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The Recent Evolution of the U.S. Beveridge Curve: Evidence from the ARDL Approach

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Abstract: Using a search and match model of employment, and labor market data from 2000 to the present, this paper provides updated empirical evidence of the U.S. Beveridge Curve – an inverse unemployment-vacancy (UV) relationship - for the periods before and after the 2007-2009 recession. Using Job Openings and Labor Turnover Survey (JOLTS) data and an enhanced econometric technique - the autoregressive distributed lag (ARDL) approach, our results confirm the existence of the Beveridge Curve for the U.S.. We also find empirical evidence of a rightward shift in the U.S. Beveridge Curve following the Great Recession, potentially indicating increases in labor market mismatch or structural frictions in the U.S. labor market.

Keywords: ARDL model, Beveridge curve, Unemployment, Vacancy

JEL Classifications: C22, D49, E24, J64

1. Introduction

It would be no exaggeration to say that the 2007-2009 recession was one of the most severe and prolonged in U.S. history. With unemployment rates reaching heights not seen since the tumultuous 1980s, few sectors have seen setbacks as severe as the national labor market. From a 10 percent peak in October of 2009, high unemployment and stagnate wages have been a persistent and unwelcome feature of a slow and tepid recovery. The Great Recession, as it is now commonly called, was unique in both its severity and the nature of the financial and housing crises that instigated it. The sheer magnitude of this disruption has led many economists and policy-makers to suggest that the historical relationship between unemployment and vacancies, an inverse correlation known as the *Beveridge Curve*, has broken down (e.g., Kocherlakota, 2010; Barnichon et al., 2010; Tasci and Lindner, 2010; Daly et al., 2012; Hobijn and Sahin, 2013). If this is the case, persistently high rates of unemployment following the recession may be the product not only of wholly inadequate monetary and fiscal policy responses, but of fundamental changes in U.S. labor market dynamics. In other words, persistent post-recession unemployment may be composed not only of cyclical factors, but of greater structural impediments as well (e.g., labor market mismatch or increased search frictions). Theoretically, this would be evidenced by a rightward shift in the Beveridge Curve and higher vacancies for a given level of unemployment. This concern was most prominently echoed in by Minneapolis Federal Reserve president Narayana Kocherlakota:

> *"What does this change in the relationship between job openings and unemployment connote? In a word, mismatch. Firms have jobs, but can't find appropriate workers. The workers want to work, but can't find appropriate jobs... Monetary stimulus has provided conditions so that manufacturing plants want to hire new workers. But the Fed does not have a means to transform construction workers into manufacturing workers*." (Kocherlakota, 2010)

If true, the policy ramifications of a change in the UV relationship are significant. Higher levels of mismatch imply an increased natural rate of unemployment, meaning a higher fraction of current unemployment is potentially beyond fiscal or monetary remedy. Traditional macroeconomic policy tools to combat joblessness would then succeed only in higher inflation rather than lower unemployment.

Needless to say, Kocherlakota's comments have inspired a great deal of debate. Other economists have argued that there is no credible evidence to conclude that workers gainfully employed at the start of the recession would somehow be unfit for the same job two years later. Whatever labor market frictions that might have arisen following the recession should thus prove temporary given a proper policy response. If this is the case, then high unemployment is still overwhelmingly cyclical and can be alleviated through expansionary fiscal or monetary policies. Structural factors would therefore be considered a negligible component of the overall unemployment picture (Mishel et al., 2010).

Ultimately, this debate is an *empirical* matter that rests on our ability to estimate the current shape and position of U.S. Beveridge Curve. Search and match models of the unemployment-vacancy (UV) relationship have been a mainstay of empirical labor economics and numerous studies have confirmed the existence of an inverse UV relationship in the U.S. (See Petrongolo and Pissarides (2001) for detailed overview). On the other hand, empirical evidence of recent (rightward) shifts in the U.S. Beveridge Curve has been much less conclusive. While some researchers have found evidence of an increase in the natural rate of unemployment, estimates of the magnitude have been fairly small and likely transitory (Daly et al., 2012).

The main objective of this is to provide robust estimates of the current shape and position of the U.S. Beveridge Curve by filling two necessary voids in the existing Beveridge Curve literature. Firstly, our estimates are based on the most recent and accurate dataset available; that is, the Job Opening and Labor Turnover Survey (JOLTS). Prior to late 2000, reliable data on U.S. vacancies was not readily available. Early studies were thus forced to use proxy variables such as help-wanted postings to loosely approximate the number of vacancies (Mandal, 2011). Beginning in December of 2000, the U.S. Bureau of Labor Statistics (BLS) began collecting official vacancy statistics through JOLTS. This has allowed modern studies to estimate the Beveridge Curve relationship with greater accuracy than was previously possible. Updated estimates derived from this dataset are important not only because it gives us a better insight into the likely shape and position of the U.S. Beveridge Curve, but also because the JOLTS has recently been subject to several non-trivial statistical revisions.[1] Downward adjustments performed by the BLS in March of 2011, for example, led some to conclude that prior studies had drastically overestimated the position of the Beveridge Curve (Konczal, 2011).

Secondly, although studies generally employ time series data/methods in examining the Beveridge Curve, few have paid little attention to nonstationarity of the selected variables in their

[1] A history of revised tables can be found on the BLS JOLTS page (http://www.bls.gov/jlt/revisiontables.htm)

models. In other words, numerous studies use the level of each variable in their regression analyses without taking into account the nonstationary nature of the JOLTS time series data. When data are nonstationary, standard statistics (e.g., *t*- and *F*-statistics) used in determining the significance of estimated coefficients are not valid (Wooldridge, 2009). Furthermore, unless nonstationary variables combine with other nonstationary variables to form stationary cointegration relationships, estimates can falsely indicate the existence of a meaningful economic relationship (spurious regression) (Harris and Sollis, 2003). To address this issue, we employ an autogressive distributed lag (ARDL) approach to cointegration or an ARDL bound testing approach (referred to here as the ARDL model) proposed by Pesaran et al. (2001). Since the ARDL model does not require the classification of variables into nonstationary $I(1)$ or stationary $I(0)$ processes, it is a convenient tool to investigate dynamic interactions among variables without worrying about nonstationarity.[2] It is hoped that this study will lead to more robust empirical findings and enhance our understanding of the U.S. Beveridge Curve relationship.

The remainder of this paper is organized as follows. The next section briefly discusses the analytical framework of the Beveridge Curve. The following section describes the empirical model associated with the ARDL approach. The last two sections present the empirical findings and make some concluding remarks.

2. The Theoretical Consideration on the Beveridge Curve

The Beveridge Curve, named after late British economist William Beveridge, posits that an inverse relationship between job vacancies and unemployment exists over the course of the business cycle. The logic behind this hypothesis is quite simple. Periods of economic expansion should (all else equal) be associated higher numbers of vacancies relative to unemployment, indicating excess demand for labor during the boom times. This is illustrated in Fig. 1 by the top-left segment of the Beveridge Curve above the 45 degree line (the Job Creation Curve). Conversely, economic contractions should be associated with higher unemployment relative to vacancies, indicating excess supply of labor following a bust (shown as the segment below the 45 degree line). The so-called natural level of unemployment (defined by Brauer (2007) as the level of unemployment arising from all sources besides the business cycle) is given by the intersection between the Beveridge Curve and the 45 degree line, where the number of job seekers/unemployed is equal to the number of job openings/vacancies, and the labor market is in its long run equilibrium (steady state) (Kaufman and Hotchkiss, 2006). An increase (decrease) in structural unemployment, and consequently a rise (decline) in the natural rate of unemployment are illustrated by rightward (leftward) shifts in the Beveridge Curve.[3]

[2] It is worth mentioning that when applying OLS and/or any cointegration technique to time series data, the first exercise is to determine the degree of integration of each variable in a model. This, of course, depends on which unit root test one uses. Given the assumption that the deterministic trend is correctly specified, for example, the standard unit root tests (i.e., Augmented Dickey-Fuller tests) are not able to detect a structural break in the series, which could lead to the false conclusion that there is a unit root, when in fact there is not (Perron, 1989). In this regard, the ARDL model is useful because it is applicable irrespective of whether the regressors are $I(0)$ or $I(1)$ and avoids uncertain unit roots and the pre-testing problem.

[3] See Blanchard and Diamond (1989) for a more thorough overview.

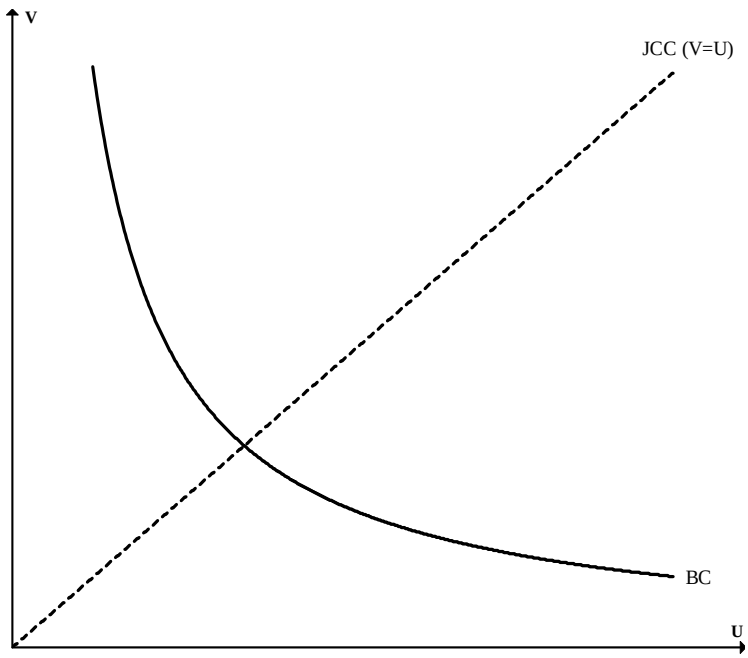

Figure 1. Theoretical Beveridge curve

To estimate the Beveridge Curve relationship more formally and with more precision, following Petrongolo and Pissarides (2001), we introduce a simple search and match model of employment. The theoretical foundation of the UV relationship begins with the matching function, which is a stylized mathematical representation of the process through which workers seeking employment are "matched" with firms seeking labor.[4] In its simplest form this model can be stated as follows:

$$M = m(U, V) \qquad (1)$$

where M is the number of hires or job matches during a given time period; U is the number of unemployed; and V is the number of vacancies. Imposing a constant return to scale Cobb-Douglas matching function, we can specify Eq. (1) as follows:

$$M = m(U)^{\alpha}(V)^{1-\alpha} \qquad (2)$$

Noting that in steady state the number of job matches (M) equals the number of job separations (S) and dividing equation (2) by the labor force (L), we get

$$S / L = m(UR)^{\alpha}(UV)^{1-\alpha} \qquad (3)$$

where UR is the unemployment rate (U/L); and VR is the vacancy rate (V/L).[5] Given S/L, the

[4] It should be emphasized that the matching function considered here has constant returns to scale and takes an unemployed worker as its only input. Hence, it ignores the fact that the majority of new hires involves already employed worker or individuals out of the labor force.

[5] This vacancy rate definition differs slightly from the official BLS calculation, where VR=V/(V+E), and E represents employment. This assumes calculations are comparable to that of the unemployment rate, although this may not always be the case (Hobijn and Sahin, 2013). This alternate definition does not differ in any significant way from the BLS methodology, and is more consistent with matching functions commonly employed in modern Beveridge Curve models (Petrongolo and Pissarides, 2001).

implicit theorem suggests a negative steady-state relationship between the unemployment rate (*UR*) and the vacancy rate (*VR*). This general setup provides the theoretical underpinnings that allow us to establish an inverse, convex relationship between vacancies and unemployment for a given stock or flow of hires/separations. We can now advance to our empirical test of this relationship.

3. Empirical Methodology

For a careful examination of the U.S. Beveridge Curve, we employ two different measures of vacancies and unemployment (measured in rates and levels), which may produce a substantially different estimates. This issue has been largely overlooked by previous studies in which Beveridge Curves are often estimated and compared using levels and rates interchangeably (e.g., Valletta, 2005; Weidner and Williams, 2011; Mandal, 2011). For this reason, two datasets are compiled for our empirical analysis; the first dataset contains the rates of vacancies and unemployment (case I), and the second dataset covers the levels of vacancies and unemployment (case II). Hence, our two models specified in a log linear form are as follows:

Case I:

$$\ln VR_t = a_0 + a_1 \ln UR_t + a_2 D_{2009\text{–}2015} + \varepsilon_t \qquad (4)$$

Case II:

$$\ln VL_t = b_0 + b_1 \ln UL_t + b_2 D_{2009\text{–}2015} + \mu_t \qquad (5)$$

where VR_t (VL_t) is the rate (level) of vacancies; UR_t (UL_t) is the rate (level) of unemployment; and ε_t (μ_t) is the standard error term. Due to the recent financial crisis and recession, the U.S. labor market may have been subject to unprecedented structural changes in the late 2000s, as has been suggested by Kocherlakota and others. To test for this possibility, a dummy variable covering the period since the recovery in June 2009 through December 2015 ($D_{2009\text{–}2015}$) is included in the estimation. In theory, we should expect the coefficient on the rate (level) of unemployment to be negative ($a_1 < 0$ and $b_1 < 0$), capturing an inverse relationship between vacancies and unemployment.

Eqs. (4) and (5) can be written as an unrestricted error-correction representation of the ARDL model as follows:

Case I:

$$\begin{aligned}\Delta \ln VR_t &= a_0' + \sum_{k=1}^{p} a_1' \Delta \ln VR_{t-k} + \sum_{k=0}^{p} a_2' \Delta \ln UR_{t-k} + a_3' D_{2009\text{–}2015} \\ &\quad + a_1 \ln VR_{t-1} + a_2 \ln UR_{t-1} + \zeta_t\end{aligned} \qquad (6)$$

Case II:

$$\begin{aligned}\Delta \ln VL_t &= b_0' + \sum_{k=1}^{p} b_1' \Delta \ln VL_{t-k} + \sum_{k=0}^{p} b_2' \Delta \ln UL_{t-k} + b_3' D_{2009\text{–}2015} \\ &\quad + b_1 \ln VL_{t-1} + b_2 \ln UL_{t-1} + \psi_t\end{aligned} \qquad (7)$$

where Δ is the difference operator and *p* is the lag order. In Eqs. (6) and (7), the coefficients of a_1, a_2 and b_1, b_2 indicate the long-run (cointegration) relationships and the coefficients of the summation signs (Σ) represent the short-run dynamics among the variables. It is worth mentioning that estimates of equations (4) and (5) yield long-run estimates, while a vector error-correction (VEC) model generate short-run estimates. Therefore, one has to take two steps in applying the standard VEC

method (i.e., Johansen test). The ARDL specifications described in equations (6) and (7) are distinguished from the standard VEC method in that a linear combination of lagged level variables is directly included as the lagged error-correction term in a model.[6] Hence, one advantage of the ARDL is that the short- and long-run parameters of the model are estimated simultaneously.[7]

The ARDL modeling begins with testing the existence of the long-run relationship (cointegration) between the variables in Eqs. (6) and (7). The null hypotheses of no long-run relationship (no cointegration) are, $H_0 : a_1 = 0, a_2 = 0$ against $H_1 : a_1 \neq 0, a_2 \neq 0$ in Eq. (6) and $H_0 : b_1 = 0, b_2 = 0$ against $H_1 : b_1 \neq 0, b_2 \neq 0$ in Eq. (7). For this, an *F*-test with two sets of asymptotic critical values (upper and lower critical values) tabulated by Pesaran et al. (2001) can be conducted on Eqs. (6) and (7). An upper critical value assumes that all the variables are $I(1)$, or nonstationary, while a lower critical value assumes that they all are $I(0)$, or stationary. If the computed *F*-statistic falls above (below) the upper (lower) bound of critical value, the null hypothesis of no cointegration can (not) be rejected, indicating that selected variables are (not) cointegrated.

4. Empirical Results

4.1 Data

Monthly data that cover the period from December 2000 to December 2015 (2000:M12-2015:M12) are used for estimation. The data span has been chosen based on availability of the JOLTS series. The level of vacancies (measured in thousands of openings) and the rate of vacancies (measured as a percentage) are calculated from BLS data. The level of unemployment (measured in thousands of workers) and the rate of unemployment (measured as a percentage) are taken from the Current Population Survey (CPS) published by the U.S. Census Bureau. All variables are converted to natural logarithms.

4.2 Empirical Results

As discussed, our ARDL modeling starts with the *F*-test to identify the existence of the long-run relationship (cointegration) between the variables in Eqs. (6) and (7). It should be noted that before estimating the equations, the specification issue to be addressed is the determination of the lag length (*p*) for the models. Bahmani-Oskooee and Brooks (1999) show that the results of the *F*-test are quite sensitive to changes in lag structures. The lag lengths in the equations are determined by the Akaike Information Criterion (AIC) and Lagrange multiplier (LM) statistics for testing the null hypothesis of no serial correlation.[8] Setting the maximum lag lengths up to 12, the results indicate that seven (*p*=7) is the optimal lag order for both cases (Table 1).[9] With the selected lag

[6] The linear combination of lagged level variables in equations (6) and (7) is a proxy for a lagged error-term (known as an error-correction term) in the standard VEC model.

[7] The ARDL is also known to be more robust and perform better for finite sample size than conventional cointegration analysis (Pesaran and Shin, 1999).

[8] Since the specifications in Eqs. (6) and (7) are based on the assumption that the error terms are serially uncorrelated, it is crucial to balance between selecting a lag length (*p*) sufficiently large to mitigate the residual serial correlation problems and one sufficiently small to avoid being over-parameterized, particularly in view of the limited time-series data available (Pesaran et al., 2001, p. 308).

[9] To ensure comparability of results of different choices of lag lengths, all regressions are computed

lengths, we then conduct the *F*-test. The results show that, with seven lags, the calculated F -statistics are 13.189 for case I and 8.682 for case II, respectively, which lie above the upper levels of the 10% critical values, thereby rejecting the null hypothesis (Table 1).[10] The results support evidence of a stable long-run relationship between unemployment and vacancies in the U.S. As a second step, therefore, we can proceed with estimating the short and long-run coefficients for both cases based on the selected ARDL models.

It should be emphasized here that, since there is a possibility of reverse causality between vacancies and unemployment, we also conduct the *F*-test using $\ln UR_t$ and $\ln UL_t$ as the dependent variables $-F(\ln UR_t|\ln VR_t)$ and $F(\ln UL_t|\ln VL_t)$ in both cases (Table 1). The results show that the null hypothesis cannot be rejected even at the 10% level for both models, supporting lack of cointegration. This finding thus suggests that there exists a long-run relationship between the variables only when $\ln VR_t$ and $\ln VL_t$ are used as the dependent variables, and the variables $\ln UR_t$ and $\ln UL_t$ can be treated as the "long-run forcing" variable in explaining $\ln VR_t$ and $\ln VL_t$ in our model.

Table 1. Results of cointegration test using *F*-statistics

	Lag order	$\chi^2(1)$	F **-statistic**
Case I			
$F(\ln VR_t\|\ln UR_t)$	7	0.267 [0.606]	13.189
$F(\ln UR_t\|\ln VR_t)$	7	2.509 [0.113]	0.026
Case II			
$F(\ln VL_t\|\ln UL_t)$	7	0.002 [0.957]	8.682
$F(\ln UL_t\|\ln VL_t)$	7	1.522 [0.217]	0.276

Note: A lag order is selected based on Akaike Information Criterion (AIC); $\chi^2(1)$ is Lagrange Multiplier (LM) statistic for testing the hypothesis of no serial correlation against order 1; *F*-statistics for both cases are estimated from a model that includes an intercept and the upper critical value for *F*-statistic at the 10% significance level is 5.930 and the lower bound critical value is 5.239; Brackets are p -values.

Table 2 summarizes the results of the long-run coefficients for cases I and II, where the dependent variable is represented by the two measures of vacancies. Our main interest is the long-run relationship between job vacancies and unemployment. The estimated coefficients of the unemployment are found to be negative and statistically significant at the 5% level in cases I and II, confirming the existence of the Beveridge Curve in the U.S.; that is, the job vacancy rate/level tends to decline (rise) as the unemployment rate/level increases (decreases). Also of greater interest is the effect of a structural break following the Great Recession on the U.S. labor market ($D_{2009–2015}$).

over the same sample period, Oct. 2001-Dec. 2015, with the first twelve observations reserved for the construction of lagged variables.

[10] The upper critical value for *F*-statistic with an intercept at the 10% significance level is 5.930 and the lower bound critical value is 5.239.

Table 2. Results of estimated long-run coefficients

Variable	Case I	Case II
$\ln UR_t$	-0.694 (-7.899)***	
$\ln UL_t$		-0.758 (-4.735)***
$D_{2009–2015}$	0.214 (4.963)***	0.285 (3.482)***
Constant	2.179 (14.914)***	15.064 (10.519)***

Note: *** and ** denote significance at the 1% and 5% levels, respectively. In parentheses are t-statistics.

The estimated coefficient on the dummy variable is found to be positive and statistically significant at the 5% level in both cases. This implies that, for a given level of unemployment, job vacancies during the Recovery period – the period following the Great Recession (July 2009-Dec. 2015) - tended to be much higher than the pre-Great Recession (Dec. 2000-Nov. 2007) and Great Recession (Dec. 2007-June 2009) periods; for example, the job vacancy rate (level) had been pushed up by approximately 21.4% (28.5%) during the Recovery period. As seen in Fig. 2, however, the rapid spike in U.S. job vacancies does not seem to be associated with a decline in unemployment, potentially indicating an increase in labor market mismatch and/or increased search frictions. Hence, these findings provide empirical evidence of a *rightward* shift in the U.S. Beveridge Curve following the Great Recession. This finding is consistent with Daly et al. (2011), Hobijn and Sahin (2012), and Diamond and Sahin (2015) in that the Beveridge Curve in the U.S. experience outward shifts during recoveries. Given the fact that the current rightward shift of the Beveridge cure has been lasting over five years since the Great Recession, however, our findings are at odds with Bernanke (2012) who finds the Beveridge Curve shifts back inward during the recovery.

Table 3 reports the short-run estimation results, which are obtained from coefficient estimates of first-differenced variables in Eqs. (6) and (7). The results show that, for cases I and II, unemployment is statistically significant at least at the 10% level and has a negative relationship with vacancies. This confirms that, as in the long-run analysis, job vacancies tend to decrease with a rise in unemployment even in the short-run. In addition, the recessionary shock is also found to have significant positive effects on vacancies in the short-run. Therefore, the results of short-run analysis appear to be consistent with those of long-run analysis. Notice that the coefficients of the error-correction terms (ec_{t-1}) are negative and statistically significant at the 5% level in both cases (Table 3). This provides further evidence of the existence of the long-run relationship among the variables (Kremers et. al., 1992). The coefficients of ec_{t-1} in Eqs. (6) and (7) are -0.316 and -0.193 are respectively, implying that deviation from the long-run equilibrium are corrected by approximately 31.6% and 19.3% in one month. Finally, the diagnostic tests on our ARDL models as a system indicate no serious problem with serial correlation and functional form specification. The cumulative sum (CUSUM) and cumulative sum of squares (CUSUMSQ) tests applied to the residuals of Eqs. (6) and (7) show that all the estimated coefficients in the long- and short-run are stable.

Table 3. Results of estimated short-run coefficients

Variable	Case I	Case II
$\Delta \ln VR_{t-1}$	-0.485 (-6.158)***	
$\Delta \ln VR_{t-2}$	-0.356 (-5.131)***	
$\Delta \ln VL_{t-1}$		-0.514 (-6.755)***
$\Delta \ln VL_{t-2}$		-0.379 (-5.361)***
$\Delta \ln UR_{t}$	-0.349 (-2.146)**	
$\Delta \ln UR_{t-1}$	-0.242 (-1.508)	
$\Delta \ln UR_{t-2}$	-0.083 (-0.515)	
$\Delta \ln UR_{t-3}$	-0.405 (-2.526)***	
$\Delta \ln UR_{t-4}$	-0.379 (-2.395)***	
$\Delta \ln UR_{t-5}$	-0.376 (-2.277)**	
$\Delta \ln UL_{t}$		-0.333 (-1.992)**
$\Delta \ln UL_{t-1}$		-0.279 (-1.670)*
$\Delta \ln UL_{t-2}$		-0.137 (-0.814)
$\Delta \ln UL_{t-3}$		-0.365 (-2.190)**
$\Delta \ln UL_{t-4}$		-0.422 (-2.595)***
$\Delta \ln UL_{t-5}$		-0.317 (-1.888)*
$D_{2009–2015}$	0.067 (2.927)***	0.055 (2.070)**
ec_{t-1}	-0.316 (-4.450)***	-0.193 (-3.415)***
Serial correlation	0.267 [0.606]	0.002 [0.957]
RESET	0.086 [0.775]	0.989 [0.320]
CUSUM	Stable	Stable
CUSUMSQ	Stable	Stable

Notes: ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively; Parentheses are t-statistics; ec_{t-1} is an error-correction term. Brackets in diagnostic tests are p-values. RESET is Ramsey's test of function form. CUSUM and CUSUMSQ indicate the cumulative sum and cumulative sum of squares tests.

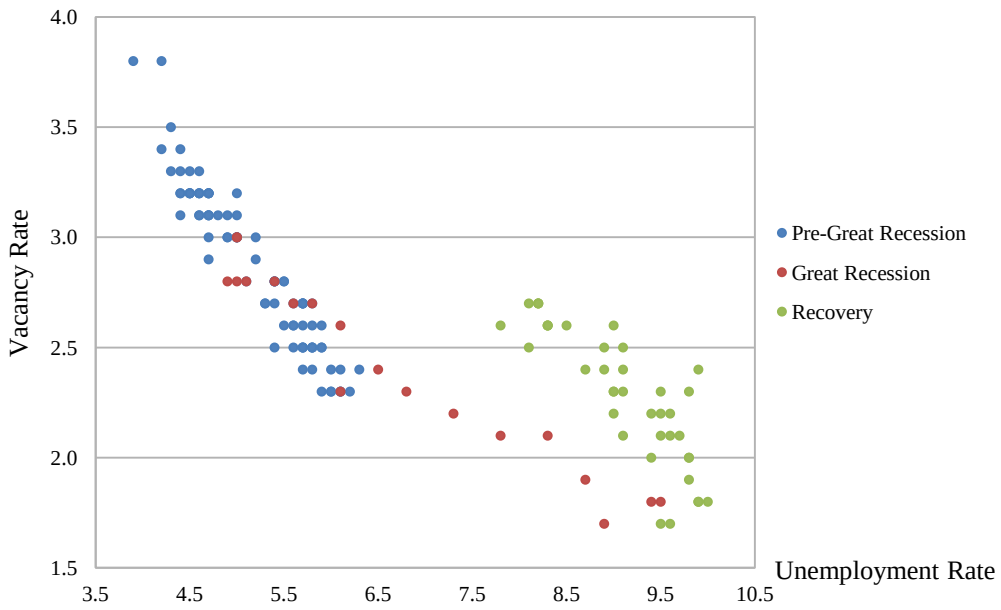

Figure 2. Vacancy rate and unemployment rate in the U.S. (Dec. 2000 - Dec. 2015)

5. Concluding Remarks

In this short paper, we empirically examine the existence of the Beveridge Curve for the United States. To tackle this issue properly, we employ the most recent and reliable dataset available (monthly Dec. 2000 to Dec. 2015) – that is, the Job Openings and Labor Turnover Survey (JOLTS), as well as an enhanced empirical framework – the ARDL approach to cointegration. It is expected that this effort would lend confidence in the robustness and reliability of our empirical findings.

Our empirical results support the existence of the Beveridge Curve for the U.S in that the job vacancy rate tends to be negatively related to the unemployment rate. We also find empirical evidence of a rightward shift in the U.S. Beveridge Curve following the end of the Great Recession. This implies that, for a given level of unemployment, job vacancies following the Great Recession have been much higher than they were in the periods before and during the contraction. This shift suggests that increases in labor market mismatch and hence structural unemployment may have increased in the years since the Great Recession.

Finally, it should be pointed out that we do not directly examine the effects of other factors affecting labor market frictions in this paper, although we conjecture that inclusion of these variables is likely to lead to a difference to the estimates. In addition, since the analysis has been conducted using national aggregate data, this paper is not able to explore regional/industrial heterogeneity that has driven the shift in the Beveridge curve after the crisis. Future research should concentrate on a regional panel for the U.S., controlling for a set of variables to get a sense of the driving forces behind the shift.

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