontrivial fraction of EN transitions are rather temporary. Slightly more than 50% of EN transitions stay in nonemployment for 3 or more months, whereas only slightly less than 40% of EU transitions stay in nonemployment for 3 or more months.

The information is limited when attention is restricted to a 4-month panel. Thus, I further match CPS respondents to one year after. Specifically, I match respondents for MIS $(1, 2, 5)$, $(2, 3, 6)$, and $(3, 4, 7)$. I then calculate the distribution of the labor force status one year after the

EU or EN transition. Among EU transitions, 70% return to employment in a year, while only about 55% of EN transitions return to employment in a year. Almost 40% of EN transitions stay out of the labor force after a year, whereas only less than 15% of EU transitions are out of the labor force after a year.

Figure A-6: Unemployment-to-Nonparticipation Transition Rate and Nonparticipation Rate

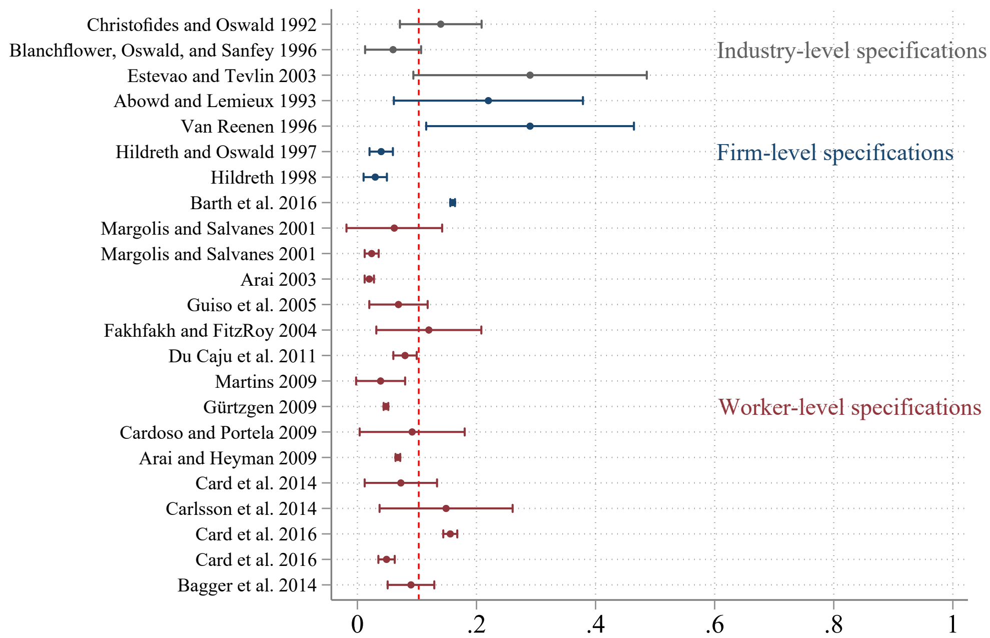


Notes: This figure plots the reasons for nonparticipation over the business cycle.

Figure A-6 plots the distribution of reasons for being out of the labor force among UN transitions and among the N stock. The composition of reasons for being out of the labor force differs from that for EN transitions, pointing to the different natures of different labor market state transitions and the difference between flows and stock.

I.4 Meta Analysis of Rent Sharing Elasticities

Figure A-7: Rent Sharing Elasticities



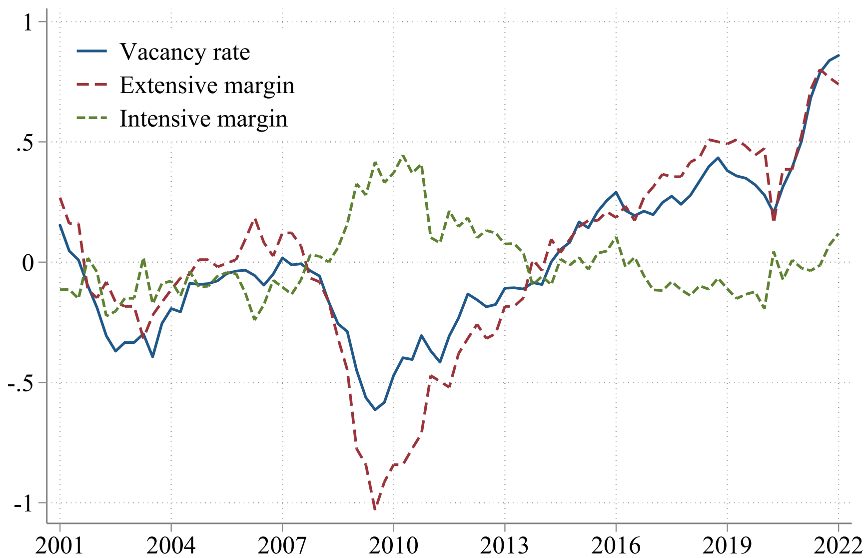
Notes: This figure summarizes rent sharing elasticities. The red dashed vertical line plots the average rent sharing elasticity among these studies.

I.5 Extensive and Intensive Margin

At any point of time, most establishments turn out to have zero vacancies. Davis, Faberman, and Haltiwanger (2013) find in JOLTS data that between 2001 and 2006, on average 88% establishments report zero vacancies at the time of survey. Thus, a natural question is whether the fluctuation in the aggregate vacancy rate is driven by the extensive margin—the fraction of establishments with non-zero vacancies, or the intensive margin—the number of vacancies within an establishment conditional on the establishment reporting at least one vacancy.

As the BLS does not publish any statistics on the extensive and intensive margin decomposition of vacancies, this question could only be answered in JOLTS confidential microdata at the establishment level. Instead, I use the NFIB Research Foundation Small Business Economic Survey. A set of indicators aggregated from the data can be accessed here. I find that in the NFIB data, 78% establishments report zero vacancies during the same sample period as in Davis, Faberman, and Haltiwanger (2013), consistent with their finding. Nevertheless, I acknowledge the sampling difference between NFIB survey and JOLTS, especially given that the former focuses on small businesses while the latter aims at providing a representative coverage of the economy. I address such a sampling difference in two steps. First, I restrict attention to small establishments in JOLTS. Second, the decomposition focuses on the cyclical fluctuation in logs, rather than comparing the levels.

Figure A-8: Extensive-Intensive Margin Decomposition



Notes: This figure decomposes the log deviation of vacancy rate into its extensive margin and intensive margin.

The exact survey question I use in this decomposition is: "Do you have any job openings that you are not able to fill right now?" I define the extensive margin as the fraction of establishments reporting have at least one vacant position. The remaining fluctuation in the vacancy rate is attributed to the intensive margin by construction. Figure A-8 plots the resulting extensive-intensive margin decomposition. The conclusion is that most of aggregate vacancy fluctuation is at the extensive margin, mitigating the concern of missing important vacancy dynamics within an establishment in the one-worker-one-job framework considered in the main text.

II Theoretical Appendix

II.1 Modified HJB Equations

II.1.1 Dynamic Stochastic Equilibrium

For the dynamic stochastic equilibrium, the HJB equation for a vacant job (v) is

$$\begin{aligned} rV^v(\Omega) &= -\kappa(\Omega) + q(\Omega)\left(V^p(\Omega) - V^v(\Omega)\right) + \lambda\left(\int \max\left\{V^v(\Omega) - \varepsilon, V^x(\Omega)\right\} \mathrm{d}F^\varepsilon(\varepsilon) - V^v(\Omega)\right) \\ &\quad + \Lambda\left(V^v(A'; U, N, V) - V^v(\Omega)\right) \mathrm{d}\Gamma(A'|A) + \sum_{X \in \Omega \setminus A} \dot{X}(\Omega) \frac{\partial}{\partial X} V^v(\Omega). \end{aligned}$$

The HJB equation for an employed worker (e) is

$$\begin{aligned} rV^e(\Omega) &= w(\Omega) + \varphi^{eu}(\Omega)\left(V^u(\Omega) - V^e(\Omega)\right) + \psi\left(\int \max\left\{V^e(\Omega) - \omega, V^n(\Omega)\right\} \mathrm{d}F^\omega(\omega) - V^e(\Omega)\right) \\ &\quad + \Lambda\left(V^e(A'; U, N, V) - V^e(\Omega)\right) \mathrm{d}\Gamma(A'|A) + \sum_{X \in \Omega \setminus A} \dot{X}(\Omega) \frac{\partial}{\partial X} V^e(\Omega). \end{aligned}$$

The HJB equation for an unemployed worker (u) is

$$\begin{aligned} rV^u(\Omega) &= z^u(\Omega) + p(\Omega)\left(V^e(\Omega) - V^u(\Omega)\right) + \psi\left(\int \max\left\{V^u(\Omega) - \omega, V^n(\Omega)\right\} \mathrm{d}F^\omega(\omega) - V^u(\Omega)\right) \\ &\quad + \Lambda\left(V^u(A'; U, N, V) - V^u(\Omega)\right) \mathrm{d}\Gamma(A'|A) + \sum_{X \in \Omega \setminus A} \dot{X}(\Omega) \frac{\partial}{\partial X} V^u(\Omega). \end{aligned}$$

The HJB equation for a nonparticipant (n) is

$$\begin{aligned} rV^n(\Omega) &= z^n(\Omega) + m^w\left(V^u(\Omega) - V^n(\Omega)\right) + \varphi^{ne}(\Omega)\left(V^e(\Omega) - V^u(\Omega)\right) \\ &\quad + \Lambda\left(V^n(A'; U, N, V) - V^n(\Omega)\right) \mathrm{d}\Gamma(A'|A) + \sum_{X \in \Omega \setminus A} \dot{X}(\Omega) \frac{\partial}{\partial X} V^n(\Omega). \end{aligned}$$

II.1.2 Transitional Dynamics Equilibrium

For the transitional dynamics equilibrium, the HJB equation for a vacant job (v) is

$$r_t V_t^v = -\kappa_t + q_t\left(V_t^p - V_t^v\right) + \lambda_t\left(\int \max\left\{V_t^v - \varepsilon, V_t^x\right\} \mathrm{d}F^\varepsilon(\varepsilon) - V_t^v\right) + \dot{V}_t^v.$$

The HJB equation for an employed worker (e) is

$$r_t V_t^e = w_t + \varphi_t^{eu}\left(V_t^u - V_t^e\right) + \psi_t \left(\int \max\left\{V_t^e - \omega, V_t^n\right\} \mathrm{d}F^{\omega}(\omega) - V_t^e\right) + \dot{V}_t^e.$$

The HJB equation for an unemployed worker (u) is

$$r_t V_t^u = z_t^u + p_t\left(V_t^e - V_t^u\right) + \psi_t \left(\int \max\left\{V_t^u - \omega, V_t^n\right\} \mathrm{d}F^{\omega}(\omega) - V_t^u\right) + \dot{V}_t^u.$$

The HJB equation for a nonparticipant (n) is

$$r_t V_t^n = z_t^n + m_t^w\left(V_t^u - V_t^n\right) + \varphi_t^{ne}\left(V_t^e - V_t^u\right) + \dot{V}_t^n.$$

II.2 Parametric Assumptions

II.2.1 Distribution of Idiosyncratic Shocks

The difference between two extreme value variables is distributed logistic.

Suppose $\tilde{\varepsilon}$ is drawn from a generalized logistic distribution with scale parameter ν and location parameter μ. Thus, the transformed random variable $\varepsilon := \tilde{\varepsilon} - \mu$ is logistic distributed with scale parameter ν with the location parameter normalized to 0. That is, the cumulative distribution function (CDF) of the random variable ε is

$$F(\varepsilon) = \frac{\exp(\varepsilon/\nu)}{1 + \exp(\varepsilon/\nu)}.$$

Here I only present the key proposition used in this paper regarding the choice probability and expected gain in value arising from the preference shock. See Train (2009) for a textbook treatment of discrete choice models.

Proposition 1. *Suppose the current state has a value of V^o. When an opportunity to switch to a new state of value V^d arises, the ex ante conditional probability of switching is*

$$CP\left(V^o, V^d\right) := \Pr\left\{V^d \geq V^o - \tilde{\varepsilon}\right\} = \frac{1}{1 + \exp\left\{-\left(V^d - V^o + \mu\right)/\nu\right\}}.$$

The expected gain in value of such a switching opportunity is

$$EG\left(V^o, V^d\right) := \int \max\left\{V^d + \mu + \varepsilon, V^o\right\} \mathrm{d}F(\varepsilon) - V^o = -\nu \log\left(1 - CP\left(V^o, V^d\right)\right).$$

Proof. The switch from origin V^o to destination V^d is made if and only if the realization of the preference shock is such that $V^d \geq V^o - \tilde{\varepsilon}$. Define $\Delta := V^d - V^o + \mu$. Thus, the choice probability is

$$
\begin{aligned}
\mathrm{CP}\left(V^o, V^d\right) &= \Pr\{\Delta + \varepsilon \geq 0\} = 1 - \Pr\{\varepsilon < -\Delta\} = 1 - F(-\Delta) \\
&= 1 - \frac{\exp(-\Delta/\nu)}{1 + \exp(-\Delta/\nu)} = \frac{1}{1 + \exp\left(-\left(V^d - V^o + \mu\right)/\nu\right)}.
\end{aligned}
$$

Conditional on the arrival of a shock, the expected gain in value is

$$
\begin{aligned}
\mathrm{EG}\left(V^o, V^d\right) &= \int \max\left\{V^o - \mu - \varepsilon, V^d\right\} \mathrm{d}F(\varepsilon) - V^o = \int \max\{-\varepsilon, \Delta\} \mathrm{d}F(\varepsilon) - \mu \\
&= -\int_{\varepsilon \leq -\Delta} \varepsilon \, \mathrm{d}F(\varepsilon) + \Delta\left(1 - F(-\Delta)\right) - \mu.
\end{aligned}
$$

Note that by applying integration by parts, we have

$$
\int \varepsilon \, \mathrm{d}F(\varepsilon) = \varepsilon F(\varepsilon) - \int F(\varepsilon) \, \mathrm{d}\varepsilon = \varepsilon F(\varepsilon) - \int \frac{\exp(\varepsilon/\nu)}{1 + \exp(\varepsilon/\nu)} \mathrm{d}\varepsilon = \varepsilon F(\varepsilon) - \nu \log\left(1 + \exp(\varepsilon/\nu)\right).
$$

We do a change of variables by setting $u = 1/\left(1 + \exp(\varepsilon/\nu)\right)$ and hence $\varepsilon = \nu \log\left(u^{-1} - 1\right)$. Thus taking the limit $\varepsilon \to -\infty$ is equivalent to $u \to 1$. Thus,

$$
\begin{aligned}
&\lim_{\varepsilon \to -\infty} \left[\varepsilon \frac{\exp(\varepsilon/\nu)}{1 + \exp(\varepsilon/\nu)} - \nu \log\left(1 + \exp(\varepsilon/\nu)\right)\right] = \lim_{u \to 1} \left[(1 - u)\nu \log\left(\frac{1}{u} - 1\right) - \nu \log\left(\frac{1}{u}\right)\right] \\
&= \nu \lim_{u \to 1} \left[(1 - u)\log(1 - u) + u \log(u)\right] = \nu \left\{\lim_{u \to 0} \left[(1 - u)\log(1 - u)\right] + \lim_{u \to 0} \frac{\log(u)}{1/u}\right\} = 0,
\end{aligned}
$$

where the last limit can be obtained by L'Hôpital's rule. Therefore,

$$
\begin{aligned}
\mathrm{EG}\left(V^o, V^d\right) &= \Delta\left(1 - F(-\Delta)\right) - \left[-\Delta F(-\Delta) - \nu \log\left(1 + \exp(-\Delta/\nu)\right)\right] - \mu \\
&= \Delta + \nu \log\left(1 + \exp(-\Delta/\nu)\right) - \mu = -\nu \log\left(\frac{\exp(-\Delta/\nu)}{1 + \exp(-\Delta/\nu)}\right) - \mu \\
&= -\nu \log\left(1 - \mathrm{CP}\left(V^o, V^d\right)\right) - \mu.
\end{aligned}
$$

□

The above proposition provides a useful characterization of the expected gains in value in relation to the choice probability such that $\mathrm{EG} = -\nu \log(1 - \mathrm{CP}) - \mu$. It is worth noting that when the variance of the taste shock ν is infinitesimal compared to the difference in value Δ, we have the following limiting cases.

Proposition 2. $\lim_{\nu/\Delta \to 0} EG\left(V^o, V^d\right) = \Delta \cdot \mathbb{1}\{\Delta \geq 0\} - \mu$.

Proof. Using the second to the last step in the proof for the previous proposition, we have

$$\lim_{\nu/\Delta\to 0} \text{EG}\left(V^o, V^d\right) + \mu = \lim_{\nu/\Delta\to 0} -\nu \log\left(\frac{\exp\left(-\Delta/\nu\right)}{1+\exp\left(-\Delta/\nu\right)}\right) = \Delta \lim_{\nu/\Delta\to 0} \frac{\nu}{\Delta} \log\left(\exp\left(\Delta/\nu\right)+1\right)$$
$$= \Delta \lim_{u\to\infty} \frac{\log\left(\exp\left(u\right)+1\right)}{u} = \Delta \lim_{u\to\infty} \frac{\exp\left(u\right)}{\exp\left(u\right)+1},$$

where the third equality performs a change of variables by substituting Δ/ν with u, and the fourth equality applies L'Hôpital's rule. Given that ν is positive, as ν/Δ approaches 0, we have $u \to +\infty$ when $\Delta > 0$ and $u \to -\infty$ when $\Delta < 0$. $\square$

The preference shock structure inherently leads to an option value. To ease interpretation, we pick the location parameter μ such that the option value is normalized to 0, that is, $\text{EG}\left(V^o, V^d\right) = \left(V^d - V^o\right) \text{CP}\left(V^o, V^d\right)$.

II.2.2 Distribution of Sunk Investment Cost

Assume a flow measure m^j of potential entrants that draw sunk investment cost of creating positions from a distribution $c \sim G$ with a support $[0, c_{\max}]$. In the aggregate, the flow measure of new job creation is thus $v^n = m^j G(V^v)$. This section derives the conditions under which the distribution is consistent with an isoelastic representation of $v^n = k(V^v)^\xi$, where k and ξ are the parameters to be estimated in the calibration procedure.

A well-defined distribution satisfies $G(c_{\max}) = 1$. Thus, consistence of the two representations requires that

$$m^j = k(c_{\max})^\xi \Rightarrow c_{\max} = \left(\frac{m^j}{k}\right)^{\frac{1}{\xi}}.$$

This reveals non-identification between the flow measure m^j of potential entrants and the support of the distribution captured $c_{\max}$. As m^j increases, there always exists a larger value for $c_{\max}$ that leads to identical new job creation behavior. The intuition is that, if each entrant tends to draw a higher entry cost, then the entry rate per potential entrant is lower. One can always increase the measure of potential entrants while reducing the entry rate to keep the measure of realized entrants constant. The non-identification of the measure of potential entrants is well-known in the empirical IO literature. It also shows that the crucial parameter is summarized by the job creation elasticity parameter ξ and a scale parameter k, conditional on which m^j and $c_{\max}$ are irrelevant.

II.3 Discussion of Free Entry

In DMP models with free entry, vacancy creation is determined by the zero-profit condition. Once created, vacancies enter the matching function to be matched with job seekers. If a vacancy is filled, it becomes a producing job. If not, it disappears at the end of the period. These features make vacancies a jump variable and isomorphic to recruiting efforts, rather than vacant jobs.

The key operative margin in the equilibrium search and matching paradigm (Pissarides, 2000) can be neatly summarized in one equation, namely, the celebrated "job creation" condition

$$0 = V = -\kappa + \beta q(\theta)J,$$

where κ is the vacancy posting cost, β the discount factor, $q(\theta)$ the vacancy filling rate as a function of the labor market tightness θ, J the value of a filled job, and V the value of a vacancy, which is pushed down to zero due to free entry.

This condition encompasses two assumptions. First, vacancies are destroyed at the end of the period if unfilled, so that $v_{t+1} = v_t \times 0 + i_t$. In other words, it assumes the vacancy outflow rate to be $o_t = 1$, and the vacancy destruction rate to be $\delta_t = 1 - q_t$. This assumption renders the law of motion of vacancies irrelevant, as vacancies only depend on new job creation.

Second, vacancy creation is infinitely elastic, so that

$$i(V) \begin{cases} = 0 & \text{if } V < 0 \\ \in (0, \infty) & \text{if } V = 0 \\ = \infty & \text{if } V > 0 \end{cases}.$$

As a result, vacancy is a jump variable. The free entry condition is both the hallmark of the textbook DMP model, and the root of the "problems" that lead to counterfactual predictions to the empirical findings in Section 2.

III Measurement Appendix

III.1 Measuring Vacancy Flows in JOLTS

The official vacancy survey for the US labor market, JOLTS, does not provide direct information on vacancy inflows and outflows. Nevertheless, combining vacancy stock with monthly hires, both available in JOLTS, reveals information on vacancy flows, once the law of motion Equation

(2) is imposed.

We need to deal with time aggregation as JOLTS is a monthly survey while vacancies can be filled at a much higher frequency. We thus consider a law of motion of vacancies at the daily frequency, as is in Davis, Faberman, and Haltiwanger (2013). Denote V_d the number of job openings stock at day d. The law of motion for vacancies from day $d-1$ to day d is

$$V_d = V_{d-1}\left(1 - q_d\right)\left(1 - \delta_d\right) + I_d,$$

where q_d is the rate at which vacancies are filled (the *filling* channel), δ_d the rate at which vacancies are withdrawn without being filled (the *destruction* channel), and I_d the number of new job openings posted at day d (which includes both the *creation* channel and the *vacating* channel). The number of hires at day d is thus $H_d = q_d V_{d-1}$. We then aggregate the daily hiring model to the monthly frequency, at which the corresponding data are collected in JOLTS. Assume there are D working days in each month t. The beginning-of-month vacancies and the end-of-month vacancies can be written as $V_{0,t} = V_{t-1}$ and $V_{D,t} = V_t$, respectively. For notational brevity, define outflow rate o_t such that $1 - o_t := \left(1 - q_t\right)\left(1 - \delta_t\right)$. The monthly law of motion for vacancies is

$$V_t = V_{t-1}\left(1 - o_t\right)^D + I_t \sum_{d=1}^{D} \left(1 - o_t\right)^{d-1},$$

and the total number of monthly hires is

$$H_t = q_t V_{t-1} \sum_{d=1}^{D} \left(1 - o_t\right)^{d-1} + q_t I_t \sum_{d=1}^{D} \left(D - d\right)\left(1 - o_t\right)^{d-1},$$

where q_t and I_t are defined as the average daily filling rate and the average daily inflows for month t (or, restrict $q_{d,t} = q_t$ and $I_{d,t} = I_t$ for all d within a given month t).

We follow Davis, Faberman, and Haltiwanger (2013) by setting the number of working days per month to 26, and the vacancy withdrawal rate to be equal to the observed layoff rate. The exact choice of the withdrawal rate makes little difference in practice, as δ_t is an order of magnitude smaller than the filling rate q_t. Thus, the outflow rate o_t is very close to the vacancy-filling rate q_t, and the distinction can be ignored without sacrifice in accuracy. With data on vacancies V_t, hires H_t, and a calibrated number of working days per month D and the withdrawal rate δ_t, this system determines a solution for the daily filling rate q_t and the daily inflows I_t. We therefore obtain both the outflow rate o_t and the inflow rate i_t.

Derivation. Plugging in the law of motion for vacancy dynamics at the daily frequency recursively, we have

$$V_{d+\Delta,t} = V_{d,t}\left(1-o_t\right)^{\Delta} + I_t \sum_{i=1}^{\Delta}\left(1-o_t\right)^{i-1},$$

where d and $d+\Delta$ are two dates with Δ days apart within the same month t. Note that $V_{0,t} = V_{t-1}$ and $V_{D,t} = V_t$. We evaluate this equation by taking $d=0$ and $\Delta = D$ and reach

$$V_t = V_{t-1}\left(1-o_t\right)^{D} + I_t \sum_{i=1}^{D}\left(1-o_t\right)^{i-1}.$$

The monthly number of hires is the sum of daily hires

$$\begin{aligned} H_t &:= \sum_{d=1}^{D} H_{d,t} = \sum_{d=1}^{D} q_t V_{d-1,t} = q_t \sum_{d=1}^{D}\left[V_{t-1}\left(1-o_t\right)^{d-1} + I_t \sum_{i=1}^{d-1}\left(1-o_t\right)^{i-1}\right] \\ &= q_t V_{t-1} \sum_{d=1}^{D}\left(1-o_t\right)^{d-1} + q_t I_t \sum_{d=1}^{D}\left(D-d\right)\left(1-o_t\right)^{d-1}. \end{aligned}$$

For notational convenience, define $r_t := 1 - o_t = \left(1-q_t\right)\left(1-\delta_t\right)$. Applying the formula for the finite sum of a geometric progression, we can simplify the above two equations as

$$\begin{aligned} V_t &= V_{t-1} r_t^D + I_t \frac{1-r_t^D}{1-r_t}, \\ H_t &= q_t V_{t-1} \frac{1-r_t^D}{1-r_t} + \frac{q_t I_t}{1-r_t}\left(D - \frac{1-r_t^D}{1-r_t}\right). \end{aligned}$$

Using the same argument as before, the system can also be rewritten in the rate representation.

Algorithm. We use an iterative procedure as in Mongey and Violante (2019).
Step 0: Guess $q_t^{(0)}$.
Step 1: Compute $r_t^{(0)} = \left(1 - q_t^{(0)}\right)\left(1-\delta_t\right)$.
Step 2: Obtain $i_t^{(i)} = \left(v_t - v_{t-1} r_t^D\right) \frac{1-r_t}{1-r_t^D}$.
Step 3: Update $q_t^{(i+1)} = H_t / \left(v_{t-1} \frac{1-r_t^D}{1-r_t} + \frac{i_t}{1-r_t}\left(D - \frac{1-r_t^D}{1-r_t}\right)\right)$.
Step 4: Check convergence: if $|q_t^{(i+1)} - q_t^{(i)}| < \varepsilon$ according to some pre-specified tolerance level ε, then convergence is reached. Otherwise, we go back to Step 1 with the new guess.

III.2 Time Aggregation

III.2.1 Gross Flows Rates Across Labor Force States

This section explains how to convert observed monthly transition probabilities constructed from the Current Population Survey to the underlying Poisson arrival rates. Thanks to the short panel dimension in the Current Population Survey, monthly transition probabilities between labor force statuses can be estimated by linking individuals longitudinally across consecutive months. We use the Bureau of Labor Statistics published labor force status flows data from 1990 to 2020. For historical data from 1967 to 1990, we use the data in Elsby, Michaels, and Ratner (2015), which is in turn tabulated by Joe Ritter and made available by Hoyt Bleakley.

Let π_t^{od} denoted the monthly transition probability from state o to state d. That is, a fraction π_t^{od} of workers who were in state o in month t became d in month $t+1$. The monthly transition matrix is given by

$$\pi_t = \begin{bmatrix} \bullet & \pi_t^{ue} & \pi_t^{ne} \\ \pi_t^{eu} & \bullet & \pi_t^{nu} \\ \pi_t^{en} & \pi_t^{un} & \bullet \end{bmatrix},$$

such that each column sums up to 1. The transition matrix π_t is readily available in the data. Denote the distribution of workers across labor force statuses by $x_t = (e_t, u_t, n_t)'$. Then the discrete-time law of motion is given by $x_{t+1} = \pi_t x_t$.

The goal is to derive its continuous-time counterpart in order to deal with the time aggregation issue. Let φ^{od} denote the Poisson arrival rate that a worker moves from state o to state d. The continuous-time transition matrix is thus given by

$$\varphi_t = \begin{bmatrix} \bullet & \varphi_t^{ue} & \varphi_t^{ne} \\ \varphi_t^{eu} & \bullet & \varphi_t^{nu} \\ \varphi_t^{en} & \varphi_t^{un} & \bullet \end{bmatrix}$$

with each column summing up to 0, such that the continuous-time law of motion is given by $\dot{x}_t = \varphi_t x_t$.

Dealing with time aggregation is equivalent to finding out the relationship between φ_t and π_t. Denote $\pi_{t,\Delta}$ the transition probability matrix when the time gap is Δ unit of time, such that $x_{t+\Delta} = \pi_{t,\Delta} x_t$. Assume π_t is diagonalizable (see Shimer, 2012, for a more technical discussion), which is always the case in the data. Let D_t be the diagonal matrix of eigenvalues of π_t and P_t the associated eigenvector matrix, such that $\pi_t = P_t D_t P_t^{-1}$. Then $\pi_{t,\Delta} = \pi_t^{\Delta} = P_t D_t^{\Delta} P_t^{-1}$. By definition, the Poisson arrival rate is the following limit

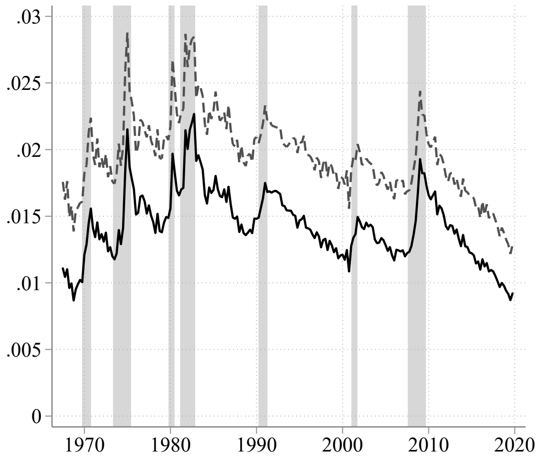
$$\varphi_t = \lim_{\Delta \to 0} \frac{\pi_{t,\Delta} - I}{\Delta},$$

where I is an identity matrix. Therefore, Poisson rate transition matrix can be written as $\varphi_t = P_t \tilde{D}_t P_t^{-1}$, where $\tilde{D}_t$ is a diagonal matrix with $\tilde{D}_t(i,i) = \log D_t(i,i), \forall i$.

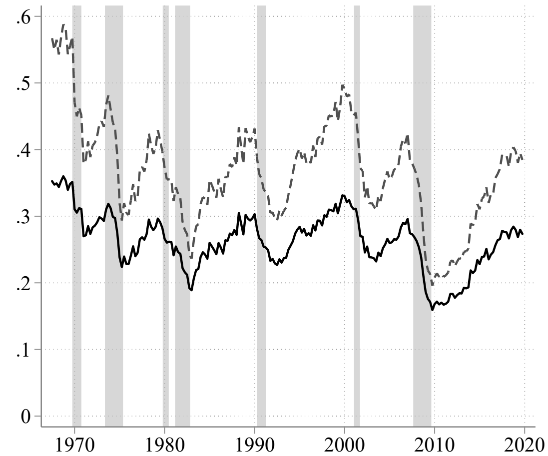
Figure A-9 plots the transition probability series in black solid lines and the time-aggregation adjusted Poisson rate series in gray dashed lines. Figure A-10 plots the corresponding HP-filtered series.

Figure A-9: Gross Worker Flow Rates

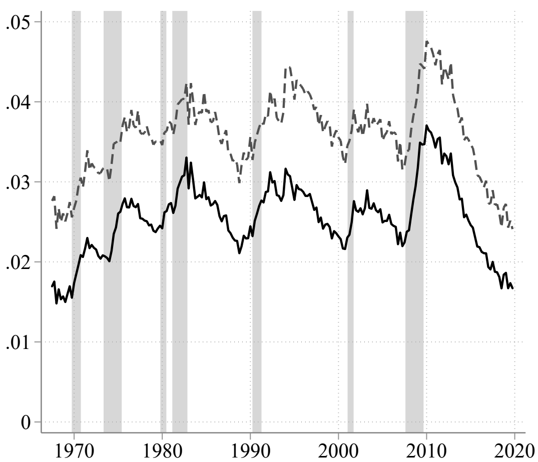
(a) Employment to Unemployment



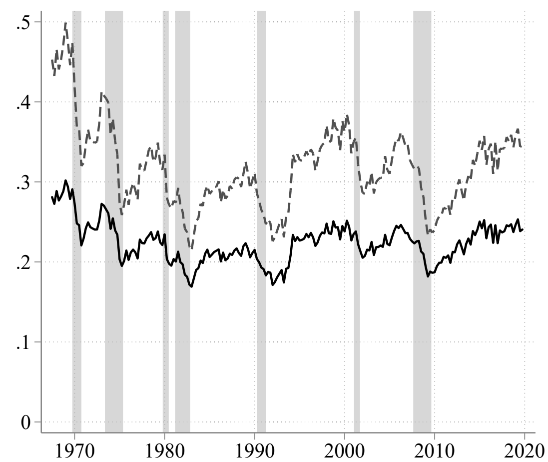
(b) Unemployment to Employment



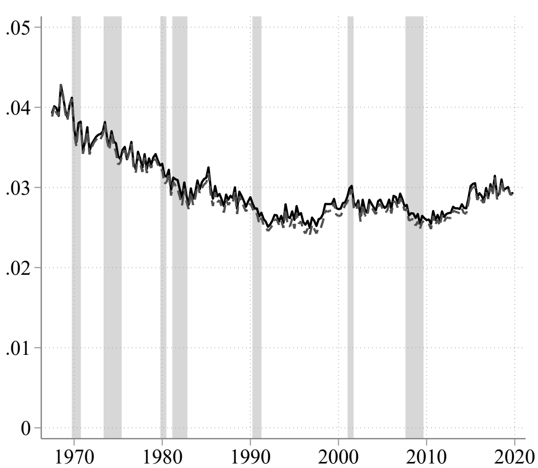
(c) Nonparticipation to Unemployment



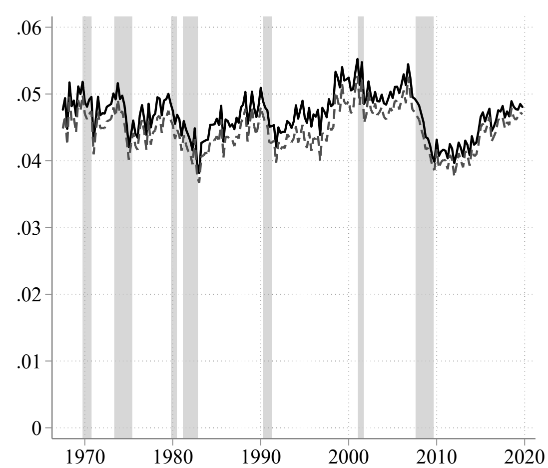
(d) Unemployment to Nonparticipation



(e) Employment to Nonparticipation

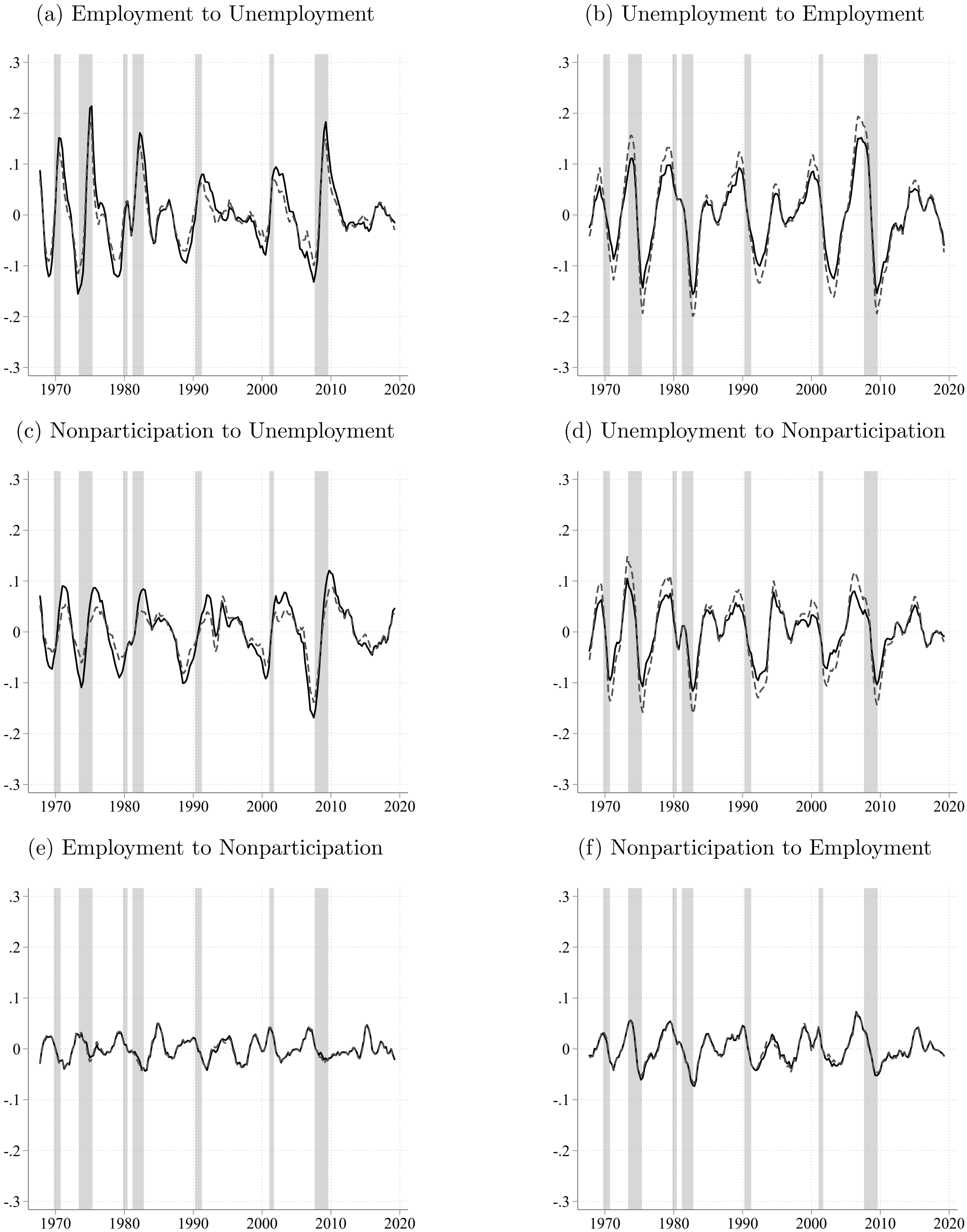


(f) Nonparticipation to Employment



Notes: Black solid lines are transition probabilities and gray dashed lines are Poisson rates.

Figure A-10: HP-Filtered Gross Worker Flow Rates



Notes: Black solid lines are transition probabilities and gray dashed lines are Poisson rates.

III.2.2 Job-to-Job Transition Rate

In the 1994 redesign of the Current Population Survey, a question is introduced that explicitly asks whether the employer the respondent is currently working for is still the same one as in the previous month. This question has now become the standard data source for measuring monthly employer-to-employer transition rates (which is also often referred to as "job-to-job" rates or J2J rates) in the US labor market since Fallick and Fleischman (2004)'s pioneering work. The monthly frequency of the CPS has minimized the potential time aggregation issue to a large extent, compared to other data sources commonly available only at the quarterly frequency, such as the labor force surveys in Europe and the administrative Longitudinal Employer-Household Dynamics (LEHD) matched employer-employee dataset. Nevertheless, the potential time aggregation bias is not guaranteed to be completely eliminated even with monthly data. We follow Mukoyama (2014) to correct for time aggregation bias in employer-to-employer transition rates. The goal is to recover the Poisson rate of changing employers, $\varphi_t^{ee'}$, from the monthly transition probability that an employed worker working for some employer at time t now work for a different employer at time $t+1$, $\pi_t^{ee'}$.

First, denote $\alpha(\tau)$ the share of employed workers at some given point of time that has never experienced any labor market transitions after τ unit of time. Thus,

$$\dot{\alpha}(\tau) = -\left(\varphi^{ee'} + \varphi^{eu} + \varphi^{en}\right)\alpha(\tau),$$

with an initial condition $\alpha(0) = 1$. The solution to this differential equation is $\alpha(\tau) = \exp\left(-\left(\varphi^{ee'} + \varphi^{eu} + \varphi^{en}\right)\tau\right)$.

Second, denote $\beta(\tau)$ the share of employed workers at some given point of time that has experienced the employer-to-employer shock exactly once but has never experienced other labor market transitions after τ unit of time. Thus,

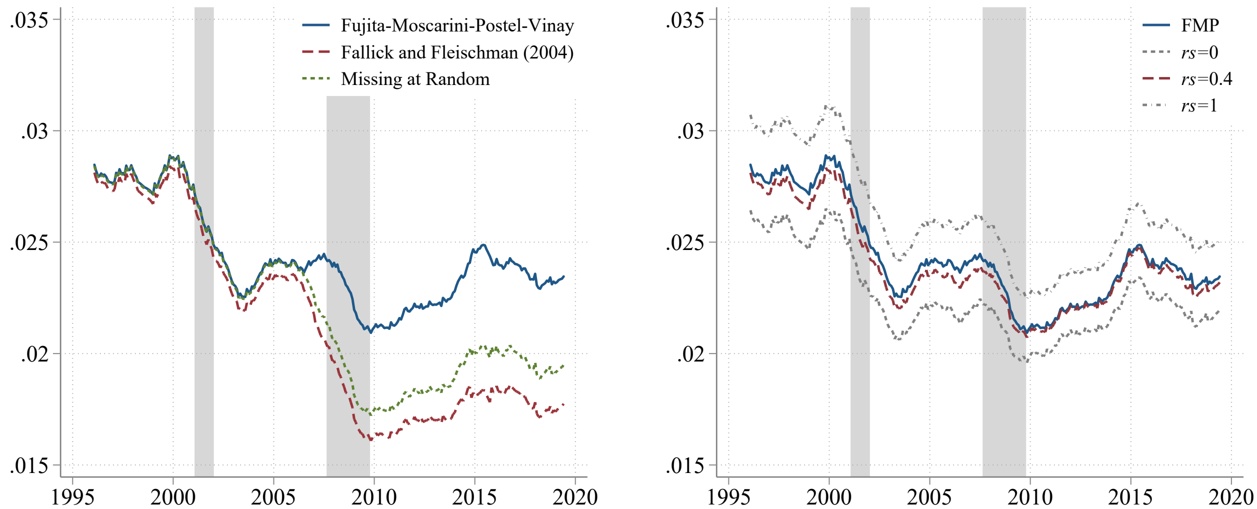
$$\dot{\beta}(\tau) = -\left(\varphi^{ee'} + \varphi^{eu} + \varphi^{en}\right)\beta(\tau) + \varphi^{ee'}\alpha(\tau),$$

with an initial condition $\beta(0) = 0$. The solution to this differential equation is $\beta(\tau) = \varphi^{ee'}\tau\alpha(\tau)$.

In the data, $\pi_t^{ee'}$ measures the fraction of employed workers working for some employer at time t now works for a different employer at time $t+1$. The time aggregation issue is that this fraction not only includes those who made an employer-to-employer transition exactly once without any other transitions after 1 unit of time, which constitute a share of $\beta(1)$, but also includes those who happened to be employed in a different employer by going through multiple

Figure A-11: Employer-to-Employer Transition Rate

(a) Raw Estimates (b) Time Aggregation Adjustment



Notes: This figure plots the employer-to-employer transition rate and its time-aggregation adjustments.

transitions. That is,

$$\pi^{ee'} = \beta\left(1\right) + \left(1 - rs\right)\left[\left(1 - \pi^{eu} - \pi^{en}\right) - \alpha\left(1\right) - \beta\left(1\right)\right],$$

where rs denotes the share of workers who go back to their previous employer after multiple transitions. We allow for the recall share r due to its importance in the US labor market (Fujita and Moscarini, 2017; Lam and Qiu, 2022). For a given recall share rs, we can obtain the Poisson rate $\varphi^{ee'}$ by solving the above equation.

The left panel of Figure A-11 plots the employer-to-employer transition rates as in Fujita, Moscarini, and Postel-Vinay (2020), together with the original Fallick and Fleischman (2004) correction and the missing-at-random imputation. The right panel of Figure A-11 plots the time-aggregation adjustments based on the FMP series. The red dashed line plots the case for an empirically sensible recall share of 0.4. The resulting corrected series tracks the original one closely, suggesting that the time aggregation bias in the employer-to-employer rate is minor. The two gray lines plot the two extremes of a recall share of 0 and 1, respectively. They also provide a tight bound for the true J2J Poisson rate. Moreover, the cyclicality of the adjusted series is barely changed compared to the original series. Although the Abowd-Zellner correction affects the levels of the transitions rates, it barely affects the cyclicality.

III.3 Classification Errors

Abowd-Zellner correction. Abowd and Zellner (1985) estimate the magnitude of classification errors, using a series of CPS reinterview surveys in which respondents were followed up to verify the accuracy of their initial responses. Their estimates are reproduced in Table A-2. Denoted by $\mathcal{E}$ the misclassification matrix such that ε_{ij} refers to the probability that an individual with actual labor market state i has a measured state j. Define F to be the 3×3 matrix of observed flows:

$$F = \begin{bmatrix} F_{EE} & F_{EU} & F_{EN} \\ F_{UE} & F_{UU} & F_{UN} \\ F_{NE} & F_{NU} & F_{NN} \end{bmatrix},$$

and F^* to be the true flows. Poterba and Summers (1986) show that the true flows can be obtained as $F^* = (\mathcal{E}^{-1})' F \mathcal{E}^{-1}$.

Table A-2: Estimates of Classification Errors

	2nd		
1st	E	U	N
E	98.78	1.91	0.50
U	0.18	88.57	0.29
N	1.03	9.52	99.21

Notes: This table reproduces Abowd and Zellner (1985, Table 6). The column "1st" refers to the status recorded in the initial interview, and the row "2nd" refers to the status determined on reinterview.

DeNUNification. Another approach assumes transitions back and forth between unemployment and nonparticipation in consecutive months to be measurement errors. For instance, it treats the temporary U state for N-to-U-to-N transitions as mismeasured. It thus recodes the data such that these transition reversals are eliminated. I follow the "deNUNification" procedure as in Elsby, Hobijn, and Şahin (2015). However, Kudlyak and Lange (2017) challenge this practice. Nevertheless, the deNUNification procedure by construction primarily lowers the levels of UN and NU transitions rate, while other flow rates are virtually unaffected.

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