

NBER WORKING PAPER SERIES

CYCLICAL UNEMPLOYMENT, STRUCTURAL UNEMPLOYMENT

Peter A. Diamond

Working Paper 18761

<http://www.nber.org/papers/w18761>

NATIONAL BUREAU OF ECONOMIC RESEARCH

1050 Massachusetts Avenue

Cambridge, MA 02138

February 2013

This paper was presented as the Mundell-Fleming Lecture at the Thirteenth Jacques Polak Annual Research Conference at the International Monetary Fund in Washington, D. C., held November 8-9, 2012. The author thanks Gadi Barlevy, Olivier Blanchard, Steven Davis, John Haltiwanger, Bart Hobijn, Marianna Kudlyak, Giuseppe Moscarini, Peter Orszag, Jim Poterba, Sarah Bloom Raskin, Robert Triest, Rob Valletta, and participants for their comments, as well as James Fogel and Caroline Shinkle for research assistance. The views expressed herein are those of the author and do not necessarily reflect the views of the National Bureau of Economic Research.

NBER working papers are circulated for discussion and comment purposes. They have not been peer-reviewed or been subject to the review by the NBER Board of Directors that accompanies official NBER publications.

© 2013 by Peter A. Diamond. All rights reserved. Short sections of text, not to exceed two paragraphs, may be quoted without explicit permission provided that full credit, including © notice, is given to the source.

Cyclical Unemployment, Structural Unemployment

Peter A. Diamond

NBER Working Paper No. 18761

February 2013

JEL No. E24,E32,E6,J23

### **ABSTRACT**

Whenever unemployment stays high for an extended period, it is common to see analyses, statements, and rebuttals about the extent to which the high unemployment is structural, not cyclical. This essay views the Beveridge Curve pattern of unemployment and vacancy rates and the related matching function as proxies for the functioning of the labor market and explores issues in that proxy relationship that complicate such analyses. Also discussed is the concept of mismatch.

Peter A. Diamond

MIT Department of Economics

50 Memorial Drive

Building E52, Room 344

Cambridge MA 02142-1347

and Federal Reserve Bank of Boston

and also NBER

[pdiamond@mit.edu](mailto:pdiamond@mit.edu)

## **“Cyclical Unemployment, Structural Unemployment”**

Peter Diamond<sup>1</sup>

*Whenever unemployment stays high for an extended period, it is common to see analyses, statements, and rebuttals about the extent to which the high unemployment is structural, not cyclical. This essay views the Beveridge Curve pattern of unemployment and vacancy rates and the related matching function as proxies for the functioning of the labor market and explores issues in that proxy relationship that complicate such analyses. Also discussed is the concept of mismatch.*

Whenever unemployment stays high for an extended period, it is common to see analyses, statements, and rebuttals about the extent to which the high unemployment is structural, not cyclical.<sup>2</sup> As the measure of the cyclical portion is viewed as identifying the size of a potential role for some forms of stimulus, this debate is about the scope for stimulative policies.<sup>3</sup> Much discussion refers to the Beveridge Curve, made salient by monthly publication by the Bureau of Labor Statistics (BLS) of the unemployment and vacancy rates that form the curve.<sup>4</sup> In bad times

---

<sup>1</sup> Peter Diamond is an Emeritus Professor of Economics at the Massachusetts Institute of Technology. This paper was presented as the Mundell-Fleming Lecture at the Thirteenth Jacques Polak Annual Research Conference at the International Monetary Fund in Washington, D. C., held November 8-9, 2012. The author thanks Gadi Barlevy, Olivier Blanchard, Steven Davis, John Haltiwanger, Bart Hobijn, Marianna Kudlyak, Giuseppe Moscarini, Peter Orszag, Jim Poterba, Sarah Bloom Raskin, Robert Triest, Rob Valletta, and participants for their comments, as well as James Fogel and Caroline Shinkle for research assistance.

<sup>2</sup> Some analyses seek a division of total unemployment between structural and cyclical portions, while others use a three-part division among frictional, structural and cyclical.

<sup>3</sup> For a 1960s example of the debate over the causes of continued high unemployment, see Solow (1964). Indeed there is a long history of claims that the latest technological or structural developments make for a new long-term high level of unemployment, but these have repeatedly been proven wrong (Woirol, 1996).

<sup>4</sup> I will use the term Beveridge Curve interchangeably for the steady state relationship between unemployment and vacancies and for a curve fitted empirically to observed points. Simple continuous

we expect to see lower vacancy rates and higher unemployment rates. Figure 1 shows the October 2012 BLS report, with data through August. As shown in Figure 1, starting with the business cycle peak in December 2007, there was a period with the monthly figures lying along a smooth downward sloping curve. However, since the June 2009 cyclic trough, the pattern has been erratic - two periods of rising vacancy rates with little impact on unemployment, two periods of falling unemployment, without steadily rising vacancy rates. Starting shortly after the trough, all the observations are noticeably above a curve that would connect the observations before and during the recession. That is, we have three observations: (1) unemployment is high, (2) vacancies are low, and (3) unemployment is higher than it was at the same vacancy rates during the recession, or, equivalently, vacancies are higher than they were at the same unemployment rates during the recession.<sup>5</sup>

Analyses using the Beveridge Curve typically assume that movements along the curve reflect cyclical effects while shifts in the curve reflect structural effects, effects expected to be sufficiently lasting to limit the potential role of stimulus policies.<sup>6</sup> Not surprisingly, the period of rising vacancies without falling unemployment generated reactions suggesting that the U.S. had just had a leap in structural unemployment – that the economy may now have a long-term higher level of unemployment as the “new normal.” This inference was taken to imply that we should not be so concerned with stimulating aggregate demand through monetary and fiscal policies.<sup>7</sup>

---

time models generate differential equations that loop around a steady state curve (Blanchard and Diamond, 1989).

<sup>5</sup> I will use the term Great Recession to cover both the NBER recession and the following recovery, which has been marked by continuing high unemployment. This coincides with the term Long Slump in Hall (2011).

<sup>6</sup> “When the economy is doing well, firms usually hire more workers and they find it more challenging to fill their available openings. Hence, the unemployment rate is low, and the vacancy rate is high. So, typically, as the economy improves, the plotted points move toward the upper left in this picture. Conversely, when economic times get worse, the plotted points move to the southeast. This creates a curve that runs from the northwest to the southeast—a curve that’s known as the Beveridge curve. However, in the Great Recession and its aftermath, we have seen something different: The Beveridge curve itself has shifted out toward the upper right. Economists see this kind of outward shift as representing a decline in the ability of the labor market to form mutually beneficial matches between workers and firms. In that sense, the labor market is less efficient. The outward shift means that firms can’t fill their available job openings as readily as we would have expected in light of the high unemployment rate.” Kocherlakota (2012).

<sup>7</sup> “The red dots in Figure 8 depict the Beveridge curve since the U. S. recession was formally declared ended in June 2009. One would normally expect the unemployment rate to decline as economic growth resumes. But here, we see evidence of increased recruiting activity on the part of the business sector

These assumptions on movements along and across curves have been in common use for a long time (see, e. g., Dow and Dicks-Mireaux, 1958). Along these lines, a division of current unemployment between cyclical and structural portions involves two steps: selecting a shape for a pair of (parallel) Beveridge Curves and selecting a point on the later, higher curve, to represent a target full-employment point. Accepting the common assumptions about shifts in the curve, one still has to ask how much of current unemployment is cyclical, that is, how much represents having high unemployment and low vacancies on a shifted, higher Beveridge Curve. Continuing cyclical unemployment presumably indicates a potential role for stimulative policy even if the full employment point has shifted. By and large, recent analyses conclude that whatever the estimated increase in structural unemployment, there remains a sizable component of cyclical unemployment.

Shifts in the Beveridge Curve are discussed in Section I together with identifying the full-employment point on a shifted curve. The focus is on the current cycle, not issues that might be raised about high unemployment over several cycles. There is a long history of recognizing a role for demography in determining the level of unemployment (e. g., Perry, 1972). Young people move among jobs much more than older people do. Older workers are more likely to retire after a layoff than younger workers. Since demography is a slow-moving variable, its trend is unlikely to play a significant role in assessing change within a single business cycle. However, trends in population aging do need to be kept in mind as part of interpreting the numbers, particularly as responses to a recession do vary with age. There is also a long history of concern about the impact of trends in technology and international trade on trend unemployment (Woirol, 1996).<sup>8</sup> This essay does not consider trend issues.

---

together with no apparent decline in the unemployment rate. One interpretation of this recent pattern is that matching jobs with workers has become more difficult in the wake of an exceptionally severe recession. If this is the case, then it is not immediately clear how monetary or fiscal policies might alleviate the problem.” Annual Report, Federal Reserve Bank of St. Louis, 2010.

<sup>8</sup> For example, consider this 1931 statement: “the real issue is not whether technological displacement causes workers to lose their jobs. It undoubtedly does. The real issue is whether over a period of years the continual introduction of new and improved machines and processes is causing a total net increase or decrease in mass employment. ...

On this issue there are two opposing points of view, each held by large numbers of earnest people.” U.S. Senate, Select Committee on Unemployment Insurance, *Unemployment Insurance*, Part 2, “Report of the Committee on Technological Unemployment to the Secretary of Labor,” November 1931, 72<sup>nd</sup> Congress, 1<sup>st</sup> Session, 1931, 560. Cited in Woirol, 1996, p. 36.

As the matching function underlies interpretations of shifts in the Beveridge Curve, Section II moves behind the data on unemployment and vacancy stocks used for the Beveridge Curve and considers labor market flow data, particularly the monthly flow of hires relative to the stocks of unemployed and vacancies. Structural unemployment is then analyzed in terms of downward movements in the matching function. Section III returns to the Beveridge Curve, considering separations from employment and the flows into unemployment.

Section IV considers studies that analyze measures of “mismatch” in the labor market, measures of the extent to which the distributions of unemployed workers and vacancies differ across regions or industries or skills. Increases in mismatch are then taken as a basis for inferences about structural changes. Section V discusses the terminology of cyclical, structural and frictional unemployment. Concluding remarks are in Section VI.<sup>9</sup> The paper does not discuss the literature assessing the effects of extended unemployment insurance or house lock, both seen in the literature as having little importance for unemployment rates at future full employment levels.

The focus is on methodology, examining reasons why the current shifts in the Beveridge Curve and the matching function might or might not be temporary. While many reasons that complicate interpretation of shifts are identified, their diverse impacts are not quantified. The presentation relies on the existing literature and contains no new empirical analysis.

## **I. Beveridge Curve<sup>10</sup>**

Consider fitting a smooth curve to the observations in Figure 1 up to some date (e. g., the last peak or the following trough). Consider another curve (perhaps a parallel shift) that lies on a later observation or set of observations that are above the first fitted curve. Assume that movement along a Beveridge Curve is cyclical, while any movement of the curve is structural (i. e., taken to

---

<sup>9</sup> For policy purposes, it is necessary to consider forecasts of the state of the economy, as policies have effects for an extended period. This paper focuses on interpreting snapshots of the state of the economy, not forecasts. We do note that currently forecasts are generally pessimistic for an extended period. Nor does the paper consider issues of inflation or inflation risk or the analysis of an Okun gap. The hiring process is analyzed without explicit discussion of wage setting.

<sup>10</sup> For an intellectual history of the curve, see Rodenburg (2011).

be long-lasting as the economy recovers). Pick a point on the lower curve to represent a full-employment point before the recession, possibly matching a particular date. Pick a point on the higher curve to represent a future full-employment point. Then the change in unemployment from the prior full-employment point to the current unemployment rate can be divided in two. The difference between prior and future full-employment points can be considered structural, while the difference in unemployment between the future full-employment point and the currently observed unemployment rate can be considered cyclical. That is, the latter gap, between the current unemployment rate and the target future full-employment point, is a measure of what might be addressed by stimulus policies despite the shift in the Beveridge Curve, assumed to be a structural, long-lasting shift.

As an example, Beveridge (1944) defined full employment as “more vacancy jobs than unemployed men.”<sup>11</sup> Dow and Dicks-Mireaux (1958) used a definition of equality of vacancies and unemployed to separate times of high and low demand, with the paper focusing on how to adjust vacancy data from labor exchanges to reflect possible multiple listings of vacancies. Figure 2 gives an example of their framework. Point 2 represents the full-employment point on a lower Beveridge Curve and point 4 the full-employment point on a higher Beveridge Curve (reflecting what they called greater “maladjustment”). If point 5 were the current position of the economy, then the difference in unemployment rates between the previous full-employment unemployment rate and the current rate, between points 2 and 5, can be divided between a structural portion between points 2 and 4 and a cyclical portion between points 4 and 5.

---

<sup>11</sup> “Full employment does not mean literally no unemployment. ... Full employment means that unemployment is reduced to short intervals of standing by, with the certainty that very soon one will be wanted in one’s old job again or will be wanted in a new job that is within one’s powers. ... Full employment in the Report means ... having always more vacant jobs than unemployed men... It means that the jobs are at fair wages, of such a kind, and so located that the unemployed men can reasonably be expected to take them; it means, by consequence, that the normal lag between losing one job and finding another will be very short.

The proposition that there should always be more vacant jobs than unemployed men means that the labour market should always be a seller’s market rather than a buyer’s market. ... The reason is that difficulty in selling labour has consequences of a different order of harmfulness from those associated with difficulty in buying labour.

...

... The greater the pace of the economic machine, the more rapidly will structural unemployment [footnote omitted] disappear, the less resistance of every kind will there be to progress.

... The demand must be adjusted to the kind of men available or the men must be capable of adjusting themselves to the demand.” Beveridge, 1945 (1944) p. 18-20.

With equality of the two rates as the definition of full employment, the past and future full-employment points lie on a single ray through the origin as in Figure 2. For current analyses that use a matching function, the equality of unemployment and vacancies is no longer an interesting concept.<sup>12</sup> A matching function approach uses the supply function of vacancies as part of determining the full employment point. Different matching functions imply different functions relating lags in filling a vacancy to the unemployment-vacancy ratio and so different supply functions of vacancies. This implies different ratios of unemployment to vacancies at different full employment equilibrium points. As a result, a downward shift in the efficiency parameter of the matching function generates a larger structural component. Barlevy (2011) contains such a calculation.

Barlevy fits a Beveridge Curve to the data from December 2000 to August 2008 by deriving the economy's possible labor market steady states. The calculation assumes given vacancy and separation rates and a Cobb-Douglas matching function, with parameters that were chosen to match some aspects of the data up to August 2008. With  $m$  as the matching function, a constant-returns-to-scale Cobb-Douglas matching function is:

$$m[u, v] = Au^\alpha v^{1-\alpha}$$

With  $s$  as the separation rate, equalizing flows into and out of unemployment gives

$$(1-u)s = Au^\alpha v^{1-\alpha}$$

Solving gives a Beveridge Curve that satisfies

$$u = \frac{s}{s + A(v/u)^{1-\alpha}}$$

---

<sup>12</sup> In reaching this conclusion while using a model of labor-market equilibrium, the matching function approach is consistent with the equilibrium approach that is inherent in the Friedman (1968) definition of the natural rate of unemployment as “the level that would be ground out by the Walrasian system of general equilibrium equations, provided there is imbedded in them the actual structural characteristics of the labor and commodity markets, including market imperfections, stochastic variability in demands and supplies, the cost of gathering information about job vacancies and labor availabilities, the costs of mobility, and so on.” (P. 8.) A footnote on the definition notes that “this "natural" rate need not correspond to equality between the number unemployed and the number of job vacancies.”



For chosen values of  $s$  and  $\alpha$ , fitting this curve to unemployment and vacancy rates yields a value of the matching function efficiency parameter,  $A$ .

Barlevy selects a full employment point on the Beveridge Curve up to August 2008 as a 5 percent unemployment rate, roughly matching average unemployment over the period used to fit the curve. A 5 percent unemployment rate lies on the estimated Beveridge Curve at a 3 percent vacancy rate. Assuming free entry of vacancies, the unemployment and vacancy rates at full-employment, together with the estimated matching function, imply a value for a filled vacancy relative to the cost of maintaining a vacancy at the point.

Barlevy selects a higher Beveridge Curve by assuming that the only parameter to change is the multiplicative (efficiency) parameter,  $A$ , of the Cobb-Douglas matching function and that the higher curve passes through the observation for December 2010.<sup>13</sup> To choose a full-employment point on the higher (later) Beveridge Curve, Barlevy assumes the same relative value of a filled vacancy as at the earlier full-employment point. That is, the profitability of having an additional worker divided by the cost of maintaining a posted vacancy at the new full-employment point is assumed to return to its previous full-employment value. This value is then plugged into the zero-profit condition for posting a vacancy and results in a full-employment ratio of unemployment to vacancies ( $U/V$ ) of 2.42, rather than the value on the lower Beveridge Curve of 1.67 (equal to a 5 percent unemployment rate divided by a 3 percent vacancy rate).<sup>14</sup> The resulting calculation by Barlevy is shown in Figure 3. The cyclical component at the time (December 2010) is given by the distance from the then-current observation to the full-employment point determined by the intersection of the higher Beveridge Curve with the ray through the origin with  $U/V$  ratio of 2.42. It is apparent from the figure that such a calculation shows that a significant portion of the increase from the previous business cycle peak to the high

---

<sup>13</sup> Barlevy does a similar fitting exercise for two earlier periods (Figure 1: 73-75 and 1980 recessions), both requiring use of a help-wanted index since the Job Openings and Labor Turnover Survey (JOLTS) had not yet started. He finds the same pattern, the economy first moves down the estimated Beveridge Curve, and then is above the curve as unemployment falls. The current, worse, recession involves a move further above the estimated curve than the two earlier examples, but any comparison is suspect given the data differences.

<sup>14</sup> For a different approach to identifying the full-employment point on a shifted Beveridge Curve, see Daly et al (2012), which empirically derives a job-creation curve by estimating the relationship between vacancies and estimates of the natural rate of unemployment as the Beveridge Curve shifted.

unemployment rate in December 2010 should be attributed to a cyclical movement, potentially worth trying to address by stimulative policies.<sup>15</sup>

This combination of both a shift in the Beveridge Curve (higher unemployment for current vacancies than previously) and a point with low vacancies and high unemployment on the shifted curve tends to lead policy discussion in two directions. Focusing on the shift in the curve, taken as structural, leads to questioning why the rise in vacancies has not lowered unemployment more, a question that links to ongoing discussions of reforming education and worker training, and gives the hiring function a central place in the discussion. The continuing lower level of vacancies draws attention to the multiple reasons why vacancies could continue to be low. Vacancies can be lower because of low profitability of anticipated production due to current and projected conditions in the output market. Vacancies can be lower because of greater difficulty in financing investment and production than previously. Vacancies can be lower because of a higher cost of production, due to the wages required for hiring given the mix of available worker skills and the level of productivity. Vacancies can be lower because of projections of possible government regulatory, spending, and tax changes. And uncertainty about all of these issues matters as well. That vacancies are indeed lower is apparent in Figure 4, showing the time series of vacancies (along with hires and quits). There were roughly 3.7 million vacancies at the end of August this year, compared with roughly 4.5 million at the end of August 2007, just before vacancies began to decline. This essay finds considerable cyclical unemployment, but does not explore the roles of different causes of this outcome. Thus cyclical unemployment is referred to as implying a role for stimulus policy, without specifying policies. Nevertheless, I report my view that while I do not think there is a single issue that fully explains the depth and severity of the current cycle, I do think that inadequate aggregate demand, the first reason cited above, is a major part of the story.

Barlevy concentrated on the steady-state relationship between unemployment and vacancies. This approach does not give a role to the dynamic pattern of movements around the steady state curve. This has been approached using a differential equation model with cycling

---

<sup>15</sup> The rise from 5 to 7.1 represents the estimate of the structural portion of the rise of unemployment to the 9.4 percent value in December 2010, which was chosen to anchor the new Beveridge Curve. In further analysis, Barlevy discusses aspects of the matching function that lead him to conclude that his estimate of the structural portion of unemployment is an upper bound, and the actual level is lower.

between good state and bad state parameters, which produces a loop around the steady-state curve. Doing this, as calibrated to fit earlier recessions and recoveries did not find large movements around the curve (Blanchard and Diamond, 1989). Whether, and how much, a difference would appear from a calibration to fit the Great Recession is an interesting question.

The next section discusses the matching function in more detail, indicating some complications in attributing all of the shift in the Beveridge Curve to structural issues, issues that are expected to still be present once the economy again nears full employment. That is, insofar as analysis of the underlying determinants of the matching function implies that its measured efficiency parameter ought to decline and then reverse as a normal part of a business cycle, then shifts in the Beveridge Curve coming from at least some of the matching function changes do not signal a lasting shift in the Curve. Moreover, consideration of the matching function is a route to analyzing how recessions with different structures imply differences in the Beveridge Curve.

## **II. Matching (Hiring) Function<sup>16</sup>**

The standard matching function relates the flow of hires to the stocks of unemployed and vacancies, although some studies have included additional variables.<sup>17</sup> The Job Openings and Labor Turnover Survey (JOLTS) provides monthly estimates of hiring, both in the aggregate and disaggregated. Roughly 16,000 establishments are asked for the number of hires (and separations) during the month as well as the number of vacancies on the last business day of the month.<sup>18</sup> The Current Population Survey (CPS) asks roughly 60,000 households about labor

---

<sup>16</sup> The term matching function has two different uses in the literature. In empirical work, it refers to hiring; in theoretical work, to a meeting of a worker and vacancy, which may or may not result in a hire.

<sup>17</sup> For an earlier survey of estimates of the matching function, see Petrongolo and Pissarides (2001). Hiring is also related to flows of new vacancies as well as to the stock in some of the literature, see Coles, and Smith (1996), Gregg and Petrongolo (1997). As discussed below, Davis, Faberman and Haltiwanger (2012b) find greater hiring per vacancy among establishments doing more hiring in cross-section data. They incorporate in the matching function a variable based on aggregate hiring, reflecting the level of desired hiring and call it “recruiting intensity.”

<sup>18</sup> A job opening requires that: 1) a specific position exists and there is work available for that position, 2) work could start within 30 days regardless of whether a suitable candidate is found, and 3) the employer is actively recruiting from outside the establishment to fill the position. Included are full-time, part-time, permanent, short-term, and seasonal openings. Active recruiting means that the establishment is taking steps to fill a position by advertising in newspapers or on the Internet, posting help-wanted signs, accepting applications, or using other similar methods.

force status of the members of these households during the survey reference week (usually the week that includes the 12th of the month). Thus an estimate of the matching function based on JOLTS and CPS relates hiring during the month to unemployment and vacancy levels at a point in the month (and/or the month before).

With the matching function playing a central role in his analysis of the Beveridge Curve, Barlevy (2011) analyzes the matching function directly, as well as indirectly through the Beveridge Curve, as described above.<sup>19</sup> That is, using the same Cobb-Douglas coefficients on unemployment and vacancies, Barlevy calculates the multiplicative (efficiency) parameter of the matching function that fits the monthly observations on hiring coming from JOLTS. His findings (Barlevy, 2011, Figure 3) are shown in Figure 5. Barlevy noted that: “as evident from figure 3, match productivity using data on new hires starts to fall around December 2007, considerably before any indications of a shift in the Beveridge Curve relating unemployment and vacancies.” (P. 89.) Furthermore, the estimated matching function efficiency parameter stops its significant decline about the time the Beveridge Curve starts shifting out. This suggests that a decline in the matching function can be part of the normal Beveridge Curve pattern in a recession and that additional factors influence the relationship between the Beveridge Curve and the matching function.

The unemployed make up only a fraction of new hires, as newly hired workers include labor market nonparticipants (those outside the labor force) and workers already employed as of the previous interview. Thus the matching function is a relationship between hiring and two proxy variables for hiring, a relationship that would change if the omitted variables changed their patterns relative to unemployment or vacancies or hiring or if disaggregation of vacancies implied a changed relationship between the aggregates. Next are examined how the hiring of nonparticipants and then of the already employed affect the measurement of the matching function. Then is examined the disaggregated data on the filling of vacancies across firms and industries and how changes over the cycle in the disaggregated pattern of vacancies can affect the measurement of the matching function.

---

<sup>19</sup> For another analysis of the efficiency parameter of the matching function, using help wanted data for vacancies, see Barnichon and Figura (2011a, b). They find that the matching function efficiency parameter has a cyclical component over the period 1967-2006.

## Flow of workers into employment

Studies of labor market worker flows have long reported on the sizable flows among all three categories, of employed, unemployed and nonparticipants. Errors in the classification of workers that are not important for measuring the stocks are important for measuring the flows and several approaches have been taken to adjust the data for misclassification, which give broadly similar results. Figure 6 shows average adjusted and unadjusted monthly flows for the period October 1995 to September 2012. Note that the large adjustments for misclassification involve nonparticipants. Using the adjusted flows, on average over this period, 2.0 million workers went from unemployed one month to employed the next (a UE flow), and a number nearly as large (1.7 million) went from being nonparticipants one month to being employed the next month (an NE flow). Thus the stock of unemployed used in both the Beveridge Curve and the matching function serves as a proxy variable for the availability of nonemployed workers to move to employed. Note that the number of nonparticipants who report that they want a job is a sizable fraction of the number of unemployed. The reasonable quality of the overall fit of the standard matching function, on average, speaks to the degree of stability of the overall proxy relationship. Indeed the strong similarity in Beveridge Curves drawn using the standard unemployment rate (shown in Figure 1 above) and using the U-6 unemployment rate (shown in Figure 7) speaks to the stability of the relationship in general terms. The U-6 measure is: Total unemployed, plus all persons marginally attached to the labor force, plus total employed part time for economic reasons, calculated as a percent of the civilian labor force plus all persons marginally attached to the labor force.<sup>20</sup>

Similar to comparing Beveridge Curves using unemployment and the U-6 measure, would be comparing estimated matching functions using just unemployment and using a weighted sum of the different elements in the U-6 measure.<sup>21</sup> However, just as differences between the Great Recession and earlier recessions and recoveries could show up as a shift in the

---

<sup>20</sup> Persons marginally attached to the labor force are those who currently 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. Discouraged workers, a subset of the marginally attached, have given a job-market related reason for not currently looking for work. Persons employed part time for economic reasons are those who want and are available for full-time work but have had to settle for a part-time schedule.

<sup>21</sup> For exploration of the use of a weighted sum of different pools of labor, see Blanchard and Diamond (1989, 1990b).

standard matching function, so, too, could changes in hiring outcomes show up as a different set of weights on the different groups of employed and nonemployed workers in a broader matching function. Indeed a key question for interpreting current circumstances is the extent to which we expect different outcomes given the differences across recessions - in severity, in length, in the state of financial firms, in the state of the housing market, and in fiscal positions of state and local governments. Another approach to the diversity of positions of new hires is to use a three dimensional analog to the Beveridge Curve, using a measure of the relevant portion of the nonparticipants, along with unemployment and vacancy rates, as has been done in Veracierto (2011).<sup>22</sup>

Figure 8 shows the time series of aggregate flows into employment from unemployment and nonparticipation since February 1990. With a large increase in the number of unemployed during recessions, the flow from unemployment to employment went up rapidly during the recessions shown and then stopped rising and, some time after, started falling. In contrast, the NE flow, from nonparticipation to employment, varied less than the UE flow and tended to fall during the recessions and then to start slowly rising, more slowly than the flow from unemployment was declining. Figure 9 shows the ratio of the two flows, showing a sharp drop in the NE/UE ratio during the recessions and slow rises afterwards. By itself, this pattern in the NE/UE ratio would tend to fit with a decline in the total amount of hiring relative to the numbers of unemployed, and so a sharp decline in the estimated matching function efficiency parameter in a typical recession, followed by a rising efficiency parameter after the trough. The NE/UE ratio peaked earlier than the start of the Great Recession and is still very low compared with the earlier available data. Comparing Figures 5 and 9, the timing of the decline in the efficiency parameter is roughly in line with the fall in NE/UE, but after that, the efficiency parameter is roughly constant while the NE/UE ratio was rising, but still low.

---

<sup>22</sup> Veracierto (2011) has considered three-state models, contrasting the results to two-state models. Summarizing the data in Figure 14 of the paper, Veracierto reports that: “these transition rates were relatively stable prior to 2007:12. However, we see that with the onset of the recession, there was a significant drop in the transition rate from nonparticipation to employment, a drop in the transition rate from unemployment to nonparticipation, a large increase in the transition rate from nonparticipation to unemployment, and a large increase in the transition rate from employment to unemployment. In turn, the transition rate from employment to nonparticipation was not significantly affected.” The paper appears to use unadjusted flow numbers.

To explore the role of these two sources of workers available to be hired, assume that some of the nonparticipants,  $\tilde{N}$ , are part of the matching function,  $\tilde{H}[U, \tilde{N}, V]$ .<sup>23</sup> As a starting place, assume that the relevant nonparticipants are perfect substitutes for the unemployed, up to a constant reflecting their availability. The constant could reflect differences in worker search intensity, in group demographic makeup, and in employer perceptions about suitability. Assume that this hiring function is Cobb-Douglas, as is the proxy function,  $H[U, V]$ , and that both functions have the same Cobb-Douglas exponents.<sup>24</sup>

$$\begin{aligned}\tilde{H}[U, \tilde{N}, V] &= \tilde{A}(U + \beta\tilde{N})^\alpha V^{1-\alpha} \\ H[U, V] &= AU^\alpha V^{1-\alpha}\end{aligned}$$

Assume that the parameters of the augmented function do not vary. Then, the measured efficiency parameter of the standard hiring function satisfies

$$\begin{aligned}AU^\alpha V^{1-\alpha} &= \tilde{A}(U + \beta\tilde{N})^\alpha V^{1-\alpha} \\ A &= \tilde{A}\left(\frac{U + \beta\tilde{N}}{U}\right)^\alpha = \tilde{A}\left(1 + \frac{\beta\tilde{N}}{U}\right)^\alpha\end{aligned}$$

Under this assumption of perfect substitutes, the ratio of the stocks of available effective job-seekers,  $\beta\tilde{N}/U$ , equals the ratio of hires, NE/UE, supporting the approach to the interpretation given above.<sup>25</sup> Note that the larger the stock of unemployed the lower the level of  $A$  for a given  $\tilde{N}$ . This would contribute to a wider loop in the dynamics around the Beveridge Curve the more severe the recession. Of course the relevant portion of the nonparticipants could also be changing as could the relative importance parameter  $\beta$ . There is no apparent reason that this part of the

---

<sup>23</sup> While some questions in the CPS can be used to estimate the nonparticipants more likely to become employed, I continue examining the standard matching function.

<sup>24</sup> It need not be the case that the estimated exponent coefficient on the standard matching function is the same as the coefficient on the augmented function, but this case is a natural starting place.

<sup>25</sup> Further steps could explore the relationship between the ratio of hires and estimates of the efficiency parameter of the matching function. And an endogenous value of  $\beta$  could be considered through an urn-ball ranking model (along the lines of Blanchard and Diamond, 1994). The high ratio of unemployed to vacancies after the trough was reached suggests that  $\beta$  might have continued declining for a period thereafter.

decline in the matching function would be long-lasting once the economy recovers, and, so, no reason to view the additional unemployment from this effect on the matching function as structural.

### **Flow of employed workers into new employment**

A similar issue for the measurement of the matching function comes from the hiring of those already employed, as workers who are employed one month are often with a different employer the following month, an EE flow. Figure 10 provides the relative sizes of different flows over the period October 1995 to September 2012, although the table includes no adjustments for misclassification, presumably a much bigger issue with change in status than with EE flows.<sup>26</sup> The table reports the flows in two ways. The top of the table relates the flows to population, and so gives the relative sizes of the absolute flows. Note that the EE flow of 1.4 percent of the population is larger than the unadjusted UE flow and almost as large as the unadjusted NE flow. From the relative sizes of adjusted and unadjusted flows in Figure 6, assuming no significant adjustment in the EE flow is called for, the flow considerably exceeds either of the other two flows into employment, emphasizing the proxy nature of the patterns in both the Beveridge Curve and the matching function. While one could examine matching functions for the separate flows into employment from the three sources, the hiring rates would depend on all three classifications of workers seeking employment or a change in employer.

Using quarterly data, tabulated on a recently constructed multi-state pilot database, Hyatt and McEntarfer (2012) reports on the time series of flows out of employment to other jobs and to non-employment (Figure 11). The flow from job to job that is without a reported nonemployment spell in between shows a sharp drop during the Great Recession and a continued very low level. This is consistent with the large drop in quits shown in the JOLTS data during the recession, and the slowly rising, but still low, level of quits during the recovery (Figure 4). Thus we appear to have a period where EE flows are way down, as are NE flows, but not UE flows.

Paralleling the logic above we can consider a matching function that incorporates a fraction of the employed, those who are readily available for a move to a different employer.

---

<sup>26</sup> Moscarini and Thomsson (2007) analyze CPS data for 1994-2006 and “revise upward current estimates of the EE flow from 2.7% to 3.2% per month.” (p. 809.) [Nagypál](#) (2008) also discusses data adjustments.



From the decline in quits and EE flows we can conclude that the relevant stock of available employed may be down considerably, although part-time work for those preferring full-time work is up. As in the consideration of the nonparticipants above, this is consistent with a decline in the measured efficiency parameter of the standard matching function during the recession and a continued low level of the efficiency parameter during the recovery, but not directly to further declines. Again there is no apparent reason to think this pattern would be long-lasting once the economy recovers.

Much of the quit portion of the EE flow (apart from quits motivated by anticipated layoffs) results in vacancies for replacement hiring. In this case, a vacancy that is filled by an employed worker generates a replacement vacancy, although with a delay and with the possibility that the two types of vacancies are filled at different speeds.<sup>27</sup> Presumably quits particularly happen in firms with high turnover. As estimated by Davis, Faberman and Haltiwanger (2012b) and discussed below in reference to Figure 12, high turnover firms fill their vacancies much more rapidly than do low turnover firms. Presumably the drop in quits implies a drop in the fraction of hiring happening in high turnover firms, and so an increase in the average time to fill a vacancy in the economy. This aggregation effect, like the others discussed below, is a reason for a temporary decline in the matching efficiency parameter, as there is no apparent reason for the relative weights to be permanently changing.

### **Filling vacancies**

JOLTS reports hires and separations for the entire month, while employment and job openings are reported for a single point in the month (the pay period including the 12<sup>th</sup> of the month and the end of the month respectively). Davis, Faberman and Haltiwanger (2012b) analyze the establishment-level data for the period from the start of the data in December 2000 through December 2006, and look at published data through December 2011. They find that the speed of filling a vacancy varies by industry, by firm size, by turnover, and by firm growth, and the proportion of hiring in different industries varies significantly over the business cycle. Thus the aggregate matching function should vary with changes in the distribution of vacancies in multiple dimensions.

---

<sup>27</sup> On such vacancy chains, see Akerlof, Rose and Yellen (1988).

Complicating the picture is the fact that much hiring happens without triggering a measured vacancy. In terms of basic measurement, they report that “Employers with no recorded vacancies at month’s end account for 45% of aggregate employment. At the same time, establishments reporting zero vacancies at month’s end account for 42% of all hires in the following month.” Of course, there can be hiring after posting a vacancy that is filled quickly enough that the hire appears in the data for the month but the vacancy did not appear at the date when outstanding vacancies were measured. Also there appears to be hiring without having a posted vacancy as an opportunity to hire is taken advantage of. These observations indicate the proxy role of measured vacancies for the matching function, as well as the proxy measure of unemployment, as argued above.

Davis, Faberman and Haltiwanger disentangle the within-month time structure of posting and filling vacancies by modeling a smooth discrete-time daily process, selecting daily parameters that are consistent with the observed monthly data, and assuming that all hires follow a vacancy. The model succeeds in accounting for two-thirds of the hires in establishments without reported vacancies, suggesting that hiring without a posted vacancy is significant, albeit less so than in the raw data. While they report multiple measures of vacancy filling, Figure 12 reports only the mean time to fill a vacancy across three different groupings of firms. They find significant differences in the speed with which vacancies are filled on average across industries - the mean time to fill a vacancy is 8.3 days in construction and 35.4 days in health and education. These are two sectors that have different hiring experiences in typical recessions and recoveries, and particularly so in the Great Recession. This should affect the matching function efficiency parameter without implying a lasting change in the parameter, beyond any continuation of trend effects, once relative hiring returns to something similar to the previous relative industry hiring pattern.

The mean time to fill a vacancy in firms with fewer than 250 employees is roughly half the rate at firms with at least 1,000 employees. Moscarini and Postel-Vinay (2012) argue that “The differential growth rate of employment between large and small U.S. firms is strongly negatively correlated (in deviations from trend) with the contemporaneous unemployment rate.” (P. 2509.) This pattern should affect the aggregate matching efficiency parameter increasing it with high unemployment and lowering it with low unemployment. The paper includes discussion

of 2009-2010. The relative performance of small firms early in the recession (2008:IV) was poor, compared to previous recessions, in line with the credit channel idea. But in 2009, already small firms did rebound, relative to large firms. Ever since, large firms have created very little employment on net. Most of job creation since 2010 is from small firms. In addition, both the vacancy rate and the vacancy filling rate of large establishments in JOLTS fell during the recession much more than at small establishments. Since 2010, this composition effect would contribute to an increase in aggregate matching efficiency parameter.<sup>28</sup>

In the third category shown in Figure 12, Davis, Faberman and Haltiwanger report that mean duration varies by a factor of ten across quintiles sorted by turnover ratio. Presumably quits occur disproportionately in higher turnover firms. Thus the drop in quits shown in Figure 4 is plausibly linked to a relative drop in the number of vacancies at higher turnover firms, and so a further source of a decline in the aggregate matching efficiency parameter. The slow recovery of quits would limit the rise of the parameter during the current recovery. The three categories of diversity in hiring rates are not simply additive, but include overlap as turnover rate plausibly varies with firm size and both of those factors vary by industry.

Davis, Faberman and Haltiwanger (2012b) note the very strong cross-section pattern that firms that do more hiring have a higher yield per vacancy. This pattern presumably interacts with other factors in determining the speeds of filling vacancies shown in the figure. They argue that

“One possibility is that employers act on other margins using other instruments, in addition to vacancies, when they increase their hiring rate. They can increase advertising or search intensity per vacancy, screen applicants more quickly, relax hiring standards, improve working conditions, and offer more attractive compensation to prospective employees. If employers with greater hiring needs respond in this way, the job-filling rate rises with the hires rate in the cross section and over time at the employer level.” (p.20).

They refer to modeling this concern as incorporating “recruiting intensity.” As recruiting intensity is not readily available as a variable, they multiply vacancies by a proxy measure for

---

<sup>28</sup> There is an important pattern of hiring relative to ages of firms. Presumably the pattern of hiring by age varies in typical cycles and may have varied differently in the Great Recession. That would be interesting to explore.

average recruiting intensity to obtain a measure of effective vacancies. To analyze aggregate matching they use the standard Cobb-Douglas matching function, but using effective vacancies.

They model effective vacancies as vacancies multiplied by aggregate hires raised to the power  $\varepsilon$ . In effect, they assume that the number of vacancies and recruiting intensity are jointly chosen to hit the hiring target (in terms of both numbers and worker match qualities), with an underlying constraint reflecting the state of the labor market underpinning the chosen levels of the two variables. They propose that the economy-wide average effective-vacancy parameter varies with the level of aggregate hiring with the same exponential coefficient on hires,  $\varepsilon$ , as fits the cross-section data. Denoting their generalized hiring function by  $G[U, V]$ , we have

$$G = AU^\alpha (G^\varepsilon V)^{1-\alpha} = AU^\alpha V^{1-\alpha} G^{(1-\alpha)\varepsilon}$$

Of course, they did not run a regression with aggregate hires on both sides of the regression. Solving for hires results in

$$G[U, V] = \{AU^\alpha V^{1-\alpha}\}^{1/(1-(1-\alpha)\varepsilon)}$$

They did not regress aggregate hires on unemployment and vacancies and then interpret the coefficients in terms of the model. Presumably the common finding of roughly constant returns to scale in estimates of the matching function (Petrongolo and Pissarides, 2001) suggests little ability to capture the effect of recruiting intensity in this way.

Davis, Faberman and Haltiwanger use a calibrated simulation approach, taking values of  $\alpha = 0.5$ ,  $\varepsilon = 0.82$  and  $A$  chosen to equate the mean value of the theoretically implied vacancy yield to the empirical vacancy yield. They find a better fit than with the standard matching function: “our recruiting intensity measure explains about one quarter of the aggregate time-series residuals produced by the standard matching function, residuals that other authors interpret in terms of mismatch or fluctuations in matching efficiency.” (Davis, Faberman and Haltiwanger, 2012b, p. 4-5.) And they examine the behavior in the Great Recession of recruiting intensity,  $G^\varepsilon$ . Figure 13 [their Figure 1] “plots national time series for the job-filling rate and recruiting intensity per vacancy. The job-filling rate rose sharply, from 4.4 percent per day in December 2007 to a peak of 6.6 percent per day in August of 2009. It fell steadily thereafter,

though it remains above prerecession levels at 4.8 percent per day as of September 2011. Recruiting intensity per vacancy fell sharply during the Great Recession, declining by over 21 percent between December 2007 and its trough. It remains 11 percent below its pre-recession level as of September 2011.” (Davis, Faberman and Haltiwanger, 2012c, p. 4.) Note that recruiting intensity started declining before the start of the recession, consistent with the timing discussion of Barlevy’s analysis above.

Thus the drop in recruiting intensity, working against the effect of the rise in unemployment per vacancy on the rate of job filling, pushed down the measured efficiency parameter of the standard matching function. The magnitude of the effect of using their generalized matching function can be seen in Figure 14 (their Figure 1) which calculates the vacancy yield – hires divided by vacancies – comparing the standard and generalized functions. Thus recruiting intensity offsets some of the decline in matching, but only a fraction. Presumably recruiting intensity will recover when the economy recovers.

The formulation does not explicitly recognize a difference between trend growth and cyclic growth in hiring. But Davis, Faberman, and Haltiwanger (2012a) Figure 5 and Table 1 show the different distributions of establishment-level growth rates comparing 2006q1-4 to 2008q3-2009q2. This shows not only a change in the mean of the cross-sectional density of employment growth rates, but also the shape, as there is little apparent change around the spike in the distribution around zero hires. While different impacts of gross hires might be captured by the presence of the U/V ratio in the Cobb-Douglas function, this analysis suggests that an alternative formulation might be promising, just as some macroeconomists’ attention to the relationship between output and employment distinguishes between a Solow growth model and Okun’s Law. The decline in the share of fast-growing establishments presumably implies a drop in the fraction of vacancies at fast-growing firms and so a drop in the measured efficiency parameter of the matching function as a normal part of the cycle.

As noted in Figure 12, Davis, Faberman and Haltiwanger have documented multiple dimensions in the cross-section pattern of the speed in filling vacancies. As the distribution of establishments across these dimensions varies over a business cycle, so too will the estimated aggregate matching function. As business cycles vary, so too should the behavior of the

matching function. The Great Recession is marked by a depth and length beyond earlier postwar cycles. Also, the Great Recession has been marked by a financial crisis and the bursting of a housing bubble. All four of these elements (depth, length, strength of financial institutions, financial position of homeowners), as well as the behavior of other economies, should affect not only the mix of establishments across measured dimensions but the willingness to hire within categories. The distribution of establishment growth is plausibly a proxy for the eagerness to fill vacancies more widely than just among fast-growing establishments. Thought of as the reservation quality of a match or the role of additional actions to recruit job applicants, firm eagerness to hire should matter for the measurement of the aggregate hiring function. The concept of recruiting intensity reminds us that the cost of posting a vacancy is endogenous to the effort put into hiring. Indeed, the growing search literature modeling firm heterogeneity in size and profitability of additional hires is a reminder not to take literally the simplest models of the determination of the number of vacancies.<sup>29</sup>

Barnichon, Elsby, Hobijn and Şahin (2012) use monthly data from the start of JOLTS to the start of the Great Recession to relate labor market variables to the vacancy-unemployment ratio, ( $V/U$ ), including the vacancy yield (hires per vacancy) and the flows of quits, other departures from employment, and entry into and exit from the labor force. Using the estimated values, they fit curves for these rates to  $V/U$  since the start of the recession. For both the vacancy yield and the quit rate the fit is good and the actual values are systematically below the fitted values. For March 2012, the vacancy yield is 38 percent below and the quit rate 13 percent below the fitted values.

They use these flow rates to estimate a Beveridge Curve relating the unemployment rate to the vacancy rate by examining steady state unemployment rates given the estimated flows at a  $V/U$  ratio. The curve fitted before the start of the recession fits the recession well but lies below (to the left of) observations since the trough, a similar picture to that in the Barlevy analysis discussed above. They then turn to vacancy yields and quit rates at the industry level (for the 7

---

<sup>29</sup> Hobijn (2012) uses CPS, JOLTS and state-level job vacancy surveys that cover about 10 percent of the labor force to produce annual vacancy and hires estimates (and so vacancy yields) for 2005 through 2011. He finds “a lot of variation in job openings rates and vacancy yields across occupations” and that “the shift in occupation mix of job openings and hires since 2007 accounts for the bulk of the decline in measured aggregate match efficiency.” (P. 4-5).

main industries for which data is available). They relate the rates to aggregate and industry vacancy-unemployment ratios and examine the relationship between fitted and actual values since the start of the recession. They find low yields in each of the industries and low quits in all but government. Thus the behavioral responses and matching issues behind the movement in the Beveridge Curve are widespread – not solely a result of aggregation across diverse industries.

Another perspective on recruiting intensity comes from the difference, noted above, between meetings of job candidates with job openings and an actual hiring. The speed of filling a vacancy depends on the time to evaluate candidates and the tradeoff between hiring one of the current applicants and waiting to examine further applicants. As the tightness of the labor market changes, so too do the reservation wages and reservation match qualities on both sides. It is plausible that the sheer number of applicants per vacancy and the range of applicant qualities are likely to be higher from the depth and length of the current period of a weak economy, leading to a slower process of hiring, at least at large firms receiving many applications. Indeed there has been such a claim based on a survey of large firms by the Corporate Executive Board (Light, 2011).

### **III. Nonparticipation and the Beveridge Curve**

Section II considered the flows into employment, including discussions of the impacts on measurement of the matching function coming from differences in hiring across firms and from the flow from nonparticipation into employment. Some such shifts in the matching function appear to be part of a normal cyclical movement as the economy moves down the Beveridge Curve. Ignoring such changes in the matching function may be a problem when projecting the estimated Beveridge Curve beyond the range of historical data, as is the case for the Great Recession. Shifts in the matching function that differ from the typical pattern in recession and recovery and show up as shifts in the Beveridge Curve open up the question of whether they are temporary or long-lasting. This section examines effects on the Beveridge Curve from flows into unemployment. The division of the flow out of employment between nonparticipation and unemployment affects the stock of unemployed and so the Beveridge Curve. Also relevant are the flows between unemployment and nonparticipation.

The flows from employment to both unemployment and nonparticipation are shown in Figure 15. The flow into unemployment went up rapidly during the recession, as with the two earlier recessions in the data, but to a much greater extent. Then the flow showed a steady drop during the recovery, again similar to the two previous recessions. However, given the magnitude of the rise, the flow out continued to be much higher than before the recession, unlike the two other recessions. In contrast, the flow into nonparticipation went down, not up, during the recession and then did not change much. As shown in Figure 16, there was a sharp drop in the ratio of EN/EU in all three of the recent recessions. The Great Recession, being more severe and longer-lasting, has had a much larger and more extended decrease in that ratio. The rise in the ratio during the recovery has only restored a fraction of the previous decline.

The flows between unemployment and nonparticipation are shown in Figure 17, with the ratio, NU/UN, in Figure 18 and the difference, NU-UN, in Figure 19. While the two flows changed a lot, there was considerable parallel shape in the movements and so the ratio, which rose in the recession and then fell, did not vary as much as the ratio of the flows from employment. The difference shows a somewhat higher level flowing into unemployment than in the period before the start of the recession, but not very large.

Kudlyak and Schwartzman (2012) analyzes the direct effect of the four flows involving nonparticipation on the unemployment rate.<sup>30</sup> They consider the six hazard rates defined by the six flows among E, U, and N. They use the steady state approximation to the stocks, given these flows. Then they ask how the unemployment rate would be different if the four hazard rates involving nonparticipation remained as they were before the recession, while the hazard rates between employment and unemployment followed the actual empirical pattern, without a change along with the altered flow hazards involving nonparticipation. Figure 20 shows their calculation for four recessions.

“We find that in the 2007-2009 recession, had flows [rates] in and out of nonparticipation remained constant, the aggregate unemployment rate would have increased by 3 percentage points, while the actual unemployment rate increased by 5.5 percentage points. The flows to and from non-participation also accounted for a substantial part of

---

<sup>30</sup> The authors have pointed out that their analysis does not include an adjustment for misclassification.



the persistence of unemployment during the recovery. Two years after the 2009 unemployment peak, the counterfactual aggregate unemployment rate would have been 2 percentage points higher than at the start of the rise in unemployment, while the actual unemployment rate is 4 percentage points higher. In contrast, in the 1981-1982 recession, the counterfactual aggregate unemployment rate increases by 2.5 percentage points, while the actual unemployment rate increased by 3.75 percentage points. Two years after the 1982 unemployment peak, the counterfactual aggregate unemployment rate and the actual unemployment rate were equal to the rate at the start of the rise in unemployment.<sup>31</sup>” (p. 1-2.)

In sum, they conclude that from this source “the data indicate that, compared to previous recessions, the 2007-2009 recession is characterized by a particularly large increase in the unemployment rate and by a particularly slow decline in the unemployment rate from its peak.” (P.9.)

Several factors are likely to have combined to generate these patterns. The large extension of unemployment benefits is likely to have increased the extent of remaining in unemployment rather than leaving the labor force. The impact on aggregate hiring from this effect is plausibly not large given the availability of so many unemployed per vacancy through most of the economy, a view supported by some studies cited in footnote 9 above. In any event, this part of the effect is likely to go away when extended benefits end, as is likely to occur once the economy recovers.

The depth and length of the recession have contributed to a very large increase in the pool of long-term unemployed and so are likely to have affected the makeup of the pool of job losers, including more people with stronger attachment to the labor force than in the usual recession.<sup>32</sup> By increasing the stock of unemployed, this pattern would contribute to the appearance of a shift in the Beveridge Curve. Thus a key question is whether the flow into long-term unemployment will return to a more typical pattern as the economy recovers.

---

<sup>31</sup> Footnote in original: The unemployment rate is a nonlinear function of the six transition rates. Thus, our work shares the same criticism as some other works (for example, Shimer (2012)) that the values of the counterfactual depend on the values at which we fix the transition rates.

<sup>32</sup> For work in progress on these flows, see Elsby, Hobijn, and Şahin (2012).

Also relevant is whether worker experience of more time in unemployment and less time in nonparticipation has current effects or would have lasting effects. In terms of the modeling above, where the input into the matching function was written as  $U + \beta \tilde{N}$ , if a would-be nonparticipant is behaving in a way that qualifies for the label unemployed, how much does the contribution to hiring change? It seems that it need not be all or even much of  $1 - \beta$ . As to the long run, experiencing long-term nonemployment matters. Whether a long spell of nonemployment has a different long-run effect if some of it is nonparticipatory rather than unemployed does not seem likely to matter.

#### **IV. Mismatch**

An argument that structural unemployment has increased during a recession and/or early recovery is sometimes invoked as an argument for a smaller potential role for stimulative policies. This essay has explored two ways of making such an argument. One was from a shift in the Beveridge Curve and the second was from a drop in the efficiency parameter of the aggregate matching function. Both arguments were examined by exploring underlying factors that contributed to the measured shifts and arguing for the need for more detailed analyses, as both shifts can appear without supporting an argument for a change in the responsiveness of unemployment to the eventual recovery and to stimulative policies. A third type of argument is to identify an increase in “mismatch” as a reason for a decrease in the potential role of stimulative policy.

Analyses of mismatch in this sense are based on how the distributions of unemployed workers and vacancies differ across regions or industries or occupations or education levels or skills. Increases in measures of mismatch are then taken as a possible basis for inferences about structural changes and the potential scope for stimulative policies. The terminology of mismatch is evocative and the concept is widely used.<sup>33</sup> For example, mismatch is used in considering the impact on economic efficiency and unemployment of the distributions of educational attainment

---

<sup>33</sup> There were 1,235 results when I went to jstor and searched over economics on mismatch and unemployment. Searching over economics just on mismatch gave a count of 2,863 results.

and of college majors relative to job opportunities. While mattering for trend issues, neither of these two seems directly relevant for discussing stimulative policy today.

Key to this approach to mismatch is to find measures that link in a clear way to the stimulus policy debate, as the link between the intuitive meaning and a particular empirical measure is not always tight. For example, the title of Barlevy (2011), analyzed in detail above, is “Evaluating the role of labor market mismatch in rising unemployment.” For Barlevy, mismatch appears to be simply a decline in the efficiency parameter of the aggregate matching function, with no additional insight from a mismatch vocabulary. And “Mismatch” is the title of Shimer (2007), which uses a model of discrete labor markets, with each worker and each filled or unfilled job located in a single market during each period. As such, the paper contains a model of all of unemployment, not separate portions for cyclical and structural reasons. Based on particular structures for the distributions of the locations of new vacancies and of relocating workers, the paper derives a Beveridge Curve and shows a good fit with the measured curve. As with Barlevy, one can use the model to extend the Beveridge Curve outside the range of previously observed unemployment rates and then look for a shift in the curve. As the model refers to all of unemployment it does not appear to connect with using mismatch as a method of distinguishing cyclical from structural effects.<sup>34</sup>

### **Dispersion in outcomes**

The business cycle hits different sectors differently. Thus, the fact that employment growth rates or unemployment rates are diverse across industries (or occupations or regions) does not address the potential of stimulus policies if we expect the pattern to reverse when going from a recession through a recovery. This observation is well presented in Valletta and Kuang (2010), which shows historical dispersion patterns in unemployment rates and employment growth rates.<sup>35</sup> Figure 21 shows dispersions in these two variables across industries. The figure shows dispersions going up sharply (with somewhat different timing) in all the recessions since the

---

<sup>34</sup> Barlevy (2011) estimates Beveridge Curves using Shimer’s mismatch approach and contrasts the fit with that of his use of an aggregate matching function, as described above (see, Barlevy’s Figure 1). He notes that while the Beveridge Curves based on the aggregate matching function approach show little shift in two earlier recessions (1972-76, 1978-84) and appears to shift starting with the trough in the Great Recession, there is a shift in all three and a much earlier current shift with Shimer’s mismatch approach.

<sup>35</sup> The figures shown are updated and provided by Rob Valletta.

mid-1970s, and then coming down sharply. Currently and previously, unemployment dispersion has not responded as rapidly as employment growth dispersion.

Figure 22 shows dispersions across states. The historical patterns are considerably more diverse than those across industries. The Great Recession rise in dispersion in employment growth has been fully offset. The rise in dispersion in unemployment rates has declined but remains high. Figure 23 shows dispersion of unemployment rates across occupations. The dispersion has fallen considerably, but remains higher than before the start of the recession. These figures argue against trying to reach an early conclusion on the importance of structural factors from the shape of such mismatch dispersion measures. Rises and then falls in such indexes appear to be a standard part of business cycles, although patterns differ across variables and recessions. This analysis leaves unanswered the basic question of how much we should expect business cycles to differ when causes and severity differ, as is a particular issue with the Great Recession.<sup>36</sup>

The term mismatch invokes a sense of inefficiency. While an avoidable or inadequately offset recession is likely to be inefficient, there is no reason to think that different size impacts on different industries or occupations in response to a drop in aggregate demand is inefficient. Nor is it the case that efficiency calls for similar rates of job filling across industries or occupations.

### **Multiple Beveridge Curves**

In addition to analyses of a single Beveridge Curve for the entire economy, separate Beveridge Curves for different regions have been a basis for measuring mismatch. Beveridge (1945) recognized labor market frictions by defining full employment as fewer unemployed than vacancies. Taking equality as the measure of full employment, regional mismatch studies following the approach of Dow and Dicks-Mireaux (1958) discussed above, have considered the differences between unemployment and vacancy levels across regions. Drawing on the presentation in Rodenburg (2011), based on Cheshire (1973), the logic is based on the

---

<sup>36</sup> Lazear and Spletzer (2012) analyze the pattern of the unemployment-vacancy ratio across industries and occupations as a measure of mismatch. They conclude that “the analysis presented here shows that the most recent recession has not resulted in any long-run increase in mismatch across industries or occupations.” (P. 24.) In general, equality of U/V across industries or occupations is not a sign of economic efficiency. Barnichon and Figura (2011b) analyze the efficiency parameter of the aggregate matching function, using a measure of mismatch based on the differences in U/V across markets.

assumption that equality of unemployment and vacancies in a region represents full employment in the region. The measure of aggregate cyclical unemployment is then defined as the excess of aggregate unemployment over aggregate vacancies and so is not affected by the regional pattern of the variables for given aggregates. Instead the mismatch analysis draws a distinction between frictional unemployment and structural unemployment.

To spell out this approach to mismatch, define frictional unemployment ( $u_f$ ), as the sum over regions of the smaller of  $U$  and  $V$  in each region. This represents the unemployment that would be eliminated if, as in the standard frictionless market model, there was sufficient matching so that there was either unemployment or vacancies but not both. Define structural unemployment ( $u_s$ ), reflecting vacancies where there are not enough unemployed workers to potentially fill the vacancies, as the sum of the (positive) excesses of  $V$  over  $U$ . Thus frictional unemployment is the level that could be solved by additional matches without interregional movement, while structural unemployment comes from worker locations that would not be sufficient to fill all vacancies, given the locations of existing vacancies. Cyclical unemployment ( $u_c$ ) for the economy as a whole, the difference between aggregate unemployment and aggregate vacancies, is equal to the sum of unemployment over all regions minus the sum of vacancies over all regions.

$$\begin{aligned} u_f &= \sum \text{Min}[U, V] = \sum \{U : U < V\} + \sum \{V : U > V\} \\ u_s &= \sum \text{Max}[V - U, 0] = \sum \{V : U < V\} - \sum \{U : U < V\} \\ u_c &= \sum U - \sum V \end{aligned}$$

Needless to say, these three add up to total unemployment.

$$u_f + u_s + u_c = \sum U$$

Consider a stimulative policy that increases vacancies. Without a theory of how vacancies affect unemployment, such as matching functions by region, there isn't a direct implication within the model of the impact of the stimulus policy on unemployment. But one could assume that the increases in vacancies in regions with more unemployed workers than vacancies is more likely to reduce unemployment than increases in vacancies in regions with

fewer unemployed than vacancies. From this argument, it follows that the presence of more structural unemployment (and so less frictional and/or cyclical unemployment) is likely to make stimulative policy less effective at reducing unemployment.

Notice that there can be an impact on the measure of structural unemployment from a cyclical change. Consider a recession for an economy with a rectangular hyperbola Beveridge Curve, so that rises in total unemployment and falls in total vacancies are roughly equal in percentage terms. The measure of cyclical unemployment,  $u_c$ , equal to the difference between total unemployment and total vacancies, rises by more than total unemployment rises, as going into a recession reduces vacancies. It follows that there is a decrease in the sum of structural and frictional unemployments,  $u_f + u_s$ , equal to  $\sum U - u_c$ . The mix of changes between the two depends on the initial distribution unemployment and vacancies across regions and the distributions of changes in unemployment and vacancies. A return to the previous aggregate values would return both frictional and structural to the same values if the regional pattern is restored. The changes in measured frictional and structural unemployment do not signal what will happen once the recovery has matched the previous peak. If the regional pattern is not restored, there could be a change in the division of their sum between the two categories in either direction. That measures of cyclical and structural are jointly connected to the state of the cycle is simply illustrated in this example.<sup>37</sup>

### **Multiple matching functions<sup>38</sup>**

Using matching functions by sector, Şahin et al (2012) compare the level of hiring that happens with the actual distribution of the unemployed with the level of hiring that would happen if a planner could costlessly move the unemployed across sectors in order to optimize, given both the impact on hiring and the expected present discounted values of additional hires across sectors.<sup>39</sup> The planner would choose to equate the efficiency-weighted vacancy-unemployment rates across

---

<sup>37</sup> There are empirical analyses of separate regions in some countries. See, for example, Börsch-Supan (1991), which questions the distinction between cyclical and structural unemployment from a shift in the Beveridge Curve, based on analysis of regional data in Germany.

<sup>38</sup> Other analyses of mismatch using hiring functions include Herz and van Rens (2011).

<sup>39</sup> The analysis allows for differences in the matching efficiency parameter across sectors but not the Cobb-Douglas exponent. From the large diversity in job-filling rates found by Davis, Faberman and Haltiwanger, it the matching functions may well differ in exponent as well.

sectors. The Şahin et al mismatch index measures the fraction of hires lost in a period because the actual allocation of unemployed does not match the planner's optimum. Their empirical finding on their mismatch measure is:

We find no significant role for geographical mismatch across U.S. states or counties. Mismatch at the 2-digit industry and 2- and 3-digit occupation level increased markedly during the recession but declined throughout 2010, an indication of a strong cyclical pattern in mismatch. A similar, but milder, hump shape in mismatch is observed around the 2001 recession. With all the caveats associated to a short sample, we do not find evidence of a significant long-run "structural" shift in mismatch after the Great Recession. (p. 3.)

The pattern of measured mismatch through the cycle can be used, as with the dispersion measures above, as a test of whether the current cycle resembles previous ones. Interpretation of similarities and differences would be more complex than with the dispersion measures described above as the Şahin et al measures represent complex combinations of the patterns of unemployment and vacancies and so is harder to interpret than a weighted standard deviation.

In addition to their mismatch index, Şahin et al calculate the excess in the level of unemployment as a consequence of the actual allocation of unemployed workers rather than the optimum allocation used in their measure of mismatch. Starting from the unemployment rate at an initial date, the additional hiring from the planner's reallocation of unemployed workers can be combined with a given separation rate to track an alternative unemployment rate thereafter, which they refer to as "mismatch unemployment." The analysis is done separately by industry, by occupation, by education level, and by state.<sup>40</sup> They report:

that an additional four percent of monthly hires were lost during the Great Recession because of the misallocation of vacancies and job seekers across occupations and

---

<sup>40</sup> The analysis is done for the actual distribution of vacancies, assuming no impact on vacancy creation of the higher filling of early vacancies. An extension considers an impact on vacancies. In the extension they find: "that this channel depresses aggregate vacancy creation relative to the planner's solution, giving a further boost to mismatch unemployment. When this additional force is factored into our counterfactuals, the contribution of mismatch to the observed rise in the unemployment rate grows by a maximum of two thirds of a percentage point. We therefore conclude that, at the analyzed level of disaggregation, mismatch can explain at most 1/3 of the recent rise in the U.S. unemployment rate since 2006." (p. 3-4.)

industries. As a result, our counterfactual analysis indicates that mismatch unemployment at the 2-digit industry level can account for 0.75 percentage points out of the 5.4 percentage point total increase in the U.S. unemployment rate from 2006 to October 2009. At the 3-digit occupation level, the contribution of mismatch unemployment rises just beyond 1.5 percentage points. (p. 3.)

They conclude that “while our benchmark planner’s allocation is derived under costless between-sector mobility, our calculations on the role of mismatch are an upper bound. In light of this remark, the finding that mismatch is not a chief determinant of the persistently high U.S. unemployment appears even more compelling.” (p. 5.)

If this measure of mismatch unemployment is to contribute to the stimulus debate, one needs to consider how the measure is relevant for evaluating the potential in additional stimulus. That is, what do we learn about the potential impact of additional stimulus from a comparison of the actual outcome (without the stimulus) with a counterfactual with optimized costless mobility. The elements they model would be part of analysis of a proposal for subsidies for worker movements across markets. Such analysis, while including elements they consider, would also need to recognize the actual mobility costs and the pattern of mobility chosen by the workers, not a planner. The workers would not necessarily relocate in an optimal pattern as the presence of search externalities that differ across markets means that worker choice on movement is not generally efficient.

For a cost-benefit analysis of stabilization policies, one wants to compare outcomes with and without a given policy. While their analysis incorporates prime factors that would be included in a benefit-cost evaluation of a mobility subsidy, it is not apparent how it would help with a benefit-cost analyses of stimulus policies. The measure of mismatch unemployment reflects hires that did not happen because workers did not move to match the optimization. It is not clear what that tells us about a limit on the change in employment after a stimulus policy. I do not see why a calculation of how different the outcome would be with costless planner-set worker relocation sheds light on this question, nor how it contributes to trying to tell apart temporary rather than long-lasting effects on unemployment.

### **Construction workers**



In addition to references to economy-wide measures, there is periodic mention of specific concerns about unemployment. Some voiced concerns are about the difficulty of filling some class of vacancies, for example those involving science, technology, engineering and math (STEM) skills. While STEM-skilled worker availability is a real concern for education and immigration issues, and so for trend employment issues, it is not apparent how that has relevance for a discussion of current stimulus policy. It is not as if STEM vacancies were the dominant source of vacancies in the economy nor that the appearance of additional hard-to-fill vacancies would dominate the effect of a stimulus on vacancies. Nor would we expect the trend issue to show sudden large movements for structural reasons.

A separately voiced concern refers to possible difficulties in worker movements across sectors, particularly out of construction given the large drop in both residential and commercial construction after the bursting of the housing bubble. For example, in an interview for The Wall Street Journal published on February 12, 2011, Philadelphia Federal Reserve Bank President Charles Plosser said: “You can't change the carpenter into a nurse easily, and you can't change the mortgage broker into a computer expert in a manufacturing plant very easily. Eventually that stuff will sort itself out. People will be retrained and they'll find jobs in other industries. But monetary policy can't retrain people. Monetary policy can't fix those problems.” This focus on the industries particularly hard hit by a recession and on the role of cross-sector, cross-occupation movements may be viewed as an issue particularly for this recession, or as a concern about stabilization policies generally.

It was well recognized that employment in construction fell strongly and recovery in construction would be slower than in the usual recession after the considerable overbuilding before the Great Recession (e. g., Hall, 2011). But, given widespread high unemployment relative to vacancies throughout the economy, it is not clear that this observation about construction seriously affects the standard analysis of the labor market effects of a stimulus program.

To put into context the issue of construction workers moving across sectors and occupations, it is useful to review the reemployment experience of unemployed construction workers and how that compares with the experience of other workers. Analysis of the

unemployment experience of construction workers is in Crump and Şahin (2012). As shown in Figure 24, unemployment among construction workers shot up as construction declined sharply, resulting in a rising share of construction workers in total unemployment. And then the share was falling rapidly.<sup>41</sup> Crump and Şahin also compare the job-finding rate of construction workers with that for total workers. The former is consistently higher (reflecting the nature of the jobs and employers in construction) but a relevant fact is that the rate was climbing for construction workers in late 2010 and 2011 while it was mildly falling for total workers.

The movement of displaced construction workers across sectors can also be put in the context of displaced workers in the economy as a whole. The biennial BLS Displaced Worker Survey examines those who lost or left their jobs at some point in the three previous calendar years.<sup>42</sup> They are asked about their status in the January following the three-year period. Thus the outcomes cover workers whose job loss was anywhere from the previous month to three years earlier. As reported on the BLS website from the 2012 survey, from January 2009 through December 2011, 6.1 million workers were displaced from jobs they had held for at least 3 years. Of these workers, 56 percent were reemployed in January 2012, 27 percent were unemployed and 17 percent were out of the labor force. The total number of workers displaced between January 2009 and December 2011 (regardless of how long they had held their jobs) was 12.9 million, of whom 57 percent were reemployed and 28 percent were unemployed in January 2012. For the prior, 2010, survey (which covered the period from January 2007 through December 2009) 49 percent of the three-year tenured workers were reemployed, 36 percent unemployed and 15 percent out of the labor force. For all workers the percentages were 49, 36, and 15.

Tasci (2012) examines reemployment rates from the BLS Displaced Worker Surveys. Figure 25 shows the rates by industry for the last three of the biennial surveys. It shows that the reemployment rates of construction workers were roughly the same as the economy-wide average in all three surveys. Data is also available by occupation, although interviews are likely

---

<sup>41</sup> Unemployment by sector reflects the last job held, so construction workers making moves and then becoming unemployed are not attributed to construction.

<sup>42</sup> Displaced workers are wage and salary workers 20 years of age and older who lost or left jobs during the previous three calendar years because their plant or company closed or moved, there was insufficient work for them to do, or their position or shift was abolished. And they are asked about their labor force status in the January following. Some data are presented for “long-tenured displaced workers”--those who had worked for their employer for 3 or more years at the time of displacement. Data on displaced workers have been collected from a special supplementary survey to the CPS conducted every 2 years since 1984.

to have more errors in identifying occupations than in identifying industries. For the occupational category “natural resources, construction, and maintenance,” the reemployment experience (48 percent in the 2010 survey for long-tenured workers and 60 percent in 2012) is roughly the same as that of the entire workforce (49 percent in 2010 and 56 percent in 2012). For all workers (regardless of how long they had held their jobs) in 2012 the percentage of this occupation reemployed is 58, as opposed to 56 for all occupations.

President Plosser’s quote raises the question of mobility between sectors. It is natural to ask whether reemployment with a move across sectors is common or uncommon and whether construction worker experience was typical or atypical. Figure 25, based on the January 2010 Displaced Workers Survey, shows the reemployment rates divided between workers staying in the same industry and moving across industries. The figure shows that movement across sectors is common and while the fraction of reemployed construction workers moving to another industry is a bit lower than typical, it is not dramatically so. Of course, many industries employ a wide range of occupations, so a movement across industries need not be a movement across occupations.<sup>43</sup>

Basically, with the ratio of unemployed to jobs very high in all sectors, concentrating on hard-hit sectors ignores other sectors and ignores the fact that movement between sectors is always happening. Given the huge volume of hires in the economy (over 3.9 million in January 2011, just before Plosser’s interview) and the diversity of paths people follow in their employment histories, a focus on these particular paths out of unemployment seems of little relevance for considering the potential in monetary policy. Stimulating the economy, increasing

---

<sup>43</sup> Hobijn (2012) uses CPS, JOLTS and state-level job vacancy surveys that cover about 10 percent of the labor force to produce estimates of cross-industry and cross-occupation hiring matrices for 2005 through 2011 (Tables 9 and 10). He finds “hires for in a particular industry or occupation are about as likely to be of someone who previously was not in the labor force (NILF) as of someone in the same industry or occupation. Second, for all industries and occupations less than 45 percent of hires are from the same industry or occupation respectively. The industry most likely to hire workers previously employed in it is “Construction”. Similarly, “Construction and Extraction” jobs are the occupation where hires are most likely to be from the same occupational group.

The last row of both tables reports the percentages of hires in the same industry and occupation conditional on a worker having a previous job. Even if one conditions on the person hired having a previous job, still for all industries and occupations more than 3 out of 10 workers are hired from a different sector and job classification.” (P. 29.) As above, in this comparison, the highest percentages are for the “Construction” industry and “Construction and Extraction” jobs. He warns of misclassification errors.

the value of more production, can draw many unemployed back into the same industry and occupation as before as firms hire more to produce more. And many occupations show up in other sectors as well. And the tighter the labor market, the harder to find already-trained workers, the greater the incentive for firms to assist and speed the retraining process.

While a concept of mismatch is often invoked in discussions of the role of stabilization policies, it is possible that the concept of mismatch does not help with evaluating a target for full employment once the economy recovers. This is not to suggest that more stimulus is always good, since that is not the case. This is not to suggest that there are not positions that are difficult to fill. That is always the case. It is not simple to project how an unusual recession and recovery will unfold.

## **V. Cyclical Unemployment, Structural Unemployment**

Whenever unemployment stays high for an extended period, it is common to see analyses, statements, and rebuttals about the extent to which the high unemployment is “structural” or “frictional,” not “cyclical.” All three terms, along with “mismatch” (discussed above in Section IV) and “full employment” are evocative and link intuitively to ways of framing policy debates about unemployment. As such, all the terms call for definition and measurement.

There are multiple debates about unemployment beyond the potential role of stimulus policies to address cyclical unemployment. These include issues about education, training and retraining, regulations governing hiring and firing, design of unemployment insurance, provision of support services, and the nature of data to be collected. This essay has considered a single question: the extent that outcomes in the labor market, particularly as seen in the Beveridge Curve, imply that the future target for unemployment, once the economy has recovered, should be different from the level of unemployment in the period before the onset of the Great Recession. I have used the term full employment to refer to the state of the labor market at a desirable previous outcome and as a desirable target for the future, without exploring what characteristics indicate a good outcome. I have referred to increases in structural unemployment as changes in the labor market that imply that the recovery target level of unemployment should be higher than the level before. The term cyclical unemployment, as a residual, measures the

excess of current unemployment over that future target, an excess that gives a potential role for stimulus policies.

Following Barlevy (2011), the first section examined the magnitudes of cyclical and structural unemployments under two assumptions – that the shift in the Beveridge Curve to fit recent data would last through the recovery and that the new full-employment equilibrium would lie on that curve at a point consistent with a higher unemployment-vacancy ratio than at the previous full employment point. Such a rise in the unemployment-vacancy ratio between full-employment points would be consistent with a lasting decline in the ability to fill jobs, consistent with a lasting decline in the matching function. Thus, a critical question is the extent to which the decline in the aggregate matching function is structural in that it will last through the recovery, and the extent to which the decline is cyclical and will reverse as the recovery approaches a new full-employment point.

The second section explored causes of the decline in the efficiency parameter of the matching function, while asking whether the causes were expected to last through a full recovery. The examination of the causes considered both the patterns in previous recoveries and possible implications of the differences in causes and magnitudes between the Great Recession and previous recessions and recoveries. Some of the causes are related to aggregating different speeds of filling vacancies across firms, industries, and occupations; others to the labor market flows among employed, unemployed and nonparticipants, as well as the flow of already employed workers to other jobs. Some changes in the distributions of vacancies and the patterns of hiring and exiting from employment are likely to reverse as the economy recovers more fully. Lower matching caused by these changes is then cyclical not structural. As the Great Recession has lasted a long time, some continuing trends that affect unemployment, such as demography and the technological impact on the distribution of jobs, may well be structural, may well have an impact on the desirable future unemployment target.

Two issues were not examined in this essay: the influence of extended unemployment insurance benefits and of house lock coming from the decline in house prices. Estimating the impact of extended benefits on both unemployment and employment is highly relevant as part of evaluating the time period and duration of extended benefits. However, as benefit extension is not likely to be continued through a full recovery, most or all of any measure of increased

unemployment from this cause is naturally presumed to go away with a full recovery and the end of extended benefits. Thus, this additional unemployment might be deemed structural in the sense of caused by the design of unemployment insurance, but not structural in the sense of lasting through a full recovery; relevant for one policy analysis but not for another.<sup>44</sup> Not answered by a projected end of extended benefits is the future effect on the unemployment rate of the very high level of long-term unemployment during the Great Recession. This effect is not obvious, as a long term unemployment spell that ends with retirement or disability may be a lasting effect and might thereby lower future unemployment rates. And the impact on future wages of reemployed long-term unemployed might or might not impact future unemployment.

Similarly, there are estimates of the impact of underwater mortgages on labor mobility and so both unemployment and employment.<sup>45</sup> Such estimation is relevant for consideration of policies to reduce the scale or scope of underwater mortgages, for example through mortgage modification programs. However, there is the expectation that house prices (and foreclosures) would in time dissipate much of the stock of underwater mortgages. Thus the impact of any reduction in labor mobility is structural in the sense of relevant for evaluating mobility-enhancing policies, but not structural in the stimulus sense used in this essay. These examples draw distinctions in the use of these terms between what is relevant for a current structural policy question and what is relevant for the cyclical issue that depends on a future state of the economy.

I have not used the term frictional unemployment, as it is basically a synonym for structural for the purpose of this essay, although it does tend to focus attention on a different set of issues and measurements. For example, one could ask whether the use of the internet has reduced the level of frictional unemployment. Or whether an expanded role for government information services connected to unemployment insurance would reduce frictional unemployment. Moreover, there are other uses of these terms which do not connect to policy issues. For example, in Mankiw's introductory text (2013), frictional unemployment is defined as "The unemployment caused by the time it takes workers to search for a job." (P. 180.) This serves the purpose of getting students to recognize some of the workings of the labor market that do not fit comfortably in a single-period demand-and-supply model that the students may have

---

<sup>44</sup> On unemployment insurance, see, for example, Daly et al (2012), Fujita (2010), Rothstein (2011).

<sup>45</sup> On house lock, see, for example, Donovan and Schnure (2011), Modestino and Dennett (2012).

learned how to use. If one measured literally how long it takes to search for jobs, perhaps in terms of the distribution of durations of completed unemployment spells, one would be looking at a measure dominated by cyclical factors, dominated by the tightness of the labor market. While useful for education, I can see no way to measure this in a way that sheds light on a suitable future choice of a full-employment target.<sup>46</sup>

Another recent use of the term is in Michaillat (2012): “*Rationing unemployment* measures the shortage of jobs in the absence of matching frictions, and *frictional unemployment* measures additional unemployment attributable to matching frictions.” (P. 1721.) This division in the theoretical analysis sharpens awareness of the implications of the critical new modeling assumptions employed in the paper. It comes from comparing two notions of equilibrium, with and without a recruiting cost, which is used to capture the role of frictions. My discussion above of the Şahin et al (2012) mismatch index questioned the relevance for evaluating stimulus policies of measuring the fraction of hires lost because the actual allocation of unemployed does not match the planner’s optimum. Similarly, I do not see how Michaillat’s comparison with this hypothetical alternative would shed light on what will happen as the economy recovers. Indeed, Michaillat notes that the greater the rationing unemployment the lower the measure of frictional unemployment. This modeling sheds light on some questions, such as the importance of search intensity, and so of unemployment benefits, for aggregate unemployment, but not directly on the size of an appropriate future unemployment target. The model has the property that the tighter the labor market, the larger the effect of search, and so of unemployment benefits, on equilibrium employment. In other words, the effect of unemployment benefits varies systematically with the tightness of the labor market, a critical fact for evaluating its impact. While a comparison with the hypothetical frictionless alternative is a way of highlighting the workings this effect, it is the direct estimate of the change in equilibrium from a policy change that we are really interested in, not the change in the differences from hypothetical alternatives.

---

<sup>46</sup> Mankiw (2013) defines structural unemployment as “The unemployment resulting from wage rigidity and job rationing. ... Workers are unemployed not because they are actively searching for the jobs that best suit their individual skills but because there is a fundamental mismatch between the number of people who want to work and the number of jobs that are available. At the going wage, the quantity of labor supplied exceeds the quantity of labor demanded; many workers are simply waiting for jobs to open up.” (P. 183-4.)

## VI. Concluding remarks

The focus of the essay has been methodological, examining the assumptions behind measures of structural unemployment, considering complications that question those assumptions, and evaluating the logical link between measurements and the potential role of stimulus policy.

This essay found multiple reasons for the measured efficiency parameter of the matching function to vary over a business cycle, and reasons for that variation to be different from earlier recessions and recoveries given the nature of the Great Recession. Unfortunately, the essay did not contain a net impact from quantifying the many effects identified and their likely extent of continuance. In short, merely noticing a shift in the Beveridge Curve, as shown in Figure 1, is not a basis for a conclusion that further stimulus policy is not appropriate; measuring structural change is not simple or easy.

Presentations of the aggregate matching function often cite the aggregate production function as a parallel construction that has proven useful. However, in considering the relationship between aggregate output and aggregate inputs, many macroeconomists make a sharp distinction between trend issues and cycle issues. Trend is addressed through a Solow production function; the cycle through Okun's law.<sup>47</sup> This essay suggests development of a similar division for analysis of the labor market, in that the efficiency parameter of the standard aggregate matching function should vary in the course of a cycle. Support for this perspective comes from the disaggregated work of Davis, Faberman and Haltiwanger, and from the cyclic variation in the relative hiring from the already-employed and the labor force nonparticipants.<sup>48</sup> The bottom line is that the Beveridge Curve has important information on the state of the labor market, but should not be viewed as a tight technical relationship and inferences should be based on the underlying factors behind the unemployment and vacancy observations.

There are many issues that received no attention in this essay. Given the huge growth in long-term unemployment in the Great Recession, studying both the causes and the consequences of that development seems very important. The essay had no explicit discussion of wages,

---

<sup>47</sup> See, e. g., Ball, Leigh and Loungani (2012).

<sup>48</sup> For an analysis of cycles and trends in the matching function efficiency parameter, see Barnichon and Figura (2012).



implicitly assuming that for identifying cyclical unemployment, wage adjustments in response to the state of the labor market are adequately captured by looking at the quantity figures. And the partial-equilibrium focus on the labor market leaves out the key general equilibrium role of employment in affecting aggregate demand.

## References

- Akerlof, George A., Andrew K. Rose and Janet L. Yellen. 1988. "'Job Switching and Job Satisfaction in the U.S. Labor Market," *Brookings Papers on Economic Activity*, 1988:2.
- Ball, Laurence, Daniel Leigh, and Prakash Loungani. 2012. Okun's Law: Fit at 50? Available at <http://www.imf.org/external/np/res/seminars/2012/arc/pdf/BLL.pdf>
- Barlevy, Gadi. 2011. "Evaluating the role of labor market mismatch in rising unemployment." *Economic Perspectives*, 3Q/2011: 82-96.
- Barnichon, Regis, Michael Elsby, Bart Hobijn, and Ayşegül Şahin. 2012. "Which industries are shifting the Beveridge curve?" *Monthly Labor Review*, 135: 6.
- Barnichon, Regis, and Andrew Figura. 2011a. "[What Drives Matching Efficiency? A Tale of Composition and Dispersion](#)." *Finance and Economics Discussion Series* 2011-10. Board of Governors of the Federal Reserve System, Washington D.C.
- Barnichon, Regis, and Andrew Figura. 2011b. "Labor Market Heterogeneities, Matching Efficiency, and the Cyclical Behavior of the Job Finding Rate." Unpublished.
- Barnichon, Regis, and Andrew Figura. 2012. "The Determinants of the Cycles and Trends in U.S. Unemployment." Unpublished.
- Beveridge, William H. 1945 (1944). *Full Employment in a Free Society*. New York: W. W. Norton & Company.
- Blanchard, Olivier Jean, and Peter Diamond. 1989. "The Beveridge Curve." *Brookings Papers on Economic Activity*, 1: 1989, 1-76.
- Blanchard, Olivier Jean, and Peter Diamond. 1990a. "The Cyclical Behavior of the Gross Flows of U.S. Workers." *Brookings Papers on Economic Activity*, 2: 85-143.
- Blanchard, Olivier Jean, and Peter Diamond. 1990b. "The Aggregate Matching Function" (with O. Blanchard), in P. Diamond, ed., Growth, Productivity, Unemployment: Essays to Celebrate Bob Solow's Birthday (Cambridge: MIT Press, 1990).

- Blanchard, Olivier Jean, and Peter Diamond. 1994. "Ranking, Unemployment Duration and Wages." *Review of Economic Studies*, 60: 417-434.
- Börsch-Supan, A. H. 1991. "Panel Data Analysis of the Beveridge Curve: Is There a Macroeconomic Relation between the Rate of Unemployment and the Vacancy Rate?" *Economica*, 58: 279-297.
- Cheshire, P. C. 1973. *Regional Unemployment Differences in Great Britain*. Regional Papers II, National Institute of Economic and Social Research. Cambridge: Cambridge University Press.
- Coles, Melvyn G. and Eric Smith. 1996. "Cross-Section Estimation of the Matching Function: Evidence from England and Wales." *Economica*, 63(252): 589–598.
- Crump, Richard, and Ayşegül Şahin. 2012. "Skills Mismatch, Construction Workers, and the Labor Market." *Liberty Street Economics*, <http://libertystreeteconomics.newyorkfed.org/2012/03/skills-mismatch-construction-workers-and-the-labor-market.html>.
- Daly, Mary C., Bart Hobijn, Ayşegül Şahin, and Robert G. Valletta. 2012. "A Search and Matching Approach to Labor Markets: Did the Natural Rate of Unemployment Rise?" *Journal of Economic Perspectives*, 26(3): 3–26.
- Davis, Steven J., R. Jason Faberman, and John C. Haltiwanger. 2012a. "Labor market flows in the cross section and over time." *Journal of Monetary Economics*, 59, 1–18.
- Davis, Steven J., R. Jason Faberman, and John C. Haltiwanger. 2012b. "The Establishment-Level Behavior of Vacancies and Hiring." NBER unpublished. National Bureau of Economic Research Working Paper 16265. revised August 2012. Cambridge, MA.
- Davis, Steven J., R. Jason Faberman, and John C. Haltiwanger. 2012c. "Recruiting Intensity During and After the Great Recession: National and Industry Evidence." *American Economic Review*: 102(3): 584–588.
- Donovan, Colleen and Calvin Schnure. 2011. "Locked in the House: Do Underwater Mortgages Reduce Labor Market Mobility?" August 2011. Unpublished.
- Dow, J. Christopher R. and Louis A. Dicks-Mireaux. 1958. "The Excess Demand for Labour: A Study of Conditions in Great Britain, 1946–56," *Oxford Economic Papers* 10(1): 1–33.
- Elsby, Michael W., Bart Hobijn, and Ayşegül Şahin. 2012. "On the Importance of the Participation Margin for Labor Market Fluctuations?" September, 2012. Unpublished.
- Fallick, Bruce, and Charles A. Fleischman. 2004. "[Employer-to-Employer Flows in the U.S. Labor Market: The Complete Picture of Gross Worker Flows.](#)" [Finance and Economics Discussion Series](#) 2004-34, Board of Governors of the Federal Reserve System working paper.

Federal Reserve Bank of St. Louis. 2010. Annual Report.

Fujita, Shigeru. 2010. “Effects of the Unemployment Insurance Benefit Extensions: Evidence from the Monthly CPS.” Federal Reserve Bank of Philadelphia, Working Paper 10-35.

Gregg, Paul and Barbara Petrongolo. 1997. “Random or Non-random Matching? Implications for the Use of the UV Curve as a Measure of Matching Effectiveness.” Discussion Paper 13, Institute for Economics and Statistics, Oxford.

Hall, Robert E. 2011. The Long Slump. *American Economic Review*, 101 (April) 431-469.

Herz, Benedikt, and Thijs van Rens. 2011. “Structural Unemployment.” Universitat Pompeu Fabra, CREI and Universitat Pompeu Fabra. Unpublished.

Hobijn, Bart (2012), “The Industry-Occupation Mix of U.S. Job Openings and Hires,” *FRB SF Working Paper 2012-09*.

Hyatt, Henry, and Erika McEntarfer. 2012. “Job-to-job Flows and the Business Cycle.” U.S. Bureau of the Census, CES 12-04. March, 2012.

Kocherlakota, Narayana. 2012. “Monetary Policy Transparency: Changes and Challenges.” speech at the 17th Annual Entrepreneur & Investor Luncheon, Minneapolis, Minnesota, June 7, 2012.

Kudlyak, Marianna, and Felipe Schwartzman. 2012. “Accounting for Unemployment in the Great Recession: Nonparticipation Matters.” Federal Reserve Bank of Richmond Working Paper 12(4).

Lazear, Edward P. and James R. Spletzer. 2012. The United States Labor Market: Status Quo or A New Normal? NBER Working Paper No. 18386

Light, Joe. 2011. “Corporate News: Jobs Open, but Hiring Remains Slow—Recruiters Say They Have Trouble Finding Candidates for Skilled Positions, and Managers Hold Out for Better Prospects.” *The Wall Street Journal*, March 7, 2011.

Mankiw, N. Gregory. 2013. *Macroeconomics*. New York: Worth Publishers. 8<sup>th</sup> edition.

Michaillat, Pascal. 2012. “Do Matching Frictions Explain Unemployment? Not in Bad Times.” *American Economic Review* 102(4): 1721–1750.

Modestino, Alicia Sasser and Julia Dennett. 2012. “Are American Homeowners Locked into Their Houses? The Impact of Housing Market Conditions on State-to-State Migration”, Federal Reserve Bank of Boston Working Paper 12(1).

Moscarini, Giuseppe, and Fabien Postel-Vinay. 2012. "The Contribution of Large and Small Employers to Job Creation at Times of High and Low Unemployment" *American Economic Review*, 102(6): 2509-2539.

Moscarini, Giuseppe and Kaj Thomsson. 2007. "Occupational and Job Mobility in the US." *Scandinavian Journal of Economics*, special issue on Macroeconomic Fluctuations and the Labor Market, December 2007, 109(4), 807-836.

[Nagypál, Éva](http://faculty.wcas.northwestern.edu/~een461/JJempirical_2008_0207.pdf). 2008. "Worker Reallocation over the Business Cycle: The Importance of Employer-to-Employer Flows." Available at [http://faculty.wcas.northwestern.edu/~een461/JJempirical\\_2008\\_0207.pdf](http://faculty.wcas.northwestern.edu/~een461/JJempirical_2008_0207.pdf)

Perry, George L. 1972. "[Unemployment Flows in the U.S. Labor Market](#)," *Brookings Papers on Economic Activity*, vol. 3(2), pages 245-292.

Petrongolo, Barbara, and Christopher A. Pissarides. 2001. "Looking into the Black Box: A Survey of the Matching Function." *Journal of Economic Literature*, 39: 390–431.

Rodenburg, Peter. 2011. "The Remarkable Transformation of the UV Curve in Economic Theory." *European Journal of the History of Economic Thought*, Taylor and Francis Journals, vol. 18(1), pages 125-153.

Rothstein, Jesse. 2011. "Unemployment Insurance and Job Search in the Great Recession." *Brookings Papers on Economic Activity* (103), Fall 2011: 143-209.

Şahin, Ayşegül, Joseph Song, Giorgio Topa, Giovanni L. Violante. 2012. "Mismatch Unemployment." [www.newyorkfed.org/research/economists/sahin/USmismatch.pdf](http://www.newyorkfed.org/research/economists/sahin/USmismatch.pdf).

Shimer, Robert. 2007. "Mismatch." *American Economic Review*, 97 (4): 1074-1101.

Tasci, Murat. 2012. "Displaced Workers and the Great Recession." *Economic Trends*, Federal Reserve Bank of Cleveland, 11.07.12

Valletta, Rob, and Katherine Kuang. 2010. "Is Structural Unemployment on the Rise?" Federal Reserve Bank of San Francisco Economic Letter 2010-34.

Veracierto, Marcelo. 2011. "Worker flows and matching efficiency." Federal Reserve Bank of Chicago, *Economic Perspectives*, 3Q/2011: 82-96.

Woirol, Gregory R. 1996. *The Technological Unemployment and Structural Unemployment Debates*. Westport, CT: Greenwood Press.

### The Beveridge Curve (job openings vs. unemployment rate) (Seasonally adjusted)

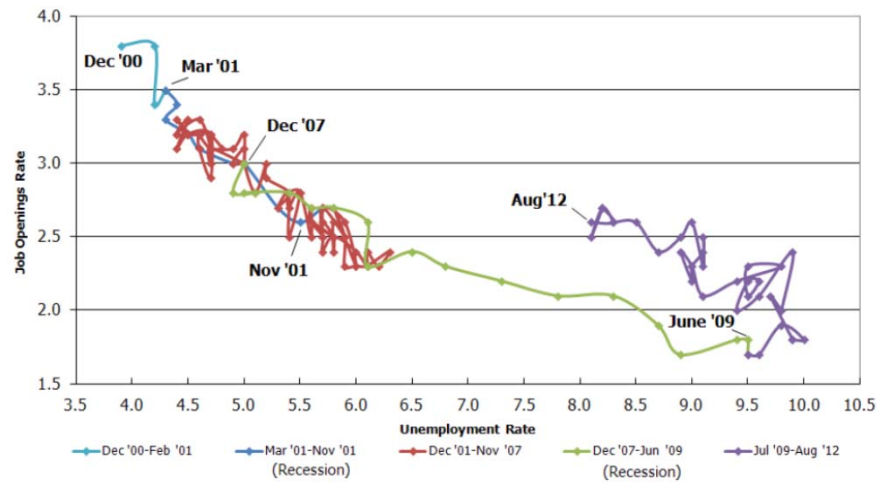
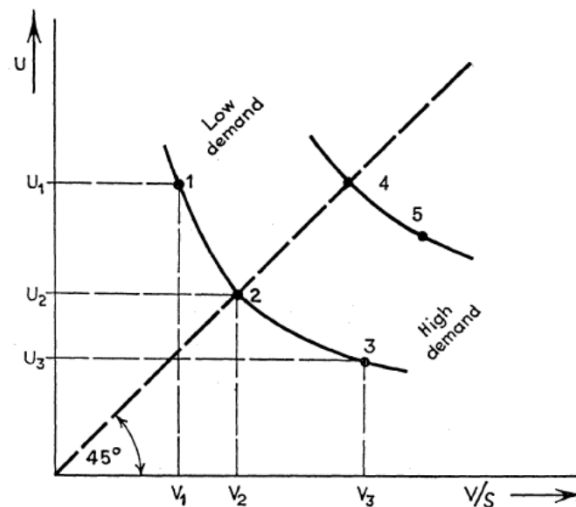


Figure 1

### Shifting Beveridge Curve



Source: "The Excess Demand for Labour. A Study of Conditions in Great Britain, 1946-56."  
J.C.R. Dow and L.A. Dicks-Mireaux, *Oxford Economic Papers*, Vol. 10, No. 1, Feb. 1958.

Figure 2

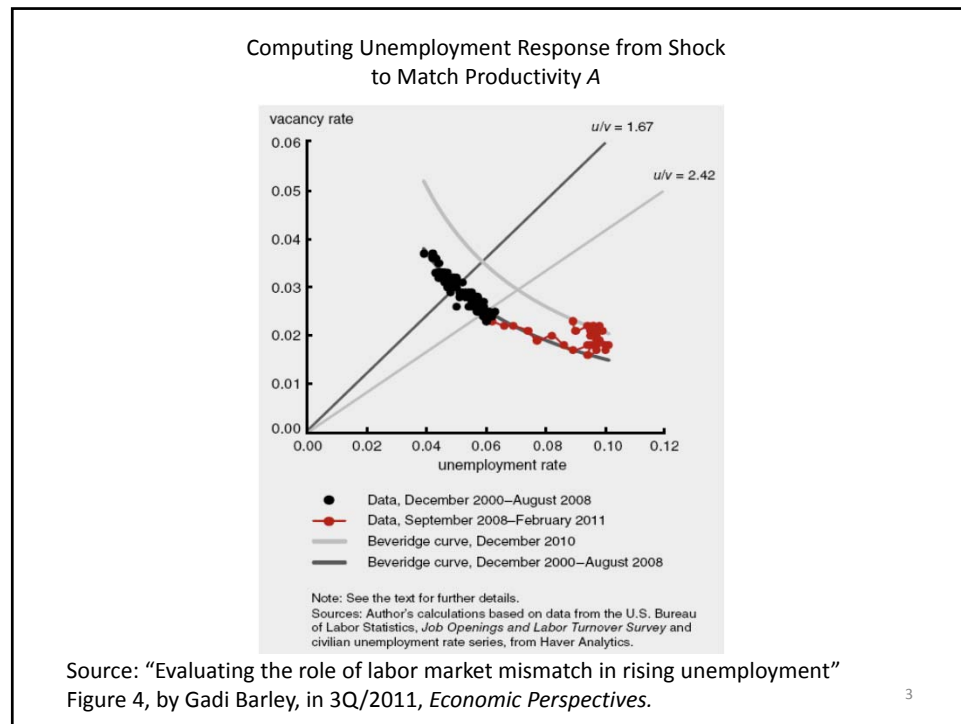
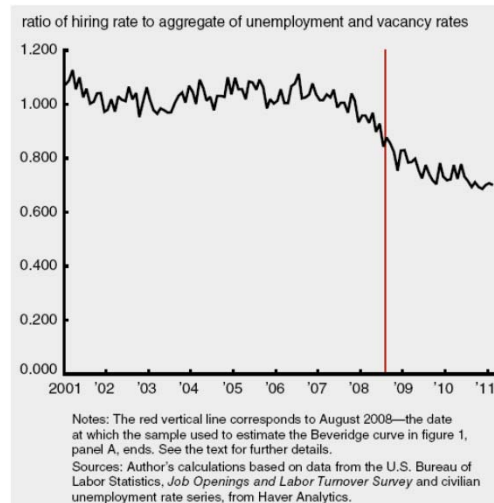


Figure 3



Figure 4

## Implied Match Productivity Using Data on New Hires, 2001-11.

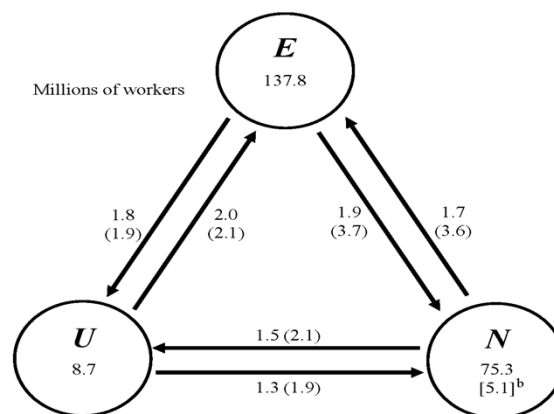


Source: “Evaluating the role of labor market mismatch in rising unemployment”  
Figure 3, by Gadi Barley, in 3Q/2011, *Economic Perspectives*.

5

Figure 5

## Average Values of Gross Stocks and Flows for Employment, Unemployment, and Not in the Labor Force, Oct 1995-Sept 2012



Source: Current Population Survey Labor Force Status Flows  
Flow data are Abowd-Zellner adjusted. The original unadjusted published numbers appear in parentheses. All numbers are averages from October 1995 through September 2012 of monthly non-seasonally adjusted observations and are millions of persons.

<sup>a</sup>. The variables  $E$ ,  $U$ , and  $N$  represent employment, unemployment, and not in the labor force respectively.

<sup>b</sup>. The bracketed stock figure for  $N$  equals the number of people who report they want a job.

Figure 6

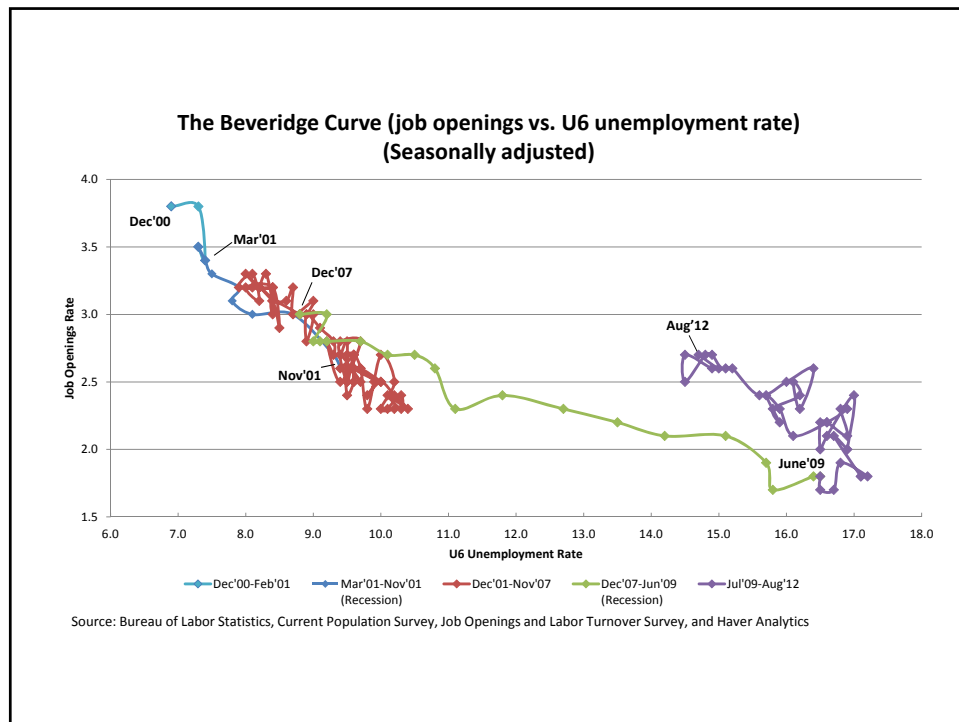


Figure 7

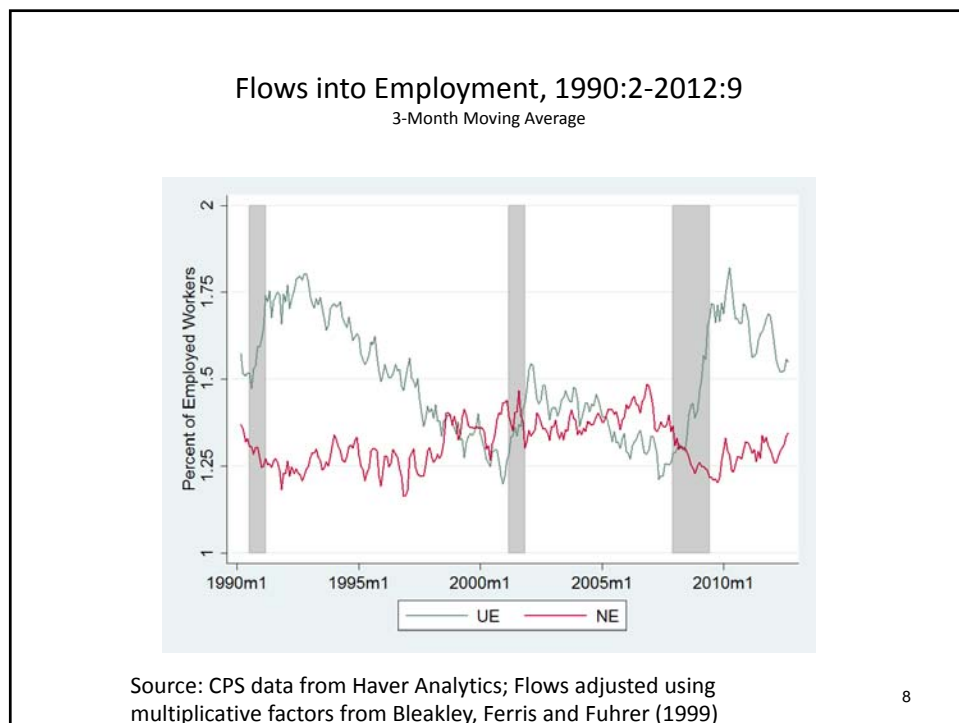
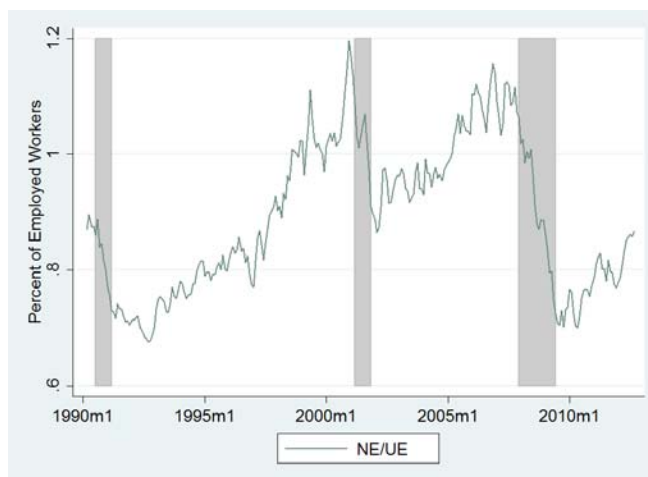


Figure 8



### Ratio of Flows into Employment, 1990:2-2012:9

3-Month Moving Average



Source: CPS data from Haver Analytics; Flows adjusted using multiplicative factors from Bleakley, Ferris and Fuhrer (1999)

9

Figure 9

### Gross Flows among Labor Market States with EE Flows, October 1995 – September 2012

(percent of population and percent of state in first month, monthly)

State in first month	State in second month			
	Same employer	New employer	Unemployed	NLF
As a percent of population				
Employed	58.5	1.4	0.8	1.6
Unemployed		0.9	2.0	0.9
NLF		1.5	0.9	31.5
As a percent of state in first month				
Employed	93.9	2.2	1.3	2.6
Unemployed		25.5	51.7	22.8
NLF		4.5	2.5	92.9

**Note:** All numbers are averages from October 1995 through September 2012  
**Source:** <http://www.federalreserve.gov/pubs/feds/2004/200434/200434abs.html>

Figure 10

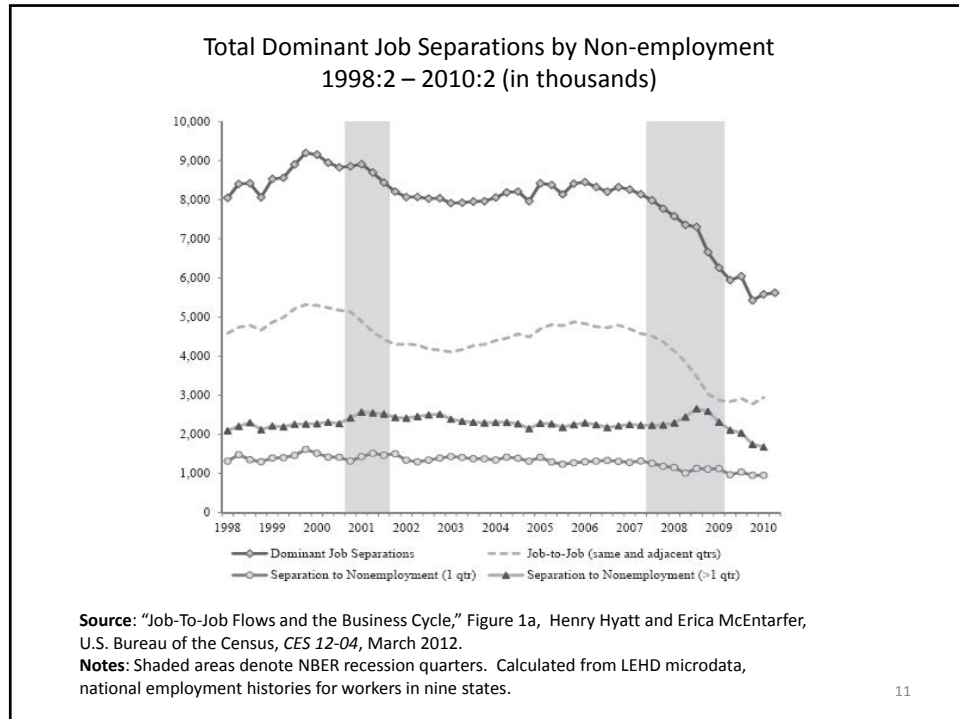


Figure 11

**Results of Hiring Dynamics Model by Industry, Size, and Turnover**

	Mean Vacancy Duration $1/f_v$ (in days)
<i>Nonfarm Employment</i>	20.0
<i>Major Industry</i>	
Natural Resources & Mining	12.8
Construction	8.3
Manufacturing	19.3
Transport, Wholesale, Utilities	19.1
Retail Trade	13.7
Information	32.0
FIRE	29.0
Professional & Business Services	20.4
Health & Education	35.4
Leisure & Hospitality	14.6
Other Services	18.8
Government	31.4
<i>Establishment Size Class</i>	
0-9 Employees	16.5
10-49 Employees	15.2
50-249 Employees	17.1
250-999 Employees	24.1
1,000-4,999 Employees	37.9
5,000+ Employees	38.9
<i>Worker Turnover Category</i>	
First Quintile (lowest turnover)	87.9
Second Quintile	52.8
Third Quintile	32.8
Fourth Quintile	18.4
Fifth Quintile (highest turnover)	8.7

**Source:** “The Establishment-Level Behavior of Vacancies and Hiring” by Steven Davis, R. Jason Faberman, and John Haltiwanger, August 12, 2012, Figure 3.

Figure 12

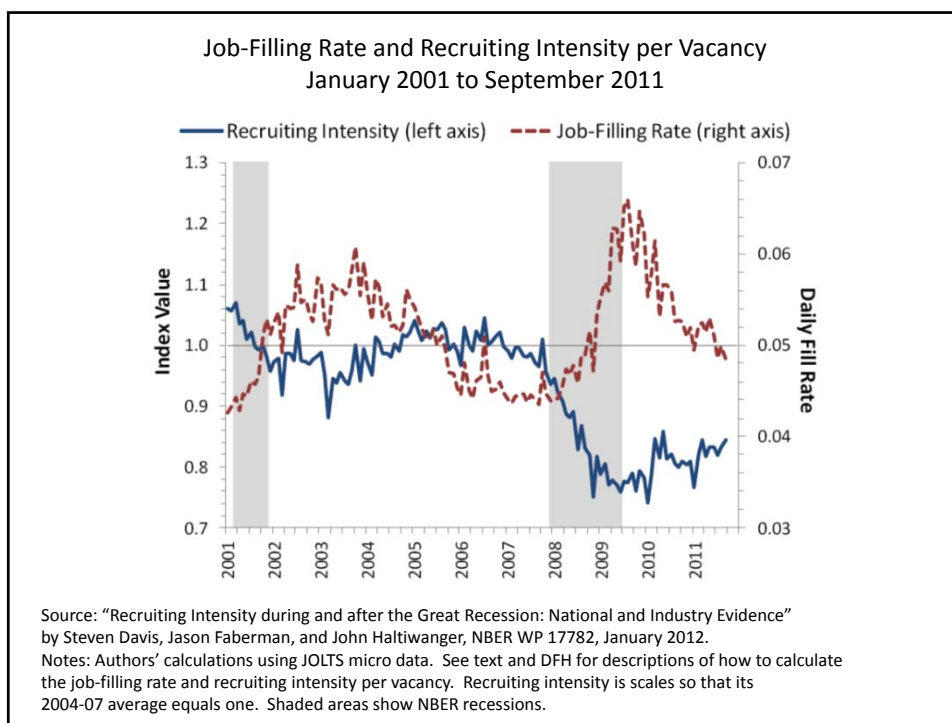


Figure 13

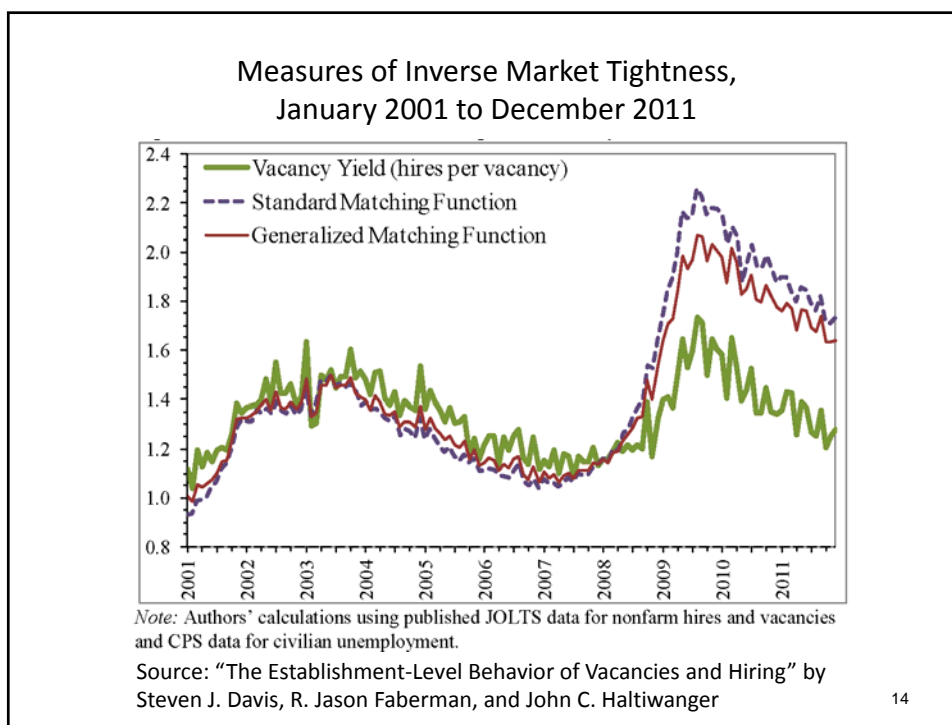
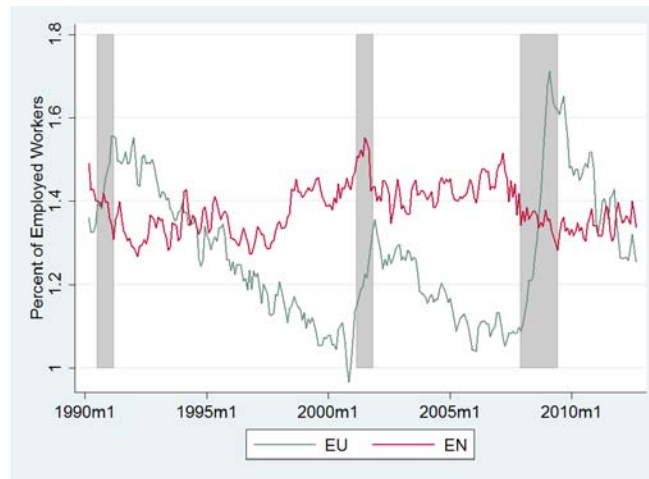


Figure 14

### Flows out of Employment, 1990:2-2012:9

3-Month Moving Average



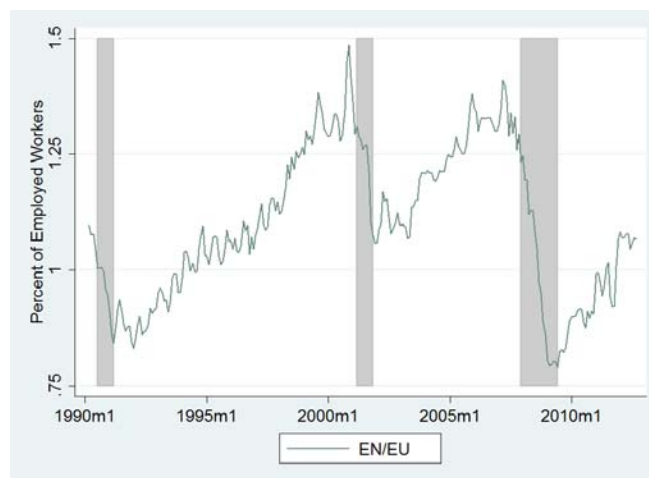
Source: CPS data from Haver Analytics; Flows adjusted using multiplicative factors from Bleakley, Ferris and Fuhrer (1999)

15

Figure 15

### Ratio of Flows out of Employment, 1990:2-2012:9

3-Month Moving Average



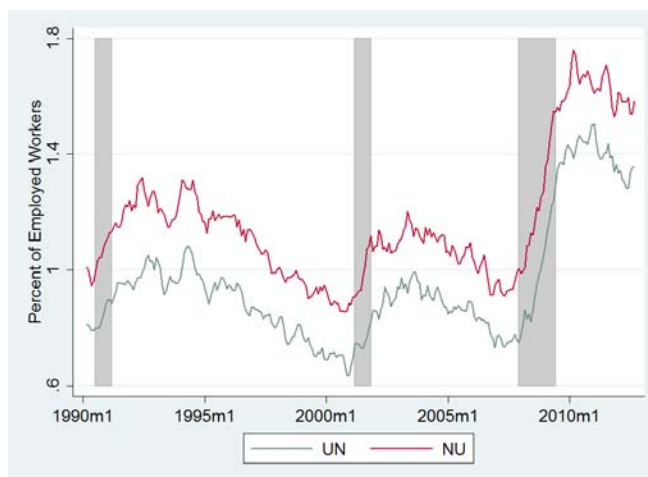
Source: CPS data from Haver Analytics; Flows adjusted using multiplicative factors from Bleakley, Ferris and Fuhrer (1999)

16

Figure 16

### Flows Between Unemployment and Not in Labor Force, 1990:2-2012:9

3-Month Moving Average



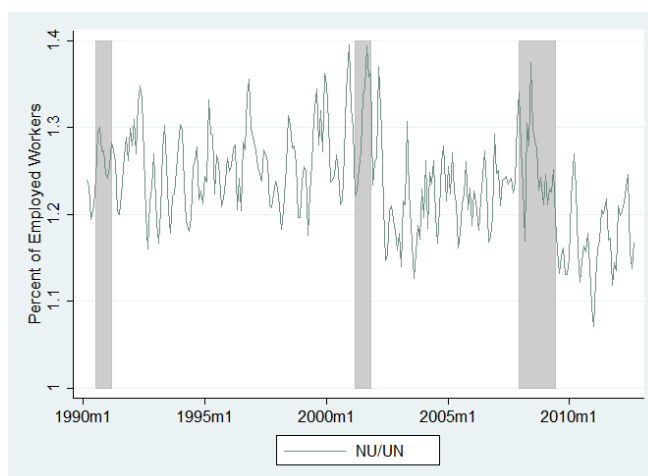
Source: CPS data from Haver Analytics; Flows adjusted using multiplicative factors from Bleakley, Ferris and Fuhrer (1999)

17

Figure 17

### Ratio of Flows Between Not in Labor Force and Unemployment, 1990:2-2012:9

3-Month Moving Average



Source: CPS data from Haver Analytics; Flows adjusted using multiplicative factors from Bleakley, Ferris and Fuhrer (1999)

18

Figure 18

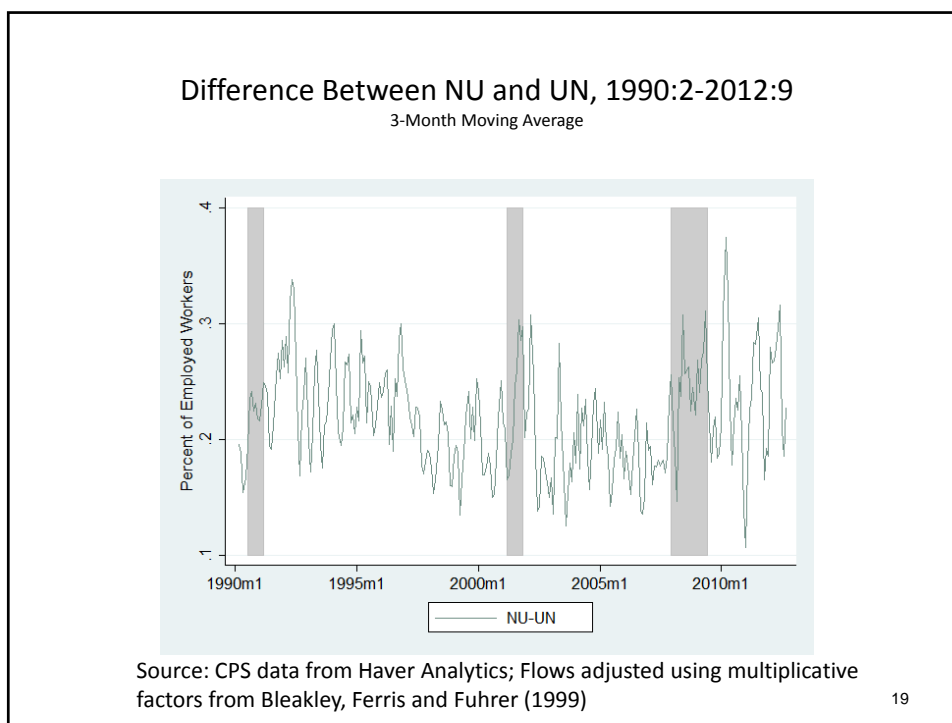


Figure 19

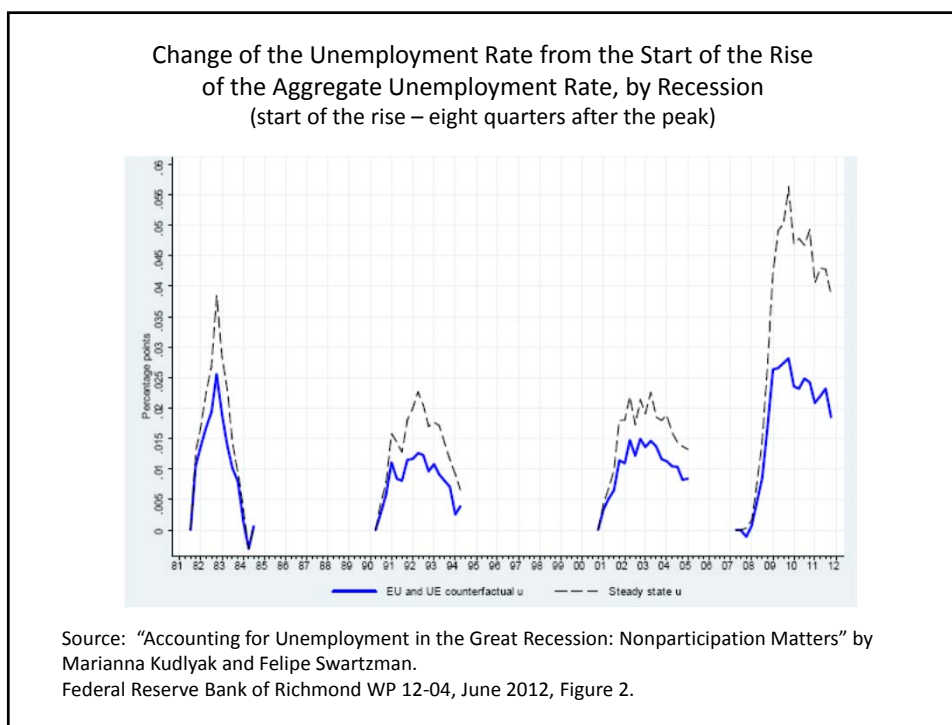


Figure 20

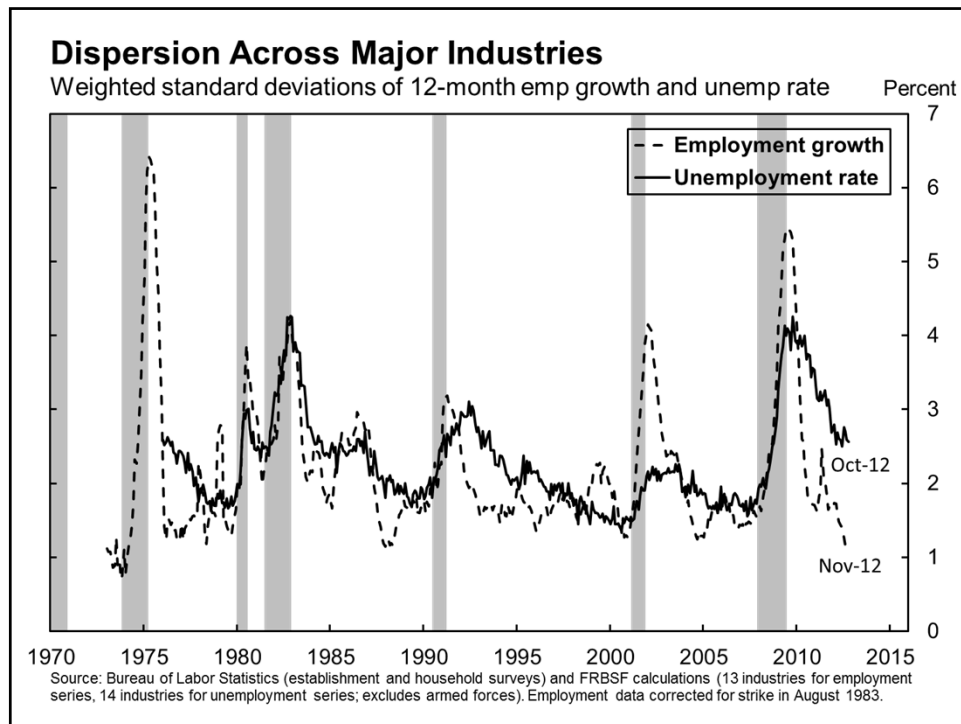


Figure 21

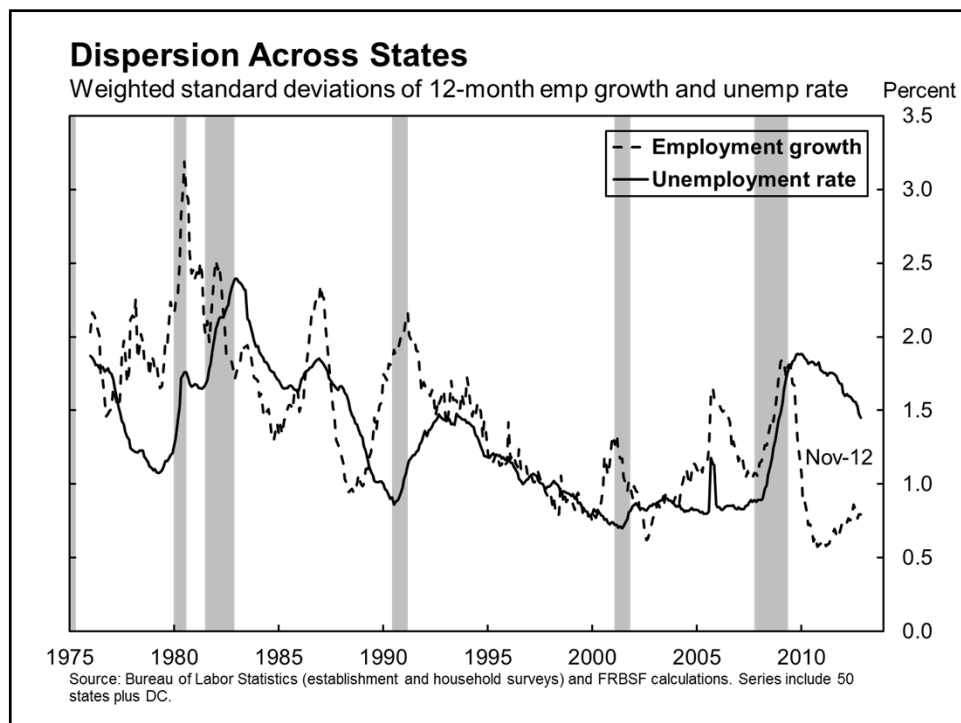


Figure 22

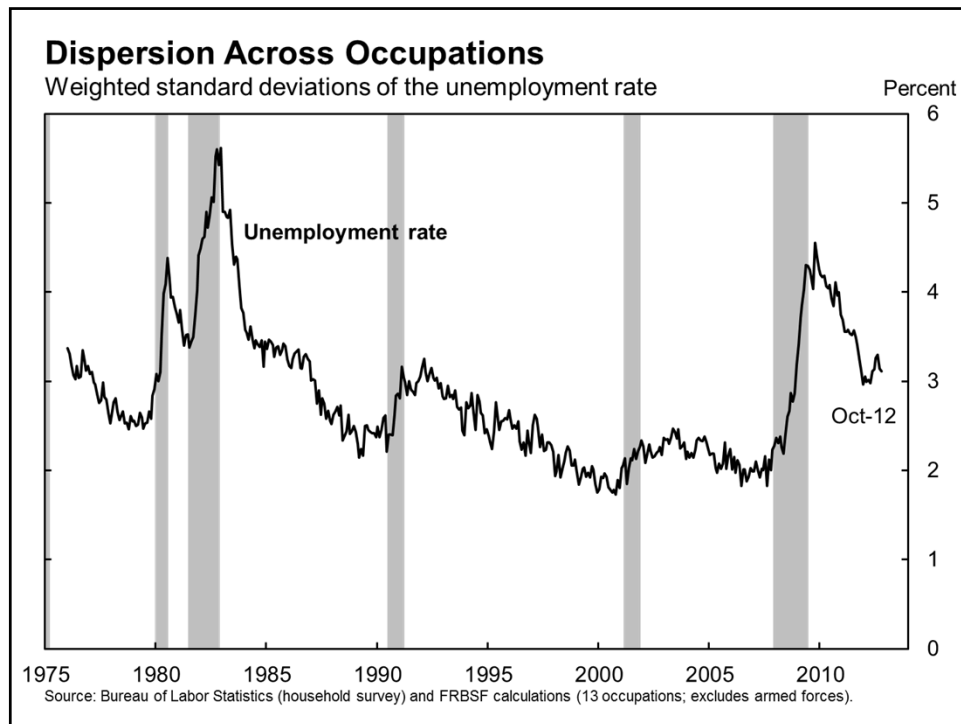


Figure 23



Figure 24



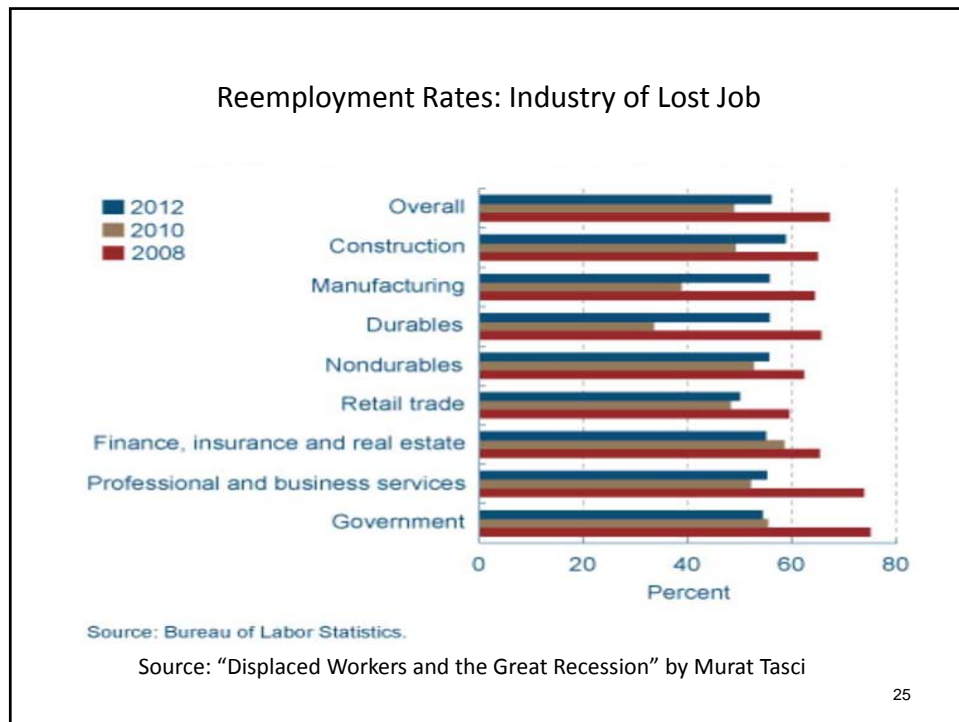


Figure 25

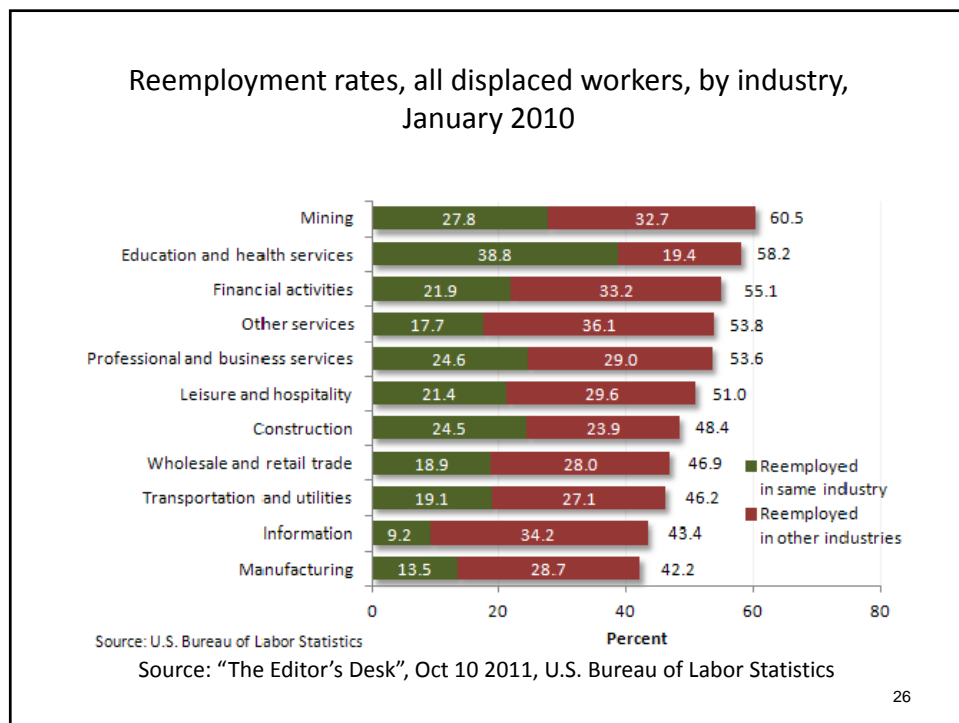


Figure 26