Aggregate Shocks and Labor Market Fluctuations

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Abstract

This paper evaluates the dynamic response of worker flows, job flows, and vacancies to aggregate shocks in a structural vector autoregression. We identify demand, monetary, and technology shocks by imposing sign restrictions on the responses of output, inflation, the interest rate, and the relative price of investment. No restrictions are placed on the responses of job and worker flows variables. We find that both investment-specific and neutral technology shocks generate responses to job and worker flows variables that are qualitatively similar to those induced by monetary and demand shocks. However, technology shocks have more persistent effects. The job finding rate largely drives the response of unemployment, though the separation rate explains up to one third. For job flows, the destruction margin is more important than the creation margin in driving employment growth. Measuring reallocation from job flows, we find that monetary and demand shocks do not have significant effects on cumulative job reallocation, whereas expansionary technology shocks have mildly negative effects. We also estimate shock-specific matching functions. Allowing for a break in 1984:Q1 shows considerable subsample differences in matching elasticities and relative shock-specific efficiency.

JEL: C32, E24, E32, J63.

Keywords: business cycles, job flows, unemployment, vacancies, vector autoregressions, worker flows.

1 Introduction

How do labor market variables, such as job and worker flows, respond to different shocks? What is the contribution of job loss and job destruction versus hiring and job creation to the evolution of aggregate employment and unemployment? Earlier research suggests that the cyclicality of employment can be best understood by looking at the flows into rather than the flows out of unemployment. This line of research is summarized in Davis, Haltiwanger, and Schuh (1996) and is consistent with the search and matching model with endogenous job destruction developed by Mortensen and Pissarides (1994).[1] Recently part of the literature has taken a different route. Hall (2005b), and Shimer (2005b) argue that the business cycle dynamics of the labor market are determined mostly by the job finding rate and not by the separation rate.[2]

This paper further examines the relationship of the labor market to the business cycle. We study both worker and job flows data. For worker flows data we take the hiring and separation rate constructed as in Shimer (2005b). The job flows data are the spliced 1947-2004 quarterly job creation and destruction series recently assembled by Faberman (2004), and Davis, Faberman, and Haltiwanger (2005). We take a look at the unconditional business cycle properties of these series. We evaluate the dynamic responses of key labor market variables to different shocks in a structural vector autoregression (SVAR). We use sign restrictions on the impulse responses of output, inflation, and the federal funds rate to identify demand, monetary, and supply shocks.[3] The sign restrictions are consistent with a basic IS-LM-AD-AS framework and with microfounded new Keynesian models. Furthermore, we divide supply shocks into neutral and embodied shocks based on the response of the price of investment, measured in output units. Our approach is asymmetric in that we leave the responses of the worker and job flows variables unrestricted. This is intentional, as we want to examine the responses of these variables, a measure of vacancies, the implied level of employment growth, the unemployment rate, and the reallocation rate to different shocks.

Section 2 describes the empirical background of the different readily available labor market data we use and presents business cycle features of the postwar U.S. worker and job flows. Unconditional filtered moments of the job versus worker flow data suggest a somewhat different picture of the labor adjustment mechanism at the business cycle frequency. Job destruction and the separation rate are positively correlated. The job creation and job finding rates are orthogonal. The job finding rate is strongly procyclical, whereas the correlation of job creation with output is low. The separation and job destruction rate are both strongly countercyclical. In terms

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[1] Davis, Haltiwanger, and Schuh (1996) and Davis and Haltiwanger (1999) study job flows. Worker flows are extensively studied in Abowd and Zellner (1985), Poterba and Summers (1986), and Blanchard and Diamond (1990).

[2] Related papers are Hall (2005a) and Shimer (2005a). See Davis (2005) on the key role cyclical fluctuations in job loss and worker displacement nevertheless play in the data.

[3] Sign restrictions achieve identification without imposing zero contraints on the impact response or on the long-run response of certain variables to shocks. Other implementations of sign restrictions can be found in Canova and De Nicolò (2002), Dedola and Neri (2004), Uhlig (2005), and Peersman (2005).

of relative volatilities, job destruction is one-and-a-half times more volatile than job creation, whereas the job finding rate is twice as volatile as the separation rate.

Section 3 lays out the SVAR. We find that responses to all shocks are qualitatively similar, with the supply shocks generating more persistent effects than monetary and demand shocks. An expansionary shock leads to a persistent hump-shaped increase in vacancies, mirrored by an increase in the job finding rate. The separation rate drops initially, but returns to its steady state value faster than the job finding rate. Responses of the job destruction rate are similar in shape but larger in magnitude than the responses of the separation rate. Compared with the finding rate, the responses of job creation have wider bands and are less hump-shaped. The bulk of the response of unemployment is due to changes in the job finding rate, though separations contribute up to one third to the response of unemployment and are especially important in the initial phase after the shock. The dynamics of the job flows data, on the other hand, suggest that the destruction margin plays a bigger role than the creation margin in driving employment growth.

We also examine the responses of job reallocation, the sum of job creation and destruction, to the different shocks. Davis and Haltiwanger (1992) propose this measure and emphasize that worker reallocation associated with their measure provides a lower bound on total worker reallocation. As in Davis and Haltiwanger (1999), we find that job reallocation falls following expansionary shocks. Focusing on cumulative job reallocation, we find no significant permanent effects after demand or monetary shocks. Expansionary technology shocks, on the other hand, have mildly negative effects on cumulative reallocation. This result is in contrast with Caballero and Hammour (2005), who find that expansionary aggregate shocks increase cumulative job reallocation.

A number of papers have documented a substantial drop in the volatility of output, inflation, interest rates, and many other macroeconomic variables since the mid-1980s.[4] There has been relatively little work in examining how this drop is related to the labor market dynamics. We take a first stab at this question by breaking our sample in a pre-1984 and post-1984 periods. We then examine the impulse responses and estimates of a matching function under the assumption of a Cobb-Douglas functional form after different shocks. Estimates of the elasticities within each sample are relatively close. However, the matching function for the pre-1984 sample shows decreasing returns to scale, whereas the post-1984 sample suggests strongly decreasing returns to scale and more congestion in the labor market. We also observe substantial shifts in the relative efficiency of the matching function following money and demand shocks versus the two technology shocks in the two subsamples.

The last subsection of section 3 discusses a reallocation shock identified from job flows variables. Section 4 concludes.

The major contribution of our paper is to offer an integrated analysis over a large sample of the response of job and worker flows to shocks identified using sign restrictions on aggregate variables while being agnostic on the responses of key labor

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[4]See, among others, Kim and Nelson (1999), McConnell and Perez-Quiros (2000), and Stock and Watson (2002).

market variables.

2 Data

For worker flows data, we use the separation and job finding rates constructed by Shimer (2005b). We briefly discuss their construction in Section 2.1. For job flows data, we take the job creation and destruction series recently constructed by Faberman (2004) and Davis, Faberman, and Haltiwanger (2005), as discussed in Section 2.2. Section 2.3 presents business cycle statistics of the data.

2.1 Separation and Job Finding Rates

The separation rate measures the rate at which workers leave employment and enter the unemployment pool. The job finding rate measures the rate at which unemployed workers exit the unemployment pool. Although the rates are constructed and interpreted while omitting flows between labor market participation and non-participation, Shimer (2005b) shows that they capture the most important cyclical determinants of the behavior of both the unemployment and employment pools. The advantage of using these data lies in its availability for a long time span. The data constructed by Shimer is available from 1947, whereas worker flow data including non-participation flows from the Current Population Survey (CPS) is available only from 1967 onwards.

The idea is to use data on the short-term unemployment rate as a measure of separations and the law of motion for the unemployment rate to back out a measure of the job finding rate. The size of the unemployment pool is observed at discrete dates $t, t+1, t+2....$ Hirings and separations occur continuously between these dates. To identify the relevant rates within a time period, assume that between dates t and $t+1$, separations and hirings occur with constant Poisson arrival rates s_t and f_t, respectively. For some $\tau \in (0,1)$, the law of motion for the unemployment pool $U_{t+\tau}$ is

$$\dot{U}_{t+\tau} = E_{t+\tau} s_t - U_{t+\tau} f_t,$$

where $E_{t+\tau}$ is the pool of employed workers. Here, $E_{t+\tau} s_t$ are simply the inflows and $U_{t+\tau} f_t$ the outflows from the unemployment pool, at $t+\tau$. The analogous expression for the pool of short-term unemployed $U_{t+\tau}^s$ (i.e., those workers who have entered the unemployment pool *after* date t) is:

$$\dot{U}_{t+\tau}^s = E_{t+\tau} s_t - U_{t+\tau}^s f_t.$$

Combining these expressions leads to

$$\dot{U}_{t+\tau} = \dot{U}_{t+\tau}^s - (U_{t+\tau} - U_{t+\tau}^s) f_t.$$

Solving the differential equation using $U_t^s = 0$ yields:

$$U_{t+1} = U_t e^{-f_t} + U_{t+1}^s,$$

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Given data on U_t, U_{t+1}, and U_{t+1}^s, this expression can be used to construct the job finding rate f_t. The separation rate then follows from

$$U_{t+1} = (1 - e^{-f_t - s_t}) \frac{s_t}{f_t + s_t} L_t + e^{-f_t - s_t} U_t, \tag{1}$$

where $L_t \equiv U_t + E_t$. Given the job finding rate, f_t, and labor force data, L_t and U_t, equation 1 uniquely defines the separation rate, s_t. Note that the rates s_t and f_t are time-aggregation adjusted versions of $\frac{U_{t+1}^s}{E_{t+1}}$ and $\frac{U_t - U_{t+1} + U_{t+1}^s}{U_{t+1}}$, respectively. The construction of s_t and f_t takes into account that workers may experience multiple transitions between dates t and $t + 1$. Note also that these rates are continuous time arrival rates. The corresponding probabilities are $S_t = (1 - \exp(-s_t))$ and $F_t = (1 - \exp(-f_t))$.

Using equation 1, observe that if $f_t + s_t$ is large, the unemployment rate, $\frac{U_{t+1}}{L_t}$, can be approximated by the steady state relationship $\frac{s_t}{f_t + s_t}$. As shown by Shimer (2005b), this turns out to be a very accurate approximation to the true unemployment rate. We use it to infer changes in unemployment from the responses of f_t and s_t in the SVAR. To gauge the importance of the job finding and separation rates in determining unemployment, we follow Shimer (2005b) and construct the following variables:

- $\frac{s_t}{s_t + f_t}$ is the approximated unemployment rate;

- $\frac{\bar{s}}{\bar{s} + f_t}$ is the unemployment rate computed with the actual job finding rate, f_t, and the average separation rate, $\bar{s}$;

- $\frac{s_t}{s_t + \bar{f}}$ is the unemployment rate computed with the average job finding rate, $\bar{f}$, and the actual separation rate, s.

The accuracy of the identification scheme for the separation and job finding rates above depends crucially on a consistent and unbiased measure of the short-term unemployment rate. We discuss some of the resulting issues in appendix B and compare the construction used by Shimer (2005b) to alternatives. For the SVAR and business cycle analysis, we stick with Shimer (2005b).

The identification of the job finding and separation rates f_t and s_t above assumes that all workers are either unemployed or employed. Transitions into and out of the labor force are not accounted for. As documented in Shimer (2005b) for the three-pool data available from the CPS from June 1967 onwards, transitions from unemployment to employment and conversely from employment to unemployment are the most important contributing factors to cyclical changes in unemployment and (albeit to a lesser extent) employment. In the overlapping sample, the job finding rate is in turn highly correlated with an analogously constructed transition rate for the three-pools data and shows a similar volatility. For the separation rate, however, the volatility of the transition rate from the three-pools data is significantly higher and the correlation between the two is lower. A further discussion can be found in appendix C.

Lastly, we want to point out that measuring the inflow side of the employment pool using the job finding rate is different from using the hiring rate. The hiring

rate sums all worker flows into the employment pool and scales them by current employment (see Fujita (2004)). Its construction is analogous to the job creation rate defined for job flows. The response of this rate to shocks is in general not very persistent, whereas the response of the job finding rate indicates persistence. This difference is due to the scaling. We return to this point below.

2.2 Job Creation and Job Destruction

The job flows literature focuses on job creation (JC) and destruction (JD) rates.[5] Gross job creation is the employment gains summed over all plants that expand or start up between $t-1$ and t. Gross job destruction, on the other hand, is the employment losses summed over all plants that contract or shut down between $t-1$ and t. To obtain the creation and destruction rates, both measures are divided by the averages of employment at $t-1$ and t. Davis, Haltiwanger, and Schuh (1996) constructed measures for both series from the Longitudinal Research Database (LRD) and the monthly Current Employment Statistics (CES) survey from the Bureau of Labor Statistics (BLS).[6] A number of researchers work only with the quarterly job creation and job destruction series from the LRD.[7] Unfortunately this series is available only for the 1972:Q1-1993:Q4 period.

In this paper we work with the quarterly job flows constructed by Faberman (2004), and Davis, Faberman, and Haltiwanger (2005) from three sources. These authors splice together data from the (i) BLS manufacturing Turnover Survey (MTD) from 1947 to 1982, (ii) the LRD from 1972 to 1998, and (iii) the Business Employment Dynamics (BED) from 1990 to 2004. The MTD-LRD data are spliced as in Davis and Haltiwanger (1999), whereas the LRD-BED splice follows Faberman (2004).[8]

A fundamental accounting identity relates the net employment change between any two points in time to the difference between job creation and destruction. We define $g_{E,t}^{JC,JD}$ as the growth rate of employment implied by job flows:

$$g_{E,t}^{JC,JD} \equiv \frac{E_t - E_{t-1}}{(E_t + E_{t-1})/2} \equiv JC_t - JD_t. \qquad (2)$$

The data spliced from the MTD and LRD of the job creation and destruction rates constructed by Davis, Faberman, and Haltiwanger (2005), pertains to the manufacturing sector. However, over the period 1951:Q2-2004:Q2, the implied growth rate of employment from these job flows data, $g_{E,t}^{JC,JD} \equiv (JC_t - JD_t)$, is highly correlated

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[5] See Davis and Haltiwanger (1992), Davis, Haltiwanger, and Schuh (1996), Davis and Haltiwanger (1999), Caballero and Hammour (2005), and Lopez-Salido and Michelacci (2005).

[6] As pointed out in Blanchard and Diamond (1990) these job creation and destruction measures differ from true job creation and destruction as (i) they ignore gross job creation and destruction within firms, (ii) the point-in-time observations do not take into account job creation and destruction offsets within the quarter, and (iii) the failure to account for newly created jobs that are not filled with workers yet.

[7] Davis and Haltiwanger (1999) extend the series back to 1948. Some authors report that this extended series is (i) somewhat less accurate and (ii) only tracks aggregate employment in the 1972Q1-1993Q4 period (See Caballero and Hammour (2005)).

[8] See Appendix D for a comparison of job flows data to worker flows data.

with the growth rate of total non-farm payroll employment, $g_{E,t} \equiv \left[\frac{E_t - E_{t-1}}{0.5(E_t + E_{t-1})} \right]$:

$Corr \left(g_{E,t}^{JC,JD}, g_{E,t} \right) = 0.89.$[9]

As in Davis, Haltiwanger, and Schuh (1996), we define gross job reallocation r_t as:

$$r_t \equiv JC_t + JD_t. \tag{3}$$

Using this definition we examine the reallocation effects of a particular shock in the SVARs. We also look at cumulative reallocation.

2.3 Business Cycle Properties

Table 1 reports correlations and standard deviations (relative to output) for the business cycle component of worker flows, job flows, the unemployment rate (u), vacancies (v) and output (y).[10] The job finding rate and vacancies are strongly procyclical. Job creation is moderately procyclical. The separation rate, job destruction and the unemployment rate are countercyclical. Job destruction is one-and-a-half times more volatile than job creation. The job finding rate is twice as volatile as the separation rate. Notice that job destruction and the separation rate are positively correlated, whereas job creation and the job finding rate are orthogonal to each other.

In Table 2 we report correlations of the three unemployment approximations described in Section 2.1 with actual unemployment, and standard deviations (relative to actual unemployment). The steady state approximation to unemployment is very accurate, and the job finding rate plays a bigger role in determining unemployment. The contribution of the job finding rate is even larger at cyclical frequencies.[11]

3 Structural VAR Analysis

In this section, we analyze the response of the key labor market variables to macroeconomic shocks using a structural vector autoregression (SVAR). The variables included in the SVAR analysis are the growth rate of the price of investment relative to the GDP deflator ($\Delta \ln p_I$), the growth rate of average labor productivity ($\Delta \ln Y/l$), the inflation rate ($\Delta \ln p$), hours ($\ln l$), worker flows (job finding and separation rates), job flows (job creation and destruction), a measure of vacancies ($\ln v$), and the federal funds rate ($\ln (1 + R)$). Worker flows are the job finding and separation rates constructed in Shimer (2005b). Job flows are the job creation and destruction series from Faberman (2004) and Davis, Faberman, and Haltiwanger (2005). Sources for the other data are given in Appendix A. The sample covers the period 1954:Q3-2004:Q2. The variables are required to be covariance stationary. To achieve stationarity, we

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[9] The correlation of $g_{E,t}^{JC,JD}$ with the growth rate of employment in manufacturing is 0.93.

[10] See appendix A for additional data sources.

[11] Shimer (2005a) uses an HP filter with smoothing parameter 10^5. His choice of an unusual filter to detrend the data further magnifies the contribution of the job finding rate to unemployment with respect to the figures we report.

linearly detrend the logarithms of the job flows variables. The estimated VAR coefficients corroborate the stationarity assumption.

Consider the following reduced form VAR given by[12]:

$$Z_t = \mu + \sum_{j=1}^{p} A_j Z_{t-j} + u_t, \ E u_t u_t' = V. \tag{4}$$

where Z_t is defined as:

$$Z_t = \left[\begin{array}{l} \Delta \ln (p_{I,t}), \Delta \ln \left(\frac{Y_t}{l_t} \right), \Delta \ln (p_t), \ln (l_t), \ln (f_t), \\ \ln (s_t), \ln (JC_t), \ln (JD_t), \ln (v_t), \ln (1 + R_t), \end{array} \right]'.$$

The reduced form residuals, u_t, are related to the structural shocks, ϵ_t, by $\epsilon_t = A_0 u_t$ or equivalently by $u_t = C \epsilon_t$, where $C = A_0^{-1}$. Also, the structural shocks are orthogonal to each other, i.e. $E \epsilon_t \epsilon_t' = I$. We identify structural shocks using sign restrictions on the responses of output, the price level, the interest rate, and the price of investment.[13]

3.1 Identification

The identifying assumptions on the impulse responses to the respective shocks are as follows:

- An expansionary monetary shock is one that has a non-negative effect on output (for 4 quarters), the price level (for 4 quarters), and a non-positive effect on the interest rate (for one quarter). A (non-monetary) demand shock instead has a non-negative effect on the interest rate on impact.

- Positive supply shocks do not lower output (for 4 quarters) and have a non-positive effect on the price level (for 4 quarters) and the interest rate (for one quarter). An embodied technology shock is a supply shock that has a non-positive effect on the price of investment (for 4 quarters). A supply shock that does not satisfy this latter restriction will be labeled a neutral technology shock.

The restrictions are summarized in Table 3.

The identification scheme is implemented following a Bayesian procedure. We adopt a Jeffreys (1961) prior on the reduced form VAR parameters:

$$p(B,V) \propto \|V\|^{-\frac{n+1}{2}},$$

where $B = [\mu, A_1, A_2]'$ and n is the number of variables in the VAR. The posterior distribution of the reduced form VAR coefficients belongs to the inverted Wishart-normal family:

$$(V|Z_{t=1,...,T}) \ \sim \ IW \left(T\hat{V}, T - k \right), \tag{5}$$

$$(B|V, Z_{t=1,...,T}) \ \sim \ N \left(\hat{B}, V (X'X)^{-1} \right), \tag{6}$$

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[12] Based on information criteria, we estimate a reduced form VAR including 2 lags, i.e. $p = 2$.

[13] The sign restriction approach to identify structural shocks was pioneered by Uhlig (2005).

where $\hat{B}$ and $\hat{V}$ are the OLS estimates of B and V, T is the sample length, $k = (np + 1)$ and X is defined as:

$$X = \left[x'_1, ..., x'_T\right]',$$

$$x'_t = \left[1, Z'_{t-1}, ..., Z'_{t-p}\right]'.$$

Consider a possible orthogonal decomposition of the variance-covariance matrix, i.e. a matrix C such that $V = CC'$. Then CQ, where Q is a rotation matrix, is also an admissible decomposition. The posterior distribution on the reduced form VAR coefficients, together with a uniform distribution over the rotation matrices, and an indicator function equal to zero on the set of IRFs that violate the identification restrictions, will induce a posterior distribution over the IRFs that satisfy the sign restrictions above.

The sign restrictions are implemented as follows:

1. Try one possible rotation, Q, for the decomposition matrix, C, for each Monte Carlo draw from the assumed inverted Wishart-normal family for (V, B) in (5) and (6). We obtain the random rotation matrix Q by generating a matrix X with independent standard normal entries, taking the QR factorization of X, and normalizing so that the diagonal elements of R are positive.

2. Check the signs of the impulse responses to all the structural shocks. If we find impulse responses that match all the restrictions, we keep the draw. Otherwise we discard it.

3. We continue until we have 1000 valid decompositions.

The acceptance rate is 32.6% on the whole sample. In the subsample estimates presented in subsection 3.5, the acceptance rate is 27.4% on the pre-1984:Q1 subsample, and 7.2% on the post-1984:Q1 subsample.

3.2   Results

Figures 3-5 report the median, 16th, and 84th percentiles of 1,000 draws from the posterior distribution of acceptable IRFs to the structural shocks of non-labor market variables (restricted in our identification scheme), labor market variables (on which we do not impose any restrictions) together with output and other variables of interest.

Even though we do not restrict the response of labor productivity, the IRFs of average labor productivity to supply shocks display a persistent increase (see Figure 6). Productivity shows no persistent response to demand and monetary shocks. The IRFs of productivity suggest that the supply shocks we identify are indeed interpretable as technology shocks, and comparable to technology shocks identified with long-run restrictions (see Lopez-Salido and Michelacci, 2005).

All labor market variables (see Figure 4) respond in a similar way to monetary and demand shocks. Also the IRFs to neutral and embodied shocks are similar to

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each other in shape and magnitude. Technology shocks generate responses that are qualitatively similar to those induced by monetary and demand shocks, but that have a more persistent effect.

The IRFs of the job finding rate and vacancies are similar in shape to the hump-shaped response of output for all shocks. The separation rate IRFs to the various shocks are U-shaped. The largest effect is reached earlier for the separation rate than for the job finding rate. The job finding rate responds about twice as much as the separation rate for all shocks. The responses of the job destruction rate are similar in shape to those of the separation rate, but are larger in magnitude. The responses of the job creation rate are the mirror image of the IRFs of the job destruction rate. Job destruction responds to shocks twice as much as job creation does.

From the job flows perspective, the destruction margin is more important in response to the four shocks we identify. Worker flows' responses suggest the opposite: the creation margin is the most important. Recall, however, that the job finding probability measures the exit rate from the unemployment pool, whereas the job creation rate measures an entry rate into the employment pool (in terms of jobs), from firms' perspective.

Figure 5 reports the IRFs of unemployment, employment growth (implied by equation 2), and the reallocation rate (equation 3).

The unemployment rate decreases for 10 quarters in response to monetary and demand shocks and overshoots its steady state value before converging back to it. The response of the unemployment rate decreases in a U-shaped way in response to technology shocks. For all shocks, the response of the unemployment rate is mostly determined by the effect on the job finding rate, although the separation rate contributes up to one third of the total effect. In terms of job flows, however, the response of employment growth is largely driven by job creation.

Figure 8 reports the median of the posterior distribution of variance decompositions, i.e., the percentage of the j-periods-ahead forecast error accounted for by the identified shocks. The forecast error of output and hours is mostly driven by supply shocks, consistent with Fisher (2003). Of the four shocks we identify, the demand shock plays the most important role in terms of the variance decomposition of job flows. Each of the other three shocks contributes half as much as the demand shock. For worker flows, technology shocks of either kind are the most important source of the forecast error variance, up to 40 quarters ahead. There is no clear pattern for vacancies.

3.3   Comparison with Existing Literature

The IRFs of job creation and destruction to a monetary shock are consistent with Trigari (2004). The differences in the responses of the interest rate and of the inflation rate stem from the different identification schemes. A monetary shock identified with contemporaneous restrictions typically has a very persistent effect on the interest rate and generates a price puzzle.[14]   Identification of monetary policy shocks via

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[14]See Altig, Christiano, Eichenbaum, and Lindé (2005) and Braun (2005).

sign restrictions implies a less persistent interest rate response and it excludes the possibility of a price puzzle by construction.

Fujita (2004) identifies a unique aggregate shock in a tri-variate VAR including worker flows variables (scaled by employment) and vacancies. This aggregate shock is identified by restricting the responses of employment growth (non-negative for 4 quarters), the separation rate (non-positive on impact), and the hiring rate (non-negative on impact). Our findings on the responses of aggregate shocks identified without restricting the behavior of worker/job flows are broadly consistent with the existence of a unique aggregate shock. However, for our identification we prefer to study the effect of aggregate shocks on worker/job flows without restricting these labor market variables.

Note that where we use the job finding probability in our VAR, Fujita (2004) includes the hiring rate to measure worker flows into employment. The hiring rate measures worker flows into employment, scaled by the size of the employment pool. The job finding rate measures the probability of exiting the unemployment pool. Although both arguably reflect movements of workers into employment (see Shimer, 2005b), the difference in scaling leads to a different qualitative behavior of the two series in response to an aggregate shock. The response of the job finding rate shows a persistent increase. Fujita's hiring rate initially increases but quickly drops below zero because of the swelling employment pool.

All four aggregate shocks increase the growth rate of employment and reduce reallocation (see Figure 5).[15] We do not find a significant permanent effect on cumulative reallocation for the monetary and demand shock (see Figure 7). For the technology shocks, the cumulative effect on reallocation is mildly negative. This is at odds with Caballero and Hammour (2005), who find that expansionary aggregate shocks have positive effects on cumulative reallocation.

Furthermore, our results do not support a Schumpeterian creative destruction effect for a neutral technology shock and are in sharp contrast with Lopez-Salido and Michelacci (2005). They find that neutral technology shocks increase job destruction and reduce employment growth. Lopez-Salido and Michelacci (2005) use a much shorter sample (1972:Q1-1993:Q4) and identify technology shocks with long-run restrictions, as in Fisher (2003).

3.4   Estimating the Matching Function

We also check if the matching process of unemployed workers and vacancies depends on the shock considered. In the standard search and matching model of Mortensen and Pissarides (1994), the number of hires is related to the size of the unemployment pool and the number of vacancies via a matching function $M(U, V)$.[16] Assuming a Cobb-Douglass functional form, the matching function is given by

$$M(U, V) = A U^{\alpha_u} V^{\alpha_v},$$

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[15]The extensive and intensive margins behave in a similar way: both hours and employment increase in response to positive aggregate shocks.

[16]Petrongolo and Pissarides (2001) survey the matching function literature.

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where α_v is the elasticity of the number of matches with respect to vacancies and measures the positive externality caused by firms on searching workers; α_u is the elasticity with respect to unemployment and measures the positive externality from workers to firms; A captures the overall efficiency of the matching function.

Under the assumption of constant returns to scale (CRS), the job finding rate can then be expressed as:

$$\ln f_t = \ln A + \alpha \left(\ln v_t - \ln u_t \right). \tag{7}$$

If we do not impose CRS, we get:

$$\ln f_t = \ln A + \alpha_v \ln v_t - (1 - \alpha_u) \ln u_t.$$

To consider the effect of the shocks we identified on the matching function, we consider a sample of 1,000 draws from the posterior distributions of A and the elasticity parameters estimated from artificial data. Each draw involves the following steps:

1. Consider a vector of accepted residuals as if the shock(s) of interest were the only structural shock(s);

2. Use this vector of accepted residuals and the VAR coefficients from the inverted Wishart-Normal family $(5) - (6)$ to generate artificial data $\tilde{Z}_t$;

3. Construct unemployment using the steady state approximation $\tilde{u}_{t+1} = \tilde{s}_t / \left(\tilde{s}_t + \tilde{f}_t \right)$ from the artificial data;

4. Regress $\ln \tilde{f}_t$ on either $\ln v_t$ and $\ln u_t$ (not assuming CRS) or $\ln \left(\tilde{v}_t / \tilde{u}_t \right)$ (under the CRS assumption).

The artificial data constructed using only monetary shocks, for example, induce a posterior distribution for α and A for an hypothetical economy in which monetary shocks are the only source of fluctuations.

Table 4 reports the median, 16th, and 84th percentiles of 1,000 draws from the posterior distributions. The first two columns show the estimates for α_v and A when we impose CRS. The CRS estimates suggest that aggregate shocks do not entail a differential effect on the matching process. The estimated efficiency parameters A are somewhat lower for monetary and demand shocks than for technology shocks, but these median estimates differ by not more than 5% and the median estimates for α_v are similar. The last three columns of Table 4 show the unrestricted estimates for α_v, α_u, and A. Not imposing CRS leads to a different picture. Estimates of α_v and α_u across the shocks are close but the sum of the coefficients is around 0.70, corresponding to decreasing returns to scale. There is a bigger difference in the median estimates of the efficiency parameter. A is more than a quarter higher in the case of the demand versus the embodied shock (1.10 compared with 0.86). This suggests matching occurs more efficiently in the wake of monetary and demand shocks than after technology shocks.

3.5 Subsample Stability

A number of papers have documented the large drop in the volatility of output, inflation, interest rates, and many other macroeconomic variables since the mid-1980s. Motivated by the results of this literature, we now break our sample in a pre-1984 and post-1984 period (see, e.g., Kim and Nelson (1999)). Figures 13 and 14 present the impulse responses of the variables in our system for the pre-1984 and post-1984 period, respectively. In general, the post-1984 responses are smaller than the pre-84 and whole sample responses. This seems the case across all shocks. Given that we normalize the shocks (impulse response to one standard deviation), this is consistent with the Great Moderation literature.

Tables 5 and 6 present the matching function estimates for the two subperiods. Three results are noteworthy: First, estimates of the elasticities α_v and α_u for the different shocks are relatively close within each sample. Second, if we do not impose CRS, all estimates for the pre-1984 sample show decreasing returns to scale. This is consistent with the results for the full sample discussed above. If we turn to the post-1984 sample, all estimates of α_v and α_u suggest strongly decreasing returns to scale (sum of both elasticities around 0.40). The elasticity of the job finding probability with respect to unemployment, $-(1 - \alpha_u)$, more than doubled for some shocks in the post-1984 sample. Petrongolo and Pissarides (2001) define this elasticity $\alpha_u - 1$ as the negative externality (congestion) caused by the unemployed on other unemployed workers. We find this negative externality doubled in the case of some shock for the post-1984 sample. Likewise Petrongolo and Pissarides (2001) define $\alpha_v - 1$ as the negative externality placed by firms on each other. This measure fell as well. The lower elasticity estimates for both α_v and α_u in the later period indicate more congestion and less-positive externalities on the labor market. Third, there has been a substantial shift in the relative efficiency of the matching function following money and demand shocks versus the two technology shocks. In the pre-1984 sample the median estimate of A in an economy with, for example, only monetary shocks is more than four times higher than the median estimate after an embodied shock. This relative efficiency is much lower in the post-1984 sample: the estimate for A in the case of the monetary shock is only half as high as the estimate for the embodied shock.

3.6 Reallocation Shocks

Although the shocks identified above have an impact on reallocation, their identification is based on an aggregate shock interpretation. This section proposes an alternative SVAR to assess the effect of a purely allocative shock. The exact role such an allocative shock plays has been a recurrent question in the study of the labor market over the business cycle.[17] Reallocation of labor across employment opportunities could be induced by demand shifts (primarily between sectors) or technological innovations (primarily between firms or establishments).

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[17]See Davis and Haltiwanger (1992) and Davis and Haltiwanger (1999).

We identify aggregate and allocative shocks by restricting the responses of the job creation and job destruction rates, together with output.[18] Placing restrictions on the job flows is similar in spirit to Davis and Haltiwanger (1999), the difference being that we also include output, average labor productivity, and vacancies in our analysis. We assume an allocative shock simultaneously increases job creation and job destruction rates, while lowering output on impact (the underlying assumption is that it takes time to reallocate labor). These restrictions should capture both between-establishment and between-sector allocative shocks. An aggregate shock, on the other hand, increases output, increases job creation, and decreases job destruction. The identifying restrictions are summarized in Table 7. Note that – as opposed to the earlier identification scheme – we place restrictions on the job flows variables. In line with the analysis above, we leave the responses of worker flows unrestricted. We restrict the response of job creation for only 2 quarters. This is done to account for the fact that even though the *number* of jobs created may be persistently high, the *rate* may decrease as soon as the employment pool expands.

Figure 9 displays the IRFs of labor market variables to an aggregate and allocative shock.[19] For ease of comparison the allocative shock presented in the figure is one that is favorable to the current allocation of resources (i.e., a negative allocative shock that increases output and lowers both job creation and destruction). Figure 10 displays the responses of the unemployment rate, the change in employment growth, and the reallocation rate. The response of output to the allocative shock is less pronounced and less persistent than to the aggregate shock. Relative to the response of output, the responses of the job finding and separation rates and vacancies behave similarly. The difference lies in the responses of job creation and job destruction. This discrepancy is consistent with the identifying sign restrictions. Aggregate shocks move job creation and job destruction in opposite directions, whereas allocative shocks imply comovement. Note that vacancies and the job finding rate increase (slightly) in response to an allocative shock that lowers reallocation. Consequently, the allocative shock *reduces* vacancy creation and the job finding rate. Figure 11 plots the response of average labor productivity to an aggregate and reallocative shock. The reallocative shock has a negative effect on labor productivity on impact and there are no significant long-run effects. Part of the literature has developed models where recessions are associated with a more efficient allocation of resources by "cleansing" out less efficient matches and creating the incentive for more efficient production opportunities. The reallocative shock identified here does not lead to a significant increase in average labor productivity and gives empirical support to the "sullying" effect of recessions studied in Barlevy (2002). The sullying effect of recessions comprises the notion that even under the cleansing of the least efficient matches, both overall productivity and match-quality of new jobs is lower in downturns.

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[18]Different identifying assumptions have been proposed in the literature. If reallocation takes place between sectors, the dispersion of sectorial employment growth rates should increase (Lillien (1982)). Furthermore, as reallocation reflects shifts in profitability across firms, measures of stock price dispersion should go up (Loungani, Rush, and Tave (1990)). See Davis and Haltiwanger (1999) for more details.

[19]The acceptance rate was 64.9%.

Figure 12 shows the cumulative responses of the reallocation rate for both the aggregate and allocative shocks. Following a positive aggregate shock, cumulative reallocation falls, then gradually recovers and stays below average. Caballero and Hammour (2005) find that positive aggregate shocks cumulatively result in increased rather than reduced reallocation (or restructuring). Our results suggest that cumulative reallocation is lower following a positive aggregate shock. Cumulative reallocation increases following the allocative shock, as defined in Table 7, and does not recover.

4   Conclusion

In this paper we carry out a joint analysis of aggregate data on job and worker flows to get a detailed view of the business cycle behavior of the postwar U.S. labor market. We report business cycle moments and calculate the dynamic response of the key labor market variables to aggregate shocks in a set of structural vector autoregressions.

Unconditional business cycle moments show that worker and job flows data paint somewhat different pictures of the labor market. In terms of relative volatilities for example, job destruction is one-and-a-half times more volatile than job creation, whereas the separation rate is half as volatile as the job finding rate. This discrepancy also emerges in the dynamic response of these variables to aggregate shocks. The job finding rate largely drives the response of unemployment whereas the separation rate explains up to one third of unemployment fluctuations. For the job flows data, on the other hand, the destruction margin is more important than the creation margin in driving employment growth. These observations integrate and confirm the results of other recent studies. We consider this evidence in favor of labor market models where the hiring or separation decision is modeled explicitly.

In terms of responses to different aggregate shocks, our main conclusion is that worker and job flows variables, qualitatively, behave very similarly. We do find that technology shocks generate more persistent effects. Monetary and demand shocks do not have significant effects on cumulative job reallocation, while expansionary technology shocks have mildly negative effects on cumulative reallocation. Estimates of the matching function corroborate the approach of existing search and matching models in that shocks imply similar matching elasticties. On the other hand, we observe substantial subsample shifts in both the estimates of these elasticities and the relative shock-specific efficiency of the matching function. Understanding what drives these shifts could clarify the interaction of the labor market with the observed drop in aggregate volatility since the mid 1980s.

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	f	s	JC	JD	u	v	y
f	6.51 [5.85,7.32]	−0.30 [−0.45,−0.13]	0.01 [−0.17,0.2]	−0.46 [−0.6,−0.31]	−0.92 [−0.94,−0.89]	0.90 [0.86,0.93]	0.83 [0.77,0.88]
s		3.20 [2.72,3.78]	−0.40 [−0.52,−0.26]	0.65 [0.56,0.72]	0.48 [0.35,0.58]	−0.52 [−0.61,−0.40]	−0.55 [−0.64,−0.44]
JC			4.72 [4.12,5.48]	−0.54 [−0.69,−0.37]	0.02 [−0.17,0.29]	0.09 [−0.09,0.29]	0.16 [−0.03,0.39]
JD				7.27 [6.42,8.28]	0.48 [0.34,0.60]	−0.60 [−0.71,−0.48]	−0.64 [−0.76,−0.5]
u					7.37 [6.54,8.28]	−0.93 [−0.95,−0.9]	−0.86 [−0.9,−0.82]
v						8.58 [8,9.36]	0.91 [0.88,0.94]
y							1 [NA]

Table 1: Correlation Matrix of Business-Cycle Components. 1954:Q3-2004Q2. Standard deviations (relative to output) are shown on the diagonal. All series were logged and detrended using a HP(1600) filter. Block-bootstrapped confidence intervals in brackets.

	Levels			BC component		
	$\frac{s_t}{s_t+f_t}$	$\frac{\bar{s}}{\bar{s}+f_t}$	$\frac{s_t}{s_t+\bar{f}}$	$\frac{s_t}{s_t+f_t}$	$\frac{\bar{s}}{\bar{s}+f_t}$	$\frac{s_t}{s_t+\bar{f}}$
$\text{Corr}(x, u_{t+1})$	0.99 [0.99,1]	0.85 [0.76,0.92]	0.79 [0.64,0.87]	0.98 [0.96,0.98]	0.90 [0.86,0.92]	0.62 [0.51,0.7]
$\text{Std}(x)/\text{Std}(u_{t+1})$	1.01 [1,1.03]	0.69 [0.6,0.83]	0.49 [0.43,0.59]	1.05 [1.02,1.08]	0.81 [0.75,0.9]	0.38 [0.33,0.46]

Table 2: Contribution of the Job Finding and Separation Rate to Unemployment: Levels and Business Cycle Component. The business cycle component is extracted with a HP(1600) filter. Block-bootstrapped confidence intervals in brackets.

Variable	Monetary Shock	Demand Shock	Neutral shock	Embodied Shock
Output	↑ (4)	↑ (4)	↑ (4)	↑ (4)
Price Level	↑ (4)	↑ (4)	↓ (4)	↓ (4)
Interest Rate	↓ (1)	↑ (1)	↓ (1)	↓ (1)
Price of Investment	–	–	–	↓ (4)

Table 3: Sign Restrictions (duration in quarters in parentheses)

	CRS		no CRS		
	α_v	A	α_v	$1-\alpha_u$	A
Monetary	0.4 [0.39,0.4]	3.50 [3.35,3.54]	0.29 [0.25,0.31]	0.55 [0.53,0.57]	1.02 [0.71,1.22]
Demand	0.39 [0.38,0.41]	3.38 [3.39,3.65]	0.29 [0.25,0.32]	0.54 [0.51,0.58]	1.10 [0.71,1.4]
Neutral	0.41 [0.41,0.41]	3.68 [3.51,3.73]	0.27 [0.25,0.30]	0.57 [0.56,0.58]	0.87 [0.7,1.04]
Embodied	0.41 [0.40,0.41]	3.63 [3.46,3.82]	0.28 [0.25,0.29]	0.58 [0.56,0.59]	0.86 [0.7,0.99]
All	0.41 [0.4,0.42]	3.70 [3.59,3.72]	0.26 [0.25,0.29]	0.58 [0.55,0.59]	0.74 [0.69,1.04]
Data	0.41 [0.4,0.41]	3.59 [3.41,3.62]	0.26 [0.24,0.28]	0.58 [0.56,0.58]	0.75 [0.67,0.96]

Table 4: Matching Function Estimates: Elasticities and Matching Efficiency. Median of the posterior distribution; 16th and 84th percentiles in parenthesis.

Pre 84	CRS		no CRS		
	α_v	A	α_v	$1-\alpha_u$	A
Monetary	0.39 [0.39,0.4]	3.49 [3.41,3.65]	0.49 [0.46,0.52]	0.3 [0.27,0.32]	8.98 [6.92,12.44]
Demand	0.4 [0.4,0.41]	3.60 [3.48,3.78]	0.47 [0.4,0.54]	0.33 [0.26,0.4]	6.98 [3.54,14.73]
Neutral	0.44 [0.43,0.45]	4.32 [4.08,4.45]	0.39 [0.32,0.46]	0.49 [0.42,0.52]	2.55 [1.45,5.3]
Embodied	0.42 [0.41,0.43]	3.85 [3.66,4.01]	0.36 [0.32,0.44]	0.48 [0.42,0.49]	2.1 [1.55,4.35]
All	0.41 [0.41,0.42]	3.77 [3.66,4.05]	0.35 [0.33,0.41]	0.48 [0.45,0.49]	1.93 [1.7,3.3]
Data	0.41 [0.41,0.42]	3.75 [3.71,3.94]	0.36 [0.32,0.41]	0.46 [0.42,0.51]	2.16 [1.44,3.72]

Table 5: Matching Function Estimates Pre 1984: Elasticities and Matching Efficiency. Median of the posterior distribution; 16th and 84th percentiles in parenthesis

Post 84	CRS		no CRS		
	α_v	A	α_v	$1 - \alpha_u$	A
Monetary	0.43 [0.42,0.45]	4.02 [3.90,4.34]	0.21 [0.16,0.23]	0.74 [0.73,0.79]	0.31 [0.22,0.36]
Demand	0.45 [0.45,0.46]	4.52 [4.39,4.66]	0.25 [0.2,0.3]	0.72 [0.69,0.75]	0.46 [0.3,0.65]
Neutral	0.43 [0.42,0.44]	3.98 [3.90,4.22]	0.21 [0.17,0.22]	0.78 [0.74,0.81]	0.28 [0.21,0.34]
Embodied	0.44 [0.43,0.45]	4.32 [4.02,4.39]	0.18 [0.14,0.21]	0.81 [0.8,0.83]	0.21 [0.15,0.26]
All	0.44 [0.43,0.45]	4.25 [4,4.38]	0.18 [0.17,0.2]	0.81 [0.81,0.85]	0.2 [0.19,0.23]
Data	0.44 [0.42,0.45]	4.26 [3.87,4.38]	0.18 [0.17,0.19]	0.84 [0.83,0.87]	0.2 [0.17,0.21]

Table 6: Matching Function Estimates Post 1984: Elasticities and Matching Efficiency. Median of the posterior distribution; 16th and 84th percentiles in parenthesis

Variable	Aggregate Shock	Allocative Shock
Output	↑ (4)	↓ (1)
Job Creation	↑ (2)	↑ (2)
Job Destruction	↓ (3)	↑ (3)

Table 7: Sign Restrictions for an Aggregate and Allocative Shock (duration in quarters in parentheses)
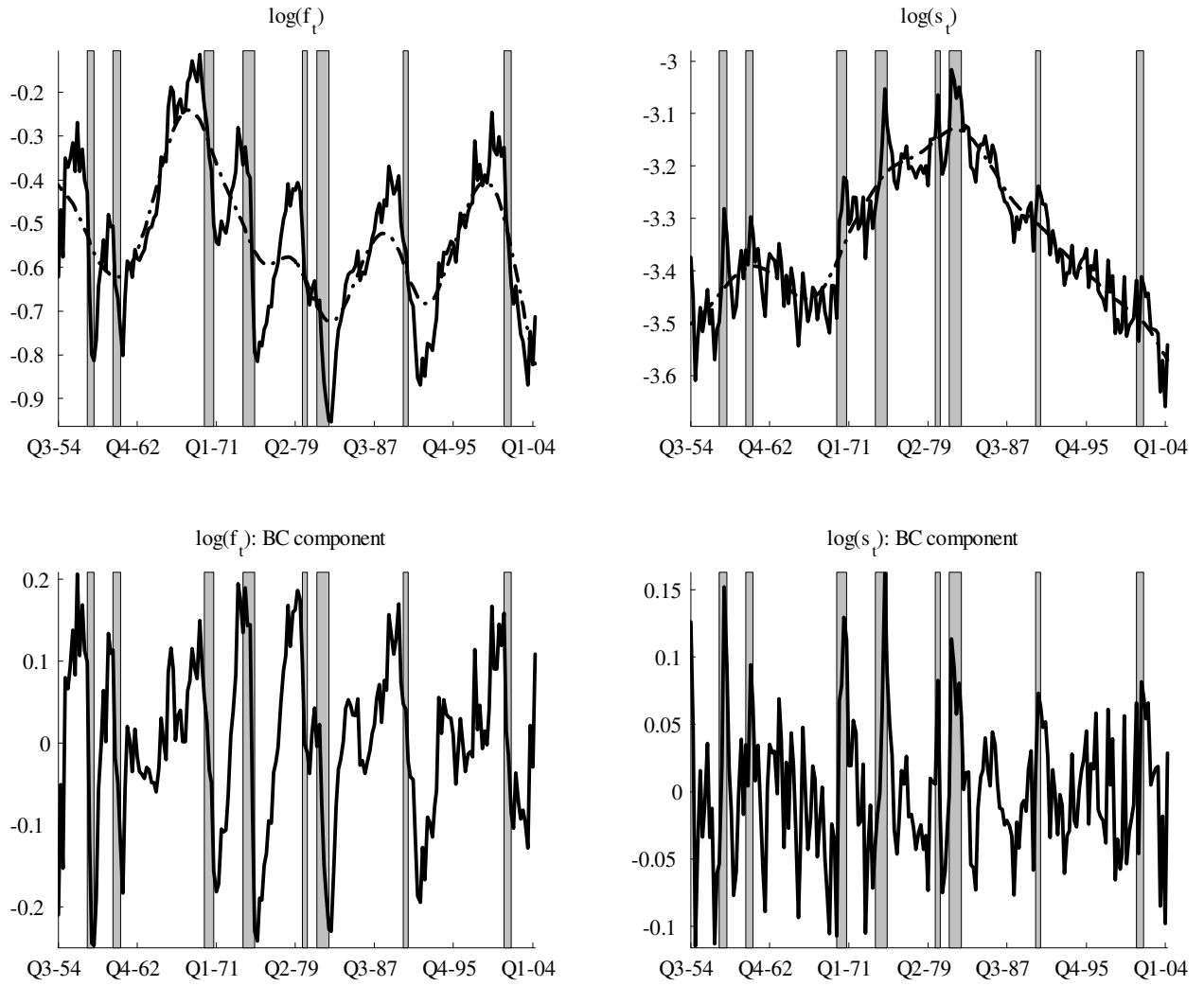
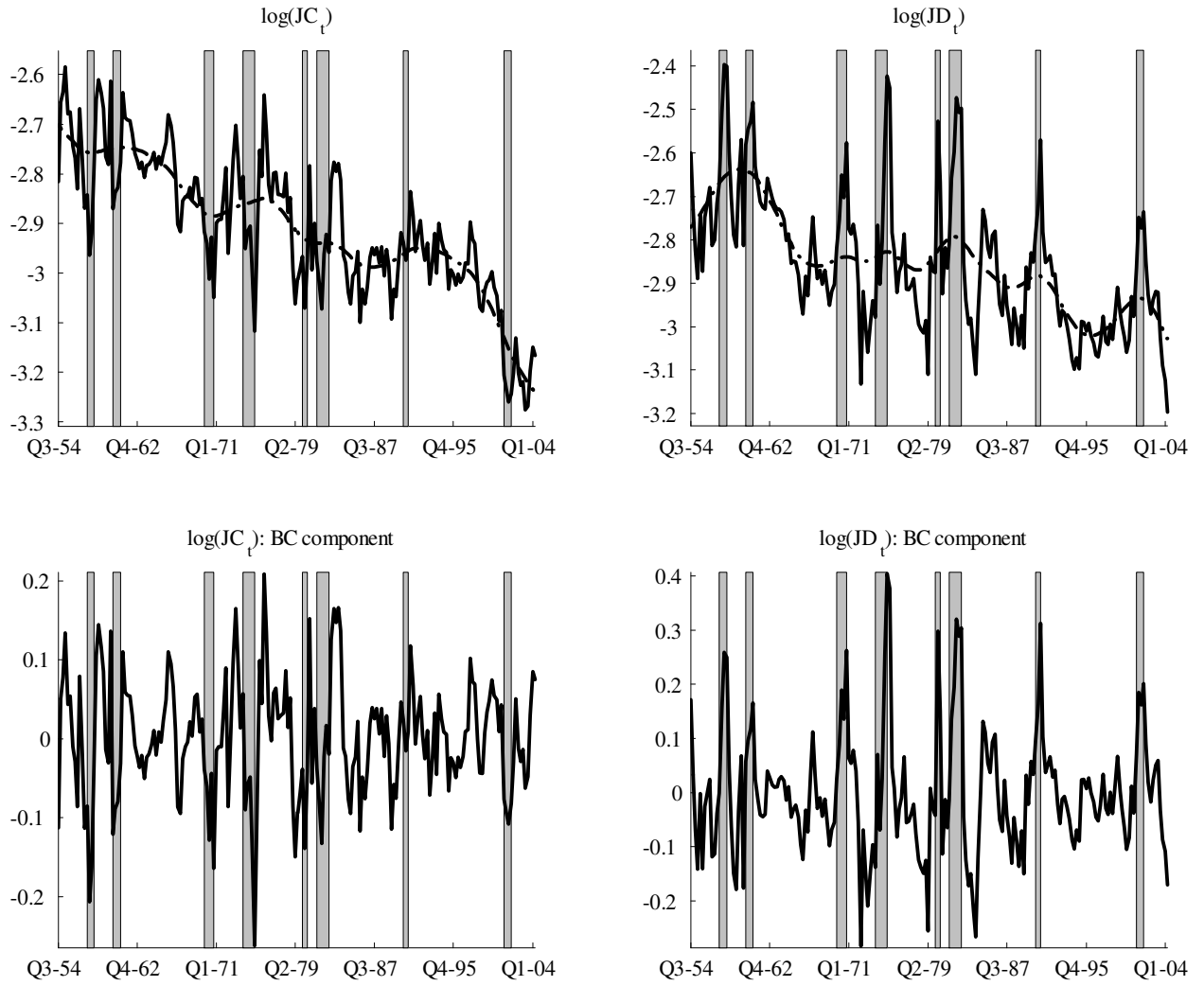Figure 1: Worker Flows: Levels and Business Cycle Components.

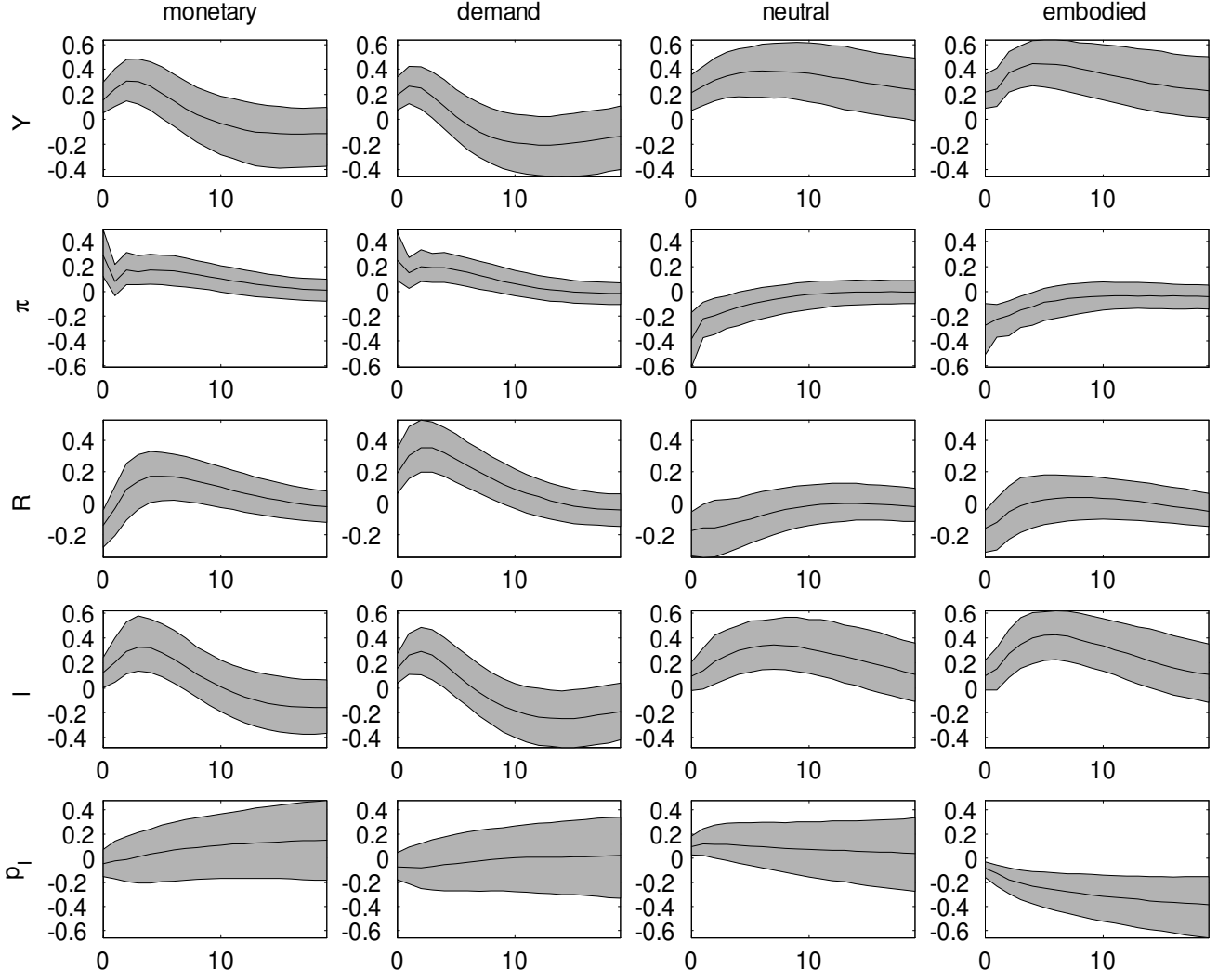Figure 2: Job Flows: Levels and Business Cycle Components.

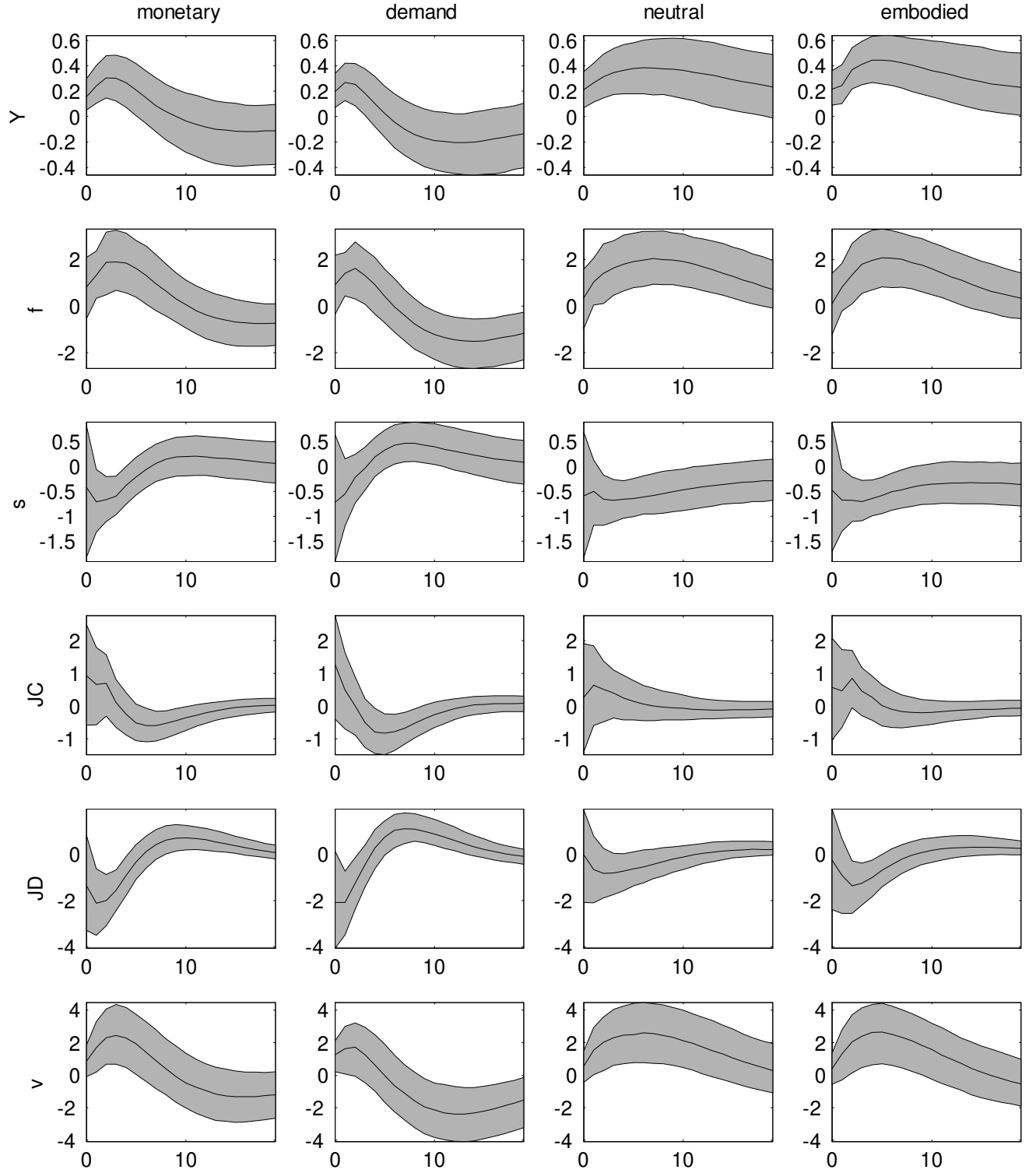Figure 3: Impulse Response Functions for Non-Labor Market Variables (% unless indicated otherwise).

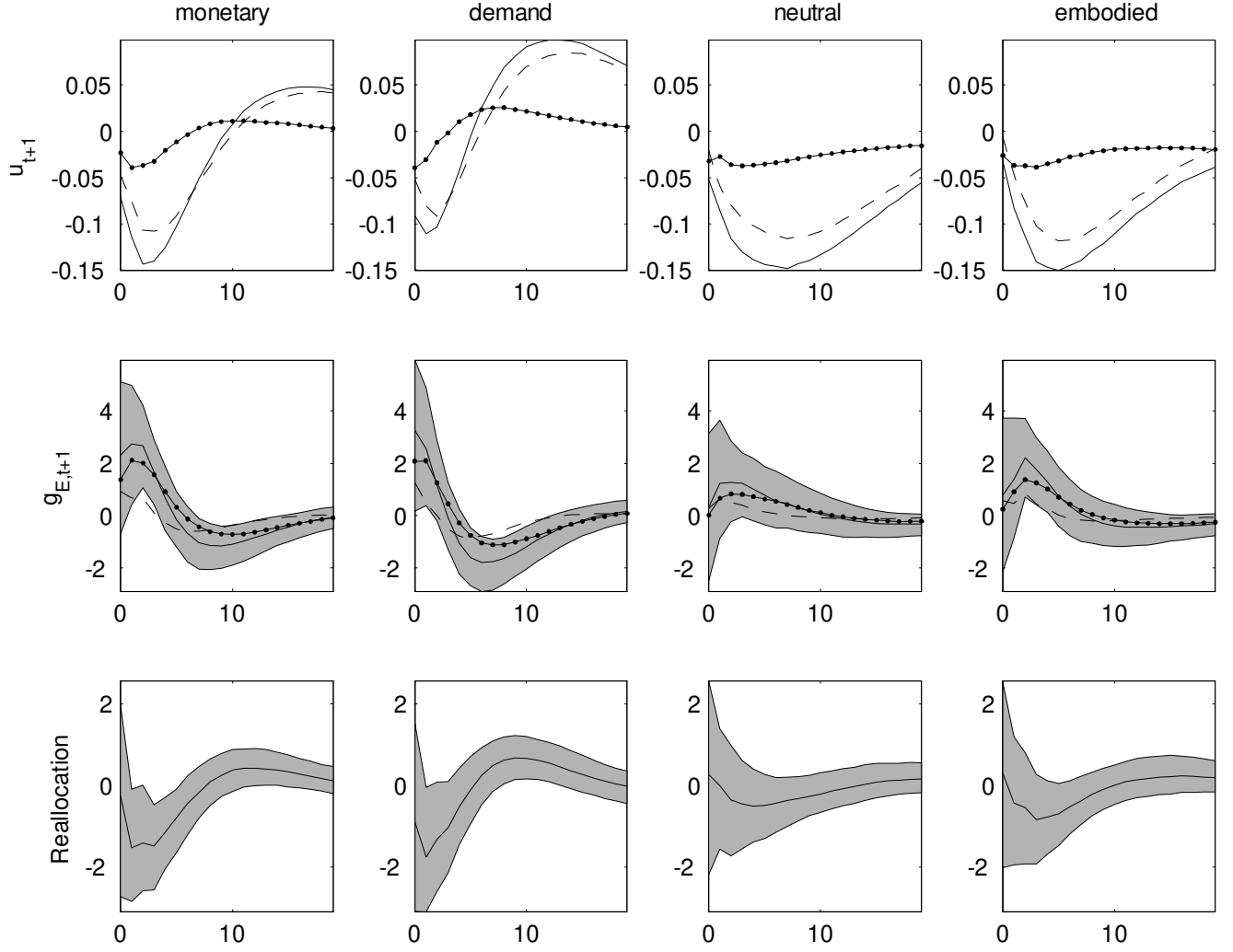Figure 4: Impulse Response Functions for Labor Market Variables (%).

Figure 5: Impulse Response Functions for Other Variables of Interest (percentage points). The dotted lines are the contributions of the separation rate (in the first row) and job destruction (second row). The dashed lines are the contributions of the job finding rate (first rate) and job creation (second row).
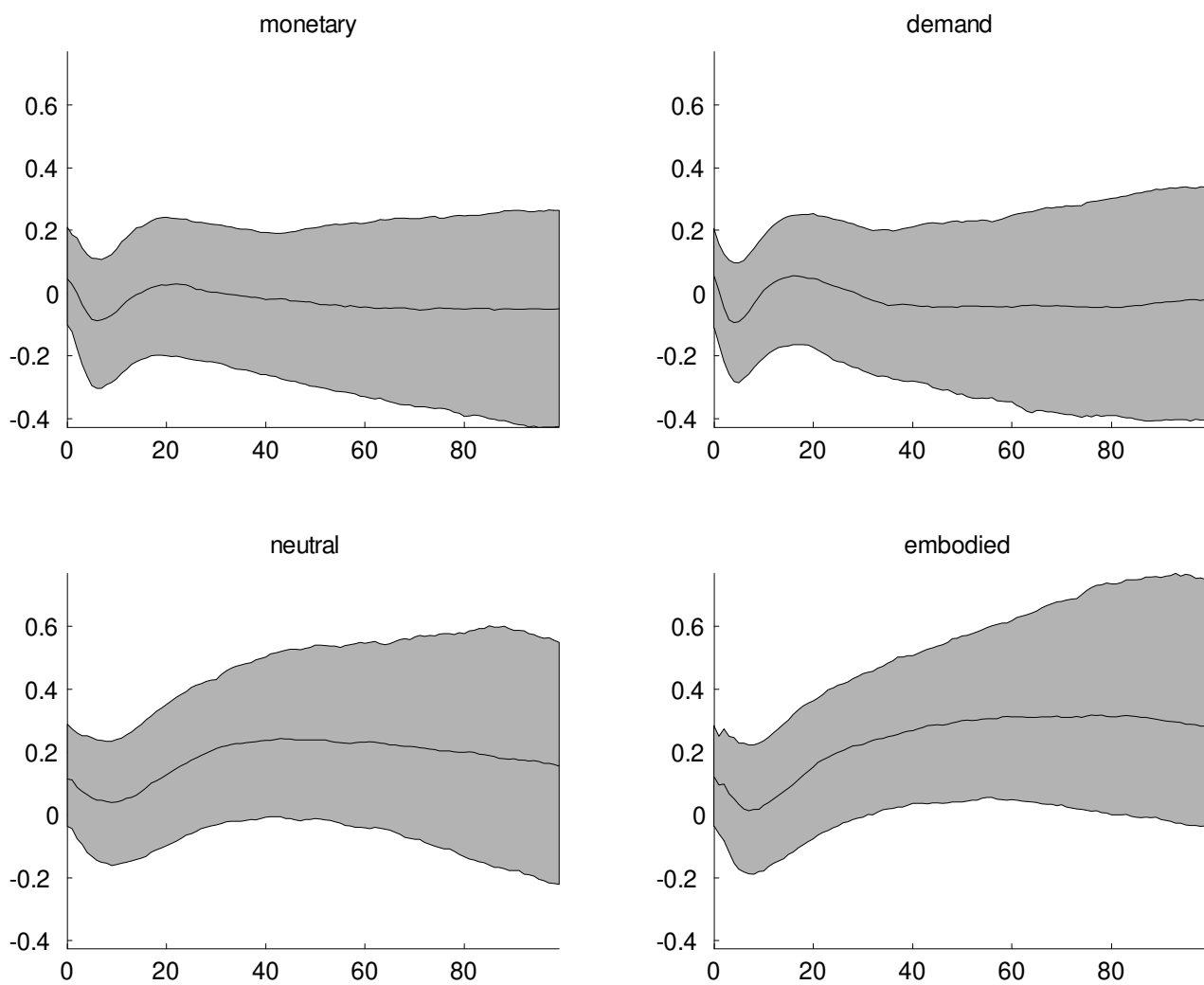
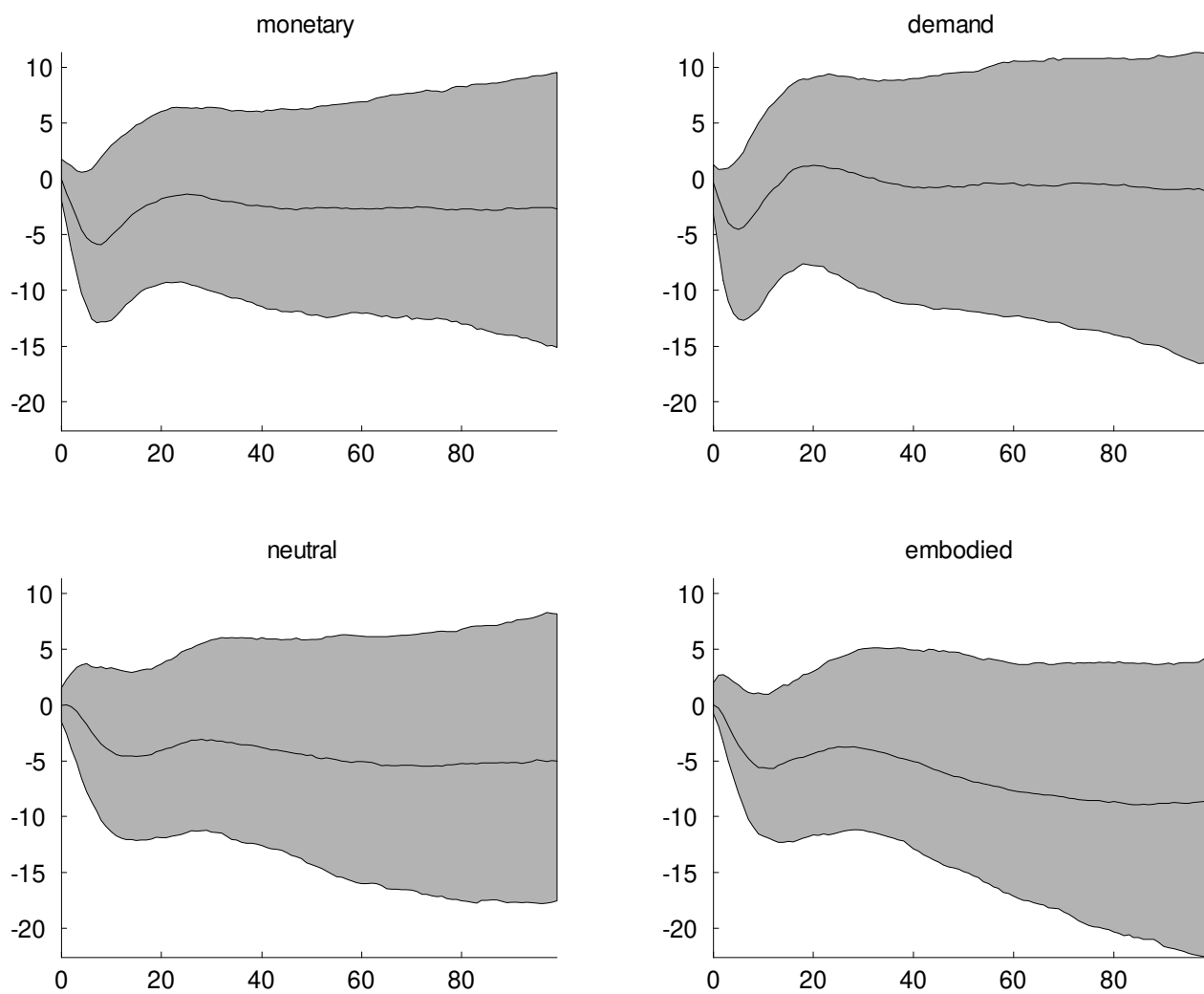Figure 6: Response of Average Labor Productivity (%)

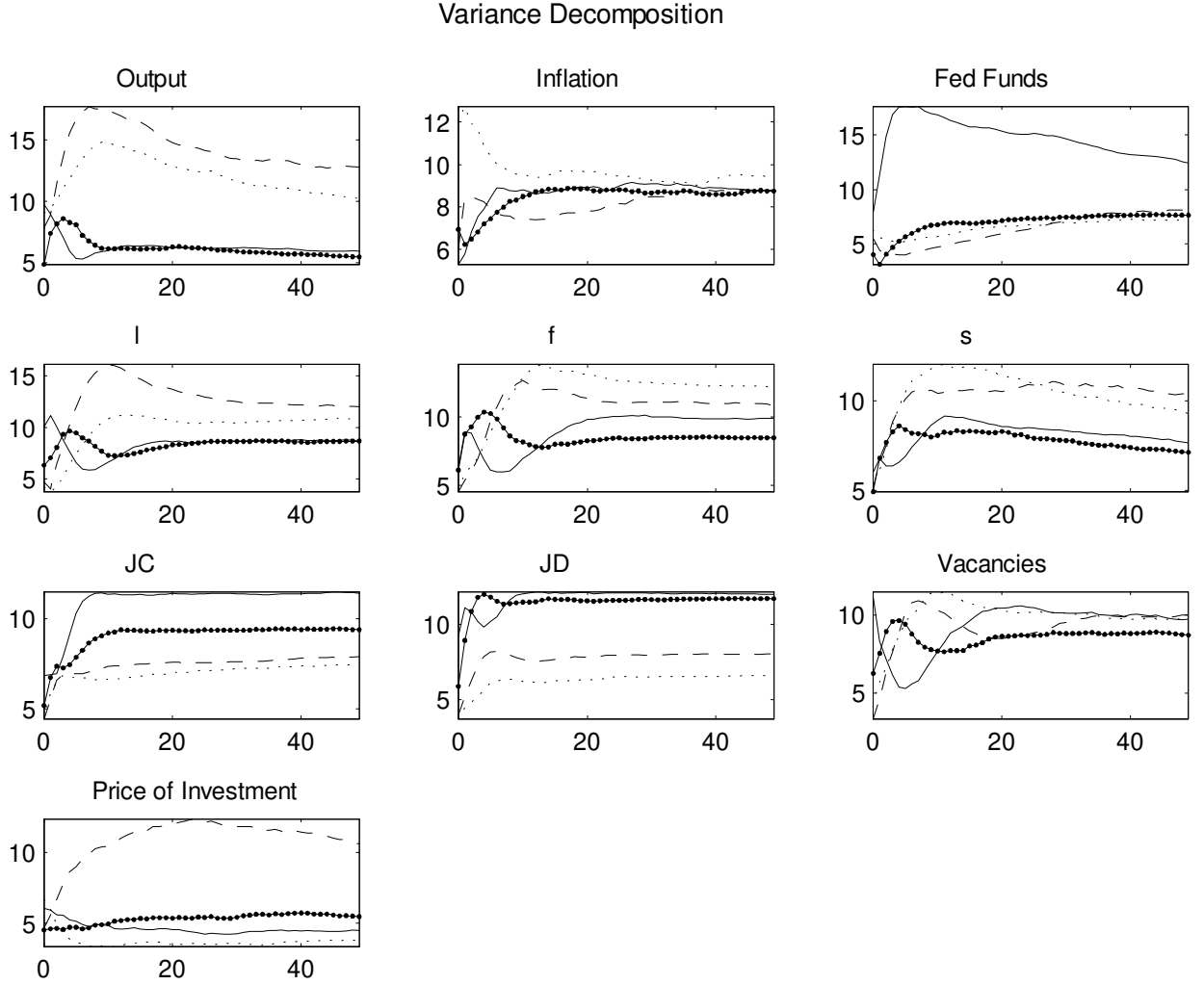Figure 7: Cumulative Effect on Reallocation Rate (percentage points)

Figure 8: Variance Decompositions. Figure shows percentage of the j-periods ahead forecast error explained by monetary shocks (points), demand shocks (solid), neutral technology (dotted), embodied technology shocks (dashed).
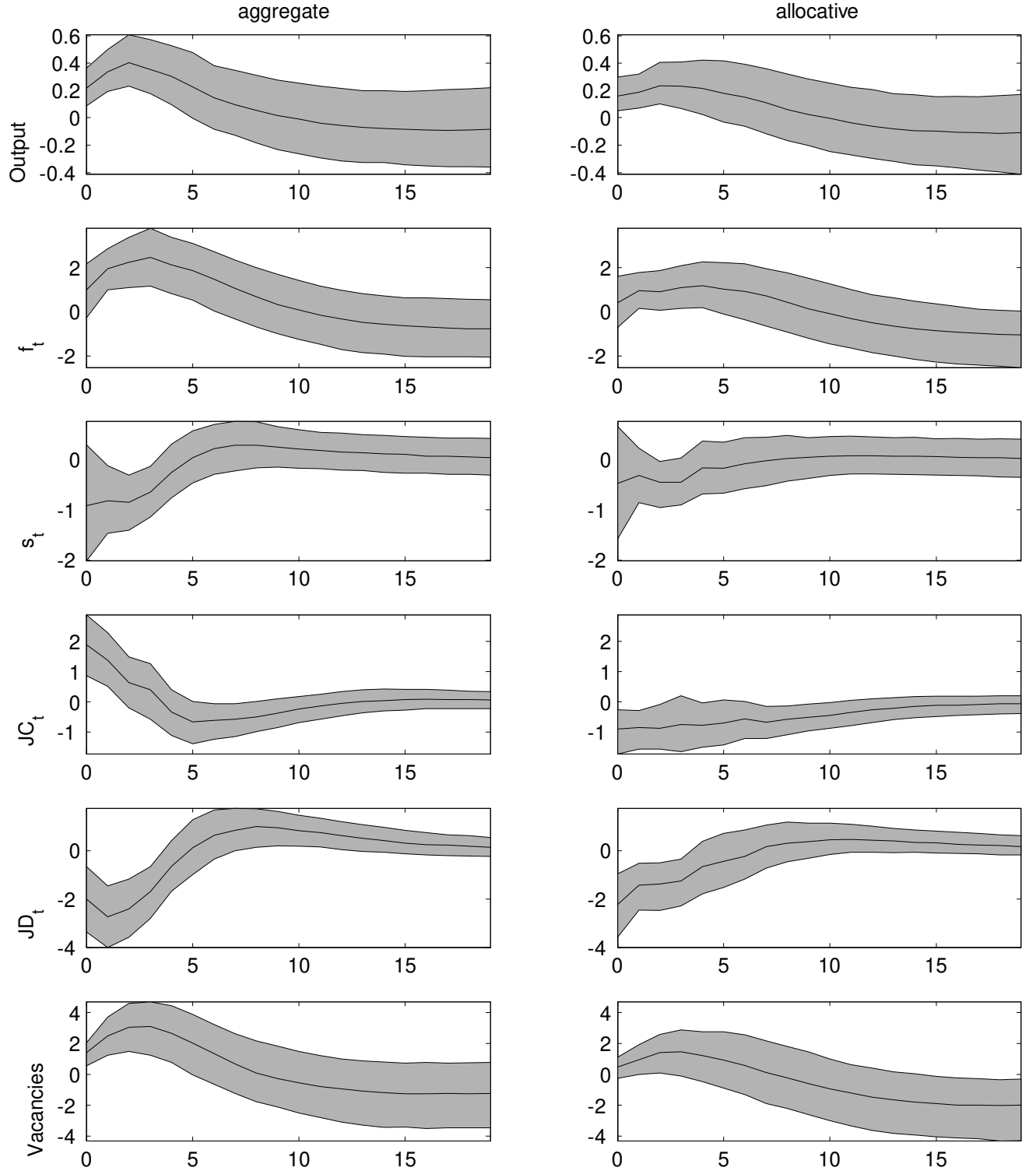
Figure 9: Aggregate versus. Allocative Shock: Impulse Response Functions for Labor Market Variables (%). For ease of comparison the allocative shocks is presented as the shock increasing current output (i.e. a 'negative' allocative shock that lowers both job creation and destruction).
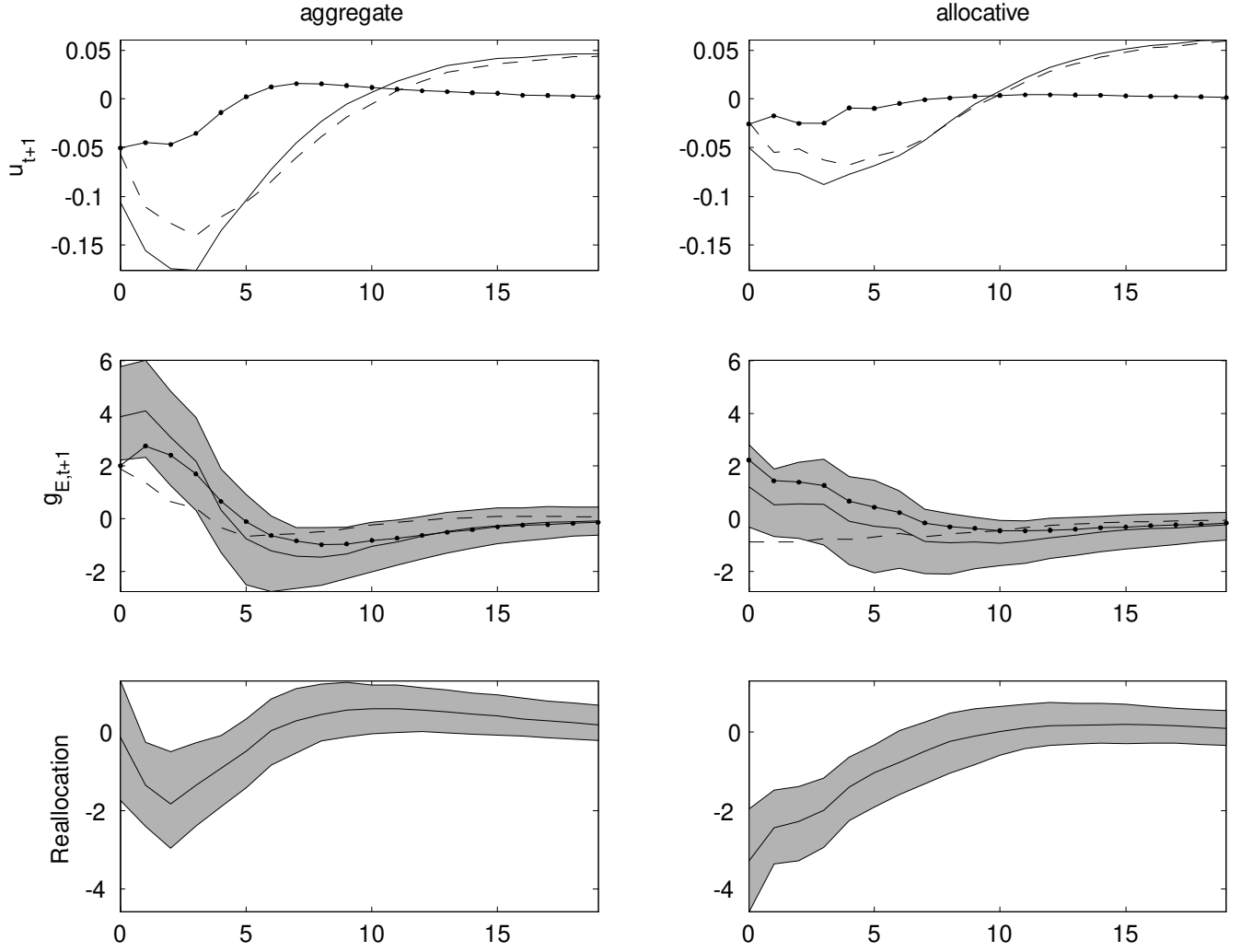
Figure 10: Aggregate versus Allocative Shock: Other Variables (ppts). The dotted lines are the contributions of the separation rate (in the first row) and job destruction (second row). The dashed lines are the contributions of the job finding rate (first row) and job creation (second row).
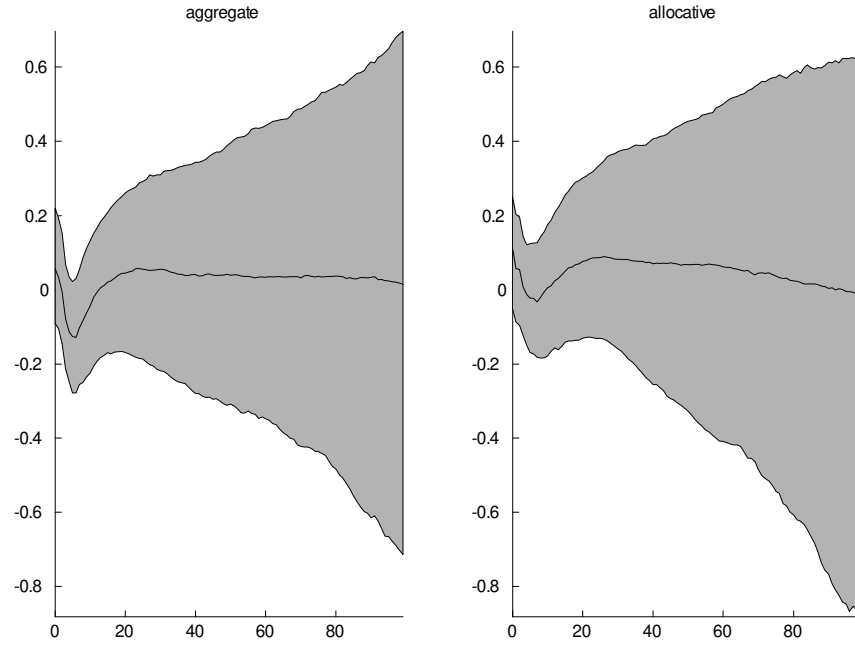
Figure 11: Aggregate versus Reallocative Shock: Response of Average Labor Productivity (%). The allocative shocks is presented as the shock increasing current output (i.e. a 'negative' allocative shock that lowers both job creation and destruction).

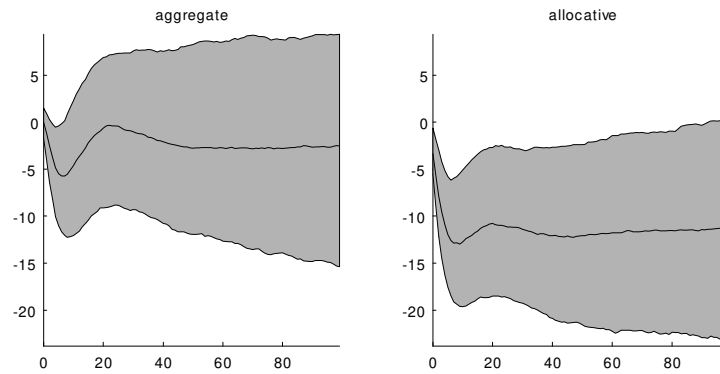

Figure 12: Cumulative Effect on Reallocation Rate (ppts). The allocative shocks is presented as the shock increasing current output (i.e. a 'negative' allocative shock that lowers both job creation and destruction).

Figure 13: Impulse Response Functions for Labor Market Variables (%): Sample and pre-1984 and post-1984 Subsamples. The green lines are the pre-1984 subsample, the red lines the post-1984 subsample, and the black lines the whole sample.
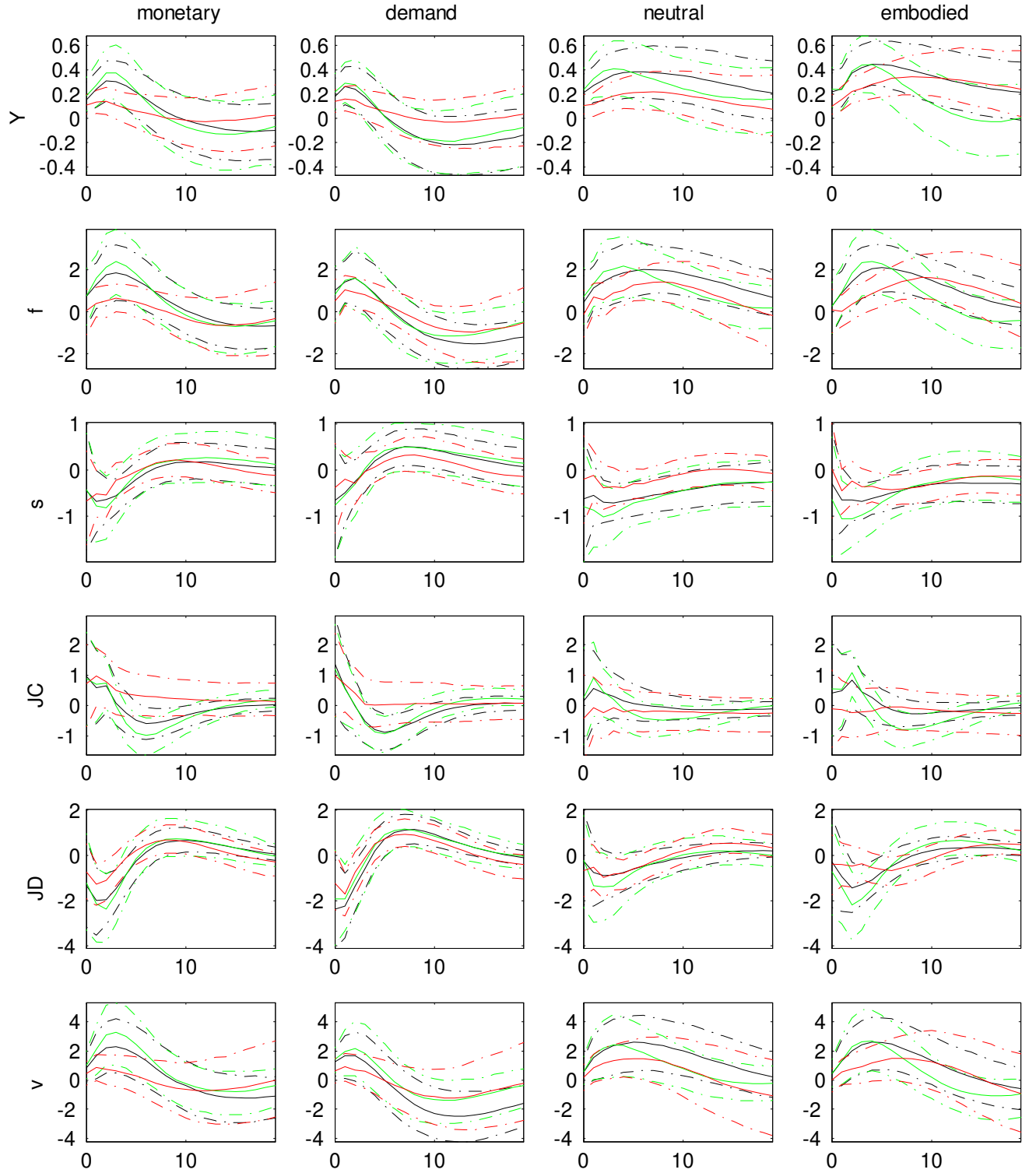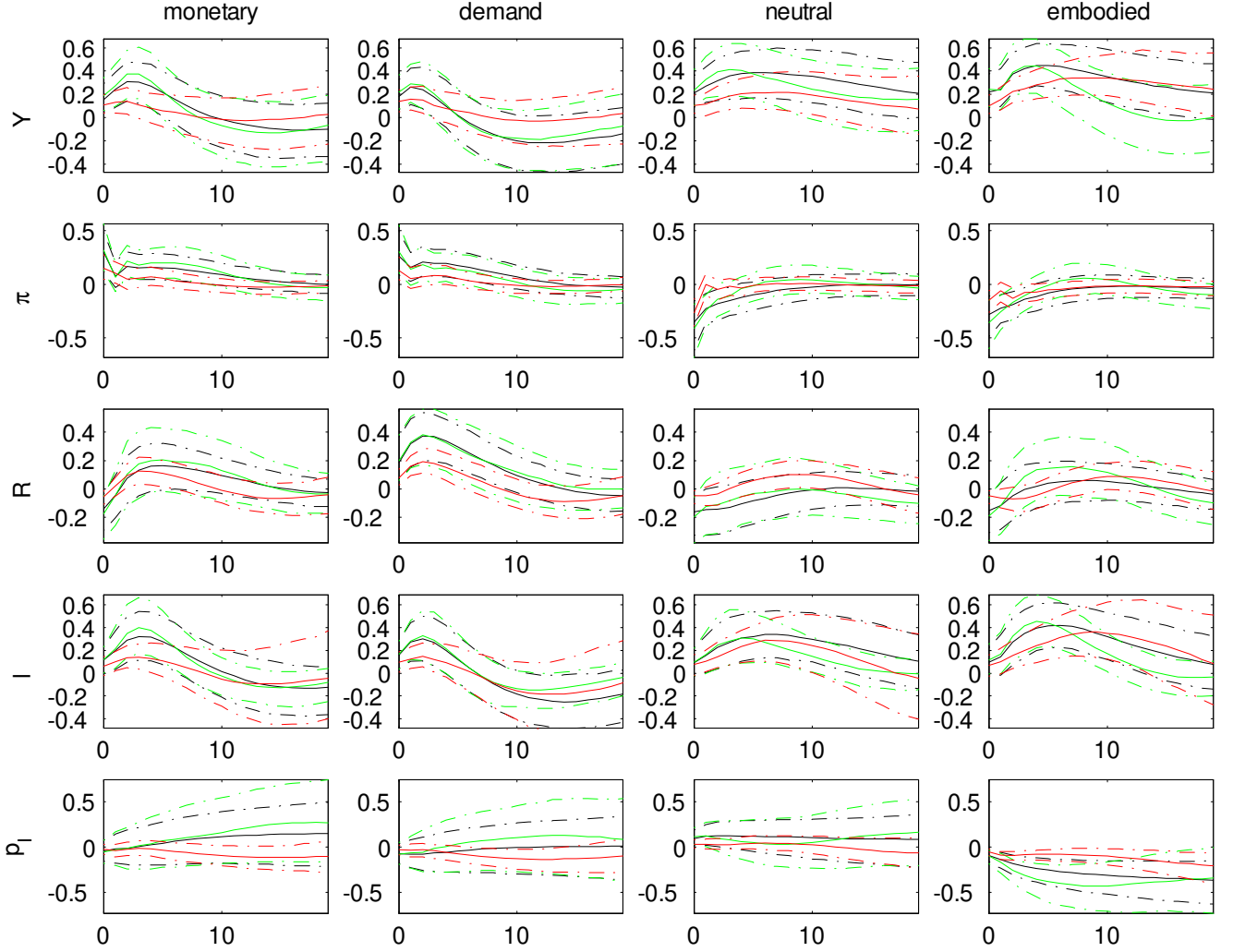
Figure 14: Impulse Response Functions for Non-labor Market Variables (%): Sample and pre-1984 and post-1984 Subsamples. The green lines are the pre-1984 subsample, the red lines the post-1984 subsample, and the black lines the whole sample.

Variable	Units	Haver (USECON)
Civilian Noninstitutional Population	Thousands	LN16N
Real GDP	Bil. Chn. 2000 $, SAAR	GDPH
GDP: Chain Price Index	Index, 2000=100, SA	JGDP
Federal Funds (effective) Rate	% p.a.	FFED
Hours of all persons (Nonfarm Bus. Sector)	Index, 1992=100, SA	LXFNH
Index of Help-Wanted Advertising in Newpapers	Index, 1987=100, SA	LHELP
Civilian Labor Force (16yrs +)	Thoursands, SA	LF
Civilian Unemployment Rate (16yrs +)	%, SA	LR

Table A.1: Raw data

A Data

Table A.1 describes the raw data used in the paper and provides the corresponding Haver mnemonics. The data are readily available from other commercial (e.g., DRI-WEFA) and non-commercial (e.g., the St. Louis FRB database FREDII) databases, as well as from the original sources (BEA, BLS, Board of Governors of the FRS).

The price of investment goods is measured as in Fisher (2003).[20] The price of investment is converted in real terms by dividing it by the GDP deflator (JGDP).

The remaining variables used in the VAR analysis are constructed from the raw data as follows:

$$\frac{Y}{l} = \frac{\text{GDPH/LN16N}}{\text{LXFNH/LN16N}}, \ \Delta \ln p = 4 \Delta \log\left(\text{JGDP}\right),$$
$$l = \frac{\text{LXFNH}}{\text{LN16N}}, \ v = \frac{\text{LHELP}}{\text{LF}}.$$

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[20]We are grateful to Jonas Fisher for sharing with us his investment price data, which we updated to 2004:Q2.

B Measuring Short-term Unemployment

The 1994 redesign of the CPS changed how the unemployment duration question is asked. The literature on the redesign furthermore indicates the presence of serious measurement problems regarding short-term unemployment in the old CPS. Prior to January 1994 unemployed workers in all eight rotation groups were asked how long they had been unemployed. Since the redesign the CPS has not asked a worker who is unemployed in consecutive months the duration of the unemployment spell. The BLS rather calculates unemployment duration as the sum of unemployment duration in the first month plus the intervening number of weeks.

To take into account the 1994 redesign of the CPS Shimer (2005b) uses the short-term unemployment rate for the full CPS sample from January 1948 up to January 1994. For the post 1994 era he works with only incoming rotation groups. The rationale for doing so is that from February 1994 to March 2004 (in the redesigned CPS), the number of short-term unemployed was 38.6% of total unemployed in the full sample but 44.6% in the incoming rotation groups. Shimer (2005b)'s use of only incoming rotation groups post 1994 leads to a consistent time series of the short-term unemployment.

This measure is not necessarily unbiased. To the extent that people underestimate their own duration of unemployment, there will be an upward bias in the short-term unemployment series prior to the redesign. In fact, evidence from Polivka and Rothgeb (1993) suggests that the duration of unemployment in the unrevised survey was not reported consistently for individuals who had been unemployed in previous months. Polivka and Miller (1998) confirm this result using the unrevised CPS from November 1992 through December 1993.[21] In the revised CPS automatic updating should eliminate such reporting inconsistencies. Unemployed individuals who are looking for work or are laid off have initial durations automatically increase by four or five weeks in the subsequent month.[22]

We find that using a Polivka-Miller adjusted short-term unemployment rate instead of Shimer's does not significantly affect the cyclical properties of s_t and f_t (see Table B.1), although their means are different (see Figure B.1).

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[21] From Polivka and Miller (1999): "When unemployment durations were collected independently from the unrevised CPS from November 1992 through December 1993 only 26.1 percent of those unemployed in consecutive months increased their reported durations by four weeks plus or minus a week. Only 15.3 percent increased their length of unemployment by exactly four weeks. Approximately 46 percent of those unemployed in consecutive months reported a duration in the subsequent month that was less than three weeks greater than the duration reported in the previous month, and 28.5 percent reported a duration that was more than five weeks greater than the length of unemployment reported in the previous month."

[22] Another source of bias could come from short jobs held between monthly interviews. Direct questioning conducted from July 1991 to October 1991 during the testing of the revised CPS indicated that only 3.2 percent of those looking for work in consecutive months had worked between interviews.

	f^{Shimer}	s^{Shimer}	f^{PM}	s^{PM}	u	v	y
f^{Shimer}	6.51 [5.8,7.3]	−0.30 [−0.45,−0.15]	0.98 [0.96,0.99]	−0.45 [−0.57,−0.31]	−0.92 [−0.94,−0.89]	0.90 [0.86,0.93]	0.83 [0.77,0.88]
s^{Shimer}		3.20 [2.7,3.8]	−0.33 [−0.47,−0.18]	0.93 [0.89,0.96]	0.48 [0.37,0.58]	−0.52 [−0.61,−0.42]	−0.55 [−0.64,−0.45]
f^{PM}			5.68 [5.1,6.4]	−0.41 [−0.54,−0.26]	−0.89 [−0.92,−0.85]	0.88 [0.84,0.91]	0.82 [0.75,0.86]
s^{PM}				3.34 [2.9,3.9]	0.59 [0.5,0.67]	−0.62 [−0.69,−0.53]	−0.64 [−0.71,−0.55]
u					7.37 [6.6,8.3]	−0.93 [−0.95,−0.9]	−0.86 [−0.9,−0.83]
v						8.58 [8,9.3]	0.91 [0.88,0.94]
y							1 [NA]

Table B.1: Correlation Matrix of Business-Cycle Components. 1954:Q3-2004Q2. Standard deviations are shown on the diagonal. All series were logged and detrended using a HP(1600) filter. Block-bootstrapped confidence intervals in brackets.
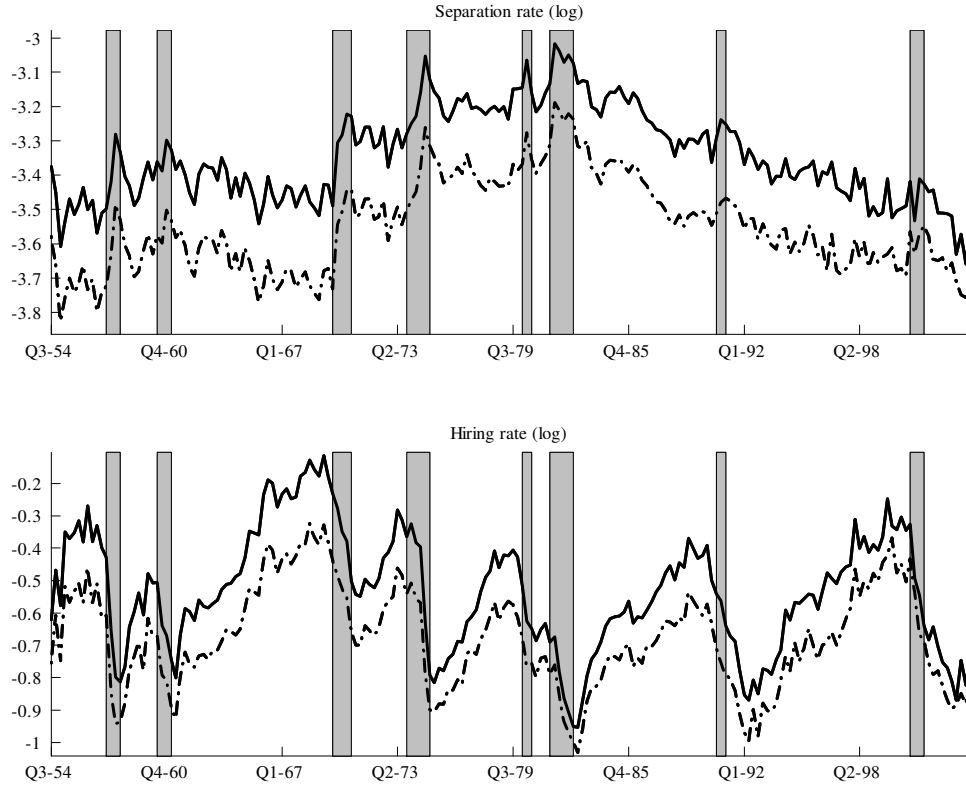
Figure B.1: Job Finding and Separation Rate: Shimer u^s (-) versus Polivka-Miller u^s(.-).

	f^{Shimer}	s^{Shimer}	λ^{UE}	λ^{EU}	λ^{UE}_{AZ}	λ^{EU}_{AZ}	y
f^{Shimer}	6.47 [5.6,7.5]	−0.24 [−0.37,−0.06]	0.87 [0.8,0.91]	−0.58 [−0.67,−0.44]	0.87 [0.8,0.9]	−0.63 [−0.71,−0.5]	0.83 [0.76,0.89]
s^{Shimer}		3.08 [2.5,4]	−0.23 [−0.38,−0.08]	0.68 [0.56,0.75]	−0.22 [−0.36,−0.07]	0.68 [0.57,0.75]	−0.50 [−0.59,−0.38]
λ^{UE}			6.08 [5.3,7.2]	−0.41 [−0.51,−0.25]	1.00 [1,1]	−0.47 [−0.56,−0.32]	0.74 [0.63,0.81]
λ^{EU}				4.80 [4,5.8]	−0.40 [−0.50,−0.24]	1.00 [1,1]	−0.71 [−0.78,−0.62]
λ^{UE}_{AZ}					5.68 [5,6.7]	−0.45 [−0.55,−0.31]	0.73 [0.61,0.8]
λ^{EU}_{AZ}						4.98 [4.2,6]	−0.75 [−0.8,−0.67]
y							1 [NA]

Table C.1: Correlation Matrix of Business-Cycle Components. 1967:Q1-2004Q2. Standard deviations are shown on the diagonal. All series were logged and detrended using a HP(1600) filter. Block-bootstrapped confidence intervals in brackets.

C   3-Pools Data

The identification of the job finding and separation rates f_t and s_t above assumes that all workers are either unemployed or employed. Transitions into and out of the labor force are not accounted for. We use gross worker flows data from the CPS to check if such a simplification is defendable at the business cycle frequency. Unfortunately the three-pool data are only available from June 1967 onwards. As in Shimer (2005b) we compute from the gross worker flows at time t transition rates λ_t^{XY} for workers who were in state X and moved to state Y during period t. We also consider the effect of adjusting the gross flows for spurious transitions stemming from corrections of missclassification errors in successive interviews. We use the weights from Bleakley, Ferris, and Fuhrer (1999). They are averages of the time varying factors calculated in Abowd and Zellner (1985) for the period January 1976 to May 1986.

Notice that the unemployment-to-employment (UE) transition rates are highly correlated to the job finding rate, and they are less volatile. The employment-to-unemployment (EU) transition rates are less correlated with the separation rate, and more volatile. This suggest that Shimer's job finding and separation rates might overstate the contribution of the hiring margin to the cyclical variation of unemployment. For data availability reasons we decided to use Shimer's data in the SVAR analysis in this paper.
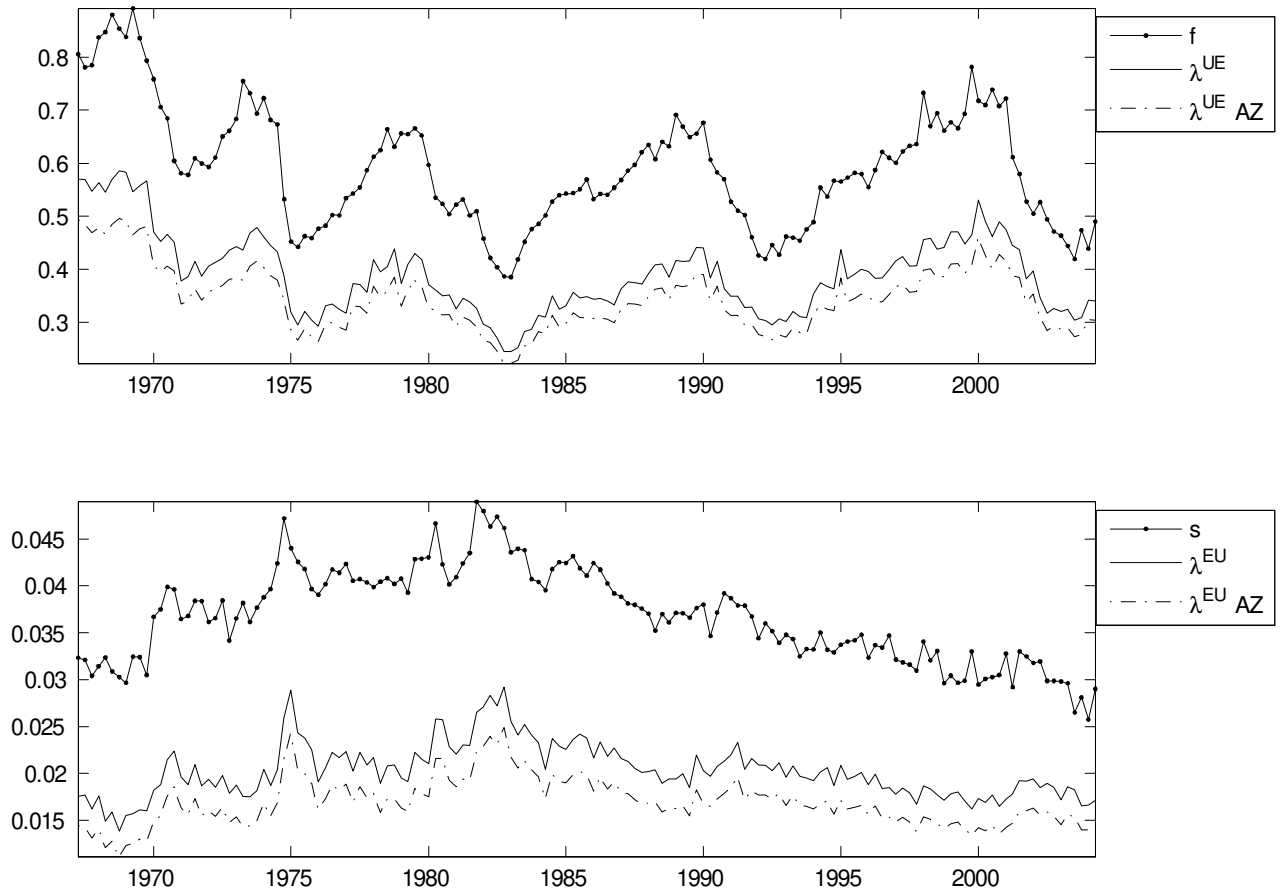
Figure C.1: Hiring and UE Transition Rate; Separation and EU Transition Rate.

D   Job versus Worker Flows Data

The job finding and separation rates focus on the unemployment pool. Ignoring the time aggregation adjustment, the job finding rate rate is equal to the number of unemployed workers who found a job within a period scaled by the size of the unemployment pool. The job flows data, on the other hand, captures the total flows into *employment*, where both job creation and destruction are scaled by employment.

Worker flows data offer an alternative way of representing employment inflows by scaling the number of workers who find a job in a given period by the size of the employment pool. If inflows from non-participation are included, this representation is analogous to the one used in job flows data in the sense that the difference between inflows and outflows yields the growth rate of employment. We take the three-pool data from Shimer (2005b) for the shorter sample (1967:Q2-2004:Q2) and undo the time aggregation to make the data comparable to the job flows data. We then construct an ins ratio from the worker flows data as the total flows into employment from unemployment (UE_t) and out-of-the-labor-force (IE_t), scaled by the total employment stock:[23]

$$ins_t \equiv \frac{UE_t + IE_t}{E_{t-1}}. \tag{8}$$

The outs ratio is the total flows out of employment to unemployment (EU_t) and out-of-labor-force (EI_t), again scaled by total employment stock:

$$outs_t \equiv \frac{EU_t + EI_t}{E_{t-1}}. \tag{9}$$

Substracting equation (9) from equation (8), we define the net change in employment implied by worker flows, $g_{E,t}^W$, as:

$$g_{E,t}^W \equiv \frac{E_t - E_{t-1}}{E_{t-1}} \equiv ins_t - outs_t. \tag{10}$$

The correlation of employment growth calculated from the raw flows as in equation (10) with BLS civilian employment growth is 0.72. Adjusting the gross flows with the means of the factors calculated as in Abowd and Zellner (1985), increases this correlation to 0.77.[24] Table D.1 presents the correlation matrix of the business-cycle components of the ins and outs ratio defined in (8) and (9). These gross flows were adjusted using the means of the time varying factors calculated as in Abowd and Zellner (1985) from January 1976 to May 1986. This table shows that the ins and outs ratios defined from worker flows have significantly different cyclical properties from the job creation and destruction series. The standard deviations of the ins and

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[23]Scaling by the average of the current and lagged employment stock as opposed to lagged total employment, does not change the results.

[24]The correlation of g_E^W with total non-farm employment growth is 0.71. For this sample the corresponding correlation of $g_E^{JC,JD}$ is 0.88. The correlation of $g_E^{JC,JD}$ with civilian employment is 0.73.

	$\frac{Ins^{AZ}}{E}$	$\frac{Outs^{AZ}}{E}$	JC	JD	u	v	y
$\frac{Ins^{AZ}}{E}$	2.74 [2.16,3.48]	0.26 [0.06,0.46]	0.36 [0.14,0.54]	−0.10 [−0.27,0.09]	0.42 [0.30,0.53]	−0.29 [−0.4,−0.14]	−0.26 [−0.41,−0.12]
$\frac{Outs^{AZ}}{E}$		2.53 [2.16,3.03]	−0.29 [−0.49,−0.07]	0.67 [0.51,0.76]	0.59 [0.47,0.68]	−0.61 [−0.70,−0.46]	−0.64 [−0.74,−0.50]
JC			4.64 [3.85,5.63]	−0.50 [−0.67,−0.27]	0.01 [−0.23,0.22]	0.03 [−0.20,0.28]	0.10 [−0.17,0.39]
JD				7.68 [6.69,8.93]	0.48 [0.30,0.61]	−0.58 [−0.71,−0.42]	−0.61 [−0.75,−0.43]
u					7.13 [6.22,8.21]	−0.95 [−0.97,−0.92]	−0.87 [−0.91,−0.81]
v						8.56 [7.90,9.49]	0.91 [0.86,0.95]
y							1.00 [NA]

Table D.1: Correlations Matrix of Business-Cycle Component of the Ins and Outs to Employment and Job Creation and Destruction Series, 1967Q2-2004Q2. Standard deviations (relative to output) are shown on the diagonal. All series were logged and detrended using a HP filter with weight 1600. Block-bootstrapped confidence intervals in brackets. "AZ" is the adjusted series using the means of the time-varying factors calculated in Abowd and Zellner (1985) for the period January 1976 to May 1986. The worker flows are scaled by employment at time t.

outs ratio are about half the standard deviations of the job creation and destruction rates. The job creation and destruction rate are negatively correlated, whereas the correlation between the ins and outs ratios is positive. Furthermore, ins_t is negatively correlated with output, whereas the correlation of job creation with output is positive. We also observe that the relative volatility of ins_t and $outs_t$ is much lower than the relative volatility of the hiring and separation rate. Measuring ins and outs of *employment* using worker flows, we find that the outs are almost as volatile as the ins.