Improving Estimates of Job Matching Efficiency with Measures of Underemployment

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Abstract

Traditional measures of unemployment can mask important changes in the labour market across the business cycle. We therefore use broader definitions of unemployment to estimate time-varying job-matching efficiency rates that are consistent with vacancies and hiring activity data for the U.S. Our efficiency rates are then modelled along with employment data to study their dynamic, non-linear relationship. We find that including part-time workers for economic reasons and marginally attached workers helps explain the changes in employment patterns observed after the global financial crisis. This finding emphasises the importance of accounting for underemployment, particularly in the last decade.

JEL Classification numbers: J21; J64; E24; E32; C58

Keywords: Beveridge curve; U6 unemployment; job matching efficiency rate; MGARCH model; dynamic correlation

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I. Introduction

Since the 2008 global financial crisis, the United States has experienced the longest expansion on record, marked with a noteworthy recovery of the labour market. However, as the unemployment rate hovers around an all-time low, businesses seeking to hire workers struggle to find qualified applicants, resulting in inefficiencies that over a prolonged period of time can be detrimental to the economy.\textsuperscript{1} Figure 1(a) shows the official unemployment rate (known as U-3) along with the job vacancy rate from 1967 to 2018. During expansionary periods, both series move closer to one another, quickly diverging as the economy enters into a recession. For the first time since the 1970s, the U.S. job vacancy rate has surpassed the traditional measure of unemployment, prompting concerns about the overall health of the labour market that arise from pronounced inefficiencies in the job matching process.

In this paper, we utilise broad measures of unemployment to estimate the rate at which job matching efficiency has changed over time, and find that accounting for differences at the intensive margin helps better describe employment dynamics in the aftermath of the global financial crisis. In particular, we consider definitions of unemployment that account for ‘discouraged’ (U-4) or ‘marginally attached’ (U-5) persons. Those individuals are neither working nor looking for work but indicate that they want and are available for a job and have looked for work sometime in the past 12 months. We also account for ‘part-time workers for economic reasons’ (U-6), those who want and are available for full-time work but have had to settle for a part-time schedule.

Figure 1(b) shows how expanding the definition of unemployment to incorporate a broader set of individuals that are underemployed over the last 25 years significantly changes the labour market picture of the U.S. economy. Therefore, we use these definitions instead of the more narrow U-3 measure to account for inefficiency rates in the job matching process.

First, we explore changes in the degree of labour market tightness, relating unemployment to vacancy rates through the Beveridge curve. We identify time variation and non-linearities

\textsuperscript{1}Recent work studying the impact of skill mismatch in the U.S. labour market following the global financial crisis can be found in Abraham (2015).
to be important empirical properties of the data. Then, we utilise the foundational labour market framework of Blanchard and Diamond (1989) and empirically estimate monthly matching efficiency rates using different definitions of unemployment, consistent with data on vacancies and hiring activities. Finally, we estimate the dynamic correlation between different job matching efficiency rates and employment.

Figure 1: Labour market indicators

Notes: Gray bars indicate NBER recession periods. Panel (a) shows the official U.S. unemployment rate from the Bureau of Labor Statistics’ Current Employment Survey along with the vacancy rate from the Bureau of Labor Statistics’ Job Openings and Labor Turnover Survey for the 2001–2018 period and obtained using the Barnichon (2010) method for the 1967–2000 period. Panel (b) shows U-3: total unemployed, as a percent of the civilian labour force (official unemployment rate); U-4: total unemployed plus discouraged workers, as a percent of the civilian labour force plus discouraged workers; U-5: total unemployed, plus discouraged workers, plus all other persons marginally attached to the labour force, as a percent of the civilian labour force plus all persons marginally attached to the labour force; and U-6: total unemployed, plus all persons marginally attached to the labour force, plus total employed part time for economic reasons, as a percent of the civilian labour force plus all persons marginally attached to the labour force; as defined by the U.S. Bureau of Labor Statistics.

We find that when including part-time workers for economic reasons, the increase in job matching efficiency rates becomes less pronounced, better describing the labour market patterns observed in the data during the 2008–2018 period. Importantly, we find that the rate at which job vacancies can be filled has been hindered by labour market frictions that are present at the intensive margin, and that accounting for part-time workers for economic reasons helps
describe the slow take up on employment identified during the latest expansion. We conclude that incorporating a broad definition of unemployment is particularly important for describing labour market dynamics following the global financial crisis.

Our work relates to the strand of the literature that has emphasized the need to account for broader definitions of unemployment. Kingdon and Knight (2006), for example, focused on the inclusion of discouraged workers making up a large proportion of those out of the employment pool. Their work indicates that potential structural issues that can amplify the mismatch in the labour market may not be captured by the traditional measure of unemployment. More recently, Feng and Hu (2013) provided evidence that the unemployment rate is not an accurate and reliable indicator of labour market health, also advocating for the need of a more comprehensive measure. There is a long-standing literature studying job matching inefficiencies in the labour market in other countries (e.g. Mumford and Smith, 1999, in Australia); its relationship to vacancies and wages (e.g. Diamond, 2011; Mavromaras et al., 2015) and to employment dynamics (e.g. Barnichon and Figura, 2015; Elsby et al., 2015); as well as its impact on changes in the labour force participation rate (e.g. Krueger, 2017).

Our paper also relates to studies of Beveridge curve dynamics after the great recession (Hobijn and Şahin, 2013), including Klinger and Weber (2016), who studied the structural or cyclical nature of Beveridge curve dynamics in Germany, finding that matching efficiency accounted for about half of the inward shift that followed institutional reforms during the great recession.

Finally, we implement econometric techniques that have been used across different fields in economics, such as an algorithm that helps identify peaks and troughs in time series (e.g. Claessens et al. (2012) utilized it to identify linkages between different phases of business and financial cycles for 44 countries) and models that account for heteroskedasticity and volatility clustering. Examples of recent work estimating these models are Bauwens et al. (2006), who provided a survey of different applications, Ledoit et al. (2003), who implemented these models with an application to international stock markets, and Fengler and Herwartz (2018), who created spillover indices from heteroskedastic volatility models for different asset classes.
We begin by describing the relationship between unemployment and vacancies in Section II, estimate various job matching efficiency rates in Section III, and relate each measure to employment in a framework that allows for time variation in their dynamics in Section IV.

II. A broad look at the Beveridge curve

This section explores the relationship between unemployment and vacancies over time in order to understand changes in the degree of mismatch in the labour market along the business cycle (Dow and Dicks-Mireaux, 1958; Lilien, 1982; Elsby et al., 2015).

Figure 2 depicts the inverse relationship between the unemployment rate and the vacancy rate in a traditional Beveridge curve coloured by 10-year intervals. On average, the Beveridge curve is downward sloping such that high vacancy rates are associated with low unemployment rates, reflecting market tightness.

Figure 2: Beveridge curve (1967–2018)

Notes: U-3 unemployment rate relative to the vacancy rate, coloured by 10-year intervals. Outward shifts in the Beveridge curve reflect tighter labour market conditions.
In the late 1970’s (blue circle) and 1980’s (orange triangles), oil shocks were followed by an outward shift in the Beveridge curve (Olivier et al., 1989). The 2007–2016 period (green x) shows the high levels of unemployment associated with the recession, with low vacancy rates indicating an unprecedented increase in labour market frictions or a decrease in job matching efficiency during the crisis. During the recovery, the Beveridge curve shifted up and outwards once again, with employers posting more job openings but not being able to fill the open vacancies. The continued expansion was followed by a state of high vacancy rates and low unemployment rates as noted in the 2017–2018 period (red asterisk).

We next focus on two sub-periods: 1994m1–2007m9 (blue) and 2007m10–2018m10 (red) for Beveridge curves constructed using different measures of unemployment in Figure 3. In general, we notice a marked contrast between unemployment and vacancy rates in both periods, with job availability being more dispersed in more recent years (vacancy rates between 1.4% and 5.7%, as opposed to 2%-4%). Unemployment rates are also higher during the global financial crisis than the 1994–2007 period, with higher vacancy rates during the recovery years as well.

An important takeaway from the Beveridge curves is that the relationship between vacancy and unemployment rates seems to change over time, prompting us to implement dynamic models that can account for heteroskedasticity in the volatility of the series for further analysis.

Another salient feature of the Beveridge curve is that depending on the measure of unemployment used, the extent to which vacancy and unemployment rates relate to one another changes significantly. Comparing the Beveridge curve with U-6, relative to the one with the traditional U-3 measure, not only the right-downward shift during the recession is more pronounced, but also, during the recovery, the left-upward shift remains higher than the 1994-2007 period.

Given that as we expand the definition of unemployment, the dynamic with vacancy rates does not change proportionally, accounting for non-linearities to model efficiencies in the job matching process will also be an important feature that we seek to incorporate in our analysis.
III. Estimating job matching efficiencies

In this section we estimate the different matching efficiency rates implied by each measure of unemployment. To this end, we build from the seminal Blanchard and Diamond (1989) labour market model to theoretically derive the transition mechanism that takes workers in and out of employment.

The underlying framework establishes that the labour force is comprised of employed and unemployed workers (Lipsey, 1960) and jobs can be filled, vacant, or idle. Job destruction,
quits, and workers entering into the labour force make up the flows into unemployment, while jobs created and openings from people who quit their jobs turn into vacancies. In the Blanchard and Diamond (1989) setup, job productivity follows a Markov process in continuous time, where workers may quit their jobs at an exogenous rate – different from job termination, a quit is connected to the posting of a new vacancy. The system can be summarised by two differential equations, representing the flow of employment and the flow of vacancies, allowing for hires \( h_t \) to be related to unemployment \( u_t \) and vacancy rates \( v_t \) with a Cobb-Douglas functional form (Pissarides, 2000; Petrongolo and Pissarides, 2001):

\[
h_t = m_t u_t^\gamma v_t^{1-\gamma}, \tag{1}
\]

where \( m_t \) is the time-varying matching efficiency that we seek to empirically estimate and \( \gamma \in (0, 1) \) represents the degree of congestion in the labour market.

The degree of congestion can be a result of the size of the labour market, geographic location, diversity of the labour force relative to diversity of jobs available, ability of ‘outsiders’ to compete with ‘insiders,’ and number of employed workers seeking job-to-job movements (Dixon et al., 2014). Following Barnichon and Figura (2011; 2015), we obtain different proxies of the congestion rate by regressing the log of the different definitions of unemployment rate on the log of the vacancy rate,

\[
\ln(u_t) = \alpha_i + \beta_i \ln(v_t) + \epsilon_{i,t}, \tag{2}
\]

where \( i = \{U3, U4, U5, U6\} \). We assume that the size of the elasticity of the unemployment rate to the vacancy rate \( (\beta) \) is inversely related to the severity of congestion externalities in the labour market,

\[
\gamma_i = \frac{1}{1 - \beta_i}, \tag{3}
\]

such that for every definition of unemployment, we obtain a different degree of congestion.

\[\text{For a cornerstone model within the job search literature, refer to Mortensen and Pissarides (1994), who connect endogenous job creation and job destruction over the business cycle.}\]
Table 1(a) shows the estimates and standard errors of the unemployment-to-vacancy elasticities under different measures of unemployment, along with the corresponding implied congestion parameters. Consistent with previously estimated congestion parameters for the U.S. (e.g. Petrongolo and Pissarides, 2001), our values fall within the 0.5–0.7 range identified in the literature, with U-6 having a slightly higher value (0.564) relative to U-3 (0.536).

Table 1: Matching efficiency under different measures of unemployment

<table>
<thead>
<tr>
<th></th>
<th>U-3</th>
<th>U-4</th>
<th>U-5</th>
<th>U-6</th>
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<tbody>
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<td></td>
<td></td>
<td></td>
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</tr>
<tr>
<td>$\gamma_i$</td>
<td>0.536</td>
<td>0.535</td>
<td>0.555</td>
<td>0.564</td>
</tr>
<tr>
<td>$\beta_i$</td>
<td>-0.867</td>
<td>-0.869</td>
<td>-0.803</td>
<td>-0.773</td>
</tr>
<tr>
<td>(0.026)</td>
<td>(0.028)</td>
<td>(0.027)</td>
<td>(0.030)</td>
<td></td>
</tr>
<tr>
<td>(b)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>average $m_{i,t}$</td>
<td>0.838</td>
<td>0.816</td>
<td>0.752</td>
<td>0.591</td>
</tr>
<tr>
<td>minimum $m_{i,t}$</td>
<td>0.558</td>
<td>0.539</td>
<td>0.503</td>
<td>0.392</td>
</tr>
<tr>
<td>maximum $m_{i,t}$</td>
<td>1.057</td>
<td>1.031</td>
<td>0.963</td>
<td>0.774</td>
</tr>
<tr>
<td>std. dev. $m_{i,t}$</td>
<td>0.133</td>
<td>0.132</td>
<td>0.122</td>
<td>0.104</td>
</tr>
</tbody>
</table>

Notes: Panel (a) shows the results of the following regression: $\ln(u^t_i) = \alpha_i + \beta_i \ln(v^t) + \varepsilon_{i,t}$, where $u^t_i$ is the U-3, U-4, U-5, or U-6 unemployment rate and $v^t$ is the vacancy rate. The congestion rates are estimated as $\gamma_i = \frac{1}{1-\beta_i}$. Panel (b) reports summary statistics for the matching efficiency $m_{i,t}$, estimated as $m_{i,t} = \frac{h_{i,t}}{u^t_i v^t (1-\gamma_i)}$, where the hiring rate data $h_{i,t}$ are obtained from the Job Openings and Labor Turnover Survey (JOLTS) from 2001 to 2018, combined with the modified synthetic JOLTS estimation from Davis et al. (2012) for the 1994–2000 period.

Given the estimated congestion parameters, we use Equation (1) to infer the matching rate.

3When regressed with lagged $u_t$ and $v_t$ values as instruments, the elasticities change insignificantly, consistent with similar findings in the literature (e.g. Barnichon and Figura, 2011).
corresponding to every definition of unemployment

\[ m_{i,t} = \frac{h_t}{u_{i,t}^\gamma v_t^{1-\gamma}} \]  (4)

and report summary statistics for the matching rates in Table 1(b). The matching efficiency rate shows that an increase in new hires relative to the number of vacancies and unemployment rate, represents a decrease in job-matching frictions and higher employment levels. Results indicate that job matching frictions increase as we account for workers who are discouraged, marginally attached, or underemployed, allowing for a more complete picture of the labour market that we seek to empirically investigate.

Given the role of labour market dynamics in understanding business cycle fluctuations (see e.g. Boz et al. 2015; Christiano et al. 2016; Mukoyama et al. 2018), we further explore the turning points of every matching efficiency rate constructed to account for different definitions of unemployment. We therefore identify the turning points in each matching efficiency time series, by implementing the Bry and Boschan (1971) algorithm as proposed by Harding and Pagan (2002).

This method identifies troughs and peaks from local minima and maxima given a censoring rule, which we set to five, as is standard in monthly series. The censoring rule ensures that each cycle (and each of its phases) has a minimum duration; thus a series which exhibits single “blips” is discounted from being wrongly identified as a cycle. In this context, we define for each of our matching efficiency rates a

- peak at time \( t \) if: \( \{(y_{t-5}, y_{t-4}, y_{t-3}, y_{t-2}, y_{t-1}) < y_t > (y_{t+1}, y_{t+2}, y_{t+3}, y_{t+4}, y_{t+5})\} \),
- trough at time \( t \) if: \( \{(y_{t-5}, y_{t-4}, y_{t-3}, y_{t-2}, y_{t-1}) > y_t < (y_{t+1}, y_{t+2}, y_{t+3}, y_{t+4}, y_{t+5})\} \).

Figure 4 shows the cycle indicators for each of the estimated efficiency matching rates. There are certain periods in which the cycles for all matching efficiency rates coincide, although as the definition of unemployment broadens, the timing of the peaks and troughs change.
When comparing M-6 to M-3 cycles, for example, the largest discrepancies in terms of cycle length occur in the mid and late 1990’s (shorter phases), mid 2000’s (longer phases), as well as 2016 (longer phase).

M-5 and M-6 exhibit similar cycle dynamics following the global financial crisis but differ towards the end of the 1990’s and mid 2000’s. To better account for the lack of synchronicity across cycles, we allow for non-linearities and heteroskedasticity to be explicitly accounted for in our empirical framework in order to investigate which of our matching efficiency measures more accurately describes the employment patterns observed through different points in time.

Figure 4: Matching efficiencies: turning points (1994–2018)

Notes: Peaks and troughs in different matching efficiency rate series are identified via the sbbf Bry and Boschan (1971) algorithm as proposed by Harding and Pagan (2002).
IV. Labour market dynamics

Given the different dynamics that each unemployment rate exhibits, we explore the relationship between all of our matching efficiency rates and employment over time, allowing for time variation in the correlation between variables. To this end, we implement the Dynamic Conditional Correlation (DCC) model introduced by Engle (2002), which is a special case of the Multivariate Generalized Autoregressive Conditional Heteroskedasticity (MGARCH) model. Traditional MGARCH models allow for the conditional variances and covariances of the error terms to follow an autoregressive-moving-average process. The DCC extension allows for the conditional covariance matrix of the error terms to be modelled as a nonlinear combination of univariate GARCH models and time-varying cross-equation weights. The advantage of the DCC MGARCH method over others, besides its parametric parsimony, is that it allows for non-linearities in the relationship across variables, which is an important feature of labour market dynamics during the period that we examine.\footnote{Holmes and Otero (2019), for example, found that matching efficiency in the U.S. labour market has been driven by factors that include distance between states, the labour force participation rate, and home-ownership and the relative affordability of housing between states. In their study, a pairwise recursive analysis is used to identify a decrease in matching efficiency in the period that followed the Great Recession, making non-linearities a key feature that we also seek to account for in our work. In a similar spirit, Muntaz and Zanetti (2015) for example, identified structural shocks in the U.S. labour market allowing for time variation and stochastic volatility.}

The model is specified as follows

\begin{align*}
y_t &= C y_{t-k} + \epsilon_t, \\
H_t &= D_t^{1/2} R_t D_t^{1/2}, \\
Q_t &= (1 - \lambda_1 - \lambda_2) R + \lambda_1 \tilde{\epsilon}_t \tilde{\epsilon}_{t-1}' + \lambda_2 Q_{t-1}, \tag{5}
\end{align*}

where $y_t$ is the vector of dependent variables (in our case the matching efficiency and employment rates), $C$ is the matrix of estimated parameters that captures the autoregressive properties of the variables, and $y_{t-k}$ is a vector with $k$ lags. The error term is $\epsilon_t = H_t^{1/2} \nu_t$, where $\nu_t$ is a vector of normal, independent, and identically distributed innovations and $H_t^{1/2}$ is the Cholesky factor of the time-varying conditional covariance matrix of the disturbances, $H_t$. \footnote{Holmes and Otero (2019), for example, found that matching efficiency in the U.S. labour market has been driven by factors that include distance between states, the labour force participation rate, and home-ownership and the relative affordability of housing between states. In their study, a pairwise recursive analysis is used to identify a decrease in matching efficiency in the period that followed the Great Recession, making non-linearities a key feature that we also seek to account for in our work. In a similar spirit, Muntaz and Zanetti (2015) for example, identified structural shocks in the U.S. labour market allowing for time variation and stochastic volatility.}
DCC MGARCH models the dynamic conditional correlations between variables by extending the model in two ways. First, each element in the diagonal matrix of conditional variances $D_t$ is modelled as a univariate GARCH process and the conditional covariances are modelled as nonlinear functions of the conditional variances.

Second, the matrix of conditional quasicorrelations, $R_t$, that weight the nonlinear combinations of the conditional variances, follows the GARCH-like process specified in Engle (2002):

$$R_t = \text{diag}(Q_t)^{-1/2} Q_t \text{diag}(Q_t)^{-1/2},$$

where $Q_t$ is the positive definite dynamic correlation matrix that ensures all elements of $R_t$ are between −1 and 1. $\lambda_1$ and $\lambda_2$ are the non-negative parameters that govern the dynamics of conditional quasicorrelations such that $\lambda_1 + \lambda_2 \in [0, 1)$; $\bar{\epsilon}_t$ is a vector of standardized residuals; and $R$ contains the quasicorrelation parameters (when $Q_t$ is stationary, $R$ is the weighted average of the unconditional covariance matrix of $\bar{\epsilon}_t$ and the unconditional mean of $Q_t$; hence the quasicorrelation and not the unconditional correlation or unconditional mean of $Q_t$ – see Aielli, 2013 for details).

Engle (2002) showed that this model can be estimated with the log-likelihood function based on the multivariate Gaussian distribution of standardized errors in two steps (one for the volatility and one for the correlation parameters). We obtain starting values for our mean equation parameters from least-squares estimation, with quasicorrelation initial values calculated from the standardized residuals, and estimate the conditional variances for each variable in the first step. The second step estimates the unknown parameters $\lambda_1, \lambda_2$ of the dynamic correlation matrix with starting values obtained from a standard grid search on the log likelihood.

Table 2 presents the conditional correlation parameters between employment and matching efficiency rates estimated with different measures of unemployment. Panel (a) shows the results for the entire time period. The high conditional correlation (0.69–0.75) between the standardized residuals of employment and matching efficiency rates suggests that regardless of the definition of unemployment, the job matching efficiency of the labour market is, on average, positively and

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$^5$ $R_t$ must be positive definite so that the covariance matrix $H_t$ is positive definite.

$^6$ If $\lambda_1 = \lambda_2 = 0$, then $Q_t = R$, reducing the model to its static counterpart, which assumes no time variation in the conditional correlations.
highly connected to employment dynamics.

Table 2: DCC MGARCH results

<table>
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<tr>
<th></th>
<th>Correlation between EMPLOYMENT and</th>
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<tr>
<td></td>
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<tr>
<td>(a) 1994–2018</td>
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<tr>
<td>4 lags</td>
<td>0.7454</td>
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<td>0.7411</td>
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<td>5 lags</td>
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<td>6 lags</td>
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<td>(b) 1994–2007</td>
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<tr>
<td>4 lags</td>
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<td>(c) 2008–2018</td>
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<tr>
<td>4 lags</td>
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</table>

Notes: Conditional quasicorrelations between standardized residuals for employment and matching rates inferred from different unemployment measures are estimated from a DCC MGARCH model allowing for $k = \{4, 5, 6\}$ lags, during different time periods. Employment data (15-64 age employment rate) are from the Organization for Economic Cooperation and Development Main Economic Indicators database.
Panel (b), however, indicates that during the 1994–2007 subperiod, the overall correlation between employment and matching rates was more muted, between 0.51 and 0.56, depending on the model specification. During this time, the M-4 estimated matching efficiency had the highest correlation to the employment rate, regardless of the number of lags used in the estimation of the parameters. This makes intuitive sense as U-4 contains discouraged workers able to re-enter the labour force only after matching with a job vacancy; whereas U-3 contains only those who would remain in the labour force as unemployed. Panel (c) shows that when we instead look at the dynamic correlations between employment and matching rates during the global financial crisis and its recovery period, it is M-6 that is more correlated with employment across all models. While correlations across M-3 to M-5 measures are never separated by more than 0.02, M-6’s correlation to employment is always 5–11% higher than the traditional M-3 efficiency rate’s correlation to employment, and it is at least 3.6% higher than any other measure. Our results provide empirical evidence that measures of underemployment, specifically those that include part-time workers for economic reasons, have become more representative of labour market dynamics in the U.S. over the past decade.

V. Conclusion

We analyse labour market data and estimate matching efficiency rates by using different measures of unemployment. We identify that labour market dynamics after the global financial crisis are associated with a slower rate of growth in the matching efficiency of unemployed workers to jobs. In particular, including part-time workers for economic reasons (to capture underemployment levels) allows for frictions in the job matching process to better describe the labour market dynamics observed throughout the latest expansionary period. Our findings suggest that changes in the labour market at the intensive margin are more important than they used to be in explaining employment dynamics.

One area for future development is to relate our work to wage growth following the financial
crisis. Traditional theory would suggest that as the level of unemployment falls, the number of available workers decreases, and the equilibrium wage rate rises, to see workers take up employment (Phelps, 1968). In the present U.S. economy, however, wage rates have remained static at a time of falling numbers in the labour force, suggesting that the matching process may be less efficient (Crawley and Welch, 2020).
References


