New Evidence, Old Puzzles: Technology Shocks and Labor Market Dynamics*

Almut Balleer
Department of Economics
University of Bonn

November 2008

Abstract

Can the standard search-and-matching labor market model replicate the business cycle fluctuations of the job finding rate and the unemployment rate? Based on *unconditional* second moments in U.S. data, Shimer (2005a) answered this question negatively. In the model, fluctuations are prominently driven by productivity shocks which are commonly interpreted as technology shocks. I estimate different types of technology shocks from structural VARs and reassess the empirical performance of the standard model based on second moments that are *conditional* on technology shocks. Most prominently, the model replicates the conditional volatility of job finding and unemployment, so that the Shimer critique is not justified. Instead the model lacks non-technological disturbances needed to replicate the overall sample volatility. In addition, positive technology shocks lead to a fall in job finding and an increase in unemployment thereby opposing the dynamics in the standard model similar to the "hours puzzle" in Galí (1999).

JEL codes: E24 E32 O33
Key Words: labor market dynamics, technology shocks, structural VAR, search and matching, business cycle

*Contact: aballeer@uni-bonn.de. I thank Monika Merz, Fabio Canova and Thijs van Rens, Markus Poschke and Michael Evers for helpful suggestions. All remaining errors are my own.

1 Introduction

U.S. business cycles are characterized by large movements into and out of employment. The standard framework commonly used to study these movements comprises search-and-matching in the labor market as first presented by Mortensen and Pissarides (1994). In the dynamic version of this model, business-cycle fluctuations of labor market variables originate in fluctuations of labor productivity. These dynamics can be characterized by gross worker flows, i.e. the dynamics of unemployed workers filling an open job vacancy and employed workers separating from an existing employment relationship. The question whether the standard model is able to replicate the business-cycle fluctuations in U.S. time series data has been one of the most controversially discussed issues in the recent macro-labor literature.

Shimer (2005a) has fuelled the debate by criticizing the standard model with respect to its empirical performance. His criticism was based on comparing second moments generated from the model to second moments in worker flow data calculated from the U.S. Current Population Survey (CPS). He showed that the model did not mirror the high volatility of the job finding rate and unemployment that is observed in the data. Even though the model evokes cyclical correlations between the these two variables and labor productivity that resemble the ones in the data, the correlation between labor productivity and the job finding rate is much too high.

While the dynamics in the standard frictional labor market model stem from fluctuations in labor productivity, the sources of these fluctuations are widely interpreted as technology shocks in the literature. Hence, labor market dynamics can be represented within a real-business-cycle (RBC) and growth model as in Merz (1995), or Andolfatto (1996). In these models technology shocks are the main driving forces of labor productivity. However, other disturbances such as demand shocks may affect labor productivity as well. Within this context, Galí (1999) demonstrated how to separately identify technology and non-technology shocks in time series data via restricting their long-run effects in structural vector-autoregressions (SVARs).

Against this background, this paper re-addresses the empirical performance of the standard search-and-matching model of the labor market in which fluctuations are driven by technology shocks. The empirical performance of the model is assessed based on second moments that are *conditional* on technology shocks rather than on unconditional moments. Since conditional and unconditional moments substantially differ in this case, the judgement of the model that is based on unconditional moments may be very misleading. In addition to the moments conditional on technology shocks, this analysis provides information about the importance of non-technology shocks and the dynamics induced by these shocks. On the one hand, this allows important insights into the failure of the model on the unconditional level as documented by Shimer. On the other hand, this delivers a meaningful guidance for the formal modelling of these dynamics on the labor market.

Two main findings emerge. First, the standard deviations of the job finding rate and the unemployment rate that are conditional on technology shocks are much lower than the unconditional ones. In addition, these standard deviations are, in fact, close to the standard deviations that are generated within a commonly calibrated version of the standard model. Consequently, the Shimer critique of the model with respect to its lack of volatility does not apply when the empirical performance is based on conditional moments. Since the technology shocks generate only a part of the overall volatility in the data, non-technology shocks play a substantial role for this volatility as well. In order to replicate the unconditional moments in the data, the standard model should therefore be augmented by additional non-technological sources of fluctuations rather than with respect to a better propagation of technology shocks as suggested in the literature.

Second, the co-movement of the job finding rate with labor productivity that is conditional on technology shocks is negative, while the conditional correlation of unemployment with productivity is positive. Put differently, job finding falls after a positive technological innovation while unemployment increases. In the standard labor market model, a positive technology shock of the same size leads to an increase in labor productivity and, hence, to an increase in the job finding rate and a fall in unemployment. This result constitutes a "job finding puzzle" from the viewpoint of the standard model that is comparable to the so-called "hours puzzle" documented in Galí (1999). Since technology shocks play a considerable role for the business cycle variance of the job finding rate and unemployment, this result supports models which are able to incorporate these effects such as New Keynesian models. Note that the correlations of these two variables with productivity that are conditional on technology shocks are of opposite sign as the respective unconditional moments. Again, non-technology shocks are necessary to fully describe the overall dynamics in the data.

This paper presents results for different types of technology shocks and different types of measures for the labor market dynamics. Based on Galí (1999), technology shocks are the only shocks that have a long-run effect on labor productivity. This assumption holds in the RBC framework with frictional labor markets that is presented in section 2. The identification of these standard Galí technology shocks within a structural VAR as well as their conditional moments that are estimated including the Shimer worker flow data are presented in section 3. In addition, Fisher (2006) has motivated the separate identification of factor-neutral and investment-specific (or capital-embodied) technology shocks from the data. In the model, both of these shocks positively affect labor productivity in the long-run, while investment-specific technology shocks have a negative long-run effect on price of investment goods relative to consumption goods in addition. Section 4 presents the identification of these two shocks based on assumptions derived from the model and documents the results. Even though investment-specific technology shocks provide an additional source of volatility in job finding and unemployment, they are not large enough to explain the high volatility in the data. Further, investment-specific and neutral technology shocks generate very similar dynamics in the worker flow data and hence support the findings from the Galí identification.

Moments conditional on neutral and investment-specific shocks from the Fisher identification are presented for job flow data in section 5. Data on job flows are generally viewed as an alternative to worker flows in order to assess the empirical performance of a model with a frictional labor market. Using recent data collected by Davis et al. (2006), the volatility result outlined above prevails. The job finding puzzle vanished however when incorporating job flows rather than worker flows in the estimation. Again, non-technological disturbances are necessary in order to fully understand the overall dynamics in the data.

Complementary to the Galí and Fisher identification, section 6 proposes a new and alternative identification strategy for technology shocks which attempts to shed light on a few issues that arise from the estimation of technology shocks and their potential impact on the results. First, I document that the identified standard Galí technology shocks have a positive and significant effect on the relative price of investment. This means that the Galí technology shocks are neither truly neutral technology shocks nor are they investment-specific technology shocks. Rather, these shocks are negatively biased towards new investment. Neither the Galí nor the Fisher identification accommodates this variation in the data. Second, the Fisher identification of technology shocks employs an assumption which fixes the effect of the investment-specific technology shock on labor productivity and consequently the correlation between this shock and the neutral technology shock. I propose a mixture of long-run zero and sign restrictions to distinguish positive productivity shocks with positive from positive productivity shocks with negative effects on the investment price. On the one hand, this provides an identification of investment-specific technology shocks alternative to the Fisher identification. Thereby I can test the critical Fisher restriction for its validity. On the other hand, I identify a new kind of technology shocks, namely positive technology shocks that are negatively biased towards investment. These shocks have so far not been taken into account in the literature as it is not clear how to interpret them. However, they are shown to play a significant role for the dynamics of the labor market variables. For both types of technology shocks following from this identification, the general results with respect to the empirical performance of the standard model based on moments conditional on these shocks continue to hold.

2 A Standard Labor Market Model

2.1 The Model

The standard labor market framework used in the following nests search-and-matching on the labor market within a real-business-cycle (RBC) and growth model as in Merz (1995). The model comprises the subsequent equations:

$$\max_{\{C_t,N_{t+1},V_t,K_{t+1}\}_{t=0}^{\infty}} \mathrm{E}_0 \sum_{t=0}^{\infty} \beta^t \left(\ln(C_t) - \frac{N_t^{1+\phi}}{1+\phi} \right)$$

subject to

$$\begin{aligned} A_t K_t^{\alpha} N_t^{1-\alpha} &\leq C_t + X_t + aV_t Z_t \\ K_{t+1} &\leq (1-\delta)K_t + I_t X_t \\ N_{t+1} &= (1-\psi)N_t + V_t^{1-\lambda}(1-N_t)^{\lambda} \\ A_t &= \exp(\gamma + \varepsilon_{at})A_{t-1} \\ I_t &= \exp(\nu + \varepsilon_{it})I_{t-1}. \end{aligned}$$

The posting of vacancies V_t creates a cost a and thereby search frictions. Employment next period is determined by those jobs that remain after exogenous separation ψ and the new job matches that are formed in this period via a commonly used Cobb-Douglas matching function with matching elasticity λ. The labor force is assumed to be constant, so that unemployment in period t can be measured by $1-N_t$. Job finding per period can be described by $F_t = (\frac{V_t}{1-N_t})^{1-\lambda}$. This therefore co-moves with labor market tightness, defined as the ratio of vacancies to unemployment. The social planner representation can be derived from a decentralized problem in which workers and firms bargain over the wage. In order to meet the Hosios condition, the bargaining weight is implicitly set equal to the matching elasticity in this setup.

As in Fisher (2006), growth is exogenously generated by two types of technological progress. A_t represents general purpose technology in the production function and will be called neutral technology in the following. I_t is referred to as investment-specific technology as makes new investment goods relatively cheaper than consumption goods and hence drives the real price of new investments down.[1] Through the capital accumulation equation it favors new investments, leads to new capital formation and hence positively

[1] This can also be described as $\frac{1}{P_t}$. Greenwood et al. (2000) derive this one-sector representation of the model from a two-sector version with a consumption and an investment sector. Empirically, investment-specific technological progress is believed to be responsible for the persistent fall in the real price of equipment goods from 1955 until 2000 as measured by Cummins and Violante (2002) among others.

affects output and labor productivity. As in Fisher, output, consumption, investment and labor productivity grow with the rate $\frac{\alpha\nu+\gamma}{1-\alpha}$ along a balanced growth path, while the capital stock grows at rate $\frac{\nu+\gamma}{1-\alpha}$. Employment, unemployment and vacancies are stationary[2].

Shocks to these two types of technology generate business cycle fluctuations in the model. Note that each one of these technology shocks also constitutes a labor productivity shock. Through its effect on labor productivity, job finding rises after a positive technology shock, while unemployment falls. In the framework of Shimer, shocks to labor productivity are not explicitly modelled as technology shocks. Shimer referred to productivity shocks to originate in neutral technology shocks only. Following from the two laws of motion for technology, the investment-specific technology shock has a permanent effect on the relative price of investment, and both technology shocks have permanent effects on labor productivity in this context. These two properties will serve as identifying restrictions in the estimation and hence, this framework serves as the suitable setup for the subsequent empirical investigation.

The standard labor market model serves as a baseline model in order to contrast its empirical performance based on unconditional moments with moments conditional on labor productivity shocks, that is, technology shocks. In this study, I focus on the second moments of the central variables that this model wants to explain, that is the dynamics in the labor market described by the job finding, job separation and unemployment rate. In addition, due to the explicit modelling of capital and capital accumulation (i.e. savings) as well as output fluctuations, the RBC setting aims much more at imitating real fluctuations outside the labor market than the standard Mortensen and Pissarides (1994) model that provides the basis for the Shimer model. This will be important for potential extensions in order to augment the performance of the model with respect to other variables and to other shocks. Put differently, as the Shimer model, the simple framework outlined above lacks many features that have been shown to be important to replicate overall dynamics in the data such as nominal or real rigidities outside the labor market. It is straightforward to add any other non-technological source of variation on productivity, e.g. demand shocks. As long as extensions of the model do not affect the validity of the identification, the results documented below remain equally valid however.[3]

---

[2]Hence, vacancies are multiplied by $Z_t = A_t^{\frac{1}{1-\alpha}} I_t^{\frac{\alpha}{1-\alpha}}$ in the budget constraint.

[3]Note that DeBock (2006) also presents a search-and-matching model with investment-specific technology shocks. However, the shocks are transitory in his framework and therefore not in line with our identification of technology shocks applied later. Michelacci and Lopez-Salido (2007) describe a search-and-matching model with permanent neutral and investment-specific technology shocks. These authors do not focus on the Shimer critique and the model presented here may be seen as a baseline version of their quite

2.2 Empirical Performance Based on Neutral Shocks

In order to obtain second moments for the variables in the model, artificial time series are generated from the model. For the first part of the paper, these series are based on the existence of neutral technology shocks only in order to be as close to Shimer as possible. Hence, $\varepsilon_{it} = 0$. The model parameters are chosen based on standard values for quarterly U.S. data, i.e. the capital share in production $\alpha = \frac{1}{3}$, the time discount factor $\beta = 0.99$, capital depreciation $\delta = 0.02$ and the elasticity of the matching function with respect to unemployment $\lambda = 0.4$. The Frisch labor supply elasticity is pinned down by $\phi = 1$. Shimer (2005a) delivers the consumption costs of posting a vacancy of $a = 0.213$ and the mean job separation rate of $\psi = 0.0361$ which is calculated from his series for my sample. The growth rate and standard deviation of the neutral technology shock ε_{at} are then calibrated to match the moments of labor productivity. This results in $\gamma = 0.0035$.

Table 1: Model's Second Moments from Neutral Shocks

	Unemployment	Job Finding	Productivity
Std. deviation	0.0492	0.0571	0.0156
	(0.178)	(0.154)	(0.0156)
Autocorr. 1st lag	0.872	0.730	0.8660
	(0.918)	(0.911)	(0.850)
Cross-Correlations			
Unemployment	1	-0.7406	-0.7705
		(-0.955)	(-0.186)
Job Finding	-	1	0.8268
			(0.056)

Notes: The numbers in brackets show respective values from the actual data. All series are HP-filtered with $\lambda = 10^5$.

Table 1 compares the second moments from the model to the unconditional moments in the Shimer worker flow data[4]. Similar to Cole and Rogerson (1999), the usual second moments displayed are the standard deviation and first lag autocorrelation of the series as well as the cross-correlation between the cyclical components of the series. Both the artificial and the data series are detrended with a very smooth HP-filter ($\lambda = 10^5$) as in Shimer in order to relate my results directly to his. In the actual data, the job finding rate

complicated framework.

[4]The data moments are exhibited in brackets. Due to availability, the data range from 1955:1 til 2004:4. This is a different horizon than the one in Shimer (2005a), the moments of job finding and unemployment are very similar, however. For details on the data, see section 3.1.

and unemployment are quite volatile, in fact, they are a lot more volatile than the job separation rate which has a standard deviation of 0.062. From this, Shimer concludes that unemployment fluctuations are mainly driven by fluctuations in the job finding rather than the job separation rate. Furthermore, the standard deviation of the job finding rate and unemployment are about ten times as large as the one in labor productivity. All series are highly autocorrelated in the first lag. Note that these data features persist when the data is detrended with the standard HP-filter for quarterly data with $\lambda = 1600$[5].

The comparison with the model moments mirrors the critique by Shimer. First, the standard deviations of job finding and unemployment generated in the model are very small compared to the ones in the data. Second, the correlation of unemployment and job finding with productivity is too high in the model compared to the data.[6] Shimer concludes that there exists no internal propagation mechanism of labor productivity shocks in the model, since the real wage strongly reacts to labor productivity shocks and hence weakens the incentives for firms to post vacancies. In order to improve its empirical performance, Shimer and also Hall (2005) have therefore proposed to introduce rigid wages into the standard framework.

3 Moments Conditional on Technology Shocks

In the model, business cycle fluctuations of labor productivity, job finding and unemployment originate in movements of technological progress. It is therefore straightforward to evaluate the empirical performance of the model based on second moments conditional on technology shocks rather than on unconditional moments. In the data, shocks other than technology shocks play a role for the overall fluctuations as well. Thus disentangling the technology shocks from other shocks potentially serves three purposes. First, I can investigate the dynamic relationships (correlations and impulse responses) between the variables of interest that are conditional on technology shocks. Second, since these may be different from the unconditional ones it may therefore be possible explain the failure of the model on the unconditional level. Third, it is possible to assess the importance of technology

[5]The respective figures are presented in Table 4 in the Appendix.

[6]Investigating sensitivity of this result to the choice of parameter values, it is possible, for example, to decrease the matching elasticity with respect to unemployment to the value proposed by Shimer of $\lambda = 0.28$ which clearly increases the volatility of job finding and unemployment. The same is true for smaller costs of posting a vacancy, since Shimer's cost value appears to be quite high compared to Merz (1995), for example. Still, the distance of the standard deviations of job finding and unemployment between model and data remains to be quite large and the values of the cross-correlations hardly change compared to before. Choosing a higher level of job separation as for example in Merz, leads to a fall in volatility due to decreasing labor market tightness.

shocks for the unconditional data dynamics.

3.1 Identification and Estimation

The effects of technology shocks on labor market variables can be investigated within a structural VAR framework with long-run restrictions based on Blanchard and Quah (1989). The main idea is to find a mapping that transforms the residuals from a reduced form VAR into structural residuals such that the latter can be interpreted as certain types of shocks such as technology shocks. These mappings typically involve assumptions on the variance-covariance matrix of the structural shocks as well as restrictions on the effects of these shocks on the variables in the VAR.

Based on Galí (1999), technology shocks are identified via the central assumption that they are the only shocks that positively affect labor productivity in the long-run. In addition, the technology shocks are orthogonal to each of the non-technology shocks estimated. These assumptions are implemented by including labor productivity in first differences and ordered first in the VAR and then applying a Cholesky decomposition to the long-run horizon forecast revision variance[7]. It has to be noted that many structural disturbances other than technological innovations can affect labor productivity in the short and medium run, but that technology shocks can be distinguished from non-technology shocks with respect to their long-run effects on this variable. With this approach, I do not exactly estimate the model outlined above. Rather the conditional moments obtained should hold for a broad class of different model specifications that fulfill the identifying assumptions. The long-run assumption about the nature of technology shocks holds in the model presented as well as in many other models, such as the neoclassical growth model or the New Keynesian model[8].

All identification alternatives presented in the following are based on the same reduced-form VAR which contains labor productivity, hours worked and the job finding and separation rate. For later comparison with alternative identification schemes, the relative price of investment is added to the VAR. The reduced-form VAR is estimated within a Bayesian framework with a Minnesota prior, similar to Canova et al. (2007). The Minnesota prior incorporates a unit root in the levels of the variables included in the VAR and a fixed residual variance which determines the tightness on own lags, other lags and potential exogenous variables as well as the decay of the lags. Using the latter parameter, this prior allows us to generate sensible results for a large number of lags, as Canova et al. outline. This addresses an often uttered criticism on the VAR approach (e.g. by Chari et al. (2005)) which states that in theory one should employ a VAR with an infinite num-

[7]See Appendix A.1 for further details.

[8]It does not hold in endogenous growth frameworks.

ber of lags (here eight lags will be employed) in order to correctly identify technology shocks using long run restrictions. Except for the decay, I will use a relatively loose prior in the estimation, see Appendix A.4 for the exact parameter values and implementation. Further, the VAR is estimated with a trend as suggested by Canova et al. (2006). Here, the trend is a dummy that is deterministically broken at 1973:2 and 1997:1. These dates have been considered as break points in the growth literature and replicate the turning points in the job separation rate and unemployment series.[9]

The baseline specification is estimated using quarterly time series data for the U.S. over the sample 1955:1-2004:4. These data encompass worker flow data produced by Robert Shimer, namely measures of the job finding rate (JF), the rate at which unemployed workers become employed, and the job separation rate (JS), the rate at which employed workers become unemployed[10]. Under the assumption of homogenous workers and a constant labor force together with the assumption that short-run unemployment only has a minor effect on unemployment, the unemployment rate can then be described by $U = \frac{JS}{JS+JF}$. Shimer's assumption that the job separation rate does not move over the cycle and, therefore, does not play a role for the fluctuations of unemployment has been criticized by Fujita and Ramey (2006) among others. In fact, the job separation rate is more strongly correlated with labor productivity than the job finding rate as can be seen from Table 4 in the Appendix. I include the job separation rate in the VAR in order to test this criticism.

Labor productivity (output per hours of all persons) is the standard non-farm business measure provided by the U.S. Bureau of Labor Statistics. The real price of investment consists of a price index for equipment and software and a consumption price deflator that is chain weighted from nondurable, service and government consumption. The standard data from the National Income and Product Accounts (NIPA) have been criticized not to take into account the price-per-quality change in the investment goods of interest (see Gordon (1990)). I use the quarterly series generated by Fisher (2006) that is based on the measure of Cummins and Violante (2002) and that takes these flaws into account[11].

[9] Appendix B presents robustness checks to this specification along various dimensions including different priors, different break points for the trend and no trend as well as different lag lengths in the VAR.

[10] This is the worker flow data officially posted on the website of Robert Shimer and documented in Shimer (2005b). For additional details, see http://home.uchicago.edu/∼shimer/data/flows.

[11] The series by Jonas Fisher was extended by Ricardo DiCecio.

Table 2: Historical Decomposition of Galí Identification

	Uncond. Sample	Conditional Moments Technology	Residual	Model
A: Standard Deviations				
JFinding	0.1542	0.0533	0.1251	0.0571
		(0.04,0.08)	(0.10,0.14)	
JSeparation	0.0620	0.0493	0.0559	
		(0.04,0.06)	(0.05,0.06)	
Unemployment	0.1786	0.0843	0.1425	0.0492
		(0.06,0.12)	(0.12,0.16)	
Productivity	0.0156	0.0117	0.0164	0.0156
		(0.01,0.02)	(0.01,0.02)	
B: Autocorrelations				
JFinding	0.9128	0.9203	0.8876	0.730
		(0.86,0.95)	(0.86,0.90)	
JSeparation	0.6336	0.9285	0.6209	
		(0.89,0.96)	(0.60,0.65)	
Unemployment	0.9218	0.915	0.9135	0.872
		(0.88,0.94)	(0.91,0.92)	
Productivity	0.8507	0.8874	0.9186	0.866
		(0.85,0.92)	(0.90,0.93)	
C: Cross-Correlations				
JFind.,Prod.	0.0567	-0.4536	0.6765	0.8268
		(-0.64,-0.07)	(0.54,0.77)	
JSep.,Prod.	-0.4392	0.3715	-0.6577	
		(0.16,0.49)	(-0.74,-0.57)	
Unemp.,Prod.	-0.1858	0.4601	-0.8041	-0.7705
		(0.19,0.63)	(-0.88,-0.69)	
JFind.,Unemp.	-0.9558	-0.9	-0.9383	-0.7406
		(-0.96,-0.74)	(-0.95,-0.91)	
JSep.,Unemp.	0.6845	0.8829	0.6309	
		(0.79,0.92)	(0.57,0.68)	
JFind.,JSep.	-0.4404	-0.5881	-0.3226	
		(-0.76,-0.19)	(-0.39,-0.21)	

Notes: All series are simulated with the respective shock operating and are detrended with the smooth HP-filter as in Shimer (2005a). Brackets show Bayesian one standard error confidence intervals from the posterior distribution.

3.2 Results

Table 2 depicts the historical decomposition of the actual time series into the technology and non-technology (or residual) components. These component series are generated assuming the exclusive presence of the respective shock and using information on the first lags in the sample. Detrending the resulting series with the smooth HP-filter as in Shimer then delivers the business cycle components of interest.[12] The historical decomposition documents the ability of the single shocks to replicate exactly those moments in the data that have been used for judging the empirical performance of the model.

Volatility is measured by the standard deviation in panel A. The standard deviations of the component series of the job finding rate and unemployment that are driven by technology shocks are less than half of the overall sample volatility. In fact, the standard deviation of job finding generated in the model is very close to the one conditional on technology shocks. If you believed that the dynamics of unemployment were driven by the job finding rate only, the standard deviation of unemployment would be equally low and close to the one in the model. As a consequence, the Shimer critique does not apply. However, a large part of the volatility still remains to be unexplained in the "residual" disturbances. In order to replicate the dynamics in the overall data, the standard search-and-matching model should consequently be augmented by additional non-technology sources of volatility, generally referred to as demand shocks. Hall (1997) has proposed a candidate for these residual shocks, called preference shocks or shocks to the marginal rate of substitution in utility. Hall decomposes macroeconomic variables into fluctuations that originate in technology, government spending and preference shocks. He bases his decomposition on equations derived from a standard RBC-model, he does not use structural VAR techniques for his analysis. He shows that preference shocks account for most of the fluctuations in hours worked. His results are therefore similar to the results documented here.

The autocorrelations conditional on technology shocks are close to the unconditional ones. The model lacks some persistence with respect to the job finding rate as the autocorrelation is a bit too low compared to the one in the data. Generally however, the model performs well in replicating the conditional and unconditional autocorrelations. The conditional co-movement of the variables is depicted in panel C of Table 2 and also in the impulse-responses to a one-standard deviation technology shock in Figure 1. Most prominently, job finding falls after a positive technology shock and the conditional correlation between job finding and productivity is negative. Regardless of the job separation rate, unemployment increases after the fall in job finding and the correlation of unemployment and productivity is posi-

[12]Note that the second moments resulting from these series do not add up to the unconditional moment.

tive. These two dynamics are the opposite of the dynamics in the overall sample and they are clearly not replicated in the model. Hence, this result challenges the conventional dynamics in the standard search-and-matching model in a similar fashion as the results in Galí (1999), known as the "hours puzzle", have challenged the RBC paradigm with frictionless labor markets.

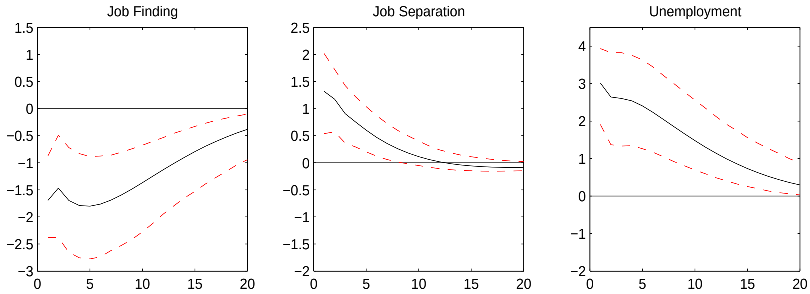
A variance decomposition adds up the impulse-response coefficients from the estimation to a certain conventional business cycle horizon. This statistic reports the respective contribution of each shock to the overall variance and therefore also highlights the importance of the shocks relative to each other. Decomposing the business cycle variance of the Galí identification into the contribution of technology and non-technology shocks, technology shocks explain up to 17% of the business cycle variance of job finding and over 20% of the variance of unemployment. Hence, an appropriate model should take these dynamics into account. However, additional disturbances, contained in the "residual" shocks, are necessary in order to understand the unconditional dynamics in the data. Galí has explained the drop in hours worked within a sticky price New Keynesian framework. Can the natural extension of this framework including search-and-matching on the labor market equally explain the drop in the job finding rate? In the baseline specification of Blanchard and Galí (2006), unemployment does not move in response to productivity shocks due to offsetting income and substitution effects. After having introduced real wage rigidities, the authors document that unemployment increases after a positive productivity shock. Here, labor market tightness and hence the job finding rate move together with unemployment replicating the dynamics documented above.[13]

Job separation significantly increases after a positive technology shock contributing to an even larger increase in unemployment. If business cycles are driven by technology shocks, this result undermines the assumption of a constant separation rate over the cycle. Instead, this result favors a theoretical context with endogenous rather than exogenously fixed job separation as in denHaan et al. (2000). A rise in job separation after a positive innovation in technology might be due to the fact that not all of the existing job matches can freely use this new technology. Hence, technological innovation is embodied in new jobs, or specific to existing vintages. Canova et al. (2007) employ a vintage human capital in order to model the "Schumpeterian creative destruction" after a neutral technology shock.[14]

[13]In contrast, Krause and Lubik (2007) present a framework in which job finding falls after a positive productivity shock mentioning that the resulting dynamics are counterfactual. This is no longer true based on conditional moments. In Christoffel et al. (2006), vacancies fall and unemployment increases after a positive productivity shock, resulting in an fall of labor market tightness and the job finding rate.

[14]However, the effect of job separation is not robust to the in- or exclusion of a trend in the estimation. See Appendix B for further details.

Figure 1: Impulse-Responses to Galí Technology Shocks



Notes: Percent responses to a positive one-standard-deviation shock. The dotted confidence intervals are one-standard-error bands.

4 Different Shocks: Fisher Identification

Fisher (2006) based on Greenwood et al. (1997) has addressed the issue that fluctuations in labor productivity might be generated not only by factor-neutral technological progress, but also by investment-specific technological innovations. Consequently, investment-specific technological progress satisfies the identifying assumption for the Galí technology shocks and hence invalidates the interpretation of these shocks to be factor-neutral. Fisher proposes a strategy to separately estimate neutral and investment-specific technology shocks and documents that the two shocks might have different effects on macroeconomic variables. Further, investment-specific technological progress contributes to a larger extend to growth and cyclical fluctuations of macroeconomic variables (in particular of output and hours worked) than neutral technology. Investment-specific technological progress thus provides a potential additional source of variation in the job finding rate and unemployment.

Recall that in the Shimer framework, it is not possible to distinguish between these two sources of variation in labor productivity, while the model in section 2 does distinguish between these two shocks. As mentioned before, the labor market dynamics that are induced by the two technology shocks are actually very similar, i.e., job finding increases and unemployment falls after both technology shocks. However, since the formation of capital takes time, productivity increases with a lag in response to investment-specific technological progress. This increases the overall standard deviation of the job finding rate and unemployment in the model in which both types of technology shocks operate, see Table 5 in the Appendix. Further, the correlation between the job finding rate and productivity is smaller than in the model with neutral shocks only. However, these effects are not large enough to replicate the unconditional data moments, hence the Shimer critique still holds.[15]

4.1 Identification

In order to identify the two types of technology shocks, Fisher imposes the assumption that investment-specific technology shocks are the only shocks that (negatively) affect the relative price of investment in the long-run and that are additionally allowed to affect labor productivity in the long-run. (Investment-)neutral technology shocks are then the only remaining shocks that affect labor productivity in the long run. Note that this assumption is true in the model outlined in section 2.1.

It is easy to implement these two assumptions ordering the first differences of the relative investment price and labor productivity first in the reduced-form VAR and applying a Cholesky decomposition to the long-run forecast revision variance. However, the effect of the investment-specific shocks on labor productivity is estimated to be negative in our baseline specification. This means that all or at least a part of the identified investment-specific shocks are not technology shocks according to the Galí definition and more importantly not positive shocks to labor productivity as the ones in the model and referred to by Shimer. Fisher addresses this problem by introducing the additional assumption that positive investment-specific shocks increase labor productivity by a fixed proportion to their effect on the investment price. Derived from the production function in the model this proportion is set to $\frac{\alpha}{(1-\alpha)}$. This additional assumption comes at a cost as it not only strongly restricts the long-run productivity effect of investment-specific shocks to a certain value but also implies a positive and fixed correlation between the investment-specific and neutral technology shocks.[16]

There exist several a few studies that consider the responses of worker flows to both neutral and investment-specific technology shocks based on the Fisher identification.[17] The work by Canova et al. (2006) is closely related to the analysis in this section of the paper. The estimation of the reduced form VAR in a Bayesian framework with a Minnesota prior is taken directly from them. However, Canova et al. employ the Fisher identification without the additional third restriction. Equally, Ravn and Simonelli (2006) identify technology shocks without the third restriction in a framework which also

[15] In this model version, the growth rates and standard deviations of the two types of technology shocks are calibrated to match the moments of labor productivity and the investment price which results in $\gamma = 0.0074$ and $\nu = -0.0117$ for our sample. The mean growth rate of labor productivity then equals $\frac{1}{1-\alpha}\gamma + \frac{\alpha}{1-\alpha}\nu$.

[16] See Figure 4 for a comparison of the responses of the restricted and the unrestricted Fisher identification. See Appendix A.2 for more details and the implementation of this identification scheme. Parallel to the model calibration I use $\alpha = \frac{1}{3}$.

[17] To my knowledge there exists no paper that has documented the effects of the basic Galí technology shocks.

incorporates fiscal and monetary policy shocks. Adding the third restriction delivers quite different dynamics induced by the investment-specific technology shock. I will discuss this issue further in section 6 in which I also propose a test for the third restriction. Complementary to these studies, there exist many contributions in the literature that estimate medium or large scale DSGE models which incorporate search-and-matching in the labor market. Here, technology shocks are usually identified based on a combination of short-run sign restrictions as in Braun et al. (2006). While these shocks should generally depict the same dynamics as the technology shocks identified in this paper, this is not always the case and seems to strongly depend on the dynamics imposed by the underlying respective model[18]. I will not elaborate on these contributions here.

4.2 Results

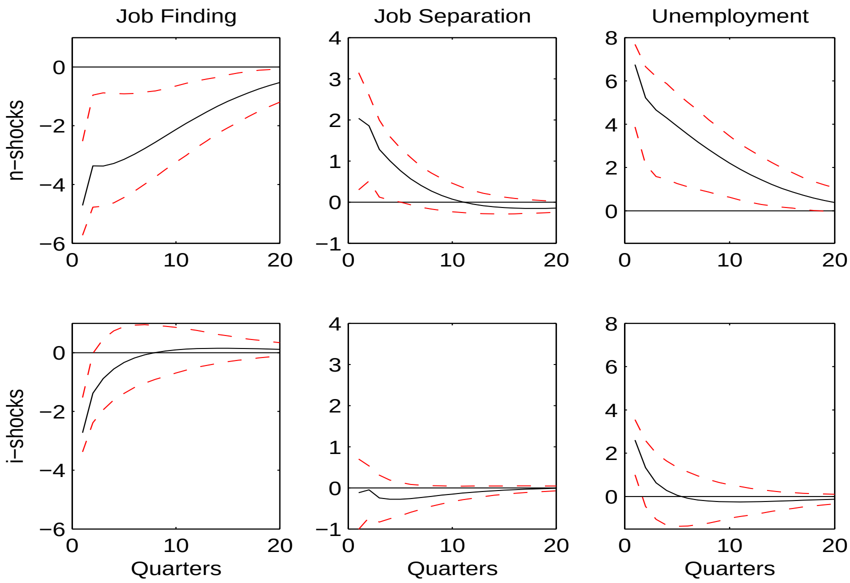
The historical decomposition of the standard deviation supplements the results from the Galí identification, see Table 6 in the Appendix. Both types of technology shocks, as well as both technology shocks taken together, generate standard deviations in the job finding rate and unemployment that are much smaller than the unconditional standard deviations, but quite close to the ones produced from the model. Again, sources other than technology are necessary to understand the unconditional volatility in the data.[19]

With respect to the conditional dynamics, Figure 2 depicts the responses of the job finding and separation rate as well as unemployment to positive one standard deviation technology shocks from the Fisher identification. Note that the responses to the neutral shock are very similar to the responses derived from the Galí identification. Job finding drops after both types of technology. This effect is stronger and more persistent after a neutral technology shock than after an investment-specific shock. The job separation rate does not significantly react to an investment-specific technology shock. The falling job finding rate positively affects the unemployment rate, but the effect is again not as strong as for the neutral technology shock. Consequently, the contrast between the conditional dynamics in the data versus the ones in the model still exists, but is weaker in case of the investment-specific shocks. This is also reflected in the conditional correlations in panel C in Table 6. The conditional correlation of job finding and productivity is much lower than the one conditional on a neutral shock, the correlation of unemployment with productivity has the same sign as the unconditional one, both of these figures are insignificant. The investment-specific technology shock therefore moderates the effect of the neutral shock. Both technology

[18] See discussion on the results in section 3.

[19] Note that here, the two technology shocks are not orthogonal. Hence, the historical decomposition is not truly a decomposition. Technology shocks and the residual disturbances are orthogonal, however.

Figure 2: Worker Flow Responses to Fisher Technology Shocks



Notes: Percent responses to a one-standard deviation shock. The dotted confidence intervals are one-standard error bands.

shocks taken together however still generate dynamics that are opposite to the unconditional dynamics and that are not replicated in the model.

Table 7 in the Appendix exhibits the contribution of the shocks to the forecast error variance of the variables in this small VAR. The neutral shock is much more important for the variances of the labor market variables than the investment-specific shock. This highlights again the importance to replicate the dynamics of this shock in an appropriate model. Together, the technology shocks explain between 45% to 60% of the variance of job finding and unemployment.[20]

5 Alternative Variables: Job Flows

Complementary to worker flows, so-called job flow data are often used to assess the empirical validity of the standard labor market model (similar to Cole and Rogerson (1999) and Davis et al. (1998)). Here, I use data from Davis et al. (2006) which encompasses the fluctuations of jobs defined as small size units ("plants") that are created and destroyed within the U.S. manufacturing sector. These data are usually referred to as job creation and

[20]This result is similar to Canova et al. (2007) who, in spite of an alternative identification of investment-specific technology shocks, document that employment effects can mainly be attributed to neutral technology shocks.

destruction rates. The dynamics in unemployment can be generated from the log difference of these two series. Note that from the perspective of the standard model job flows and worker flows are indistinguishable, i.e., when a worker moves into or out of a job, the job match is automatically created or destroyed.

In the following, the same exercise as in the Fisher identification in section 4 is repeated by using job flows rather than worker flows. Table 3 presents the unconditional moments from this set of data together with the familiar moments from the model. Focusing on the unconditional moments in the first column, note that job destruction is about twice as volatile as job creation. All series are less persistent than the worker flow series, while the cross-correlations between the variables are very similar. The correlation of unemployment with productivity is smaller in the job flow data than in the worker flow data. With regard to the empirical performance of the standard model based on unconditional second moments, this means that while the model now replicates the standard deviation of job creation (in fact the standard deviation is a little too high in the model), it does not mirror the volatility of the job destruction rate and hence unemployment. A natural extension of this model would include endogenous job destruction as in Mortensen and Pissarides (1998) or denHaan et al. (2000) in order to account for fluctuations in this variable. As before, the correlation of job creation and unemployment is too high in the model compared to the data.

Conditional on investment-specific and neutral technology shocks, the standard deviation in job creation is even smaller than the unconditional one and consequently too large in the model. More importantly, the two technology shocks generate a standard deviation of job destruction and unemployment that is only about a third of the one in the data. The model actually matches the conditional standard deviations of unemployment. Complementary to this result, technology shocks explain about 15% to 20% of the business cycle variance of job creation, destruction and unemployment as is exhibited in Table 8 in the Appendix. This means that endogenous job destruction alone cannot realign the moments from the model with the unconditional moments. My result supports the findings from the previous sections that an additional non-technological disturbance is needed in order to explain the fluctuations observed unconditionally.

Panel C of Table 3 depicts the conditional cross-correlations of the labor market variables with each other and productivity. Figure 5 in the Appendix also visualizes the dynamics induced by the two technology shocks. Most importantly, job creation and labor productivity are positively correlated after both technology shocks. As a consequence, the "job finding puzzle" after a neutral technology innovation from before disappears. Unemployment still increases after a positive neutral shock, due to the strong increase in job destruction (This is also reflected in the positive co-movement of these variables with productivity). Even though insignificant, in a model with endogenous job destruction and vintage technologies, job destruction may increase after a positive shock to technology if it can only be used in newly formed jobs rendering many existing job matches technologically obsolete. Then, these effects provide a valid and easy explanation to the rise in unemployment or parallel the fall in hours after a technology shocks and, hence, to the hours puzzle documented by Galí (1999). Note that the investment-specific technology shocks induce dynamics that are different from the ones generated by neutral technology shocks and that are similar to those expected from the standard model: Job creation goes up and job destruction falls after a positive innovation in investment-specific technology. As a consequence, unemployment decreases before converging back to zero. The responses after the investment-specific shocks exhibit greater persistence than the ones after a neutral shock. However, investment-specific technology shocks are not important enough to explain the unconditional moments. Again, an additional source of fluctuations is necessary here.

Are the results from the Fisher identification with worker and with job flows are truly comparable? Plotting the structural shocks from the two estimations and calculating their correlation, it is possible to see that the investment-specific shocks are almost identical in both specifications. The neutral shocks from both estimations are positively correlated (the correlation coefficient is about 0.6), but not identical. Alternatively, both job and worker flow data can be included into one common specification. This is also important in the light of the joint dynamics of these two data concepts which has been an issue in the literature. The results show that the effects of the neutral shock on job creation and job destruction hardly change. Job creation drops on impact after a positive neutral technology shock, but then rises with a hump-shape above zero.

6 Alternative Identification

6.1 Motivation and Identification

This section investigates to which extend the results outlined above in sections 3.2 and 4.2 strongly rely on the imposed identification assumption for the technology shocks, or whether they are robust to an alternative identification scheme as well. To motivate, let us briefly return to the Galí identification of technology shocks. In fact, the identified Galí shocks have a significant and positive effect on the relative price of investment. These shocks are therefore negatively biased towards investment and mistakenly labelled factor-neutral, see Figure 6 in the Appendix[21].

[21] Balleer and van Rens (2008) document that these shocks are not only biased negatively towards investment, but also towards skilled labor.

Table 3: Historical Decomposition from Fisher Identification - Job Flows

	Uncond. Sample	Conditional Moments Inv. Tech.	Neu. Tech.	All Tech.	Residual	Model
A: Standard Deviations						
Creat.	0.0764	0.0425	0.0325	0.0426	0.0723	0.0903
		(0.03,0.05)	(0.03,0.04)	(0.04,0.05)	(0.07,0.08)	
Dest.	0.1316	0.0484	0.0453	0.0558	0.1176	
		(0.03,0.07)	(0.03,0.07)	(0.04,0.07)	(0.11,0.13)	
Unemp.	0.1773	0.0582	0.0466	0.0752	0.1587	0.0659
		(0.04,0.09)	(0.03,0.07)	(0.05,0.10)	(0.15,0.17)	
Prod.	0.0156	0.0175	0.0189	0.0135	0.0102	0.0156
		(0.01,0.02)	(0.01,0.02)	(0.01,0.02)	(0.01,0.02)	
B: Autocorrelations						
Creat.	0.6204	0.8184	0.9085	0.7968	0.6446	0.5727
		(0.74,0.92)	(0.81,0.96)	(0.73,0.86)	(0.60,0.69)	
Dest.	0.7210	0.8289	0.6303	0.7727	0.7152	
		(0.64,0.89)	(0.48,0.83)	(0.66,0.86)	(0.70,0.74)	
Unemp.	0.6839	0.8163	0.5715	0.7202	0.6837	0.8752
		(0.71,0.87)	(0.38,0.77)	(0.63,0.80)	(0.67,0.70)	
Prod.	0.8470	0.858	0.8193	0.8661	0.8526	0.8541
		(0.81,0.90)	(0.78,0.86)	(0.85,0.88)	(0.80,0.89)	
C: Cross-Correlations						
JC,P	0.0194	0.3992	0.1158	0.2051	0.0861	0.4660
		(0.19,0.55)	(-0.23,0.40)	(0.05,0.34)	(-0.06,0.27)	
JD,P	-0.4514	-0.3717	0.2872	0.0024	-0.6328	
		(-0.63,0.07)	(-0.21,0.47)	(-0.22,0.25)	(-0.78,-0.47)	
U,P	-0.3433	-0.5719	0.2186	-0.1124	-0.5077	-0.4415
		(-0.71,-0.26)	(-0.38,0.45)	(-0.31,0.10)	(-0.67,-0.35)	
JC,U	-0.7371	-0.6233	-0.4039	-0.6894	-0.7248	-0.5887
		(-0.80,-0.31)	(-0.66,-0.13)	(-0.79,-0.55)	(-0.75,-0.70)	
JD,U	0.9199	0.7285	0.7636	0.8401	0.9049	
		(0.46,0.88)	(0.52,0.90)	(0.68,0.90)	(0.89,0.91)	
JC,JD	-0.4130	0.17	0.3464	-0.1506	-0.3613	
		(-0.31,0.60)	(-0.05,0.64)	(-0.39,0.15)	(-0.41,-0.31)	

Notes: All series are simulated with the respective shock operating and are detrended with the smooth HP-filter as in Shimer (2005a). Brackets show Bayesian one standard error confidence intervals from the posterior distribution.

The Fisher identification separates technology shocks that have an effect on the relative price of investment from technology shocks that do not have an effect on the relative price of investment and hence are truly investment-neutral. However, the Fisher identification disregards those shocks that have a positive effect on both productivity and the price. When estimated without the third restriction on the productivity effect of investment-specific shocks, these shocks are incorporated into the investment-specific technology shocks in the Fisher identification. The difference between the results from the Fisher identification with and without the third restriction documents that these shocks may play an important role in the overall dynamics of these two variables. More precisely, labor productivity falls in response to these unrestricted investment-specific technology shocks (see discussion in section 4). Additionally, these unrestricted shocks produce labor market dynamics that are quite different from the ones generated by the restricted shocks. Namely, job finding increases in a hump-shape after a positive investment-specific technology shock and job separation falls. As a result, unemployment decreases.[22] The unrestricted shocks also play a much larger role for the business cycle variance of the labor market variables than the restricted shocks.

Against this background, I propose an alternative identification of technology shocks which separates those shocks that have the same and those that have a different effect on labor productivity and the investment price. The identification strategy imposes the following assumptions:

1. Technology shocks are assumed to be the only shocks that affect the relative price of investment and labor productivity in the long run.

2. Out of these shocks, investment-specific technology shocks are those shocks that affect labor productivity positively and the relative price of investment negatively in the long run.

3. Out of these shocks, investment-unspecific technology shocks are those shocks that affect labor productivity positively and the relative price of investment positively in the long run.

Figure 7 in the Appendix visualizes the assumed responses of price and productivity to the two newly identified shocks. Based on this, I can now test Fisher's third identifying assumption based on the effect of the first shock in a more general context in which all shocks are in fact orthogonal.

Further, I can assess the properties and importance for business-cycles of those shocks that are technology shocks, but are investment-unspecific. These shocks might have mistakenly been labelled investment-specific technology in the unrestricted Fisher identification. What are technology shocks that

[22] See Canova et al. (2007) for the effects of the unrestricted shocks.

drive the relative price of investment up? In the model outlined in section 2 these are the mirror image of investment-specific technology shocks. In that case, they would have a negative impact on output and hence on labor productivity however. As a consequence, the model outlined above does not accommodate these shocks and it is therefore not clear how to interpret them in this context. Balleer and van Rens (2008) suggest to identify technology shocks which originate in the labor market. More precisely, they document that technology shocks that are biased towards skilled labor have a positive effect on the relative price of investment and could therefore capture the variation of the data documented here.[23]

This mixture of long-run zero and sign restrictions are implemented similar to the Galí and Fisher identifications. I order the relative price of investment and labor productivity first in the VAR and impose zero restrictions on the long-run effects of all but the first two shocks on these variables. Sign restrictions similar as in Peersman (2005) are then applied to the upper left 2-by-2 system of the long-run horizon forecast revision matrix according to the restrictions outlined above. The remaining elements of the long-run effects can then be calculated subsequently. For further details of the implementation of the long-run sign restrictions, see Appendix A.3.

Note that the Galí, Fisher and the alternative identification strategies all offer an alternative decomposition of the long-run variance of the investment price and productivity[24]. The Fisher and Galí identification each impose an extra zero restriction on this system. This means that by construction the Fisher identification does not deliver shocks that induce the same effect on the price and productivity as the Galí identification. Thus, the Fisher identification does not provide a decomposition of the Galí technology shocks. My alternative identification is more closely related to the Galí identification as this scheme decomposes Galí's productivity shocks into investment-specific and -unspecific shocks. I can now test Fisher's third identifying assumption based on the effect of the first shock in a more general context in which all shocks are in fact orthogonal. Further, I can assess the importance of those shocks that resulting from the unrestricted Fisher identification might have been labelled investment-specific technology shocks by mistake and can explore their properties. However, it is no longer possible to distinguish between investment-specific and investment-neutral shocks in this setup.

[23]The identification of these shocks originates in the effect of technological progress on the skill premium in a model which allows for both skilled and unskilled labor in production. The fact that the investment price increases in responses to these shocks provides evidence for capital-skill substitutability in the data.

[24]This is true if the price is ordered second in the Galí identification. The remaining elements of the first two rows of this matrix are always zero.

6.2 Results

Regarding volatility, the standard deviations conditional on investment-specific technology shocks are very close to the results from the Fisher identification. The two identified technology shocks together generate a conditional standard deviation that is again less than half of the unconditional standard deviation in job finding, separation and unemployment[25]. This is not surprising, since the alternative identification is just a different decomposition of the technology shocks from the other identification schemes.

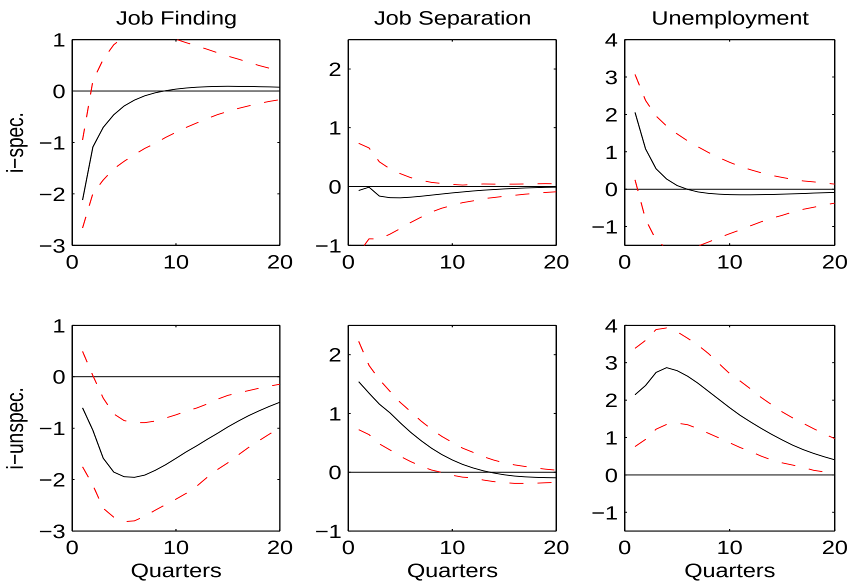
More interesting in this respect are the labor market dynamics induced by the two new shocks documented in Figure 3. For both types of shocks, job finding drops and unemployment increases supporting the findings of the Fisher and Galí identification. There are significant differences between the responses of the two shocks however. After an investment-specific productivity shock job separation does not move significantly. Note that the dynamics of this shock are very similar to the ones I have documented for the restricted Fisher investment-specific technology shocks. Indeed, the estimated relationship between the effect of this shock on the price and productivity is very close to the one imposed via the third restriction. After an investment-unspecific shock job finding does not react on impact and subsequently decreases in a hump-shape, job separation significantly rises and the rising unemployment inherits the hump-shape from the effects on the job finding rate[26].

The variance decomposition in Table 10 in the Appendix sheds light on the relative importance of investment-specific -unspecific technology shocks. The investment-unspecific technology shock is more important for the business cycle variance of labor productivity than the investment-specific technology shock. The investment-specific technology shock explains more of the variance of the relative investment price in the first two horizons, while the investment-unspecific shock is more important in the longer run. This means that a substantial part of the dynamics in the unrestricted investment-specific shocks are not driven by positive productivity shocks and this highlights the importance of distinguishing the two types of shocks. The investment-unspecific shock explains a substantial fraction of the job finding and separation rate and consequently unemployment. This shock is generally more important for the business cycle variation of the labor market variables than

[25] Table 9 in the Appendix exhibits the historical decompositions for this identification scheme

[26] Note that the inverse of this shock is an investment-specific technology shock with a negative effect on productivity. The resulting dynamics are strikingly close the the ones from the unrestricted Fisher identification, compare Canova et al. (2007). This means that the major part of the unrestricted investment-specific technology shocks consists of shocks that do not positively affect labor productivity and are consequently not in line with our model.

Figure 3: Productivity Shocks from Sign Restrictions



Notes: Percent responses to a one-standard deviation shock. The dotted confidence intervals are one-standard error bands.

the investment-specific technology shock. Together, both shocks explain about 20% to 25% of the business cycle variation in job finding and unemployment.

Investment-unspecific technology shocks have not been identified so far. The reason clearly lies in the fact that they are difficult to interpret in the context of a standard model as the one outlined in section 2. Here I have shown that they carry some weight with respect to the dynamics on the labor market. As argued above, these shocks could reflect skill-biased technology shocks as identified in Balleer and van Rens (2008). Skill-biased technology shocks have a negative effect on total hours worked and thus induce similar dynamics to the shocks identified here.

7 Conclusion

Starting from Shimer (2005a), this paper re-investigates the empirical performance of the standard search-and-matching model. This study provides an important contribution to the ongoing debate as it judges the empirical performance of the model on basis of moments conditional on technology shocks rather than on unconditional moments. My analysis breaks down the second moments of labor productivity, the job finding, job separation and unemployment rate into the contribution of technology and non-technology shocks. These shocks are identified within a SVAR framework with conventional long-run restrictions and a combination of long-run zero and sign restrictions.

I find that technology shocks cannot be the source of the high volatility in the job finding rate and unemployment present in the data. As a result, the standard deviation of these variables that is generated from a standard model replicates the volatility conditional on technology shocks. A large part of the volatility remains unexplained in the residual from the structural estimation. This residual might be called non-technology or demand shock. In order to mirror the overall volatility in the data, the model should be augmented with an additional non-technological source of volatility rather than with respect to the propagation of technology shocks as proposed by Shimer. A potential candidate for these disturbances are government spending shocks. Ravn and Simonelli (2006) have shown that these shocks indeed mirror the dynamics of our "residual" disturbances as they drive labor productivity and labor market tightness up and unemployment down.

Technology shocks induce a negative co-movement between job finding and productivity and a positive co-movement between unemployment and productivity, while the respective figures in the overall sample are directly the opposite. Put differently, job finding falls and importantly contributes to an increase in unemployment after a positive technology shock. This result contradicts the effects generated in the standard search-and-matching model, but may for example be explained in a New Keynesian context. This puzzle vanishes when job flow data rather than worker flow data are employed in the specification. In any case, additional non-technological disturbances are needed in order to replicate the unconditional correlation between productivity, the job finding rate and unemployment.

In the different specifications, I distinguish technology shocks that are factor-neutral or investment-specific as in Galí (1999) and Fisher (2006). The role of technology shocks for labor market dynamics is further assessed through a distinction of positive productivity shocks that have either a negative or a positive effect on the relative price of investment. The latter my be called investment-unspecific technology shocks. First, this identification tests and verifies a critical assumption in the Fisher identification on the effect of investment-specific technology shocks on labor productivity. Second, this procedure investigates the relationship between constrained and unconstrained investment-specific technology shocks. I find that investment-unspecific technology shocks might by mistakenly labelled investment-specific in the unconstrained identification. In addition, these shocks play a significant role for labor market fluctuations. However, it is not clear what these shocks really are and they have so far not been taken into account explicitly. Balleer and van Rens (2008) potentially deliver an answer to this. Technology shocks that are skill-biased induce similar dynamics in the investment price and the labor market as the shocks identified here.

References

Andolfatto, David, "Business Cycles and Labor-Market Search," *The American Economic Review*, 1996, *86* (1), 112–132.

Balleer, Almut and Thijs van Rens, "Cyclical Skill-Biased Technological Change," Working Paper, 2008.

Blanchard, Olivier and Danny Quah, "The Dynamic Effects of Aggregate Demand and Supply Disturbances," *The American Economic Review*, 1989, *79* (4), 655–673.

_ and Jordi Galí, "A New Keynsian Model with Unemployment," Working Paper, 2006.

Braun, Helge, Reinout DeBock, and Riccardo DiCecio, "Aggregate Shocks and Labor Market Fluctuations," Working Paper, Federal Reserve Bank of St. Louis 2006.

Canova, Fabio, David Lopez-Salido, and Claudio Michelacci, "On the robust effects of technology shocks on hours worked and output," Working Paper, 2006.

_ , _ , and _ , "Schumpeterian Technology Shocks," Working Paper, 2007.

Chari, V. V., Patrick J. Kehoe, and Ellen R. McGrattan, "A Critique of Structural VARs Using Business Cycle Theory," Working Paper, 2005.

Christiano, Lawrence J., Martin Eichenbaum, and Robert Vigfusson, "What Happens After a Technology Shock," *NBER Working Papers*, 2003, (10254).

Christoffel, Kai, Keith Kuester, and Tobias Linzert, "Identifying the Role of Labor Markets for Monetary Policy in an Estimated DSGE Model," Working Paper Series 635, ECB June 2006.

Cole, Harold L. and Richard Rogerson, "Can the Mortensen-Pissarides Matching Model Match the Business Cycle Facts?," *International Economic Review*, 1999, *40* (4), 933–959.

Cummins, Jason G. and Giovanni Luca Violante, "Investment-Specific Technical Change in the US (1947-2000): Measurement and Macroeconomic Consequences," *Review of Economic Dynamics*, 2002, *5* (2), 243–284.

Davis, Steven J., John C. Haltiwanger, and Scott Schuh, *Job Creation and Destruction*, Cambridge: MIT Press, 1998.

—, R. Jason Faberman, and John Haltiwanger, "The Flow Aproach to Labor Markets: New Data Sources and Micro-Macro Links," Working Paper 12167, NBER 2006.

DeBock, Reinout, "Investment-Specific Technology Shocks and Labor Market Frictions," Working Paper, 2006.

denHaan, Wouter J., Garey Ramey, and Joel Watson, "Job Destruction and the Propagation of Shocks," *The American Economic Review*, June 2000, *90* (3), 482–498.

Fisher, Jonas D.M, "The Dynamics Effects of Neutral and Investment-Specific Technology Shocks," *Journal of Political Economy*, 2006, *114* (3), 413–451.

Fujita, Shigeru and Garey Ramey, "The Cyclicality of Job Loss and Hiring," Working Paper, 2006.

Galí, Jordi, "Technology, Employment, and the Business Cycle: Do Technology Shocks Explain Aggregate Fluctuations?," *The American Economic Review*, 1999, *89* (1), 249–271.

Gordon, Robert J., *The Measurement of Durable Goods Prices*, Chicago: University of Chicago Press, 1990.

Greenwood, Jeremy, Zvi Hercowitz, and Per Krusell, "Long-Run Implications of Investment-Specific Technological Change," *American Economic Review*, 1997, *87* (3), 342–362.

—, —, and —, "The role of investment-specific technological change in the business cycle," *European Economic Review*, 2000, *44*, 91–115.

Hall, Robert E., "Macroeconomic Fluctuations and the Allocation of Time," *Journal of Labor Economics*, 1997, *15* (1), S223–S250.

—, "Employment Fluctuations with Employment Wage Stickiness," *American Economic Rewview*, 2005, *95* (1), 53–69.

Kadiyala, K. Rao and Sune Karlsson, "Numerical Methods for Estimation and Inference in Bayesian VAR-Models," *Journal of Applied Econometrics*, 1997, *12* (2), 99–132.

Krause, Michael and Thomas Lubik, "The (ir)relevance of real wage rigidity in the New Keynesian model with search frictions," *Journal of Monetary Economics*, 2007, *54*, 706–727.

Merz, Monika, "Search in the Labor Market and the Real Business Cycle," *Journal of Monetary Economics*, 1995, *36*, 269–300.

Michelacci, Claudio and David Lopez-Salido, "Technology Shocks and Job Flows," *Review of Economic Studies*, 2007, *74*, 1195–1227.

Mortensen, Dale T. and Christopher A. Pissarides, "Job Creation and Job Destruction in the Theory of Unemployment," *Review of Economic Studies*, 1994, *61* (3), 397–415.

Mortensen, Dale T and Christopher A. Pissarides, "Technological Progress, Job Creation, and Job Destruction," *Review of Economic Dynamics*, 1998, *1*, 733–753.

Peersman, Gert, "What Caused the Early Millenium Slowdown? Evidence Based on Vector Autoregressions," *Journal of Applied Econometrics*, 2005, *20*, 185–207.

Ravn, Morten O. and Saverio Simonelli, "Labor Market Dynamics and the Business Cycle: Structural Evidence for the United States," Working Paper, 2006.

Shapiro, M. and M. Watson, "Sources of Business Cycle Fluctuations," *NBER Macroeconomics Annual*, 1988, pp. 111–148.

Shimer, Robert, "The Cyclical Behavior of Equilibrium Unemployment and Vacancies," *American Economic Review*, 2005, *95* (1), 25–49.

_ , "Reassessing the Ins and Outs of Unemployment," Working Paper, 2005.

Uhlig, Harald, "Do Technology Shocks Lead to a Fall in Total Hours Worked," *Journal of the European Economic Association*, 2004, *2* (2-3), 361–371.

_ , "What are the effects of monetary policy on output? Results from an agnostic identification procedure," *Journal of Monetary Economics*, 2005, *52*, 381–419.

Appendix

A Identification and Estimation

A.1 Standard Long-Run Identification

Identification involves finding a mapping A of the residuals from a reduced form VAR into so-called structural residuals such that these can be interpreted as technology shocks. More precisely, name v_t the residuals from a reduced form VAR with $E[v_t v_t'] = \Omega$. The relationship between the structural and reduced form residuals is then $e_t = Av_t$ which induces $A\Sigma_e A' = \Omega$. The remaining assumptions in order to pin down A then need to come from restrictions on the matrix of long-run effects. These assumptions can be incorporated as zero restrictions in the matrix of long-run effects $C \equiv \sum_{i=0}^{\infty} \Phi_i A$, where Φ_i are the impulse-response coefficients.

In the case of the Galí identification, all identified shocks, i.e. the neutral technology shock plus the remaining $n-1$ non-technology shocks, are assumed to be orthogonal. In addition, the variance of the structural residuals is normalized such that $\Sigma_e = I$. If labor productivity is ordered first in the VAR, a lower triangular structure of the matrix C satisfies Galí's assumption that only neutral technology shocks drive labor productivity in the long run. This is easily obtained by decomposing the variance of the k-step ahead forecast error $\eta_{t,k} = X_{t+k} - E_t(X_{t+k})$ which is equal to

$$MSE(k) = (\sum_{i=0}^{k} \Phi_i)\Omega(\sum_{i=0}^{k} \Phi_i)'$$

with the Cholesky decomposition[27]. In the application, $k = \infty$ has to be approximated by some large value, here k is 80 quarters. It has to be noted that this procedure uniquely pins down the effect of the neutral technology shock on all variables in the VAR and that the result is not affected by the additional (unnecessary) zero restrictions in the matrix of long-run effects.

The reduced form VAR for all baseline specifications is estimated in a Bayesian framework in the main application. More precisely, I obtain 1000 draws of the posterior distribution of the reduced form coefficients and then apply the identification procedure to each of these in order to produce draws of the distribution of the structural coefficients.[28] The point estimates exhibited then correspond to the median and the confidence intervals to the

[27]See for example Uhlig (2004). Note that the variables important for identification, here labor productivity, need to enter in first differences in the VAR for this equation to hold.

[28]This approach goes back to Canova (1991) and Gordon and Leeper (1994) and is feasible if the system is just identified, that is, if there exists a unique mapping between draws of the residual variance covariance matrix and draws of the identification matrix A.

16th and 84th percentiles of the posterior distribution (this is equivalent to one standard error).

A.2 Restricted Fisher Identification

The restricted Fisher identification is very similar to the Galí identification, apart from a few issues.[29] First, if the the real investment price is ordered first and labor productivity second in the VAR, the matrix of long-run effects may be lower triangular in order to impose the first two restrictions, namely that only investment-specific technology shocks affect the investment price in the long run and only technology shocks may be sources of long-run fluctuations in labor productivity. In addition, the third restriction implies that $\frac{c_{21}}{c_{11}} = \frac{\alpha}{1-\alpha}$, where c_{ii} are the respective elements of the matrix of long-run effects C. Since the lower triangular structure already imposes the number of conditions necessary for the identification of A, I need to relax one of the other assumptions in order to maintain exact identification. Here, the third restriction results in a positive correlation between neutral and investment-specific technology shocks. Hence, Σ_e is no longer diagonal, but rather

$$\Sigma_e = \begin{bmatrix} 1 & \rho & O \\ \rho & 1 & O \\ O & O & I \end{bmatrix}.$$

Naming Λ the lower triangular Cholesky factor from the decomposition of the k-step ahead forecast error, the identification matrix is then $A = FB$ with $F = (\sum_{i=0}^{k} \Phi_i)^{-1}$ and

$$B = \begin{bmatrix} 1 & 0 & O \\ b & \sqrt{(1+b^2)} & O \\ O & O & I \end{bmatrix}.$$

With $b = \frac{\frac{\alpha}{1-\alpha}\lambda_{11} - \lambda_{21}}{\lambda_{22}}$, with λ_{ii} being the elements of Λ, the correlation between the two technology shocks is pinned down as $\rho = \frac{-b}{\sqrt{(1+b)^2}}$.

A.3 Alternative Identification

The alternative identification combines long-run zero restrictions as in the Fisher identification with sign restrictions on the long-run effects of the structural shocks on the real investment price and labor productivity. Assuming $\Sigma_e = I$, the n elements of the matrix A that maps the reduced form into structural residuals have to be determined such that $AA' = \Omega$ and our

[29]Note that Fisher imposes his restrictions in a different fashion, namely in an instrumental variable framework, similar to Shapiro and Watson (1988). I thank Fabio Canova for the solution of the implementation of the Fisher restrictions as explained above.

long-run restrictions are fulfilled. Note that this is equivalent to finding a decomposition L of the long-run forecast revision variance such that

$$LL' = \Sigma^{\infty} = (\sum_{i=0}^{\infty} \Phi_i)\Omega(\sum_{i=0}^{\infty} \Phi_i)'.$$

Consider the same order of variables as in the Fisher identification, i.e. the real price of investment and labor productivity are ordered first in the VAR. First, I assume that only the two types of productivity shocks can affect the real investment price and labor productivity in the long run. This means that $l_{13} = l_{14} = ... = l_{1n} = 0$ and $l_{23} = l_{24} = ... = l_{2n} = 0$ and results in

$$L_{1:2,1:2}L'_{1:2,1:2} = \Sigma^{\infty}_{1:2,1:2}.$$

Next, I implement sign restrictions on this upper left 2-by-2 system in a similar fashion as in Peersman (2005). This involves a rotation of $L_{1:2,1:2}$ using an orthonormal matrix Q (i.e. $QQ' = I$):

$$Q = \left[\begin{pmatrix} \cos(\theta) & -\sin(\theta) \\ \sin(\theta) & \cos(\theta) \end{pmatrix}\right].$$

As in Peersman (and similar to Uhlig (2005)), our VAR is estimated in a Bayesian framework. For each draw of the posterior distribution of the reduced form VAR coefficients, I calculate the long-run forecast revision variance. I then randomly draw θ from a uniform distribution $[0, \pi]$, use Q to calculate the upper left elements of the matrix L and check whether our sign restrictions are satisfied. In the application, I draw 100 candidates from the posterior distribution of the reduced from coefficients and another 100 values of θ for the rotation. I compute the impulse responses for all draws that satisfy the sign restriction and report the median and the 16th and 84th percentile from the resulting distribution. On average over a third of the draws satisfies the sign restrictions.

After having implemented the restrictions, I can now proceed to calculate the remaining elements of the matrix L such that this matrix provides a valid decomposition of the long-run variance. For the remaining elements of the first two columns, I use that $L_{3:n,1:2}L'_{1:2,1:2} = (\Sigma^{\infty}_{1:2,3:n})'$. Now I still need to determine the lower right elements of L. Note that these elements do not impose any of the restrictions nor are they related to the shocks of interest. I use the information on the first two rows and columns in order to adjust the lower right elements of the long-run variance. This 'remaining' block of the variance is then decomposed using the Cholesky decomposition. Having found all elements of L, I can then determine the matrix A via $A = (\sum_{i=0}^{\infty} \Phi_i)^{-1}L$.

A.4 Estimation of the BVAR

All baseline results are based on the reduced form VAR that is estimated in a Bayesian framework with a Minnesota prior. The Minnesota prior consists of a normal prior for the VAR coefficients and a fixed and diagonal residual variance. The prior mean d_0 is restricted such that it represents a random walk structure on the VAR coefficients, i.e. in the standard case, the prior mean on the first lag is set to unity and the prior mean on the other lags (remaining parameters) is set to zero. Here, this is reflected by the fact that all variables enter the VAR in first differences resulting in a zero mean for all lags.

The prior variance $\Sigma_{d_0} = \Sigma_{d_0}(\phi)$ of the coefficients depends on three hyper-parameters ϕ_1, ϕ_2 and ϕ_3, that determine the tightness and decay on own lags, other lags and exogenous variables. Except for the decay, a loose prior is chosen for the hyper-parameters, namely $\phi_1 = 0.2$, $\phi_2 = 0.5$ and $\phi_3 = 10^5$. The decay parameter $d = 7$. The advantage of the structure of the Minnesota prior is exactly this ability to separately deal with the lags of the variables, i.e. own and other lags, as well as exogenous variables. Together with a normal likelihood of the data the Minnesota prior produces a posterior that can be derived analytically. Hence, the estimation does not rely on sampling procedures.

B Robustness

B.1 Specification

This section investigates the robustness of the main results from the Fisher identification: The low standard deviation conditional on neutral and investment-specific technology shocks in job finding and unemployment and the drop in the job finding rate after positive innovations of both types of technology. Table 12 summarizes the results. The first set of robustness checks uses the baseline specification with the Minnesota prior and adjusts the lag length and decay of these lags in the specification. A high decay parameter is necessary for a large number of lags to generate both significant and sensible results. Using a smaller number of lags together with a smaller decay on these lags, or similarly a flat prior for the estimation of the reduced form VAR, qualitatively supports the findings in the baseline specification, but is not significant, however. Further, the results are robust to relaxing the assumption of a fixed residual variance within a Normal-Wishart prior structure. The prior suggested by Kadiyala and Karlsson (1997) employs the same mean for the coefficients as the Minnesota prior and generalizes the Minnesota prior in terms of a non-diagonal, unknown residual variance. Compared to the Minnesota prior, the coefficient variance additionally weights the effect of the exogenous variables on a variable with its respective variance and fixes $\phi_1 = 1$.

The baseline specification includes a broken dummy-trend into the specification which is not uncontroversial. In fact, the question of whether or not to include a trend into the specification is closely related to the debate on how to specify hours worked in a similar structural VAR. Here, it has been shown that if specified in first differences or HP-filtered, hours worked fall after a positive Galí-type technology shock, while they increase after the same type of shock if specified in levels (see Galí (1999) and Christiano et al. (2003) respectively). The fall in hours worked after a positive technology shock contradicts the standard RBC paradigm and has become famous as the “hours puzzle” in the literature. In fact, a trend as the one applied here takes out slow-moving components from the series and is therefore related to taking first differences of the labor market variables. Canova et al. (2006) argue that if the variables are specified in levels, long-run restrictions may pick up the slowly moving components of the variables, even though they aim at explaining business cycles fluctuations.

Figure 8 shows the results for the baseline specification without the dummy breaks. The job finding rate still decreases after positive innovations of both technology shocks. This means that the “job finding” puzzle is is robust to including a trend or not in the specification. Note further that job separation now falls significantly after both shocks. In fact, it falls by such a large extend that the unemployment rate falls in the longer horizon which reflects the result from the hours debate. In addition, the results from the entire sample are compared to results for subsamples suggested by Fisher (2006). Here, no trend is incorporated into the specification, the results are robust to an inclusion of trend breaks as in the baseline specification, however. In the latter sample, investment-specific technology shocks induce an initial fall in the job finding rate and a subsequent, (borderline) significant increase. Job separation does not react to a neutral shock, but decreases significantly after an investment-specific technology shock. Hence, these shocks do generate dynamics different from the neutral shocks in this sample.

B.2 Data

The facts resulting from the worker flow data of Shimer are not uncontroversial in the literature. Fujita and Ramey (2006) have assembled a dataset in which the volatility and cyclical patterns are driven by the job separation rather than the job finding rate. This is similar to the features in the data on job flows. The Fujita and Ramey dataset does not encompass the same sample as the one by Shimer; it ranges from 1976:3 to 2004:4. Table 11 compares the resulting moments to the Shimer moments for this sample. As stated by the authors, the standard deviation of the job separation rate is higher and the one of job finding is lower in their data series compared to Shimer. This suggests a larger role for the first series in the dynamics of unemployment. Job separation is also more persistent. The correlations of the job finding and separation rates with productivity are much lower than in the Shimer series. Comparing the output on conditional second moments for this sample estimated with both the Shimer and the Fujita and Ramey worker flow data is very similar to the output for the second Fisher subsample discussed in the previous subsection. In fact, no large differences emerge for either the dynamics of the job finding rate nor the dynamics of the job separation rate.

C Additional Tables and Graphs

Table 4: Second Moments for Shimer Data Flows

	Unemployment	Finding	Separation	Productivity
Std. deviation	0.1181	0.1019	0.0497	0.0105
	(0.1786)	(0.1542)	(0.0620)	(0.0156)
Autocorr. 1st lag	0.8345	0.8137	0.4409	0.6881
	(0.9180)	(0.9115)	(0.6357)	(0.8503)
Cross-Correlations				
Unemployment	1	-0.9254	0.6346	-0.3051
		(-0.9558)	(0.6845)	(-0.1858)
Finding	-	1	-0.2947	0.1443
			(-0.4404)	(0.0567)
Separation	-	-	1	-0.4826
				(-0.4392)
Productivity	-	-	-	1

Notes: Series are in logs and detrended with standard Hodrick-Prescott filter for quarterly data with $\lambda = 1600$ and compared to smooth filter with $\lambda = 10^5$ in brackets.

Table 5: Model's Second Moments from Two Technology Shocks

	Unemployment	Job Finding	Productivity
Std. deviation	0.0659	0.0903	0.0156
	(0.178)	(0.154)	(0.0156)
Autocorr. 1st lag	0.8752	0.5727	0.8541
	(0.918)	(0.911)	(0.850)
Cross-Correlations			
Unemployment	1	-0.5887	-0.4415
		(-0.955)	(-0.186)
Job Finding	-	1	0.4660
			(0.056)

Notes: The numbers in brackets show respective values from the actual data. All series are HP-filtered with $\lambda = 10^5$.

Table 6: Historical Decomposition of Fisher Identification

	Uncond. Sample	Conditional Moments Inv. Tech.	Neu. Tech.	All Tech.	Residual	Model
A: Standard Deviations						
Find.	0.1542	0.0627	0.0667	0.0622	0.1288	0.0903
		(0.05,0.08)	(0.05,0.09)	(0.05,0.08)	(0.11,0.15)	
Sep.	0.0620	0.0412	0.0485	0.0501	0.0545	
		(0.04,0.05)	(0.04,0.06)	(0.04,0.06)	(0.05,0.06)	
Unemp.	0.1786	0.0692	0.0972	0.0907	0.1536	0.0659
		(0.06,0.09)	(0.07,0.13)	(0.07,0.12)	(0.13,0.18)	
Prod.	0.0156	0.0183	0.0184	0.0129	0.0156	0.0156
		(0.01,0.02)	(0.01,0.02)	(0.01,0.02)	(0.01,0.02)	
B: Autocorrelations						
Find.	0.9115	0.71	0.7991	0.8749	0.9032	0.5727
		(0.61,0.82)	(0.68,0.88)	(0.81,0.92)	(0.88,0.92)	
Sep.	0.6857	0.9279	0.8973	0.8902	0.628	
		(0.86,0.96)	(0.84,0.94)	(0.84,0.93)	(0.59,0.68)	
Unemp.	0.9180	0.7576	0.8181	0.9033	0.9166	0.8752
		(0.67,0.87)	(0.74,0.87)	(0.87,0.92)	(0.90,0.93)	
Prod.	0.8503	0.9011	0.8567	0.8908	0.9207	0.8541
		(0.85,0.95)	(0.80,0.90)	(0.86,0.91)	(0.90,0.94)	
C: Cross-Correlations						
JF,P	0.0567	-0.1386	-0.5467	-0.3117	0.7035	0.4660
		(-0.33,0.17)	(-0.71,-0.25)	(-0.52,0.00)	(0.58,0.80)	
JS,P	-0.4392	-0.3959	0.2916	0.2381	-0.6236	
		(-0.59,-0.18)	(0.08,0.45)	(0.04,0.40)	(-0.73,-0.52)	
U,P	-0.1858	-0.1205	0.5093	0.3431	-0.8185	-0.4415
		(-0.47,0.16)	(0.28,0.68)	(0.07,0.54)	(-0.89,-0.72)	
JF,U	-0.9558	-0.8211	-0.9016	-0.8493	-0.9416	-0.5887
		(-0.90,-0.73)	(-0.96,-0.78)	(-0.93,-0.74)	(-0.95,-0.92)	
JS,U	0.6845	0.4726	0.8101	0.7607	0.592	
		(0.15,0.69)	(0.62,0.89)	(0.61,0.86)	(0.52,0.65)	
JF,JS	-0.4404	0.1531	-0.4475	-0.2861	-0.2827	
		(-0.19,0.44)	(-0.69,-0.03)	(-0.58,0.07)	(-0.37,-0.17)	

Notes: All series are simulated with the respective shock operating and are detrended with the smooth HP-filter as in Shimer (2005a). Brackets show Bayesian one standard error confidence intervals from the posterior distribution.

Table 7: Variance Decomposition in Fisher Identification

	Investment-specific Shock				Neutral Shock			
Quarters	1	8	16	32	1	8	16	32
Price	65.41	83.59	90.34	95.24	4.95	2.81	1.81	0.95
	(42,84)	(63,94)	(76,96)	(88,98)	(1,21)	(0,14)	(0,9)	(0,5)
Prod.	14.06	14.35	12.90	11.39	70.09	77.78	83.22	86.80
	(9,18)	(12,17)	(11,15)	(10,13)	(52,79)	(68,83)	(78,86)	(85,88)
Find.	15.30	6.28	5.97	5.99	44.11	36.84	37.04	36.70
	(8,23)	(4,11)	(3,10)	(3,10)	(23,57)	(13,55)	(13,56)	(13,56)
Sep.	1.86	2.90	3.18	3.24	17.90	19.57	19.62	20.02
	(0,8)	(1,10)	(1,11)	(1,11)	(2,42)	(4,44)	(5,43)	(5,43)
Unemp.	8.74	4.54	4.58	4.61	56.32	42.69	41.77	41.21
	(3,15)	(2,9)	(2,9)	(2,9)	(34,68)	(14,61)	(13,61)	(13,61)

The values for the investment-specific shock, the neutral shock and the (omitted) residual disturbances add up to 100 for each variable at each time horizon. Reported numbers are median estimates of the posterior distribution and Bayesian one standard error confidence intervals. All numbers are percent.

Table 8: Variance Decomposition in Fisher Identification - Job Flows

	Investment-specific Shock				Neutral Shock			
Quarters	1	8	16	32	1	8	16	32
Price	74.51	92.78	96.59	98.39	3.46	0.79	0.37	0.17
	(54,89)	(81,98)	(91,99)	(96,100)	(0,15)	(0,4)	(0,2)	(0,1)
Prod.	12.30	12.03	11.09	10.54	79.39	85.58	87.73	88.86
	(9,15)	(11,14)	(10,12)	(10,11)	(72,84)	(83,87)	(86,89)	(88,89)
Creat.	6.79	6.49	6.57	6.60	4.48	9.11	9.68	9.68
	(1,15)	(2,13)	(2,12)	(2,12)	(0,16)	(3,21)	(3,22)	(3,22)
Dest.	1.23	3.81	4.01	4.03	19.73	14.13	14.15	14.15
	(0,5)	(1,11)	(1,11)	(1,11)	(2,44)	(5,34)	(5,34)	(5,34)
Unemp.	1.36	4.78	4.82	4.82	12.03	10.85	11.09	11.08
	(0,7)	(1,13)	(1,13)	(1,13)	(1,31)	(4,25)	(4,25)	(4,25)

Notes: The values for the investment-specific shock, the neutral shock and the (omitted) residual disturbances add up to 100 for each variable at each time horizon. Reported numbers are median estimates of the posterior distribution and Bayesian one standard error confidence intervals. All numbers are percent.

Table 9: Historical Decomposition of Sign Identification

	Uncond. Sample	Conditional Moments I-Specific	C-Specific	Both Shocks	Residual
A: Standard Deviations					
Find.	0.1542	0.0487	0.052	0.0618	0.1301
		(0.04,0.06)	(0.04,0.07)	(0.05,0.08)	(0.11,0.14)
Sep.	0.0620	0.0384	0.0495	0.0496	0.0547
		(0.03,0.05)	(0.04,0.06)	(0.04,0.06)	(0.05,0.06)
Unemp.	0.1786	0.0556	0.079	0.088	0.1538
		(0.04,0.08)	(0.06,0.11)	(0.07,0.11)	(0.13,0.17)
Prod.	0.0156	0.0125	0.0105	0.0131	0.0159
		(0.01,0.02)	(0.01,0.02)	(0.01,0.02)	(0.01,0.02)
B: Autocorrelations					
Find.	0.9115	0.8194	0.9452	0.8666	0.9023
		(0.72,0.91)	(0.91,0.96)	(0.80,0.91)	(0.88,0.92)
Sep.	0.6857	0.9448	0.9201	0.8931	0.6309
		(0.91,0.96)	(0.87,0.95)	(0.85,0.93)	(0.59,0.66)
Unemp.	0.9180	0.872	0.933	0.905	0.9182
		(0.79,0.93)	(0.91,0.96)	(0.86,0.92)	(0.90,0.92)
Prod.	0.8503	0.9221	0.9294	0.8926	0.9231
		(0.89,0.96)	(0.88,0.98)	(0.87,0.91)	(0.91,0.94)
C: Cross-Correlations					
JF,P	0.0567	0.0018	-0.0358	-0.3627	0.7064
		(-0.46,0.31)	(-0.41,0.25)	(-0.52,-0.01)	(0.61,0.79)
JS,P	-0.4392	-0.0847	-0.1673	0.2865	-0.6164
		(-0.55,0.37)	(-0.53,0.29)	(0.07,0.45)	(-0.70,-0.54)
U,P	-0.1858	-0.1208	-0.098	0.4024	-0.8217
		(-0.61,0.48)	(-0.52,0.40)	(0.08,0.58)	(-0.89,-0.74)
JF,U	-0.9558	-0.7742	-0.8053	-0.8331	-0.9413
		(-0.89,-0.61)	(-0.92,-0.66)	(-0.92,-0.73)	(-0.95,-0.92)
JS,U	0.6845	0.5607	0.7934	0.7472	0.5932
		(0.13,0.83)	(0.61,0.88)	(0.63,0.83)	(0.51,0.65)
JF,JS	-0.4404	0.2122	-0.2493	-0.2275	-0.2833
		(-0.36,0.54)	(-0.58,0.17)	(-0.53,0.08)	(-0.37,-0.18)

All series are simulated with the respective shock operating and are detrended with the smooth HP-filter as in Shimer (2005a). Brackets show Bayesian one standard error confidence intervals from the posterior distribution.

Table 10: Variance Decomposition in Sign Identification

	Investment-specific Shock				Investment-unspecific Shock			
Quarters	1	8	16	32	1	8	16	32
Prod.	23.47	26.03	27.61	29.51	57.26	65.45	67.75	68.56
	(2,56)	(2,62)	(2,65)	(3,69)	(26,83)	(29,89)	(30,92)	(29,95)
Price	27.25	39.59	40.51	36.67	13.43	23.70	39.54	54.30
	(11,50)	(15,62)	(12,69)	(8,72)	(1,37)	(4,53)	(11,69)	(20,83)
Find.	18.39	6.45	6.18	6.22	3.01	13.24	16.82	17.24
	(6,34)	(3,15)	(3,15)	(3,15)	(0,13)	(4,29)	(6,36)	(6,38)
Sep.	1.75	2.49	2.66	2.69	10.91	13.37	13.46	13.54
	(0,8)	(0,10)	(1,10)	(1,10)	(3,28)	(4,33)	(4,33)	(4,33)
Unemp.	12.15	5.14	5.24	5.25	12.40	19.77	21.52	21.49
	(2,29)	(2,15)	(2,15)	(2,14)	(1,32)	(6,40)	(6,43)	(7,43)

The values for the investment-specific shock, the neutral shock and the (omitted) residual disturbances add up to 100 for each variable at each time horizon. Reported numbers are median estimates of the posterior distribution and Bayesian one standard error confidence intervals. All numbers are percent.

Table 11: Comparing Shimer with Fujita and Ramey Data

	Unemployment	Finding	Separation	Productivity
Std. deviation	0.1807	0.1211	0.0861	0.0150
	(0.1614)	(0.1531)	(0.0525)	(0.0150)
Autocorr. 1st lag	0.9332	0.9078	0.8075	0.8341
	(0.9501)	(0.9316)	(0.5475)	(0.8746)
Cross-Correlations				
Unemployment	1	-0.9494	0.8965	-0.0322
		(-0.9564)	(0.4996)	(-0.0254)
Finding	-	1	-0.7124	-0.0477
			(-0.2252)	(-0.1148)
Separation	-	-	1	-0.1559
				(-0.4445)
Productivity	-	-	-	1

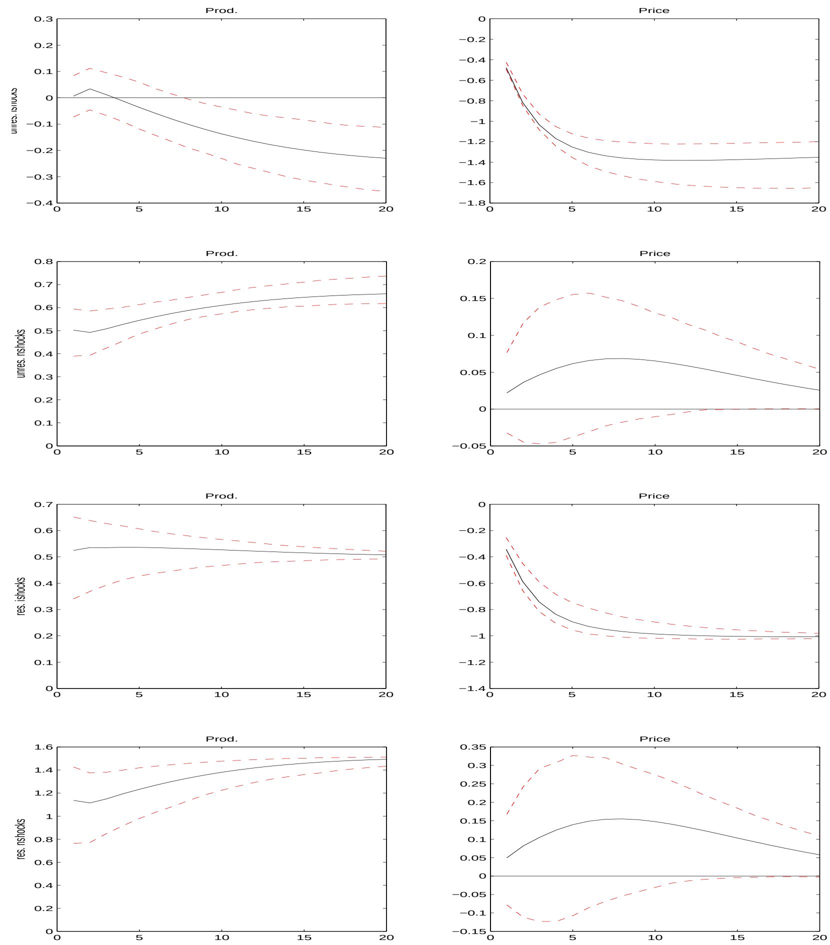
Series are in logs and detrended with smooth Hodrick-Prescott filter with $\lambda = 10^5$. Sample: 1976:1-2004:4. Numbers in brackets are respective values for the Shimer data.

Table 12: Robustness of the Fisher Identification

	Conditional Standard Deviation				Impulse Response	
	Job Finding		Unemployment		Job Finding	
	i-shock	n-shock	i-shock	n-shock	i-shock**	n-shock
Baseline	0.0627	0.0667	0.0692	0.0972	-,sign.	-,sign.
Baseline specification with Minnesota prior changed to						
4 lags, decay 7	0.0651	0.071	0.0808	0.1129	-,sign.	-,sign.
12 lags, decay 7	0.069	0.0702	0.847	0.1053	-,sign.	-,sign.
8 lags, decay 4	0.579	0.0477	0.0745	0.0689	-;+,not sign.	-,not sign.
3 lags, decay 1	0.0533	0.0567	0.0706	0.0809	-,not sign.	-,not sign.
Flat prior (OLS equivalent) with						
2 lags	0.0511	0.0609	0.727	0.0971	-,not sign.	-,not sign.
3 lags	0.0533	0.0649	0.0737	0.0899	-;+,not sign.	-,not sign.
K and K prior*	0.651	0.0738	0.689	0.1037	-,sign.	-,sign.
Trend specification						
no break	0.0667	0.0595	0.058	0.0494	-,sign.	-,sign.
Fisher subsamples without break						
1955:I-1979:II	0.0828	0.0853	0.0784	0.0895	-,sign.	-,sign.
1982:III-2004:IV	0.0352	0.059	0.0777	0.0402	-;+,sign.	-,sign.
Fujita and Ramey subsample without break						
1976:III-2004:IV	0.0424	0.0699	0.0622	0.0528	-;+,sign.	-,sign.

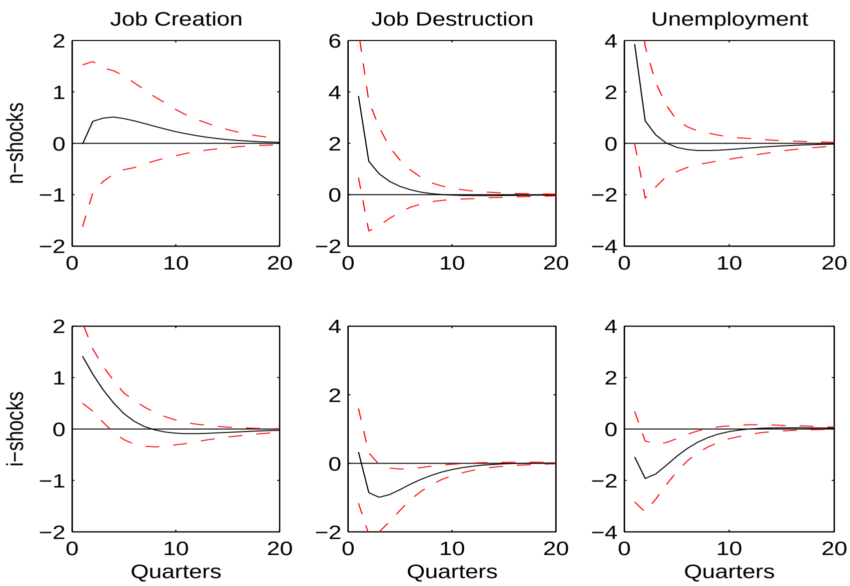
Notes: **Describes the effect on impact. Here, -;+ indicates initial drop, then hump-shaped increase. *Kadiyala and Karlsson prior with Minnesota structure, same parameters as in baseline specification.

Figure 4: Restricted and unrestricted Fisher Identification



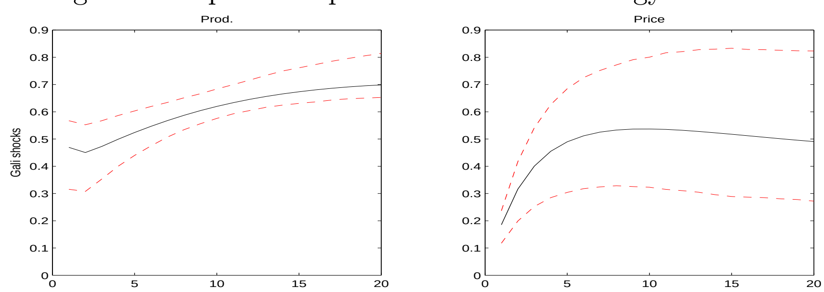
Notes: Percent responses to a one-standard deviation shock. The dotted confidence intervals are one-standard error bands. The horizon on the x-axis depicts quarters.

Figure 5: Job Flow Responses to Fisher Technology Shocks



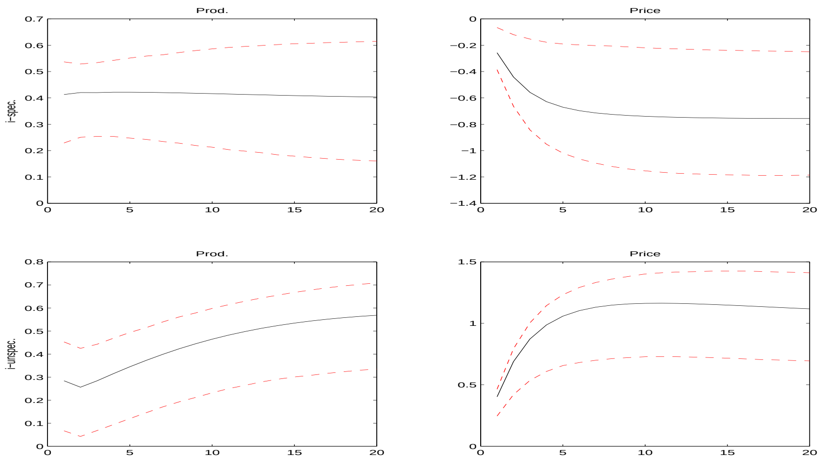
Notes: Percent responses to a one-standard deviation shock. The dotted confidence intervals are one-standard error bands.

Figure 6: Impulse-Responses to Galí Technology Shocks



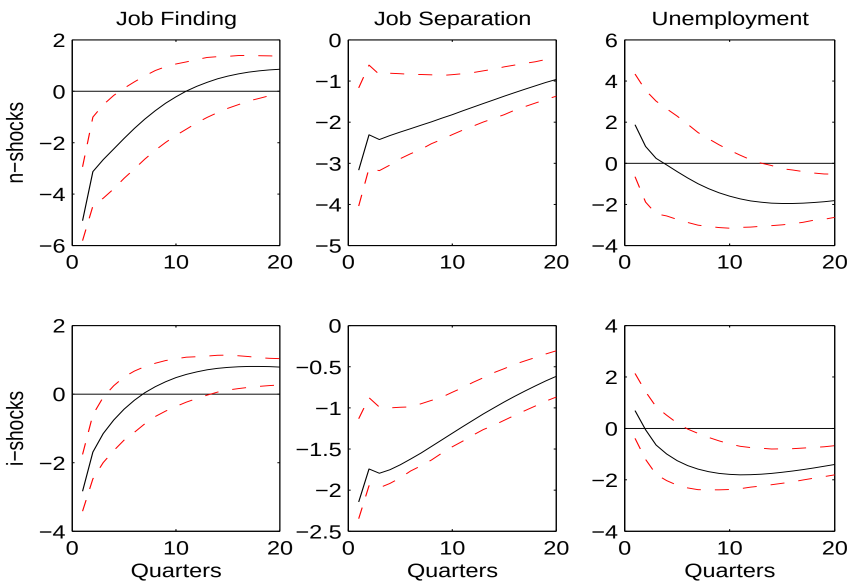
Notes: Percent responses to a positive one-standard-deviation shock. The dotted confidence intervals are one-standard-error bands.

Figure 7: Sign Identification - Price and Productivity



Notes: Percent responses to a one-standard deviation shock. The dotted confidence intervals are one-standard error bands. The horizon on the x-axis depicts quarters.

Figure 8: Fisher Technology Shocks - No Trend



Notes: Percent responses to a one-standard deviation shock. The dotted confidence intervals are one-standard error bands.