WP/15/58

IMF Working Paper

A Stock-Flow Accounting Model of the Labor Market: An Application to Israel

Yossi Yakhin and Natalya Presman

INTERNATIONAL MONETARY FUND

 WP/15/58

IMF Working Paper

Office of Executive Director (OEDNE) and the Bank of Israel

A Stock-Flow Accounting Model of the Labor Market: An Application to Israel

Authorized for distribution by Bas B. Bakker and Menno Snel

March 2015

Abstract

The paper utilizes a theoretical stock-flow accounting model of the labor market, similar to Blanchard and Diamond (1989). Identifying restrictions are derived from the theoretical model and are imposed on a SVAR system. The estimation allows for decomposing fluctuations to their cyclical and structural components. The model is applied to the Israeli economy. The estimates suggest that non-cyclical factors account for at least half of the decline of the unemployment rate during the period between 2004-Q1, when unemployment peaked at 10.9 percent, and 2011-Q4, when it marked a trough at 5.4 percent; suggesting a shift inward of the Beveridge curve.

JEL Classification Numbers: E24, E32, J6

Keywords: Structural unemployment, Beveridge curve, SVAR with sign restrictions

Authors' E-Mail Addresses: yyakhin@imf.org; natalya.presman@boi.org.il

Contents

1 Introduction

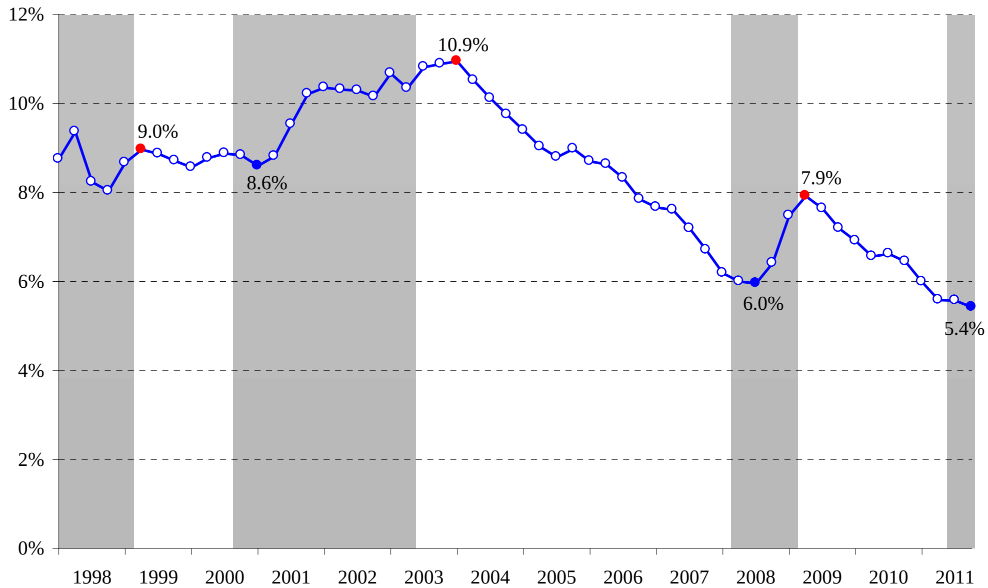
Since the early 2000s the unemployment rate in Israel has declined steadily at comparable points in the business cycle (Figure 1a). Comparing business cycle peaks, unemployment reached local lows of 8.6 percent in 2001-Q1, 6.0 percent in 2008-Q3 and 5.4 percent in 2011-Q4. These dates are about two quarters after the peak of each business cycle. Comparing recession periods, the unemployment rate reached local highs of 9.0 percent in 1999-Q2 and 10.9 percent in 2004-Q1 and then fell to 7.9 percent in 2009-Q2.[1]

There are two possible explanations: (1) Unemployment variation is cyclical in nature and the difference in unemployment rates reflects variation in business cycle intensity. For example, it may be the case that the deterioration of internal security in Israel at the beginning of the 2000s caused a more severe recession relative to other downturns and therefore resulted in higher unemployment rate. (2) The fall in unemployment rate is driven by structural factors. These may include, for example, regulation, changes in matching technology between unemployed workers and vacant jobs, shifts in the composition of sectors, and labor supply developments.

Another way of looking at the data is by observing the comovement of vacancies and unemployment. Figure 1b displays the vacancy rate against the unemployment rate for the period 1998 to 2011. With the exception of the period until 2001-Q1, the data clearly display the Beveridge curve - a negative comovement between unemployment and vacancies. During economic expansions unemployment tends to fall and vacancies rise and during recessions the opposite happens; that is, cyclical fluctuations are manifested as movements along the Beveridge curve. However, it is also appears that the Beveridge curve has shifted inward, and by the end of 2008 this shift is clearly visible in the figure. This observation suggests that structural forces were also at work during our sample period.

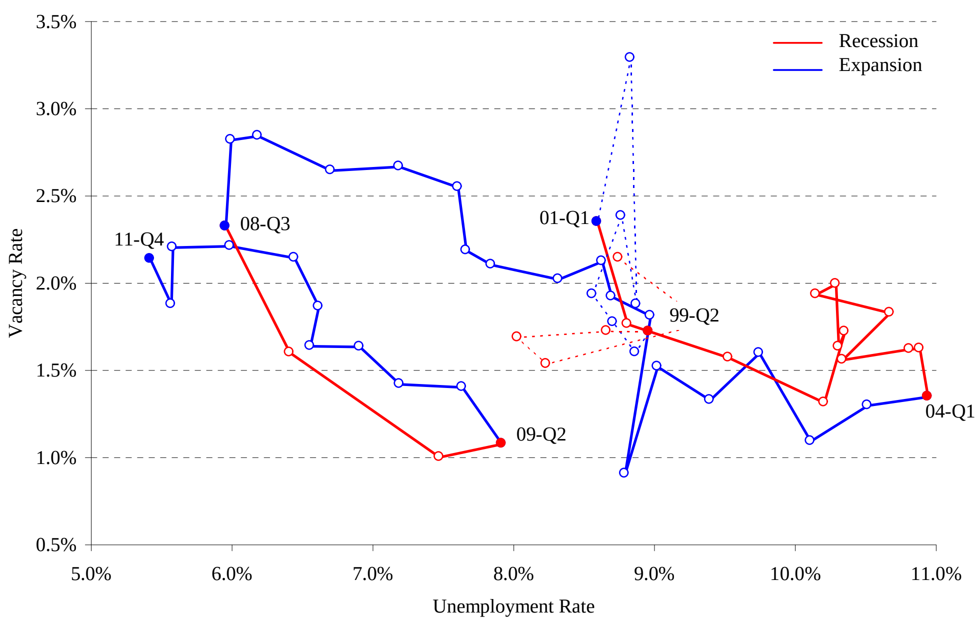
[1] Djivre and Yakhin (2011) document business cycle chronology in Israel. They mark 2000-Q3 and 2008-Q1 as business cycle peaks. 2011 is beyond their sample period, however it seems that the Israeli economy reached another peak somewhere during the second or third quarter of 2011. 1999-Q1, 2003-Q2 and 2009-Q1 are marked as troughs.

Figure 1a: The Unemployment Rate, 1998-2011



Shadowed areas represent recession periods - Djivre and Yakhin (2011).

Figure 1b: The Beveridge Curve, 1998-2011



Vacancy rate is calculated as business sector vacancies divided by the labor force. Unemployment rate is calculated as total number of unemployed divided by the labor force. Unemployment and the labor force are measured based on working age population, i.e. 15 years old and older.

This observation is consistent with the fact that the Israeli labor market has gone through several structural changes during the sample period: unemployment insurance benefits were cut several times and the duration of eligibility was shortened, average education level of participants in the labor force has risen, the use of private sector intermediaries for job search has become more common, and so did the employment of workers via subcontractors.

In order to evaluate the importance of cyclical factors versus structural ones we exploit the comovement of unemployment and vacancies, together with labor force fluctuations, for decomposing unemployment variation to cyclical and non-cyclical factors. Negative comovement of unemployment and vacancies typically reflects business cycle fluctuations along a Beveridge curve, while movements in the same direction are often associated with structural changes that shift the curve.[2] In this paper we follow the approach of Blanchard and Diamond (1989), (BD hereafter). We first use a modified version of their stock-flow accounting model of the labor market to study the response of unemployment and vacancies to cyclical and structural innovations. We then use the insights of the theoretical model for imposing identifying restrictions in our empirical analysis.

Our estimates suggest that non-cyclical factors are accounted for at least half of the decline of the unemployment rate during the period between 2004-Q1, when unemployment peaked at 10.9 percent, and 2011-Q4, when it marked a trough at 5.4 percent. Moreover, our estimates suggest that the Beveridge curve has started to shift inward at the beginning of 2004, well before it became visible to the naked eye.

Focusing on movements of unemployment and vacancies that are driven by cyclical shocks allows us to depict the Beveridge curve for the Israeli economy. During our sample period, 1998-2011[3], its slope is about -3, suggesting that a decline of 1 percent in the stock of unemployed workers is associated with a rise of 3 percent in vacancies, on average.

[2] See, among others, Pissarides (1985), Blanchard and Diamond (1989), and Shimer (2005).

[3] Data on vacancies are available only since 1998 from the Employers' Survey of the Ministry of Economy. Prior to that data were available from the Employment Service, but only until 1991 - see footnote 4.

That is, vacancies are much more responsive to cyclical shocks than unemployment. Furthermore, the impulse response functions suggest that on impact vacancies are about 10 times more responsive than unemployment, and that they fully respond to the shock within one quarter while unemployment is more sluggish. These results imply counter-clockwise loops of unemployment and vacancies around the Beveridge curve during the business cycle (unemployment is measured on the horizontal axis). Similar results are reported by Blanchard and Diamond (1989) and Barnichon and Figura (2010) for the US economy and by Pissarides (1985) and Wall and Zoega (2002) for the British economy.

Time series from the Israeli labor market were used for the estimation of elements of search and matching models by Berman (1997) and Yashiv (2000). Both researchers use data from the Israeli Employment Service for periods no later than 1990. Special institutional environment endowed these data with uniquely high quality.[4] Berman (1997) focuses on the estimation of the matching function. He exploits the richness of his dataset to construct an instrumental variable in order to overcome the simultaneity bias inherited in this kind of estimation, as the outflow of new hires depletes both stocks of unemployed workers and vacant jobs. Yashiv (2000) uses limited information techniques for the estimation of the deep parameters of a complete search and matching model.

The rest of the paper is organized as follows. The next section lays down a theoretical stock-flow accounting model of the labor market, similar to the model of BD. The main differences from BD are discussed at the end of the section. Section 3 describes our empirical strategy and maps results from the theoretical model into short-run and long-run identifying restrictions in our econometric analysis. Section 4 describes the data and presents the estimation results. In particular, we discuss the estimated impulse response functions in light of the results of the theoretical model, and use a decomposition of the data to track movements of the Beveridge curve during the past decade. Section 5 concludes.

[4] Until March 1991 private intermediaries in the labor market were illegal, and all private sector hiring of workers for jobs not requiring a college degree was required by law to pass through the Employment Service. See Berman (1997).

2 A Stock-Flow Accounting Model of the Labor Market

In this section we set up a simple theoretical framework for analyzing the joint movement of unemployment and vacancies. The specification of the model is heavily based on the work of Blanchard and Diamond (1989); however, we modify their model in order to achieve a more natural interpretation, in our view, of the driving forces of the model economy and to simplify the presentation in some dimensions that are not important for our results. We point out the differences from Blanchard and Diamond at the end of this section. Economic behavior in the model, such as decisions to join the labor force or to shut down jobs, is set in an ad-hoc manner; in that sense the model is a reduced form representation of the labor market. Given our assumptions about economic behavior, the dynamics in the model are derived from accounting identities of workers and jobs in and out of unemployment and of vacancy, respectively.

We focus on three types of shocks that affect the labor market: shocks to aggregate activity, to matching efficiency, and to labor supply. Fluctuations in aggregate activity are captured by changes in job creation and job destruction parameters. Movements in aggregate activity generate the Beveridge relation in the model, i.e. a negative comovement between unemployed workers and vacant jobs. Movements in matching efficiency are captured by changes in matching technology and the separation rate between workers and jobs due to quitting or firing, i.e. break down of matches for reasons other than job destruction. Changes in matching efficiency generate a positive comovement between unemployed workers and vacant jobs. Finally, changes in labor supply are captured by exogenous shifts in the labor force. Movements in the labor supply generate no clear comovement between unemployed workers and vacant jobs.

2.1 Specification

2.1.1 The Labor Force

Let L denote the labor force, E employed workers, and U unemployed workers. By definition:

$$L = E + U \tag{1}$$

We assume that the labor force moves together with aggregate employment; specifically:

$$L = \Phi + aE \qquad 0 < a < 1 \qquad \Phi > 0 \tag{2}$$

where Φ is an exogenous shifter of labor supply which reflects the size of working-age population and preferences towards leisure. Substituting for E gives:

$$L = \frac{\Phi}{1-a} - \frac{a}{1-a}U \tag{3}$$

and:

$$\dot{L} = -\frac{a}{1-a}\dot{U} \tag{4}$$

where a dot above a variable represents its derivative with respect to time.

It should be noted that the specification of (2) captures the effect of discouraged workers reentering the labor force as employment rises. This specification was criticized by Janet Yellen in her discussion on the work of Blanchard and Diamond (1989) on the grounds that it is reasonable to assume that discouraged workers react to vacancies rather than employment. Nevertheless, simple Granger causality tests (not shown) support the specification of equation (2) as employment is found to Granger cause the labor force, while vacancies do not.[5]

[5] The test was implemented on the first difference of the log of the variables and included two lags; sample period was 1998-Q1 to 2011-Q4. Employment was found to Granger cause the of the labor force at 10 percent significance level.

2.1.2 Matching Technology

As is standard in search models of the labor market, new hires, H, are created by matching vacant jobs, V, to unemployed workers, where each worker is matched to one job and vice versa. Matching technology is summarized by the matching function:

$$H = \alpha m(U,V) \qquad \alpha > 0 \tag{5}$$

where α is a technology parameter that reflects the efficiency of the matching process, and $m(\cdot)$ is at least once continuously differentiable function that satisfies:

$$m(\cdot) \geq 0 \quad , \quad m(0,V) = m(U,0) = 0 \quad , \quad m_U, m_V > 0$$

Note that this specification assumes that new hires come only from the ranks of the unemployed, and it does not allow for movement of inactive workers, i.e. people outside the labor force, directly into employment. In the data, however, at quarterly frequency the number of new hires that come from the ranks of inactive workers is about twice as large as the number of new hires that come from the ranks of the unemployed.[6] This is at least partly a result of mismeasurement due to time aggregation, and not necessarily because most workers actually find jobs without a period of search.[7] Since our data are in quarterly frequency, it may well be that many of the new hires in period t were observed as inactive workers in period $t-1$, even though they did go through a period of unemployment in between.

2.1.3 Vacancies

Separation between workers and jobs can occur either because the match is of "low quality", i.e. a mismatch (quitting and firing), or because the job is "destroyed". After a separation occurs we assume the job becomes vacant only if the separation was because of a mismatch, otherwise it is vanished. The separation rate due to a mismatch is denoted by q. A fall in

[6] Based on data from the Labor Force Survey of the Central Bureau of Statistics for the period 1998-2011.

[7] See Shimer (2012) for discussion of time aggregation problem and its treatment.

q represents better matching efficiency. The job destruction rate is denoted by d.[8] Finally, each period a flow of c jobs is created and becomes vacant. A rise in c and a fall in d represent an expansion of aggregate activity in the economy.

A vacant job may be filled, in line with the matching process, or destroyed (with probability d); when separation occurs due to low quality of the match (with probability q) the job becomes vacant; and when new jobs are created they first enter the state of vacancy before they are filled. Therefore:

$$\dot{V} = -H - dV + qE + c$$

Substitute for E and H using (1) and (5) to get:

$$\dot{V} = -\alpha m\,(U, V) - dV + q\,(L - U) + c \tag{6}$$

2.1.4 Unemployment

Separation between workers and jobs can occur either because of low quality of the match with probability q, or because the (filled) job is destroyed with probability d. After a separation occurs we assume that the worker stays in the labor force. We do not model explicitly job-to-job movement of workers and therefore q should be thought of as the quitting rate plus firing rates that result in unemployment. We also assume that workers who move into the labor force first become unemployed before they find a job. Finally, unemployment falls one-to-one with new hires. We therefore have:

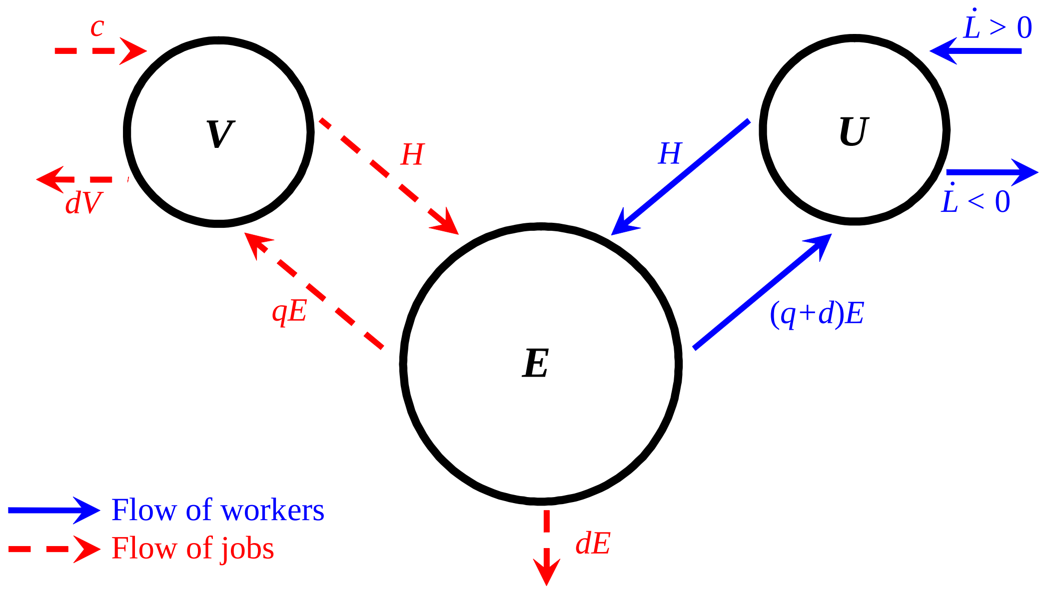
$$\dot{U} = -H + (q + d)\,E + \dot{L}$$

Substituting for E, $\dot{L}$ and H using (1), (4), and (5), we get:

$$\dot{U} = -\,(1 - a)\,\alpha m\,(U, V) + (1 - a)\,(q + d)\,(L - U) \tag{7}$$

[8] Following BD we assume that the job destruction rate of filled jobs equals that of vacant jobs, although it is likely that the destruction rate of the latter is greater. This assumption does not affect the qualitative results of the model; however, it does affect the exact specification of our long-run identifying restriction in the empirical analysis. In order to account for this discrepancy, and potentially other misspecifications, we impose sign restrictions on the empirical model. These restrictions are looser than the exact equality constraints that come out of the theoretical model. See section 3.3 below.

Figure 2: The Flow of Workers and Jobs



E - Employed	U - Unemployed	c - Job creation
H - Hires	V - Vacancies	d - Job destruction rate
L - Labor force		q - Quitting rate

Equations (3), (6), and (7) provide a system in unemployment, U, vacancies, V, and the labor force, L, that characterizes their evolution in equilibrium. Figure 2 summarizes the flows in and out the different states in the labor market.

2.2 Steady State

In steady state $\dot{V} = \dot{U} = 0$, therefore by (6) and (7):

$$\begin{aligned} \alpha m\left(U_{ss}, V_{ss}\right) &= -dV_{ss} + q\left(L_{ss} - U_{ss}\right) + c \\ \alpha m\left(U_{ss}, V_{ss}\right) &= \left(q + d\right)\left(L_{ss} - U_{ss}\right) \end{aligned}$$

and from (3):

$$L_{ss} = \frac{\Phi}{1-a} - \frac{a}{1-a} U_{ss}$$

Substituting for L_{ss} and then for V_{ss} gives:

$$
\begin{aligned}
V_{ss} &= \frac{c}{d} - \frac{1}{1-a}\left(\Phi - U_{ss}\right) && (8) \\
\alpha m\left(U_{ss}, \frac{c}{d} - \frac{1}{1-a}\left(\Phi - U_{ss}\right)\right) &= \frac{q+d}{1-a}\left(\Phi - U_{ss}\right) && (9)
\end{aligned}
$$

Equation (9) solves for U_{ss}, and given the solution for U_{ss}, we can recover V_{ss} and L_{ss}.

Notice that since $m\left(U,V\right)$ is increasing in both arguments the left-hand-side (LHS) of equation (9) is an increasing function of U_{ss}. The right-hand-side (RHS) is falling with U_{ss}. For $U_{ss} = 0$ the LHS equals zero while the RHS is positive. For $U_{ss} = \Phi$ the LHS is positive while the RHS equals zero. Therefore, by continuity and monotonicity of both sides, a unique steady state exists.

2.3 Dynamics

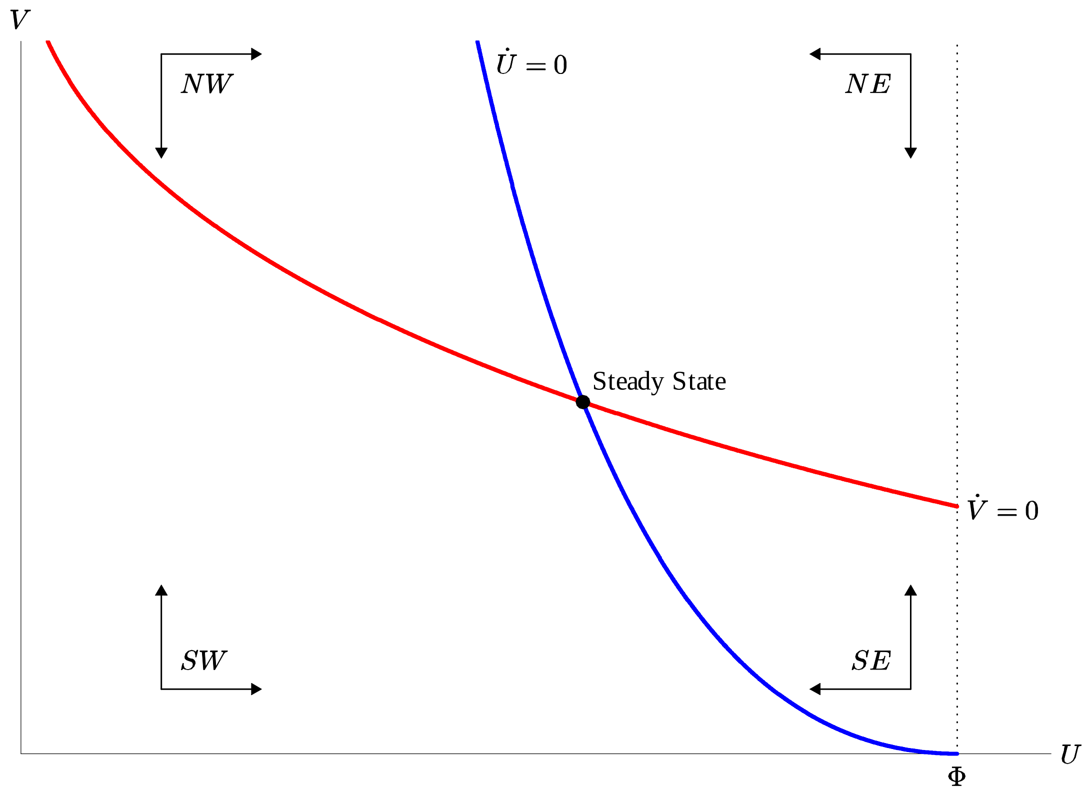
We now turn to characterizing the dynamics of the system using a phase diagram in the $U - V$ space.

First note that unemployment is bounded above by Φ: if $E = 0$ then $L = U = \Phi$, and in this case a rise in employment by one worker has a net effect of reducing unemployment by $1 - a$ workers; this is because the employed person has a direct effect of reducing unemployment by 1 and raising the labor force by a causing unemployment to fall by $1-a$. We therefore conclude that U cannot exceed Φ.

Substituting for L using equation (3) into (6) and (7) results in a dynamic system in unemployment and vacancies:

$$
\begin{aligned}
\dot{U} &= -\left(1-a\right)\alpha m\left(U,V\right) + \left(q+d\right)\left(\Phi - U\right) && (10) \\
\dot{V} &= -\alpha m\left(U,V\right) - dV + \frac{q}{1-a}\left(\Phi - U\right) + c && (11)
\end{aligned}
$$

Figure 3: Phase Diagram of Unemployment and Vacancies



Equating the left hand sides of both equations to zero characterizes the loci $\dot{U} = 0$ and $\dot{V} = 0$. Notice that:

$$\left.\frac{\partial V}{\partial U}\right|_{\dot{U}=0} = -\frac{(1-a)\,\alpha m_U + q + d}{(1-a)\,\alpha m_V} < 0$$

$$\left.\frac{\partial V}{\partial U}\right|_{\dot{V}=0} = -\frac{\alpha m_U + \frac{q}{1-a}}{\alpha m_V + d} < 0$$

Which suggests:

$$\left|\left.\frac{\partial V}{\partial U}\right|_{\dot{V}=0}\right| = \frac{(1-a)\,\alpha m_V}{(1-a)\,\alpha m_V + (1-a)\,d}\left|\left.\frac{\partial V}{\partial U}\right|_{\dot{U}=0}\right| - \frac{d}{(1-a)\,\alpha m_V + (1-a)\,d} < \left|\left.\frac{\partial V}{\partial U}\right|_{\dot{U}=0}\right|$$

That is, both loci $\dot{U} = 0$ and $\dot{V} = 0$ are downward sloping, and the locus $\dot{U} = 0$ is steeper than the locus $\dot{V} = 0$ at the point of intersection, i.e. at the steady state, as depicted in Figure 3.

Suppose we are at a point somewhere on the locus $\dot{U} = 0$ and V rises. A rise in V creates more matches and therefore raises the outflow from unemployment making $\dot{U}$ negative. Algebraically for a given level of U a rise in V reduces the right hand side of (10). Therefore, above the locus $\dot{U} = 0$ unemployment falls and similarly below it unemployment rises.

Now suppose we are at a point on the locus $\dot{V} = 0$ and U rises. A rise in U affects vacancies through two channels: first, more unemployed workers create more matches and therefore the outflow from the pool of vacant jobs to that of filled jobs rises, making $\dot{V}$ negative. Second higher unemployment implies a lower level of employment which reduces the inflow of jobs to the vacant state due to separation, this also makes $\dot{V}$ negative. Algebraically for a given level of V a rise in U reduces the right hand side of (11). Therefore, at points located to the right of the locus $\dot{V} = 0$ vacancies fall, and at points located to its left vacancies rise.

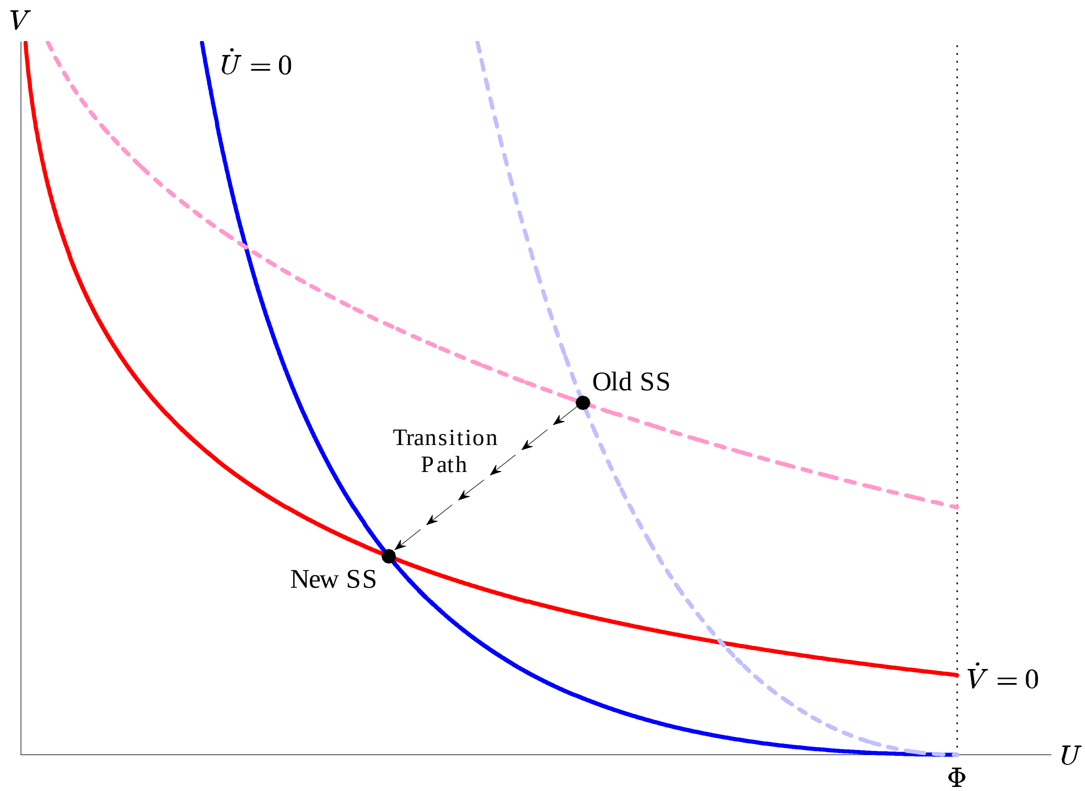
These dynamic effects are represented by the arrows plotted in Figure 3.

2.4 The Effect of Matching Efficiency (α and q)

Improvements in matching efficiency are captured by a rise in matching technology, α, and/or a fall in separation rate due to quitting and firing, q. Suppose the economy starts from steady state and is suddenly hit by a once and for all positive matching efficiency shock. Higher matching efficiency implies that, for a given level of U and V, either more matches are created, increasing the outflow from the states of unemployment and vacancy, and/or the inflow into these states falls due to fewer break-ups of matches. Both effects imply that U and V fall.

More formally, from equations (10) and (11) a rise in α and/or a fall in q shift both $\dot{U} = 0$ and $\dot{V} = 0$ loci inward, suggesting that U and V fall together as the old steady state is now located at the NE quadrant of the phase diagram.

Figure 4: The Dynamic Effect of a Rise in Matching Efficiency, Higher α and/or Lower q



To find the exact evolution of U and V over time notice that equation (8) characterizes the relationship between V_{ss} and U_{ss} for any value of α and q. From this relation it follows that all steady states lie on a straight line with slope $\frac{1}{1-a}$ (for fixed values of c, d, a and Φ); therefore, both U_{ss} and V_{ss} fall.

The dynamics of the system when the economy is located somewhere along the locus define by (8), even if it is out of steady state, is found by evaluating (10) and (11) at a point that satisfies $V = \frac{c}{d} - \frac{1}{1-a}(\Phi - U)$. In that case we get:

$$\dot{V}\Big|_{V=\frac{c}{d}-\frac{1}{1-a}(\Phi-U)} = \frac{1}{1-a}\,\dot{U}\Big|_{V=\frac{c}{d}-\frac{1}{1-a}(\Phi-U)}$$

and therefore:

$$\left.\frac{\partial V}{\partial U}\right|_{V=\frac{c}{d}-\frac{1}{1-a}(\Phi-U)} = \left.\frac{\dot{V}}{\dot{U}}\right|_{V=\frac{c}{d}-\frac{1}{1-a}(\Phi-U)} = \frac{1}{1-a}$$

This suggests that the system moves along a straight line (with slope $\frac{1}{1-a}$) towards the new steady state, as depicted in Figure 4.

For future reference notice that we have:

$$\Delta V_{ss} = \frac{1}{1-a}\Delta U_{ss} < 0 \tag{12}$$

which using (3) suggests:

$$\Delta L_{ss} = \Delta U_{ss} - \Delta V_{ss} = -\frac{a}{1-a}\Delta U_{ss} > 0 \tag{13}$$

This equation suggests that as matching efficiency improves the rise in employment, $\Delta L_{ss} - \Delta U_{ss}$, equals the fall in vacancies, $-\Delta V_{ss}$. We will use the long-run relations between unemployment, vacancies and the labor force as identifying restrictions later in our SVAR estimation.

2.5 The Effect of Aggregate Activity (c and d)

Movements in aggregate activity are captured by changes in job creation and job destruction parameters, c and d, respectively. In our setting we are agnostic about whether these shocks originate in aggregate demand or aggregate supply, all that matters in the model is that firms open jobs and shut them down. This section studies the effect of movements in the supply of jobs on vacancies and unemployment.

Suppose the economy starts from steady state and suddenly the supply of jobs rises through a rise in c. Equation (11) suggests that a higher c implies that more vacancies are created, i.e. $\dot{V}$ becomes positive. Equation (10) suggests that momentarily U is unchanged as it is independent of c, but as V increases more matches are created making $\dot{U}$ negative, as a result unemployment falls.

Figure 5: The Dynamic Effect of A Rise In Job Creation, Higher c - Positive Aggregate Activity Shock

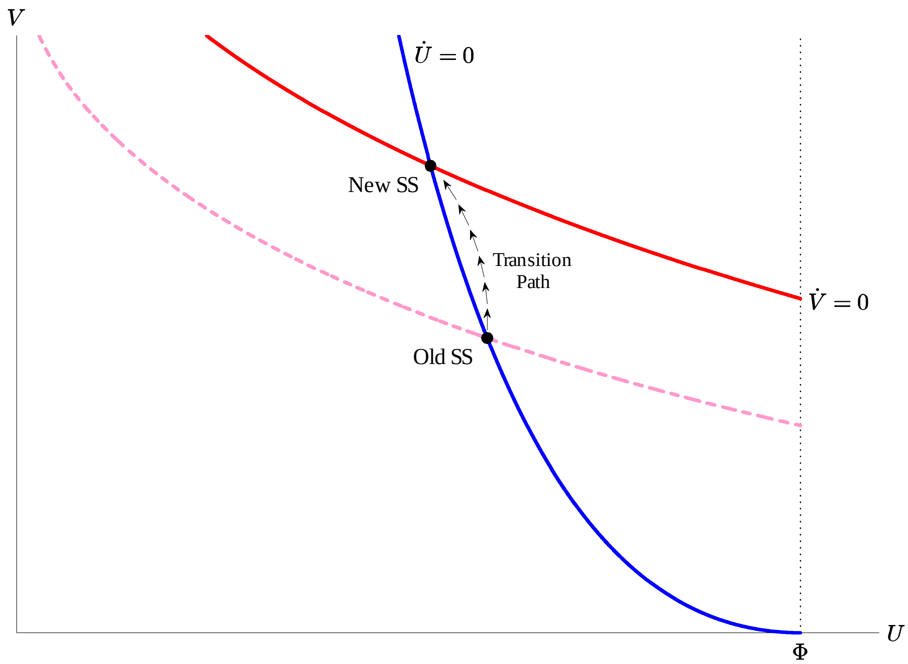
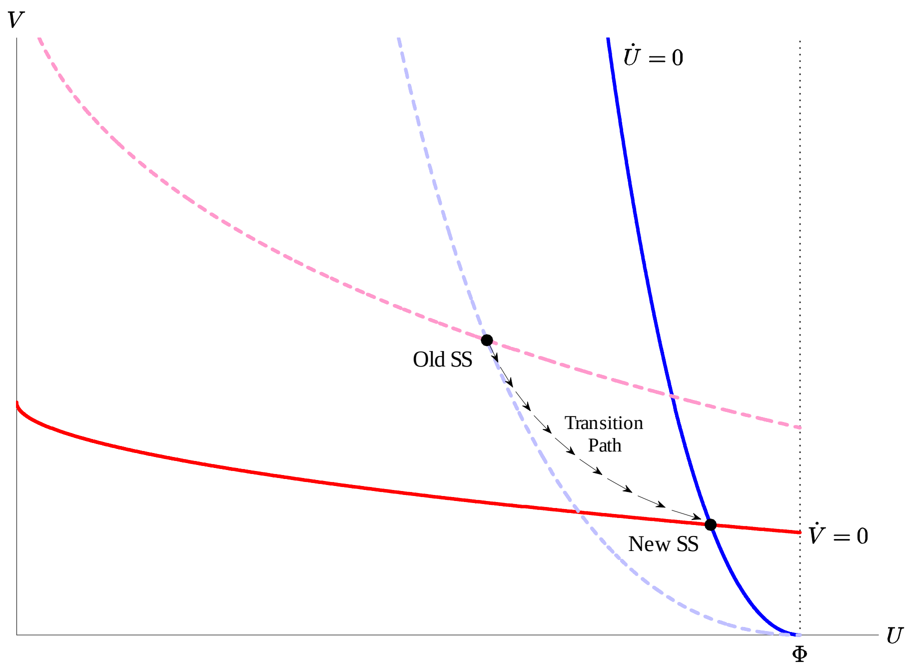


Figure 6: The Dynamic Effect of A Rise In Job Destruction, Higher d - Negative Aggregate Activity Shock



Furthermore, these equations suggest that the locus $\dot{U} = 0$ is unchanged while the locus $\dot{V} = 0$ shifts outward, locating the old steady state on the boundary between the SW and SE quadrants of the phase diagram as depicted in Figure 5, and in the new steady state there are more vacancies and fewer unemployed.

Now suppose the economy starts from steady state and suddenly the supply of jobs falls through a rise in d. Equation (10) suggests that a higher d raises unemployment as more employed workers lose their jobs, making $\dot{U}$ positive. Equation (11) suggests that as the job destruction rate increases more vacancies are shut down which reduces their stock and $\dot{V}$ becomes negative. After the first instant the rise in unemployment increases the stream of matches causing V to fall even further although moderating the rise in U; similarly, the fall in vacancies reduces the stream of new matches causing U to rise even further although moderating the fall in V. Equations (10) and (11) also imply that in response to a rise in d the locus $\dot{U} = 0$ shifts outward and the locus $\dot{V} = 0$ shifts inward, suggesting that U rises and V falls as the old steady state is now located at the NW quadrant of the phase diagram as depicted in Figure 6.

The negative comovement of unemployment and vacancies in response to aggregate activity shocks gives rise to the Beveridge relation in the model.

2.6 The Effect of Labor Supply (Φ)

Changes in the labor supply are captured by movements in Φ; as equation (2) makes clear shifts in Φ alter the labor force for any level of employment. Suppose the economy starts from steady state and suddenly the supply of labor rises through a rise in Φ. On impact, the rise in labor supply raises unemployment one-to-one, as we assume that new entrants to the labor force first become unemployed before moving to employment. As unemployment rises more matches are created which in turn reduces vacancies and offsets the initial jump in unemployment. That is, on impact unemployment overshoots its long-run level and then, along the convergence path, vacancies and unemployment gradually move towards a new steady state with less vacancies and more unemployed relative to the old steady state.

More formally, we start the analysis by establishing the shift in steady state. From (9) we derive:

$$\frac{dU_{ss}}{d\Phi} = \frac{\alpha m_{V_{ss}} + q + d}{(1-a)\,\alpha m_{U_{ss}} + \alpha m_{V_{ss}} + q + d} \; ,$$

suggesting that $0 < \frac{dU_{ss}}{d\Phi} < 1$, and from (8):

$$\frac{dV_{ss}}{d\Phi} = -\frac{1}{1-a}\left(1 - \frac{dU_{ss}}{d\Phi}\right),$$

and since $0 < \frac{dU_{ss}}{d\Phi} < 1$ it follows that $\frac{dV_{ss}}{d\Phi} < 0$. That is, in the new steady state there are fewer vacancies and more unemployed workers relative to the old one, as suggested earlier.

On impact, the rise in Φ raises unemployment by $\Delta\Phi$ and leaves vacancies unchanged, moving the system to $\left(U_{ss}^{old} + \Delta\Phi, V_{ss}^{old}\right)$.[9] Also, from (10) and (11) both loci, $\dot{U} = 0$ and $\dot{V} = 0$, shift outward, and at the point $\left(U_{ss}^{old} + \Delta\Phi, V_{ss}^{old}\right)$ both $\dot{U}$ and $\dot{V}$ become negative, which suggests that after the initial jump both U and V gradually fall as the effect of the rise in matches dominates their movement. It turns out that the system converges to the new steady state monotonically along a straight line as depicted in Figure 7.[10]

[9] Notice that the rise in Φ affects the *stock* of workers and therefore causes a jump in L and U. This is in contrast to previous impulses, i.e. changes in α, q, c, and d, that affect the *flows* of workers and jobs with no impact on the stock of unemployed and vacant jobs at the instant the shocks occur.

[10] First, using (10) and (11) we evaluate $\dot{V}$ and $\dot{U}$ at $\left(U_{ss}^{old} + \Delta\Phi, V_{ss}^{old}\right)$, the point to which the system jumps on impact. Since at $\left(U_{ss}^{old}, V_{ss}^{old}\right)$ both $\dot{V}$ and $\dot{U}$ equal zero, and since by assumption $\Delta\Phi > 0$, it follows that after the initial jump $\dot{V}, \dot{U} < 0$. Notice also that for any point in the $U - V$ space:

$$\frac{dV}{dU} = \frac{\dot{V}}{\dot{U}} = \frac{-\alpha m(U,V) - dV + \frac{q}{1-a}(\Phi - U) + c}{-(1-a)\,\alpha m(U,V) + (q+d)(\Phi - U)}$$

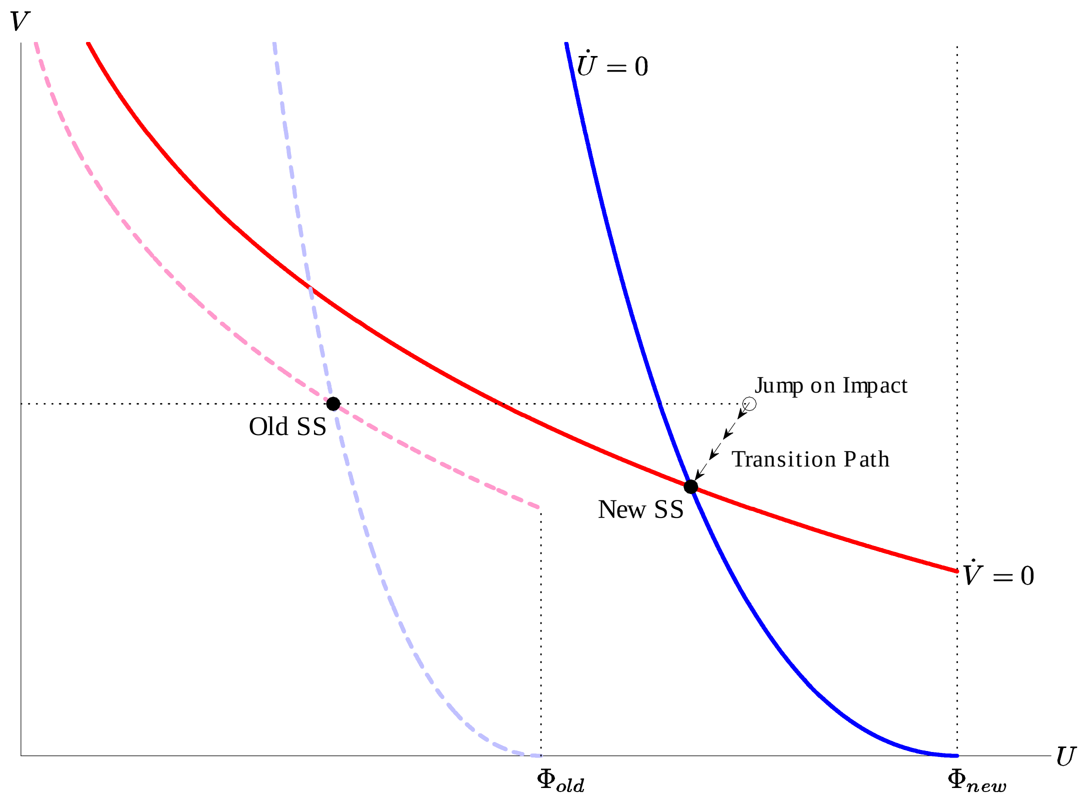
and at $\left(U_{ss}^{old} + \Delta\Phi, V_{ss}^{old}\right)$, after using (8) to substitute for V_{ss}^{old}, we get:

$$\left.\frac{dV}{dU}\right|_{(U,V)=\left(U_{ss}^{old}+\Delta\Phi, V_{ss}^{old}\right)} = \frac{1}{1-a}$$

Suggesting that U and V move initially at a slope $\frac{1}{1-a}$.

Next, notice that the slope between the new steady state, $(U_{ss}^{new}, V_{ss}^{new})$, and $\left(U_{ss}^{old} + \Delta\Phi, V_{ss}^{old}\right)$ equals $\frac{1}{1-a}$, and we evaluate again $\frac{dV}{dU}$ but this time at any point along the straight line between these points; that is, for $0 < \lambda \leq 1$ consider points that satisfy $(U,V) = \lambda\,(U_{ss}^{new}, V_{ss}^{new}) + (1-\lambda)\left(U_{ss}^{old} + \Delta\Phi, V_{ss}^{old}\right)$.

Figure 7: The Dynamic Effect of A Rise In Labor Supply, Higher Φ



Notice that although the model gives a clear pattern for the evolution of U and V in response to movements in labor supply it is unclear what is the overall correlation between these variables. On impact U rises while V is unchanged, suggesting no correlation; in the transition period both variables fall, suggesting a positive comovement; and a comparison of the new steady state to the old one suggests a negative comovement.

Using (8) to substitute for $V_{ss}^{new/old} = \frac{c}{d} - \frac{1}{1-a}\left(\Phi^{new/old} - U_{ss}^{new/old}\right)$ gives:

$$\left.\frac{dV}{dU}\right|_{(U,V)=\lambda(U_{ss}^{new},V_{ss}^{new})+(1-\lambda)(U_{ss}^{old}+\Delta\Phi,V_{ss}^{old})} = \frac{1}{1-a}$$

We therefore conclude that the convergence path is along a straight line with slope $\frac{1}{1-a}$.

2.7 Difference from Blanchard and Diamond

As mentioned, our model is heavily based on the work of Blanchard and Diamond (1989). Nevertheless, we deviate from their model in two aspects.

First, and most importantly, we capture fluctuations in aggregate activity through changes in the processes of job creation and job destruction. In our model these movements give rise to the Beveridge curve, i.e. a negative comovement between unemployment and vacancies. In contrast, the BD model combines the probability of an unproductive job to become productive (π_1), i.e. job creation probability, and the probability of a productive job to become unproductive (π_0), i.e. job destruction probability, to generate shocks with two very different outcomes. (1) They consider changes in the potential stock of productive jobs, $\frac{\pi_1}{\pi_0+\pi_1}$ (after normalizing the sum of productive and unproductive jobs to unity), as representing cyclical fluctuations in aggregate activity that generate the Beveridge relation. This works in a similar way to aggregate activity shocks in our model. And (2) they analyze changes in the flow of reallocation, in BD terminology, from productive to unproductive jobs, $\pi_0\frac{\pi_1}{\pi_0+\pi_1}$. In their model this shock results in a *positive* comovement between unemployment and vacancies. This is different from our results where fluctuations associated with job creation and job destruction parameters generate the Beveridge relation.

Furthermore, BD analyze movements in aggregate activity keeping reallocation constant, and vise versa. Given that both shocks depend on the probabilities of job creation and job destruction these exercises seem improbable. More specifically, stimulating aggregate activity by raising $\frac{\pi_1}{\pi_0+\pi_1}$ while keeping reallocation, $\pi_0\frac{\pi_1}{\pi_0+\pi_1}$, constant implies a negative comovement between π_1 and π_0; however, in considering the reverse exercise, i.e. raising reallocation while keeping aggregate activity constant, a positive comovement is implied. Since the data display negative comovement between job creation and job destruction, we view BD's first impulse exercise, that is impulsing aggregate activity while keeping reallocation constant, as more relevant.[11] Since reallocation shocks result in coun-

[11] For evidence on the comovement between job creation and job destruction see the appendix.

terfactual implications, at least in the specification of BD, we chose to focus on matching efficiency fluctuations as the main driver of positive comovement between unemployment and vacancies.

Second, BD chose to model the process of job creation as a rate out of the stock of unproductive jobs, that is the total of potential jobs minus filled jobs and vacancies. Under their specification the locus $\dot{V} = 0$ need not be downward sloping throughout the region $0 \leq U \leq \Phi$; assuming $\lim_{U \to 0} m_U \to \infty$, as is standard in the literature, the curve may have a positive slope for high enough U under some combinations of parameter values. Nevertheless, all our results go through unchanged under BD's specification, with only one exception: in response to movements in the job destruction rate, π_0, the system may generate a positive comovement between U and V. This happens only in the special case where the locus $\dot{V} = 0$ has a positive slope for high enough levels of unemployment and the steady state happens to be located far enough in that region. In that case a rise in job destruction results in a rise in vacancies, suggesting a counterfactual positive correlation between the series.[12] The reason behind this result is that as jobs are being destroyed the pool of unproductive jobs increases, which in turn creates more new jobs that re-enter the market as vacancies. Our assumption of an exogenous flow of job creation shuts down this counterfactual channel, and therefore we feel comfortable with simplifying the BD model along this dimension.

3 Empirical Strategy

In this section we set up a three-variable structural vector auto-regression (SVAR) model for unemployment, business sector vacancies and the labor force. The results of the theoretical model motivate the imposition of short-run and long-run restrictions that allow identifying the "structural shocks" of aggregate activity, matching efficiency and labor supply.

[12] For evidence on the comovement between job destruction and vacancies see the appendix.

3.1 Empirical Specification

As discussed in the previous section we distinguish between three types of shocks: (1) aggregate activity shocks, denoted by u^{aa} in the empirical model, (2) matching efficiency shocks, u^{me}, and (3) labor supply shocks, u^{ls}. We assume that the vector of structural innovations, $u \equiv \left[u^{aa}, u^{me}, u^{ls}\right]'$, is $iid - Normal$ over time, its elements are contemporaneously uncorrelated, and we normalize the variance of each innovation to unity, that is:

$$u_t \overset{iid}{\sim} N(0, I)$$

We use insights from the model of the previous section to impose identifying restrictions on the empirical SVAR model:

$$A_0 y_t = C + \textstyle\sum_{i=1}^{p} A_i y_{t-i} + B u_t \tag{14}$$

where y_t is a 3×1 vector of data on unemployed workers, business sector vacancies, and the labor force. A_0, A_1,. . .,A_p and B are 3×3 coefficient matrices, and C is a 3×1 vector of coefficients. Note that since we assume standard normal structural shocks the standard deviations of the underlying disturbances are embedded in the matrix B.

We use data in logs and since the levels of at least some variables are non-stationary (see section 4.1 below) we estimate the model in log first differences. Specifically we define:

$$y_t \equiv \begin{bmatrix} \Delta \log(U_t) \\ \Delta \log(V_t) \\ \Delta \log(L_t) \end{bmatrix}$$

Assuming A_0 is invertible the reduced form representation is given by:

$$y_t = \varphi + \textstyle\sum_{i=1}^{p} \phi_i y_{t-i} + \varepsilon_t \qquad \varepsilon_t \overset{iid}{\sim} N(0, \Omega) \tag{15}$$

where:

$$\begin{aligned} \varphi &= A_0^{-1} C \\ \phi_i &= A_0^{-1} A_i \qquad i = 1, \ldots, p \\ \varepsilon_t &= A_0^{-1} B u_t \qquad \Rightarrow \qquad A_0 \varepsilon_t = B u_t \\ \text{and} \qquad \Omega &= A_0^{-1} B B' A_0^{-1\prime} \end{aligned}$$

The reduced form representation, equation (15), is estimated with no restrictions, and for the identification of the structural parameters we impose restrictions on the matrices A_0 and B as guided by our theoretical model.

3.2 Short Run Restrictions

First, the diagonal elements of A_0 are normalized to unity. Next, we use the theoretical model to impose identifying restrictions; the model is summarized by equations (3), (6) and (7), which are rewritten here for convenience:

$$\begin{aligned} L &= \frac{\Phi}{1-a} - \frac{a}{1-a}U \\ \dot{U} &= -(1-a)\,\alpha m(U,V) + (1-a)(q+d)(L-U) \\ \dot{V} &= -\alpha m(U,V) - dV + q(L-U) + c \end{aligned}$$

The model suggests that an increase in aggregate activity, i.e. higher c and lower d, reduces unemployment and increases vacancies. The labor force is affected only indirectly through movements in unemployment. *We will therefore assume that u^{aa} affects U and V contemporaneously, and its effect on the labor force is delayed.*

The model suggests that an increase in matching efficiency, i.e. higher α and lower q, reduces both unemployment and vacancies. The labor force is affected only indirectly through movements in unemployment. *We will therefore assume that u^{me} affects U and V contemporaneously, and its effect on the labor force is delayed.*

The model suggests that a rise in labor supply, i.e. higher Φ, increases the labor force, and that unemployment and vacancies are affected only indirectly through movements in the labor force. Nevertheless, since by definition a rise of the labor force must be immediately reflected in the sum of unemployed and employed workers *we will assume that u^{ls} affects L contemporaneously, that L affects U contemporaneously, and that the effect on vacancies is delayed.*

These restrictions imply the following structure of the matrices A_0 and B:

$$A_0 = \begin{bmatrix} 1 & 0 & A_{0,13} \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \qquad B = \begin{bmatrix} B_{11} & B_{12} & 0 \\ B_{21} & B_{22} & 0 \\ 0 & 0 & B_{33} \end{bmatrix}$$

Three comments are in order. First, the matrices A_0 and B affect the likelihood function only through the product $A_0^{-1}B$ which is given by:

$$A_0^{-1}B = \begin{bmatrix} B_{11} & B_{12} & -A_{0,13}B_{33} \\ B_{21} & B_{22} & 0 \\ 0 & 0 & B_{33} \end{bmatrix} \tag{16}$$

This suggests that our specification is observationally equivalent to setting A_0 to the identity matrix and allowing a non-zero entry at the $1,3$ position (first row, third column) of the matrix B.

Second, notice that under our specification the $2,3$ (and $3,2$) elements of the matrix $A_0^{-1}BB'A_0^{-1\prime}$ equals zero; that is, the *structural model* implies that the *reduced form* innovations of vacancies and the labor force are uncorrelated, i.e. $\Omega_{23} = 0$. Since there are no restrictions on the estimation of the model in its reduced form the point estimate of this element is different from zero and we will be able to test whether the data reject this restriction.

Finally, notice that in the current specification there is nothing that distinguishes aggregate activity shocks from matching efficiency shocks, suggesting that the upper-left 2×2 block of the matrix B is not identified. Formally, although the order condition for identification is met, the rank condition is not. We complete the identification of the matrix B by imposing long-run restrictions.

3.3 Long-Run Restrictions

To complete the identification we need to impose restrictions that distinguish aggregate activity fluctuations from matching efficiency shocks. To that end we use the long-run relation between the variables after a shock to matching efficiency, as derived in Section

2.4. Specifically, we use equation (13):

$$\Delta L_{ss} = \Delta U_{ss} - \Delta V_{ss}$$

and verify that $\Delta V_{ss}, \Delta U_{ss} < 0$ and $\Delta L_{ss} > 0$, as suggested by (12) and (13).

The equation above was derived from our stock-flow accounting model and therefore it hinges on the exact assumptions of that model. If, for example, we relax the assumption that the destruction rate of vacant jobs equals that of filled jobs the equality does not hold, although the inequalities are still valid. As a robustness check we will therefore relax the long-run identifying restrictions and use only sign restrictions. That is, we will impose that after an improvement in matching efficiency unemployment and vacancies cannot rise, and the labor force cannot fall.

Using the methodology of Blanchard and Quah (1989), these restrictions imply various constraints on the coefficients of the matrix $A_0^{-1}B$. Let $C(1)$ denote the matrix of cumulative impulses to the reduced form disturbances:

$$C(1) = \left(I - \textstyle\sum_{i=1}^{p} \phi_i\right)^{-1}$$

Let $D(1)$ denote the cumulative impulses of the structural disturbances:

$$D(1) \equiv C(1)\, A_0^{-1} B$$

The long run effect of a matching efficiency shock is given by the second column of:

$$\begin{bmatrix} C_{11} & C_{12} & \cdot \\ C_{21} & C_{22} & \cdot \\ C_{31} & C_{32} & \cdot \end{bmatrix} \begin{bmatrix} \cdot & B_{12} & \cdot \\ \cdot & B_{22} & \cdot \\ \cdot & 0 & \cdot \end{bmatrix} = \begin{bmatrix} \cdot & C_{11}B_{12} + C_{12}B_{22} & \cdot \\ \cdot & C_{21}B_{12} + C_{22}B_{22} & \cdot \\ \cdot & C_{31}B_{12} + C_{32}B_{22} & \cdot \end{bmatrix}$$

where C_{ij} is the i, j element of the matrix $C(1)$, and we used the result for $A_0^{-1}B$ in (16). We therefore get that the long-run effects of a matching efficiency shock are given by:

$$\Delta \log(U_{ss}) = C_{11}B_{12} + C_{12}B_{22} \tag{17}$$

$$\Delta \log(V_{ss}) = C_{21}B_{12} + C_{22}B_{22} \tag{18}$$

$$\Delta \log(L_{ss}) = C_{31}B_{12} + C_{32}B_{22} \tag{19}$$

We now specify the exact restriction we used for each case.

3.3.1 Case 1: Strict Equality, $\Delta L_{ss} = \Delta U_{ss} - \Delta V_{ss}$

Equation (13) puts a long-run restriction on the variation of the first difference of the levels of the variables in the system, not on their logs. In that respect it might be more natural to define the variables in these terms and not in log first difference. Nevertheless, we rewrite equation (13) to conform with our logarithmic specification as follows:

$$\frac{\Delta L_{ss}}{L_{ss}} = \frac{U_{ss}}{L_{ss}}\frac{\Delta U_{ss}}{U_{ss}} - \frac{V_{ss}}{L_{ss}}\frac{\Delta V_{ss}}{V_{ss}}$$

Note that for a generic variable X_{ss} we can approximate $\frac{\Delta X_{ss}}{X_{ss}} \cong \Delta \log(X_{ss})$, and therefore:

$$\Delta \log(L_{ss}) \cong \frac{U_{ss}}{L_{ss}}\Delta \log(U_{ss}) - \frac{V_{ss}}{L_{ss}}\Delta \log(V_{ss})$$

and using equations (17), (18), and (19) we get:

$$B_{12} = \frac{\frac{U_{ss}}{L_{ss}}C_{12} - \frac{V_{ss}}{L_{ss}}C_{22} - C_{32}}{C_{31} + \frac{V_{ss}}{L_{ss}}C_{21} - \frac{U_{ss}}{L_{ss}}C_{11}} B_{22} \tag{20}$$

The coefficients of the matrix $C(1)$ are derived from the estimation of the model in reduced form, and we use sample averages of $\frac{U_t}{L_t}$ and $\frac{V_t}{L_t}$ as estimates for the steady state value of these ratios. Therefore, equation (20) simply puts a linear restriction on the coefficients of the matrix B. After deriving the point estimates we verify that the system converges to a point with fewer vacancies and unemployed and a bigger labor force.

3.3.2 Case 2: Sign Restrictions

In this case we use only sign restrictions:

$$\Delta V_{ss}, \Delta U_{ss} < 0 \qquad , \qquad \Delta L_{ss} > 0 \tag{21}$$

In this case there is a continuum of observationally equivalent estimates of the matrix B, each generates a different set of impulse response functions. More specifically, the likelihood function depends on the variance-covariance matrix $A_0^{-1}BB'A_0^{-1\prime}$; therefore, post-multiplying the matrix B by a unitary matrix Q, i.e. a matrix that satisfies $QQ' = Q'Q = I$, leaves the value of the likelihood function unchanged. This gives rise to a continuum of observationally equivalent estimates for the matrix B, since for any estimate of B an alternative estimate $\widetilde{B} = BQ$ yields the exact same value for the likelihood function. In order to find all observationally equivalent estimates we start from the estimate of B we found for the previous case, in which $\Delta L_{ss} = \Delta U_{ss} - \Delta V_{ss}$, and use the unitary matrix:

$$Q = \begin{bmatrix} (-1)^i \cos(\theta) & (-1)^i \sin(\theta) & 0 \\ (-1)^{j+1} \sin(\theta) & (-1)^j \cos(\theta) & 0 \\ 0 & 0 & 1 \end{bmatrix} \qquad 0 \leq \theta \leq \pi \qquad , \qquad i, j \in \{1, 2\}$$

This matrix maintains (in $\widetilde{B}$) the short-run restrictions we placed on B. Varying θ from $0°$ to $180°$ in small steps[13], while evaluating for each θ all combinations of i and j, covers the whole range of possible unitary matrices. For each $\widetilde{B} = BQ$ we check whether the restrictions in (21) are satisfied; we only keep the estimates that obey these restrictions.

Below we will focus our attention on the estimate whose impulses are closest to the median across all estimates. That is, for each shock-variable pair we have many impulse response functions, one for each $\widetilde{B}$ that obeys our sign restrictions, and we calculate the median path for that pair.[14] Next, for each $\widetilde{B}$ we calculate the sum of squared distances of its impulse from the median path and then sum the results across all shock-variable pairs. Finally, we choose the matrix $\widetilde{B}$ that generates the smallest sum of squared distances.[15]

[13] We used steps of $6''$.

[14] Different horizons along this path may pick up estimates from different $\widetilde{B}$s.

[15] This procedure is recommended by Fry and Pagan (2011).

4 Data and Estimation Results

4.1 The Data

We use data on unemployed workers, vacant jobs in the business sector and the labor force.[16] Data are in quarterly frequency and are seasonally adjusted. For the unemployed and the labor force, time series with uniform definitions are available since the first quarter of 1995; a time series for vacancies is available from the first quarter of 1998. The sample ends at the fourth quarter of 2011. The data are displayed in Figures 8a and 8b.

The labor force clearly displays an upward time trend that, by eyeballing the figure, seems to be deterministic. The labor force increased during the sample period by 2.7 percent per annum, this rate is higher than the growth rate of working-age population that was 2.2 percent per annum during the same period; the difference is due to a rise in the participation rate of women. While the labor force of males grew at a rate of 2.3 percent per annum, the female labor force grew by 3.2 percent. Since 2003, the Israeli government took several steps targeted at widening labor market involvement of low-participation groups, including stiffening entitlement criteria for the Social Security benefits, cutting child allowances and introducing experimental 'from welfare to work' program.[17] Additionally, the mandatory retirement age was gradually raised by two years during 2004-9.[18]

[16]Data on unemployed workers and the labor force are from the Israeli Central Bureau of Statistics (CBS). These series are compiled by the CBS from its Labor Force Survey. At the first quarter of 2012 the CBS made a transition from quarterly to monthly Labor Force Survey, simultaneously changing the sampling methodology and the definition of the labor force characteristics. This transition caused a break in the series which undermines the ability to compare between 'new' and 'old' time series. Although the CBS suggested chaining coefficients to bridge over the break, these coefficients are inadequate for chaining the series backward to 1998. Data on vacancies are from the Employers Survey of the Ministry of Economy.

[17]See for example Box 5.2 in the Bank of Israel Annual Report 2006 for the evaluation of the influence of a cut in child allowances on labor force participation among parents in large families and Box 5.1 in the Bank of Israel Annual Report 2005 and Box 5.3 in the Bank of Israel Annual Report 2008 for the description of Israeli 'from welfare to work' program.

[18]For the evaluation of the effect of the change in the Retirement Age Law on participation of older population in the labor force see Box 5.1 in the Bank of Israel Annual Report 2010.

Figure 8a: Unemployment and Vacancies
(1995-2011, Seasonally Adjusted, Thousands)

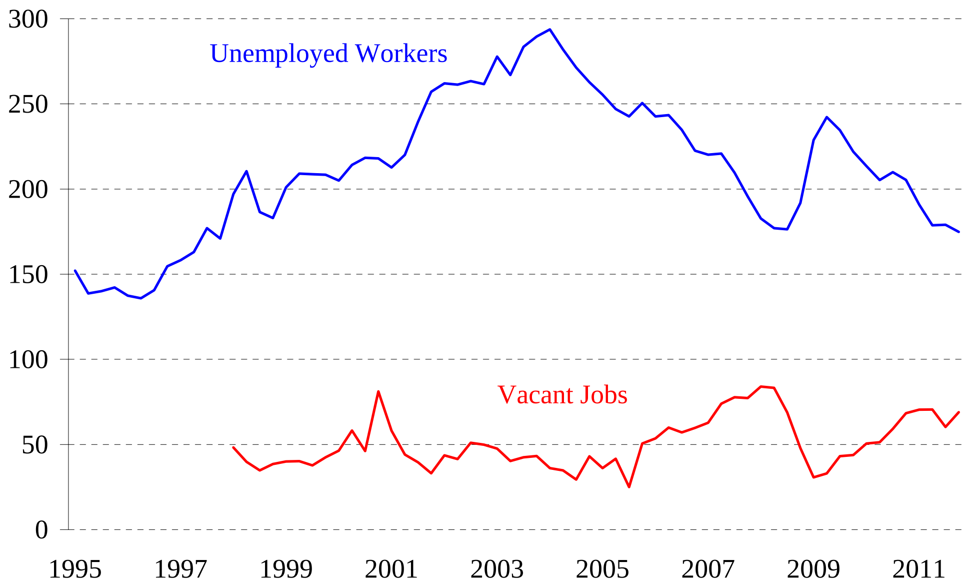
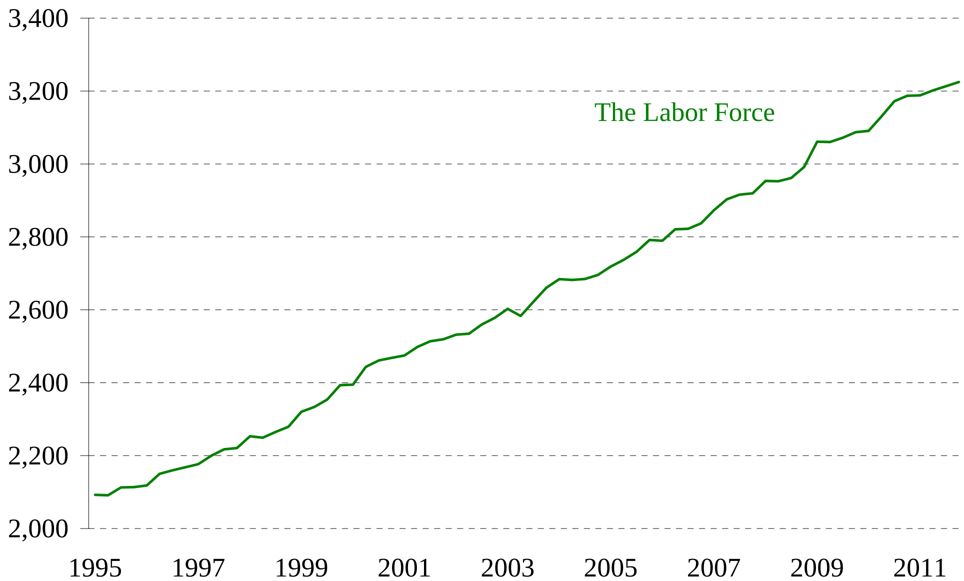


Figure 8b: The Labor Force
(1995-2011, Seasonally Adjusted, Thousands)



Unemployment and vacancies do not display any visible trend over the sample period although statistically a deterministic linear trend turned out positive and significant for both series. Persistence is evident in both series with auto-correlation coefficients of 0.96 for unemployed workers and 0.76 for vacancies. Unemployment and vacancies also display negative comovement, with a correlation coefficient of -0.53 during the sample period, suggesting that aggregate activity shocks dominate their movement.

Unit root tests (Augmented Dickey-Fuller) indicate that we cannot reject the hypothesis of unit root in the series of unemployed workers (in logs) for any reasonable significance level. For (log) vacancies we reject the null at 10 percent significance level, and for the labor force (in logs) the test statistic is very close to the 10 percent rejection region after accounting for a deterministic time trend. Given these results, and since we reject the null of unit root in the log first difference for all series, we choose to estimate the model in log first differences.[19]

4.2 Estimation Results

We now turn to analyzing the results of the SVAR estimation. The model is estimated for the period 1998-Q1 to 2011-Q4, where the starting date is dictated by the availability of the data on vacancies. We include two lags in the model even though formal lag-length criteria (not shown) indicate the inclusion of only one lag.[20] We do that because we believe that the labor market is slow to adjust to shocks as frictions in the market cause it to react not only to developments in the current and previous quarter but also to less recent developments. The impulse response functions of unemployment (discussed below) support

[19] In addition, cointegration tests (not shown) suggest the series are not cointegrated, similar to the result of BD for the American economy. It should be noted that the results of the unit root and cointegration tests might be driven by our short sample period. Nevertheless, we feel comfortable estimating the model without an error correction term as it seems (by the eyeball metric) that during our sample period the forces that pull the system into a joint random trend were at best negligible and since the theoretical model does not suggest a cointegrated system.

[20] Likelihood ratio tests, Akaike information criterion, Schwarz information criterion and Hannan-Quinn information criterion all support the inclusion of only one lag.

our view, as the reaction of unemployment to aggregate activity and labor supply shocks is spread over three quarters. For comparison, Blanchard and Diamond (1989) include lags up to a year for the American labor market. It is probably the case that our short sample induced a minimal lag structure on the information criteria in order to save on degrees of freedom.

4.2.1 Reduced-Form Innovations

Before analyzing the impulse response functions we review the correlations between the reduced-form innovations as they summarize the contemporaneous comovement of the system. Table 1 reports the correlation matrix and standard deviations of the reduced-form innovations. The innovations of unemployment and vacancies are negatively correlated suggesting that aggregate activity shocks dominate their contemporaneous movement, this is consistent with our earlier observation of the raw data. The table also displays a strong positive correlation between the innovations of unemployment and the labor force; this result is consistent with our assumption in the theoretical model that as new workers join the labor force they first enter the state of unemployment, although it does not exclude the possibility of some movement directly into employment. In addition, it may also indicate that the labor force is not very responsive to shocks other than labor supply, i.e. a small a in terms of the theoretical model, since both aggregate activity and matching efficiency shocks generate negative comovement between unemployment and the labor force. Finally notice that the correlation between the innovations to vacancies and the labor force is close to zero. Recall that this is consistent with our identification restriction on the matrix B. The associated significance level of the over-identifying test is 0.98, suggesting that we are far from rejecting the null that this correlation is in fact zero.

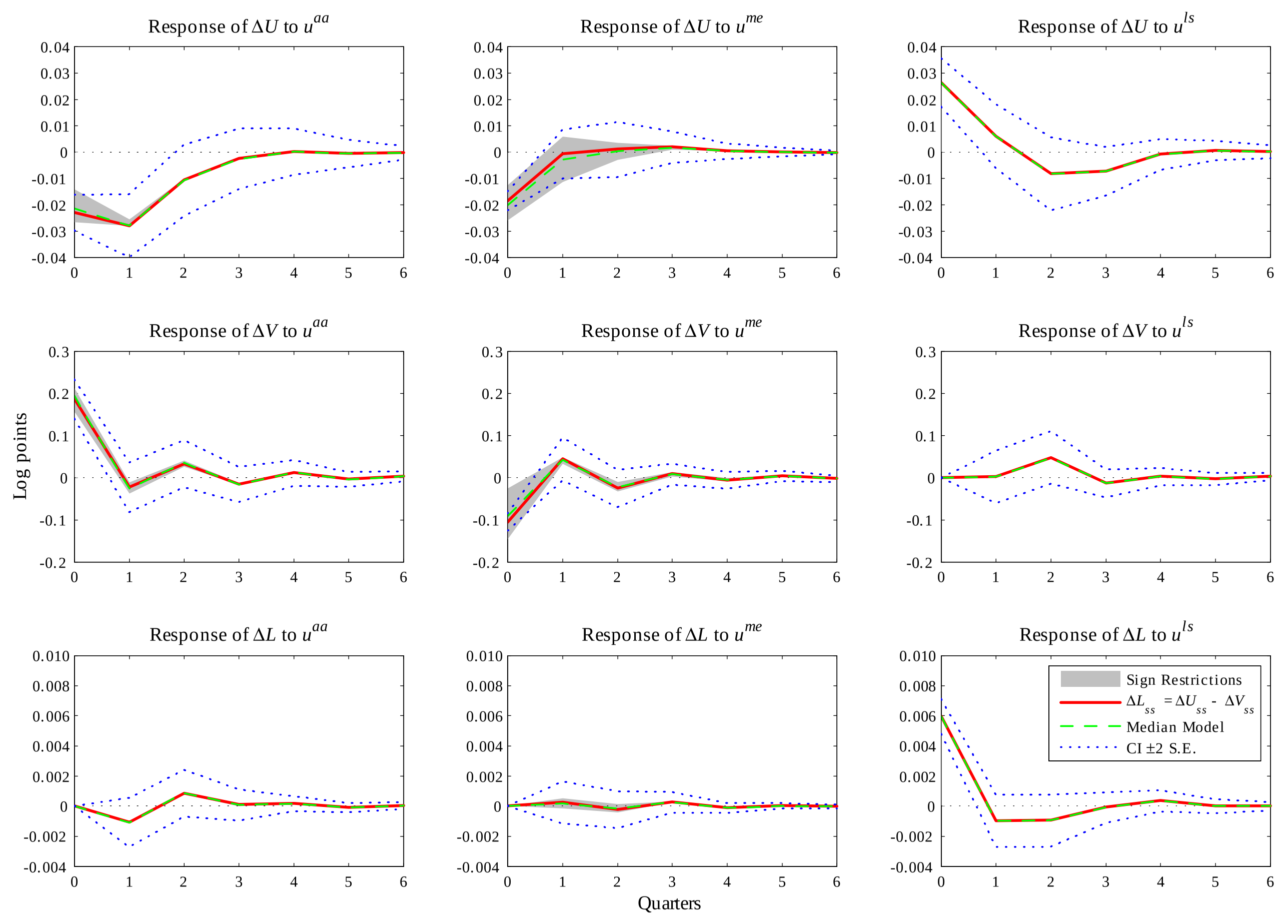
Table 1: Correlation between Reduced-Form Innovations, 1998-2011

	Correlations			STD
	ΔUnemployment	ΔVacancies	ΔLabor Force	(in log points)
ΔUnemployment	1.00			0.040
ΔVacancies	-0.27	1.00		0.214
ΔLabor Force	0.67	0.003	1.00	0.006

4.2.2 Impulse Response Functions and Variance Decomposition

Figure 9 displays the impulse response functions of the different specifications; the grey areas cover the impulses of *all* models that obey the sign restrictions, the dashed lines are the impulses of the median model of that set, the bold lines are the impulses of the model that uses equation (13) as an identifying restriction and the dotted lines mark its ± 2 standard errors confidence interval. Notice that the theoretical restriction generates impulses that are almost indistinguishable from the impulses of the median model. This is not to say that these impulses are more "reasonable" than those that only use sign restrictions, as all models reach exactly the same value of the likelihood function; nevertheless, we can conclude that the theoretical model is practically as representative of the set of models that obey the sign restrictions as the median model; the fact that these impulses rely on economic theory endow them with an additional virtue. In the analysis below we will therefore focus only on the theory-based model. Also notice that the range of impulses that obey the sign restrictions is fairly tight around our chosen model, suggesting that our focus on only one model does not miss much of the dynamics in the system.

Figure 9: Impulse Response Functions of Unemployment, Vacancies and the Labor Force



The grey areas cover the impulses of all models that obey the sign restrictions $\Delta U_{ss}, \Delta V_{ss} < 0$ and $\Delta L_{ss} > 0$, the dashed lines are the impulses of the median model of that set, the bold lines are the impulses of that use the restriction $\Delta L_{ss} = \Delta U_{ss} - \Delta V_{ss}$ from the theoretical model, and the dotted lines mark its ± 2 standard errors confidence interval (standard errors were calculated analytically).

Table 2: Estimates of the Matrix $B^{1,2}$

	Coef.	STD
$B_{\Delta U,aa}$	-0.0229	0.0034
$B_{\Delta U,me}$	-0.0185	0.0018
$B_{\Delta U,ls}$	0.0264	0.0045
$B_{\Delta V,aa}$	0.1866	0.0232
$B_{\Delta V,me}$	-0.1052	0.0102
$B_{\Delta L,ls}$	0.0060	0.0006

[1] $B_{x,y}$ is the on-impact effect of shock y on variable x; where, U is unemployment, V vacancies, L labor force, aa aggregate activity, me matching efficiency, and ls labor supply.

[2] The elements $B_{\Delta V,ls}$, $B_{\Delta L,aa}$, and $B_{\Delta L,me}$ are set to zero by the short-run restrictions.

Table 2 reports the estimation results of the elements of the matrix B. The entries of B give the value of the impulse response functions on impact. All coefficients are of the expected sign and statistically significant, and the behavior of the impulse response functions are much in line with the predictions of the theoretical model.

A positive aggregate activity shock reduces unemployment and increases vacancies, giving rise to the Beveridge relation. Notice that vacancies are much more responsive and react more quickly to the shock relative to unemployment. As aggregate activity expands by one standard deviation vacancies rise immediately by approximately 20 percent and do not change much in subsequent periods; unemployment falls much more moderately and its reaction is more sluggish as it continue to fall during the next two quarters. That is, aggregate activity shocks result in a strong and swift reaction in vacancies and a more moderate and persistent movement, in the opposite direction, of unemployment. These dynamics give rise to counter-clockwise loops of unemployment and vacancies around the

Beveridge curve.[21] Labor supply does not react on impact to aggregate activity shocks by assumption, and its movement in following periods is insignificant.

A positive matching efficiency shock reduces both unemployment and vacancies. Labor supply does not react on impact to matching efficiency shocks by assumption, and its movement in following periods is insignificant.

A positive labor supply shock raises both the labor force and unemployment, as suggested by the model.[22] Taking into account that during our sample period the labor force is about 12 times bigger than the pool of unemployed workers, and that its contemporaneous elasticity with respect to labor supply innovation is about one quarter of that of unemployment it follows that on impact the absolute rise in the labor force is about three times larger than the rise in unemployment. This suggests a large movement of new entrants to the labor force directly into employment, and as we already mentioned in section 2.1.2, this may be a reflection of time aggregation in the data. Also notice that after the initial rise in unemployment it tends to fall, offsetting its initial rise, two to three quarters after the shock. This result supports the overshooting of unemployment, as suggested by theory. It should be noted, however, that the result is only near significance.[23] Vacancies do not react, by assumption, to labor supply shocks on impact. However, contrary to the prediction of the theoretical model they tend to rise in following periods and their reaction is near significance.[24] This may suggest some misspecification. For example, it may be the case that the rise in labor supply reduces real wages which, in turn, raises vacancies along a fixed labor demand schedule. This motivates richer models, theoretical and empirical, that include both prices (wages) and quantities (workers and jobs) allowing the estimation of a Phillips curve alongside the Beveridge curve, accounting for their interdependence.

[21] Counter-clockwise loops of unemployment and vacancies are reported by Blanchard and Diamond (1989) and Barnichon and Figura (2010) for the US economy and by Pissarides (1985) and Wall and Zoega (2002) for the British economy.

[22] In this case all long-run identifying restrictions generate identical results, by construction.

[23] The effect two quarters after the shock is insignificant, and after three quarters the effect is negative at 6.2 percent significance level (in a one-tailed test).

[24] The effect two quarters after the shock is positive at 6.4 percent significance level (in a one-tailed test).

Table 3: Variance Decomposition (in percents)

Quarters After the Shock	ΔUnemployment			ΔVacancies			ΔLabor Force		
	aa	me	ls	aa	me	ls	aa	me	ls
0	33.5	21.8	44.8	75.9	24.1	0.0	0.0	0.0	100.0
1	54.7	14.3	31.0	72.9	27.1	0.0	3.1	0.2	96.7
2	55.2	13.4	31.4	69.4	26.2	4.5	4.9	0.3	94.8
3	54.1	13.2	32.7	69.2	26.1	4.8	4.9	0.5	94.6
4	54.1	13.2	32.7	69.2	26.1	4.8	4.9	0.5	94.6

aa = Aggregate Activity, me = Matching Efficiency, ls = Labor Supply
After 4 quarters the variance decomposition is practically identical to the long run values. Note, however, that since the dependent variables in the system converge to zero quickly (as they are expressed in first differences), the variance decomposition of longer horizons is of no practical interest.

The variance decomposition reveals the source of fluctuations of each variable for different horizons. Table 3 presents the results. First note the dominance of aggregate activity shocks in the variation of both unemployment and vacancies (in first log difference). On impact 76 percent of the variance of vacancies originates in aggregate activity shocks; in subsequent quarters its weight falls moderately to 69 percent. For unemployment, initially 33 percent of its variation is accounted for by aggregate activity fluctuation, and after one quarter this share jumps to 55 percent. These large shares are responsible for the observed negative comovement of vacancies and unemployment in the data. Second, matching efficiency shocks account for only a small share, although not negligible, of the variation of unemployment and vacancies. Next, labor supply shocks is the largest driver of unemployment on impact, with a share of 45 percent of unemployment variation, but in subsequent quarters this share falls to 33 percent as the importance of aggregate activity shocks rises. Finally, labor supply shocks account for almost all the variation in the labor force and almost none of the variation in vacancies.

4.2.3 Historical Decomposition of Unemployment and Vacancies

In this section we evaluate how much of the fall in unemployment since 2004 is attributed to cyclical fluctuations and how much to other factors. This decomposition is important for the conduct of monetary policy, for example. If policymakers overestimate the share attributed to cyclical factors then they are likely to follow a too aggressive monetary policy. In periods of economic expansion policymakers might interpret a fall in unemployment as signaling an overheated economy with greater inflationary pressures than there actually present, as a result they might raise the interest rate more aggressively than necessary.

Using the moving average representation of the system, the SVAR methodology allows decomposing the variation of the endogenous variables to movements accounted for by each of the structural shocks. However, this decomposition requires estimates of the shocks starting far in the distant history, which of course are not available; as a result our decomposition involves an additional deterministic term that depends on the initial state of the system at the beginning of the sample. We add to this term the effect of the deterministic growth as accounted for by the constant term in the estimated system. This decomposition allows us to evaluate how much of the movement in unemployment and vacancies can be attributed to movements along the Beveridge curve, as captured by aggregate activity shocks, and how much is accounted for by shifts of the Beveridge curve.

Figure 10 presents the evolution of unemployment against vacancies throughout our sample period as accounted for by each component. Data are presented as log-deviations relative to the first quarter of 2004, the quarter in which unemployment reached its highest level in our sample. We also point out five observations: the start date of the sample (after accounting for first-differencing and two lags), 1998-Q4; the end date of the sample, 2011-Q4; and three local extremum of unemployment, reflecting the turning points of the business cycle: in 2004-Q1 around the trough of the recession of the second intifada unemployment rate peaked at 10.9 percent, in 2008-Q3 just before the escalation of the global financial crisis unemployment rate reached a low of 6.0 percent, and three quarters later in 2009-Q2 it peaked at 7.9 percent. It should be noted that the end date of the sample, 2011-Q4, also coincides with a local minimum of unemployment with a rate of 5.4 percent.

The results are in line with the prediction of the theoretical model. Aggregate activity shocks generate the Beveridge relation, a strong negative correlation between unemployment and vacancies; matching efficiency shocks generate a positive comovement, and labor supply shocks generate no clear pattern of comovement. The deterministic term supports the negative comovement of unemployment and vacancies during the sample period.

Table 4 summarizes the results numerically for our period of interest, 2004-Q1 to 2011-Q4. Aggregate activity shocks were the main driver of unemployment during that period, they account for almost half, 48.4 percent, of the fall in the number of unemployed workers. Labor supply shocks account for 28.7 percent and matching efficiency account for 20.8 percent. Vacancies were driven primarily by aggregate activity and matching efficiency shocks. The rise in vacancies is explained by aggregate activity shocks as they contribute more than 150 percent of the rise; this movement was offset by improvement in matching efficiency. Labor supply shocks had only a marginal effect on vacancies. The labor force was driven almost entirely by the deterministic trend. This result is not surprising given the evolution of the labor force as depicted in Figure 8b. The labor force was also affected by labor supply shocks, but to a much lesser extent relative to the dominance of the deterministic trend; the effects of aggregate activity and matching efficiency are negligible.

For the decomposition of the *rates* of unemployment and vacancies we subtract the decomposed elements of the labor force (in logs) from those of unemployment and vacancies (also in logs). Results are reported in the right column of Table 4. Since 2004-Q1 the unemployment rate fell by 5.5 percentage points, of which only 2 percentage points are attributed to cyclical factors. The difference relative to the decomposition of the number of unemployed is driven by the properties of the labor force. The dominance of the deterministic trend in the latter is transmitted into the unemployment rate, thereby downplaying the importance of other components.

Figure 10: Historical Decomposition of Unemployment and Vacancies (log changes relative to 2004-Q1)

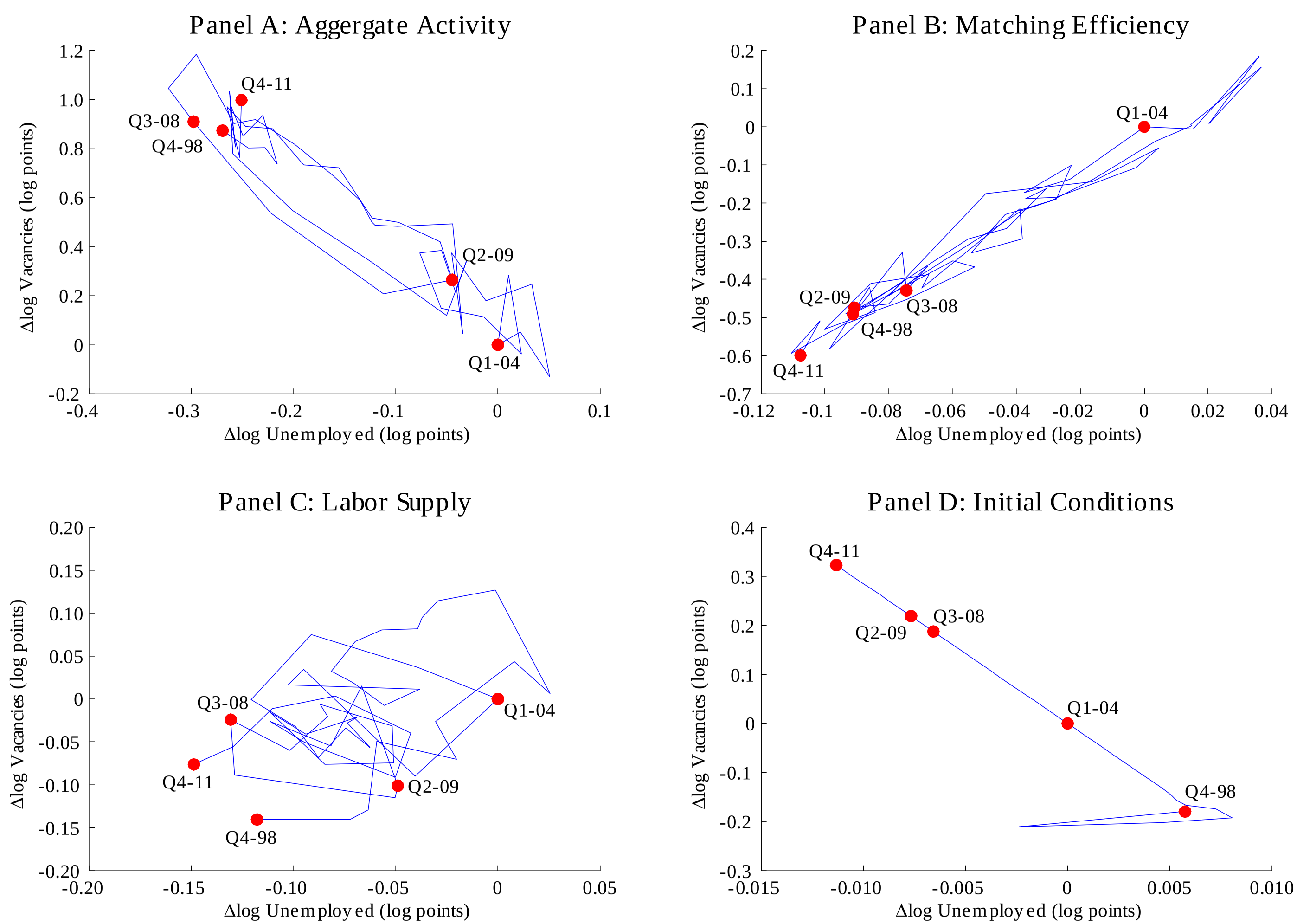


Table 4: Historical Decomposition of Unemployment, Vacancies and the Labor Force, 2004-Q1 to 2011-Q4[1]

	AA	ME	LS	DT	Not AA	Total	AA	ME	LS	DT	Not AA	Total
	Unemployed, $\Delta \log (U)$						Unemployment Rate, $\Delta \log (U/L)$					
Log Points	-0.251	-0.108	-0.149	-0.011	-0.268	-0.519	-0.254	-0.108	-0.122	-0.218	-0.449	-0.702
Share (Percents)	-48.4	-20.8	-28.7	-2.2	-51.6	-100	36.1	15.4	17.4	31.1	63.9	100
Percentage Points[2]							-2.0	-0.9	-1.0	-1.7	-3.5	-5.5
	Vacancies, $\Delta \log (V)$						Vacancy Rate, $\Delta \log (V/L)$					
Log Points	0.997	-0.599	-0.076	0.323	-0.352	0.645	0.995	-0.600	-0.049	0.116	-0.533	0.462
Share (Percents)	154.6	-92.9	-11.8	50.1	-54.6	100	215.6	-130.0	-10.7	25.2	-115.6	100
Percentage Points[2]							1.7	-1.0	-0.1	0.2	-0.9	0.8
	Labor Force, $\Delta \log (L)$											
Log Points	0.003	0.001	-0.027	0.207	0.181	0.184						
Share (Percents)	1.4	0.4	-14.6	112.7	98.6	100						

[1] AA = Aggregate Activity, ME = Matching Efficiency, LS = Labor Supply, DT = Deterministic Term, Not AA = ME + LS + DT.

[2] Percentage points are calculated as the shares times the actual change in the unemployment rate (-5.5) and the vacancy rate (+0.8).

The vacancy rate rose by 0.8 percentage points since 2004-Q1, of which 1.7 percentage points are attributed to cyclical factors and −0.9 to non-cyclical factors, although these mainly reflect matching efficiency.

We interpret our measure of aggregate activity shocks as representing business cycle fluctuations. This interpretation is supported by the fact that the aggregate activity components of unemployment and vacancies are highly correlated with (linearly) detrended business sector GDP (in logs), the correlation coefficients are −0.95 and 0.93, respectively, for the period since 2004-Q1[25]; and in particular they are by far the most cyclical components. This is vividly seen from the Beveridge curve in Panel A of Figure 10. The observation of 2004-Q1, when the economy was at the trough of the business cycle, is located at the lower right end of the graph, then as the economy recovered it moved upward along the Beveridge curve until 2008-Q3, then as the global financial crisis hit the economy moved down the curve until 2009-Q2, and then again as recovery started it moved upward along the curve until 2011-Q4. We therefore feel comfortable interpreting aggregate activity shocks as business cycle fluctuations.

Nevertheless, at least two reservations to the association of business cycles with aggregate activity shocks are in order. First, the impulse response functions suggest that aggregate activity shocks have a permanent effect on the level of unemployment and vacancies (Figure 9). After a shock hits the economy our results suggest that there is no endogenous mechanism that pulls unemployment and vacancies back to their original level, only the effect on their rate of change is transitory; unless additional shocks in the opposite direction occur, unemployment and vacancies would not return to their original level. In that sense the estimated model suggests that the levels of unemployment and vacancies are a random walk. The interpretation of aggregate activity shocks as cyclical is therefore inconsistent with the traditional real business cycle literature that views business cycles as

[25] The correlation coefficients are −0.84 and 0.81 during the period prior to 2004-Q1.

transitory deviations from the trend, either deterministic or stochastic.[26] Nevertheless, as described above, the joint movement of unemployment and vacancies that is driven by aggregate activity shocks matches remarkably the business cycle chronology in Israel. In that sense, and as suggested by Aguiar and Gopinath (2007) for several emerging economies, cyclical fluctuations can be interpreted as trend shocks. It is conceivable that given the nature of the shocks during our sample period - the second intifada at the early 2000s and the global financial crisis in late 2008 - the identified aggregate activity shocks conform to Aguiar and Gopinath interpretation of business cycles.

Second, the matching efficiency components also display non-negligible cyclical movement. Over the full sample period the correlation coefficients between the matching efficiency components of unemployment and vacancies and (linearly) detrended business sector GDP (in logs) are -0.55 and 0.56, respectively, although these correlations are lower, around 0.4 in absolute value, for the period starting 2004-Q1. This result suggests that some of the fall in unemployment that we characterize as non-cyclical is actually correlated with the business cycle. In terms of our theoretical model, it may well be the case, for example, that workers are more likely to quit inadequate jobs when the economy is booming and vacant jobs are abundant, and hold more tightly to their jobs during recessions. As a result we underestimate the contribution of cyclical factors to the fall in unemployment since 2004-Q1. If we assign *all* the movement in matching efficiency to cyclical factors then our decomposition suggests that nearly half of the reduction in the unemployment rate is driven by non-cyclical factors. However, we view this estimate as a lower bound.

4.2.4 The Shift of the Beveridge Curve Since 2004

In this section we track the evolution of the Beveridge curve since 2004. Figure 11 displays unemployment against vacancies, both expressed in rates out of the labor force; the dashed

[26] See, for example, King Plosser and Rebelo (1988).

line tracks their evolution over time.[27] Data are logged and presented as deviations from 2004-Q1, when unemployment peaked at 10.9 percent.[28] For each data point of the first quarter in a calendar year the figure also displays the Beveridge curve, as suggested by our decomposition, that goes through that point.[29] For completeness, the figure also presents the evolution of unemployment and vacancies prior to 2004.

Notice that our estimated Beveridge curves is steeper than the slope generated by the raw data during the period 2004-Q1 to 2008-Q2. The slope of the Beveridge curve is -2.95, while the slope of the regression line of the raw data in that period is -1.64. This finding suggests that for a given rise in vacancies, a movement along a constant Beveridge curve is insufficient to explain the full decline in unemployment; the figure therefore shows a steady shift inward of the Beveridge curve. The observed rise in vacancies in parallel to a fall in unemployment between 2004-Q1 and 2008-Q2 was the result of a combined movement upward along the Beveridge curve, due to the expansion of aggregate activity, together with a shift inward of the curve. Only the turning of the business cycle at the end of 2008, and the movement downward along the curve, made the shift visible to the naked eye.

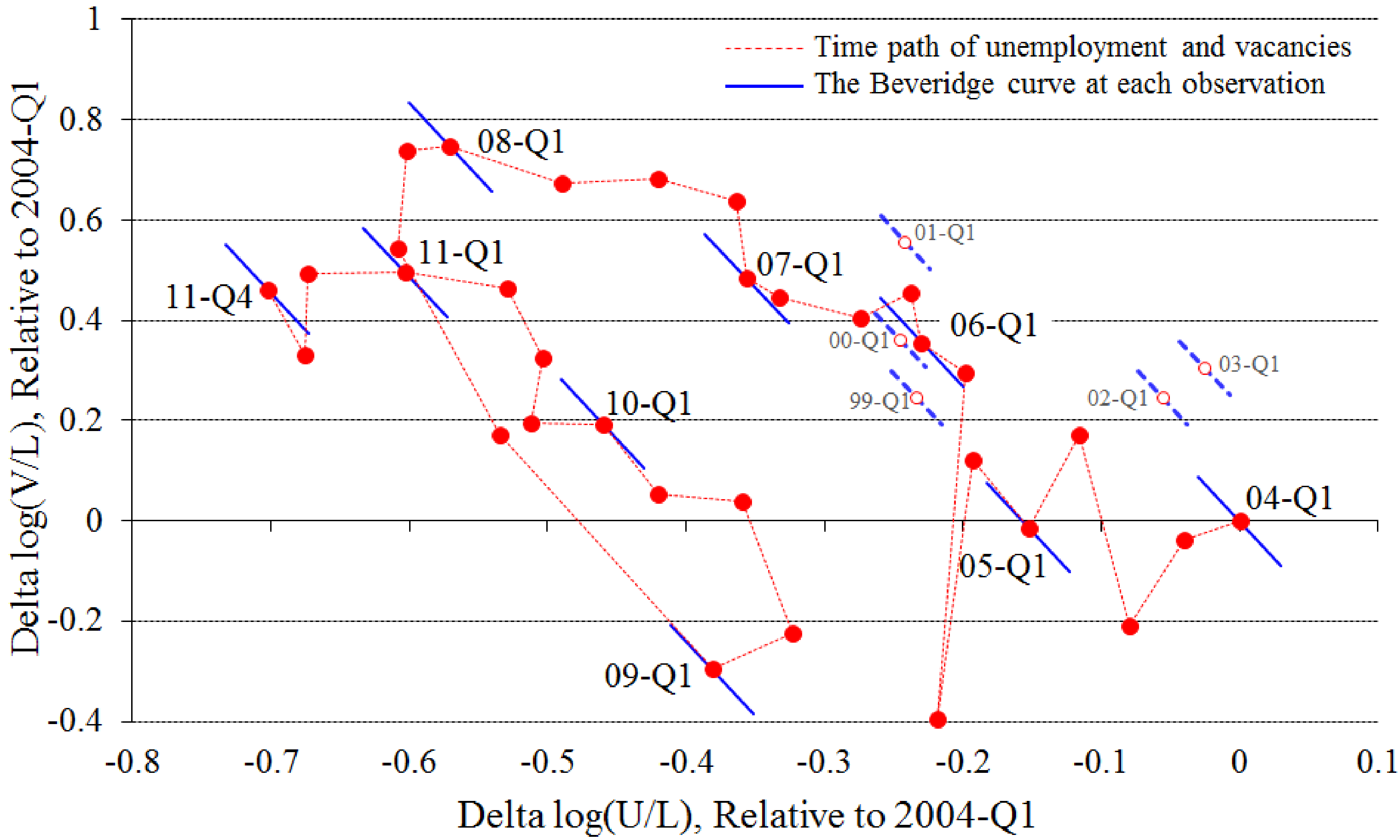
Throughout this period the curve seems to have shifted outward in two occasions: between 2005 and 2006 and between 2009 and 2010. However, recall that, as suggested by the impulse response functions, the dynamics of unemployment and vacancies generate counter-clockwise loops during the business cycle. This pattern is visible in Figure 11 during the recession starting at the end of 2008 and during the expansion that followed.

[27] Note that vacancies are divided by the labor force, not by the total number of jobs (filled and vacant). We do that for two reasons: the first reason is practical - from our estimation we can express the Beveridge curve only in these terms. And second, when expressed in rates, theory also derives the Beveridge curve in these terms. In steady state the equation $(q+d)(L-U) = \alpha m(U,V)$ defines the Beveridge curve. Assuming the matching function is homogeneous of degree one we get the Beveridge curve expressed in terms of rates out of the labor force: $(q+d)(1-(\frac{U}{L}) = \alpha m(\frac{U}{L}, \frac{V}{L})$. The assumption of homogeneity of degree one is standard in the literature; see Yashiv (2007) in a survey paper.

[28] We take logs of rates so the resulting variables are linear functions of the log levels. This transformation simplifies significantly the mapping of our estimated Beveridge curve into the units of the figure.

[29] The slope of the Beveridge curve was estimated by regressing the aggregate activity component of $log(V) - log(L)$ on the aggregate activity component of $log(U) - log(L)$.

Figure 11: The Shift of the Beveridge Curve, 2004-2011
(log changes relative to 2004-Q1)



This suggests that the Beveridge curve did not actually shift outward during the expansion of 2009-2010, or if it did its movement was more moderate than implied by the figure. Similar reasoning suggests that the figure understates the shift inward of the Beveridge curve during the expansion period between 2004 and 2008.

As for the period prior to 2004, it seems that the Beveridge curve has mostly shifted outward, although that movement is much smaller in magnitude relative to the shift inward that followed. Our estimates suggest that by as early as 2005-2006 the Beveridge curve was located back at its position from 1999.

The immediate question that rises from the analysis is why has the Beveridge curve shifted inward, or putting differently what factors have driven its movement. Our analysis is silent about this issue as our methodology only allows us to measure the fluctuations of unemployment and vacancies that are consistent with structural shocks, it does not reveal the underlying factors that drive them. Strictly speaking, our "matching efficiency" shocks, for example, are merely shocks that move unemployment and vacancies in the same direction in the long run; there is nothing in our methodology that links them to indicators that reflect the efficiency of the matching process.

Nevertheless, we should note that stricter unemployment benefits and social security regulations since the early 2000s may have shifted of the Beveridge curve, as these policies may be manifested as both labor supply and matching efficiency fluctuations, which fits the results of the historical decomposition.

Since the early 2000s the level of unemployment insurance benefits in Israel was cut several times[30] and duration of eligibility was shortened for large groups of unemployed.[31]

[30] In 1999 the ceiling level of unemployment insurance was reduced for those who earned more than an average wage; in 2002-2006 a temporary general cut of 4% took place for all groups of recipients; in 2002 benefits for those taking part in vocational training programs were cut by 30% for new entrants; and in 2007 benefits were cut by 25% for those under age 28.

[31] Duration of eligibility was shortened in 1998 for unemployed under age 35 who refused to accept a job; in 2000 for unemployed who returned to receive benefits within 4 years and for unemployed under age 35; in 2002 for unemployed under age 25; in 2007 for those aged 25-28. Duration of eligibility for unemployed in vocational training programs was limited in 2003.

These measures tend to lower the reservation wage of workers and thereby expand the labor supply. In addition, search theory suggests that lower unemployment benefits results in higher search intensity as the moral hazard effect of unemployment insurance is reduced, at the same time matching quality might deteriorate as unemployed workers are incentivized to accept less suitable jobs in order to avoid periods of unemployment.[32]

In terms of our model, a rise in search intensity can be interpreted, in a reduced form sense, as an improvement in matching efficiency. The reason is that a higher search effort is likely to result in more matches for any level of unemployed and vacancies, similar to an improvement in search technology, i.e. a higher α in terms of our model. In contrast, the deterioration of matching quality reduces matching efficiency, i.e. lower q; nevertheless, this effect is at least partially offset by the rise in search effort. In sum, theory is consistent with the hypothesis that labor market regulation may have had an important role in shifting the Beveridge curve inward. We should stress, however, that although this interpretation is reasonable it is speculative and other factors, such as the increasing use of human resource placement companies for job search and employment of workers via subcontractors, or a composition effect due to a rise in the education level of participants in the labor force may also explain the shift of the Beveridge curve. Further research is required in order to evaluate the contribution of each factor.

5 Conclusion

The decline in the unemployment rate in recent years calls for its decomposition to cyclical and non-cyclical factors. To that end we utilized the comovement of unemployment and vacancies, together with labor force fluctuations, for the identification of cyclical movements along a fixed Beveridge curve and structural movements that shift the curve. The identification restrictions were derived from a simple theoretical stock-flow accounting model of

[32] For a discussion of the effect of unemployment insurance design on the labor market see a survey of recent theoretical and empirical literature by Tatsiramos and van Ours (2012) and references therein.

the labor market similar to that of Blanchard and Diamond (1989). Our estimates suggest that non-cyclical factors account for at least half of the decline of the unemployment rate during the period between 2004-Q1, when the unemployment rate peaked at 10.9, and 2011-Q4, when it marked a trough at 5.4 percent.

We also find that the slope of the Beveridge curve is about -3; that is, a cyclical movement of 1 percent in the pool of unemployed is associated, on average, with a 3 percent movement in the opposite direction in the number of vacant jobs. This number may serve as a benchmark for evaluating labor market developments in real time.

Our results suggest that the shift of the Beveridge curve in recent years was driven by factors that improved matching efficiency and raised the labor supply. These may include stricter unemployment benefits and social security regulations, rising education level of labor market participants, a rise in private sector intermediaries in the labor market and the rise in employment via subcontractors. Nevertheless, we should emphasize that the analysis in this paper merely decomposes unemployment and vacancies to time series that are conceptually consistent with fluctuations in "aggregate activity", "matching efficiency", and "labor supply". The latter are just abstract categories that may reflect developments in a whole set of more specific factors (such as regulation, sectorial composition, labor market intermediaries etc.). Further research is needed in order to evaluate the role of each factor in contributing to the movement of the Beveridge curve.

A Appendix: The Comovement of Job Creation, Job Destruction and Vacancies

In section 2.7 we argued in favor of our specification of the theoretical model relative to that of BD. Among other things, we argued that the specification of BD implies a positive correlation between job destruction and vacancies and between job destruction and job creation. In this appendix we show that the data display negative comovements.

Figure A1: Job Destruction and Vacancies (1999Q1-2010Q1, Seasonally Adjusted, Thousands)

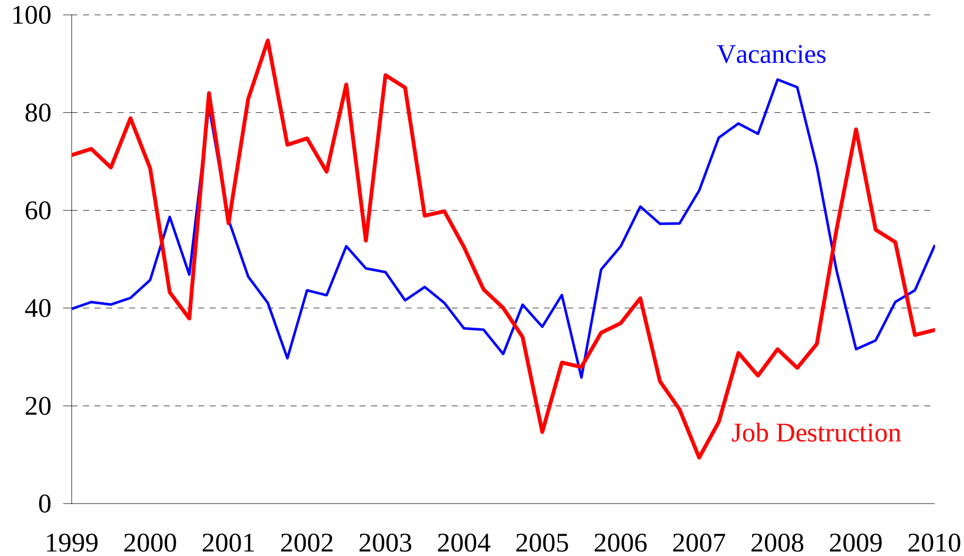


Figure A2: Job Destruction and Job Creation (1999Q1-2010Q1, Seasonally Adjusted, Thousands)

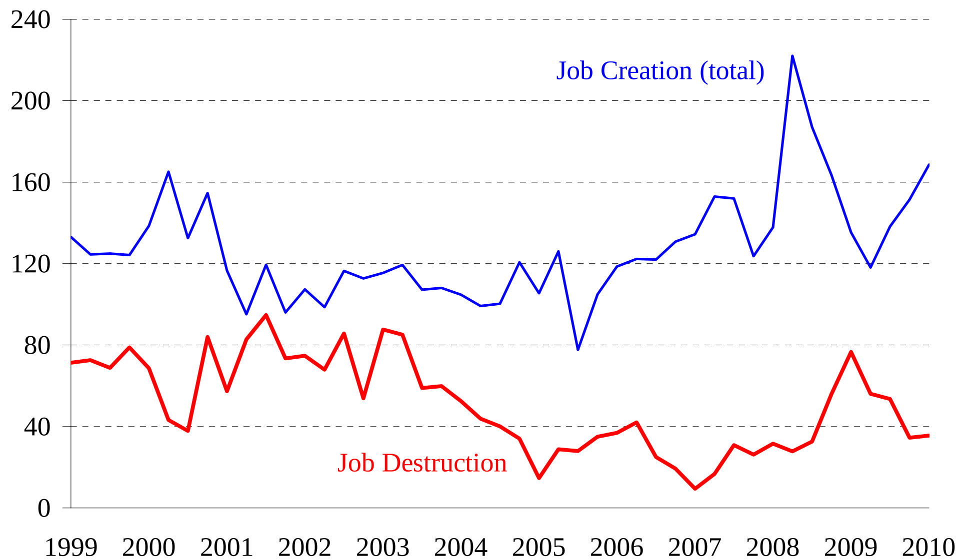


Table A1: Correlation Coefficients between Job Destruction and Vacancies and Job Creation

	Job destruction		
	Corr.	T-Stat.	Prob.[1]
Vacancies	−0.348	2.432	0.010
Job creation (vacancies)	−0.346	2.415	0.010
Job creation (new hires)	−0.114	0.750	0.229
Job creation (total)	−0.245	1.657	0.052

[1] One tailed test.

Table A1 reports the correlation coefficients between job destruction and vacancies and between job destruction and job creation for the period 1999-Q1 to 2010-Q1, and Figures A1 and A2 display the time path of the series. All series are seasonally adjusted. We measure job creation in three ways; as the number of vacant new jobs, the number of new hires that expand the staff of workers, and the sum of the two series (see description below). Job destruction is negatively correlated both with vacancies and job creation. All coefficients are significant at 5 percent significance level of one tailed test, with the exception of job creation measured from new hires. These results support our arguments in the text.

A.1 Data Source

The data on vacancies, hires and separations are weighted aggregate series constructed from firm-level observations of the Employers Survey managed by the Ministry of Economy. Data are in quarterly frequency and available since 1998. The survey represents businesses operating in the private sector and employing at least one employee. Although the survey was designed as a panel, it went through two major adjustments leaving each time only one quarter of the firms on the overlap. During 1998-2001, the first sample of roughly

2,500 employers was drawn from a private database and represented, on average, 140,000 businesses per quarter.[33] The sample was composed of three layers of 6 groups of industries, two size groups and 4 geographic areas, giving a total of 48 intersections. This sample underrepresented businesses in health and education services in the private sector and in agriculture. In order to improve the representativeness of the sample, starting from 2002 a new sample was drawn from the National Insurance Institute official database. This sample is composed of 88 intersections of 11 industry groups and 8 size groups. This sample was partly replaced and expanded to roughly 3,000 employers in the third quarter of 2009. The current sample represents over 190,000 employers, covering more than 80 percent of the private sector businesses.

Vacancies: The Employers Survey explicitly asks if a firm is currently actively searching for workers to fill open positions. As defined by the survey, an "active search" means advertising through different channels, applying to manpower agencies and/or government employment services and alike. Counted are full-time, part-time, permanent, temporary and limited-time jobs.

Job creation: Starting the first quarter of 1999 the questionnaire of the survey enables us to distinguish between vacancies and new hires originating from job creation (expansion of the staff) and job turnover (replacement of workers). Using this information we calculate the series of job creation in vacancies and in new hires. We also calculate a series of total job creation summing up job creation in new hires and in vacancies.

Job destruction: Starting the first quarter of 1999, firms are asked to classify the reasons for separations to (1) the end of a temporary job, (2) dismissal due to staff reduction, (3) dismissal due to mismatch, (4) resignation and (5) retirement. We define the first two reasons as "job destruction". Unfortunately the question about the reasons for separation

[33] BDI-COFACE business information group provided the dataset.

was omitted from the survey after the first quarter of 2010; as a result our time series of job destruction ends at that date.

References

[1] Aguiar, M., Gopinath, G., 2007. "Emerging Market Business Cycles: The Cycle Is the Trend." Journal of Political Economy 115(1), pp. 69-102.

[2] Bank of Israel, 2006. "The Mehalev Program: From Income Support to Employment Support (the 'Wisconsin Program')." The Bank of Israel Annual Report - 2005, Box 5.1, pp. 201-206.

[3] Bank of Israel, 2007. "Child Allowances and the Labor Force Participation Rate Among Parents of Large Families." The Bank of Israel Annual Report - 2006, Box 5.2, pp. 201-205.

[4] Bank of Israel, 2009. "Visions for Employment, the Revised Israeli 'Wisconsin Plan'." The Bank of Israel Annual Report - 2008, Box 5.3, pp. 229-232.

[5] Bank of Israel, 2011. "The Effect of Change in the Retirement Age Law on Participation of the Older Population in the Labor Force." The Bank of Israel Annual Report - 2010, Box 5.1, pp. 198-203.

[6] Barnichon, R., Figura, A., 2010. "What Drives Movements in the Unemployment Rate? A Decomposition of the Beveridge Curve." Board of Governors of the Federal Reserve System, Finance and Economics Discussion Series 2010-48.

[7] Berman, E., 1997. "Help Wanted, Job Needed: Estimation of a Matching Function from Employment Service Data." Journal of Labor Economics 15(1) Pt. 2, pp. S251-S292.

[8] Blanchard, O. J., Diamond, P., 1989. "The Beveridge Curve." Brookings Papers on Economic Activity 20(1), pp. 1-60.

[9] Blanchard, O. J., Quah, D., 1989. "The Dynamics of Aggregate Demand and Supply Disturbances." American Economic Review 79(4), pp. 655-673.

[10] Djivre, Y., Yakhin, Y., 2011. "Business Cycles in Israel, 1987-2010: The Facts." The Maurice Falk Institute for Economic Research in Israel, the Hebrew University, Working Paper No. 11.02.

[11] Fry, R., Pagan, A., 2011. "Sign Restrictions in Structural Vector Autoregressions: A Critical View." Journal of Economic Literature 49(4), pp. 938-960.

[12] King, R. G., Plosser, C. I., Rebelo, S. T., 1988. "Production, Growth and Business Cycles: II. New Directions." Journal of Monetary Economics 21(2-3), pp. 309-341.

[13] Pissarides, C. A., 1985. "Short-Run Equilibrium Dynamics of Unemployment, Vacancies, and Real Wages." American Economic Review 75(4), pp. 676-690.

[14] Shimer, R., 2005. "The Cyclical Behavior of Equilibrium Unemployment and Vacancies." American Economic Review 95(1), pp. 25-49.

[15] Shimer, R., 2012. "Reassessing the Ins and Outs of Unemployment." Review of Economic Dynamics 15(2), pp. 127-148.

[16] Tatsiramos, K., and van Ours, J. C., 2012. "Labor Market Effects of Unemployment Insurance Design." Centre for Economic Policy Research, Discussion Paper No. 9196.

[17] Wall, H. J., Zoega, G., 2002. "The British Beveridge Curve: A tale of Ten Regions." Oxford Bulletin of Economics and Statistics 64(3), pp. 257-276.

[18] Yashiv, E., 2000. "The Determinants of Equilibrium Unemployment." American Economic Review 90(5), pp. 1297-1322.

[19] Yashiv, E., 2007. "Labor Search and Matching in Macroeconomics." European Economic Review 51(8), pp. 1859-1895.