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DISCUSSION PAPER SERIES

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Kailing Shen
Australian National University and IZA

Yanran Zhu
Australian National University

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IZA – Institute of Labor Economics

Schaumburg-Lippe-Straße 5–9
53113 Bonn, Germany

Phone: +49-228-3894-0
Email: publications@iza.org

www.iza.org

ABSTRACT

Labor Force Transition Dynamics: Unemployment Rate or Job Posting Counts?

Job posting counts (JPCs) are increasingly being used as indicators of employment dynamics, but they have not received sufficient research attention to establish their value as a metric of these dynamics. This study aims to assess the efficacy of the traditional survey-based unemployment rate versus big-data-based JPCs in capturing labor market transitions in the United States. Using the Current Population Survey, our comparison focuses on the ability of these two types of metrics to predict individuals' transitions between employment and unemployment. Unlike with the unemployment rate, we not only examine the raw national JPCs but also consider four additional versions of JPCs that measure labor demand at various disaggregated levels. Our findings suggest that JPCs and the unemployment rate provide comparable predictive power for labor market transitions, with each capturing different aspects of the variation in these transitions. The estimated coefficients of both types of metrics remain statistically significant when considered together. Notably, the correlation between the unemployment rate and labor market transitions switches signs when year fixed effects are added, but a similar phenomenon is not observed when JPCs are examined. Among the various versions of JPCs, the most refined measure—JPCs by state, occupation, and industry—demonstrates the strongest predictive capabilities, outperforming other JPC measures and the unemployment rate.

JEL Classification: J64, J23, J63

Keywords: job posting counts, labor market transitions, unemployment rate

Corresponding author:
Kailing Shen
Australian National University
Canberra, ACT
Australia

E-mail: kailing.shen@anu.edu.au

1 INTRODUCTION

The unemployment rate has traditionally been the primary metric for analyzing labor market dynamics. However, in recent years, using job posting counts (JPCs) to conduct analysis of these dynamics has gained popularity. Unlike the official unemployment rate, which is subject to publication delays and is available only monthly, JPCs offer almost real-time access to labor market information. This immediate availability of data can be critical during periods of economic volatility, such as during the recent pandemic.

Numerous studies have explored the time-series characteristics of the unemployment rate and its effect on labor market transitions during business cycles and various economic shocks (Bentolila & Bertola, 1990; Caballero & Hammour, 1994; Davis & Haltiwanger, 2001; Howe, 1990). However, there remains a noticeable gap in similar studies examining JPCs. This study aims to fill that gap by comparing the effectiveness of JPCs and the unemployment rate in capturing the dynamics of employment–unemployment transitions. It is worth noting that our validation exercises do not establish causal relationships or make conclusive claims about the effects of these two measures. Rather, we aim to explore their potential comparative complementarity in predicting labor market dynamics. By doing so, this research aligns closely with the original purposes of these metrics.

Broadly, this study provides an opportunity to compare traditional survey-based metrics with those derived from big data in labor economics. Scholars have demonstrated increasing interest in integrating survey data with other sources of information (Lohr & Raghunathan, 2017). The availability of large-scale big data has opened new avenues for nowcasting the unemployment rate (e.g., Moriwaki, 2020). Rather than considering the unemployment rate as the sole "correct" measure of the labor market, we treat JPCs and the unemployment rate as equally valuable measures.

Our empirical analysis focuses on the United States labor market from 2010 to 2019, covering a ten-year period. We utilize the Current Population Survey (CPS) as our primary source of "true" employment–unemployment transitions. Rivera Drew, Flood, and Warren (2014) suggest that the CPS's data linkage complexities when utilizing its longitudinal design precede our study period, thus our data-management process is relatively simple.

For the benchmark metric of the unemployment rate, we use the commonly used seasonally adjusted monthly unemployment rate for individuals aged 25 to 54. To construct the comparison metric (i.e., JPCs), we utilize job posting data from Lightcast (formerly Burning Glass). To exploit the full potential of these data and enhance the granularity of our analysis, we derive four adjusted versions of JPCs using the reweighting-estimation-transformation (RWET) approach proposed by Shen and Taska (2020). These JPCs measure labor demand at various local levels as defined by: 1) state; 2) state and occupation; 3) state and industry; and 4) state, occupation, and industry.

Figs. 1 and 2 confirm the overall consistency of the trends of the unemployment rate, JPCs, and the transition probabilities between employment and unemployment. They also indicate substantial similarities in the correlations between both metrics and the transition probabilities. Together, they suggest the broad sensibility of our validation/comparison exercise.

Our ten-year-long CPS transition sample corresponds to pairs of consecutive calendar months experience of individuals. Only people who are in the labor force—either employed or unemployed—in both months are selected in our study. As Table 1 reveals, many more transition samples begin with being employed than with being unemployed. Furthermore, only a small proportion, less than one percent, of people who began as employed became unemployed in the subsequent month. In contrast, almost one-quarter of those initially unemployed became employed in the following month. Labor market transitions show substantial heterogeneity across demographic groups: male, younger, single, divorced, and less-educated individuals are more likely to switch between employed and unemployed states; whereas female, older, and more-educated individuals are less likely to switch between these states.

Individuals may become unemployed by choice or involuntarily. Given that JPCs measure demand flow and the unemployment rate is a stock measure, the distinction of JPCs may be reflected in their correlation with different types of unemployment: layoffs, quits, and (re)entrants. Therefore, we divide the switchers of our transition sample accordingly. Table 1, panel b shows a broadly balanced number of switchers to and from unemployment, with slightly more people transitioning *to* employment, which is consistent with the general improvement of the labor market during the period. Notably, these transitions are primarily driven by layoffs, with voluntary quits accounting for a smaller proportion of transitions from employment. The heterogeneity across demographic groups for switchers when they are grouped by unemployment types is not the same as it when considering overall labor market transitions. Female, younger, single, or divorced individuals are more likely to quit, while those less educated are more likely to be laid off. Table 1, panel b also demonstrates that more-educated individuals have more control over their employment. The descriptives confirm the validity of the data used here.

Our main empirical results are presented in Tables 2 and 3. Table 2, panel a demonstrates that a higher unemployment rate correlates with lower transitions of employed individuals to unemployment in the short run (i.e., within year), while the correlation is positive in the long run (i.e., across years). In contrast, Table 2, panel b demonstrates that the correlation between various JPC metrics and employment–unemployment transitions is stable, that is, higher JPCs are correlated with lower transitions to unemployment regardless of whether year fixed effects or any other controls are considered. Table 2, panel c is constructed to enable the two types of metrics to compete in "explaining" employment–unemployment transitions. The table demonstrates that individual correlation patterns for both of the measures survive, indicating that both JPCs and the unemployment rate function as metrics that capture distinctive aspects of the variations of the transitions.

The design and evidence presented in Table 3 mirrors those presented in Table 2, except that the transitions of unemployed individuals to employment are examined. Also consistent across Tables 2 and 3 are the stronger correlations of the more granular JPC measures with labor market transitions, indicating not only the validity and usefulness of the RWET approach of adjusting JPCs to the local labor markets, but also the local nature of labor market transitions. That is, shocks to the labor market do not spread to the national level and reach a new equilibrium instantaneously.

In addition, we demonstrate the sensitivity of the correlation direction of the unemployment rate and labor market transitions is not an artifact of the specific version of the unemployment rate. Thus, from a practical perspective, JPCs seem to be a far more robust metric than the unemployment rate for capturing labor market dynamics.

We further examine the robustness of our main analysis using subsamples divided by the types of unemployment. The results presented in Tables 4 and 5 suggest that the explanatory power of both types of metrics primarily pertains to layoffs rather than quits. The competition of the coefficients of the unemployment rate and JPCs when the layoffs and quits subsamples are considered is very much in line with the results when the full overall transitions are studied. However, the JPCs do not significantly contribute to the explanation for individuals transitioning because of quits or new entrants; the unemployment rate plays a more salient role in the explanation for such transitions.

The results of the heterogeneity of the correlations with labor market transitions of the JPC and unemployment rate metrics are presented in Figs. 3 and 4. While there is no clear heterogeneity across education, gender, and age groups when transitions to employment are examined, when transitions to unemployment are examined, the correlations of the various measures do vary substantially for male and less-educated individuals.

In summary, this study validates the big-data-based JPCs in their capacity to capture labor market transitions. Our study also finds that JPCs can be a more robust metric than the unemployment rate in their correlation with overall labor market transitions. In addition, the evidence found in our study suggests that while most transitions to and from unemployment are due to layoffs, unemployment due to quits or (re)entrants is correlated with the unemployment rate metric but not with JPCs. Finally, our results suggest that the adjusted JPCs provide insights on a more granular level and can thus better capture local labor market dynamics. From a policy perspective, our study suggests that given many economies are experiencing unprecedented rapid changes, it can be beneficial to complement traditional measures such as the unemployment rate, which are still important, with real-time metrics such as JPCs.

The remainder of this paper is organized as follows: Section 2 discusses the CPS data and job posting data used in the study; Section 3 presents the descriptive evidence; Section 4 presents the main regression evidence; Section 5 discusses the evidence for subsamples. Section 6 concludes the study.

2 DATA

Three data sources from the United States are used in this study: the monthly microdata from the CPS, the monthly unemployment rates from the Bureau of Labor Statistics, and the job posting data supplied by Lightcast.

2.1 CPS Individual Transition Sample

Specifically, we construct labor market transitions using the monthly CPS microdata. We identify individuals across consecutive months using combinations of household identification and personal identification. Given that our job posting data are sequentially available starting from 2010, and given that the COVID-19 pandemic dramatically reshaped the labor market in 2020, our study period spans the ten years in between, that is, from 2010 to 2019. The raw CPS data in this period have 17,911,401 observations covering 3,498,678 individuals in 1,400,452 households.

We keep individuals in interviewed households, excluding those associated with the armed forces or living in group quarters. Our sample is further limited to the reference person, partner of the reference person, or child of the reference person of the primary families or individuals within households. Our transition sample is constructed from the monthly dataset, where each observation represents an individual's labor market status transition record across two consecutive calendar months, referred to as month t and $t+1$. In the design of CPS, respondents are surveyed for four months, rotated out for eight months, and then surveyed for a second four-month period. Therefore, one individual could correspond to multiple observations.[1]

To maintain data consistency, we exclude the very small fraction of transition samples where individuals experienced an age drop or age change greater than 1, underwent a gender or race change, or displayed an implausible change in their education level. We kept transition records only if the individual was part of the labor force, that is, either employed (E) or unemployed (U) in both month t and $t+1$. All 623,042 individuals in the final sample were aged 25 to 54, had educational attainment lower than the doctoral level, and were neither part of the armed forces nor self-employed.

In total, we recorded 1,610,285 transitions between employment and unemployment,[2] of which 1,540,887 (or 95.7 percent) began from an employment status (E_tE_{t+1} or E_tU_{t+1}), and 69,398 (4.3 percent) began from an unemployment status (U_tE_{t+1}, or U_tU_{t+1}). In general, most individuals in the labor force are employed.

[1] For example, if an individual was employed in both January and February but unemployed in March. Then, this person will have two observations in our transition sample: 1) this person has a "continuing employment" transition record for January and February; and 2) this person has a "employment to unemployment" transition record for February and March.

[2] To achieve sample size balance across months for our analysis transition sample, we adjusted the weight. Let the weight for sample i of month m be $w_{i,m}$. Let the average weight of observations in month m be $\overline{w_m}$. Let the number of observations in month m be N_m. Let the average N_m across all months be $\overline{N}$. The adjusted weight $\widehat{w_{i,m}} = \frac{w_{i,m}}{\overline{w_m}} \times \frac{\overline{N}}{N_m}$. It is easy to prove the mean of $\widehat{w_{i,m}}$ is unit, and the sum of weight for each month's sample is constant, $\overline{N}$.

2.2 Unemployment Rate

We examined both seasonally adjusted and unadjusted unemployment rates for ages 25–54 years. Although the results vary slightly, the seasonally adjusted unemployment rate demonstrated a stronger correlation than the unadjusted rates with the labor market transitions we investigated. Therefore, to subject the JPCs to a more rigorous test, only results using the seasonally adjusted rates are presented and discussed.

2.3 Lightcast Job Posting Counts

Our JPCs are constructed using the unduplicated version of Lightcast's weekly job posting data for the United States. Lightcast is a major supplier of job posting data sets in the United States. Their data has been extensively used in previous labor market studies (e.g., Acemoglu, Autor, Hazell, & Restrepo, 2022; Braxton & Taska, 2023; Deming & Noray, 2020; Hershbein & Kahn, 2018).

To facilitate the comparison of JPCs with the unemployment rate data, we align the job posting datasets with those of CPS. Specifically, we match four variables across these two sets of data: calendar month, state, industry, and occupation. To align with the CPS transition sample, we project all job postings dated in calendar dates into their corresponding calendar months, retaining only the nonduplicated postings as defined by the data provider. We also limit the dataset to the job postings of the 50 states and the District of Columbia, excluding territories, postings related to the armed forces industry (CsdInferredNAICS = 928110), postings related to armed forces occupations (CsdONET = 55), or postings with a missing state.

The first two digits of both the industry and occupation codes are used to match job postings with individuals in the CPS transition sample. The industry categories used in the CPS and the job posting data are largely similar, with several exceptions. Specifically, durable, and nondurable goods manufacturing in CPS are merged to align with the manufacturing industry in the job posting data. Similarly, services for private households and other services, excluding public administration in CPS, are consolidated to match the corresponding category in the job posting data. Consequently, our data cover 19 industries. The occupation categories in CPS and the job posting data are identical, resulting in 22 occupations. The concordance tables are included in the Appendix.

In total, we have a very large number of postings: 237,212,983. Noticing these job postings corresponds to a much smaller number of unique combinations even when we consider all four variables of interest, we instead use the combination level data with frequency weights. In particular, the raw posting data corresponds to 2,226,423 combinations of month × state × occupation × industry. This much smaller data set (2,226,423 / 237,212,983 = 0.94 percent) significantly reduces our computing costs.

Besides the raw national JPCs that most people currently use to depict labor market situations, we introduce four additional JPC measures through the RWET method. The RWET method is designed to address the small sample size issue in relatively "thin" markets. A labor market may become thin when JPCs are examined at fine categories, where not all cells have a positive number of job postings. The RWET method allows us to leverage all job postings across the country simultaneously, rather than only within each cell, to estimate changes in this case.

The implementation of the RWET approach in our study is slightly different from that described in Shen and Taska (2020) because we are using a collapsed dataset of job postings. Specifically, let there be N_0 job posting combinations for the 3,652 days for the period 2010–2019; call this set A. Let the frequent weight for set A be $w_{mn,s,occ,ind}$, which is the number of job postings for calendar month mn, state s, occupation occ, and industry ind.

Without loss of generality, let us construct JPCs adjusted by state, occupation, and industry for 2010 January. Let there be N_1 job posting combinations for the 31 days for 2010 January; call this set B. Obviously, set B is a subset of set A. First, we can pool the two sets together and set dummy Y to be one if the observation comes from set B. For every observation from A, we set its weight, w' to be $w_{mn,s,occ,ind}/3652$; for every observation from set B, w' is $w_{2010.1,s,occ,ind}/31$.

Next, we conduct a probit estimation control for dummies of state, occupation, and industry, with w' as the weight. Post-estimation, we can calculate, $\hat{p}_{2010.1,s,ind,occ}$, the predicted probability of any combination of state, occupation, and industry to come from 2010 January instead of a random date of the 10-year period. Finally, if we take the JPCs of set A as unit, then the relative JPCs adjusted by state, occupation, and industry are then $\hat{p}_{2010.1,s,ind,occ} / (1 - \hat{p}_{2010.1,s,ind,occ})$.

We can derive such adjusted JPCs for every month, state, occupation, and industry combinations. Furthermore, we can use the same approach to construct JPCs adjusted by the following :1) state; 2) state × occupation; and 3) state × industry, in addition to the JPCs adjusted by 4) state × occupation × industry, as shown above. These are the four adjusted JPC measures used in addition to the raw national JPCs in this study.

3 DESCRIPTIVE EXPLORATIONS

We begin our empirical analysis by presenting two complementary sets of figures. In both Fig. 1 and Fig. 2, the transitional probabilities between employment and unemployment, P_{EU} and P_{UE}, are used as benchmarks. Here P_{EU} refers to the probability of an employed individual in month t being unemployed in month $t+1$; P_{UE} refers to the probability of an unemployed individual in month t being employed in month $t+1$. Fig. 1 compares the longitudinal dynamics of P_{EU} and P_{UE} with those of the two key metrics under examination: the unemployment rate and JPCs; Fig. 2 focuses on the correlations between pairs of these measures using scatter plots.

Given that the time-series properties of P_{EU}, P_{UE}, and JPCs differ significantly from those of the unemployment rate, adjustments are made to ensure meaningful comparisons in Fig. 1. Not only are the negative values of P_{UE} and JPCs used, but P_{EU}, $(-P_{UE})$, and $(-JPC)$ are also adjusted to have the same mean and standard deviation as the unemployment rate. The results in Fig. 1 reveal a consistent decrease in the unemployment rate throughout the study period, 2010–2019, indicating a continuous improvement in the labor market. This trend is also reflected in the concurrent increase of P_{UE} and JPCs, and in the decrease of P_{EU}.

In addition to the overall consistency of the trends in these four aggregate measures, Fig. 1 reveals that the unemployment rate exhibits smoother variability compared with the other three measures. This discrepancy in variability is not surprising considering that the unemployment rate is a stock measure, while JPCs and transition probabilities are flows. Overall, Fig. 1 provides reassurance because it demonstrates long-term similarities between the trends of the unemployment rate, JPCs, and the labor market transition probabilities.

Fig. 2 focuses on the correlations between the unemployment rate JPC metrics and the transition probabilities. These correlations are presented separately for P_{EU} and P_{UE} in Fig. 2a and b, respectively. The unemployment rate is presented on the left y-axis (an increasing sequence), while JPCs are presented on the right y-axis (a decreasing sequence). This arrangement allows for a clearer visualization of the patterns.

As expected, in Fig. 2a, lower unemployment rates are associated with lower transition probabilities from employment to unemployment (P_{EU}), while lower JPC values correspond to higher P_{EU}. Note that we have used reversed orders for the right y-axis to represent JPCs. The two scatter plots largely overlap, and their fitted lines follow similar trends.

Fig. 2b mirrors the construction of Fig. 2a but focuses on the transition probabilities from unemployment to employment (P_{UE}). The scatter plot reveals a negative correlation between P_{UE} and the unemployment rate, but a positive correlation between P_{UE} and JPC values. The two fitted lines superimposed on the scatter plots have slightly different slopes, reflecting the magnitude differences between the two metrics. However, their correlations with P_{UE} are remarkably similar, making it challenging to determine which metric is more precise or superior.

Overall, Fig. 2 reveals significant similarities in the correlations between the unemployment rate and transition probabilities, as well as between JPCs and transition probabilities. Both metrics exhibit comparable explanatory power in relation to labor market transitions. This observation represents a key insight of this study, emphasizing the validity of comparing these measures in relation to their influence on labor market dynamics.

The basic descriptive statistics of our CPS transition sample are presented in Table 1, which provides an intuitive broad picture of the labor market transitions in the United States. Table 1, panel a presents the sample means of all individuals, categorized by their initial labor market status, either employed (E_t) or unemployed (U_t), and further segmented according to realized transitions: those who remain employed ($E_t E_{t+1}$), those who transition from employment to unemployment ($E_t U_{t+1}$), and vice versa for unemployed individuals ($U_t E_{t+1}$, and $U_t U_{t+1}$).

Interestingly, Table 1, panel a reveals significant disparity between the number of individuals employed and unemployed in the labor market. Our 10-year sample includes nearly 1.5 million individuals who began as employed, and only 69,398 who began as unemployed. It is worth noting that within the employed subset, the proportion transitioning to unemployment is minimal, accounting for only 0.9 percent. In contrast, approximately one-quarter of initially unemployed individuals transition to employment within one month. As a result, transition balance occurs because the small proportion of a large group of employed people transitioning to unemployment is offset by a greater proportion of a smaller group of unemployed people transitioning to employment.

Examining demographic characteristics, Table 1, panel a reveals several interesting patterns relating to employment–unemployment transitions. Females are more likely to remain either employed or unemployed, while males are more prone to transitioning between these states. Immigrants and non-White individuals are more likely to become unemployed, whereas immigrant (non-White) individuals are more(less) likely to secure employment if unemployed. Single and divorced individuals are found to have a higher likelihood of becoming unemployed and remaining unemployed, while married individuals are more likely to become reemployed and stay employed.

The data also suggest that age and education play significant roles in these transitions. Younger individuals (aged 25–29 and 30–34) are more likely to switch between employment states, either becoming unemployed or getting reemployed. Prime age groups (aged 35–39 and 40–44) tend to stay employed and have a higher likelihood of getting reemployed if they become unemployed. Older age groups (aged 45–49 and 50–54) tend to remain either employed or unemployed, meaning they are more likely to stay in their current labor market state. When it comes to education, employment–unemployment transition rates in either direction appear to be relatively high among those with lower education levels. As education level increases, individuals tend to have a higher likelihood of remaining employed or getting reemployed if they become unemployed.

Individuals may leave their jobs involuntarily because of negative shocks in the product market, resulting in a higher unemployment rate or fewer job postings. Conversely, individuals may leave their jobs voluntarily for better opportunities outside their current employer, which is particularly relevant in a tight labor market, leading to a lower unemployment rate or more job postings. In these two cases, the correlation between our metrics and the transition probability from employment to unemployment can be in opposite directions depending on the causes of unemployment. Therefore, it is important to consider the unemployment state based on these causes.

To address this, Table 1, panel b expands on Table 1, panel a by specifically focusing on individuals who transitioned between employment states rather than remaining employed or unemployed. Those who become unemployed are further divided into two groups: those who were laid off and those who quit their previous jobs. Those who are reemployed are divided into three groups: those who were previously laid off, those who quit their previous jobs, and new entrants or reentrants into the labor market.

Table 1, panel b reveals that a similar number of individuals transitions in both directions, with slightly more individuals transitioning into employment. This pattern is consistent with the continuously improving labor market during our study period in the 2010s. Interestingly, most transitions in both the $E_t U_{t+1}$ and $U_t E_{t+1}$ subsamples are attributed to individuals being laid off, accounting for 89 percent and 72 percent, respectively. The categories of quitters represent the smallest proportion in both subsamples, accounting for 10.8 percent and 9.9 percent, respectively. Additionally, new entrants and reentrants constitute a significant 18 percent of the transitions from unemployment to employment ($U_t E_{t+1}$), which is nearly twice the proportion of quitters.

When examining individual characteristics, we find that among those who underwent labor market transitions, women are more likely to experience unemployment because of quitting or entrance to the labor market, which is consistent with the relatively lower labor market attachment of women. Non-White, single, divorced, and younger individuals exhibit similar patterns to those of women. Finally, individuals with lower levels of education (high school or below) are more likely to be laid off, while those with higher levels of education appear to have more autonomy in their employment decisions and are more likely to quit or become new entrants. These patterns provide support for the validity of our transition sample.

4 MAIN EMPIRICAL EVIDENCE

4.1 Accounting for Transitions from Employment to Unemployment

Table 2 presents our main empirical evidence for the explanatory power of the unemployment rate compared with JPCs in accounting for transitions from employment to unemployment, $P(U_{t+1}|E_t)$. In a parallel analysis, Table 3 examines transitions from unemployment to employment: $P(E_{t+1}|U_t)$.

Table 2 consists of three panels. Panels a and b focus on the unemployment rate and JPCs separately, while panel c includes both metrics simultaneously, providing a battleground for their competition in explaining $P(U_{t+1}|E_t)$. In all these regressions, despite our dependent variable being dichotomous, we utilize linear probability models instead of probit or logit models to incorporate fixed effects. This consideration is essential because of the complex correlations we are exploring. It is important to reiterate that our focus is not to establish causality. Furthermore, to ensure that the estimated coefficients from the various JPC measures are comparable in magnitude to those of the unemployment rate, we proportionally adjust the JPCs. Specifically, the raw national JPCs are expressed in millions, while the four adjusted JPCs are scaled to 100s.

The specifications become increasingly comprehensive from left to right in Table 2, panel a. In column (1), only unemployment rate is included, and the coefficient of unemployment rate, 0.0916, is statistically significant. This suggests that a decrease of one percentage point in the unemployment rate is associated with a (0.000916/0.00954=) 9.6 percent decrease in the probability of transitioning from employment to unemployment: $P(U_{t+1}|E_t)$.

As we gradually introduce demographic controls and various fixed effects related to the year, region, industry, and occupation, a significant development unfolds. The coefficient of the unemployment rate undergoes a dramatic shift, becoming negative and statistically significant. The introduction of the year fixed effect is the pivotal moment in this transformation. It indicates that the years with lower transition probabilities $P(U_{t+1}|E_t)$ are also characterized by lower unemployment rates. Interestingly, within each year, cells with higher $P(U_{t+1}|E_t)$ values are correlated with lower unemployment rates, which presents a counterintuitive pattern. Given this complex relationship between the stock measure (unemployment rate) and the flow measure ($P(U_{t+1}|E_t)$), we believe it is premature to offer an economic interpretation. Instead, we consider it as a descriptive observation of the intricate dynamics between these two measures.

Panel b of Table 2 examines the raw JPC as well as the four adjusted JPCs in the simplest and most saturated specifications of panel a. The first specification involves the comparison of these different versions of JPCs without any additional controls. Across all measures, we find a consistently negative and statistically significant coefficient, indicating a strong correlation with the transition probability $P(U_{t+1}|E_t)$. Interestingly, the adjusted measures reveal a slightly larger coefficient magnitude, suggesting that these fine-tuned measures provide a better explanation for the transition probability. In the second specification in panel b, we focus on the most saturated model from panel a. Unlike the significant changes observed for the unemployment rate, the estimated coefficients of all five JPCs did not change signs, rather they remained statistically significant for the most part while becoming less negative.

In panel c of Table 2, we directly compare the unemployment rate and JPCs in the same regressions. Notably, whether without any additional controls or with the most saturated specification, the coefficients of the unemployment rate and various JPC measures maintain the same sign and remain statistically significant. That is, although the magnitude of the coefficients may be smaller, relationships observed in the separate analyses hold even when these metrics are included together.

Overall, Table 2 offers several important findings. First, the relationship between unemployment rate and transition probability $P(U_{t+1}|E_t)$ is not constant but varies across and within years: it is more positively correlated across years, and it leans toward a negative correlation within years. Second, while there is some overlap, the unemployment rate and JPCs largely tap into different parts of the variations in our dependent variable. Third, not all JPC measures are created equal: local JPCs demonstrate a greater propensity to account for transition probability $P(U_{t+1}|E_t)$.

4.2 Accounting for Transitions from Unemployment to Employment

As stated, Table 3, mirrors the design of Table 2 but examines the transition from unemployment to employment. Its three parts are defined similarly. It is important to note the smaller sample size for this table. As discussed, the number of unemployed individuals in the labor market is significantly less than the number of employed individuals in the labor market.

In panel a of Table 3, we observe a significant change in the sign of the unemployment rate's coefficient: from being statistically significant and negative, it essentially zeroes out. This shift in characteristics occurs when we introduce year fixed effects, indicating that within a given year, the unemployment rate is not strongly correlated with the probability of transitioning to employment. However, across years, periods with a higher likelihood of transition from unemployment to employment are those with lower unemployment rates. This seems to suggest that the cross-year variation of the unemployment rate is much more robust in its capacity to predict unemployment–employment transition probabilities than the within-year fluctuations of the unemployment rate.

Panel b of Table 3 mirrors the exercise in panel a but uses JPCs. We observe that without any controls, the coefficient for JPCs is approximately three to four times that of the unemployment rate, comparable to the relative magnitudes observed between panels a and b of Table 2. Furthermore, the fluctuation in the coefficients of our four fine-tuned JPC measures is similar, albeit slightly surprising. The coefficient at the state level appears higher, but given the magnitude of the standard error, the difference across columns is not significant. With the introduction of the most saturated controls, we notice a pattern similar to that observed in Table 2. Thus, we see that the explanatory power of JPCs is more potent at the granular, local level than at the broad national level.

Panel c of Table 3 directly compares the JPCs and the unemployment rate. The patterns we see here are familiar: the coefficient, even in the absence of other controls, remains relatively unchanged. The coefficients of the unemployment rate do not display any meaningful difference in values.

The most substantial change is observed in the coefficients of JPCs, but only when no controls are applied. This essentially tells us that the variations in the transition from unemployment to employment, which form the basis for generating the coefficients for unemployment rate and JPCs, are quite different. There is only a slight overlap in the variations used, indicating that these two measures, with their distinct properties and natures, are utilized in different ways.

In short, JPCs prove to be a more robust measure than the unemployment rate because their coefficients do not undergo drastic changes in sign as more controls are added.

4.3 Transitions to Unemployment by Reasons for Unemployment

Table 4 delves deeper into the transitions from employment to unemployment by examining the causes of unemployment. This table is divided into two parts: panel a investigates the transition from employment to unemployment due to layoffs, and panel b investigates the transition from employment to unemployment due to quits.

The sample used here is identical to the one utilized in Table 2. One might argue that a multinomial model could be more appropriate here but given the exploratory nature of this study and our desire to incorporate fixed effects, we continue to use the linear probability model.

In panel a, the unemployment rate and JPCs are competing in their explanatory power. We observe that the coefficients are quite similar to those in panel c of Table 2. Thus, the factors accounting for the transition due to layoffs closely resemble those generally accounting for the transition from employment to unemployment.

Panel b presents transitions from employment to unemployment because of voluntary quits. Here, the coefficient shows an inversion in signs, albeit with a magnitude about one-tenth of that for layoffs, when no controls are applied. Thus, when the unemployment rate is higher, there are fewer quits, which is countercyclical and intuitive. Moreover, JPCs seem to have no correlation with the incidence of quits.

Once we incorporate granular-level fixed effects, the unemployment rate loses its relevance in this context. Therefore, the explanatory power of the unemployment rate and JPCs primarily pertains to layoffs rather than quits.

4.4 Transitions to Employment by Reasons for Unemployment

Table 5 is designed similarly to Table 4 but shifts focus to examine transitions from unemployment to employment. Specifically, we categorize these transitions by the causes of unemployment: layoffs, quits, and new entrants or reentrants into the job market.

For those transitioning from unemployment caused by layoffs to employment, the competition of the coefficients of the unemployment rate and JPCs is very much in line with the overall transitions from unemployment to employment. In contrast, the JPCs do not significantly contribute to the explanation for transitions because of quits or new entrants; the unemployment rate plays a much more relevant role in explaining such transitions. Specifically, when the unemployment rate is higher, the transition from unemployment (caused by quits or new entries) to employment slows down.

When combined with the findings from Table 4, these results suggest that unemployment caused by quits or (re)entrance into the workforce tends to be more subdued when the overall unemployment rate is high and becomes more active when the unemployment rate is low. This is regardless of the direction of the transition (from employment to unemployment, or vice versa).

However, for people experiencing layoffs, the signs of correlation between unemployment rate/JPCs and transition probabilities all changed when the direction of transitions switched. Such differences across the quits/(re)entrance samples and laid off samples reflect the complexity of the labor market dynamics beyond just broadly defined employment/unemployment states.

5 ROBUSTNESS ACROSS DEMOGRAPHIC GROUPS

In this section, we examine the robustness of the main empirical evidence presented in Section 4 for different demographic groups. For each subsample, we present estimated coefficients in the most saturated specification with unemployment rate, raw JPCs, and the four adjusted JPCs separately considered in sets of six regressions. Given that the correlation between unemployment rate and transition probabilities switches signs depending on whether year fixed effects are considered, we also present estimated coefficient of unemployment rate when no controls are considered. Thus, for each subsample, we have seven estimated coefficients. This large number of coefficients is presented graphically in Figs. 3 and 4.

5.1 Transitions from Unemployment to Employment

Fig. 3a, b, and c present the estimated coefficients for subsamples divided by education, gender, and gender × age groups, respectively. The salient gender differences over work life profile motivate us to separately investigate the robustness of our main results by gender when different age groups are examined.

Fig. 3a demonstrates that estimated coefficients of JPCs and unemployment rate without controls are quite similar, while estimated coefficient of unemployment rate with controls vary significantly, particularly for the less-educated individuals. This could imply that the sensitivity of the coefficient of unemployment rate is mostly due to the less-educated group. That is, their unemployment to employment transitions might be captured very differently by unemployment rate. Panel b of Table 3 suggests that males who transition to employment are more sensitive to both types of metrics. Although Table 3, panel c further divides the two gender groups into finer age groups, the results are largely like those presented in panel b. The coefficients are similar across age groups and vary across gender groups.

In short, the heterogeneity seems to be more pronounced for males and the less-educated groups for various metrics' correlations to transitions from employment to unemployment.

5.2 Transitions from Unemployment to Employment

Fig. 4 is constructed in the same way as Fig. 3 except transition from unemployment to employment is examined. Estimated coefficients as presented in Fig. 4 largely indicate that the estimated coefficients of the unemployment rate and various JPCs are mostly not statistically different from zero when demographic subsamples are used. This suggests that with such narrowly defined groups, neither type of metric significantly correlates with individuals' transitions from unemployment to employment.

But the above pattern is only valid when controls are considered. In contrast, the estimated coefficients for unemployment rate without controls suggest a quite different pattern. In this case, higher unemployment rates consistently correlate with fewer transitions from unemployment to employment. This pattern is quite stable across all groups by education, gender, or age levels.

Considered together, the evidence in Fig. 4 suggests that unemployment to employment transition is a highly demographic-specific experience, the overall correlation between unemployment rate and reemployment probability might be due to changes in the composition of the unemployment pool. The evidence in Fig. 4 could be explained if the proportion of those who are much less likely to be reemployed increases when the unemployment rate increases. In this case, although each subgroup of unemployed individuals experiences the same reemployment probabilities, the overall unemployment–employment transition process slows down.

6 CONCLUSION

This study validates the newly popular JPCs as indicators of labor market dynamics. This is done by extensive comparison of JPCs and unemployment rate in their correlations with individuals' transitions between employment and unemployment in the United States economy. The results suggest that JPCs and the unemployment rate provide comparable predictive power for labor market transitions, while both types of metrics capture different aspects of the variations in these transitions. That is, they are not substitutes for each other.

One salient difference between these two metrics is reflected in the robustness of the correlations between JPCs and labor market transition probabilities regardless of the set of controls. This robustness is not found when the unemployment rate is examined. Specifically, the correlations between unemployment rate and labor market transitions are intuitive when year fixed effects are not considered. That is, higher unemployment rates are correlated with higher transition probability to unemployment and lower transition probability from unemployment. But when year fixed effects are considered, these correlations change signs. We suspect that the stock nature of the unemployment rate might be one reason for this sensitivity of its correlation with flow measures such as transition probabilities. However, further investigation needed to examine such abnormalities is beyond the scope of this study.

Another more subtle difference between these two metrics relates to the fact that JPCs can be adjusted at rather granular local levels, and this metric thus becomes even stronger in its predictive capabilities, outperforming more coarsely measured JPCs and unemployment rate. In addition to being timely, low cost, and nonintrusive, the flexible and rich nature of JPCs are found to be an added advantage of this big-data-based measure.

Despite the advantages of JPCs, the findings here suggest the potential of unemployment rates to explain involuntary and voluntary unemployment simultaneously, whereas the JPCs seems to be more capable of explaining involuntary unemployment only.

All the above findings were robust to examinations by demographic subgroups; however, the subgroups of male and less-educated individuals had more sensitivity to the choice of metric. This and all the other main findings of this study lead us to consider our work to be a starting point. However, the perspective of our study has produced new insights about labor market dynamics and the efficacy of a new type of metric in explaining these dynamics.

Finally, we note that our study uses only a small part of the information provided by job posting data. The potential to combine the strengths of JPC and unemployment rate data to deepen understanding of labor market dynamics remains an underexplored research area. Nonetheless, with the collection and processing of job posting data mostly conducted by the private sector, with many technical details undisclosed and unscrutinized, caution is warranted when using it to examine the labour market.

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FIGURES AND TABLES

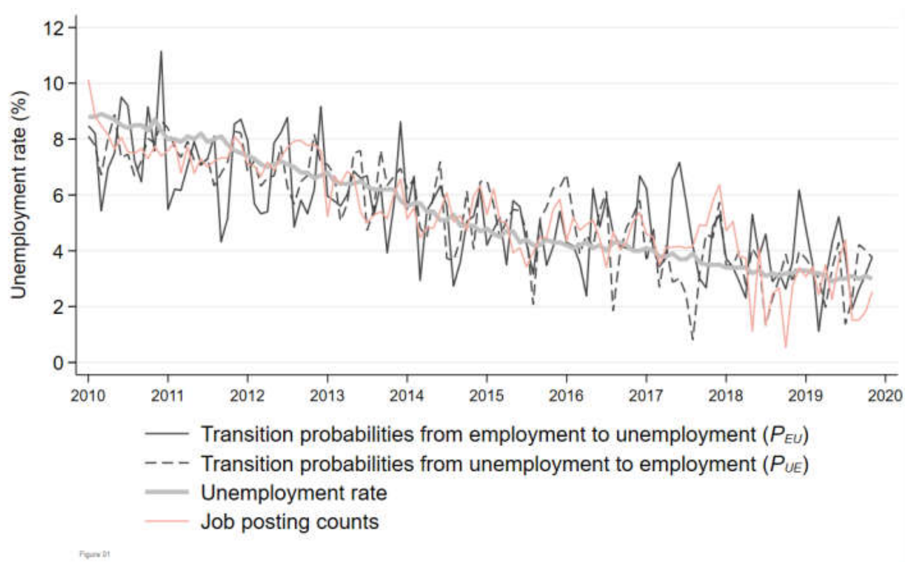

Fig. 1. Longitudinal Dynamics of Transition Probabilities, Unemployment Rate, and JPCs

Notes:

1. Three data sources are used in this figure. P_{EU} and P_{UE} are derived from monthly CPS microdata; monthly unemployment rate is obtained from the Bureau of Labor Statistics (BLS); the JPCs are from the unduplicated version of Lightcast's weekly job posting datasets.
2. P_{EU} refers to the probability of an employed individual in month t being unemployed in month $t+1$; P_{UE} refers to the probability of an unemployed individual in month t being employed in month $t+1$. The mean and (standard deviation) of raw P_{EU} and P_{UE} are 0.009543(0.002403) and 0.275013(0.067821) respectively. For the unemployment rate and JPCs, the mean and (standard deviation) are 0.053983(0.018903) and 1,966,344(671,725) respectively.
3. To ensure the comparability, we use the negative values of P_{UE} and JPCs. Additionally, we adjust P_{EU}, $(-P_{UE})$, and $(-JPC)$ to have the same mean and standard deviation as the unemployment rate.

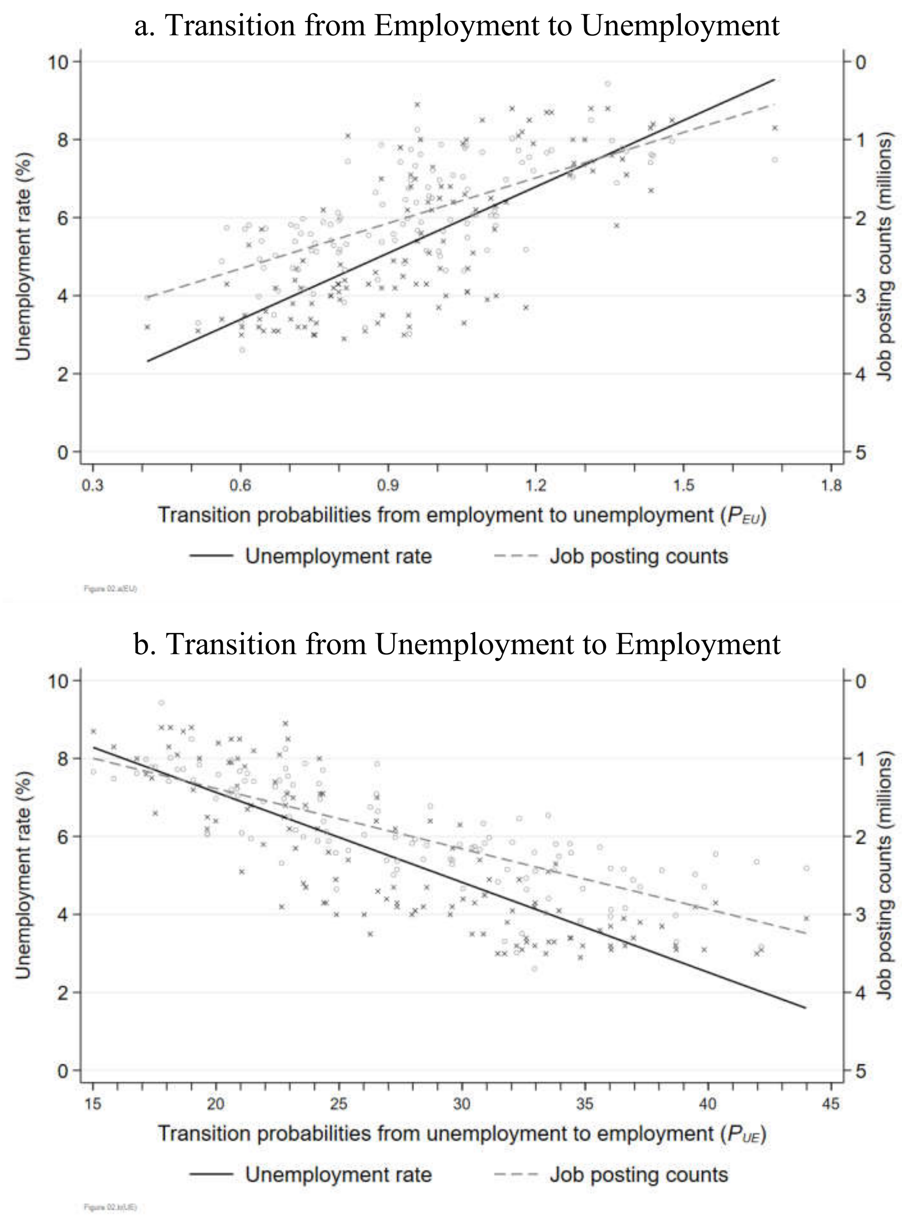

Fig. 2. Correlation between Transition Probabilities and Unemployment Rate and JPCs

Notes:

4. Three data sources are used in this figure. P_{EU} and P_{UE} are derived from monthly CPS microdata; monthly unemployment rate is obtained from the BLS; the JPCs are from the unduplicated version of Lightcast's weekly job posting datasets.
5. The unemployment rate is presented on the left y-axis (an increasing sequence), while JPCs are presented on the right y-axis (a decreasing sequence).
6. P_{EU} refers to the probability of an employed individual in month t being unemployed in month $t+1$; P_{UE} refers to the probability of an unemployed individual in month t being employed in month $t+1$. The mean and (standard deviation) of raw P_{EU} and P_{UE} are 0.009543(0.002403) and 0.275013(0.067821) respectively. For the unemployment rate and JPCs, the mean and (standard deviation) are 0.053983(0.018903) and 1.966344(0.671725) respectively.

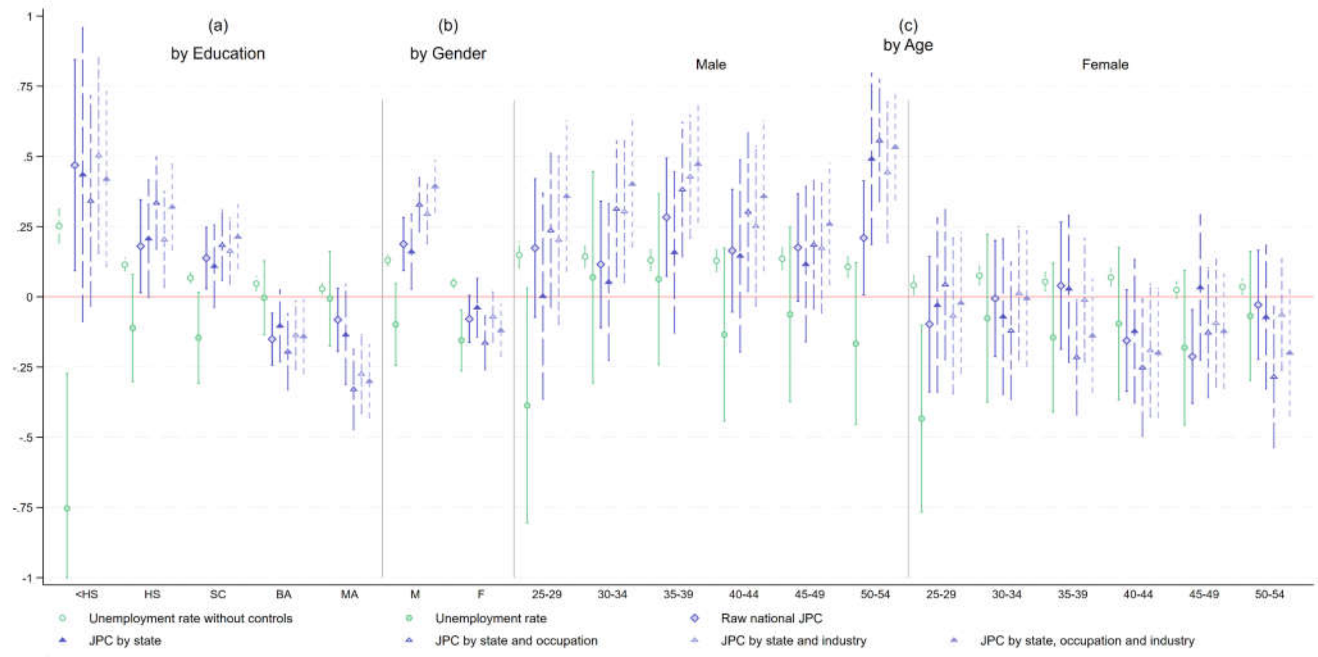

Fig. 3. Heterogeneity across Demographic Groups: Transition from Employment to Unemployment

Notes:

1. The dependent variable, $P(U_{t+1}|E_t)$, is the probability of an employed individual in month t being unemployed in month t + 1.
2. All regressions are weighted using the adjusted longitudinal weights of CPS. The adjustment allows us to achieve sample size balance across months for our analysis transition sample. In particular, let the weight for sample i of month m be $w_{i,m}$. Let the average weight of observations in month m be $\overline{w_m}$. Let the number of observations in month m be N_m. Let the average N_m across all months be $\overline{N}$. The adjusted weight $\widehat{w_{i,m}} = \frac{w_{i,m}}{\overline{w_m}} \times \frac{\overline{N}}{N_m}$. It is easy to prove the mean of $\widehat{w_{i,m}}$ is unit, and the sum of weight for each month's sample is constant, $\overline{N}$.
3. The coefficients for unemployment rate presented are based on two sets of regressions: one without any controls (green hollow circles) and another with demographic controls; and year, state extended Core-Based Statistical Area (CBSA), occupation, and industry fixed effects (green solid circles). Additionally, coefficients for all JPC measures are based on regressions with demographic controls; and year, state extended CBSA, occupation, and industry fixed effects.
4. Demographic controls include dummies for female, immigrant, non-White, married, and divorced individuals; five age groups (30–34, 35–39, 40–44, 45–49, and 50–54); and four education levels (high school, some college or associate degree, bachelor's, and master's). The omitted age group is 25–29 years. The omitted education group is less than high school. The CBSA dummies are extended so that separate dummies are created for each state's non-CBSA area.
5. <HS, HS, SC, BA, and MA denote less than high school, high school, some college or associate, bachelor's, and master's, respectively. M refers to male and F refers to female.

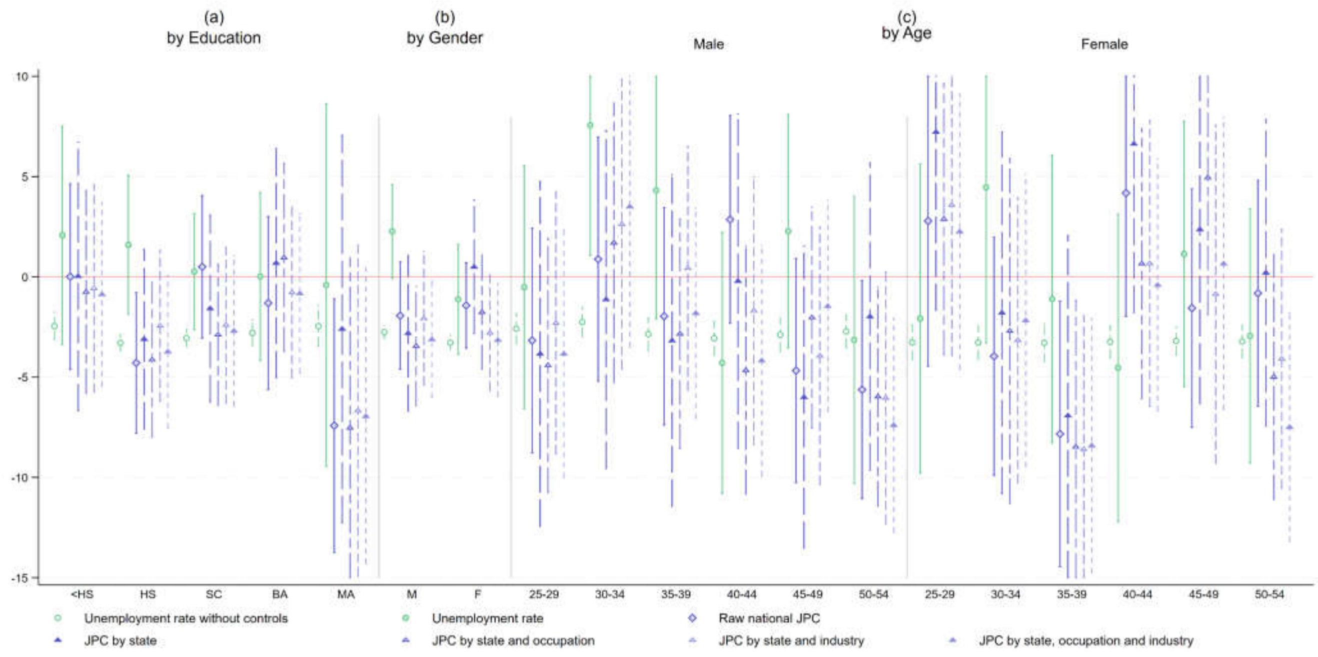

Fig. 4. Heterogeneity across Demographic Groups: Transition from Unemployment to Employment

Notes:

1. The dependent variable, $P(E_{t+1}|U_t)$, is the probability of an unemployed individual in month t being employed in month t + 1.
2. All regressions use the adjusted longitudinal weights of CPS as explained in note 2 of Fig. 3.
3. The coefficients for the unemployment rate presented are based on two sets of regressions: one without any controls (green hollow circles) and another with demographic controls; and year, state extended CBSA, occupation, and industry fixed effects (green solid circles). Additionally, coefficients for all JPC measures are based on regressions with demographic controls; and year, state extended CBSA, occupation, and industry fixed effects.
4. Demographic controls include dummies for female, immigrant, non-White, married, and divorced individuals; five age groups (30–34, 35–39, 40–44, 45–49, and 50–54); and four education levels (high school, some college or associate degree, bachelor's, and master's). The omitted age group is 25–29 years. The omitted education group is less than high school. The CBSA dummies are extended so that separate dummies are created for each state's non-CBSA area.
5. <HS, HS, SC, BA, and MA denote less than high school, high school, some college or associate, bachelor's, and master's, respectively. M refers to male and F refers to female.

Table 1. Sample Means.

a. Employed and Unemployed Individuals by Transitions Experienced

Individual characteristics	Employed (E_t)			Unemployed (U_t)		
	E_tE_{t+1}	E_tU_{t+1}	All	U_tE_{t+1}	U_tU_{t+1}	All
Female	.472	.418	.471	.432	.450	.446
Immigrant	.192	.228	.192	.227	.182	.194
Non-White	.210	.241	.210	.256	.308	.295
Marital status						
Single	.227	.317	.228	.330	.375	.362
Married	.645	.522	.644	.510	.449	.467
Divorced	.128	.162	.128	.160	.176	.171
Age						
25–29	.154	.199	.154	.207	.188	.193
30–34	.165	.173	.165	.177	.174	.174
35–39	.165	.156	.165	.160	.155	.156
40–44	.168	.158	.168	.157	.154	.154
45–49	.175	.160	.175	.155	.163	.161
50–54	.173	.154	.173	.145	.166	.161
Education						
Less than high school	.069	.148	.070	.149	.131	.135
High school	.249	.334	.250	.323	.331	.330
Some college	.282	.283	.282	.288	.299	.296
Bachelor	.268	.171	.267	.172	.174	.174
Master	.132	.065	.132	.068	.064	.066
# of individuals	1,526,515	14,372	1,540,887	17,661	51,737	69,398
% of individuals	99.1	0.9	100	25.4	74.6	100

b. Individuals with Changed Employment Status: Categorized by Unemployment Cause

Individual characteristics	E_tU_{t+1}			U_tE_{t+1}			
	Laid off	Quit	All	Laid off	Quit	Entrants	All
Female	.407	.515	.418	.389	.485	.570	.432
Immigrant	.237	.156	.228	.232	.191	.221	.227
Non-White	.239	.253	.241	.241	.227	.323	.256
Marital status							
Single	.312	.345	.317	.312	.374	.383	.330
Married	.527	.478	.522	.527	.467	.457	.510
Divorced	.161	.177	.162	.161	.159	.160	.160
Age							
25–29	.190	.271	.199	.177	.274	.289	.207
30–34	.169	.205	.173	.172	.197	.189	.177
35–39	.156	.150	.156	.161	.158	.150	.160
40–44	.160	.146	.158	.164	.140	.136	.157
45–49	.166	.110	.160	.166	.119	.128	.155
50–54	.158	.118	.154	.160	.112	.108	.145
Education							
Less than high school	.151	.124	.148	.158	.126	.130	.149
High school	.334	.325	.334	.336	.305	.281	.323
Some college	.283	.283	.283	.274	.298	.332	.288
Bachelor	.167	.199	.171	.165	.208	.186	.172
Master	.065	.069	.065	.067	.062	.071	.068
# of individuals	12,816	1,556	14,372	12,711	1,747	3,203	17,661
% of individuals	89.2	10.8	0.9	72.0	9.9	18.1	25.4

Notes:

1. Panel a presents the sample means of all individuals, categorized by their initial labor market status—either employed (E_t) or unemployed (U_t), and further segmented according to realized transitions: those who remain employed (E_tE_{t+1}), those who transition from employment to unemployment (E_tU_{t+1}), and vice versa for unemployed individuals (U_tE_{t+1}, and U_tU_{t+1}).
2. Panel b categorizes individuals transitioning from employment to unemployment into two groups based on their reason for unemployment: those who were laid off and those who quit their previous jobs. For individuals transitioning from unemployment to employment, panel b distinguishes three groups: those who were laid off, those who quit their previous jobs, and a third group comprising new entrants or reentrants into the labor market.
3. Individuals with some college or associate are labeled as some college for brevity.

Table 2. Accounting for Transition from Employment to Unemployment.

	(1)	(2)	(3)	(4)	(5)
a. Unemployment Rate					
Unemployment rate	0.0916***	0.0972***	−0.1334***	−0.1337***	−0.1254***
	(0.0075)	(0.0069)	(0.0479)	(0.0477)	(0.0476)
Demographic controls		Y	Y	Y	Y
Year FE			Y	Y	Y
CBSA FE				Y	Y
Occupation FE					Y
Industry FE					Y
# of observations	1,540,887	1,540,887	1,540,887	1,540,887	1,540,887
R^2	0.000	0.001	0.003	0.004	0.007
b. Job Posting Count (JPC) Measures					
JPC measures	Raw national counts	Adjusted by: State	Adjusted by: State and occupation	Adjusted by: State and industry	Adjusted by: State, occupation, and industry
Without any controls					
JPC measures	−0.2484***	−0.4259***	−0.3987***	−0.3898***	−0.3888***
	(0.0196)	(0.0382)	(0.0353)	(0.0339)	(0.0356)
With demographic, year, CBSA, occupation, and industry FE controls					
JPC measures	−0.0598*	−0.0654	−0.1185***	−0.1255***	−0.1733***
	(0.0346)	(0.0460)	(0.0361)	(0.0363)	(0.0347)
c. Unemployment Rate Compared with JPC Measures					
Without any controls					
Unemployment rate	0.0617***	0.0723***	0.0669***	0.0642***	0.0596***
	(0.0116)	(0.0096)	(0.0090)	(0.0089)	(0.0085)
JPC measures	−0.0960***	−0.1222***	−0.1554***	−0.1645***	−0.1919***
	(0.0273)	(0.0428)	(0.0379)	(0.0359)	(0.0390)
With demographic, year, CBSA, occupation, and industry FE controls					
Unemployment rate	−0.1235***	−0.1230**	−0.1196**	−0.1201**	−0.1175**
	(0.0477)	(0.0477)	(0.0474)	(0.0473)	(0.0473)
JPC measures	−0.0576*	−0.0599	−0.1141***	−0.1219***	−0.1701***
	(0.0347)	(0.0460)	(0.0359)	(0.0362)	(0.0346)

Notes:

1. All regressions are weighted using the adjusted longitudinal weights of CPS as explained in note 2 of Fig. 3. The weighted mean of the dependent variable, $P(U_{t+1}|E_t)$, is 0.009543.
2. Demographic controls include dummies for female, immigrant, non-White, married, and divorced individuals; five age groups (30–34, 35–39, 40–44, 45–49, and 50–54); and four education levels (high school, some college or associate degree, bachelor’s, and master’s). The omitted age group is 25–29 years. The omitted education group is less than high school. The CBSA dummies are extended so that separate dummies are created for each state’s non-CBSA area.
3. To ensure comparability of the estimated coefficients, the raw national JPCs is in millions, and the four adjusted JPCs are in 100s. In this sample, the weighted mean of unemployment rate is 0.053983; raw national JPCs is 0.019663 (millions);

JPCs adjusted by 1) state, 2) state and occupation, 3) state and industry, and 4) state, occupation, and industry, are 0.009955, 0.009937, 0.009958 and 0.009954.

4. $p < .10$, ** $p < .05$, *** $p < .01$.

Table 3. Accounting for Transition from Unemployment to Employment.

	(1)	(2)	(3)	(4)	(5)
			a. Unemployment Rate		
Unemployment rate	−2.9716***	−3.0707***	0.6746	0.7801	0.8945
	(0.1336)	(0.1377)	(0.9667)	(0.9484)	(0.9475)
Demographic controls		Y	Y	Y	Y
Year FE			Y	Y	Y
CBSA FE				Y	Y
Occupation FE					Y
Industry FE					Y
# of observations	69,398	69,398	69,398	69,398	69,398
R^2	0.016	0.022	0.026	0.042	0.055
			b. Job Posting Count (JPC) Measures		
JPC measures	Raw national counts	Adjusted by			
		State	State and occupation	State and industry	State, occupation, and industry
Without any controls					
JPC measures	7.8942***	13.4388***	11.9763***	11.3440***	10.9469***
	(0.4435)	(0.9529)	(0.7796)	(0.7282)	(0.6533)
With demographic, year, CBSA, occupation, and industry FE controls					
JPC measures	1.8336**	1.6165	3.1216***	2.5832**	3.3495***
	(0.9282)	(1.4327)	(1.0427)	(1.0499)	(0.9451)
			c. Unemployment Rate Compared with JPC Measures		
Without any controls					
Unemployment rate	−2.2207***	−2.5592***	−2.3500***	−2.3948***	−2.2581***
	(0.2410)	(0.2067)	(0.1748)	(0.1892)	(0.1892)
JPC measures	2.4062***	2.6124*	3.7406***	3.2672***	3.8879***
	(0.8125)	(1.3679)	(0.9968)	(0.9783)	(0.8846)
With demographic, year, CBSA, occupation, and industry FE controls					
Unemployment rate	0.8279	0.8356	0.6902	0.7693	0.6970
	(0.9513)	(0.9559)	(0.9548)	(0.9497)	(0.9496)
JPC measures	1.8170*	1.5810	3.0903***	2.5581**	3.3273***
	(0.9295)	(1.4394)	(1.0472)	(1.0520)	(0.9468)

Notes:

1. All regressions are weighted using the adjusted longitudinal weights of CPS as explained in note 2 of Fig. 3. The weighted mean of the dependent variable, $P(E_{t+1}|U_t)$, is 0.275013.
2. Demographic controls include dummies for female, immigrant, non-White, married, and divorced individuals; five age groups (30–34, 35–39, 40–44, 45–49, and 50–54); and four education levels (high school, some college or associate degree, bachelor's, and master's). The omitted age group is 25–29 years. The omitted education group is less than high school. The CBSA dummies are extended so that separate dummies are created for each state's non-CBSA area.
3. To ensure comparability of the estimated coefficients, the raw national JPCs is in millions, and the four adjusted JPCs are in 100s. In this sample, the weight mean of unemployment rate is 0.053983; raw national JPCs 0.019663 (millions); JPCs

adjusted by 1) state, 2) state and occupation, 3) state and industry, and 4) state, occupation, and industry, are 0.009929, 0.009908, 0.009909 and 0.009903.

4. $p < .10$, ** $p < .05$, *** $p < .01$.

Table 4. Transition from Employment to Unemployment: Categorized by Cause of Unemployment.

	(1)	(2)	(3)	(4)	(5)
		Adjusted by			
Job posting count (JPC) measures	Raw national counts	State	State and occupation	State and industry	State, occupation, and industry
a. Unemployed Due to Layoffs					
Without any controls					
Unemployment rate	0.0681***	0.0786***	0.0731***	0.0707***	0.0659***
	(0.0110)	(0.0092)	(0.0085)	(0.0084)	(0.0081)
JPC measures	−0.0892***	−0.1098**	−0.1440***	−0.1520***	−0.1803***
	(0.0261)	(0.0424)	(0.0377)	(0.0349)	(0.0382)
With demographic, year, CBSA, occupation and industry FE controls					
Unemployment rate	−0.1257***	−0.1253***	−0.1219***	−0.1224***	−0.1199***
	(0.0458)	(0.0458)	(0.0455)	(0.0455)	(0.0454)
JPC measures	−0.0610*	−0.0586	−0.1123***	−0.1189***	−0.1683***
	(0.0329)	(0.0449)	(0.0348)	(0.0344)	(0.0334)
b. Unemployed Due to Quits					
Without any controls					
Unemployment rate	−0.0065**	−0.0063**	−0.0062***	−0.0064***	−0.0063***
	(0.0032)	(0.0027)	(0.0023)	(0.0023)	(0.0022)
JPC measures	−0.0068	−0.0124	−0.0115	−0.0125	−0.0116
	(0.0089)	(0.0143)	(0.0116)	(0.0108)	(0.0104)
With demographic, year, CBSA, occupation and industry FE controls					
Unemployment rate	0.0021	0.0023	0.0023	0.0024	0.0023
	(0.0140)	(0.0139)	(0.0140)	(0.0140)	(0.0140)
JPC measures	0.0035	−0.0013	−0.0018	−0.0030	−0.0018
	(0.0107)	(0.0151)	(0.0121)	(0.0114)	(0.0107)

Notes:

1. All regressions are weighted using the adjusted longitudinal weights of CPS as explained in note 2 of Fig. 3. The weighted mean of the dependent variable in panel a, $P(L_{t+1}|E_t)$, is 0.008529; in panel b, $P(Q_{t+1}|E_t)$, is 0.001014.
2. Demographic controls include dummies for female, immigrant, non-White, married, and divorced; five age groups (30–34, 35–39, 40–44, 45–49, and 50–54); and four education levels (high school, some college or associate degree, bachelor's, and master's). The omitted age group is 25–29 years. The omitted education group is less than high school. The CBSA dummies are extended so that separate dummies are created for each state's non-CBSA area.
3. To ensure comparability of the estimated coefficients, the raw national JPCs is in millions, and the four adjusted JPCs are in 100s. In samples of both panel a and panel b, the weight mean of unemployment rate is 0.053983, raw national JPCs is 0.019663 (millions), JPCs adjusted by 1) state, 2) state and occupation, 3) state and industry, and 4) state, occupation, and industry, are 0.009955, 0.009937, 0.009958 and 0.009954.
4. $p < .10$, ** $p < .05$, *** $p < .01$.

Table 5. Transition from Unemployment to Employment: Categorized by Cause of Unemployment.

	(1)	(2)	(3)	(4)	(5)
Job posting count (JPC) measures	Raw national counts	Adjusted by			
		State	State and occupation	State and industry	State, occupation, and industry
a. Unemployed Due to Layoffs					
Without any controls					
Unemployment rate	−1.8555***	−2.4978***	−2.2459***	−2.3729***	−2.1759***
	(0.3516)	(0.2615)	(0.2108)	(0.2318)	(0.2234)
JPC measures	4.7340***	5.3020***	6.5300***	5.4338***	6.2588***
	(1.1683)	(1.7706)	(1.1975)	(1.2941)	(1.1012)
With demographic, year, CBSA, occupation, and industry FE controls					
Unemployment rate	2.2159*	2.2329*	1.9947*	2.1325*	2.0135*
	(1.2095)	(1.2110)	(1.2065)	(1.2044)	(1.2023)
JPC measures	3.4703***	3.0839*	5.0622***	3.6604***	4.8687***
	(1.3006)	(1.8311)	(1.2426)	(1.4065)	(1.1817)
b. Unemployed Due to Quits					
Without any controls					
Unemployment rate	−2.5103***	−2.5424***	−2.5208***	−1.9691***	−2.1919***
	(0.7875)	(0.6212)	(0.5711)	(0.5437)	(0.5422)
JPC measures	−1.3701	−2.8947	−2.6508	0.6488	−0.6098
	(2.2547)	(3.3298)	(2.6178)	(2.5779)	(2.3611)
With demographic, year, CBSA, occupation, and industry FE controls					
Unemployment rate	−3.8520	−3.7335	−3.6917	−3.8662	−3.7884
	(3.0540)	(3.0615)	(3.0699)	(3.0626)	(3.0677)
JPC measures	1.6151	−1.1528	−1.7743	2.2604	0.0604
	(2.7345)	(4.0934)	(3.1934)	(2.9014)	(2.7053)
c. Unemployed Due to Entering/Reentering					
Without any controls					
Unemployment rate	−2.8879***	−2.5581***	−2.4338***	−2.4512***	−2.3421***
	(0.4883)	(0.4293)	(0.3560)	(0.3711)	(0.3584)
JPC measures	−0.9331	0.2439	0.9831	0.8252	1.4056
	(1.4549)	(2.3840)	(1.8619)	(1.8329)	(1.7508)
With demographic, year, CBSA, occupation and industry FE controls					
Unemployment rate	−0.7015	−0.7413	−0.7812	−0.7861	−0.8183
	(1.8348)	(1.8347)	(1.8577)	(1.8446)	(1.8570)
JPC measures	−1.7496	−0.8402	0.1501	0.4701	0.9331
	(1.8615)	(2.7943)	(1.9496)	(2.0228)	(1.8517)

Notes:

1. All regressions are weighted using the adjusted longitudinal weights of CPS as explained in note 2 of Fig. 3. The weighted means of the dependent variable in panel a, $P(E_{t+1}|L_t)$, is 0.289699; in panel b, $P(E_{t+1}|Q_t)$, is 0.278270; in panel c, $P(E_{t+1}|R_t)$, is 0.231707.
2. Demographic controls include dummies for female, immigrant, non-White, married, and divorced individuals; five age groups (30–34, 35–39, 40–44, 45–49, and 50–54); and four education levels (high school, some college or associate degree,

bachelor's, and master's). The omitted age group is 25–29 years. The omitted education group is less than high school. The CBSA dummies are extended so that separate dummies are created for each state's non-CBSA area.

3. To ensure comparability of the estimated coefficients, the raw national JPCs is in millions. In all three panels, the weight mean of unemployment rate is 0.053983 and raw national JPCs is 0.019663 (millions).
4. The four adjusted JPCs are in 100s. The weighted means of the JPCs exhibit minor variations across the three samples. In panel a, the weighted mean of four JPCs adjusted by 1) state, 2) state and occupation, 3) state and industry, and 4) state, occupation, and industry, are 0.009927, 0.009911, 0.009902, and 0.009905, respectively; in panel b, 0.009950, 0.009927, 0.009920, and 0.009925; and, in panel c, 0.009919, 0.009895, 0.009935, and 0.009912.
5. $p < .10$, ** $p < .05$, *** $p < .01$.

APPENDIX

Concordance Table A1. Industry Categories in CPS and Job Postings Data.

Current Population Survey (CPS)			Job Postings Data	
	Share of individuals			Share of job postings
	Employed	Unemployed		
(1) Agriculture, forestry, fishing, and hunting	0.9	2.0	Agriculture, Forestry, Fishing and Hunting	0.12
(2) Mining	0.7	0.8	Mining	0.37
(3) Construction	6.4	12.8	Construction	1.12
(4) Manufacturing–durable goods *(5) Manufacturing–nondurable goods*	11.7	10.9	Manufacturing	7.39
(6) Wholesale trade	2.8	2.3	Wholesale Trade	0.74
(7) Retail trade	9.4	11.0	Retail Trade	9.12
(8) Transportation and warehousing	4.6	4.5	Transportation and Warehousing	3.55
(9) Utilities	1.1	0.5	Utilities	0.39
(10) Information	2.3	2.2	Information	2.78
(11) Finance and insurance	5.8	3.5	Finance and Insurance	7.30
(12) Real estate and rental and leasing	1.8	1.7	Real Estate and Rental and Leasing	1.66
(13) Professional and technical services	7.5	6.0	Professional, Scientific, and Technical Services	8.59
(14) Management, administrative, and waste management services	4.2	8.9	Management, administrative and waste management services	3.93
(15) Educational services	9.9	6.0	Educational Services	4.20
(16) Healthcare and social services	14.3	10.0	Healthcare and Social Assistance	17.02
(17) Arts, entertainment, and recreation	1.7	2.2	Arts, Entertainment, and Recreation	0.61
(18) Accommodation and food services	5.1	8.2	Accommodation and Food Services	5.96
(19) Private households *(20) Other services, except private households*	4.1	4.3	Other Services (except Public Administration)	1.36
(21) Public administration	5.8	2.3	Public Administration	1.96
Missing	*dropped*		Missing	21.83
(22) Armed forces	*dropped*		Armed forces	*dropped*

Notes:

1. The two manufacturing industries in CPS are combined, as are the two services industries, to match the categories in the job posting data.
2. Only a very small proportion of CPS observations do not have industry information, so these observations were dropped; however, a very large proportion of job posting data do not have industry information, so these observations were kept in the construction of various job posting count (JPC) measures, except for JPCs adjusted for state and industry, and JPCs adjusted for state, occupation, and industry.

Concordance Table A2. Occupation Categories in CPS and Job Postings Data.

Current Population Survey (CPS)			Job Postings Data	
	Share of individuals			Share of job postings
	Employed	Unemployed		
(1) Management occupations	11.4	6.8	Management occupations	11.57
(2) Business and financial operations occupations	5.6	3.8	Business and financial operations occupations	6.66
(3) Computer and mathematical science occupations	4.0	2.2	Computer and mathematical science occupations	11.32
(4) Architecture and engineering occupations	2.5	1.3	Architecture and engineering occupations	3.11
(5) Life, physical, and social science occupations	0.9	0.5	Life, physical, and social science occupations	0.97
(6) Community and social service occupations	1.9	1.1	Community and social service occupations	1.12
(7) Legal occupations	1.1	0.6	Legal occupations	0.74
(8) Education, training, and library occupations	6.8	4.4	Education, training, and library occupations	2.47
(9) Arts, design, entertainment, sports, and media occupations	1.8	2.1	Arts, design, entertainment, sports, and media occupations	2.33
(10) Healthcare practitioner and technical occupations	6.4	2.2	Healthcare practitioner and technical occupations	11.52
(11) Healthcare support occupations	2.4	2.5	Healthcare support occupations	2.13
(12) Protective service occupations	2.6	1.6	Protective service occupations	1.09
(13) Food preparation and serving related occupations	3.9	6.2	Food preparation and serving related occupations	3.80
(14) Building and grounds cleaning and maintenance occupations	3.3	5.9	Building and grounds cleaning and maintenance occupations	1.34
(15) Personal care and service occupations	2.8	3.9	Personal care and service occupations	1.84
(16) Sales and related occupations	8.8	9.8	Sales and related occupations	11.76
(17) Office and administrative support occupations	12.3	12.2	Office and administrative support occupations	10.29
(18) Farming, fishing, and forestry occupations	0.6	1.6	Farming, fishing, and forestry occupations	0.08
(19) Construction and extraction occupations	5.2	11.8	Construction and extraction occupations	1.07
(20) Installation, maintenance, and repair occupations	3.7	3.2	Installation, maintenance, and repair occupations	3.09
(21) Production occupations	6.2	7.8	Production occupations	2.69
(22) Transportation and material moving occupations	5.9	8.8	Transportation and material moving occupations	5.18
Missing	*dropped*		Missing	3.84
(23) Armed forces	*dropped*		Armed forces	*dropped*