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Mismatch Unemployment During COVID-19 and the Post-Pandemic Labor Shortages*

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Abstract

We examine the extent to which mismatch unemployment—employment losses relative to an efficient allocation where the planner can costlessly reallocate unemployed workers across sectors to maximize output—shaped labor market dynamics during the COVID-19 pandemic and the subsequent recovery episode characterized by labor shortages. We find that, for the first time in our sample, mismatch unemployment turned negative at the onset of the pandemic. This result suggests that the efficient allocation of job seekers would involve reallocating workers toward longer-tenure and more-productive jobs, even at the expense of fewer hires. We show that sectoral differences in job separations were the main driver behind this result, while differences in vacancies caused positive mismatch unemployment during the recovery episode. We also establish an empirical link between mismatch unemployment and the surge in the labor cost during the recovery, documenting that sectors with larger mismatch unemployment experienced higher employment cost growth.

Keywords: Mismatch, reallocation, unemployment, labor shortages
JEL Codes: E24, E32, J63, J64

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1 Introduction

Deep recessions are often marked by significant increases in unemployment, as witnessed during the Great Recession and, more recently, the COVID-19 recession. These periods of economic downturn trigger large inflows of workers into unemployment and a slowdown in hiring, raising concerns about the effective reallocation of labor. Sectors hit hardest by a recession shed workers, and these workers must then seek reemployment in a labor market where the impact and pace of recovery may greatly vary across sectors. Şahin, Song, Topa, and Violante (2014) explored such dynamics around the Great Recession by examining "mismatch unemployment," defined as the excess unemployment that arises from a mismatch between the sectors where job seekers search for work and the sectors where jobs are available. They found that this mismatch unemployment accounted for at most one-third of the total increase in unemployment during the Great Recession.

Similar to the Great Recession, the COVID-19 pandemic was a severe macroeconomic shock with lingering labor-market effects. Unlike before, the pandemic's impact was highly concentrated in specific sectors, and the subsequent recovery episode was marked by intense sector-specific labor shortages and a surge of employer costs. As a result of these unique circumstances, a strong interest in understanding the sources of unemployment dynamics and employer costs during this period has emerged among policymakers and researchers.

This paper makes several contributions to the analysis of unemployment dynamics during the COVID-19 recession, with important lessons that can be carried over to periods of labor market reallocation and volatility. First, we document substantial heterogeneity in labor-market outcomes, such as market tightness, job-separation rates, and productivity across sectors (i.e., industries, occupations, or states) in the U.S. Our data highlight not only the diverse labor market characteristics among sectors prior to the pandemic but also large and varied changes that occurred during and after the pandemic. Second, we leverage the unique evolution of these variables to revisit the role of mismatch unemployment in shaping unemployment during and after the COVID-19 recession. We decompose the contributions of sector-level differences in productivity, separations, and market tightness to aggregate outcomes and mismatch unemployment. Finally, we establish an empirical link between mismatch unemployment and labor cost pressures observed during the recovery episode characterized by tight labor markets and labor shortages, highlighting how sectoral imbalances influence dynamics of labor cost as well. This analysis recognizes that the key inputs to the measurement of mismatch unemployment—such as sectoral differences in productivity, separations, and market tightness—directly affect employer costs. We argue that the mismatch measure serves as a high-frequency indicator that captures these complex dy-

namics, offering valuable insights for both researchers and policymakers in understanding and addressing inflationary pressures emanating from the labor market.

In order to quantify the extent of mismatch unemployment during the COVID-19 recession, we use the framework developed by Şahin, Song, Topa, and Violante (2014). Here, the planner takes the total number of unemployed as well as sector-specific levels of matching efficiency, vacancies, job-separation rates, and productivities as given and chooses the allocation of unemployed across these sectors to maximize output. We feed the empirical counterparts of these inputs to the solution of the planner's problem and obtain the efficient allocation, separately for definitions of sectors as industries, occupations, or U.S. states.

Next, we present key data inputs to obtain the efficient allocation: job-separation rate, market tightness, and productivity across industries, occupations, and states from 2000 to 2023. For separations, we document significant heterogeneity across industries, occupations, and states, which vary both by sector and over time. Notably, even before the pandemic, industries like construction, food preparation, and transportation exhibited higher separation rates, while industries such as health care and social assistance had lower rates. During the pandemic, disruptions disproportionately raised separation rates in sectors such as food services, accommodation, and personal care, but the recovery saw these rates gradually revert to pre-pandemic levels. As with job separations, market tightness varied significantly across sectors before the pandemic. In 2019, industries like health care and social assistance, wholesale trade, and professional services had relatively tighter labor markets, as did occupations in healthcare, computer and mathematical fields, and engineering. In 2020, market tightness declined sharply across most sectors, with the steepest drops in highly exposed high-contact industries and occupations. However, certain fields, such as healthcare support and community services, experienced negligible changes in this period. The recovery of 2021-2022 saw a marked increase in market tightness across all sectors, with the most pronounced fluctuations occurring in food, accommodation, transportation, healthcare, and technical occupations due to widespread labor shortages. Changes in productivity from 2019 to 2022 are less pronounced compared to shifts in separation rates and market tightness. While the relative ranking of productivity across industries remained largely stable, occupations such as healthcare, transportation, and legal showed more significant fluctuations. Changes in productivity were even less noticeable at the state level. Overall, the data indicate that substantial volatility in separations and market tightness suggest a need for significant worker reallocation to attain efficiency, but productivity variations might play a lesser role.

We combine these data inputs with our model to estimate mismatch unemployment and study its underlying sources. Our findings reveal that while the mismatch unemployment rate—the gap between the observed unemployment rate and the efficient allocation—across

industries and occupations increased significantly during the COVID-19 recession, it did not reach the levels observed during the Great Recession. Conversely, geographic mismatch unemployment at the state level rose more sharply during the COVID-19 episode compared with the Great Recession, though the overall level of geographic mismatch remained small throughout the sample period. The differences in the extent of mismatch between these two recessions can be attributed to the COVID-19 recession's sector-specific nature, which was relatively short-lived compared with the protracted recovery following the financial crisis.

We further show that while the mismatch index—the fraction of efficient hires lost due to mismatch—mirrored the previous readings up until the pandemic, it turned negative during the depths of the COVID-19 recession for the first time in our sample. This result means that the efficient allocation of job-seekers implied *fewer* hires than those empirically observed.

In order to dissect the sources behind the negative mismatch index at the onset of the COVID-19 recession, we study simplified versions of the planner's problem where we incrementally eliminate sector-specific differences in (i) job-separation rate and (ii) productivity, and we compare outcomes from these sub-problems with the planner's full problem in the baseline model. We find that when we abstract from job-separation rate differences between sectors, the mismatch index remains positive. This divergence differs from the findings of Şahin, Song, Topa, and Violante (2014), who found similar mismatch indices using both of these versions of the planner's problem. Our results highlight a critical role for sectoral heterogeneity in shaping mismatch dynamics at the onset of the COVID-19 pandemic. We do so by highlighting the distinct role that various sector-specific shocks played during this episode. Specifically, the planner reallocates job seekers away from certain sectors with large increases in job-separation rates at the onset of the pandemic, even at the cost of lower job-finding rates. However, this trend reverses quickly and the mismatch index becomes positive again, as separation rates quickly return to pre-pandemic levels.

Next, we analyze mismatch unemployment during the recovery from the COVID-19 episode between 2021 and 2022 that was characterized by tight labor markets and "labor shortages." We find that the planner's allocation of unemployed job seekers across sectors in this episode is primarily driven by differences in vacancies, rather than job separations. For instance, industries that experienced the largest increases in tightness (e.g., manufacturing, accommodation and food services, information) are those where the planner increases the number of job seekers the most. Importantly, we show that mismatch indices from all versions of the planner's problem are similar during this episode, as other sources of sectoral heterogeneity do not matter as much during the recovery.

We conclude the paper by establishing a link between model-implied sectoral mismatch unemployment and an empirical measure of labor costs, namely the employment cost index

(ECI). The underlying heterogeneity that drives mismatch unemployment—variations in market tightness, job-separation rate, and productivity—can influence labor costs by creating challenges in filling vacancies, retaining workers, and sustaining productivity growth. Our analysis shows that when these factors are accounted for, the mismatch index correlates strongly with ECI growth. In particular, sectors where there are larger labor shortages (i.e., the efficient allocation implies that more job-seekers should be diverted toward that sector relative to the data) are also those that experience a higher ECI growth. We believe that this finding has important implications for policy making, as headline labor market indicators such as unemployment or participation rates may not fully signal the underlying labor cost dynamics. Our results suggest that the mismatch index could serve as a valuable metric for assessing labor cost pressures, inflation dynamics and ultimately monetary policy. This is especially valuable because direct labor cost measures such as the ECI are available only at the quarterly frequency and come at very high levels of aggregation.[1] The mismatch index can be computed at the monthly frequency for many detailed industry and occupation groups with the currently available data sources, providing more timely insights as to the sources of labor cost pressures.

Related literature. This paper contributes to the literature on the role of labor market mismatch and reallocation in shaping labor market aggregates, particularly around major recessions (e.g., Barlevy, 2002; Haltiwanger, Hyatt, McEntarfer, and Staiger, 2021; Huckfeldt, 2022). Recent studies have examined the impact of reallocation during the COVID-19 recession on aggregate labor market outcomes (e.g., Barrero, Bloom, Davis, and Meyer, 2021; Forsythe, Kahn, Lange, and Wiczer, 2022). Our paper is closely related to the seminal work of Şahin, Song, Topa, and Violante (2014), who introduced the concept of mismatch unemployment—where imbalances between vacancies and unemployed job seekers across sectors result in reduced hiring and increased unemployment, with a focus on the Great Recession. Pizzinelli and Shibata (2023) assess mismatch unemployment during COVID-19 and compare the U.S. and the U.K. in a version of the model with non-participation, but they do so by abstracting from differences in job-separation rates and productivity levels across sectors. Our paper also studies the pandemic recession and the subsequent recovery. Crucially, we focus on the distinct sector-specific labor market shocks and demonstrate that a model relying solely on market tightness to gauge mismatch unemployment produces significantly different outcomes when sectoral heterogeneity is not accounted for.

This paper also contributes to the extensive literature examining the evolution of labor market outcomes during and after the pandemic (e.g., Gallant, Kroft, Lange, and No-

[1] The ECI is available at broad industry groups.

towidigdo, 2020; Gregory, Menzio, and Wiczer, 2020; Birinci, Karahan, Mercan, and See, 2021; Mitman and Rabinovich, 2021; Petrosky-Nadeau and Valletta, 2021; Duval et al., 2022; Kapička and Rupert, 2022; Shapiro, 2022; García-Cabo, Lipińska, and Navarro, 2023; Hornstein, Karabarbounis, Kurmann, Lalé, and Ta, 2023). Our study complements this body of work by analyzing the role of time-varying and sector-specific shocks in shaping labor market imbalances throughout this period. Notably, we establish a strong empirical link between measures of mismatch and labor costs, suggesting that policymakers seeking high-frequency, disaggregated and timely signals of cost pressures in the labor market should consider mismatch unemployment and its underlying sources as critical indicators to monitor.

The rest of the paper is organized as follows. Section 2 outlines the framework used to derive measures of mismatch unemployment. Section 3 discusses the measurement of the model inputs and presents our empirical findings on differences in labor market outcomes across sectors in the pandemic era. Section 4 presents our mismatch unemployment measures, followed by an analysis of its underlying sources. Section 5 explores the relationship between mismatch unemployment and labor costs. Section 6 concludes.

2 A model of mismatch unemployment

We now define mismatch unemployment and describe its measurement. In the exposition below, we closely follow the material in Şahin, Song, Topa, and Violante (2014) to establish notation. We first present a simple model where sectors differ only in levels of matching efficiency and vacancies taken as given by a planner. We then describe a richer version of the model where sectors also differ in their job-separation rate and productivity. We compare the implications of these two frameworks later on in our analysis.

2.1 Simple model

Time t is discrete. The economy consists of $i \in \{1, 2, \ldots, I\}$ sectors and is populated by a unit mass of risk-neutral workers whose labor market status can either be employed e_{it} or unemployed u_{it}, satisfying $\sum_i (e_{it} + u_{it}) = 1 \ \forall t$. In each sector, unemployed workers search for jobs and firms post vacancies in a frictional labor market that is subject to random search. The number of new matches, or hires h_{it}, in period t is given by:

$$h_{it} = \Phi_t \phi_{it} m\left(u_{it}, v_{it}\right) = \Phi_t \phi_{it} v_{it}^{\alpha} u_{it}^{1-\alpha},$$

where Φ_t is the aggregate matching efficiency common across sectors; ϕ_{it} is sector-specific matching efficiency; $m\left(u_{it}, v_{it}\right)$ is the matching function for a given number of vacancies v_{it} and the unemployed u_{it} in sector i, which we assume takes the Cobb-Douglas form; and α

is a matching elasticity parameter. The total number of hires in the economy at time t is:

$$h_t = \sum_i h_{it}. \tag{1}$$

In this model, there are two simplifying assumptions, both of which we relax in the next section. First, we assume that a common fraction δ_t of existing matches are exogenously destroyed at each period in each sector. Second, once matched, a firm-worker pair produces the same amount of output regardless of sector; i.e., productivity is common across sectors.

Mismatch unemployment compares forgone hires relative to a benchmark where the planner can costlessly reallocate unemployed job seekers across sectors to maximize output. Taking as given the number of vacancies across sectors $\{v_{it}\}_{i=1}^{I}$, aggregate unemployment u_t, sector-specific matching efficiencies $\{\phi_{it}\}_{i=1}^{I}$, and the aggregate matching efficiency Φ_t, the planner allocates unemployed job seekers across sectors to maximize total hires, and thus total output. Formally, the planner's problem can be written as:

$$\begin{aligned} \max_{\{u_{it}\}_{i=1}^{I}} \quad & \Phi_t \sum_i \phi_{it} m\left(u_{it}, v_{it}\right) \\ \text{s.t.} \quad & \sum_i u_{it} = u_t. \end{aligned}$$

The efficient allocation of workers $\{u_{it}^*\}_{i=1}^{I}$ satisfies the following set of first-order conditions:

$$\phi_{1t} m_{u_1}\left(u_{1t}^*, v_{1t}\right) = \phi_{2t} m_{u_2}\left(u_{2t}^*, v_{2t}\right) = \ldots = \phi_I m_{u_I}\left(u_{It}^*, v_{It}\right), \tag{2}$$

where m_{u_i} denotes the partial derivative of the matching function with respect to u_i. The efficient allocation is intuitive: The planner reallocates unemployed workers across sectors such that the matching probabilities are equalized.

Total hires under the planner's allocation h_t^* can be written as:

$$h_t^* = \Phi_t v_t^{\alpha} u_t^{1-\alpha} \left[\sum_i \phi_{it} \left(\frac{v_{it}}{v_t}\right)^{\alpha} \left(\frac{u_{it}^*}{u_t}\right)^{1-\alpha} \right]. \tag{3}$$

The first-order conditions in Equation (2) and the Cobb-Douglas matching function imply that for any two sectors i and j, we have:

$$\frac{v_{it}}{u_{it}^*} = \left(\frac{\phi_{jt}}{\phi_{it}}\right)^{1-\alpha} \frac{v_{jt}}{u_{jt}^*}.$$

Combining this condition with Equation (3), we can express optimal hires as:

$$h_t^* = \bar{\phi}_t \Phi_t v_t^{\alpha} u_t^{1-\alpha}, \tag{4}$$

where $\bar{\phi}_t = \left[\sum_{i=1}^{I} \phi_{it}^{\frac{1}{\alpha}} \left(\frac{v_{it}}{v_t}\right)\right]^{\alpha}$ captures the vacancy weighted average matching efficiency.

The direct effect of mismatch on reducing the number of hires can be summarized by:

$$\mathcal{M}_{\phi t} = 1 - \frac{h_t}{h_t^*}, \tag{5}$$

which is the fraction of hires lost due to mismatch. Using Equation (4) and the definition of h_t in Equation (1), we can express the mismatch index as:

$$\mathcal{M}_{\phi t} = 1 - \sum_{i=1}^{I} \left(\frac{\phi_{it}}{\bar{\phi}_t}\right) \left(\frac{v_{it}}{v_t}\right)^{\alpha} \left(\frac{u_{it}}{u_t}\right)^{1-\alpha}. \tag{6}$$

This measure summarizes only the effect of reallocating the stock of unemployed for a given period t on hiring. That is, *given* the stock of unemployed u_t, $M_{\phi t}$ simply captures how many more hires could have been achieved in period t—a "direct" effect. However, it does not consider the dynamic effect that lower unemployment this period might have on increasing hires in the subsequent period. If unemployment is lower in period t under the efficient allocation, a higher market tightness in period $t+1$ translates to an "indirect effect" of further lowering unemployment for that period—an effect that is distinct from simply reallocating the given number of unemployed u_t efficiently each period. We discuss this further below.

Unemployment due to mismatch. We obtain the efficient level of unemployment u_t^* as follows. First, using Equations (1) and (6), we define the aggregate job-finding rate as total hires per unemployed worker:

$$f_t = \frac{h_t}{u_t} = (1 - \mathcal{M}_{\phi t})\, \bar{\phi}_t \Phi_t \left(\frac{v_t}{u_t}\right)^{\alpha}.$$

Analogously, using Equation (4), the efficient job-finding rate in period t is given by:

$$f_t^* = \frac{h_t^*}{u_t^*} = \bar{\phi}_t \Phi_t \left(\frac{v_t}{u_t^*}\right)^{\alpha}.$$

This implies that we can express the optimal job-finding rate f_t^* as a function of job-finding rate f_t, the mismatch index $\mathcal{M}_{\phi t}$, and the ratio of the observed to efficient unemployment

rates, u_t and u_t^*, respectively:

$$f_t^* = f_t \frac{1}{1 - \mathcal{M}_{\phi t}} \left(\frac{u_t}{u_t^*} \right)^{\alpha}.$$

Having defined f_t and f_t^*, we can compute the efficient unemployment rate u_t^*, for a given initial mass of unemployed U_0^*, using the following recursion:

$$U_{t+1}^* = \frac{\left(1 - e^{-(s_t + f_t^*)}\right) s_t}{s_t + f_t^*} L_t + e^{-(s_t + f_t^*)} U_t^*,$$

where L_t is the size of the labor force, and s_t and f_t are calculated as in Shimer (2005) using the Current Population Survey (CPS).[2] We then obtain the unemployment rate as $u_t^* = \frac{U_t^*}{L_t}$. We initialize the mass of unemployed under the efficient allocation to $U_0^* = L_0 \times \frac{s_0}{f_0^* + s_0}$, where we assume that the $u_0^* = u_0$, implying $f_0^* = f_0 \times \frac{1}{1 - \mathcal{M}_{\phi t}}$.

2.2 Model with additional sectoral heterogeneity

As in Şahin, Song, Topa, and Violante (2014), we also consider a case where sectors differ not only in matching efficiency and vacancies, but also in terms of productivity and job separation rates. In this model version, maximizing the number of hires is not equivalent to maximizing output given differences in productivity and match longevity across sectors.

Introducing these two dimensions of heterogeneity is straightforward. Consider now an economy where sectors differ in labor productivity z_{it} (i.i.d. across sectors) and job destruction rates δ_{it}. Suppose further that all sectors in the economy are subject to aggregate productivity Z_t and aggregate separation rate Δ_t shocks.

Şahin, Song, Topa, and Violante (2014) show that the efficient allocation of unemployed workers $\{u_{it}^*\}_{i=1}^I$ in this case satisfies the following condition:

$$\frac{z_{it}}{1 - \beta (1 - \Delta_t)(1 - \delta_{it})} \phi_{it} m_{u_i} \left(\frac{v_{it}}{u_{it}^*} \right) \forall i, t, \tag{7}$$

where $\beta \in (0, 1)$ is the workers' discount factor. For conciseness, let x_{it} encode the two additional dimensions of heterogeneity, given by:

$$x_{it} = \frac{z_{it} \phi_{it}}{1 - \beta (1 - \Delta_t)(1 - \delta_{it})}.$$

The FOCs in this model are identical to the FOCs in Equation (2) except that sectoral differences in matching efficiency ϕ_{it} are instead replaced by the term x_{it} that takes into

[2] Appendix A.4 provides details for the construction of these time series.

account the additional sources of heterogeneity.

Following similar steps, we can construct the mismatch index for this model as:

$$\mathcal{M}_{xt} = 1 - \sum_{i=1}^{I} \left(\frac{\phi_{it}}{\bar{\phi}_{xt}}\right) \left(\frac{v_{it}}{v_t}\right)^{\alpha} \left(\frac{u_{it}}{u_t}\right)^{1-\alpha}, \tag{8}$$

where

$$\bar{\phi}_{xt} = \sum_{i=1}^{I} \phi_{it} \left(\frac{x_{it}}{\bar{x}_t}\right)^{\frac{1-\alpha}{\alpha}} \left(\frac{v_{it}}{v_t}\right), \quad \bar{x}_t = \left[\sum_{i=1}^{I} x_{it}^{\frac{1}{\alpha}} \left(\frac{v_{it}}{v_t}\right)\right]^{\alpha}.$$

Henceforth, we refer to the model in Section 2.1 as the "simple model" and the one with richer heterogeneity in Section 2.2 as the "full model." We now turn to discussing the key empirical data inputs for constructing the mismatch measures under these two models.

3 Measurement and model calibration

To arrive at monthly mismatch measures, the model requires a number of labor market variables, both in the aggregate and by sector. In this section, we describe how we obtain the necessary model inputs in the data spanning December 2000 up until December 2023.[3] In the sectoral analysis, we consider industries at the two-digit 2022 NAICS level, occupations at the two-digit 2010 SOC level, and all U.S. states. Appendix A provides details on measurement, and Tables A1 and A2 present a list of industries and occupations that our analysis covers.

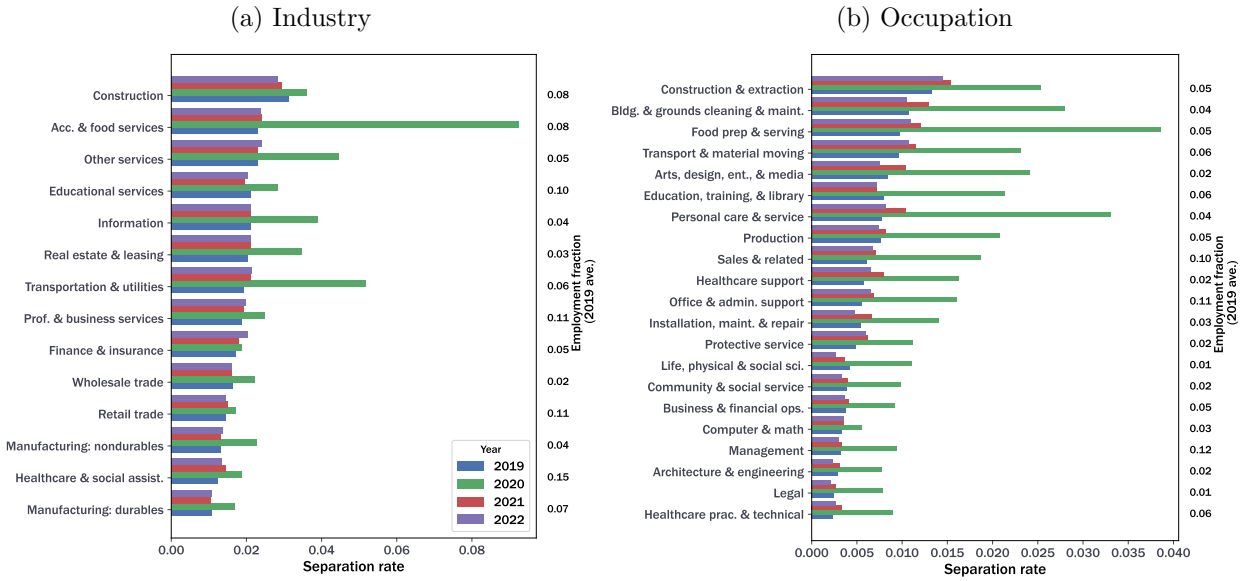
Job-separation rates. To obtain job-separation rates in the aggregate and across industries and states, we use quarterly data from the Business Employment Dynamics (BED) database covering 2000 Q4 to 2023 Q2. The quarterly separation rates in the BED reflect those of private industries. We convert the quarterly rates into monthly ones and assume that separation rates remain constant within a quarter. For the occupation-level analysis, we rely on the Current Population Survey (CPS) microdata covering January 2010 to December 2023. We calculate the job-separation rate as the fraction of employed workers in a month who report being unemployed in the following month.[4]

Figure 1 and Figure A1 demonstrate the extent of heterogeneity in separation rates across industries, occupations, and states. To keep the discussion concise, we present separation rates over four years that cover the pre-pandemic period (2019) and the COVID-19 recession (2020), as well as the recovery characterized by tight labor markets and labor shortages

[3] Whenever the analysis uses value-added data from the Bureau of Economic Analysis (BEA), data availability requires us to stop our analysis on December 2022. For the occupation-level analysis, we cover January 2010 to September 2023 due to the availability of vacancy data.

[4] We operate in discrete time and use separation rates interchangeably with separation probabilities following the convention in the literature.

Figure 1: Job-separation rates by sector



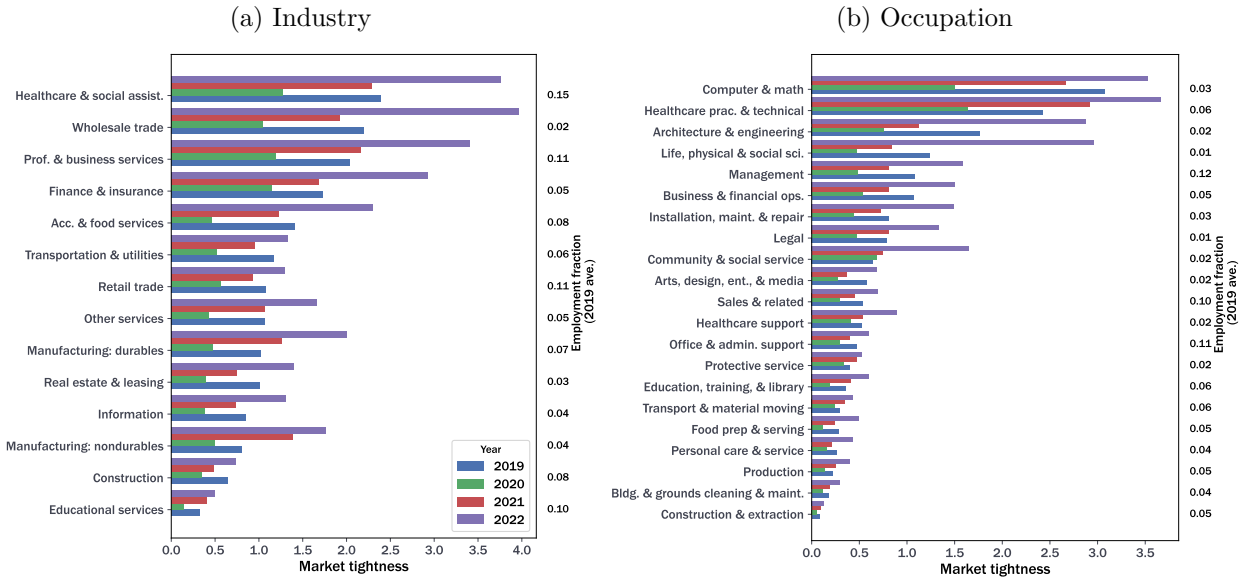
Note: Panel (a) presents separation rates by industry at the two-digit NAICS level using the BED between 2019 and 2022. Quarterly separation rates are converted to monthly rates and averaged over each year. Panel (b) presents average separation rates by occupation at the two-digit SOC level using the CPS between 2019 and 2022. Each panel is ordered based on its level of job-separation rate in 2019 (blue bars). On the right axis, we include average monthly sectoral employment shares in 2019.

(2021–2022). Overall, we see significant differences in job-separation rates across industries, occupations, and states and over time.

Figure 1 shows that prior to the pandemic (blue bars), there already was significant heterogeneity in separation rates across occupations and industries. Construction, food preparation, and transportation-related sectors typically experienced higher separation rates. For example, in 2019, the separation rates in health care and social assistance industries were roughly half that of accommodation and food services industries. The pandemic (green bars) disproportionately affected certain industries. For instance, occupations related to food, accommodation, transportation, and personal care services—jointly constituting 15 percent of total employment in 2019—saw the largest increases in separation rates. In the context of the model in Section 2, this implies that the planner has a motive to reallocate unemployed individuals from sectors with higher increases to those with relatively lower increases in separation rates. Finally, during the recovery period (red and purple bars) separation rates reverted toward their pre-pandemic values. Appendix Figure A1 reveals similar patterns across U.S. states.

Unemployment, vacancies, and labor force. We obtain unemployment and labor force stocks, in the aggregate as well as by industry and occupation using the CPS. For state-level statistics, we use the Local Area Unemployment Statistics (LAUS). Vacancies in the

Figure 2: Labor market tightness by sector



Note: This figure plots sector-specific labor market tightness—the vacancy-unemployment ratio—for each year between 2019 and 2022. Panel (a) presents tightness by industry at the two-digit NAICS level. Panel (b) presents tightness by occupation at the two-digit SOC level. Unemployment levels come from the CPS, vacancies by industry are from the JOLTS, and vacancies by occupation are from Burning Glass. Annual values report monthly averages. Each panel is ordered based on its level of labor market tightness in 2019 (blue bars). On the right axis, we include average monthly sectoral employment shares in 2019.

aggregate, by industry, and state come from the Job Openings and Labor Turnover Survey (JOLTS).[5] For occupation level vacancies, we use data compiled by Burning Glass. Using information on unemployment and vacancies, we are able to construct measures of sector-specific market tightness.

Figure 2 presents how labor market tightness evolved from 2019 through 2022 for industries and occupations, while Figure A2 presents the same for U.S. states. Similar to job separations, market tightness across sectors are highly heterogeneous, even prior to the large labor market shocks during and after the pandemic. By industry, health care and social assistance, wholesale trade, and professional and business services featured relatively tighter labor markets in 2019. Computer and mathematical, healthcare, and engineering occupations were also tighter than other occupations in 2019. Unsurprisingly, market tightness saw significant declines across the board in 2020, with disproportionate declines observed for highly exposed industries and occupations. Interestingly, certain occupations did not experience significant declines in tightness, e.g., those related to healthcare support as well

[5]For the industry-level analysis, we need to link JOLTS industries based on the 2022 North American Industry Classification System (2022 NAICS) to CPS industries. To recode CPS industries into JOLTS industries, we begin by cross-walking 1990 Census to 2012 Census industries, then cross-walking 2012 Census industries to 2017 Census and NAICS industries. Finally, we crosswalk 2017 Census and NAICS industries to 2022 NAICS industries.

as community and social services. The labor market recovery in 2021–2022 was characterized by a significant rise in market tightness across all sectors. This sudden increase leading to labor shortages was felt unevenly across sectors, with relatively large swings in food, accommodation, and transportation industries, as well as health, computer and mathematical, and engineering occupations.

Productivity. For the analysis by industry and state, we proxy for productivity by value-added and GDP, respectively, from the National, Industry, and State Economic Accounts published by the Bureau of Economic Analysis (BEA). For each industry and state, we split annual values for value-added and GDP equally across the twelve months within the year, adjusting for inflation using 2019 as the base year.[6] We then divide these monthly productivity series with monthly employment by industry from the CPS and by state from the LAUS. These steps allow us to arrive at monthly value-added-to-employment and GDP-to-employment ratios as our productivity measures, z, for industries and states. As for occupations, we take the real hourly median wage from the Occupational Employment Statistics (OES) survey as our measure of productivity, covering January 2010 to December 2022. As in Şahin, Song, Topa, and Violante (2014), we normalize this productivity measure for each occupation to unity at the beginning of the sample to capture the effects of relative productivity changes.

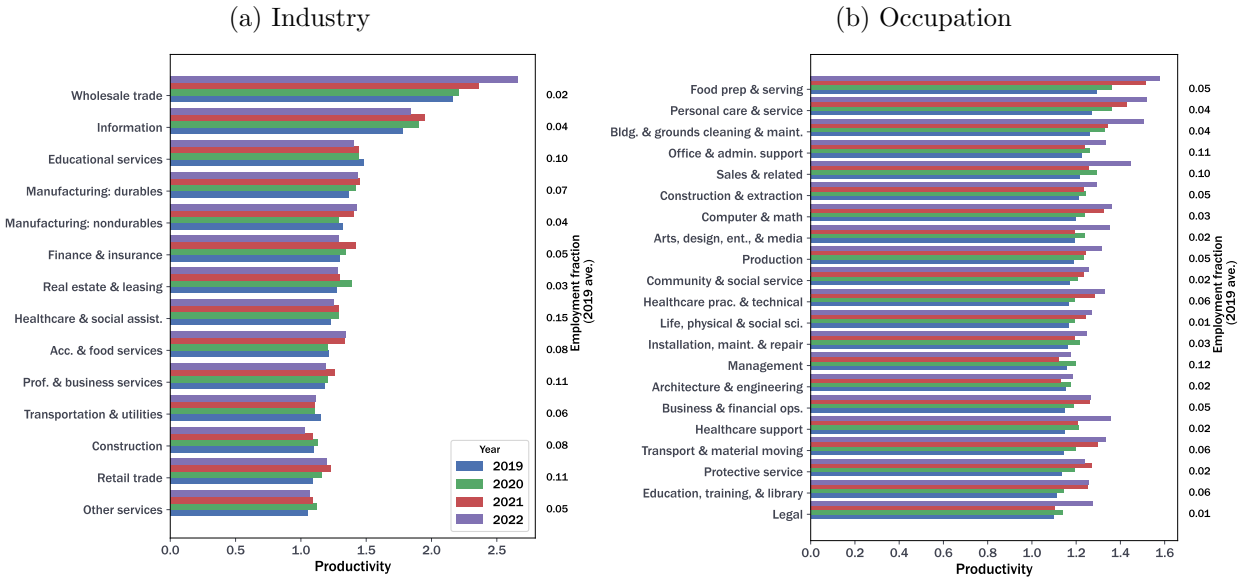
Figures 3 and A3 present the evolution of productivity for each of our sectoral cuts. Given that we normalize productivity to unity at the start of the sample, the figures depict the sectors' differential productivity growth.

We highlight two important results. First, almost all occupations experienced relatively large increases in their real hourly median wage during the 2021-2022 labor shortage episode. Second, the relative changes in productivity measures between 2019-2022 are not as large as those seen for separation rates and market tightness. For industries, the ranking of productivity remained roughly the same, while for occupations, some relatively larger swings can be observed for a selected number of occupations such as healthcare, transportation, and legal. Productivity changes are even less apparent across states. All in all, to the extent that the full model implies that large *relative* changes in separations, market tightness, and productivity would drive a larger reallocation of job seekers under the efficient allocation, the data suggest that productivity may play less of a role in this context.

Matching function. For the industry- and occupation-level analysis, each sector's matching function efficiency ϕ_i is set to be those estimated by Şahin, Song, Topa, and Violante

[6] Quarterly value-added data by industry is available only after 2018. We keep to annual data between 2000 and 2022 for consistency.

Figure 3: Productivity by sector



Note: This figure presents sector-specific productivity measures for each year between 2019 and 2022. Panel (a) presents productivity by industry at the two-digit NAICS level. We utilize annual value-added data from the BEA as a proxy for productivity. We split each industry's annual value added evenly across the twelve months of the relevant year and adjust for inflation using 2019 as the base year. Monthly value-added per worker is then calculated by dividing this figure by the industry's monthly employment level obtained from the CPS. Panel (b) presents productivity by occupation at the two-digit SOC level. We use the real hourly median wage from the OES divided by employment as a proxy for productivity. Industries and occupations in both panels are ordered based on their levels of productivity in 2019 (blue bars). On the right side of each panel, we include each sector's average monthly employment share over 2019. Following Şahin, Song, Topa, and Violante (2014), we normalize productivity measures to unity at the beginning of the sample—2000 for industry-level analysis and 2010 for occupation-level analysis—to capture changes in relative productivity over time.

(2014), differentiated between the pre- and post-2008 periods. For the state-level analysis, we assume a uniform matching function efficiency of 1. We also set the matching function elasticity parameter to $\alpha = 0.5$.

4 Understanding mismatch during COVID-19

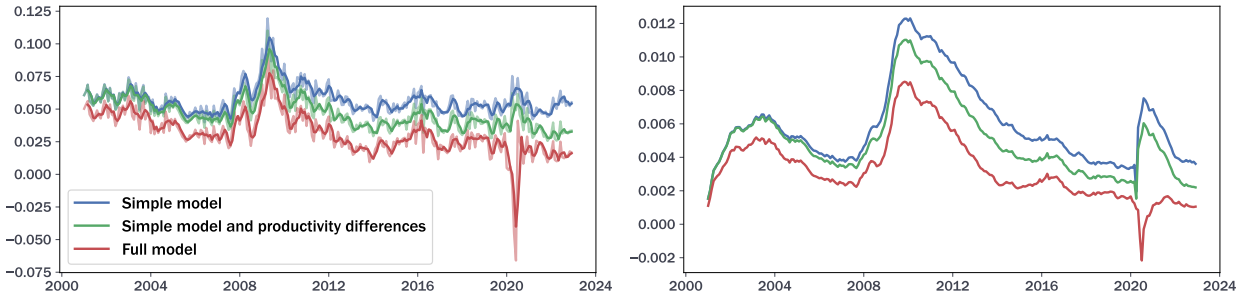
In this section, we combine the model and data to measure mismatch in the labor market during and after the COVID-19 episode and analyze its underlying drivers. Importantly, we contrast the implications of the simple and the full model. Below, we present results from the industry-, occupation-, and state-level analysis in order.

4.1 Industry-level analysis

Mismatch index and mismatch unemployment rate. We first present the mismatch index when sectors consist of industries. The blue line in Figure 4 Panel (a) presents the mismatch index given by Equation (6) in the simple model. Consistent with the findings of Şahin, Song, Topa, and Violante (2014), the degree of mismatch rose substantially during the Great Recession and remained elevated until 2013. Using more recent data that cover the

Figure 4: Industry-level mismatch index and mismatch unemployment rate

(a) Mismatch index (b) Mismatch unemployment rate ($u - u^*$)



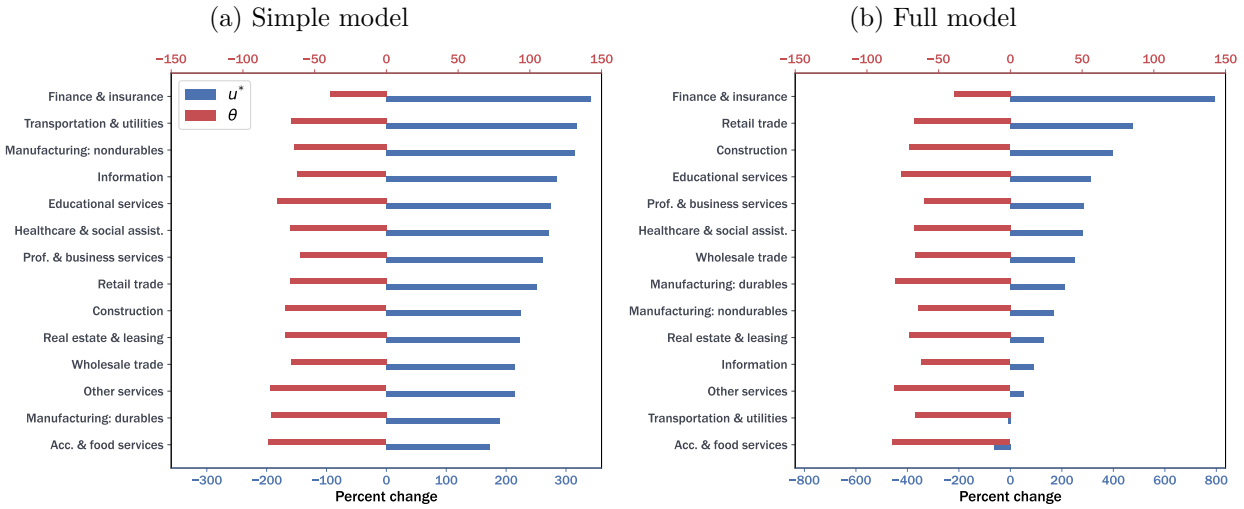
Note: Panel (a) plots the mismatch index—as described in Equation (6) for the simple model and in Equation (8) for the full model—at the industry-level. We incorporate increasing levels of heterogeneity, with the blue line including only differences in vacancies and matching efficiency across industries (the "simple model"), the green line incorporating differences in productivity, and the red line further incorporating differences in job separation rates (the "full model"). Lighter lines present raw series and darker lines present series that are smoothed using a 3-month moving-average. Panel (b) plots the mismatch unemployment rate as the difference between the aggregate unemployment rate in the data u_t and counterfactual unemployment rate series implied by the efficient allocation of the unemployed across industries u_t^*.

pandemic and subsequent recovery, we see that mismatch in the simple model rose during the pandemic but not nearly as much as it did during the Great Recession. In the absence of other sources of heterogeneity apart from vacancies v and matching efficiency ϕ, market tightness across industries changed much less during the pandemic than during the Great Recession. These findings are echoed by Figure 4 Panel (b), which presents the mismatch unemployment rate as the difference between aggregate unemployment in the data u_t and the counterfactual unemployment series implied by the efficient allocation of the unemployed across industries u_t^*. Under the simple model, the unemployment rate due to mismatch during the pandemic rose by only 0.8 percentage points in comparison to 1.2 percentage points during the Great Recession, relative to pre-recession levels.

Incorporating richer industrial heterogeneity changes these conclusions, particularly for the pandemic episode. The red line in Panel (a) of Figure 4 presents the mismatch index in Equation (8) under the full model. While the mismatch indices from the simple and full models track each other closely before the pandemic, they diverge during COVID-19. When heterogeneity in productivity and job separations across industries are accounted for, the mismatch index turns *negative* during the pandemic for the first time since 2000. That is, the efficient allocation dictates *fewer* hires and *higher* unemployment than that observed in the data, confirmed by the negative mismatch unemployment rate in Panel (b).

Sources of mismatch at the onset of COVID-19. A negative mismatch index can arise when industries experience large relative changes in productivity and separation rates. For example, a large negative productivity shock to certain industries with high matching efficiencies may prompt the planner to reallocate job seekers to more productive industries,

Figure 5: Changes in efficient allocation and tightness by industry: 2020 vs 2019



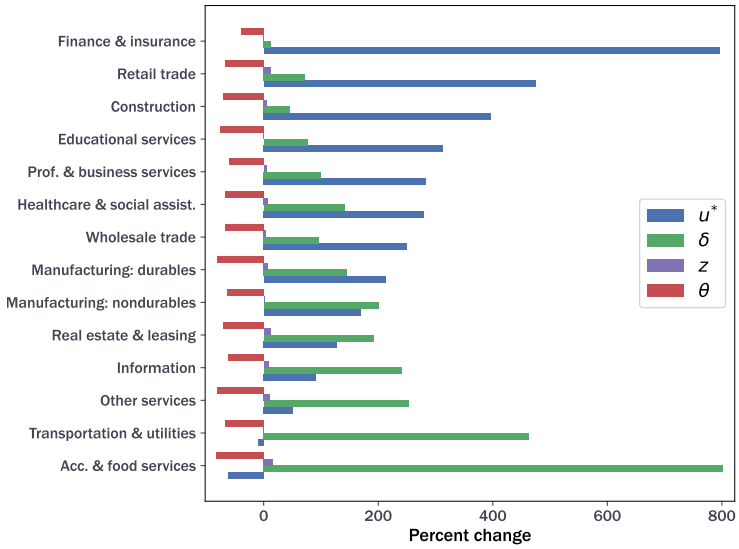
Note: This figure shows the percent change in the efficient allocation of unemployed job-seekers u^*_{it} (bottom axis) and the percent change in market tightness θ_{it} (top axis) by industry, comparing the March to June 2020 average (the height of the pandemic) to the same period in 2019. Panels (a) and (b) present results from the simple model and the full model, respectively. In each panel, industries are ranked by the change in the efficient allocation of unemployed job-seekers u^*_{it}.

even at the expense of fewer hires.

To dissect why the mismatch index and the mismatch unemployment rate turned negative during the pandemic, we consider an intermediate case where we only add heterogeneity in productivity to the simple model—shown by green lines in Figure 4. The similarity between the simple and intermediate models implies that the negative mismatch index and the negative mismatch unemployment rate in the full model is explained by changes in relative job-separation rates across industries. Ultimately, the efficient allocation implies drawing workers away from industries that experienced exceptionally high job-separation rates at the onset of the pandemic.

Figure 5 provides further insights into the differences between the simple and the full model. Focusing on the most severe period of the pandemic (March to June 2020), Panel (a) ranks industries based on the percent change in unemployed job seekers that the planner would like to allocate to each industry, relative to the efficient allocation for the same period in 2019 (bottom axis) under the simple model. For reference, the percent change in market tightness is also presented on the top axis. Panel (b) presents results for the full model. We observe large differences in industry rankings between the simple and the full model. For example, comparing the changes in u^* between the simple and the full model, we find that the full model allocates a relatively higher number of unemployed workers toward construction and durables manufacturing but allocates relatively fewer workers toward transportation industries. This is reflective of the economic conditions during the pandemic that saw large

Figure 6: Sources of mismatch by industry in the full model: 2020 vs 2019

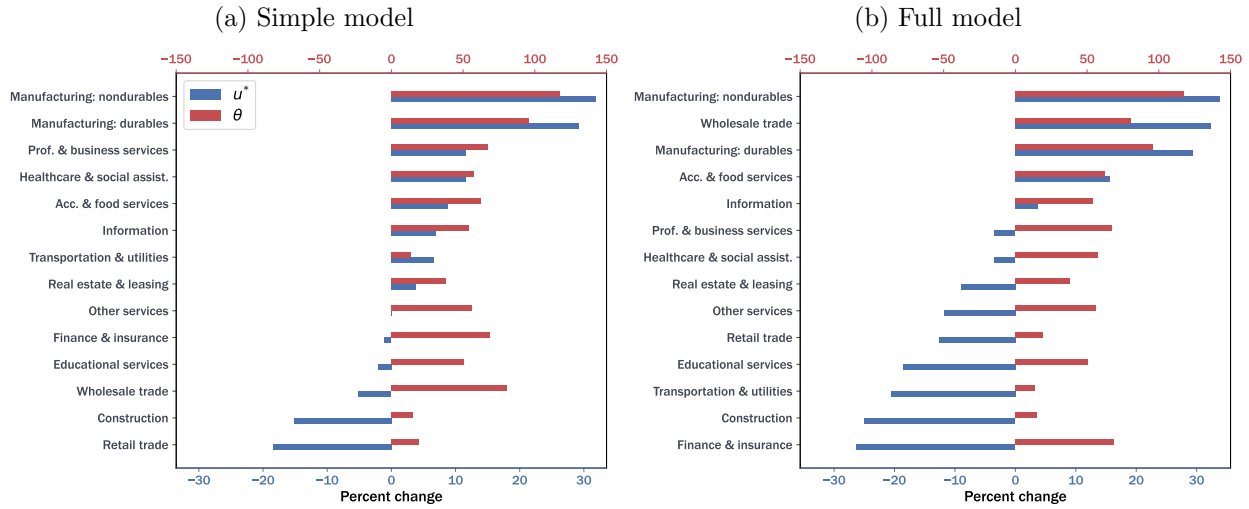


Note: This figure shows the percent change in the efficient allocation of unemployed job-seekers u^*_{it} in the full model, market tightness θ_{it}, job separations δ_{it}, and productivity z_{it} by industry, comparing March-June 2020 (the height of the pandemic) to the same period in 2019. Industries are ranked based on the change in the efficient allocation of unemployed job-seekers u^*_{it}.

shifts away from traveling and leisure toward goods consumption and real estate. While the accommodation and food services industry is ranked last in both panels, the full model implies a substantially different allocation of job seekers: close to a 200 percent increase under the simple model but roughly a 50 percent decrease under the full model. These differences suggest that apart from changes in market tightness—the sole determinant of changes in the simple model—other industry-specific shocks, especially to separation rates, became relevant during the pandemic.

To fully capture why the two approaches differ in their efficient allocations, Figure 6 unpacks the underlying sources of heterogeneity utilized by the full model. Industries are once again ranked by the percent change in job seekers allocated to each industry between the same two periods. We plot the percent changes in the job-separation rate, productivity, and market tightness—the three sources of heterogeneity that influence the efficient allocation. In this episode, differential changes in job-separation rates across industries were the primary determinant of the changes in the efficient allocation of job seekers, as evidenced by the strong negative correlation between the change in efficient job seekers and the change in job-separation rates by industry—a pattern that is absent for market tightness or productivity changes. In particular, Figure 6 shows that industries with the smallest increase in the job-separation rate at the onset of COVID-19 typically saw the largest increase in the number of job seekers under the efficient allocation. Returning to the mismatch indices in Figure 4, this result reinforces the idea that mismatch in the simple and full models diverge due to

Figure 7: Changes in efficient allocation and tightness by industry: 2022 vs 2019



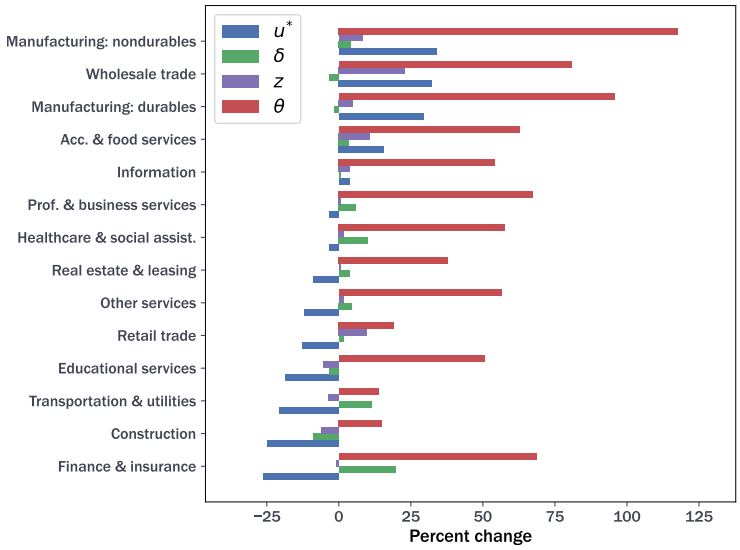
Note: This figure shows the percent change in the efficient allocation of unemployed job-seekers u^*_{it} (bottom axis) and the percent change in market tightness θ_{it} (top axis) by industry, comparing the March to June 2022 average (the height of the pandemic) to the same period in 2019. Panels (a) and (b) present results from the simple model and the full model, respectively. In each panel, industries are ranked by the change in the efficient allocation of unemployed job-seekers u^*_{it}.

the large degree of heterogeneity in job-separation rate changes across industries.

Sources of mismatch during the recovery from COVID-19. We now turn to the recovery episode characterized by tight labor markets and labor shortages that followed the pandemic. Figure 7 presents the changes in the efficient allocation of job seekers between 2022 and 2019 by industry, as in Figure 5. What is noticeably different between 2022 (Figure 7) and 2020 (Figure 5) is that the change in the allocation of job seekers in 2022 appears to be mostly driven by changes in market tightness instead of job-separation rates. Crucially, we also show that these results are more similar between the simple and the full models. This is intuitive given that the efficient outcomes between the two models are more similar when their dispersion is mostly explained by changes in market tightness—which is endogenous to both models. During this episode, under both models, industries that experienced the largest increases in market tightness (e.g. manufacturing, accommodation and food services, information) are unsurprisingly those that also observed larger increases in job seekers. Figure 8 confirms this result for the full model: Unlike in 2020 (Figure 6), in 2022, changes in job-separation rates played a minor role relative to changes in market tightness in determining the efficient allocation of job-seekers.

Taking stock. The mismatch indices from our industry-level analysis under the simple and full models track each other up until the start of the COVID-19 recession. They diverge when the dispersion in labor market outcomes is driven by a factor other than endogenous

Figure 8: Sources of mismatch by industry in the full model: 2022 vs 2019



Note: This figure shows the percent change in the efficient allocation of unemployed job-seekers u^*_{it} in the full model, market tightness θ_{it}, job separations δ_{it}, and productivity z_{it} by industry, comparing March-June 2022 (the height of the pandemic) to the same period in 2019. Industries are ranked based on the change in the efficient allocation of unemployed job-seekers u^*_{it}.

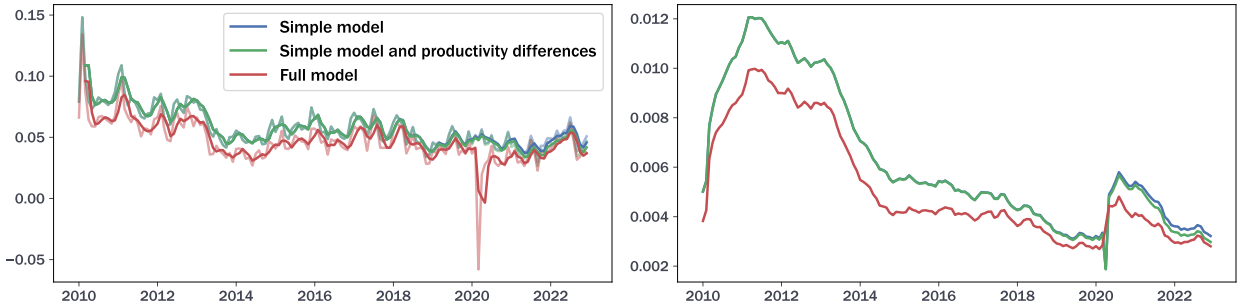
labor market tightness. The full model reveals that, at the onset of the pandemic, the differential changes in job-separation rates across industries drove differences in the outcomes and were responsible for the divergence between the mismatch indices. However, during the recovery episode following the COVID-19 recession—characterized by tight labor markets and labor shortages—industries differed mostly along the severity with which labor shortages emerged—summarized by differential changes in market tightness across industries. As a result, the mismatch indices in both models began to track each other once again.

4.2 Occupation-level analysis

We now move to an analysis at the occupation level. As discussed in Section 3, we use occupations at the 2-digit SOC level. In Figure 9, we plot the mismatch index and the mismatch unemployment rate in the simple, intermediate and full models. We make similar observations in the industry-level analysis. First, mismatch was much larger and more persistent in the aftermath of the Great Recession relative to the COVID-19 recession. Second, the simple and full models diverged during the pandemic. The negative mismatch index once again implies that the efficient allocation prescribes *less* hiring at the onset of the pandemic. Despite the negative mismatch index observed for one month, the mismatch unemployment rate does not turn negative in this episode, as seen in Panel (b). This is because less hiring (a flow variable) in a month under the planner's allocation is not quantitatively large and persistent enough to overturn positive mismatch unemployment (a

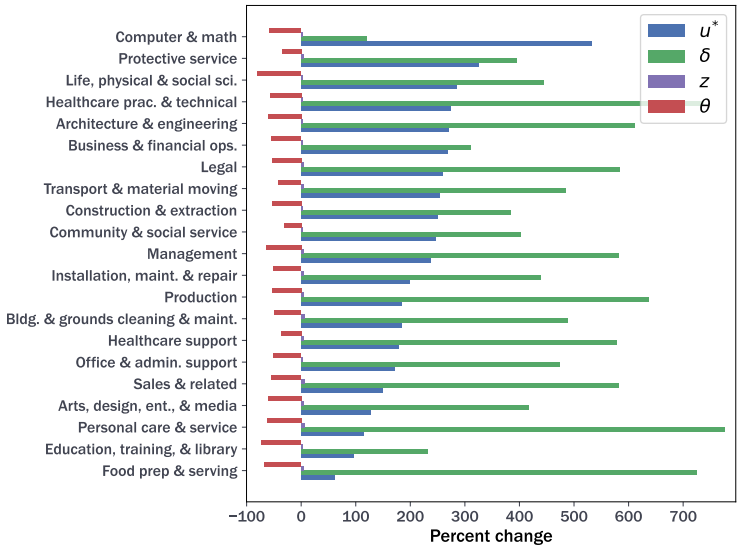
Figure 9: Occupation-level mismatch index and mismatch unemployment rate

(a) Mismatch index (b) Mismatch unemployment rate ($u - u^*$)



Note: Panel (a) plots the mismatch index—as described in Equation (6) for the simple model and in Equation (8) for the full model—at the occupation-level. We incorporate increasing levels of heterogeneity, with the blue line including only differences in vacancies and matching efficiency across industries (the "simple model"), the green line incorporating differences in productivity, and the red line further incorporating differences in job separation rates (the "full model"). Lighter lines present raw series and darker lines present series that are smoothed using a 3-month moving-average. Panel (b) plots the mismatch unemployment rate as the difference between the aggregate unemployment rate in the data u_t and counterfactual unemployment rate series implied by the efficient allocation of the unemployed u_t^*.

Figure 10: Sources of mismatch by occupation in the full model: 2020 vs 2019



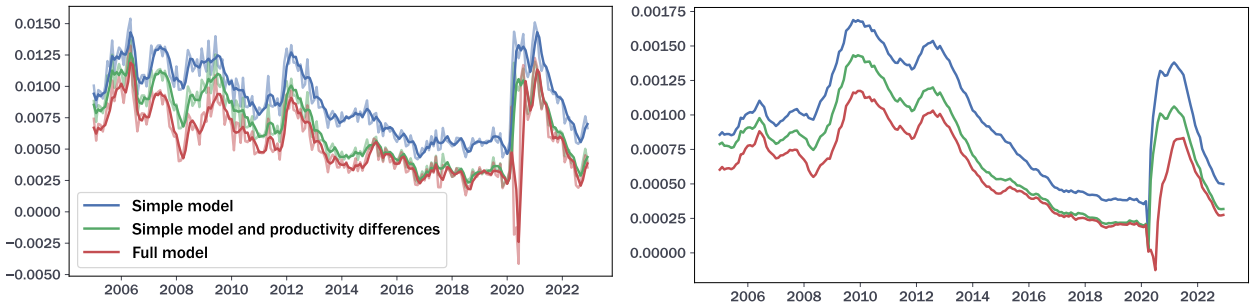
Note: This figure shows the percent change in the efficient allocation of unemployed job-seekers u_{it}^* in the full model, market tightness θ_{it}, job separations δ_{it}, and productivity z_{it} by occupation, comparing March-June 2020 (the height of the pandemic) to the same period in 2019. Occupations are ranked based on the change in u_{it}^*.

stock variable). Recall from Section 2 that this gap is explained not only by the direct effect of reallocating job seekers period-by-period but also by the dynamic effects of lower unemployment and higher tightness over time.

Finally, as seen in Figure 10, the changes in the efficient allocation of job seekers between 2020 and 2019 were largely driven by the differential changes in job-separation rates across occupations. High-contact occupations that observed larger increases in separation

Figure 11: State-level mismatch index and mismatch unemployment rate

(a) Mismatch index (b) Mismatch unemployment rate ($u - u^*$)



Note: Panel (a) plots the mismatch index—as described in Equation (6) for the simple model and in Equation (8) for the full model—at the state-level. We incorporate increasing levels of heterogeneity, with the blue line including only differences in vacancies and matching efficiency across industries (the "simple model"), the green line incorporating differences in productivity, and the red line further incorporating differences in job separation rates (the "full model"). Lighter lines present raw series and darker lines present series that are smoothed using a 3-month moving-average. Panel (b) plots the mismatch unemployment rate as the difference between the aggregate unemployment rate in the data u_t and counterfactual unemployment rate series implied by the efficient allocation of the unemployed across industries u_t^*.

rates (food preparation/serving, personal care and service, and those related to arts and entertainment) are also the occupations where the efficient allocation increases the allocation of job seekers the least in between these two years. However, there are some exceptions. For example, occupations in education, training, and library experienced a relatively lower increase in separations, but at the same time suffered from a larger decline in tightness, resulting in a relatively lower allocation of job seekers during this episode.

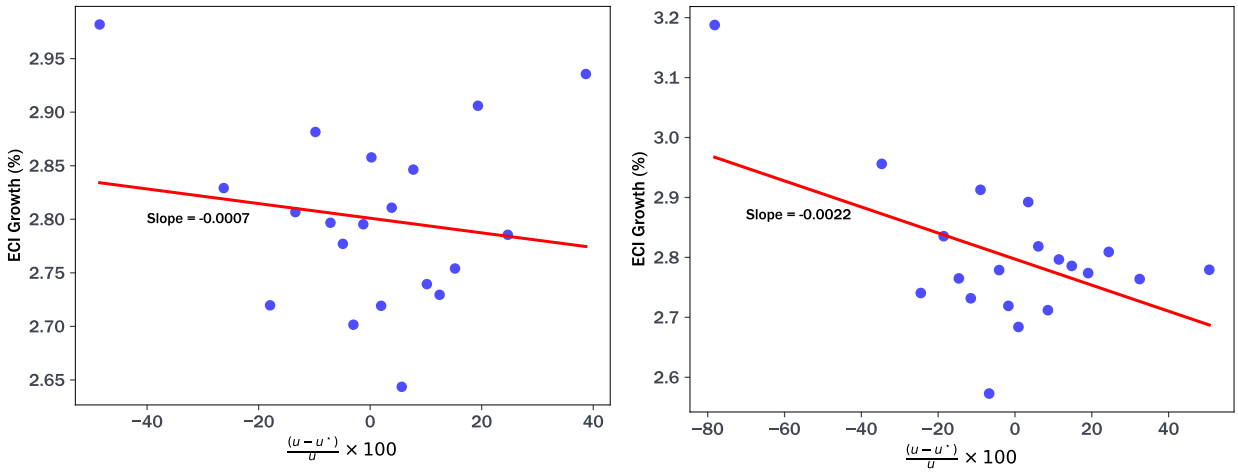
A noticeable difference between occupation- and industry-level analysis is the role of productivity differences in determining the extent of labor market mismatch overtime. The simple and the intermediate models diverge after several years for industries (Figure 4) but not for occupations (Figure 9). This suggests that productivity differences across occupations are not a major source of mismatch unemployment, whereas productivity differences across industries play a larger for mismatch unemployment.

4.3 State-level analysis

We also explore the magnitude of mismatch when labor markets are partitioned by U.S. states. As seen in Figure 11, regardless of the extent of heterogeneity incorporated into the model, the mismatch index and thus the mismatch unemployment rate have been quantitatively small over our sample. There are small fluctuations in mismatch during the Great Recession and the pandemic. That geographical mismatch is low is consistent with the findings in Şahin, Song, Topa, and Violante (2014).

Figure 12: Changes in mismatch unemployment rate and ECI growth

(a) Simple model (b) Full model



Note: This figure presents binscatter plots that relate the ratio of industry-specific unemployment gap to the industry's unemployment in the data and year-on-year ECI growth covering 2003:Q1 to 2020:Q4, controlling for time and industry fixed effects, and weighted by employment shares of each industry. Panel (a) is for the simple and Panel (b) is for the full model.

5 Mismatch unemployment and employer costs

The recovery following the COVID-19 pandemic was marked by an exceptionally tight labor market and widespread labor shortages. Labor costs rose dramatically, sparking interest in understanding their drivers. In this section, we demonstrate that mismatch unemployment and labor costs are correlated. The efficient allocation of job-seekers is driven by sectoral outcomes that may be directly tied to labor cost pressures. Specifically, sectors with tight labor markets, low separations, and rising productivity—conditions associated with rising labor costs—are the ones toward which the planner would direct workers.

Our measure for labor costs is the Employment Cost Index (ECI) for total compensation published by the BLS at quarterly frequency available at the industry level.[7] The ECI is an index tracked by the Fed to gauge inflationary pressures arising from the labor market.

Using data between 2003:Q1 and 2020:Q4, Figure 12 presents binscatter plots of the ratio of industry-specific unemployment gaps to the industry's unemployed workers in the data $(u_{it} - u^*_{it})/u_{it}$ against the year-on-year growth of industry-level ECI, controlling for time and industry fixed effects, and is weighted by industry employment shares. Panel (a) presents results for the simple model and Panel (b) for the full model. This figure reveals an important insight: ECI growth is negatively associated with the degree of excess unemployment relative

[7]We note a few points about linking ECI and JOLTS industries. The two JOLTS industries "arts, entertainment, and recreation" and "mining and logging" are not present in ECI data. The "transportation, warehousing and utilities" industry in JOLTS is split into "utilities" and "transportation and warehousing" in ECI. We take the average of these two categories while concording it to its single JOLTS equivalent.

to the efficient benchmark within an industry. This implies that when $u_{it} - u_{it}^*$ becomes more positive, i.e., the planner seeks to divert job seekers away from industry i, ECI growth for that industry declines. One way to interpret this is that, for industries where there is a surplus of job-seekers from the point of view of the planner (say, due to slack in the labor market or low productivity), ECI growth tends to be lower. This implies that the framework in Section 2 is useful not only in identifying the size and sources of mismatch unemployment, but also as a tool to detect the emergence of employer cost pressures in the labor market.

While this negative correlation holds true under both models, the relationship is much tighter under the full model incorporating richer heterogeneity across industries, including market tightness, separations, and productivity. Specifically, the change in ECI growth with respect to a change in the industry-specific unemployment gap ratio is statistically significant and an order of magnitude larger in the full model. This implies that the additional shocks (and not just variation in market tightness alone) are important in determining changes in employer costs. As argued earlier, all these three sources of heterogeneity contribute to employer costs through hiring, retaining, and keeping workers productive.

6 Conclusion

This paper contributes to our understanding of labor market dynamics during and after the COVID-19 recession by highlighting the significant role of sectoral heterogeneity in shaping mismatch unemployment. We show that while the mismatch unemployment rate across industries and occupations exhibited a sizable increase during the COVID-19 recession, it did not reach the levels observed during the Great Recession. We also find that the mismatch index turned negative at the onset of the pandemic for the first time since 2000, implying that the efficient allocation reallocated job seekers toward sectors with lower job-separation rates at the onset of the pandemic at the expense of fewer aggregate hires than observed. Importantly, we show that when we abstract from heterogeneity in job-separation rates, the mismatch index remained positive, indicating that job separations were the main driver behind the negative mismatch index. In terms of mismatch dynamics after the COVID-19 recession, we show that sectoral differences in market tightness were the primary reason behind the positive mismatch index. Finally, we show that sectors with larger mismatch unemployment typically saw higher labor cost growth.

Our results have implications for policymakers who track labor costs as a gauge of inflationary pressures originating from the labor market. We show that the mismatch index could serve as a proxy for labor costs, given that direct cost measures are typically available at the quarterly frequency and at aggregate levels, while the mismatch index can be constructed monthly and for detailed industry and occupation levels.

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Online Appendix of: Mismatch Unemployment During COVID-19 and the Post-Pandemic Labor Shortages

Serdar Birinci, Yusuf Mercan and Kurt See

A Measurement

We conduct our empirical analysis at the industry, occupation and U.S. state levels. In this section, we outline the measurement of model inputs and discuss data sources for these definitions of what constitutes a sector in the model.

A.1 Employment, unemployment and vacancies

A.1.1 Industry-level analysis

- Data sources: Job Openings and Labor Turnover Survey (JOLTS) for vacancies; Current Population Survey (CPS) for unemployment, employment, and labor force levels.
- Time coverage: December 2000 to November 2023.
- We cover two-digit 2022 North American Industry Classification System (NAICS) industries, listed in Table A1.
- Additional notes:
  - For unemployment and employment, we restrict our sample to those aged 16 and older. We also drop those in the armed forces from our sample.
  - We calculate employment and unemployment levels using BLS replicate weights (variable COMPWT) and seasonally adjust the time series.
  - For each industry, we calculate our own measure of labor market tightness by dividing seasonally adjusted JOLTS vacancies by seasonally adjusted unemployment levels from CPS microdata. Unemployment by industry is based on the last industry a worker was employed in.
  - Concording industries between the JOLTS and the CPS: For the CPS, we use codes based on the 1990 Census Bureau industrial classification system to ensure consistency across years. JOLTS industries, however, are based on the 2022 NAICS. To the best of our knowledge, no direct crosswalk exists between the two. To recode CPS industries into JOLTS industries, we begin by crosswalking the

1990 Census to 2012 Census industries, then crosswalk 2012 Census industries to 2017 Census and NAICS industries. Finally, we map 2017 Census and NAICS industries to 2022 NAICS. In this process, some Census 1990 codes were split into multiple industries with different NAICS equivalents in later Census years and, as a result, map to multiple JOLTS industries. For such cases, we evenly split their weights into relevant JOLTS industries.

Table A1: Two-digit NAICS 2022 industries

NAICS 2022 code	**Industry**
21	Mining and logging
23	Construction
31-33	Nondurable goods manufacturing
33	Durable goods manufacturing
42	Wholesale trade
44-45	Retail trade
48-49	Transportation, warehousing, and utilities
51	Information
52	Finance and insurance
53	Real estate and rental and leasing
54	Professional and business services
61	Educational services
62	Health care and social assistance
71	Arts, entertainment, and recreation
72	Accommodation and food services
81	Other services
92	Government

Note: This table lists the two-digit NAICS 2022 industries we include in our analysis. CPS industries are concorded to NAICS 2022 JOLTS industries using the procedure described in the main text and data appendix.

A.1.2 State-level analysis

- Data sources: We use JOLTS for vacancies and Local Area Unemployment Statistics (LAUS) for unemployment, employment, and labor force levels.
- Time coverage: December 2000 to December 2023.
- For each state, we calculate labor market tightness by dividing seasonally adjusted vacancies by seasonally adjusted unemployment levels. These series closely track the tightness series that JOLTS provides directly. We prefer our own measure, as the direct measure from the JOLTS is often rounded up or down to one decimal point, especially for recent episodes.

A.1.3 Occupation-level analysis

- Data source: We use data provided by Burning Glass (BG) for vacancies and CPS for unemployment and employment levels.
- Time coverage: January 2010 to September 2023.
- We cover two-digit 2010 SOC codes, listed in Table A2.
- Additional notes:
  - For unemployment and employment, we restrict our sample to those aged 15 and older. We also drop those in the armed forces from our sample.
  - The occupation of an unemployed worker is taken to be the one in the last job.
  - We calculate employment and unemployment levels using weights provided by IPUMS (variable wtfinl) and seasonally adjust.
  - For each occupation, we calculate our own measure of tightness by dividing the seasonally adjusted vacancies by the seasonally adjusted unemployment levels.

A.2 Job-separation rates

A.2.1 Industry- and state-level analysis

- Data source: Business Employment Dynamics (BED) from the Bureau of Labor Statistics (BLS).
- Time coverage: 2000:Q4 to 2023:Q2.
- Additional notes:
  - We extract the seasonally adjusted, quarterly job-loss rate for all private industries. We then convert quarterly to monthly rates using the following formula:

    $$x_t = 1 - \left(1 - x_t^{qrt}\right)^{1/3},$$

    where x_t is the monthly job-loss rate and x_t^{qrt} is the quarterly job-loss rate.
  - For the national 3-digit NAICS data, the industry code is 300 followed by the 3-digit 2022 NAICS code. We extract the 3-digit NAICS code to map BED industries onto JOLTS industries.

Table A2: Two-digit SOC occupations

SOC 2010 code	Occupation
11	Management
13	Business and financial operations
15	Computer and mathematical
17	Architecture and engineering
19	Life, physical, and social science
21	Community and social service
23	Legal
25	Education, training, and library
27	Arts, design, entertainment, sports, and media
29	Healthcare practitioners and technical
31	Healthcare support
33	Protective service
35	Food preparation and serving related
37	Building and grounds cleaning and maintenance
39	Personal care and service
41	Sales and related
43	Office and administrative support
47	Construction and extraction occupations
49	Installation, maintenance, and repair
51	Production
53	Transportation and material moving

Note: This table lists the 2-digit SOC occupations we include in our analysis.

- Note that the BED data do not include information for the industry labeled "government/public administration" because its highest level of aggregation is "total private."
- Additionally, the JOLTS combines NAICS codes 1133 ("logging") and 21 ("mining") into a single category called "logging and mining." The closest match in BDM is NAICS 113 ("forestry and logging," which includes 1133, "logging"). Therefore, for the BED, we classify NAICS codes 113 (instead of JOLTS' 1133 "logging") and 21 under "logging and mining."

A.2.2 Occupation-level analysis

- Data source: CPS.
- Time coverage: January 2010 to December 2023.
- The job separation rate is defined as the fraction of employed workers in an occupation

in a period who report being unemployed in the next period. We restrict the sample to persons aged 15+ and not in the armed forces.

A.3 Productivity

A.3.1 Industry-level analysis

For industry-level analysis, our measure of productivity is given by the ratio of industry value-added to employment. The construction of employment measures have been discussed above. Here, we outline details on our measure of value-added.

- Data source: Bureau of Economic Analysis (BEA) - Value Added by Industry
- Time coverage: 2000:Q4 to 2022:Q4
- Construction of productivity measure:
  - First, we obtain annual nominal value added across industries. We then split the aggregate annual value added equally across 12 months in the year to get the aggregate monthly value added, and adjust for inflation using 2019 as the base year.
  - We combine this data with seasonally adjusted, monthly employment levels aggregated across industries from CPS microdata, and calculate the monthly value-added-to-employment ratio.

A.3.2 State-level analysis

We implement the same procedures applied to industry-level value-added. To calculate state-level productivity, we divide state-level GDP (adjusted for inflation using 2019 as the base year) by seasonally adjusted, monthly employment levels aggregated across states from the Local Area Unemployment Statistics (LAUS).

A.3.3 Occupation-level analysis

- Data source: Occupational Employment Statistics (OES).
- Time coverage: 2010 to 2022.
- We take real hourly median wages as our productivity measure at the occupation level. We assume that productivity as measured by wages remains constant within a year. We normalize the productivity of each occupation to unity at the beginning of the sample and focus on the relative evolution of productivities.

A.4 Measuring unemployment inflow and outflow rates

We now elaborate on the measurement of unemployment inflow and outflow rates using the CPS, following the methodology developed Shimer (2012). In addition to monthly data on the number of employed and unemployed, the CPS also provides the number of workers with at most five weeks of unemployment, i.e., the short-term unemployed.[1] We use this extra variable in the measurement of unemployment rates, as discussed below.

Let U_t, U_t^S, and L_t denote the number of unemployed, short-term unemployed, and labor force participants at time t, respectively. Further, let s_t and f_t denote the unemployment inflow (job-separation) and unemployment outflow (job-finding) *hazard rates*, respectively. The *instantaneous* change in the number of unemployed individuals at time t satisfies:

$$\frac{dU_t}{dt} = -f_t U_t + s_t \left(L_t - U_t\right). \tag{A1}$$

Moreover, the discrete-time law of motion for unemployment is given by:

$$U_{t+1} = U_{t+1}^S + \left(1 - F_t\right) U_t,$$

where F_t is the outflow *probability*. The number of unemployed at time $t+1$ equals the number of short-term unemployed at $t+1$ plus the number of unemployed at t who do not find a job within the period. Solving for F_t and given data on unemployment, we calculate the job-finding probability as:

$$F_t = 1 - \frac{U_{t+1} - U_{t+1}^S}{U_t}.$$

Assuming a Poisson process for job arrivals maps the job-finding probability to the job-finding hazard rate, $f_t = -\log\left(1 - F_t\right)$. Solving Equation (A1) yields the law of motion:

$$U_{t+1} = \frac{\left(1 - e^{-(s_t + f_t)}\right) s_t}{s_t + f_t} L_t + e^{-(s_t + f_t)} U_t.$$

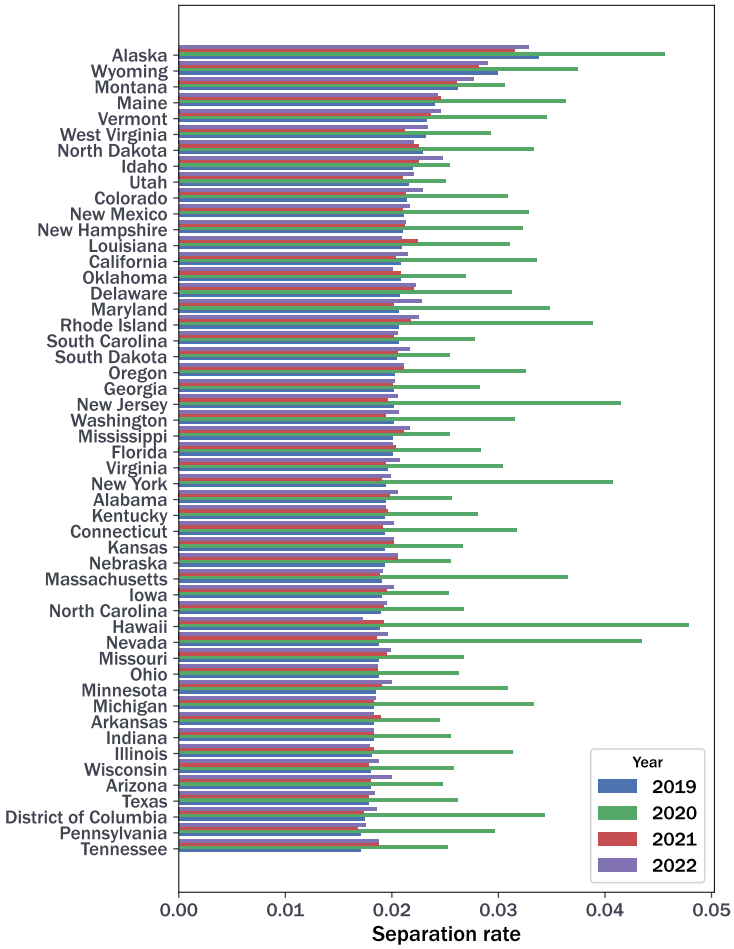
Given data on unemployment, labor force, and the job-finding rate, we numerically solve this non-linear equation to calculate the job-separation rate s_t. This empirical measure of s_t and the efficient job-finding rate f_t^* are then used to iterate on the law of motion for unemployment to calculate the efficient unemployment rate discussed in Section 2.

[1] The redesign of the CPS in 1994 caused a discontinuity in the time series for short-term unemployed due to a change in the way unemployment duration was recorded, as discussed by Polivka and Miller (1998) and Shimer and Abraham (2002). We correct for this by multiplying the number of short-term unemployed by a constant of 1.16 after 1994, as in Elsby, Hobijn, and Şahin (2010). Shimer (2012) finds similar results with alternative ways of correction.

B Additional results for the state-level analysis

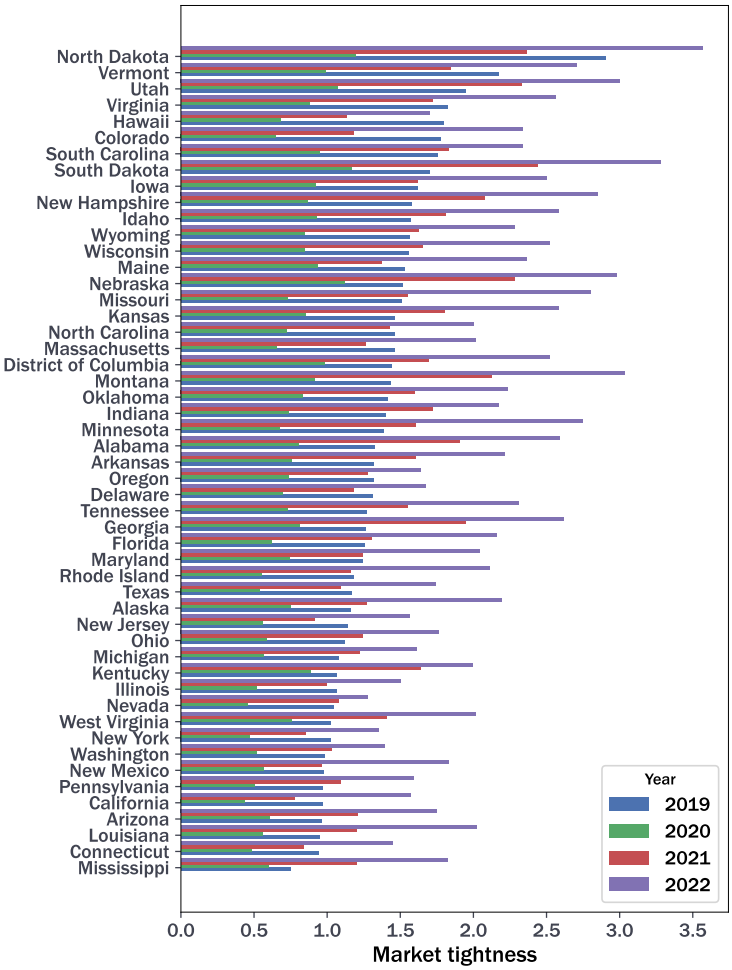
This section provides supplemental results for the state-level analysis in the main text.

Figure A1: Job-separation rates by state



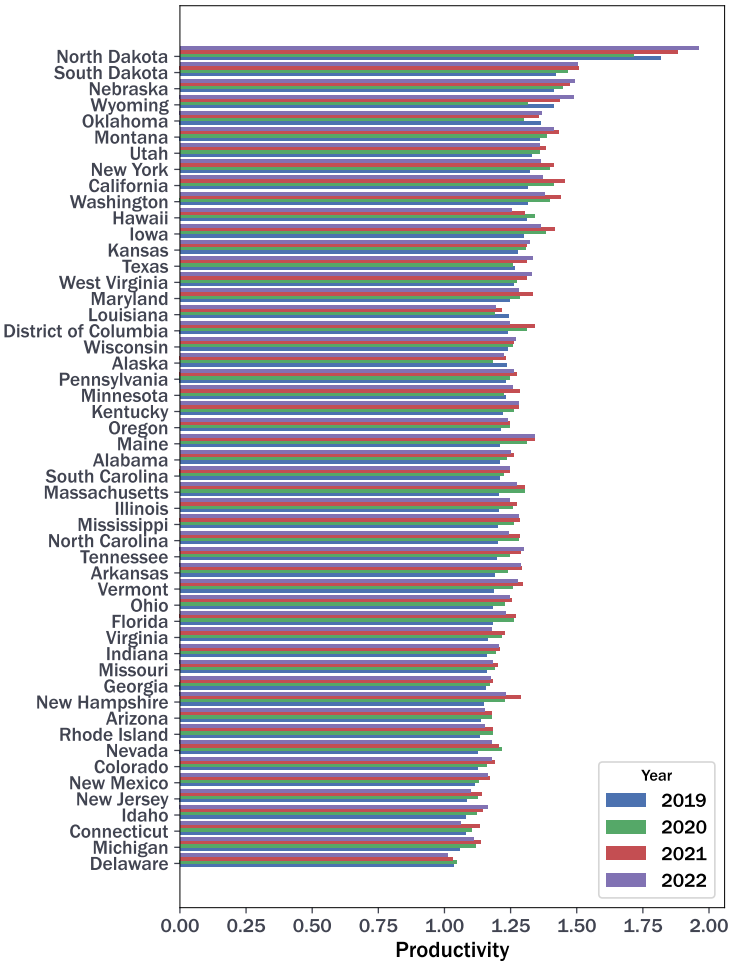
Note: This figure plots state-specific job-separation rates from the BED between 2019 and 2022. Quarterly separation rates are converted to monthly rates and averaged by year. States are ordered by their job-separation rate in 2019.

Figure A2: Labor market tightness by state



Note: This figure plots state-specific labor market tightness—the ratio of vacancies to unemployed workers—for each year between 2019 and 2022. Unemployment is from the LAUS and vacancies are from the JOLTS. Monthly values are averaged by year. States are ordered by tightness in 2019.

Figure A3: Productivity by state



Note: This figure presents state-specific productivity measures between 2019 and 2022. We use annual GDP from the National, Industry, and State Economic Accounts provided by the BEA. We split annual GDP evenly across months within the year and adjust for inflation using 2019 as the base year. Monthly real output per worker is then calculated by dividing monthly real GDP by a state's monthly employment from the LAUS. We normalize productivity to unity at the beginning of the sample to capture relative changes over time. States are ordered by their productivity in 2019.