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# Supply Shocks, Demand Shocks, and Labor Market Fluctuations\*

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## Abstract

We use structural vector autoregressions to analyze the responses of worker flows, job flows, vacancies, and hours to shocks. We identify demand and supply shocks by restricting the short-run responses of output and the price level. On the demand side we disentangle a monetary and non-monetary shock by restricting the response of the interest rate. The responses of labor market variables are similar across shocks: expansionary shocks increase job creation, the hiring rate, vacancies, and hours. They decrease job destruction and the separation rate. Supply shocks have more persistent effects than demand shocks. Demand and supply shocks are equally important in driving business cycle fluctuations of labor market variables. Our findings for demand shocks are robust to alternative identification schemes involving the response of labor productivity at different horizons and an alternative specification of the VAR. However, supply shocks identified by restricting productivity generate a higher fraction of responses inconsistent with standard search and matching models.

JEL: C32, E24, E32, J63.

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

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# 1 Introduction

Hall (2005) and Shimer (2004) argue that the Mortensen-Pissarides matching model (Mortensen and Pissarides, 1994) is unable to reproduce the volatility of the job-finding rate, unemployment, and vacancies observed in the data. A growing literature has attempted to augment the basic Mortensen-Pissarides model in order to match these business cycle facts.<sup>1</sup> Although most of this literature considers shocks to labor productivity as the source of fluctuations, some authors invoke the responses to other shocks as a potential resolution (see Silva and Toledo, 2005). These analyses are based on the assumption that either the unconditional moments are driven to a large extent by a particular shock, or the responses of the labor market to different shocks are similar. In this paper, we take a step back and ask what the contributions of different aggregate shocks to labor market fluctuations are and to what extent the labor market responds differentially to shocks. The labor market variables we analyze are worker flows, job flows, vacancies, and hours. Including both worker and job flows allows us to analyze the different conclusions authors have reached with respect to the importance of the hiring versus separation margin in driving changes in employment and unemployment. Including aggregate hours relates our work to the literature on the response of hours to technology shocks.

We identify three aggregate shocks – supply shocks, monetary, and non-monetary demand shocks – using a structural vector autoregression. We place restrictions on the signs of the dynamic responses of aggregate variables as in Uhlig (2005) and Peersman (2005). The first identification scheme we consider places restrictions on the short-run responses of output, the price level, and the interest rate. We require that supply shocks move output and the price level in opposite directions, while demand shocks generate price and output responses of the same sign. Monetary shocks additionally lower the interest rate on impact; other demand shocks do not. These restrictions are motivated by a basic IS-LM-AD-AS framework or by new-Keynesian models. We leave the responses of job flows, worker flows, hours and vacancies unrestricted.

The main results for the labor market variables are as follows: The responses of hours, job flows, worker flows, and vacancies are at least qualitatively similar across shocks. A positive demand or supply shock increases vacancies, the job-finding and creation rates, and decreases the separation and job-destruction rates. As in Fujita (2004), the responses of vacancies and the job-finding rate are persistent and hump shaped. Furthermore, the responses induced by demand shocks are less persistent than those induced by supply shocks. Across shocks, changes in the job-finding rate are responsible for the bulk of changes in unemployment, although separations contribute up to one half on impact. Changes in employment, on the other hand, are mostly driven by the job destruction rate. As in Davis and Haltiwanger (1999), we find that job reallocation falls following expansionary shocks, especially for demand-side shocks. We find no evidence of differences in the matching process of unemployed workers and vacancies in response to different shocks. Finally, each of the demand side-shocks is at least as important as the supply side shock in explaining fluctuations

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<sup>1</sup>See, for example, Hagedorn and Manovskii (2006) and Mortensen and Nagypal (2005).

in labor market variables.

There is mild evidence in support of a technological interpretation of the supply shocks identified by these restrictions. The response of labor productivity is positive for supply shocks at medium-term horizons, whereas insignificantly different from zero for the demand shocks. To check the robustness of our results, we modify our identification scheme by restricting the medium-run response of labor productivity to identify the supply-side shock, while leaving the short-run responses of output and the price level unrestricted. This identification scheme is akin to a long-run restriction on the response of labor productivity used in the literature. Consistent with the first identification scheme, technology shocks tend to raise output and decrease the price level in the short run.

Interestingly, the labor market responses to supply shocks under this identification scheme are less clear cut. In particular, the responses of vacancies, worker and job flows to supply shocks are not significantly different from zero. Again, the demand side shocks are at least as important in explaining fluctuations in the labor market variables as the supply shock. We also identify a technology shock, using a long-run restriction on labor productivity, and a monetary shock, via the recursiveness assumption used by Christiano, Eichenbaum, and Evans (1999). Again, we find that the responses to the technology shock are not significantly different from zero. The responses to the monetary shock are consistent with the ones identified above. The contribution of the monetary shock to the variance of labor-market variables exceeds that of the technology shock.

We also analyze the subsample stability of our results. We find a reduction in the volatility of shocks, consistent with the Great Moderation literature, for the post-1984 subsample. The main conclusions from the analysis above apply to both subsamples.

Furthermore, we use a small VAR including only non-labor market variables and hours to identify the shocks. We then uncover the responses of the labor market variables by regressing them on distributed lags of the shocks. Our findings are robust to this alternative empirical strategy.

Our results suggest that a reconciliation of the Mortensen-Pissarides model should equally apply to the response of labor market variables to demand side shocks. Furthermore, the response to supply side shocks is much less clear cut than implicitly assumed in the bulk of the literature. In a related paper, Braun, De Bock, and DiCecio (2006) further explore the labor market responses to differentiated supply shocks (see also Lopez-Salido and Michelacci, 2005).

Also, our findings suggest that the “hours debate” spawned by Galì (1999) is relevant for business cycle models with a Mortensen-Pissarides labor market. In trying to uncover the source of business cycle fluctuations, several authors have argued that a negative response of hours worked to supply shocks is inconsistent with the standard real business cycle (RBC) model. These results are often interpreted as suggesting that demand-side shocks must play an important role in driving the cycle and used as empirical support for models that depart from the RBC standard by incorporating nominal rigidities and other frictions. We provide empirical evidence on the response of job flows, worker flows, and vacancies. This is a necessary step to evaluate the empirical soundness of business cycle models with a labor market structure richer

than the competitive structure typical of the RBC models or the stylized sticky-wages structure often adopted in new-Keynesian models. The importance of demand shocks in driving labor-market variables and the atypical responses to supply shocks can be interpreted as a milder version of the “negative response of hours” findings.

The paper is organized as follows. Section 2 describes the data used in the analysis. Section 3 describes the identification procedure. Results are presented and discussed in Section 4. Section 5 contains the robustness analysis. Section 6 concludes.

## 2 Worker Flows and Job Flows 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 over the business cycle. The advantage of using these data lies in its availability for a long time span. The data constructed by Shimer are available from 1947, whereas worker flow data including non-participation flows from the Current Population Survey (CPS) are available only from 1967 onward.

The separation and job-finding rates are constructed using 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 job-finding 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:

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

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

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

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

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

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

These measures allow us to disentangle the contributions of the job-finding and separation rates to changes in the unemployment rate.

Note that we measure the inflow side of the employment pool using the job-finding rate and not 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, as opposed to that of the job-finding rate. 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.<sup>2</sup> Gross job creation sums up employment gains at all plants that expand or start up between  $t-1$  and  $t$ . Gross job destruction, on the other hand, sums up employment losses at 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).<sup>3</sup> A number of researchers work only with the quarterly job creation and job destruction series from the LRD.<sup>4</sup> 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).

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:

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

The data spliced from the MTD and LRD of the job-creation and -destruction rates constructed by Davis, Faberman, and Haltiwanger (2005) pertain to the manufacturing sector. However, over the period 1954: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 with the growth rate of total non-farm payroll employment,  $g_{E,t} \equiv \left[ \frac{E_t - E_{t-1}}{0.5(E_t + E_{t-1})} \right]$ :  $Corr(g_{E,t}^{JC,JD}, g_{E,t}) = 0.89$ .<sup>5</sup>

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

$$r_t \equiv JC_t + JD_t. \quad (3)$$

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<sup>2</sup>See Davis and Haltiwanger (1992), Davis, Haltiwanger, and Schuh (1996), Davis and Haltiwanger (1999), Caballero and Hammour (2005), and Lopez-Salido and Michelacci (2005).

<sup>3</sup>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) they fail to account for newly created jobs that are not filled with workers yet.

<sup>4</sup>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 1972:Q1-1993:Q4 period (see Caballero and Hammour (2005)).

<sup>5</sup>The correlation of  $g_{E,t}^{JC,JD}$  with the growth rate of employment in manufacturing is 0.93.

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<sup>6</sup> of worker flows, job flows, the unemployment rate ( $u$ ), vacancies ( $v$ ), and output ( $y$ ).<sup>7</sup> 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.<sup>8</sup>

## 3 Structural VAR Analysis

In this section, we describe the reduced-form VAR specification and provide an outline of the Bayesian implementation of sign restrictions. The variables included in the SVAR analysis are the growth rate of average labor productivity ( $\Delta \ln Y/H$ ), the inflation rate ( $\Delta \ln p$ ), hours ( $\ln H$ ), 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:Q2-2004:Q2. The variables are required to be covariance stationary. To achieve stationarity, we linearly detrend the logarithms of the job flows variables. The estimated VAR coefficients corroborate the stationarity assumption.

Consider the following reduced-form VAR:<sup>9</sup>

$$Z_t = \mu + \sum_{j=1}^p B_j Z_{t-j} + u_t, \quad Eu_t u_t' = V, \quad (4)$$

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<sup>6</sup>We used the band-pass filter described in Christiano and Fitzgerald (2003) for frequencies between 8 and 32 quarters to extract the business-cycle component of the data.

<sup>7</sup>See Appendix A for data sources.

<sup>8</sup>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.

<sup>9</sup>Based on information criteria, we estimate a reduced form VAR including 2 lags, i.e.,  $p = 2$ .



where  $Z_t$  is defined as:

$$Z_t = \begin{bmatrix} \Delta \ln \left( \frac{Y_t}{H_t} \right), \Delta \ln(p_t), \ln(H_t), \ln(f_t), \\ \ln(s_t), \ln(JC_t), \ln(JD_t), \ln(v_t), \ln(1 + R_t) \end{bmatrix}'.$$

The reduced-form residuals ( $u_t$ ) are mapped into the structural shocks ( $\epsilon_t$ ) by the structural matrix ( $A_0$ ) as follows:

$$\epsilon_t = A_0 u_t.$$

The structural shocks are orthogonal to each other, i.e.,  $E(\epsilon_t \epsilon_t') = I$ .

We employ identification schemes of the structural shocks that use prior information about the signs of the responses of certain variables. First we use short-run output and price responses to distinguish between demand and supply shocks. Then, we alternatively identify supply-side technology shocks by restricting the medium-run response of labor productivity.<sup>10</sup>

### 3.1 Implementing Sign-Restrictions

The identification schemes we consider are implemented following a Bayesian procedure. We impose a Jeffreys (1961) prior on the reduced-form VAR parameters:

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

where  $B = [\mu, B_1, \dots, B_p]'$  and  $n$  is the number of variables in the VAR. The posterior distribution of the reduced-form VAR parameters belongs to the inverse Wishart-Normal family:

$$(V|Z_{t=1,\dots,T}) \sim IW(T\hat{V}, T - k), \quad (5)$$

$$(B|V, Z_{t=1,\dots,T}) \sim N(\hat{B}, V(X'X)^{-1}), \quad (6)$$

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

$$X = \begin{bmatrix} x'_1, \dots, x'_T \end{bmatrix}',$$

$$x'_t = \begin{bmatrix} 1, Z'_{t-1}, \dots, Z'_{t-p} \end{bmatrix}'.$$

Consider a possible orthogonal decomposition of the 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 parameters, a uniform distribution over rotation matrices, and an indicator function equal to zero on the set of IRFs that violate the identification restrictions induce a posterior distribution over the IRFs that satisfy the sign restrictions.

The sign restrictions are implemented as follows:

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<sup>10</sup> As a robustness check, we also combine long-run and short-run restrictions more commonly used in the literature (see Section 5)

1. For each draw from the inverse Wishart-Normal family for  $(V, B)$  in (5) and (6) we take an orthogonal decomposition matrix,  $C$ , and draw one possible rotation,  $Q$ .<sup>11</sup>
2. We check the signs of the impulse responses for each structural shock. If we find a set of structural shocks that satisfy the restrictions, we keep the draw. Otherwise we discard it.
3. We continue until we have 1,000 draws from the posterior distribution of the IRFs that satisfy the identifying restrictions.

## 4 Price and Output Restrictions

The basic IS-LM-AD-AS model can be used to motivate the following restrictions to distinguish demand and supply shocks. Demand shocks move the price level and output in the same direction in the short run. Supply shocks, on the other hand, move output and the price level in opposite directions. On the demand side, we further distinguish between monetary and non-monetary shocks: Monetary shocks lower the interest rate on impact whereas non-monetary demand shocks do not. The price level and interest rate responses are restricted for one quarter, the output response is restricted for four quarters. These restrictions are similar to the ones used by Peersman (2005).<sup>12</sup> The identifying restrictions are summarized in Table 3.

Figures 2 and 3 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, labor market variables, and other variables of interest. Recall that labor market variables are left unrestricted. Note that the response of output is hump-shaped across shocks and more persistent for supply shocks. Furthermore, the response of hours is positive for all shocks and the response of labor productivity is positive for supply shocks.

For the response of the labor market variables displayed in Figure 3, the following main observations emerge:

**Similarity Across Shocks** The labor market variable responses are qualitatively similar across shocks. However, supply shocks generate more persistent responses than demand shocks. Also, the IRFs of the labor market variables to supply shocks are less pronounced. A larger fraction of responses involve atypical responses of the labor market variables, such as an increase in job destruction on impact.

**Worker Flows, Unemployment, and Vacancies** The job-finding rate and vacancies respond in a persistent, hump-shaped manner. Separations are less persistent.

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<sup>11</sup>We obtain  $Q$  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.

<sup>12</sup>Peersman (2005) additionally restricts the response of the interest rate for supply shocks and the response of the oil price to further disentangle supply shocks.

The unemployment rate decreases for ten quarters in response to demand shocks and overshoots its steady-state value. In response to supply shocks, the unemployment rate decreases in a U-shaped way, displaying a more persistent response and no overshooting. The response of the unemployment rate to all shocks is mostly determined by the effect on the job-finding rate. However, the separation rate contributes up to one half of the total effect on impact. The largest effect on unemployment is reached earlier for the separation rate than for the job-finding rate.

**Job Flows, Employment Dynamics, and Job Reallocation** The response of employment growth is largely driven by job destruction. The responses of the job-destruction rate are similar in shape to those of the separation rate, but 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. Note that a sizable number of the responses of job flows to supply shocks involve a decrease in job creation and an increase in job destruction. All shocks increase the growth rate of employment and reduce reallocation. The drop in reallocation is more pronounced for demand shocks. We do not find a significant permanent effect on cumulative reallocation.

The similarity across shocks may support the one-shock approach taken in the literature studying the business cycle properties of the Mortensen-Pissarides model. Although the persistence of the effects differs, all shocks raise job finding, vacancies, and job creation; they lower separations and job destruction in a similar fashion. The difference in persistence across shocks casts doubts on a reconciliation of the Mortensen-Pissarides model with the observed labor market behavior that is specific to a particular shock. The considerable fraction of atypical responses to supply shocks suggests that a further analysis of shocks different from the one we consider is necessary (see Braun, De Bock, and DiCecio, 2006; Lopez-Salido and Michelacci, 2005).

The hump-shaped response of the job-finding rate and vacancies to shocks is not consistent with the Mortensen-Pissarides model and with most of the literature. This finding is in line with Fujita (2004), who 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 four quarters), the separation rate (non-positive on impact), and the hiring rate (non-negative on impact). Our identification strategy confirms these findings without restricting worker flow 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.

The mildly negative effect on cumulative reallocation is at odds with Caballero and Hammour (2005), who find that expansionary aggregate shocks have positive effects on cumulative reallocation.

For monetary policy shocks, the IRFs of aggregate variables are consistent with Christiano, Eichenbaum, and Evans (1999), who use a recursiveness restriction to identify a monetary policy shock. However, Christiano, Eichenbaum, and Evans (1999) obtain a more persistent interest rate response and inflation exhibits a price puzzle. The latter difference is forced by our identification scheme. The job flows responses are consistent with estimates in Trigari (2004) and the worker flows and vacancies responses with those in Braun (2005).

The last row of Figure 2 shows the IRFs of labor productivity for 100 quarters. Average labor productivity, which is unrestricted, displays a persistent yet weak increase in response to supply shocks. On the other hand, productivity shows no persistent response to demand and monetary shocks. The medium-run response of labor productivity to supply shocks is consistent with a “technology shocks” interpretation.

Table 5 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 errors of output and labor productivity are mostly driven by supply shocks. Interestingly, demand shocks seem to play a more important role for the labor market variables than the supply shock. The greater importance of demand shocks suggests that more attention should be paid to other shocks in the evaluation of the basic labor market search model.

A growing literature is analyzing the response of hours worked to technology shocks in VARs. Shea (1999), Galì (1999, 2004), Basu, Fernald, and Kimball (2004), and Francis and Ramey (2005) argue that hours decrease on impact in response to technology shocks. This result is at odds with the standard RBC model, which implies an increase in hours worked in response to a positive technology shock. The conclusion drawn is that the RBC model should be amended by including nominal rigidities, habit formation in consumption and investment adjustment costs, a short-run fixed proportion technology, or different shocks.<sup>13</sup> Our results on the importance of demand shocks in driving labor-market variables and on atypical responses of these variables to supply shocks can be interpreted as an extension of the “negative hours response” findings, though in a milder form.

Table 6 shows the variance contributions of the shocks at business cycle frequencies. The contribution of shock  $i$  to the total variance is computed as follows:

- we simulate data with only shock  $i$ , say  $Z_t^i$ ;
- we band-pass filter  $Z_t^i$  and  $Z_t$  to obtain their business cycle components,  $(Z_t^i)^{BC}$  and  $(Z_t)^{BC}$ , respectively;
- the contribution of shock  $i$  is computed by dividing the variance of  $(Z_t^i)^{BC}$  by the variance of  $(Z_t)^{BC}$ .

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<sup>13</sup>Christiano, Eichenbaum, and Vigfusson (2004), on the other hand, argue that the negative impact response of hours to technology shocks is an artifact of over-differencing hours in VARs.

## 4.1 Matching Function Estimates

We can further analyze the possibly differential response of the labor market to shocks by estimating a shock-specific matching function. In the Mortensen-Pissarides model, the number of hires is related to the size of the unemployment pool and the number of vacancies via a matching function  $M(U, V)$ .<sup>14</sup> Assuming a Cobb-Douglas functional form, the matching function is given by

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

where  $\alpha_v$  is the elasticity of the number of matches with respect to vacancies and measures the positive externality caused by firms on searching workers;  $\alpha_u$  is the elasticity with respect to unemployment and measures the positive externality from workers to firms; and  $A$  captures the overall efficiency of the matching process.

Under the assumption of constant returns to scale (CRS), i.e.,  $\alpha_u + \alpha_v = 1$ , the job-finding rate can then be expressed as

$$\ln f_t = \ln A + \alpha (\ln v_t - \ln u_t). \quad (7)$$

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 process, 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 constructed as if the shock(s) of interest were the only structural shock(s);
2. use this vector of accepted residuals and the VAR parameters to generate artificial data  $\tilde{Z}_t$ ;
3. construct unemployment using the steady-state approximation  $\tilde{u}_{t+1} = \tilde{s}_t / (\tilde{s}_t + \tilde{f}_t)$  from the artificial data;
4. regress  $\ln \tilde{f}_t$  on either  $\ln \tilde{v}_t$  and  $\ln \tilde{u}_t$  (not assuming CRS) or  $\ln (\tilde{v}_t / \tilde{u}_t)$  (under the CRS assumption).

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

Table 7 reports the median, 16th, and 84th percentiles of 1,000 draws from the posterior distributions for the output and price identification scheme. The first two

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<sup>14</sup>Petrongolo and Pissarides (2001) survey the matching function literature.

columns show the estimates for  $\alpha_v$  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 the supply shock, but the median estimates differ by less than 5%. The last three columns of Table 7 show the unrestricted estimates for  $\alpha_v$ ,  $\alpha_u$ , and  $A$ . Estimates of  $\alpha_v$  and  $\alpha_u$  across shocks are close and the sum of the coefficients is around 0.70, corresponding to decreasing returns to scale. There are no significant differences in the median estimates of the efficiency parameter  $A$ .

## 5 Robustness

We analyze the robustness of our results by considering medium-run and long-run restrictions on productivity to identify technology shocks. We also consider subsample stability and a minimal VAR specification to identify the shocks of interest.

### 5.1 Restricting the Medium-Run Response of Labor Productivity

We push further the technological interpretation of supply shocks by identifying them as ones that increase labor productivity in the medium run. We leave unrestricted the short-run responses of output and the price level. This allows us to capture, as supply shocks, “news effects” on future technological improvements (see Beaudry and Portier, 2003) and is akin to the long-run restrictions used in the literature. We will analyze the latter in the next subsection. The advantage of this medium-run restriction is that it allows us to identify the other shocks within the same framework as above.

In particular, we require that a technology shock raise labor productivity throughout quarters 33 to 80 following the shock. The demand-side shocks, on the other hand, are restricted to have no positive medium-run impact on labor productivity, while affecting output, the price level, and the interest rate as above. The identifying restrictions are summarized in Table 4. This restriction is similar, in spirit, to the long-run restriction on productivity adopted by Galí (1999). Uhlig (2004) and Francis, Owyang, and Roush (2006) identify technology shocks in ways similar to ours. According to Uhlig (2004), a technology shock is the only determinant of the  $k$ -periods-ahead forecast error variance. Francis, Owyang, and Roush (2006) identification is data-driven and attributes to technology shocks the largest share of the  $k$ -periods-ahead forecast error variance.

Figures 4 and 5 report the median, 16<sup>th</sup>, and 84<sup>th</sup> percentiles of 1,000 draws from the posterior distribution of acceptable IRFs to the structural shocks. By construction, the demand-side shocks identified satisfy the restrictions in the previous section as well. The responses of all variables to demand-side shocks and of output and inflation to supply shocks are almost identical to the ones above. A sizable fraction (49.3 percent) of the supply shocks identified by restricting productivity in the medium run generate short-run responses of output and prices of opposite sign. Note that the

responses of the labor market variables to the supply shocks are smaller in absolute value than under the previous identification scheme. Furthermore, a sizeable fraction of the responses of labor market variables points to a reduction in employment and hours and an increase in unemployment.

For the variance decomposition displayed in Table 9, we again find that the two demand shocks are more important than supply shocks in driving fluctuations in labor market variables. This is also true for the variance contributions at business cycle frequencies, displayed in Table 6.

Table 8 shows the matching function estimates under the labor productivity identification scheme. The estimates are very similar. Now, only the efficiency of the matching process in response to non-monetary demand shocks is lower than the corresponding estimate for the supply shock under constant returns to scale.

## 5.2 Restricting Labor Productivity using a Long-Run Restriction

Following Galí (1999), we now identify technology shocks using long-run restrictions. Technology shocks are the only shocks to affect average labor productivity in the long run. The long-run effects of the structural shocks are given by

$$Z_{\infty} = \Theta \epsilon_t, \\ \Theta \equiv [I - A(1)]^{-1} A_0^{-1}.$$

The identifying assumption boils down to assuming that the first row of matrix  $\Theta$  has the following structure:

$$\Theta(1, :) = [\Theta(1, 1), 0_{1 \times 9}].$$

We additionally identify monetary policy shocks via a recursiveness assumption as in Christiano, Eichenbaum, and Evans (1999) by assuming that the 9<sup>th</sup> column of  $A_0$  has the following structure<sup>15</sup>:

$$A_0(:, 9) = [0_{1 \times 9}, A_0(9, 9)]'.$$

This identification assumption can be interpreted as signifying that the monetary authority follows a Taylor-rule-like policy, which responds to all the variables ordered before the interest rate in the VAR.

Figure 6 shows the impulse responses to a technology shock. Note that none of the response of the labor market variables are significantly different from zero.

Figure 7 shows the response to a monetary policy shock. The responses are consistent with the ones identified above.

Table 10 displays the variance decompositions and variance contributions at business cycle frequencies. Note that although monetary policy shocks contribute much

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<sup>15</sup>Notice that there is one overidentifying restriction. The first element of  $\epsilon_t$  would be just identified by imposing the long-run restriction. The identification of monetary policy shocks imposes one additional zero restriction.

less to variance of output and productivity than the technology shocks, fluctuations in the labor market variables are to a much larger extent driven by the monetary shock.

### 5.3 Subsample Stability<sup>16</sup>

Several papers<sup>17</sup> documented a drop in the volatility of output, inflation, interest rates, and other macroeconomic variables since the early- or mid-1980s. Motivated by these findings, we estimate our SVAR with pre-1984 and post-1984 subsamples. The post-1984 responses have similar shapes, but are smaller than the pre-1984 and the whole sample responses for all the shocks. This is consistent with a reduction in the volatility of the structural shocks. However, supply shocks have more persistent effects in the post-1984 subsample for both identification schemes. The responses of labor market variables to supply shocks identified by restricting productivity are insignificantly different from zero for both subsamples.

In terms of forecast error decomposition, supply shocks are the most important for output in the post-1984 subsamples; for hours, monetary shocks are the most important in the pre-1984 subsample, while in the post-1984 subsamples the three shocks we identify are equally important.<sup>18</sup> For worker and job flows, each demand shock is at least as important as the supply shock, across subsamples and identification schemes.

### 5.4 Small VAR

To further check the robustness of our results, we used a lower-dimensional VAR containing labor productivity, inflation, the nominal interest rate, and hours to identify the shocks using the same sign restrictions as above. For a draw that satisfies the identifying restrictions we then regressed

$$z_t = a + \sum_{j=0}^T \beta_j^M \hat{\varepsilon}_{t-j}^M + \sum_{j=0}^T \beta_j^D \hat{\varepsilon}_{t-j}^D + \sum_{j=0}^T \beta_j^S \hat{\varepsilon}_{t-j}^S + \nu_{z,t},$$

where  $(\varepsilon^M, \varepsilon^D, \varepsilon^S)$  denote the three shocks identified in the minimal VAR,  $z_t$  is one of the variables not contained in the VAR, i.e. either vacancies, the job-finding rate, the separation rate, the job-creation rate, or the job-destruction rate. Also,  $a$  and  $\nu_{z,t}$  denote a constant and an i.i.d. error term, respectively. The length of the moving average terms was set to thirty, i.e.,  $T = 30$ . The impulse responses for the labor market variables are given by the respective  $\beta_j$ .

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<sup>16</sup>The full set of IRFs and variance decompositions for the two subsamples is available upon request from the corresponding author.

<sup>17</sup>See Kim and Nelson (1999), McConnell and Perez-Quiros (2000), and Stock and Watson (2003).

<sup>18</sup>Our results on the increased importance in the later subsamples of supply shocks in accounting for the forecast error of output are consistent with Fisher (2006). On the other hand, for hours, Fisher (2006) argues that the importance of technology shocks decreased post-1982.



For both identification schemes, the qualitative conclusions are similar to above. The responses of the job-finding rate and vacancies to a non-monetary demand shock are, however, less persistent than above. Furthermore, the responses to supply shocks are even less pronounced than for the VAR specification discussed in Section 3 above.<sup>19</sup> Again, demand shocks are as important as supply shocks in driving fluctuations of the labor market variables.

## 6 Conclusion

This paper considers alternative short-run, medium-run, and long-run restrictions to identify structural shocks in order to analyze their impact on worker flows, job flows, vacancies, and hours. We find that demand shocks are more important than supply shocks (technology shocks more specifically) in driving labor market fluctuations. When identified via short-run price and output restrictions, supply shocks have qualitatively similar effects to demand shocks. They raise employment, vacancies, the job-creation rate, and the job-finding rate while lowering unemployment, separations and job destruction. These effects are more persistent for supply shocks. When identified via medium-run or long-run restrictions on labor productivity, however, supply shocks do not have a clear cut effect on the labor market variables.

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<sup>19</sup>The figures are available upon request.

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	$f$	$s$	$JC$	$JD$	$u$	$v$	$h$	$APL$	$y$
$f$	6.27 [5.54,6.99]	-0.48 [-0.63,-0.29]	-0.04 [-0.24,0.15]	-0.53 [-0.66,-0.39]	-0.98 [-0.99,-0.96]	0.95 [0.93,0.97]	0.96 [0.93,0.98]	0.20 [-0.03,0.4]	0.88 [0.81,0.92]
$s$		2.55 [2.21,2.99]	-0.55 [-0.68,-0.37]	0.86 [0.78,0.91]	0.54 [0.39,0.66]	-0.62 [-0.73,-0.49]	-0.48 [-0.61,-0.33]	-0.63 [-0.77,-0.44]	-0.67 [-0.78,-0.53]
$JC$			4.26 [3.61,4.97]	-0.58 [-0.7,-0.41]	0.08 [-0.10,0.26]	0.04 [-0.17,0.24]	-0.11 [-0.3,0.09]	0.53 [0.33,0.68]	0.14 [-0.11,0.36]
$JD$				6.73 [5.89,7.59]	0.53 [0.40,0.63]	-0.65 [-0.76,-0.53]	-0.53 [-0.66,-0.39]	-0.70 [-0.82,-0.54]	-0.72 [-0.84,-0.58]
$u$					7.27 [6.39,8.24]	-0.95 [-0.96,-0.93]	-0.95 [-0.97,-0.92]	-0.18 [-0.38,0.01]	-0.86 [-0.90,-0.81]
$v$						8.84 [8.13,9.78]	0.95 [0.94,0.97]	0.34 [0.14,0.53]	0.94 [0.9,0.96]
$h$							1.10 [1.01,1.19]	0.17 [-0.06,0.38]	0.89 [0.84,0.93]
$APL$								0.65 [0.56,0.77]	0.58 [0.43,0.7]
$y$									1 [NA]

Table 1: Correlation matrix of business-cycle components.

Standard deviations (relative to output) are shown on the diagonal. All series were logged and detrended using a BP(8,32) filter. Block-bootstrapped confidence intervals in brackets.

	Levels			BC component		
	$\frac{s_t}{s_t+f_t}$	$\frac{\bar{s}}{\bar{s}+f_t}$	$\frac{s_t}{s_t+f}$	$\frac{s_t}{s_t+f_t}$	$\frac{\bar{s}}{\bar{s}+f_t}$	$\frac{s_t}{s_t+f}$
Corr( $x, u_{t+1}$ )	0.99 [0.99,1]	0.85 [0.76,0.92]	0.79 [0.64,0.87]	0.99 [0.99,1]	0.93 [0.90,0.95]	0.74 [0.62,0.82]
Std( $x$ ) / Std( $u_{t+1}$ )	1.01 [1,1.03]	0.69 [0.6,0.82]	0.49 [0.42,0.58]	1.03 [1.01,1.05]	0.79 [0.73,0.86]	0.31 [0.28,0.36]

Table 2: Contribution of the job finding and separation rates to unemployment: levels and business-cycle components.

The business cycle component is extracted with a BP(8,32) filter. Block-bootstrapped confidence intervals in brackets.

Variable	Demand shocks		Supply shocks
	Monetary	Other	
Output	$\uparrow 1 - 4$	$\uparrow 1 - 4$	$\uparrow 1 - 4$
Price level	$\uparrow 1 - 4$	$\uparrow 1 - 4$	$\downarrow 1 - 4$
Interest rate	$\downarrow 1$	$\uparrow 1$	—

Table 3: Sign restrictions: demand and supply shocks

Variable	Demand shocks		Supply shocks
	Monetary	Other	
	not $\uparrow 33 - 80$	not $\uparrow 33 - 80$	$\uparrow 33 - 80$
Output	$\uparrow 1 - 4$	$\uparrow 1 - 4$	—
Price level	$\uparrow 1 - 4$	$\uparrow 1 - 4$	—
Interest rate	$\downarrow 1$	$\uparrow 1$	—

Table 4: Sign restrictions: demand and supply shocks

	4			8			20			32		
	M	D	S	M	D	S	M	D	S	M	D	S
Output	9.5 [2.7,23.8]	6.4 [1.6,19.9]	13.4 [3.8,30.9]	8.1 [2.5,21.3]	5.8 [2.4,13.4]	14.4 [4.4,32.5]	7.1 [2.8,15.5]	7.0 [2.5,16.7]	12.3 [3.9,28.2]	6.7 [2.8,15.1]	6.9 [2.7,6.9]	11.5 [3.7,26.3]
Inflation	6.8 [2.1,18.6]	8.6 [2.4,24.8]	9.5 [2.3,27.8]	8.4 [2.5,21.3]	9.6 [2.8,26.4]	8.5 [2.4,23.7]	8.7 [2.9,21.5]	9.6 [3.7,23.4]	9.0 [3.3,21.3]	9.1 [3.4,19.7]	10.2 [4.2,10.2]	9.3 [3.7,20.9]
Int. rate	4.8 [1.6,11.7]	19.6 [5.4,29.6]	5.2 [1.3,18.3]	6.9 [2.4,14.8]	20.0 [6.4,38.4]	5.4 [1.6,14.9]	7.7 [3.0,17.1]	17.7 [6.9,32.3]	7.0 [2.5,15.0]	8.0 [3.3,16.4]	16.3 [6.9,16.3]	8.0 [3.3,15.7]
Hours	8.4 [1.2,26.6]	7.8 [1.4,26.5]	8.5 [1.4,27.4]	8.9 [1.8,25.5]	6.0 [1.9,17.1]	10.9 [2.2,29.8]	8.6 [2.8,19.2]	9.0 [3.0,19.2]	10.8 [3.2,25.1]	9.1 [3.1,18.9]	9.2 [3.5,9.2]	10.4 [3.8,22.8]
Job Finding	9.3 [2.0,27.8]	6.8 [1.7,22.8]	8.2 [2.2,25.7]	9.4 [1.9,26.3]	6.1 [2.2,16.0]	10.4 [2.5,28.7]	8.5 [2.7,18.7]	10.7 [4.1,21.6]	10.0 [3.2,25.4]	8.6 [3.1,18.6]	11.2 [4.4,11.2]	10.1 [3.5,23.8]
Separation	8.7 [2.7,22.5]	6.3 [1.7,18.0]	8.8 [2.4,22.3]	8.5 [3.2,19.8]	8.5 [3.3,17.7]	10.0 [3.3,21.9]	8.8 [3.8,16.7]	10.0 [4.2,18.5]	10.8 [4.0,21.1]	8.6 [3.8,15.3]	9.5 [4.3,9.5]	11.0 [4.4,20.7]
JC	7.2 [2.1,20.9]	9.7 [3.5,21.7]	7.2 [2.5,19.0]	8.6 [3.4,18.7]	12.6 [5.4,22.8]	7.8 [3.1,18.0]	9.6 [4.3,20.0]	12.5 [5.7,22.1]	8.4 [3.6,17.4]	9.6 [4.4,19.5]	12.5 [5.7,12.5]	8.4 [3.7,17.3]
JD	11.5 [3.8,27.8]	10.3 [2.7,26.1]	6.6 [2.2,17.9]	11.4 [4.1,24.9]	11.9 [4.1,24.8]	7.5 [3.0,17.5]	11.3 [4.4,25.3]	12.7 [4.9,25.3]	7.5 [3.1,16.5]	11.2 [4.4,24.9]	12.8 [5.1,12.8]	7.7 [3.2,16.1]
Vacancies	9.0 [1.0,27.0]	5.5 [1.1,19.4]	7.9 [1.1,25.9]	8.5 [1.4,25.5]	6.3 [2.5,14.6]	9.3 [1.6,27.8]	9.0 [3.0,18.3]	11.5 [4.3,24.3]	8.6 [2.5,22.0]	9.3 [3.3,18.7]	11.4 [4.7,11.4]	8.8 [3.3,20.8]
APL	4.4 [1.0,16.5]	4.8 [1.4,15.7]	7.7 [1.4,27.9]	4.6 [1.4,14.9]	5.7 [1.6,16.6]	7.4 [1.6,24.7]	4.5 [1.3,14.3]	5.4 [1.5,17.0]	6.6 [1.6,22.7]	4.5 [1.3,14.5]	5.5 [1.5,5.5]	7.4 [1.7,24.2]

Table 5: Variance decompositions for output and price restrictions: percentage of the j-periods ahead forecast error explained by monetary (M), other demand (D), and supply shocks (S). Numbers in brackets are 16th and 84th percentiles obtained from a bootstrap with 1,000 draws.

	Price-Output Restriction			Labor Productivity Restriction		
	Monetary	Demand	Supply	Monetary	Demand	Supply
Output	9.3 [3.4,20.6]	12.5 [4.3,25.9]	9.8 [2.9,23.5]	8.8 [3.4,19.6]	12.3 [4.7,25.1]	7.5 [2.0,19.4]
Inflation	6.1 [1.7,16.1]	12.4 [4.3,29.5]	10.3 [3.4,25.2]	6.6 [2.0,15.0]	13.9 [4.7,28.8]	8.8 [2.4,22.4]
Int. rate	6.5 [2.3,14.3]	15.5 [4.7,33.6]	5.8 [1.6,14.4]	6.4 [2.4,13.7]	16.0 [6.0,33.9]	6.2 [1.8,16.8]
Hours	9.3 [2.6,24.1]	13.8 [4.0,31.6]	9.1 [2.6,23.1]	8.8 [2.5,22.2]	14.8 [4.8,32.2]	7.8 [2.1,20.5]
Job Finding	9.5 [2.6,24.3]	12.8 [3.5,31.1]	9.2 [2.8,22.5]	9.5 [3.3,22.8]	13.8 [4.2,30.6]	8.0 [2.1,20.5]
Separation	9.3 [3.6,22.0]	10.9 [3.4,27.6]	8.7 [2.7,29.8]	9.9 [3.7,20.8]	11.2 [3.7,27.3]	8.1 [2.6,19.4]
JC	7.3 [2.3,18.7]	11.4 [4.4,24.1]	6.2 [1.8,15.7]	7.1 [2.4,19.2]	11.6 [4.6,23.5]	6.6 [2.1,16.6]
JD	9.5 [2.9,22.8]	13.3 [3.6,28.7]	6.3 [1.8,16.3]	9.3 [3.4,20.8]	13.7 [4.1,29.7]	7.1 [1.8,16.6]
Vacancies	9.7 [2.3,23.0]	12.5 [3.9,27.4]	8.6 [2.3,22.0]	9.1 [2.7,22.7]	13.0 [4.6,28.3]	8.0 [2.0,19.7]
APL	7.5 [2.8,17.0]	10.5 [3.6,20.8]	8.8 [2.6,21.1]	7.4 [2.7,16.4]	9.9 [4.0,20.8]	8.5 [2.7,20.9]

Table 6: Variance Contributions at the Business Cycle Frequency in percent, see text. Numbers in brackets are 16th and 84th percentiles obtained from a bootstrap with 1.000 draws.

	CRS		no CRS		
	$\alpha_v$	$A$	$\alpha_v$	$\alpha_u$	$A$
Monetary	0.39 [0.38,0.40]	3.35 [3.30,3.58]	0.27 [0.24,0.30]	0.44 [0.42,0.47]	0.81 [0.65,1.14]
Other Demand	0.39 [0.38,0.40]	3.33 [3.24,3.52]	0.27 [0.25,0.31]	0.46 [0.44,0.48]	0.92 [0.77,1.29]
Supply	0.41 [0.41,0.42]	3.69 [3.61,3.86]	0.27 [0.25,0.31]	0.43 [0.43,0.44]	0.85 [0.72,1.14]
All	0.40 [0.40,0.41]	3.54 [3.49,3.69]	0.25 [0.25,0.29]	0.43 [0.43,0.44]	0.75 [0.69,1.01]
Data	0.40 [0.40,0.41]	3.55 [3.44,3.66]	0.25 [0.25,0.29]	0.43 [0.43,0.43]	0.74 [0.70,1.02]

Table 7: Matching function estimates for output and price restrictions: elasticities and matching efficiency.

Median of the posterior distribution; 16<sup>th</sup> and 84<sup>th</sup> percentiles in parenthesis.



	CRS		no CRS		
	$\alpha_v$	$A$	$\alpha_v$	$\alpha_u$	$A$
Monetary	0.39 [0.39,0.4]	3.46 [3.29,3.53]	0.26 [0.24,0.32]	0.44 [0.42,0.46]	0.83 [0.64,1.29]
Other Demand	0.38 [0.37,0.39]	3.18 [3.14,3.37]	0.26 [0.23,0.31]	0.43 [0.42,0.47]	0.80 [0.59,1.33]
Supply	0.39 [0.38,0.40]	3.42 [3.30,3.57]	0.26 [0.23,0.32]	0.45 [0.42,0.47]	0.79 [0.66,1.30]
All	0.39 [0.39,0.39]	3.40 [3.26,3.50]	0.25 [0.23,0.31]	0.43 [0.42,0.46]	0.73 [0.61,1.17]
Data	0.40 [0.40,0.41]	3.50 [3.44,3.65]	0.25 [0.24,0.29]	0.42 [0.42,0.44]	0.70 [0.65,1.01]

Table 8: Matching function estimates for productivity restrictions: elasticities and matching efficiency.

Median of the posterior distribution; 16<sup>th</sup> and 84<sup>th</sup> percentiles in parenthesis.

	4			8			20			32		
	M	D	S	M	D	S	M	D	S	M	D	S
Output	8.0 [2.2,21.5]	5.4 [1.3,16.0]	7.6 [1.4,24.3]	7.2 [2.0,18.5]	5.3 [2.3,10.8]	8.3 [2.0,26.4]	5.8 [2.2,13.0]	6.5 [2.6,14.5]	10.4 [3.1,26.0]	5.1 [2.0,11.5]	5.7 [2.3,12.9]	10.9 [3.8,26.2]
Inflation	7.0 [2.4,19.0]	8.7 [2.7,23.7]	6.9 [1.8,22.3]	9.1 [2.9,20.8]	10.6 [3.4,24.7]	7.6 [2.2,20.6]	10.2 [3.8,21.8]	10.7 [4.1,22.6]	8.3 [2.8,28.9]	10.7 [4.5,20.3]	11.5 [5.0,21.8]	8.2 [3.0,18.2]
Int. rate	4.5 [1.8,10.4]	19.5 [6.5,41.4]	5.6 [1.3,18.3]	6.5 [2.4,13.8]	20.5 [7.4,29.7]	6.4 [1.7,16.7]	7.3 [3.0,16.8]	20.5 [7.4,32.7]	8.0 [2.6,16.8]	7.9 [3.3,15.9]	16.8 [7.7,28.5]	8.3 [3.1,17.3]
Hours	7.1 [0.9,24.5]	8.0 [1.4,25.8]	6.4 [1.1,21.4]	7.3 [1.2,25.4]	6.1 [2.0,16.9]	6.8 [1.5,20.8]	9.0 [3.4,18.8]	6.1 [4.0,20.1]	7.3 [2.2,18.6]	10.4 [3.8,20.1]	11.2 [4.9,20.9]	7.3 [2.5,17.3]
Job Finding	9.5 [2.9,27.0]	7.3 [1.9,20.9]	6.1 [1.4,19.6]	9.8 [2.6,25.0]	6.4 [2.5,14.7]	6.6 [1.7,19.9]	8.5 [3.2,18.7]	6.4 [4.7,21.5]	7.8 [2.4,19.4]	9.1 [3.5,19.5]	11.8 [5.1,21.7]	7.9 [2.7,19.1]
Separation	8.9 [2.7,21.8]	6.2 [1.9,19.4]	7.4 [2.1,20.5]	8.5 [3.2,18.7]	8.7 [3.6,18.3]	8.4 [2.9,19.9]	8.8 [4.2,16.0]	8.8 [4.7,18.7]	9.3 [3.8,19.0]	8.9 [4.8,15.4]	10.1 [5.0,17.2]	9.3 [3.9,19.2]
JC	7.4 [2.2,23.2]	9.3 [3.4,21.1]	7.4 [2.8,19.5]	8.8 [3.6,20.1]	12.4 [5.7,21.9]	8.2 [3.3,18.7]	9.8 [4.3,20.4]	12.4 [6.3,21.6]	8.4 [3.6,17.8]	9.9 [4.4,20.1]	12.5 [6.5,21.4]	8.5 [3.8,17.6]
JD	11.2 [4.2,26.1]	10.5 [2.9,26.1]	6.9 [2.2,18.6]	10.9 [4.4,23.4]	11.9 [4.5,24.6]	7.7 [2.9,17.6]	11.1 [4.8,23.1]	11.9 [5.5,25.3]	7.8 [3.0,16.8]	11.1 [5.0,23.0]	13.2 [5.7,25.4]	7.9 [3.2,16.7]
Vacancies	8.8 [1.2,26.8]	5.2 [1.1,19.8]	6.5 [0.8,21.4]	7.6 [1.6,24.5]	6.5 [2.5,14.7]	7.0 [1.4,21.2]	8.6 [3.0,18.5]	6.5 [4.9,23.5]	7.8 [2.5,18.6]	9.0 [3.4,19.5]	12.3 [5.3,23.3]	8.4 [3.1,17.8]
APL	4.9 [0.9,17.8]	4.5 [1.4,12.8]	7.6 [1.5,26.0]	5.2 [1.4,15.1]	5.7 [1.7,15.4]	8.0 [1.7,25.4]	5.5 [1.4,15.5]	5.7 [1.7,16.2]	7.7 [1.5,25.4]	5.0 [1.4,14.0]	5.7 [1.5,15.4]	8.1 [1.7,26.0]

Table 9: Variance decompositions for productivity restriction: percentage of the j-periods ahead forecast error explained by monetary (M), other demand (D), and supply shocks (S). Numbers in brackets are 16th and 84th percentiles obtained from a bootstrap with 1,000 draws.

	4		8		20		32		Business Cycle	
	M	Tech	M	Tech	M	Tech	M	Tech	M	Tech
Output	5.9 [3.3,9.6]	21.4 [10.9,41.5]	14.2 [8.1,19.7]	35.1 [22.0,51.7]	10.4 [5.4,14.3]	56.1 [39.4,66.9]	12.1 [4.1,11.6]	64.0 [47.4,73.8]	12.1 [7.7,23.6]	15.1 [6.0,25.2]
Inflation	1.2 [0.3,2.9]	25.7 [4.33,32.6]	0.9 [0.7,3.3]	26.4 [5.0,32.7]	1.4 [1.4,6.2]	25.8 [6.0,30.8]	3.3 [1.5,6.3]	24.9 [6.7,30.7]	3.3 [1.8,8.9]	30.3 [4.0,31.2]
Int. rate	50.5 [38.4,54.0]	5.7 [0.7,10.8]	32.9 [23.9,38.9]	6.1 [1.0,12.5]	26.3 [19.2,32.3]	5.4 [1.6,12.3]	32.3 [16.6,28.3]	6.6 [2.8,14.6]	32.3 [26.6,51.6]	6.1 [1.2,12.0]
Hours	4.4 [2.4,7.9]	1.3 [0.8,10.7]	17.1 [10.0,24.4]	6.9 [2.1,16.2]	18.4 [9.7,23.6]	21.4 [4.5,26.6]	14.6 [8.8,22.0]	22.3 [4.8,27.4]	14.6 [8.1,25.5]	7.9 [2.1,13.1]
Job finding	5.2 [2.9,9.1]	2., 2 [1.1,9.7]	18.6 [11.4,27.0]	2.7 [1.9,11.1]	22.7 [12.7,28.5]	9.2 [3.0,17.9]	14.6 [12.1,27.3]	9.3 [3.3,18.4]	14.6 [8.1,26.1]	9.1 [2.1,13.6]
Separation	9.4 [5.6,13.9]	1.8 [1.2,7.5]	16.7 [9.7,21.4]	4.3 [2.4,9.9]	12.8 [7.5,17.2]	9.9 [3.5,15.5]	16.5 [6.1,14.6]	13.6 [4.3,20.3]	16.5 [9.7,24.8]	7.4 [2.0,12.1]
JC	4.9 [2.5,8.1]	3.3 [2.1,9.2]	4.9 [2.8,8.2]	5.5 [2.5,11.3]	5.4 [4.0,10.1]	5.5 [2.8,11.4]	6.6 [4.0,10.1]	5.5 [3.0,11.5]	6.6 [4.9,14.7]	4.1 [1.5,10.4]
JD	9.9 [6.1,14.9]	3.4 [1.3,9.1]	17.6 [10.8,22.4]	4.2 [1.8,9.7]	16.2 [10.27,21.4]	4.4 [2.0,10.2]	13.3 [10.3,21.4]	4.7 [2.1,10.4]	13.4 [9.0,23.5]	5.3 [1.4,11.6]
Vacancies	10.6 [6.5,15.5]	0.5 [0.2,7.4]	25.0 [15.6,31.7]	3.0 [1.4,10.4]	21.7 [12.5,26.6]	6.3 [2.3,15.1]	17.3 [10.9,24.0]	6.2 [3.5,15.9]	17.3 [10.1,29.6]	7.5 [2.0,12.8]
APL	2.1 [0.8,4.3]	37.1 [22.3,69.3]	1.6 [0.7,3.7]	41.2 [26.1,74.8]	0.8 [0.7,3.5]	42.4 [29.0,80.6]	6.2 [0.6,7.1]	47.0 [36.2,84.8]	6.2 [3.6,12.5]	25.7 [14.3,50.5]

Table 10: Variance decompositions for recursiveness and long-run restrictions: percentage of the j-periods ahead forecast error explained by monetary (M) and technology shocks (Tech) . The last column presents the variance contributions at the business cycle frequency (see text). Numbers in brackets are 16th and 84th percentiles obtained from a bootstrap with 10,000 draws.

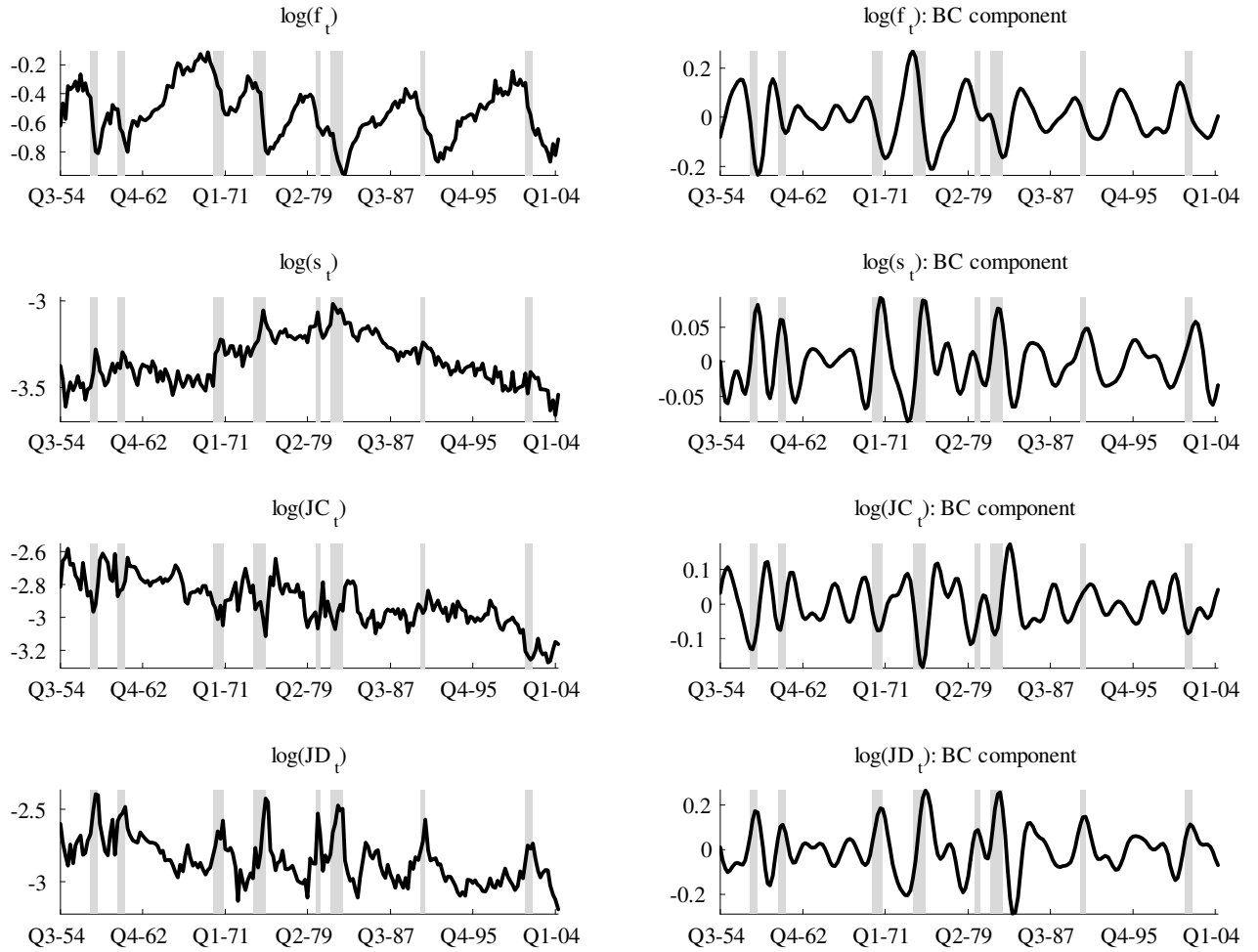


Figure 1: Worker and job flows: levels and business-cycle components.  
The business-cycle component is extracted with a BP(8,32) filter. Shaded areas denote the NBER recessions.

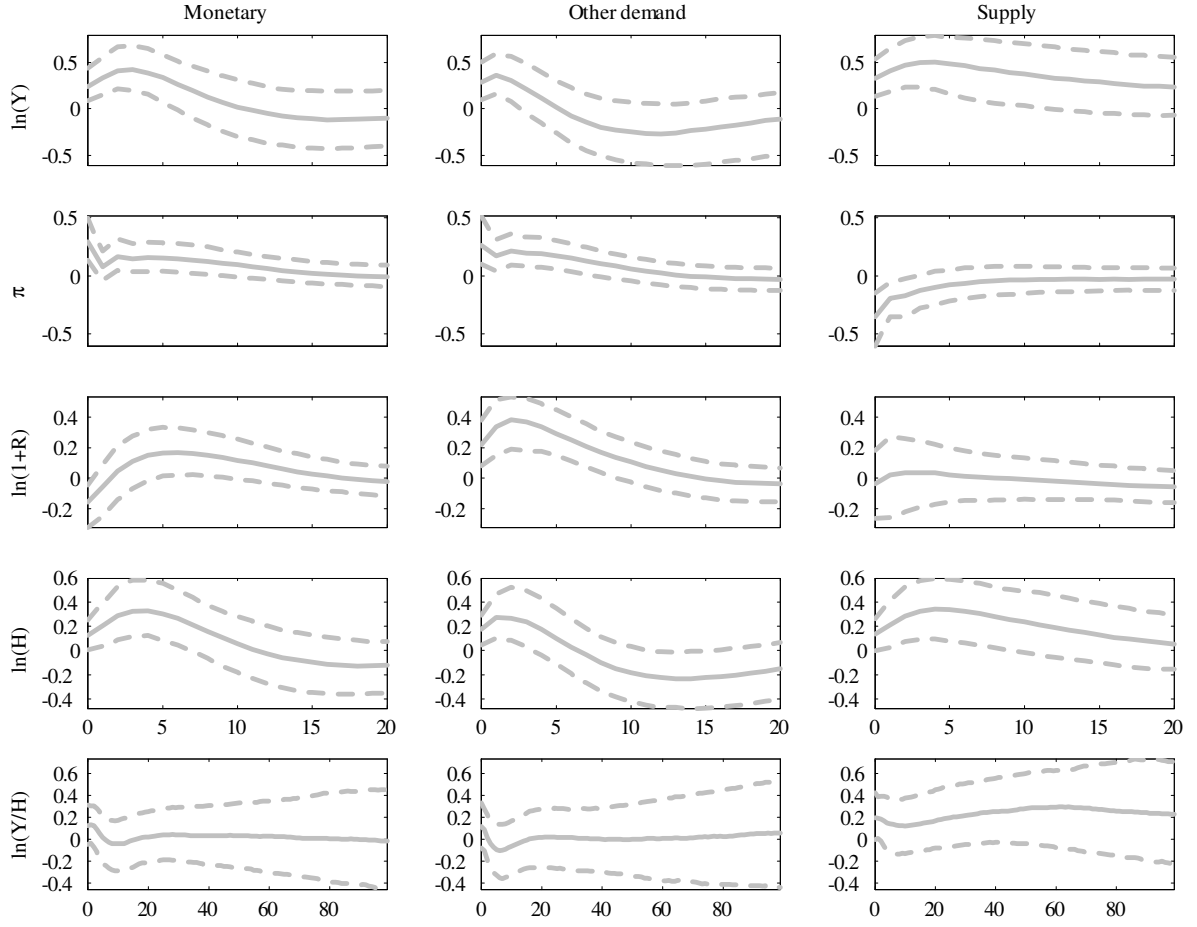


Figure 2: Price Restriction: IRFs for non-labor market variables and hours (%): demand and supply shocks. Median (solid), 16<sup>th</sup> and 84<sup>th</sup> percentiles (dashed) of posterior distributions.

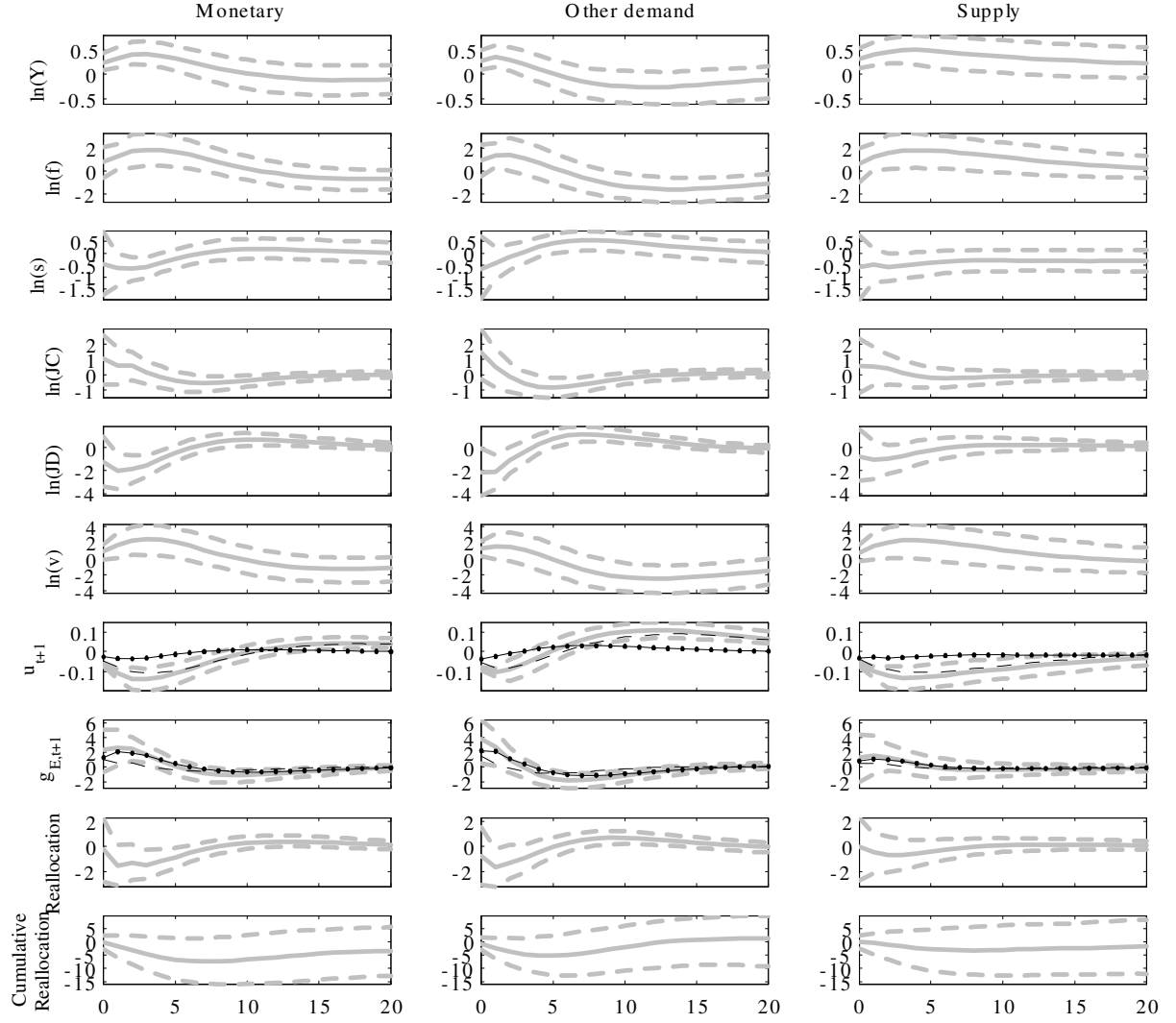


Figure 3: Price Restriction: IRFs for labor market variables (%): demand and supply shocks.

Median (solid), 16<sup>th</sup> and 84<sup>th</sup> percentiles (dashed) of posterior distributions.

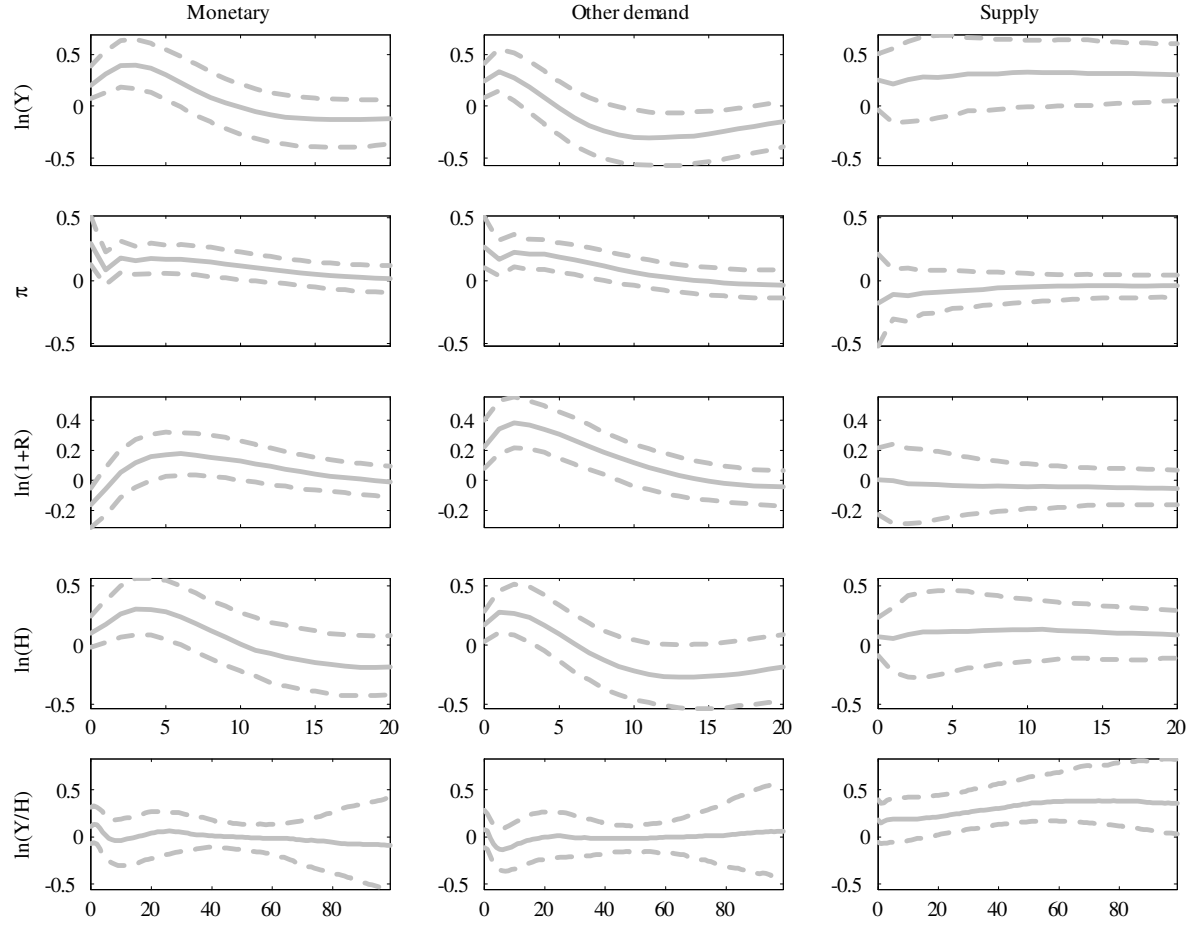


Figure 4: Labor Productivity Restriction: IRFs for non-labor market variables and hours (%): demand and supply shocks. Median (solid), 16<sup>th</sup> and 84<sup>th</sup> percentiles (dashed) of posterior distributions.

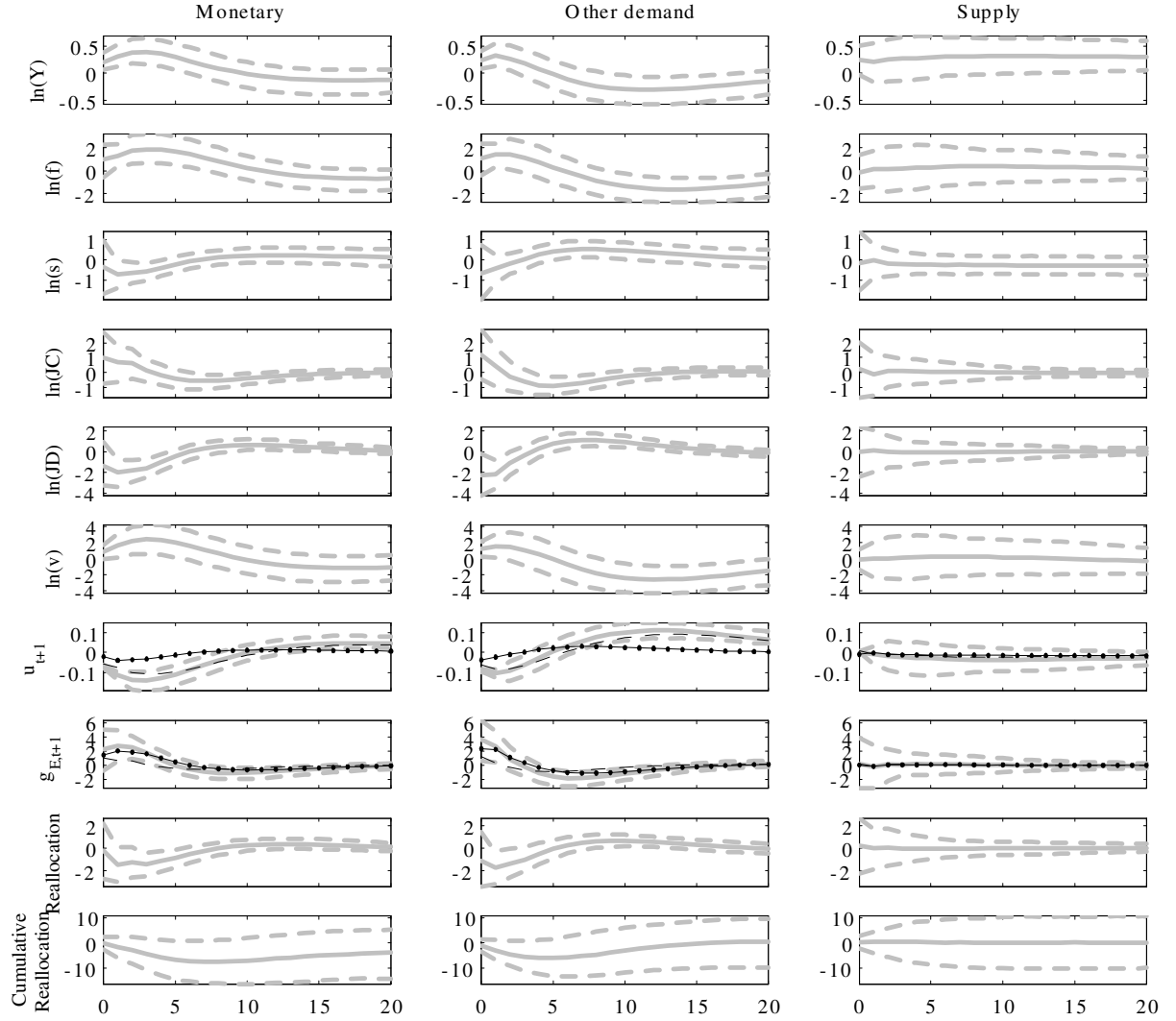


Figure 5: Labor Productivity Restriction: IRFs for labor market variables (%): demand and supply shocks.

Median ( $16^{th}$  and  $84^{th}$  percentiles (dashed) of posterior distributions.



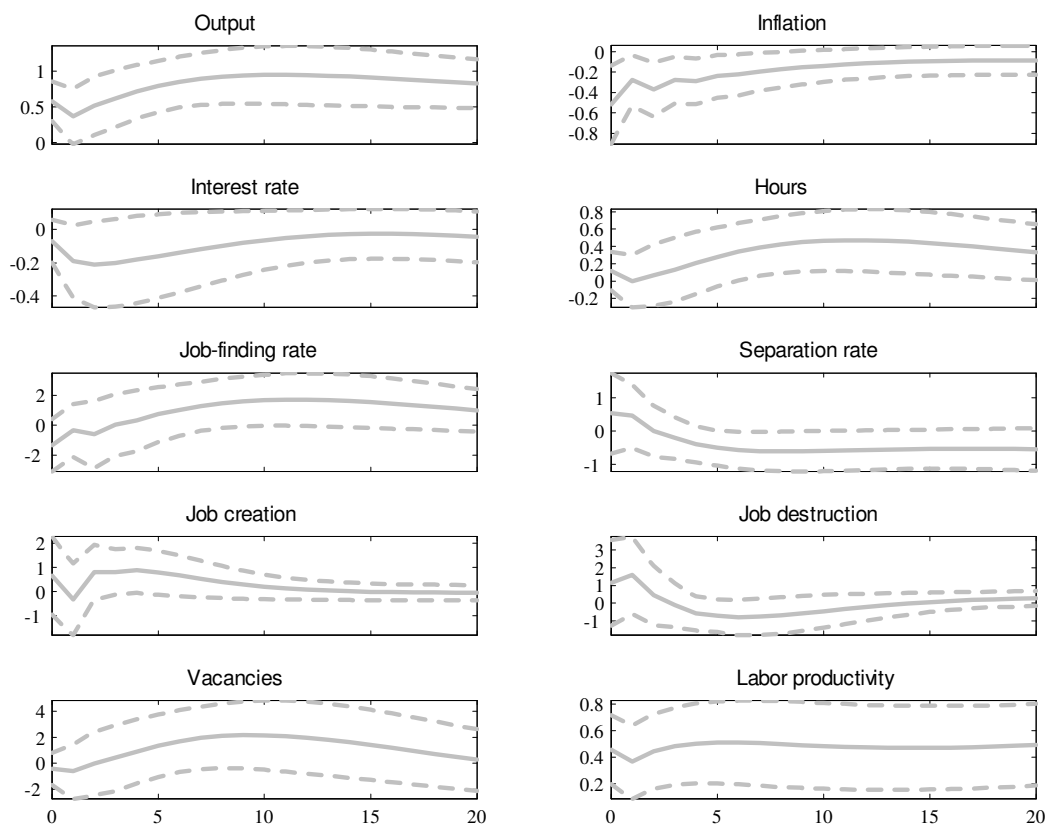


Figure 6: IRF's to a technology shock identified with a long-run restriction on productivity.

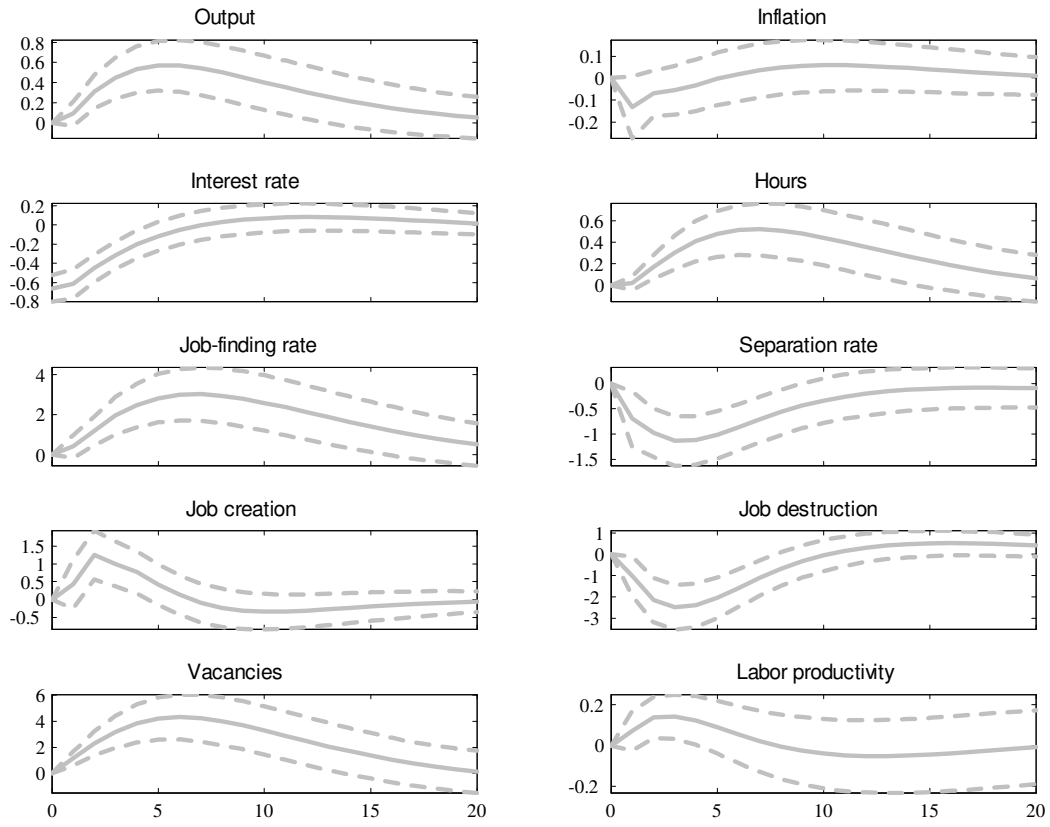


Figure 7: IRF's to a monetary shock identified with a contemporaneous restriction.

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

Table A.1: Other data

## A Other Data

Table A.1 describes the data (other than the job flows and worker flows data) used in the paper and provides the corresponding Haver mnemonics. The data are readily available from other commercial and non-commercial databases, as well as from the original sources (Bureau of Economic Analysis, Bureau of Labor Statistics, Board of Governors of the Federal Reserve System).

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

$$\Delta \ln p = 4\Delta \log(JGDP), \quad H = \frac{LXNFH}{LN16N}, \quad v = \frac{LHELP}{LF}.$$