The Flow of Vacancies and Unemployment

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Abstract. The U.S. unprecedented tight labor market has been driving inflation pressure since the break of the pandemic. Currently, dropping vacancies is cooling off the labor market. This study analyzes the flow of vacancies and unemployment within the Beveridge relationship during such a period. The Cobb-Douglas matching function is adopted to analyze labor market dynamics. The epilogue of the regressive model finds a proper estimation of the matching function, which the study uses to show that the matching efficiency has worsened since 2022. The study concludes that cooling off the labor market with barely an increase in unemployment is unattainable under the super tight monetary condition.

Keywords: Labor market, matching efficiency, vacancies, unemployment.

1. Introduction

The U.S. labor market has been tightening since 2021. Core inflation increases as the vacancy-to-unemployment ratio rises at an unprecedented level. Figure 1 plots the highly positive relationship between the two variables. The flow of vacancies and unemployment is vital to evaluate future inflation risk. Blanchard, Domash, and Summers (2022) conclude that unemployment will rise as the V/U ratio falls to cool off the labor market. In contrast, Figura and Waller (2022) point out that reducing job openings might only mildly affect unemployment.

Given that job openings have declined recently, will unemployment move in the opposite direction to alleviate wage inflation? To date, several studies have evaluated fluctuations in labor markets. Mortensen and Pissarides (1993) use vacancy/unemployment flow data to assess labor market shocks. Petrongolo and Pissarides (2001) explain the estimation of the Beveridge curve and summarize matching mechanisms at that date. Barnichon and Figura (2015) reveal how dispersion and composition affect the matching efficiency. Based on these studies, this study adopts a regression model to analyze the post-pandemic matching efficiency between unemployment and available jobs. It links the matching efficiency and Beveridge curve to evaluate the flow of vacancies and unemployment. It also investigates demand side facts to give implications about the future labor market tightness.

Section 2 presents the log-linear regression model of the matching function. Section 3 reports the regression result and plots the movements of pertinent variables. Section 4 discusses facts and implications. Section 5 concludes.

2. Model and Data

2.1 Theoretical model

The matching function is a model that reflects the efficiency μ and elasticity σ of the matching process in a frictional market. In this study, a Cobb-Douglas matching function is adopted to describe the process of matching unemployed job seekers and vacant jobs in the U.S. labor market. The versions are expressed in the following way:

$$M = \mu U^{1-\sigma} V^{\sigma} \tag{1}$$

$$f = \mu\theta^{\sigma} \tag{2}$$

$$\ln f = \ln \mu + \sigma \ln \theta \tag{3}$$

The number of new hires who find jobs during the unemployment period M is related to the number of unemployed workers U and the number of job vacancies V in matching function (1). Since job finding rate is the ratio of unemployed persons who became employed to unemployed, $f = \frac{M}{U}$, the function is redefined as equation (2) with$\theta = \frac{V}{U}$. Then I take logs in (2) and get a simple log-linear form of matching function in (3).

2.2 Empirical model

Following studies of Domash and Summers (2022) and Barnichon and Shapiro (2022), this study adopts the vacancy-to-unemployment ratio θ in model (3) to assess the labor market tightness. I decompose the log form of matching efficiency in (3), where $\ln \mu_t = a + \varepsilon_t$. The time series expression is :

$$\ln f_t = \sigma \ln \theta_t + a + \varepsilon_t \tag{4}$$

Then the study evaluates the rephrased matching function of the U.S. labor market with a linear regression model (4). The log form of job finding rate is the dependent variable, and the log form of labor market tightness is the independent variable. The elasticity of matching function σ is the coefficient of the independent variable, a is the constant term, and ε_t is the error term in the estimation model. The error term explains the unobserved level of matching efficiency between job openings and unemployment.

Seasonally adjusted monthly time series data are used to build the model. I measure the job finding rate from Current Population Survey and access vacancies and unemployment numbers from U.S. Bureau of Labor Statistics. Observed data start in December 2000 and end in June 2023. Figure 2 illustrates the observed job finding rate and labor market tightness in log forms over time.

3. Results

Table 1 presents the regression result. All regression estimates are significant at the 1 percent level. Column 1 reports estimates derived from OLS. However, the low Durbin-Watson test value implies the serial correlation problem in the residuals. Residuals are not independent at different periods. The correlogram of residuals helps identify the order of an autoregressive model. Hence, I assume that ε_t follows an AR (1) model. Column 2 shows estimation results in an autoregressive GLS model of order 1. However, the Lagrange Multiplier test result suggests serial correlation. Then an autoregressive moving average GLS model is formulated. Column 3 reports estimates obtained from ARMA(1,2) GLS method. Model selection criteria guide my choice of (p,q) value. Estimates in column 3 fit best with observed data and are preferred in the analysis. Meanwhile, results of the ARMA model also pass the correlation test. Thus, the model (4) can predict the matching efficiency more precisely.

I estimate these variables from the ARMA GLS model output in table 1. The constant term is -1.313 in the regression model. The elasticity of matching function is 0.173. In the framework, $\ln \mu_t = a + \varepsilon_t$. The error term is estimated as the difference between the actual and predicted values $\ln f_t$. Next, I measure the log form of matching efficiency as the sum of the constant term and residuals and convert logarithms to continuous values. Figure 3 plots movements of labor market tightness, job finding rate and its fitted value, and matching efficiency. All plotted series are 12-month moving averages. The matching efficiency fluctuates between 24% and 29%, suggesting significant room for efficiency improvement.

Figure 3A illustrates the tightness of labor market activities. The V/U ratio drops rapidly due to the pandemic and reaches a historically high level in early 2023. Dropping job openings explains the current slowing down V/U ratio. The unemployment number stabilizes at a shallow level. Figure 3B demonstrates the movement of job finding rate. Figure 3C reports the trend of matching efficiency. Both labor market tightness and matching efficiency were dwindling in every prior recession. The matching efficiency drops gradually since the zenith in 2022. The matching efficiency even began to fall several months before the tight labor market reached its highest level.

4. Implications

The Beveridge curve is a typical representation of dynamics in labor markets. It demonstrates the relationship between job opening rates and unemployment rates in an economy over time. The unemployment flow model is expressed based on the steady state of labor market:

$$u^* = \frac{s}{s+f} \tag{5}$$

with u^* the natural rate of unemployment, s the job separation rate, and f the job finding rate. Combing function (2) and function (5), I obtain:

$$u^* = \frac{s}{s+\mu\theta^{\sigma}} \tag{6}$$

Figure 4 shows the U.S. Beveridge curve, which started in December 2000. The current upward steepening Beveridge curve suggests two facts. First, the labor market is very tight and pushes the V/U ratio. Second, following function (6), the decreasing matching efficiency shifts the Beveridge curve outwards. Although the labor market still performs actively under the tight financial condition, it is more difficult for job seekers to secure suitable jobs. Furthermore, the possibility of employer callbacks drops rapidly with unemployment duration (Kroft et al. 2013). The average unemployment duration is ticking upward.

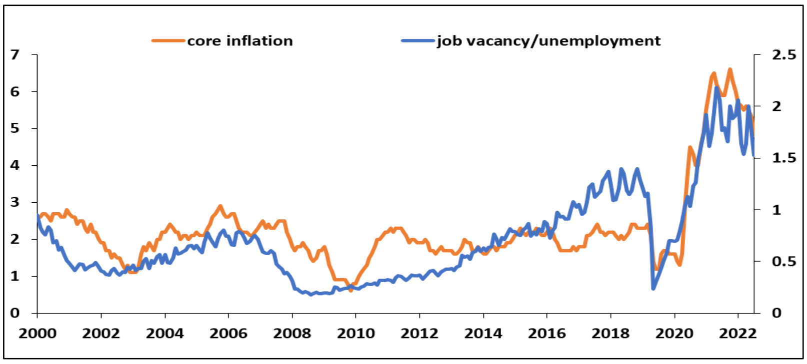
The decline in the job openings rate in recent months shows a softening labor market. Core inflation also weakens along with the decreasing V/U ratio. Some researchers maintain that it is possible to cool off the labor market, corresponding with a significant fall in vacancies and only a mild increase in the unemployment rate. Thus, if vacancies decline without affecting unemployment, the Beveridge curve will shift downwards accompanied by better job matching. Nevertheless, figure 3A and figure 3C imply that job openings are declining along with a worse matching efficiency. The Beveridge curve will hardly shift back when the matching process worsens.

Moreover, a soft landing suggests a parallel matching efficiency compared to the pre-pandemic level. The pre-pandemic average matching efficiency is 0.27, and openings number is 6361 in thousands estimated from data between 2015 and 2019. The matching efficiency is already 1.2% lower than the pre-pandemic level. On the contrary, the vacancy level is still 50% greater than the pre-pandemic level. Meanwhile, the efficiency even continues its downward trend. Consequently, the low unemployment level assumption does not align with a significant vacancy decline and a worse matching.

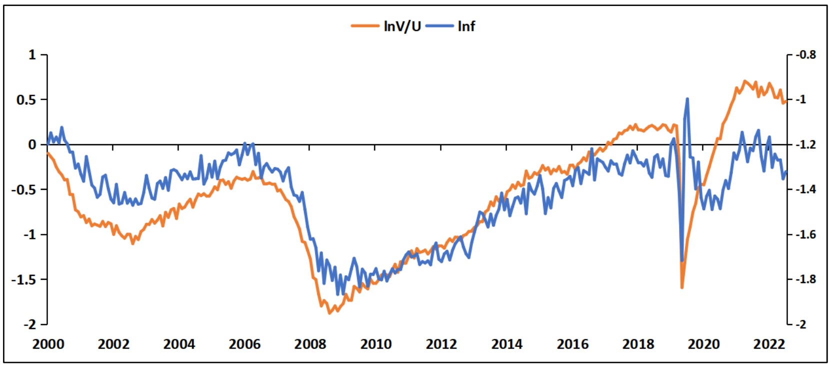
Changes in job vacancies and unemployment levels may also exhibit lag effects. For instance, firms respond quickly to increased demand for goods and services by posting more job vacancies. Nevertheless, job seekers might take more time to secure those jobs. Likewise, the current unemployment level might respond slowly to moderate demand in the labor market. Plots of cyclical behavior of vacancies and unemployment indicate that the unemployment rate falls subsequently to a significant level as vacancies decrease in historical U.S. business cycles (Diamond and Şahin 2015). Therefore, vacancies may decline faster than the unemployment level given the falling trend of matching efficiency. As businesses face reduced profitability due to declining demand, they often reduce their workforce through layoffs during the economic recession. The long-term unemployment fluctuation may consist more of an increase in layoffs than quits (Elsby et al. 2010).

Other demand side facts also suggest a declining demand sign. Over the past two years, hiking nominal wages supported increased consumer demands. Figure 5 illustrates the relationship between pre-pandemic and post-pandemic real personal income. Red line represents the pre-pandemic annual growth rate from 2015 to 2019, nearly 3.1%. The real personal income growth rate has remained below the pre-pandemic level for almost two years.

Additionally, figure 6 portrays that the delinquency rate on credit loans has risen rapidly since 2022. Credit consumption is unsustainable under the restrictive monetary policy. Impaired resident balance sheets after the rate hiking can not uphold spending continually. As consumer confidence declines, demands for goods and services might cool off further. These changes in demand will gradually pass on to the unemployment rate and the economy.



Source: U.S. Bureau of Labor Statistics; author’s calculation.
Figure 1. V/U ratio and core inflation

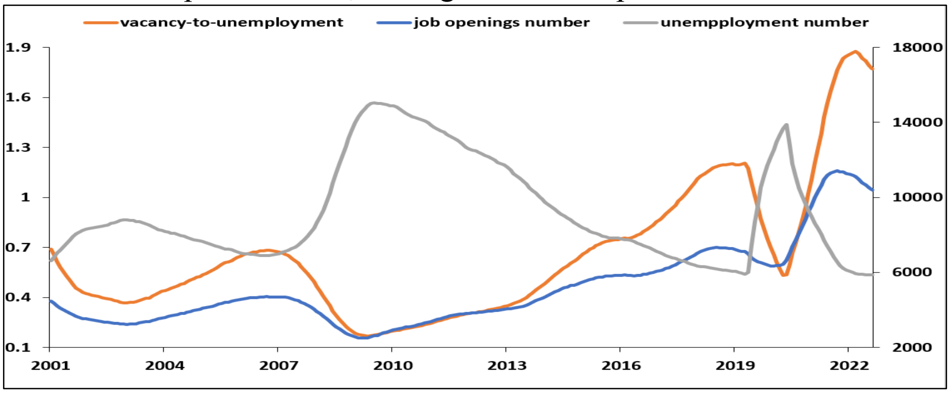


Source: U.S. Bureau of Labor Statistics; author’s calculation.
Figure 2. Log form of job finding rate and labor market tightness

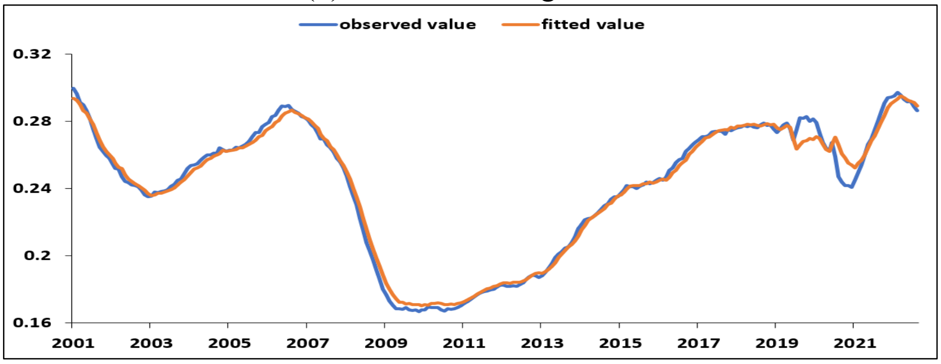
Table 1. Regression results

Variable	1 OLS	2 AR (1) GLS	3 ARMA (1,2) GLS
a	-1.29*** (0.01)	-1.292*** (0.029)	-1.313*** (0.065)
lnθ	0.237*** (0.012)	0.235*** (0.027)	0.173*** (0.027)
AR(1)	-	0.841*** (0.034)	0.979*** (0.015)
MA(1)	-	-	-0.363*** (0.062)
MA(2)	-	-	-0.227*** (0.062)
adjusted R^2	0.61	0.88	0.89

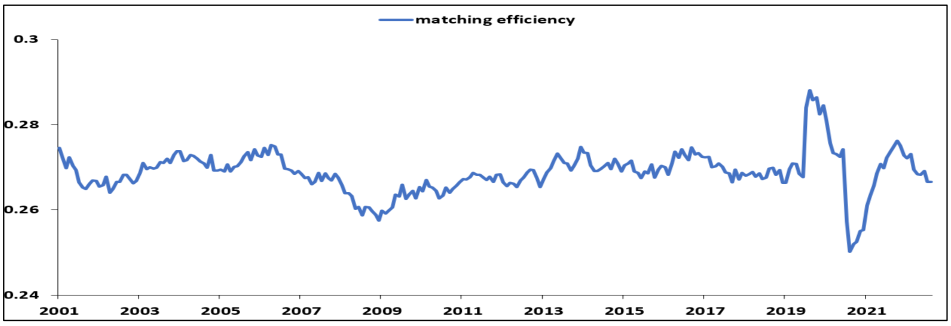
Notes: Standard errors are reported in parentheses. *Significant at 10 percent level, **Significant at 5 percent level, ***Significant at 1 percent level.



(1)Labor market tightness



(2)Job finding rate and its fitted value



(3)Matching efficiency

Figure 3. Labor market movements

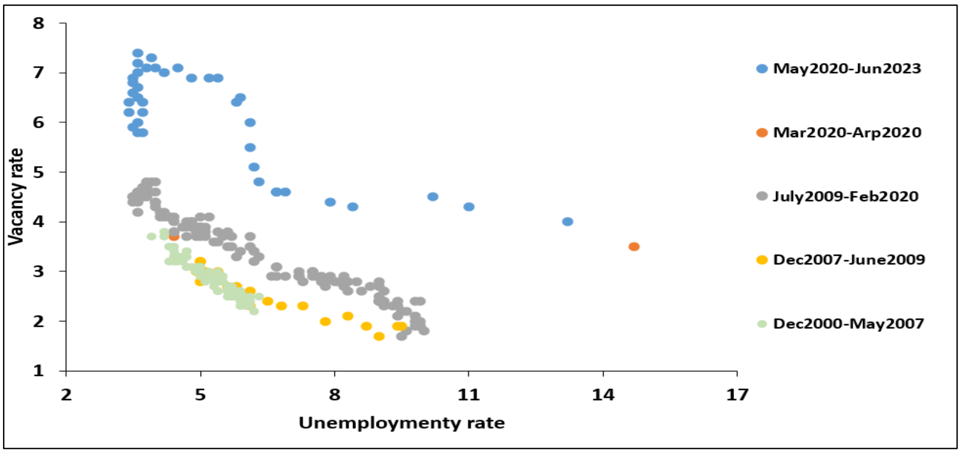


Figure 4. Beveridge curve

Source: U.S. Bureau of Labor Statistics

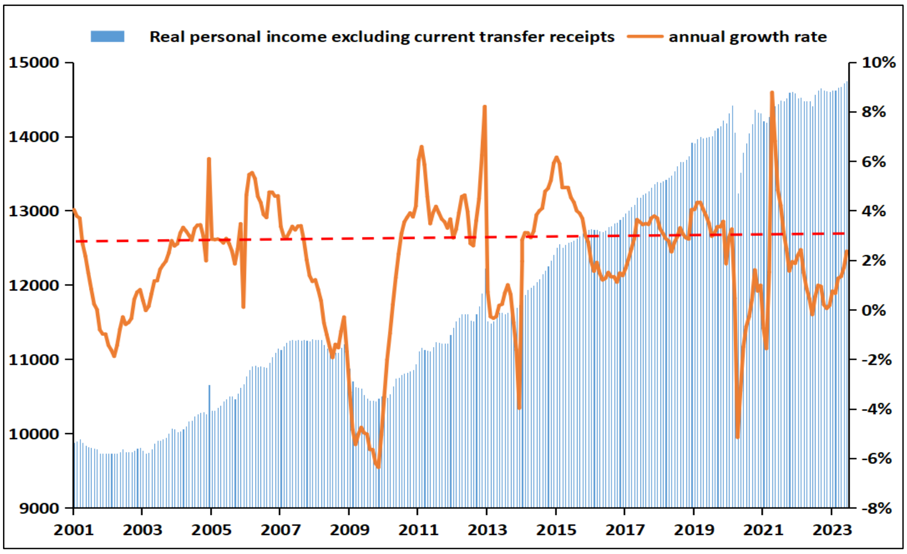


Figure 5. Personal income
Source: U.S. Bureau of Economic Analysis.

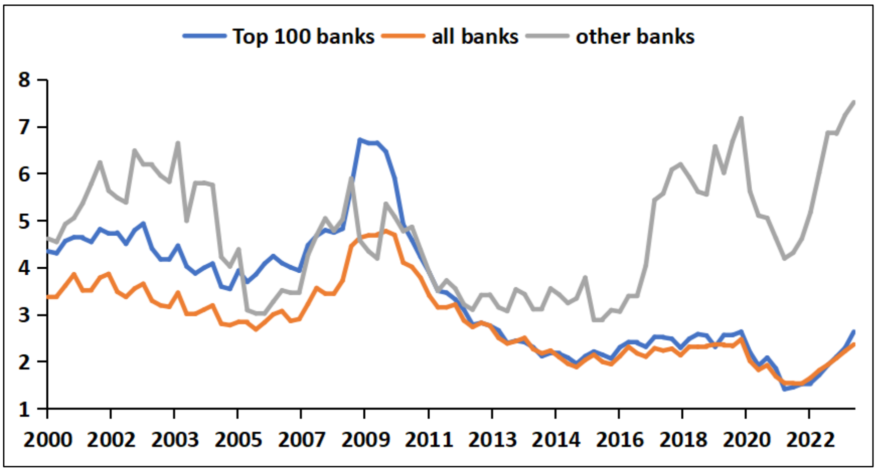


Figure 6. Delinquency rate on credit card loan
Source: Board of Governors of the Federal Reserve System (US).

5. Conclusion

This study constructs a Cobb-Douglas matching function and formulates a regression model to capture the evolution of the matching efficiency. ARMA method is adopted on the error term to alleviate the autocorrelation bias. The revised ARMA (1,2) GLS regression model fits well with the observed data. The movement of matching efficiency establishes a worse matching process between vacancies and unemployment after the pandemic. The matching efficiency started to fall before the labor market was very tight. The study also combines the Beveridge curve and the matching function. It investigates why the Beveridge curve shifts.

The descending matching efficiency and robust labor activities shift the Beveridge curve outwards. A significant vacancy fall always aligns with comparable unemployment increases in historical business cycles. Given the tight financial condition, the falling trend of matching efficiency can not restore the Beveridge relationship to nearly the pre-pandemic level. Other demand side facts also assume that the pressure of descending demands on goods and services will lead to more layoffs by firms. Consequently, cooling off the labor market with barely an increase in unemployment is unattainable. Following Okun's law, an increase in unemployment is associated with negative impacts on real output. The soft landing assumption is hardly eloquent. This suggests that government employment agencies disseminate information more effectively to match jobs and workers better. Active labor market policies are also welcome to assist workers in securing jobs.

Clearly, much work must be done to examine behavior of vacancies and unemployment based on micro-foundations. This study does not decompose the matching efficiency into observable characteristics in the labor market. I plan to pursue the pertinent research in future work.

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