Vacant Jobs*

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Abstract

Canonical theories of frictional labor markets conceptualize separations as job destruction and vacancies as job creation. Yet, workers exiting the labor force hence vacating their positions, dubbed the vacating channel, is an empirically important source of both separations and vacancies. It is absent in standard models that treat vacancies as isomorphic to recruiting efforts, while I document facts on vacancy dynamics that point to an alternative view of vacancies as part of the job life cycle. I develop a model that incorporates the vacating channel and discipline the model by properties of labor market flows. It brings novel insights into the business cycle theory of unemployment: 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 vacated vacancies.

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1 Introduction

Labor market frictions are manifested by the coexistence of vacancies and unemployment. The canonical theory of a frictional labor market, the Diamond-Mortensen-Pissarides (DMP) model, rests on two pillars: First, vacancies arise from job creation, determining unemployed workers' job-finding prospects; second, separations arise from job destruction, describing employed workers' job-losing instances. Yet, the act of workers leaving the labor force and vacating their positions—I call it the vacating channel throughout the paper—is an empirically important source of both vacancies and separations. This paper shows that the vacating channel has important macroeconomic implications on the functioning of the labor market, including business cycle fluctuations in unemployment and impacts of changing interest rates.

Not all vacancies reflect new labor demand. When a worker leaves the labor force for reasons that change her own labor market attachment, the job remains profitable. The employer hence has the incentive to advertise the position and 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. Conceptually, the vacating channel represents a different source of separations from standard job destruction caused by negative productivity shocks to the jobs. It also represents a different source of vacancies from standard job creation that captures employers' desire to create new jobs. Empirically, worker exits are a prevalent form of separations: more than half of the employment outflows are workers exiting the labor force; and vacated positions are a prevalent form of vacancies: more than half of the vacant jobs are vacated ones.

The vacating channel is especially evident in episodes of labor shortages, where negative aggregate labor supply shocks are followed by spikes in vacancies. However, introducing the labor supply margin into an otherwise standard DMP model would predict the opposite: 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.[1] The vacating channel is further corroborated by establishment-level evidence that a worker's voluntary quit leads to an increase in vacancies.

I develop a model incorporating the vacating channel to reconcile these empirical regularities and analyze the implications of the vacating channel. I introduce two main elements into the DMP model. First and foremost, the model treats vacancies as vacant periods over the life cycle of jobs rather than isomorphic to recruiting efforts. Creating a new job requires a sunk investment to set up the position,[2] while advertising a vacancy only incurs a flow recruiting

[1] To be precise, this describes the prediction under rational expectations, as the vacancy posting margin in the DMP model operates through employers' expectations. In the case of an unexpected one-time change in labor force exits, employers' incentive to post vacancies is unaffected.

[2] 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

cost. Potential entrants draw a stochastic position setup cost, which implies a finite elasticity of job creation, as opposed to the commonly assumed infinite elasticity implied by the free entry condition. This elasticity is later estimated from the data and is identified by the relative volatility between created and vacated vacancies. 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 job-to-job switchers.[3]

The model is calibrated to the US labor market over the business cycle. It replicates the means and standard deviations of not only flows between employment and unemployment (i.e., the separation and job-finding rates) in conventional analyses, but also flows into and out of the labor force. 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.

Incorporating the vacating channel is not only empirically relevant but also brings novel insights missing in standard models. First, I revisit the role of the labor force participation margin in the equilibrium theory of unemployment fluctuations. Conventional wisdom ascribes a negligible role to the participation margin, based on the empirical observation of its little volatility and cyclicality, and the good approximation of a two-state representation of unemployment. Thus, the majority of research on unemployment flows abstracts from the labor force participation margin. This paper provides a novel perspective. The employment-to-nonparticipation (EN) quit rate is procyclical. In recessions, fewer EN quits reduce vacancies through the vacating channel, contributing to the deterioration of unemployed workers' job-finding prospects. Thus, the procyclicality of EN causes job-finding fluctuations, while still consistent with a statistical decomposition that suggests a major role of job-finding rate fluctuations in explaining unemployment volatility.[4] The calibrated model finds that the vacating channel is an impor-

with an interdependent production process (Kuhn, Luo, Manovskii, and Qiu, 2022).

[3]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.

[4]See Shimer (2012); Fujita and Ramey (2009); Elsby, Michaels, and Solon (2009). Studies by Jung and Kuhn (2014); Elsby, Hobijn, and Şahin (2015) have extended the analysis to a three-state flow decomposition of unemployment volatility.

tant driver of unemployment fluctuations, accounting for almost one-third of the business cycle variation in unemployment.

Second, I revisit the impact of real interest rates on the labor market. Conventional wisdom maintains that higher real interest rates depress employers' job creation incentive, hence increasing unemployment (Hall, 2017). This paper highlights two different sources of vacancies that respond differently to interest rates. Newly created vacancies involve a sunk investment in setting up the job, whereas vacated vacancies have already embodied the sunk investment. Therefore, as an investment activity, the job creation channel is responsive to interest rates; but the vacating channel is not. 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 potential 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 post-war empirical regularities). The current labor market, however, features the so-called "Great Resignation," where the high vacancy rate is mainly attributed to the vacating channel from the surge in workers' quits. Thus, the overall impact of raising interest rates is attenuated, and a soft landing is conceivable.[5]

Why is the vacating channel absent in standard theories of a frictional labor market? Besides one apparent reason that the labor supply margin is commonly abstracted away, the root of the issue lies in the modeling of vacancies as isomorphic to recruiting efforts. As a result, the number of vacancies is a jump variable. The key for the vacating channel to be operative is to consider vacancies as "vacant jobs"—a vacancy is part of the life cycle of a job. A job is born vacant, when an entrepreneur creates it. In the presence of labor market frictions, it takes time for a vacant job to be matched with a worker. After some time, the worker may exit the labor market for reasons orthogonal to the productivity of the job, and a vacancy arises from an existing position being vacated. Eventually, a job, either vacant or filled, can be destroyed due to negative productivity shocks to the job, completing the life cycle of the job. A job has its life cycle because it has embodied the sunk investment to physical or organizational capital. The traditional view of vacancies as recruiting efforts attributes all vacancy fluctuations to vacancy inflows. I show that, instead, vacancy outflows account for most of cyclical vacancy fluctuations in the data. This is a robust empirical regularity across countries. Such importance of the stock nature of vacancies is consistent with the vacant jobs view.

[5]This does not constitute a policy recommendation but provides one input for policy evaluations. A full-fledged quantitative model for monetary policy would be needed, but it is beyond the scope of this paper.

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.[6] However, despite the voluminous literature studying unemployment, relatively little is known about vacancies except for the cyclical properties. 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 empirical measurements of employer heterogeneity in recruiting intensity and hiring practices.[7] 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. This paper studies different sources of vacancies. I document the prevalence of the vacating channel and the flow decomposition of vacancy dynamics. Both facts are in contrast to what is implied by the textbook model of a frictional labor market.

Second, the paper makes a theoretical contribution to the equilibrium theory of frictional labor markets. The novel vacating channel arises from the marriage 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).[8] On the labor supply side, the model is related to three-state models that incorporate labor force participation decisions into search-and-matching models.[9] This paper proposes a novel parsimonious formulation

[6]See Abraham and Katz (1986); Abraham and Wachter (1987); Blanchard and Diamond (1989) for early contributions.

[7]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.

[8]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).

[9]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 the three-state model with empirical evidence exploiting

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]

Third, the paper contributes to understanding the sources of unemployment fluctuations over the business cycle. This literature is so large that I do not attempt to provide a comprehensive review, but summarize the main ideas. The conventional wisdom 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.[11] 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.

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

the unexpected elimination of federal unemployment benefit extensions.

[10]The vacating channel is discussed from the perspective of the aggregate labor market, rather than a specific establishment. Both in the data and in the model, a job-to-job transition generates a vacated vacancy at one establishment but at the same time fills a vacancy at another establishment. On the contrary, a worker exiting the labor market generates a vacated vacancy without filling another vacancy. In defining the terminology of the vacating channel, I focus on workers exiting the labor force, rather than job-to-job transitions, although both are incorporated in the model.

[11]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). The empirical analyses by Fujita and Ramey (2009) and Elsby, Michaels, and Solon (2009), although agree that the job finding rate accounts for more unemployment fluctuations than the separation rate, 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. Coles and Moghaddasi Kelishomi (2018), on the other hand, emphasize a dominant structural role of the separation rate, despite its seemingly minor role in an accounting decomposition.

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

2 Facts

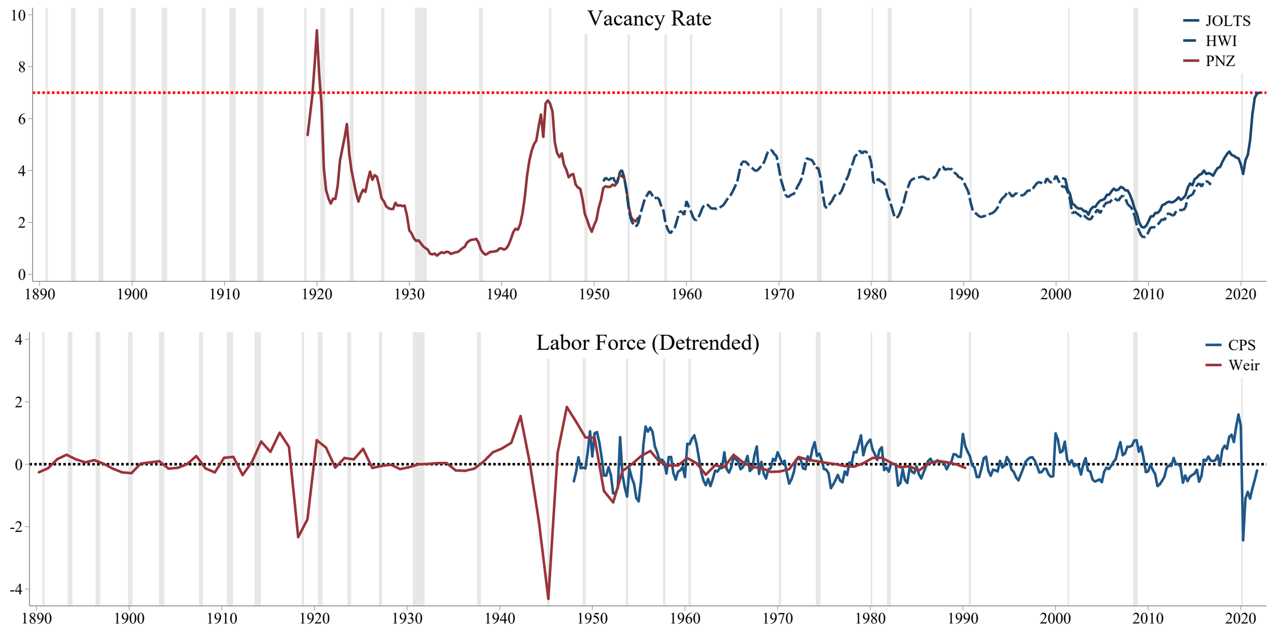
This section documents three main facts. First, I provide evidence of the vacating channel both in the aggregate and in the cross-section of establishments. Moreover, compared to newly created vacancies, vacated vacancies are both more prevalent in the labor market and more volatile over the business cycle. Second, I document reasons for workers' transitions from employment to nonparticipation. The findings point to non-market factors being the primary driver, such as caring for family, retirement, and education, rather than productive 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 Vacated Vacancies

2.1.1 Historical Episodes

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 the Covid pandemic, 7 out of 100 jobs are vacant. This is widely perceived as unprecedented in the context of the post-war labor market data that researchers today are accustomed to. The vacancy rate of 7% reaches a record high since the introduction

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



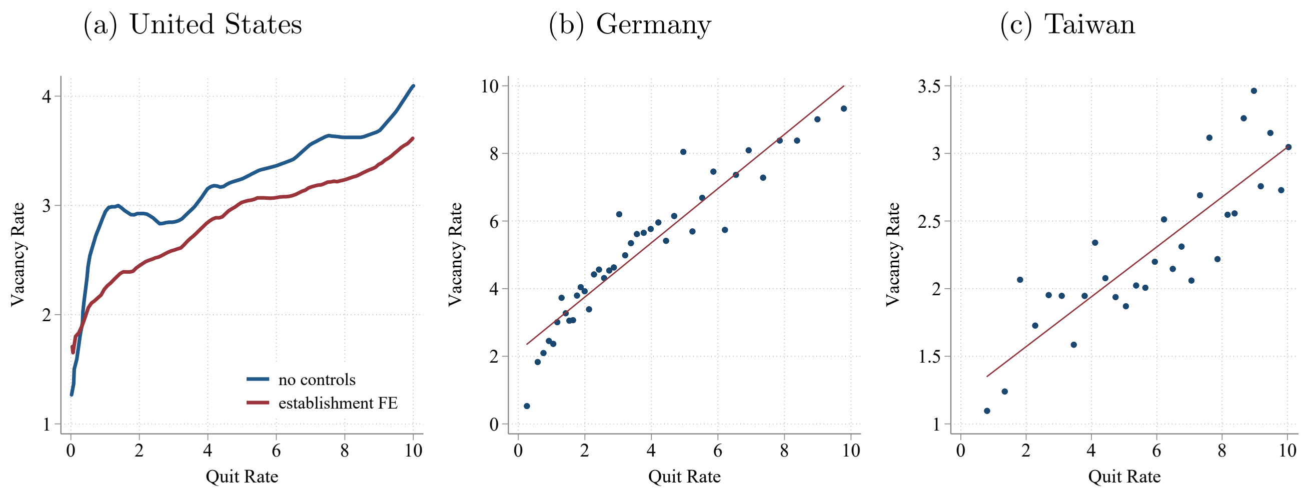
Notes: Vacancy data for December 2000 onward are monthly series obtained from the Job Openings and Labor Turnover Survey (JOLTS). Historical vacancy data are monthly series obtained from Petrosky-Nadeau and Zhang (2021), which are in turn based on the MetLife help-wanted advertising index from NBER macrohistory files for January 1919 to December 1950 and the composite Help-Wanted Index constructed by Barnichon (2010) for January 1951 to December 2016. Labor force data for January 1948 onward are monthly series obtained from the Current Population Survey (CPS), for 1890 to 1990 are annual series from Weir (1992). Labor force data are 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).

of the Job Openings and Labor Turnover Survey in 2000, and more than doubles the average in the post-war US labor market according to the Composite Help-Wanted Index (Barnichon, 2010).

Digging into historical data, however, unveils that such a great labor shortage is not without precedent. Figure 1 identifies two similar historical episodes, around 1918 and 1943. In these three historical episodes (the 1918 influenza pandemic, World War II, and the COVID pandemic), the labor market experienced massive labor force outflows (about 3%, 5%, and 3% drop in the size of the labor force, respectively), as indicated by the bottom panel of Figure 1. They all lead to high vacancies, as shown in the top panel of Figure 1. The fact that the labor market experienced high vacancies as an aftermath of massive labor force exits reveals the vacating channel.[12]

[12]It is not the focus of this paper to study the underlying sources of aggregate labor supply shocks, be it the disease, the war, or something else. The point of Figure 1 is to visually illustrate the vacating channel, made apparent by the aggregate labor supply shocks.

Figure 2: Establishment-Level Evidence of Vacated Vacancies



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

2.1.2 Micro Evidence

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; and (3) there is active recruiting for workers from outside the establishment. These conditions mirror those that define unemployment. This section also utilizes 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.[13]

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 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

[13] 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.

cross-sectional establishment data.[14] 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 as an establishment experiences more quits, it posts more vacancies. This result shows the existence of the vacating channel.

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 Aggregate Importance

The previous result suggests that vacancies arise from two sources: in addition to newly created positions, the most commonly studied source of vacancies, vacancies are also generated from existing positions by workers quitting their jobs. I call them created vacancies and vacated vacancies, respectively. A natural question is: how prevalent are vacated vacancies compared with created 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

[14] I am currently in the process of applying for on-site access to JOLTS confidential microdata that have a panel dimension, delayed due to COVID on-site restrictions at the BLS. The panel structure allows one to estimate an event-study design at the establishment level. Denote by i an establishment, t a time period, τ the event time, and T the maximal leads and lags of the event study specification. Consider

$$y_{i,t} = \sum_{\tau=-T}^{T} \beta_\tau x_{i,t+\tau} + \alpha_i + \alpha_t + \varepsilon_{i,t},$$

where α_i and α_t capture establishment fixed effects and time fixed effects, and $\varepsilon_{i,t}$ the regression residual. The coefficients of interest are β_τ's, which measure the response of vacancies τ periods after (or before) a quit.

Figure 3: Share of Vacated Vacancies in the Aggregate

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

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. Third, I negotiated a proprietary dataset containing linked vacancy-personnel information that allows for tracking the life cycle of a position.

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. This measure is constructed using JOLTS, with details of measuring vacancy inflows relegated to Appendix III.1. On the outflow side, I attribute the smaller one between hires and separations at an establishment as hires that fill vacated vacancies, and the remaining hires, if any, as to fill created vacancies.[15] 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.[16] Panel (a) and (b) of Figure 3 plot the share of vacated vacancies among inflows and outflows, respectively. It shows that vacated vacancies in fact are the more prevalent form of vacancies than created vacancies. Moreover, the share of vacated vacancies is procyclical, indicating that vacated vacancies are more volatile 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, 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 (c) and (d) of Figure 3. Since the

[15] Consider an establishment has 5 hires and 3 separations last month. The imputation 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.

[16] 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.

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.

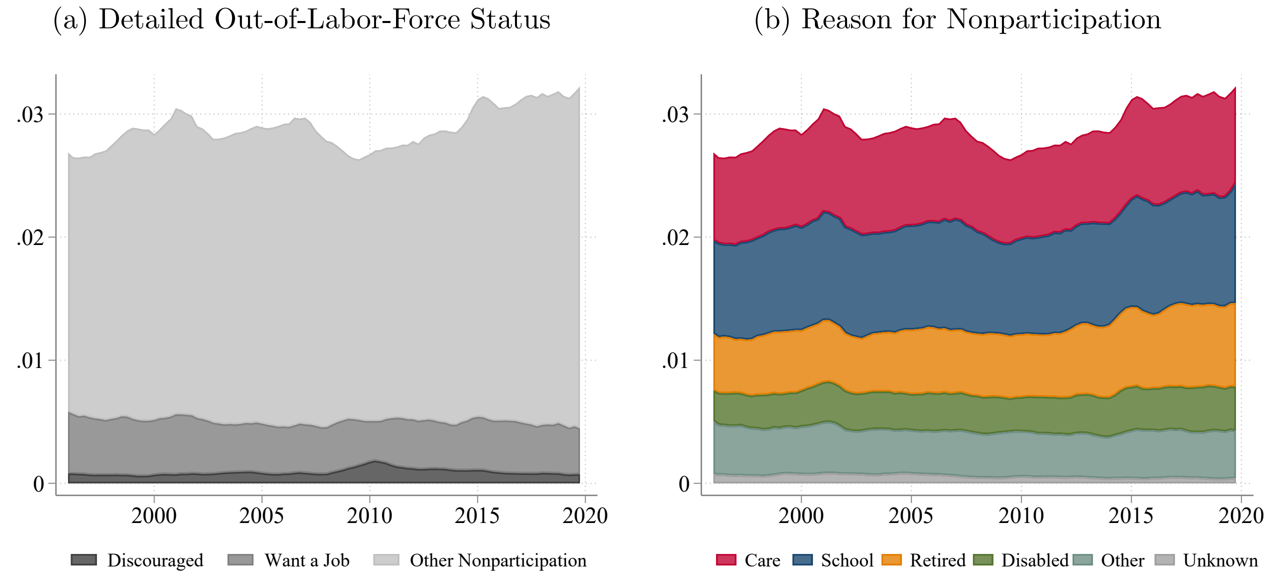
2.2 Employment-to-Nonparticipation Transitions

This section studies the worker side of the vacating channel, using the Current Population Survey (CPS) data extracted from IPUMS (Flood et al., 2022). At any point in time, the population is classified into three labor force states: (1) employed workers who are working, (2) unemployed workers who are not working but actively looking for a job (within the last 4 weeks), (3) nonparticipants out of the labor force who are not working and not searching. I use the short-panel dimension of the CPS design to measure month-to-month transitions in workers' labor force status. For example, the probability that an employed worker leaves the labor force in a particular month can be calculated as the proportion of employed workers who report being out of the labor force in the following month. Figure A-5 plots the time series of all six gross worker flow rates, and Figure A-6 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).

The monthly employment-to-nonparticipation (EN) transition rate is about 3%. 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-5 and A-6. Furthermore, 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).

Why do employed workers quit to nonparticipation? I approach this question in two ways. In the first approach, 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

Figure 4: Employment-to-Nonparticipation Transition Rate



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

"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.[17]

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% of EN transitions are into discouraged workers. This suggests that depressed job prospects are a negligible reason for EN 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. 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 nonmarket 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

[17]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.

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. This suggests modeling EN transitions as triggered by preference shocks at the worker side.

In the second approach, I construct a measure of the reason for not being in the labor force. 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.

Panel (b) of Figure 4 plots employment-to-nonparticipation transition rates by reason. On average, 18.6% of employment-to-nonparticipation transitions are retirement, 10.7% are due to disability or illness, 29.0% go to school, 26.7% take care of the family, 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 family care and school attendance. These two components account for close to the remaining 60% of employment-to-nonparticipation transitions. This approach corroborates the finding that both the procyclicality and the magnitude of EN transitions are driven by nonmarket reasons.

This paper focuses on the aggregate labor market patterns consistent across demographic groups, although there are indeed differences by demographics (see Appendix Figure A-2 and discussions therein). The distributions of reasons among UN transitions and N stocks are reported in Appendix Figure A-3.

2.3 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.[18] It turns out that vacancy outflows account for the majority of vacancy flucutations over the business cycle. This finding provides a cautionary note against the widespread practice of interpreting high vacancies as evidence of strong labor demand.

2.3.1 Inflow-Outflow Decomposition

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:[19]

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

The decomposition relies on a "steady state" approximation of vacancy rate when $v_t \approx v_{t-1}$. 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:[20]

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

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

[18] 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.

[19] 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.

[20] 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.

state approximation such that

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

Consider the following variance decomposition

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

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, whereas vacancy inflows account for 26.3%, with a residual of −0.5%.[21]

2.3.2 Visualization of the Flow Analysis

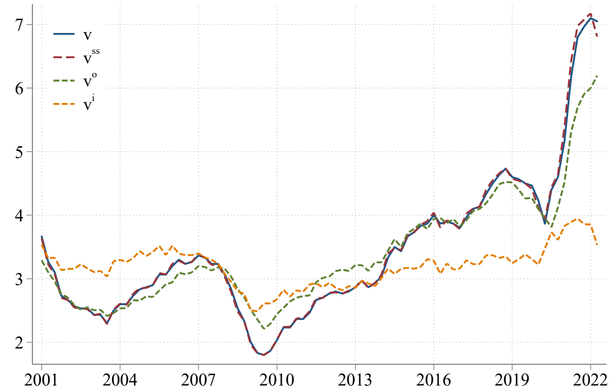
In this section, I utilize vacancy data from several countries, each with own unique strength. In particular, these data provide direct measures on vacancy inflows and outflows. Although there may be discrepancies in definitions and sampling frames across different surveys, I do not seek to compare the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

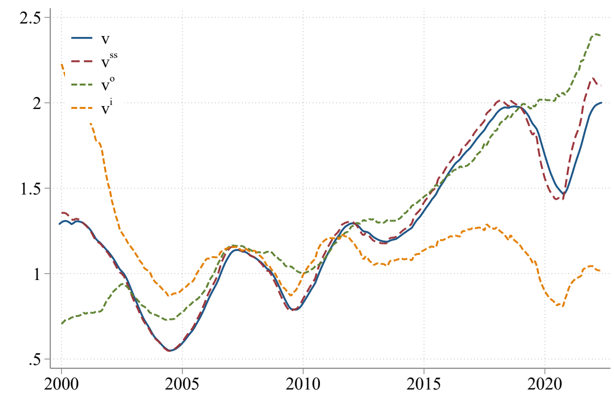
[21] If one zooms in to the Great Labor Shortage by comparing Q4 2021 with Q1 2020, 75.5% of the increase in the vacancy rate can be accounted for by a drop in the vacancy outflow rate, and 28.1% by an increase in vacancy inflow rate, and −3.6% by a residual. Thus the Great Labor Shortage is, in an accounting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

Figure 5: The Inflow-Outflow Decomposition of Vacancies

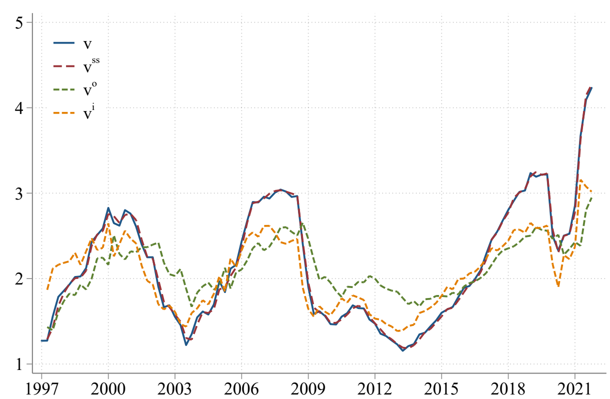
(a) United States



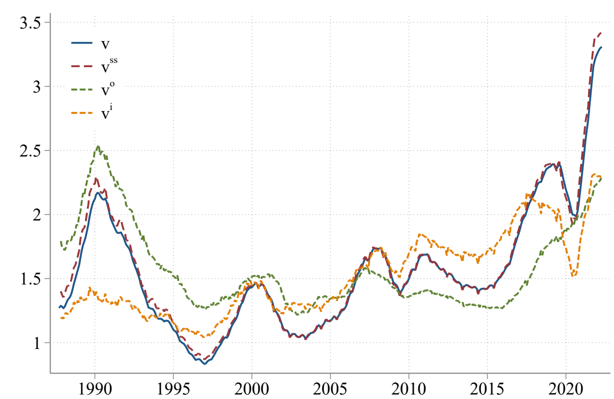
(b) Germany



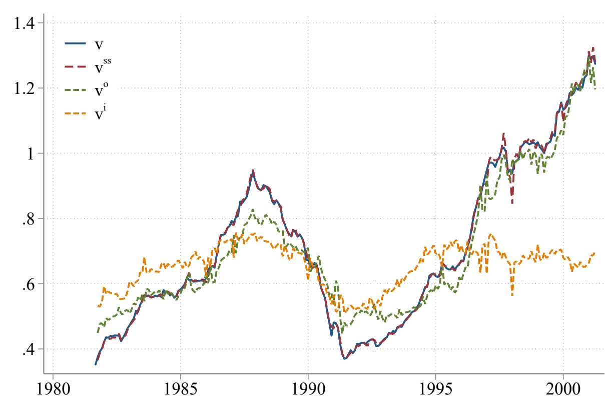
(c) Netherlands



(d) Austria



(e) United Kingdom



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).

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.

2.4 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 shows that workers' voluntary quits lead to vacancies. Historical episodes of labor shortages reveal that, in the aggregate, massive labor force outflows led to skyrocketing vacancies. Micro employer vacancy survey data reveal 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. Second, Section 2.2 shows that 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. 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. 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.

These two facts are not only empirically relevant on their own rights, but also generate interesting interactions as summarized by the vacating channel this paper focuses on. 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 2.3 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 efforts that can adjust immediately from one period to the next, so vacancies and labor market tightness are jump variables. As a consequence, vacancies are determined solely by the inflow, whereas the realized outflow has no bearing on the vacancy stock.[22]

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 a formal framework.

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

[22]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.

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.[23] These idiosyncratic shocks serve as a means to rationalize the flow rates among different labor market states for agents without ex-ante heterogeneity.

Search and Matching. Labor market frictions are characterized by an aggregate matching function $M\left(\{U, E, N\}, V\right)$, where U, E, N, V are the measures of unemployed workers, employed workers, nonparticipants, vacant jobs, respectively.[24] 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 $M\left(S, V\right)$ is assumed to exhibit constant returns to scale. Thus the worker contact rate per search intensity is $p\left(\theta\right) = M/S$ and job contact rate $q\left(\theta\right) = M/V$, where $\theta \coloneqq V/S$ defines the effective labor market tightness.[25]

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. 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 $G\left(c\right)$. 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.

[23] 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.

[24] 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.

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

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.

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 whether or not to exit the labor force depending on the realization of the preference shock, which 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. 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., $V^{e'} - V^e = 0$.[26]

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.[27] 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 $\varphi^{eu} = \varphi^{px} = \lambda\left(1 - F^{\varepsilon}\left(V^p - V^x\right)\right)$.

[26] 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.

[27] 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."

The HJB equation for an unemployed worker (u) is

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

The unemployed worker enjoys a flow utility of z^u. With rate $\varphi^{ue} = p(\theta)$, which is a function of the equilibrium labor market tightness, the unemployed worker finds a job and becomes 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 $\varphi^{un} = \psi(1 - F^\omega(V^u - V^n))$.

The HJB equation for a vacant job (v) is

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

The owner of the vacant job pays a flow cost of κ. With rate $\varphi^{vp} = q(\theta)$, 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 $\varphi^{vx} = \lambda(1 - F^\varepsilon(V^v - V^x))$.

The HJB equation for a nonparticipant (n) is

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

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 $\varphi^{ne}(\theta)$, 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. Potential entrants compare 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 $v^n = m^j G(V^v)$. 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 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 1.

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.

Table 1: 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.

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 $\Gamma\left(A'|A\right)$. In this case, the equilibrium is a set of value functions $\{V^{s}\left(\Omega\right)\}$ that are functions of the aggregate state variables $\Omega:=\{A,U,N,V\}$.[28] The dynamic stochastic equilibrium is defined such that the modified HJB equations hold with the understanding that laws of motion

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

hold. For instance, the modified HJB equation for a filled job is

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

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

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

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

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. 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. 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

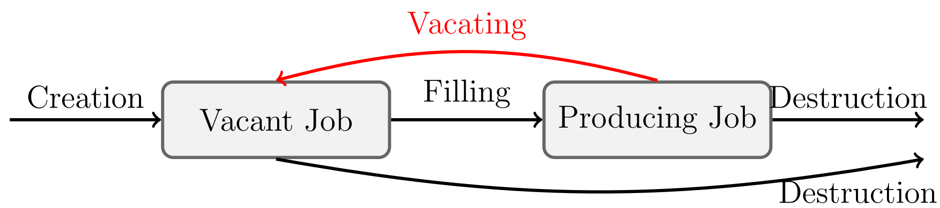
The model features three states on the worker side: employed workers (e), unemployed workers (u), and nonparticipants (n), as well as three states on the job side: filled jobs (p), vacant jobs (v), and destroyed jobs (x). The equilibrium characterizes both gross worker flows among three states and job 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 9 for a discussion of related contributions and see Hagedorn, Manovskii, and Mitman (2020) for empirical evidence on the relevance of the two paradigms). 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 deci-

Figure 6: The Life Cycle of a Job



Notes: This figure summarizes the life cycle of job.

sion 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 (e.g., it does not feature an endogenous firm size distribution).

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 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).[29] 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 $z_t^u = z^u A_t$ and $z_t^n = z^n A_t$ in line with the empirical evidence in Chodorow-Reich and Karabarbounis (2016), and $\kappa_t = \kappa A_t$ consistent with Hagedorn and Manovskii (2008). These parameters are summarized in the top panel of Table 2.

Note that I deliberately 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), who argue that 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 criticism 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

[29] See Appendix Figure A-4 for a summary of estimates from the rent-sharing literature.

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 $\varphi^{ue}, \varphi^{ee'}, \varphi^{ne}$ 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 2.

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 2.

Internal Estimation: Outer Loop (Simulated Method of Moments). The outer loop involves matching business cycle moments through the simulated method moments. Specially, for a

Table 2: 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	0.3481	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^j	10.7	Std Share of Vacated Vac.

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

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 ξ^j. The 4 parameters of the outer loop estimation are summarized in the bottom panel of Table 2.

4.2 Model Validations

Table 3 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.[30] 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

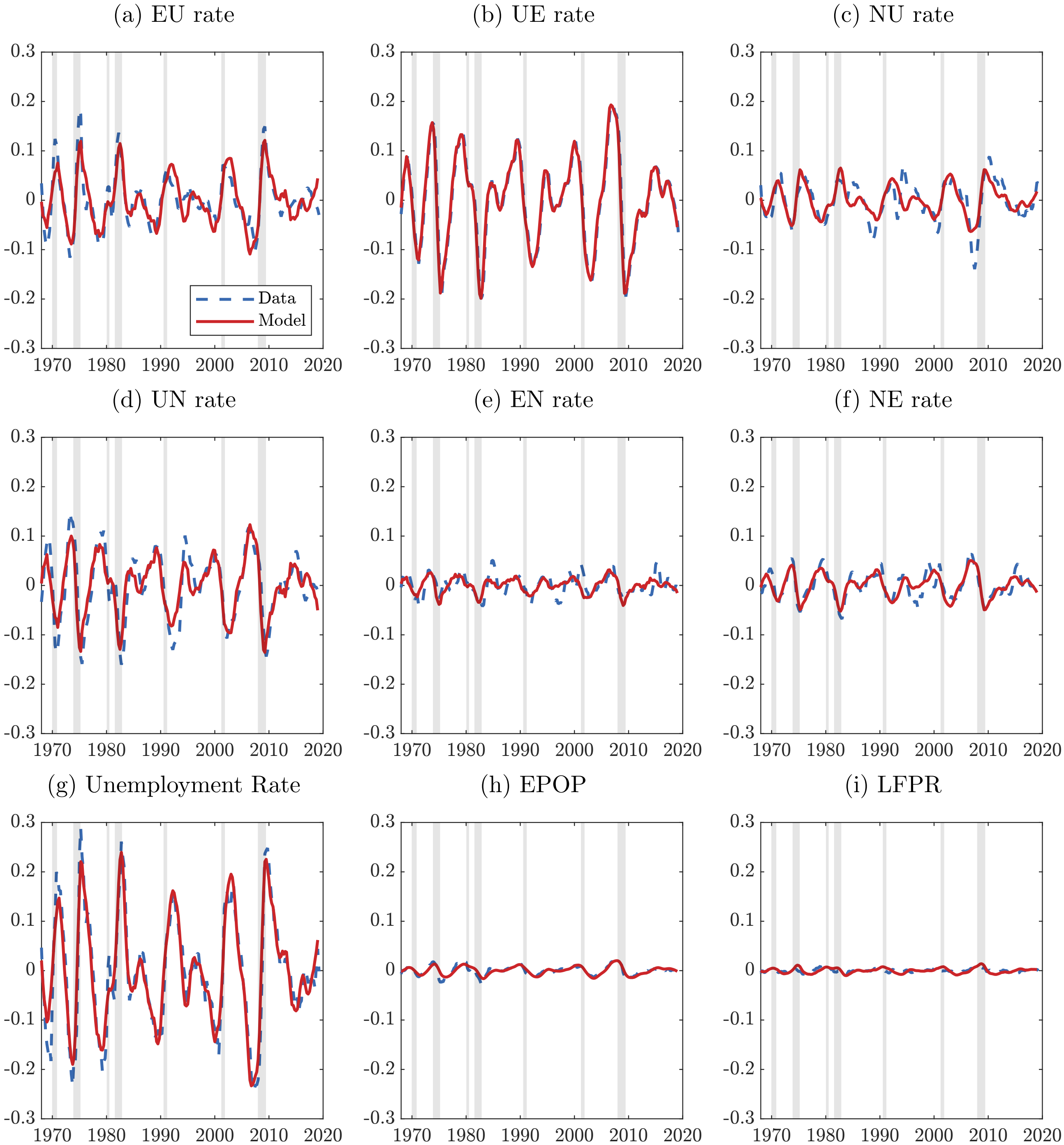
First, I assess the model's ability to reproduce the US labor market history. To do so, I ask the model to match the history of the (log detrended) job finding rate, by selecting a path of realized aggregate productivity shocks. I then input the path of realized aggregate productivity shocks into the 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 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

[30] Shimer (2005) claims 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. The model proposed in this paper resolves both "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 3: 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

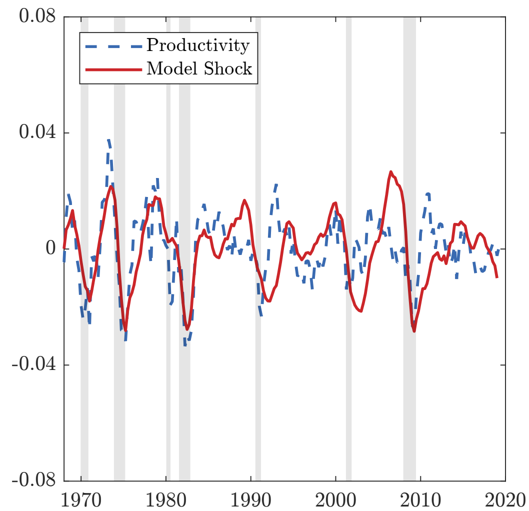
Notes: The first order moment refers to the average in the data and the steady state level in the model. The second order moment refers to the standard deviation of the series that is (seasonally adjusted in the data), quarterly averaged, logged, and HP-detrended.

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 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

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.

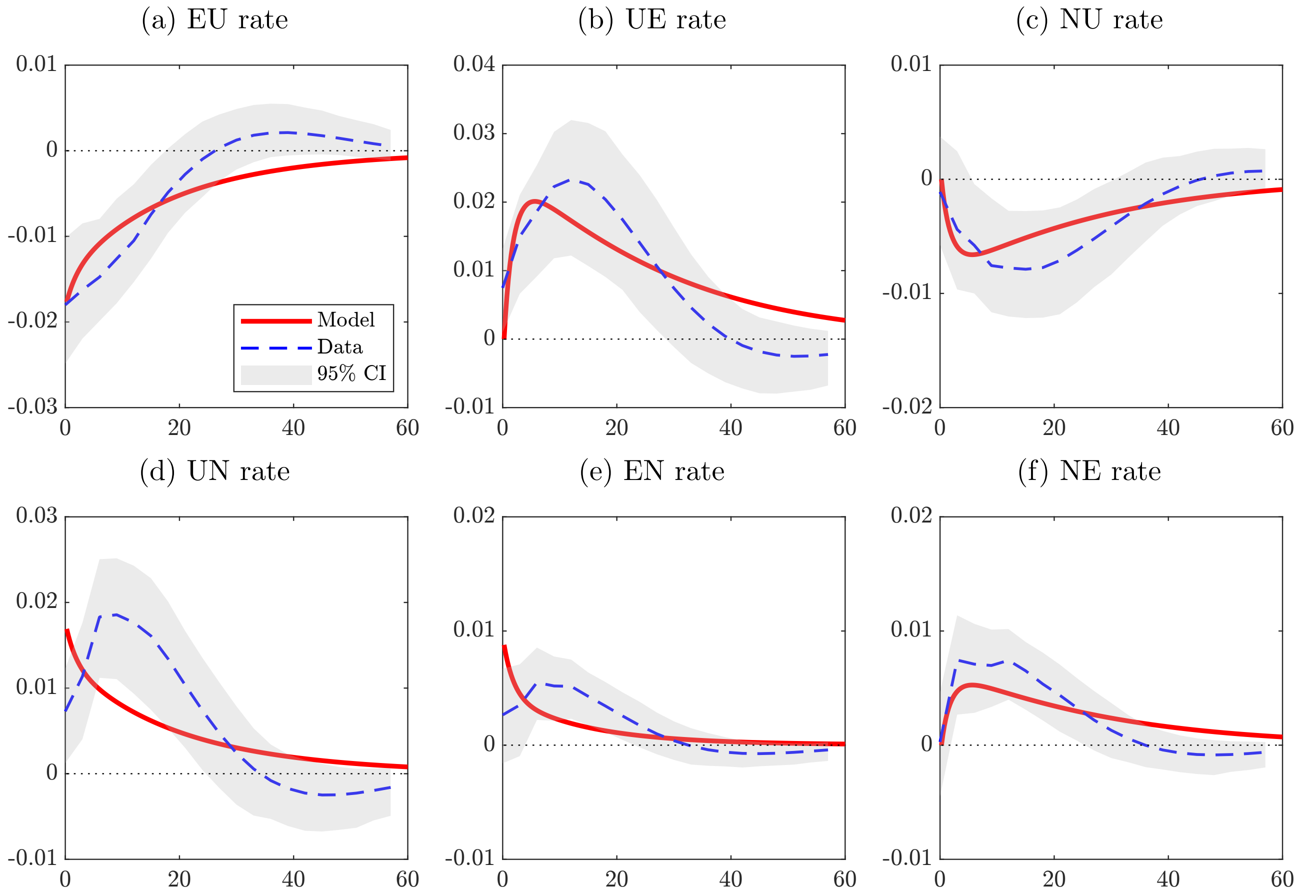
flow rates in response to a 1% drop in the aggregate productivity, both in the model (red solid lines) and in the data (blue dashed lines). Although these moments are completely untargeted, the model predicts plausible dynamics.

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.

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-

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.

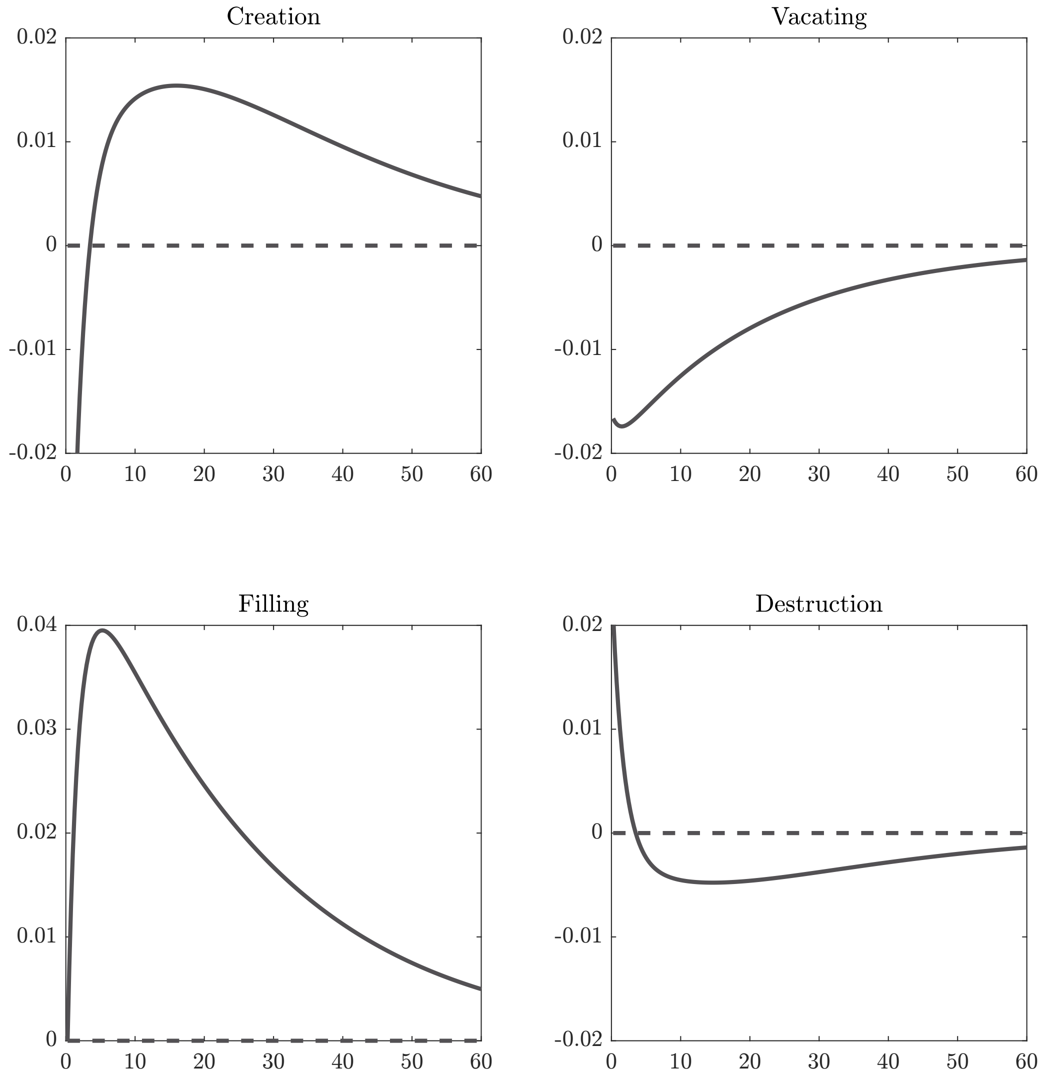
sloping Beveridge curve as vacancies move in the opposite direction to unemployment, thus resolving the second Shimer (2005) puzzle.

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 2.3 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? 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.

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 our empirical finding in Section 2.3 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.

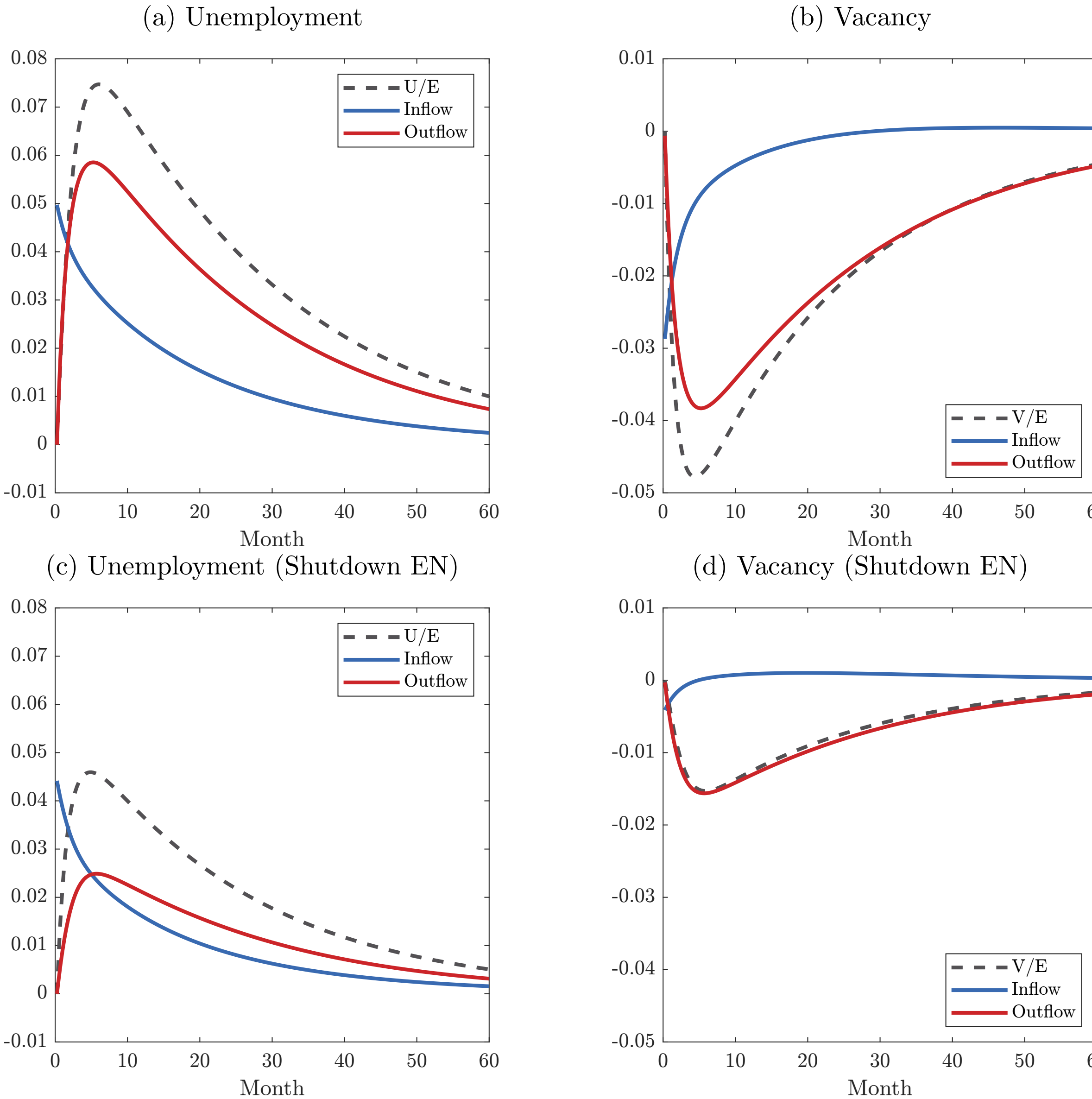
Lastly, the *destruction* channel first spikes, reflecting vacancy destruction, a similar force to job destruction. To the extent that the negative productivity shock reduces the value of a job and hence a vacant job, employers are more likely to exit when facing idiosyncratic production cost. The logic 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: 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.

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.

5 Applications

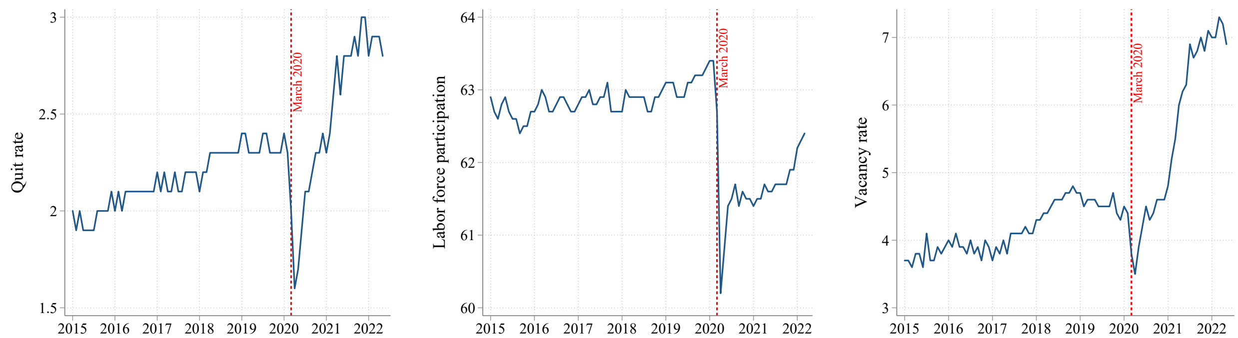
5.1 The Great Resignation

Figure 12 summarizes the three key unique features in the post-pandemic labor market. First, Figure 12a 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 12b 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 12c 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 increases by 25% thus matching the spike in the quit rate in Figure 12a. 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 13. 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.

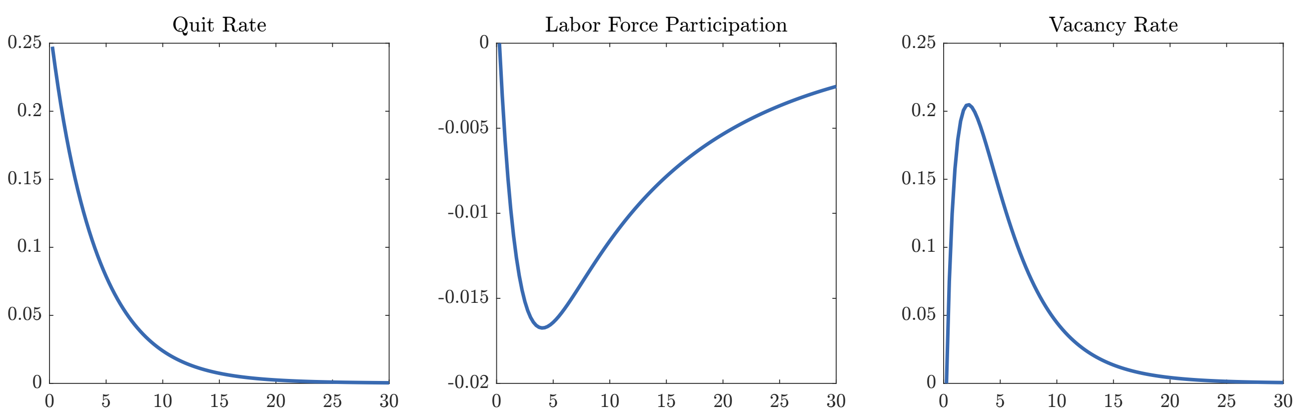
Figure 12: Great Labor Shortage in the Data

(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 13: 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.

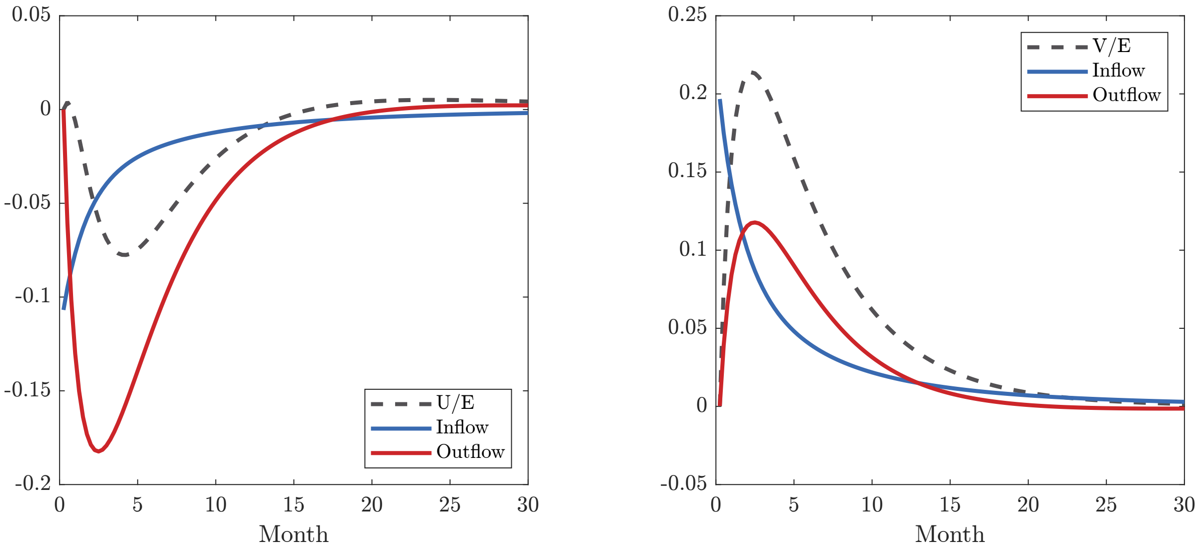
5.2 Is "Lump of Labor Fallacy" Really a Fallacy?

Figure 14 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.

Figure 14: Unemployment and Vacancy Response to Great Resignation Shock

(a) Unemployment Decomposition

(b) Vacancy Decomposition



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.

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 states. Note that all curves in Figure 14 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 14. 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.

5.3 Is "Soft Landing" Possible?

As briefly described in the introduction, the current 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."

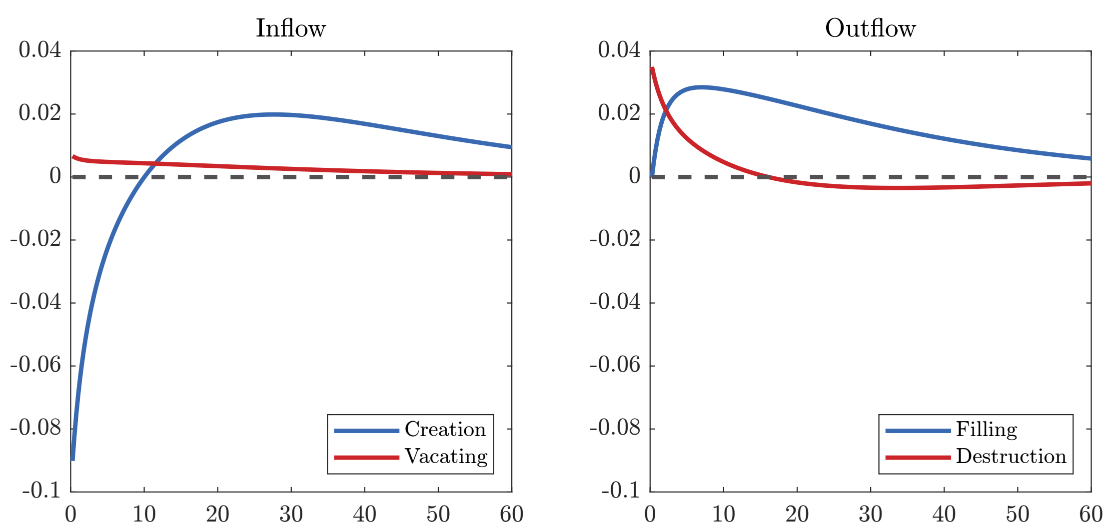
Is "soft landing" possible? There seem to be divided views among economists. Motivated by the unusually high vacancy rate, several Fed officials have suggested that "soft landing" is possible through a decrease in vacancies while going back to the point on the Beveridge curve in 2019, thus leaving unemployment 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 novel perspective to this question. The key idea is that as job creation is an investment activity, it indeed responds a lot to changes in interest rates. That is, a tightening monetary policy depresses job creation. But job creation, according to the evidence and theory in this paper, is but one vacancy channel. There are other vacancy channels. In particular, the vacating channel, may not respond as much as the job creation channel. So whether soft landing is possible crucially depends on the source of vacancies. 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.

To see how different vacancy channels respond to interest rate shocks, I conduct the following experiment. Consider an interest rate shock of 1 percentage point (or, 25% deviation). Figure 15 reports the response of different vacancy channels. 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 12%. This is because job creation is an investment activity that pays the sunk cost today but only reaps the benefits in the future. This is 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 experiment formalizes the key novel insight that different vacancy channels respond differently to a tightening monetary policy, and the aggregate impact crucially depends on which channel dominates.

Martellini, Menzio, and Visschers (2021) 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, hence the overall impact on unemployment is attenuated. Their mechanism is also featured in this paper.

Figure 15: Impulse Response Function of Vacancy Channels



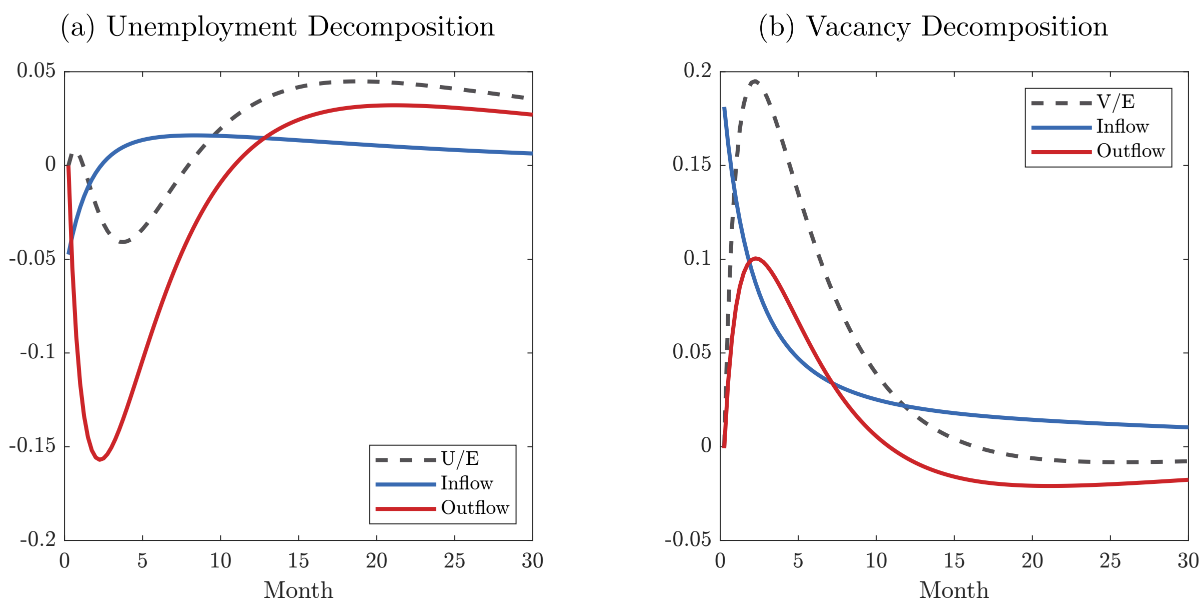
Notes: This figure plots the impulse response functions of the creation, vacating, filling, and destruction channel, in response to a 1 percentage point increase in the annual real interest rate.

As for the outflows, both channels respond in the expected direction, but the effect is minor compared to the response of the job creation channel. The filling channel is persistent, but one should note that the filling channel itself is an equilibrium outcome (because it depends on the labor market tightness) that results from the responses of the inflow channels in the first place.

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 5.1 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 5.1 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 14. 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.

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.

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 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., Auclert, 2019; Huo, Kato, and Ríos-Rull, 2022).

6 Conclusion

A vacancy is a vacant job, part of the life cycle of a job. A job can become vacant if the worker quits the job for reasons unrelated to the productivity of the job (the vacating channel). 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 a "vacant job" 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. 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.

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APPENDICES FOR ONLINE PUBLICATION

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.

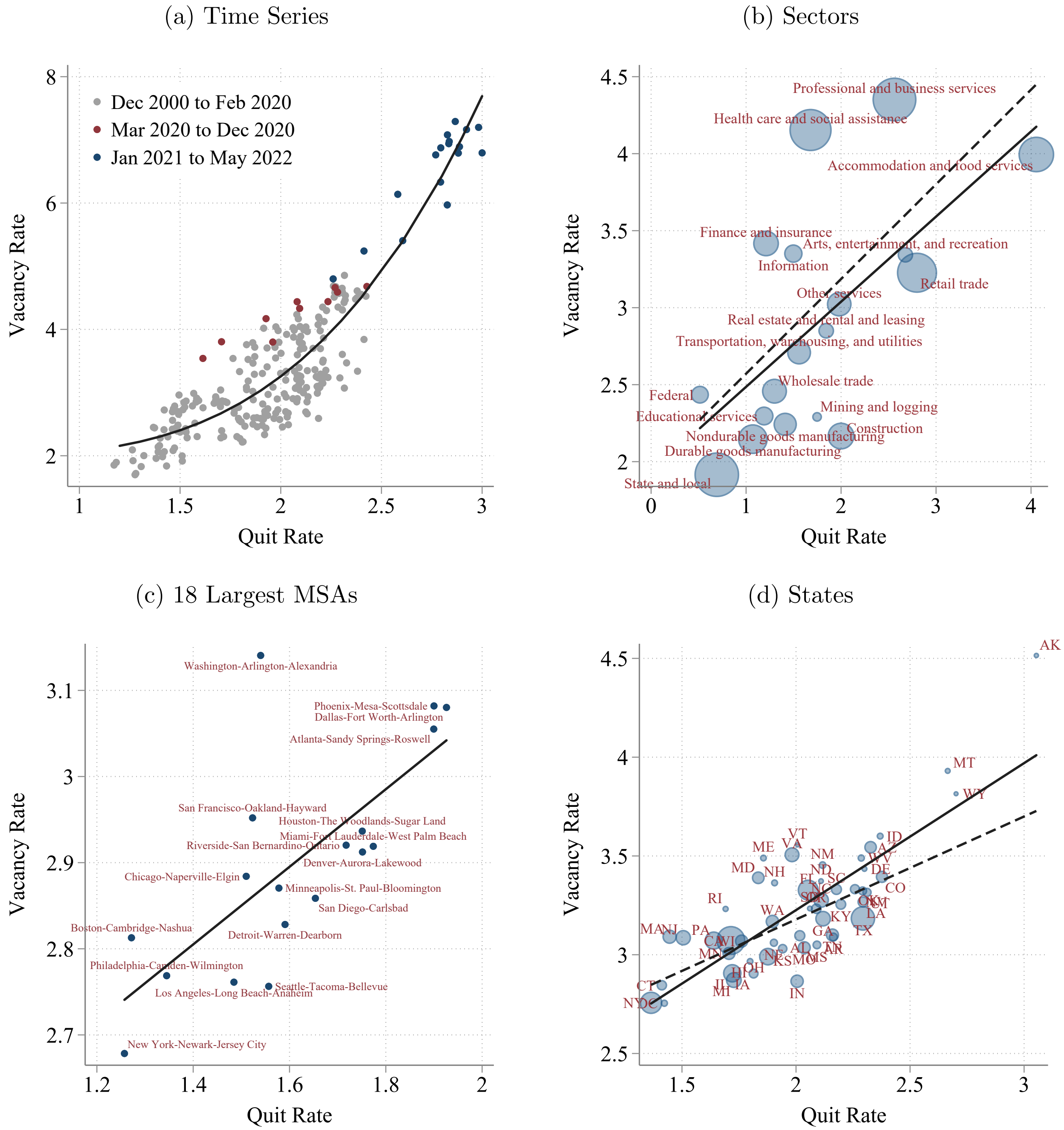
Table A-1: Vacancies and Quits

	(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



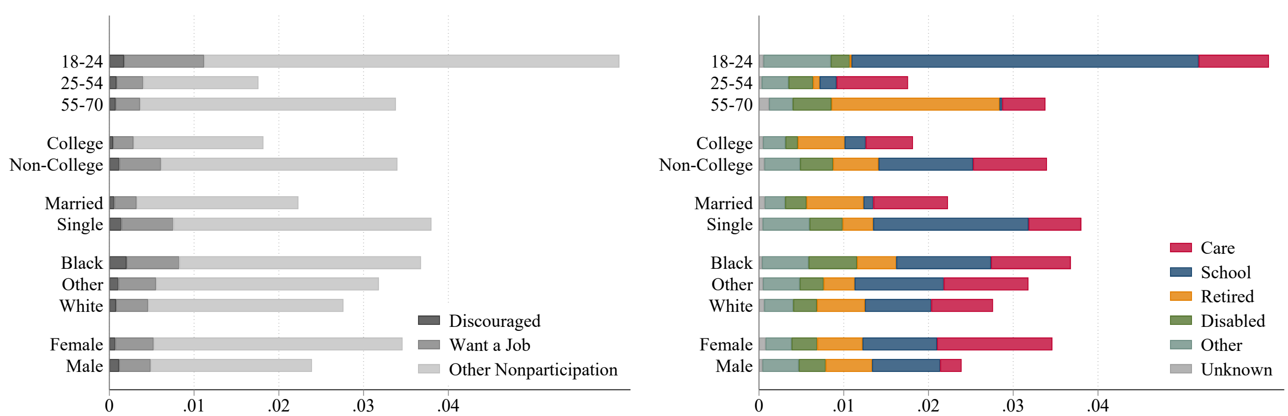
Notes: This figure plots the relationship between vacancy rate and quit rate. Panel (a) shows their relationship in the time series, with each dot representing a monthly period. Panel (b) shows their relationship across sectors, with the size of the circle representing the size of the sector. Panel (c) 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 Reasons for Nonparticipation

The distribution of reasons for leaving employment to nonparticipation differs by demographic group. 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 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.

Figure A-2: Employment-to-Nonparticipation by Demographics

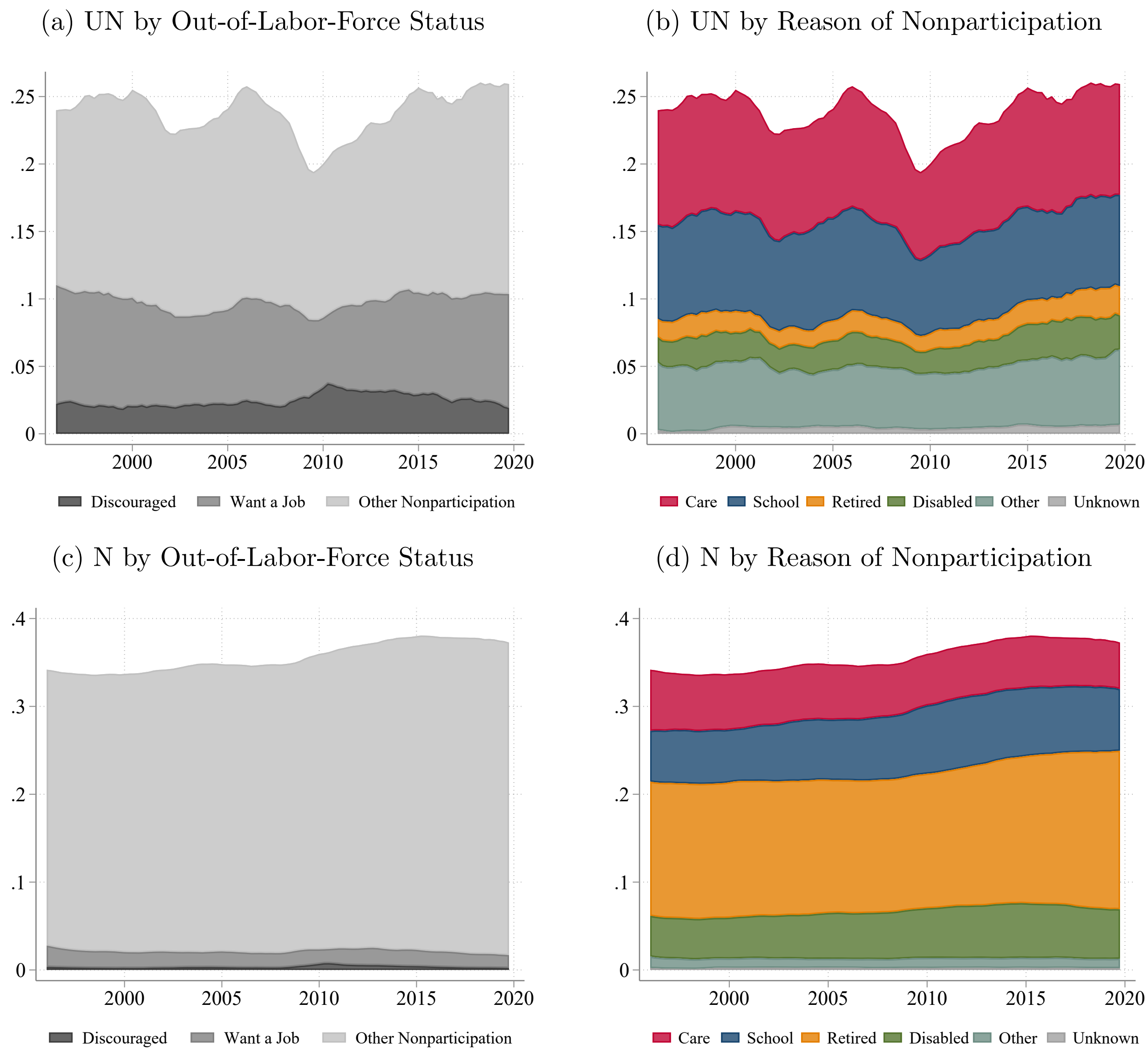
(a) Detailed Out-of-Labor-Force Status (b) Reason for Nonparticipation



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

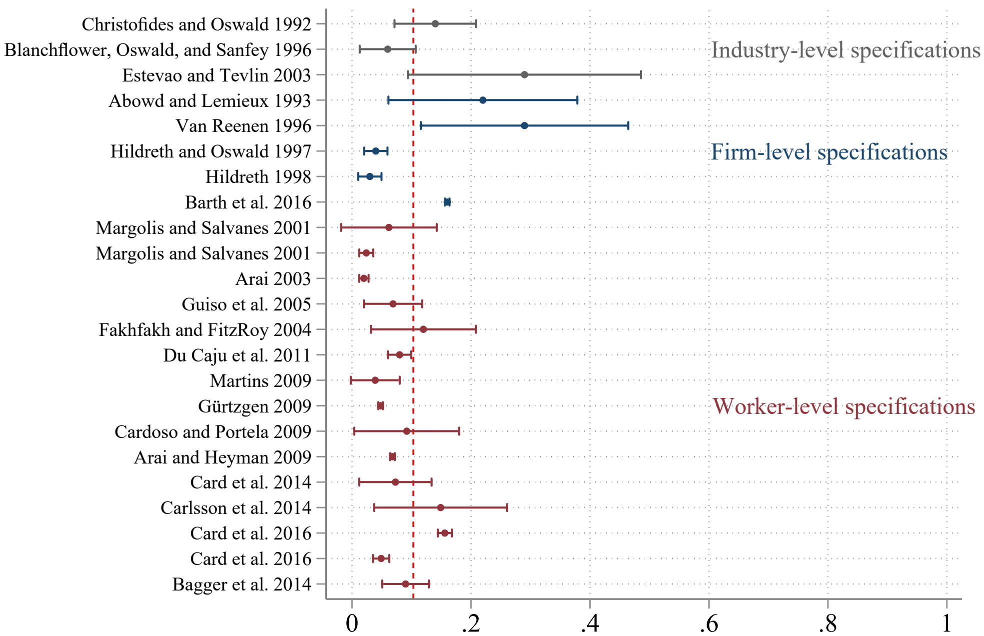
I.3 Meta Analysis of Rent Sharing Elasticities

Figure A-3: Unemployment-to-Nonparticipation Transition Rate and Nonparticipation Rate



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

Figure A-4: Rent Sharing Elasticities



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

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

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

The HJB equation for an unemployed worker (u) is

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

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 Preference Shock

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

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

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

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

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,

$$\begin{aligned}
&\lim_{\varepsilon\to-\infty}\left[\varepsilon\frac{\exp(\varepsilon/\nu)}{1+\exp(\varepsilon/\nu)} - \nu\log\left(1+\exp(\varepsilon/\nu)\right)\right] = \lim_{u\to1}\left[(1-u)\,\nu\log\left(\frac{1}{u}-1\right)-\nu\log\left(\frac{1}{u}\right)\right]\\
&= \nu\lim_{u\to1}\left[(1-u)\log(1-u)+u\log(u)\right] = \nu\left\{\lim_{u\to0}\left[(1-u)\log(1-u)\right] + \lim_{u\to0}\frac{\log(u)}{1/u}\right\} = 0,
\end{aligned}$$

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. $\lim_{\nu/\Delta\to0} EG\left(V^o,V^d\right) = \Delta\cdot\mathbb{1}\{\Delta\geq0\}-\mu$.

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

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

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 $\Delta < 0$. □

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, $\mathrm{EG}\left(V^o, V^d\right) = \left(V^d - V^o\right) \mathrm{CP}\left(V^o, V^d\right)$.

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

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

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

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

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

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

The monthly number of hires is the sum of daily hires

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

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

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

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 $r_t^{(0)} = \left(1 - q_t^{(0)}\right)(1 - \delta_t)$.
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

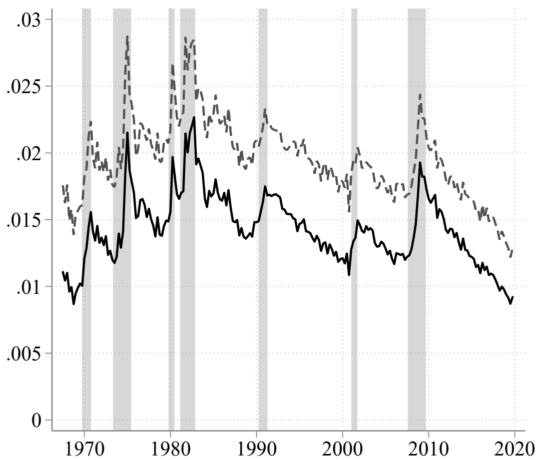
$$\varphi_t = \lim_{\Delta \to 0} \frac{\pi_{t,\Delta} - I}{\Delta},$$

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 $\tilde{D}_t(i,i) = \log D_t(i,i), \forall i$.

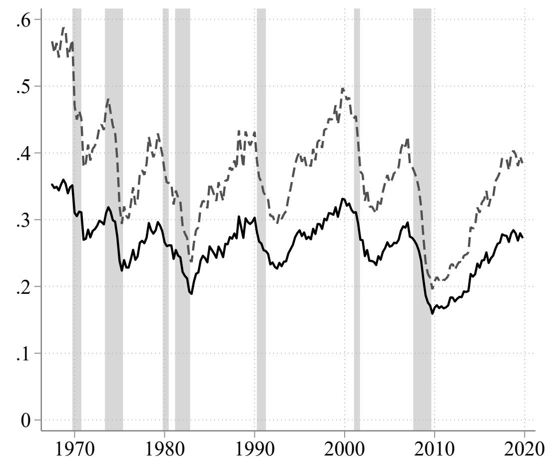
Figure A-5 plots the transition probability series in black solid lines and the time-aggregation adjusted Poisson rate series in gray dashed lines. Figure A-6 plots the corresponding HP-filtered series.

Figure A-5: Gross Worker Flow Rates

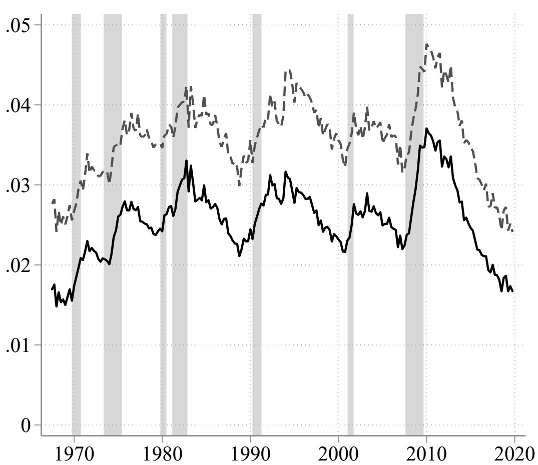
(a) Employment to Unemployment



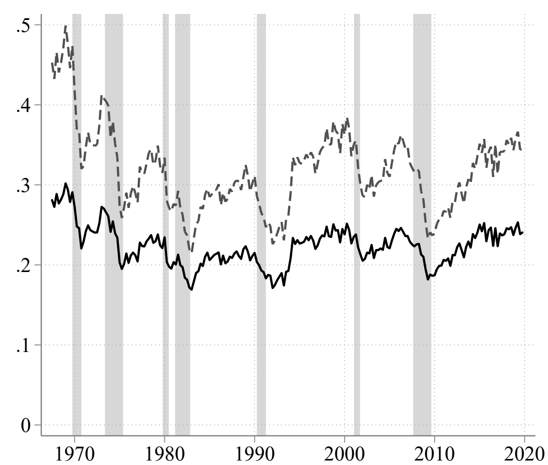
(b) Unemployment to Employment



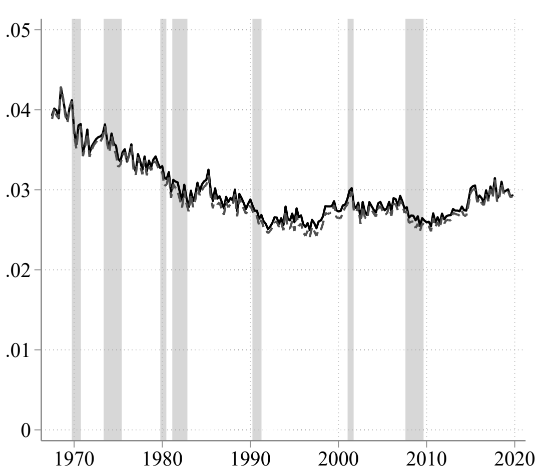
(c) Nonparticipation to Unemployment



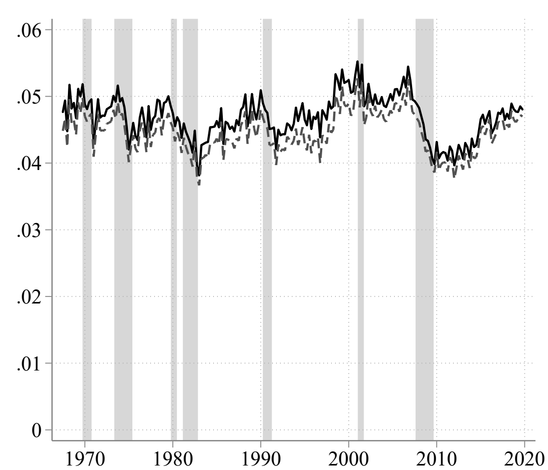
(d) Unemployment to Nonparticipation



(e) Employment to Nonparticipation



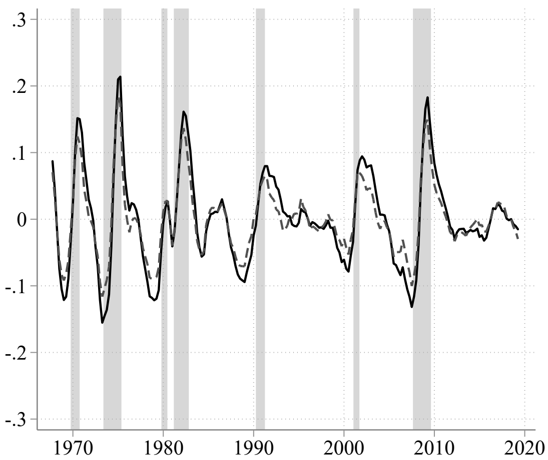
(f) Nonparticipation to Employment



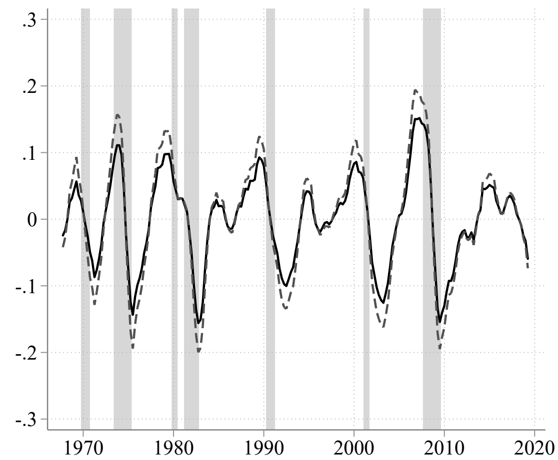
Notes: Black solid lines are transition probabilities and gray dashed lines are Poisson rates.

Figure A-6: HP-Filtered Gross Worker Flow Rates

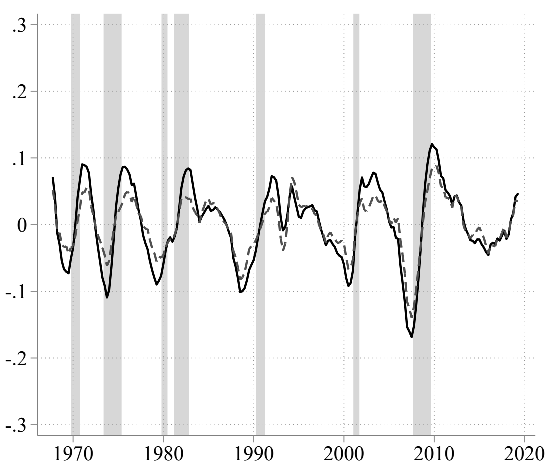
(a) Employment to Unemployment



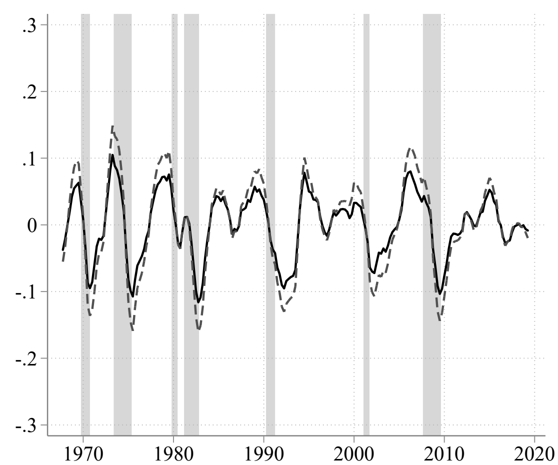
(b) Unemployment to Employment



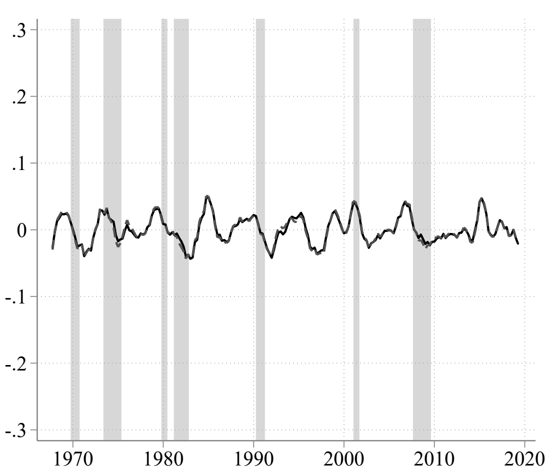
(c) Nonparticipation to Unemployment



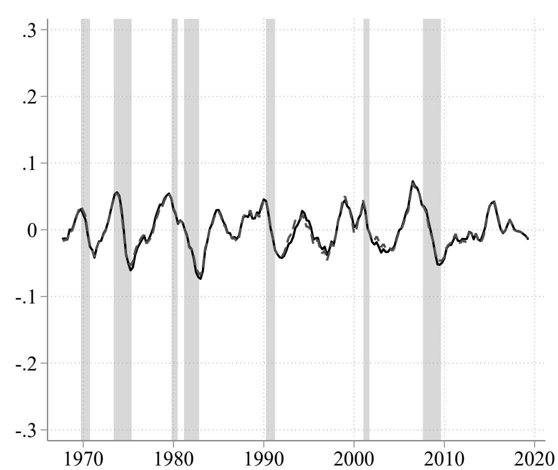
(d) Unemployment to Nonparticipation



(e) Employment to Nonparticipation



(f) Nonparticipation to Employment



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

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

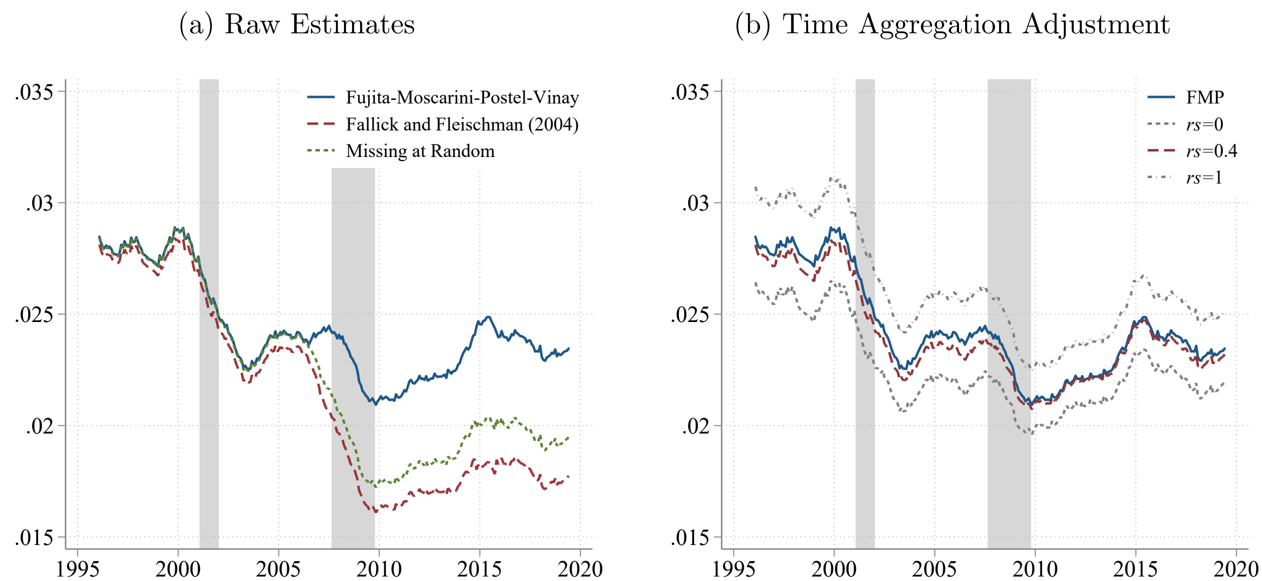
Second, denote $\beta(\tau)$ the share of employed workers at some given point of time that has experienced the employer-to-employer shock exactly once but has never experienced other labor market transitions after τ unit of time. Thus,

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

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-7: Employer-to-Employer Transition Rate



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

transitions. That is,

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

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-7 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-7 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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