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

by Almut Balleer

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JEL classification: E24, E32, O33

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Abstract

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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 flow 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. In addition, the correlation between the job finding rate and the unemployment rate with labor productivity is much too high in the model.

While the dynamics in the standard frictional labor market model stem from fluctuations in labor productivity, "a change in labor productivity is most easily interpreted as a technology or supply shock" (Shimer (2005a), p. 25). 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 overall unconditional moments.[1] Since conditional and unconditional moments substantially differ in this case, the

[1] I am not the first to address conditional moments with respect to labor market dynamics. Michelacci and Lopez-Salido (2007), Ravn and Simonelli (2006), Fujita (2009) and many others all have also used SVARs in order to investigate the effect of different shocks on worker and job flows. I will refer to differences in the focus as well as methods and results below.

judgement of the model that is based on unconditional moments may be very misleading. The results provide answers to various issues of importance to the standard labor market model. First, one can gain important insights into the failure of the model to generate sufficient volatility on the unconditional level as documented by Shimer. Second, 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. Put differently, unconditional dynamics may encompass various different dynamics on the conditional level. Since the identified shocks are structural, the results deliver a meaningful guidance for the formal modelling of the labor market dynamics. Third, if the identified shocks are in fact shocks to the business cycle, their effect on the rate of job separations sheds light on the validity of assuming a constant job separation rate in a business-cycle model.

Two main findings emerge. With respect to volatility, 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 that is driven by technology shocks. 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. I show that shocks to the marginal rate of substitution between consumption and leisure, so-called preference shocks, may work in this respect. Further, job separations significantly move after both types of estimated shocks. This means that it is not reasonable to assume the job separation rate to be constant over the cycle.

With respect to the conditional correlations, 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 is a much more serious challenge to the empirical performance of the standard model than the Shimer volatility in unemployment puzzle. Hence, this result supports models which are able to incorporate these effects. Since the correlations of these two variables with productivity that are conditional on technology shocks are of opposite sign as the respective unconditional moments, non-technology shocks are necessary again to fully describe the overall dynamics in the data. However, I show that preference shocks are not suitable to explain the remaining variation 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. Note that the identification employed uses an additional assumption on the effect of investment-specific technology shocks on labor productivity that goes back to Fisher. This assumption has an important effect on the results and has been neglected by many other authors in similar studies (such as Canova et al. (2007) and Ravn and Simonelli (2006)). Here, 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 referred to 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:

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

subject to

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

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 η. 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 $F_t = \mu(\frac{V_t}{1-N_t})^{1-\eta}$ and thus 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.[2] Through the capital accumulation equation it favors new investments, leads to new capital formation and hence positively 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[3]. 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 positive effect on labor productivity, job finding rises after a positive technology shock, while unemployment falls. 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

[2]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.

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

technology shocks have permanent effects on labor productivity. 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.[4]

The labor market model outlined above differs in many respects from the standard Mortensen and Pissarides (1994) model that provides the basis for the Shimer model. Utility is not linear, but follows the standard assumptions in the RBC literature. 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. 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. However, as in Shimer, this study focusses on the second moments of the central variables that this model wants to explain, that is the dynamics in the job finding, job separation and unemployment rate.

Both the Shimer model and the model outlined above lack 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. 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. 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 empirical results documented below remain equally valid. In section 3, I will consider preference shocks which move the marginal rate of substitution between consumption and leisure. In the model, this means that the parameter χ will be replaced by a stochastic process of the form $\ln(x_t) = \rho_x \ln(x_{t-1}) + \varepsilon_{xt}$.

2.2 Empirical Performance Based on Neutral Shocks

Due to the difference to the Shimer model, I re-consider the empirical performance of the model outlined above. To keep the framework as simple as possible, I start with considering neutral shocks as the only source of variation in the model. For this, I calibrate the model and generate artificial time series from the model, compute the respective second moments and compare them to the unconditional ones in the data. I choose a set of standard parameters for the calibration: a capital share in production of $\alpha = \frac{1}{3}$,

[4] 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. Their model is much more complicated than the standard model here and aims at describing different results in the data.

the time discount factor of $\beta = 0.99$ and capital depreciation of $\delta = 0.02$. The Frisch labor supply elasticity is pinned down by $\phi = 1$ and $\chi = 1$. In line with Mortensen and Nagypal (2007), the elasticity of the matching function with respect to unemployment is set to $\eta = 0.46$. The constant of the matching function ($\mu = 1.5$) and the cost of posting vacancies ($a = 0.02$) are calibrated such that the steady state labor market tightness is equal to one and the respective job finding rate equals the mean quarterly job finding rate of 1.5 in the worker flow data used later in the estimation. The same data delivers the mean quarterly job separation rate of $\psi = 0.09$.[5]

The first and second column of Table 1 compare the second moments in the data to those that are generated from the model driven by neutral shocks only. Hence, $\varepsilon_{it} = 0$. The growth rate and standard deviation of the neutral technology shock ε_{at} are then calibrated to match the standard deviation of labor productivity which results in $\gamma = 0.0035$. 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 and unemployment are a lot more volatile than the job separation rate. 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.

The comparison with the model moments mirrors the Shimer volatility in unemployment puzzle. 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.

Hagedorn and Manovskii (2008) and many other authors have argued that Shimer's volatility in unemployment puzzle disappears for a different calibration of the model, more precisely for a different calibration of the outside option of the workers in the wage bargaining. This parameter is not considered here. Within the framework used above, the parameters are chosen such that the volatility in the job finding rate and unemployment is as high as possible[7]. Put differently, the aim of this study is not to find a calibration

[5]For more details on the data and the sample, see section 3.1.

[6]Table 7 shows that these result do not depend on the choice of the smoothing parameter in the HP-Filter.

[7]Investigating sensitivity of this result to the choice of parameter values, it is possible,

such that the model driven by technology shocks matches the unconditional moments in the data. Rather, the output from this model in the standard calibration is to be compared to the moments that are conditional on technology shocks.

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 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[8]. It has to be noted that many structural disturbances other than technological innovations can affect labor produc-

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for example, to increase the matching elasticity with respect to unemployment to the value proposed by Shimer of $\lambda = 0.72$ which clearly decreases the volatility of job finding and unemployment.

[8] See the Technical Appendix for further details.

Table 1: Historical Decomposition of Galí Identification

	Uncond. Sample	Model I	II	Conditional Moments Technology	Residual
A: Standard Deviations					
JFinding	0.1542	0.0536	0.0417	0.0548	0.1229
				(0.04,0.08)	(0.10,0.14)
JSeparation	0.062			0.0503	0.056
				(0.04,0.06)	(0.05,0.06)
Unemployment	0.1786	0.0519	0.0404	0.0881	0.1409
				(0.06,0.12)	(0.12,0.16)
Productivity	0.0156	0.0156	0.0116	0.0116	0.0166
				(0.01,0.02)	(0.01,0.02)
B: Autocorrelations					
JFinding	0.9128	0.9071	0.9061	0.9189	0.8869
				(0.86,0.95)	(0.86,0.90)
JSeparation	0.6336			0.9256	0.6158
				(0.89,0.95)	(0.59,0.66)
Unemployment	0.9218	0.845	0.8443	0.9131	0.9109
				(0.88,0.93)	(0.90,0.92)
Productivity	0.8507	0.8701	0.868	0.8927	0.9206
				(0.86,0.92)	(0.90,0.94)
C: Cross-Correlations					
JFind.,Prod.	0.0567	0.8625	0.8522	-0.436	0.6739
				(-0.66,-0.10)	(0.52,0.77)
JSep.,Prod.	-0.4392			0.3544	-0.6703
				(0.11,0.48)	(-0.74,-0.59)
Unemp.,Prod.	-0.1858	-0.7776	-0.7668	0.4613	-0.8014
				(0.17,0.63)	(-0.88,-0.70)
JFind.,Unemp.	-0.9558	-0.9272	-0.9266	-0.9041	-0.9359
				(-0.96,-0.75)	(-0.95,-0.91)
JSep.,Unemp.	0.6845			0.885	0.6302
				(0.80,0.92)	(0.56,0.69)
JFind.,JSep.	-0.4404			-0.596	-0.3167
				(-0.76,-0.19)	(-0.40,-0.19)

Notes: All series are detrended with the smooth HP-filter as in Shimer (2005a). For the conditional moments, the series are simulated with the respective shock operating only. The point estimate is the median, the confidence intervals are 68% Bayesian bands from the posterior distribution. Calibration I of the model matches the unconditional standard deviation of labor productivity, calibration II matches the same moment, conditional on technology shocks.

tivity 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[9].

All identification alternatives presented in the following are based on the same reduced-form VAR which contains labor productivity, 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 cited criticism on the VAR approach (e.g. by Chari et al. (2008)) which states that in theory one should employ a VAR with an infinite number 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[10]. 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.[11]

The baseline specification is estimated using quarterly time series data for the U.S. over the sample 1955:1-2004:4. The job finding and separation rates are taken from the worker flow data produced by Robert Shimer[12]. 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

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

[10]The prior variance of the coefficients depends on three hyper-parameters $\phi_1 = 0.2$, $\phi_2 = 0.5$ and $\phi_3 = 10^5$, that determine the tightness and decay on own lags, other lags and exogenous variables. The decay parameter is set to $d = 7$.

[11]See Fernald (2007) for empirical evidence on the trend breaks. Appendix A 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.

[12]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.

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[13]. Labor productivity and the relative price of investment are included in growth rates in growth rates in the VAR, while the job finding and separation rates are included in levels.

Under the assumption of homogenous workers and a constant labor force, the unemployment rate can be approximated by the steady state unemployment rate $\tilde{u} = \frac{js}{js+jf}$. Linearizing this relationship, one can also deduct the impulse-response of unemployment from the responses of the job finding and the job separation rates. 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 (forthcoming) 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 the first column in Table 1. I include the job separation rate in the VAR in order to test this criticism.

3.2 Results

3.2.1 The Shimer puzzle

Table 1 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. 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.[14]

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, if the model is calibrated to match the standard deviation of labor productivity that is conditional on technology shocks (calibration II in column 3 of Table 1), the standard deviation of the job finding rate

[13]The series by Jonas Fisher was extended by Ricardo DiCecio. I thank both for making their data available to me.

[14]Note that the second moments resulting from these series do not add up to the unconditional moment. Note also that all results discussed also hold for HP-filtered data using the standard parameter of $\lambda = 1600$ as can be seen in Table 7 in the Appendix.

generated in the model is close to and lies within the confidence bands of the standard deviation that is conditional on technology shocks.

The model assumes a constant job separation rate over the business cycle. The estimated standard deviation of the job separation rate that is conditional on both technology shocks and non-technology shocks is, however, significantly positive. 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).

Addressing the empirical performance of the model with constant job separation nevertheless, one should therefore consider the volatility of unemployment that is driven by the job finding rate only, setting the job finding rate to its mean value throughout the sample period. The unconditional standard deviation of 0.1525 is then contrasted with the 0.0548 conditional on technology shocks and 0.1237 conditional on non-technology shocks (see first row in Table 2). The standard deviation in unemployment that is generated by the model therefore lies within the confidence bands conditional on technology shocks. As a result, conditional on technology shocks, the model works well to replicate the volatility in the job finding rate and unemployment. As a consequence, the Shimer critique does not apply.

While the model works well to generate the volatility that is conditional on technology shocks, it, however, still fails to explain the overall volatility in the sample. In fact, a large part of the volatility still remains to be unexplained in the "residual" disturbances as depicted in the last column of Table 1[15]. 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, namely preference shocks or shocks to the marginal rate of substitution between consumption and leisure.[16] As mentioned in section 2, it is easy to incorporate these kinds of shocks into the model. After a positive preference shock, agents in the economy want to consume and work more, hence they are willing to accept a lower wage in order to become employed which increases the incentive for firms to post vacancies and decreases unemployment. Panel A and B of Table 2 depict the unconditional and conditional moments in the data (assuming a constant job separation rate) as well as

[15]In a parallel developed paper, Barnichon (2008) also shows the importance of non-technology shocks for worker flows. He argues that these remaining shocks are monetary policy shocks.

[16]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.

Table 2: The Role of Job Separation and Preference Shocks

	Unconditional Sample	Model Pref. Shocks	Conditional Moments Technology	Residual
A: Standard Deviations				
JFind. and Unemp.	0.1526	0.1314	0.0548	0.1238
			(0.04,0.08)	(0.10,0.14)
Productivity	0.0156	0.0165	0.0116	0.0165
			(0.01,0.02)	(0.01,0.02)
B: Autocorrelations				
JFind. and Unemp.	0.9128	0.832	0.9207	0.8873
			(0.85,0.95)	(0.86,0.90)
Productivity	0.8507	0.9184	0.8902	0.9208
			(0.86,0.92)	(0.90,0.94)
C: Cross-Correlations				
JFind.,Prod.	0.0489	-0.7702	-0.4347	0.662
			(-0.64,-0.07)	(0.53,0.76)
Unemp.,Prod.	-0.0489	0.892	0.4332	-0.6626
			(0.07,0.64)	(-0.76,-0.53)

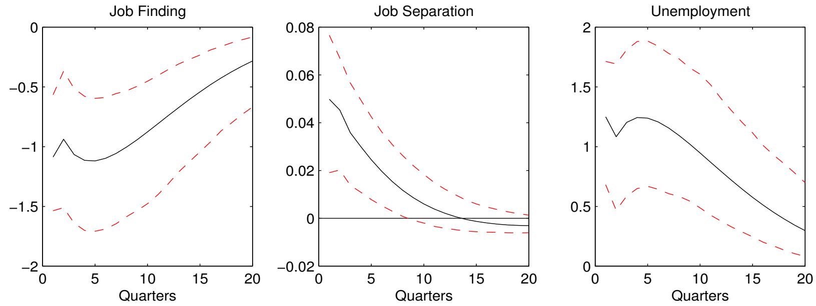
Notes: All series are detrended with the smooth HP-filter as in Shimer (2005a). Unemployment is calculated with a job separation rate that is constant and set equal to its mean value over the sample. For the conditional moments, the series are simulated with the respective shock operating only. The point estimate is the median, the confidence intervals are 68% Bayesian bands from the posterior distribution. The model is driven by preference shocks only and is calibrated such that it matches the conditional standard deviation of labor productivity.

the moments from the model that is driven by preference shocks only. The model is calibrated to match the standard deviation of labor productivity that is conditional on the non-technology shocks which involves $\rho_x = 0.5$ and $\sigma_x = 0.2$. Preference shocks are suitable to generate high volatility in these two variables as suggested by Hall.

3.2.2 The "job finding puzzle"

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 1 and also in the impulse-

Figure 1: Impulse-Responses to Galí Technology Shocks



Notes: Responses in percentage points to a positive one-standard-deviation shock. Confidence intervals are 68% Bayesian bands.

responses to a one-standard deviation technology shock in Figure 1[17]. 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 positive. These two effects are opposite to those in the overall sample and the exact contrary to what the standard model proposes. 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.[18]

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.

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

[17]The response of unemployment is calculated from the linearized relationship between the approximated unemployment rate and the responses of the job finding and separation rates according to $\hat{u}_t = \frac{f}{(s+f)^2}\hat{s}_t - \frac{s}{(s+f)^2}\hat{f}_t$, where s and f are the mean values of the two rates respectively.

[18]Researchers have questioned that the identified shocks can in fact be interpreted as technology shocks. Appendix A shows robustness for this finding using an alternative measure of technology derived by Basu et al. (2006).

finding rate? In the case of hours, fixed demand in the short run leads firms to adjust hours worked after a positive technology shock. Since it is much more costly to adjust employment rather than hours worked, it is not clear that the same mechanism works equally well in this context. In their specification with real rigid wages, Blanchard and Galí (2006) 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. Barnichon (2008) uses a similar reasoning to generate the fall in labor market tightness which he documents in a similar SVAR-framework as the one presented here. However, as conjectured, his model is not able to generate the large fall in labor market tightness and strong increase in unemployment that we see in the data.[19]

There exist explanations for this empirical finding different from a New Keynesian setup. Balleer and van Rens (2008) document that the shocks that have been identified as neutral technology shocks in the Galí identification are in fact positively biased towards new skills (as they have a positive effect on the wage premium of high to low skilled workers). Consider a framework in which two types of workers are used in production and are to some degree substitutable. After a positive skill-biased technology shock, high-skilled workers become more productive than low-skilled workers and overall labor productivity increases. Low-skilled workers will then be substituted out of employment. The job finding rate for low-skilled workers will drop, while it will potentially increase for high-skilled workers. If the negative effect on low-skilled is larger than the positive effect on high-skilled workers, the overall job finding rate drops and unemployment increases.

Regardless of the mechanism, a model driven by technology shocks is again not suitable to explain the overall dynamics in the data. Rather, non-technology shocks are needed in order to model the unconditional dynamics in the data. Reconsidering the preference shocks from above, these kinds of shocks have been popular in the RBC-literature in order to explain the empirical correlation of labor productivity with hours[20]. Table 2 documents that the correlations of the job finding rate and unemployment with productivity that are generated by preference shocks in the model are opposed to the ones conditional on non-technology shocks in the data, however. After a positive preference shock, agents want to consume more and hence decrease investments. Capital falls and, after an initial increase, output falls as a consequence. Due to the increase in employment, labor productivity falls

[19]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.

[20]See for example Bencivenga (1992) on the Dunlop-Tarshis observation.

which induces a negative correlation of this variable with the job finding rate and a positive one with unemployment. Hence, preference shocks are not suitable to explain the conditional correlations within this setup. It has to be noted that in a New Keynesian setup, the induced correlations are different and preference shocks could replicate the empirical dynamics. A distinction between skill-biased and skill-neutral shocks could also provide two shocks that match the conditional correlations in the data.

As exhibited in Figure 1, job separation significantly increases after a positive technology shock contributing to an even larger increase in unemployment. 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. As is documented in greater detail in Appendix A, the effect of job separation is not robust neither when considering different sub-samples nor to the in- or exclusion of a trend in the estimation.

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.

In the original Shimer framework, it is not possible to distinguish between these two sources of variation in labor productivity, while the model in section 2 does differentiate 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 second column of Table 8 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.[21]

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.[22]

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. 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

[21] In this simulation of the model, 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 $\frac{1}{1-\alpha}\gamma + \frac{\alpha}{1-\alpha}\nu$.

[22] See Figure 6 for a comparison of the responses of the restricted and the unrestricted Fisher identification. See the Technical Appendix for more details and the implementation of this identification scheme. Parallel to the model calibration I use $\alpha = \frac{1}{3}$.

the additional third restriction. Equally, Ravn and Simonelli (2006) identify technology shocks without the third restriction in a framework which also 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 Fujita (2009) or 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 depends on the fact that the co-movement between labor input and productivity in the short run is explicitly used for identification.

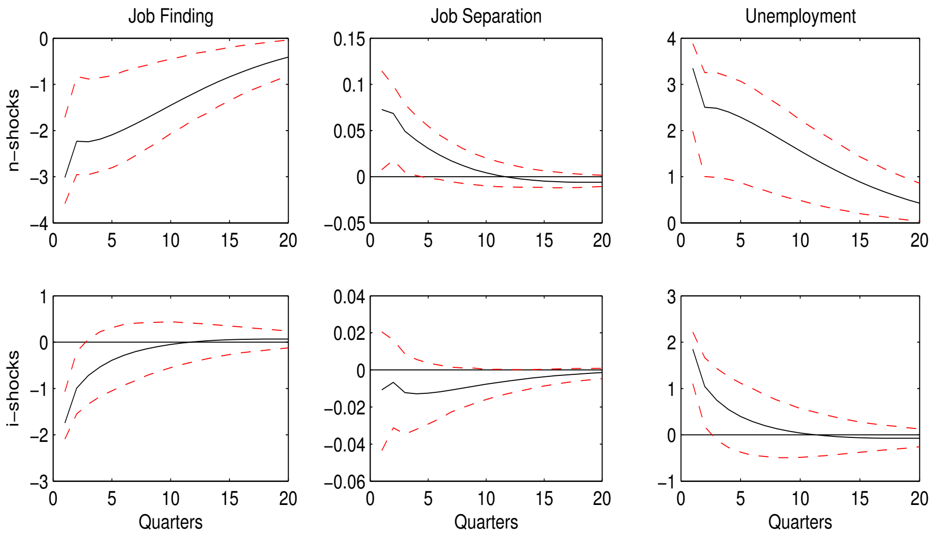
4.2 Results

The historical decomposition of the standard deviation supplements the results from the Galí identification, see Table 8 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.[23]

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 8. 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,

[23] 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: Impulse-Responses to Fisher Technology Shocks



Notes: Percentage responses to a positive one-standard-deviation shock. Confidence intervals are 68% Bayesian bands.

both of these figures are insignificant. The investment-specific technology shock therefore moderates the effect of the neutral shock. Both technology shocks taken together however still generate dynamics that are opposite to the unconditional dynamics and that are not replicated in the model.

Table 6 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.[24]

5 Alternative Variables: Job Flows

Instead of worker flows, so-called job flow data have often been used to assess the empirical validity of the standard labor market model (similar to Cole and Rogerson (1999) and Davis et al. (1998)). 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

[24]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.

automatically created or destroyed. In the data, these two concepts show quite different unconditional business-cycle moments however, and hence it is interesting to consider conditional moments in job flows complementary to the above.

Here, I use data from Faberman (2006) which encompasses the fluctuations of jobs defined as small size units ("plants") that are created and destroyed within the U.S. manufacturing sector[25]. The resulting rates are usually referred to as job creation and destruction rates and both are measured in percent of employment. Unemployment dynamics are approximated by unemployment growth which results from taking the difference between the job destruction and creation rate. 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 conditional and unconditional moments from this set of data together with the familiar moments from the model.

Note that in this sample, that job destruction is about twice as volatile as job creation. Both series are less persistent than the worker flows, while the cross-correlations between the variables are qualitatively similar, but quite different in value from the ones in the worker flow series. 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. The model does not aim at explaining the positive correlation between productivity and job creation with unemployment.

Conditional on investment-specific and neutral technology shocks, the standard deviation in job creation is even smaller than the unconditional one. 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. Hence, job destruction does move after technology shocks, but most of its volatility stems from non-technological disturbances. This means that endogenous job destruction alone cannot realign the moments from the model with the unconditional moments. Complementary to this result, technology shocks explain only up to 17% of the business cycle variance of job creation and destruction as is exhibited in Table 9 in the Appendix. 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.

[25]The data is also described in Davis et al. (2006). I thank Jason Faberman for making the data available to me.

Table 3: Historical Decomposition from Fisher Identification - Job Flows

	Uncond. Sample	Model	Conditional Moments Inv. Tech.	Neu. Tech.	All Tech.	Residual
A: Standard Deviations						
Creat.	0.0765	0.0775	0.0455	0.0336	0.041	0.0732
		(0.0717)	(0.04,0.06)	(0.03,0.04)	(0.03,0.05)	(0.07,0.08)
Dest.	0.1311		0.0547	0.0473	0.0583	0.1214
			(0.04,0.08)	(0.03,0.07)	(0.04,0.07)	(0.11,0.13)
Unemp.	1.0612	0.0708	0.3921	0.2604	1.7027	3.9574
		(0.0657)	(0.25,0.57)	(0.17,0.40)	(1.27,2.17)	(3.78,4.16)
Prod.	0.0156	0.0156	0.0174	0.0191	0.013	0.01
		(0.0129)	(0.01,0.02)	(0.02,0.02)	(0.01,0.01)	(0.01,0.01)
B: Autocorrelations						
Creat.	0.6177	0.8655	0.8254	0.9051	0.8226	0.6383
		(0.8671)	(0.75,0.90)	(0.81,0.96)	(0.76,0.89)	(0.60,0.67)
Dest.	0.7222		0.8247	0.6189	0.7751	0.7146
			(0.63,0.88)	(0.45,0.82)	(0.65,0.86)	(0.70,0.74)
Unemp.	0.6683	0.8607	0.8133	0.5611	0.9457	0.9455
		(0.8632)	(0.69,0.86)	(0.33,0.77)	(0.93,0.96)	(0.94,0.95)
Prod.	0.8507	0.8482	0.8563	0.8141	0.864	0.8514
		(0.855)	(0.80,0.90)	(0.77,0.85)	(0.85,0.88)	(0.79,0.90)
C: Cross-Correlations						
JC,P	0.1545	0.5141	0.4224	0.2328	0.2206	0.0636
		(0.4087)	(0.21,0.57)	(-0.12,0.46)	(0.08,0.34)	(-0.08,0.24)
JD,P	-0.4733		-0.4225	0.2207	-0.0073	-0.6159
			(-0.65,-0.02)	(-0.31,0.43)	(-0.22,0.23)	(-0.76,-0.45)
U,P	-0.4449	-0.4427	-0.5901	0.0538	0.1561	-0.0678
		(-0.3506)	(-0.72,-0.35)	(-0.47,0.37)	(-0.13,0.40)	(-0.14,0.02)
JC,U	-0.7176	-0.8718	-0.6134	-0.3034	0.2599	0.114
		(-0.8749)	(-0.79,-0.31)	(-0.56,-0.05)	(0.11,0.43)	(0.04,0.19)
JD,U	0.9242		0.7912	0.782	0.3496	0.1383
			(0.59,0.90)	(0.58,0.89)	(0.25,0.45)	(0.10,0.18)
JC,JD	-0.4187		0.0523	0.4158	-0.0813	-0.3764
			(-0.33,0.49)	(0.07,0.65)	(-0.32,0.22)	(-0.42,-0.34)

Notes: All series are detrended with the smooth HP-filter as in Shimer (2005a). The point estimate is the median, the confidence intervals are 68% Bayesian bands from the posterior distribution. The model is calibrated to match the unconditional standard deviation of labor productivity and the same figure that is conditional on both technology shocks (in brackets).

Panel C of Table 3 depicts the conditional cross-correlations of the labor market variables with each other and productivity. Figure 7 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). Strikingly, 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.[26] 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[27]. To summarize, since the two data concepts not only generate quite different unconditional statistics, but also react differently to the estimated shocks, it seems reasonable to try to distinguish the different concepts and model the empirical dynamics of these two sets of data in a theoretical framework as well.

[26]Michelacci and Lopez-Salido (2007) do a similar empirical exercise with job flow data. They document similar responses after a neutral technology shock, but different responses after an investment-specific technology shock due a different identification.

[27]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 new investment and mistakenly labelled factor-neutral, see Figure 8 in the Appendix[28].

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.[29] 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 investment-specific technology shocks from those other shocks. 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.

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

[29] See Figure 9 in the Appendix.

3. Out of these shocks, the remaining shocks may affect labor productivity positively and the relative price of investment positively in the long run.

These assumptions are implemented with a mixture of long-run zero and sign restrictions 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.[30].

Figure 10 in the Appendix visualizes the assumed responses of price and productivity to the two newly identified shocks. Not surprisingly, the new shocks turn out to be negatively biased towards investment and may consequently called investment-unspecific technology shocks. 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[31]. 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.

What are technology shocks that drive the relative price of investment up? In the model outlined in section 2, shocks that have a positive effect on the relative price of investment negatively affect labor productivity and, hence, are not technology shocks. 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

[30]For further details of the implementation of the long-run sign restrictions are contained in the Technical Appendix.

[31]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.

skilled labor have a positive effect on the relative price of investment and could therefore capture the variation of the data documented here.[32] Once more, this points to the use of a more complex production function with which it is possible to distinguish between low and high skilled labor in order to replicate the empirical dynamics.

6.2 Results

Table 11 in the Appendix exhibits the historical decompositions for this identification scheme. 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. This is not surprising, since the alternative identification is just a different decomposition of the technology shocks from the other identification schemes.

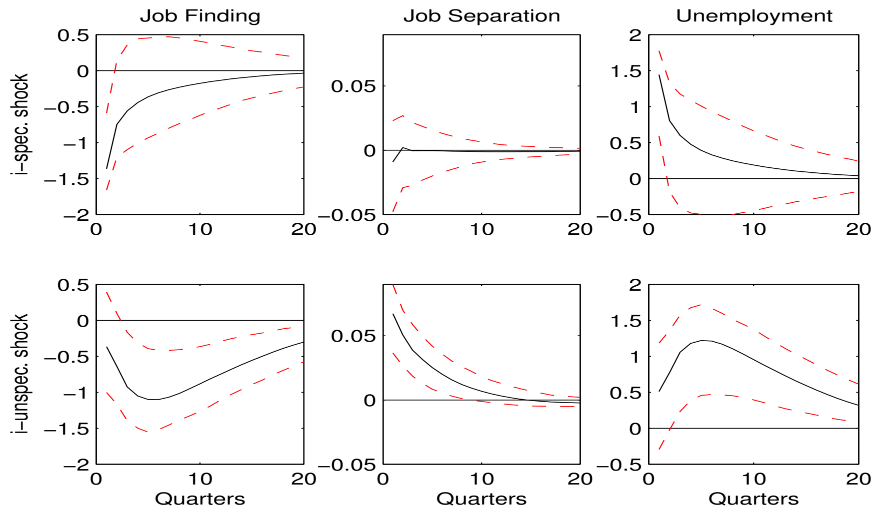
More interesting in this respect are the labor market dynamics induced by the two new shocks documented in Figure 3 and Table 11. For both types of shocks, job finding drops and unemployment increases supporting the findings of the Fisher and Galí identification. There are significant differences between 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[33].

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 tech-

[32] 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.

[33] 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, see Figure 9 in the Appendix or 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: Responses in percentage points to a one-standard deviation shock. Confidence intervals are 68% Bayesian bands.

nology 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 between 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 the investment-specific technology shock. Together, both shocks explain about 20% 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 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 the recent ongoing debate on the empirical performance of the Mortensen-Pissarides search-and-matching model, this study provides an important contribution to the 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. Ravn and Simonelli (2006) identify government spending shocks in a similar SVAR. Their shocks indeed mirror the dynamics of our "residual" disturbances as they drive labor productivity and labor market tightness up and unemployment down. Barnichon (2008) argues that these shocks are shocks to monetary policy. Here, I investigate an idea by Hall (1997) that preference shocks in the form of shocks to the marginal rate of substitution between consumption and leisure are important for labor market dynamics. These shocks in fact add a lot of volatility to the model.

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. The study by Balleer and van Rens (2008) contains evidence that these effects may be explained through a distinction between high- and low-skilled labor in production. Since the identified technology shocks are (possibly) biased towards the productivity of high-skilled labor, low-skilled labor gets substituted out of production. Further results in this paper show that the "job finding 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 different specifications, I distinguish technology shocks that are factor-neutral or investment-specific as in Galí (1999) and Fisher (2006). I document that the two main results are robust to these extensions. 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, these shocks cannot be interpreted in the context of the standard model. From Balleer and van Rens (2008), it is reasonable to assume that these shocks are the same as skill-biased technology shocks in their paper. Technology shocks that are skill-biased induce similar dynamics in the investment price and the labor market as the shocks identified here. This result again provides empirical foundation to allowing for a more sophisticated production function in this class of model in which low- and high-skilled labor are substitutable in production.

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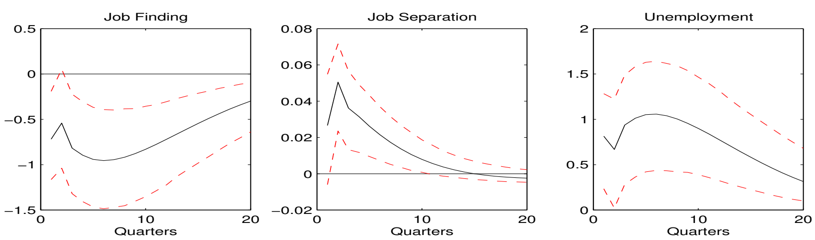
Appendix

A Robustness

A.1 Are the estimated shocks really technology shocks?

Many researchers have questioned that the structural residuals that are identified from a Galí-style VAR are in fact estimates of technological progress. Supporting the findings from Galí, a recent piece of evidence from Basu et al. (2006) has documented that their measure of technological progress, derived as a "sophisticated" Solow residual from a very different exercise, also induces a contractionary effect on hours worked. Here, I use this measure in order to support the effect of technology on the job finding and separation rate from my estimation in two different ways. First, I incorporate "true" total-factor-productivity (TFP) instead of labor productivity into my SVAR with long-run restrictions. Neutral technology shocks are then the only shocks that move TFP in the long run. As depicted in Figure 4, the effects of these shocks on the job finding rate, the job separation rate and unemployment are very similar to the ones from the estimation with labor productivity. Second, as suggested by Basu et al. (2006), I regress four lags of their technology measure (dz) on job finding and job separation. Here, I detrend the two rates as in the VAR by regressing them on a dummy trend broken at 1973:2 and 1997:1. Table 4 shows the results, for impulse-responses, one could simply add the estimated coefficients. Here, TFP has a negative effect on the job finding rate. The effect on the job separation rate is also negative, but since this effect is small (and insignificant), unemployment still increases after a shock to TFP.

Figure 4: Impulse-Responses to BFK Technology Shocks



Notes: Responses in percentage points to a positive one-standard-deviation shock. Confidence intervals are 68% Bayesian bands.

A.2 Specification

This section investigates the robustness of the main results from the Fisher identification. As documented above, the neutral shocks from the Fisher identification and the Galí identification are very similar in fact. The robustness analysis focusses on the two main results: The low standard deviation conditional on neutral and invest-ment-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 5 summarizes the results.

The first set of robustness checks deals with the prior and the lag length in the estimation of the reduced form VAR. Clearly, the baseline specification with the Minnesota prior is different from a standard OLS specification with 2 to 4 lags in the VAR. In the Minnesotay prior, 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 (OLS equivalent) 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

Table 4: Regression on BFK Measure

Dependent variable	Regressor				
	dz	dz(-1)	dz(-2)	dz(-3)	dz(-4)
JFinding	-0.6250*	-0.3429	-0.4441*	-0.5339*	-0.3447
JSeparation	-0.1473	0.0305	-0.0835	-0.1753	-0.1848

Notes: The star * denotes significance based on one standard error bands.

Table 5: Robustness of the Fisher Identification

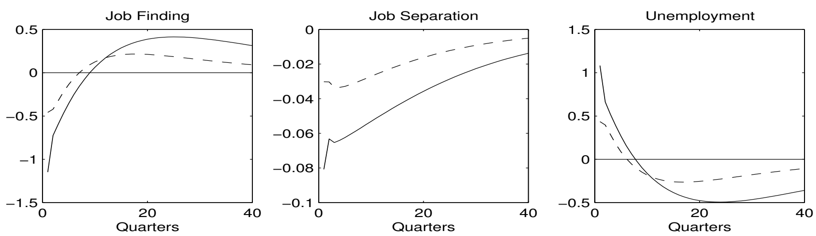
	Conditional Standard Deviation				Impulse Response	
	Job Finding		Unemployment		Job Finding	
	i-shock	n-shock	i-shock	n-shock	i-shock**	n-shock
Baseline	0.0627	0.0667	0.0692	0.0972	-,sign.	-,sign.
Baseline specification with Minnesota prior changed to						
4 lags, decay 7	0.0651	0.071	0.0808	0.1129	-,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.

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 11 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.

Figure 5: Shimer versus Fujita-Ramey



Notes: Solid lines depict Shimer data, broken lines show Fujita and Ramey data. Responses in percentage points to a positive one-standard-deviation shock. Confidence intervals are 68% Bayesian bands.

A.3 Data

The worker flow data of Shimer and the respective business-cycle facts are not uncontroversial in the literature. Fujita and Ramey (forthcoming) have also calculated worker flows from the CPS. The Fujita and Ramey dataset does not encompass the same sample as the one by Shimer; it ranges from 1976:3 to 2004:4[34]. As stated by the authors, the standard deviation of the

[34] I thank Shigeru Fujita for making the data available to me.

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. Figure 5 shows that the responses in both datasets are quite similar. Note that job separation decreases after a positive technology shock. However, this is mainly due to the subsample rather than the difference in the measurement of the data. In fact, results for the job separation rate are not robust to subsample choices or different specifications.

B Additional Tables and Graphs

Table 6: Variance Decomposition in Fisher Identification

	Investment-specific Shock				Neutral Shock			
Quarters	1	8	16	32	1	8	16	32
Price	59.27	78.02	86.83	93.30	6.55	4.47	3.07	1.58
	(31,79)	(52,91)	(68,95)	(83,98)	(1,27)	(1,20)	(0,14)	(0,7)
Productivity	13.50	14.12	12.94	11.46	68.33	76.50	82.49	86.43
	(8,19)	(11,18)	(11,16)	(10,13)	(50,78)	(67,82)	(77,86)	(84,88)
JFinding	15.92	6.73	6.23	6.28	46.86	42.34	42.98	42.70
	(8,23)	(4,12)	(3,11)	(3,11)	(28,59)	(18,58)	(19,58)	(19,58)
JSeparation	1.87	3.02	3.46	3.62	19.27	21.26	21.15	21.59
	(0,9)	(1,11)	(1,11)	(1,11)	(3,41)	(4,43)	(5,43)	(5,43)
Unemployment	15.19	6.38	6.00	6.02	49.44	43.54	43.86	43.48
	(8,22)	(3,12)	(3,11)	(3,10)	(31,61)	(19,59)	(20,59)	(19,59)

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. The point estimate is the median, the confidence intervals are 68% Bayesian bands from the posterior distribution. All numbers are percent.

Table 7: Galí Identification with Standard Detrending

	Uncond. Sample	Model I	Model II	Conditional Moments Technology	Conditional Moments Residual
A: Standard Deviations					
JFinding	0.1019	0.0407	0.0251	0.0327	0.0835
				(0.02,0.05)	(0.07,0.10)
JSeparation	0.0497			0.0255	0.0444
				(0.02,0.03)	(0.04,0.05)
Unemployment	0.1181	0.041	0.0252	0.0479	0.0928
				(0.03,0.07)	(0.08,0.11)
Productivity	0.0105	0.0105	0.0066	0.0066	0.009
				(0.00,0.01)	(0.00,0.01)
B: Autocorrelations					
JFinding	0.8137	0.8008	0.8031	0.7939	0.7688
				(0.68,0.87)	(0.71,0.80)
JSeparation	0.4409			0.7408	0.3913
				(0.66,0.83)	(0.32,0.44)
Unemployment	0.8345	0.6784	0.6791	0.7325	0.8136
				(0.64,0.79)	(0.79,0.83)
Productivity	0.6881	0.6651	0.6651	0.7161	0.7286
				(0.64,0.80)	(0.70,0.76)
C: Cross-Correlations					
JFind.,Prod.	0.1443	0.9522	0.9532	-0.7619	0.5986
				(-0.87,-0.48)	(0.45,0.72)
JSep.,Prod.	-0.4826			0.4837	-0.6975
				(0.22,0.63)	(-0.80,-0.60)
Unemp.,Prod.	-0.3051	-0.6943	-0.696	0.7441	-0.8329
				(0.55,0.84)	(-0.89,-0.72)
JFind.,Unemp.	-0.9254	-0.8405	-0.8408	-0.908	-0.8984
				(-0.96,-0.75)	(-0.92,-0.86)
JSep.,Unemp.	0.6346			0.8453	0.5455
				(0.68,0.91)	(0.44,0.61)
JFind.,JSep.	-0.2947			-0.5102	-0.1169
				(-0.71,-0.04)	(-0.22,0.05)

Notes: All series are detrended with the HP-Filter with $\lambda = 1600$. The point estimate is the median, the confidence intervals are 68% Bayesian bands from the posterior distribution. Calibration I of the model matches the unconditional standard deviation of labor productivity, calibration II matches the same moment, conditional on technology shocks.

Table 8: Historical Decomposition of Fisher Identification

	Uncond. Sample	Model	Conditional Moments Inv. Tech.	Neu. Tech.	All Tech.	Residual
A: Standard Deviations						
Find.	0.1542	0.0775	0.0684	0.0741	0.0671	0.1283
		(0.0717)	(0.05,0.09)	(0.05,0.11)	(0.05,0.09)	(0.11,0.15)
Sep.	0.062		0.0401	0.048	0.0512	0.0543
			(0.03,0.05)	(0.04,0.06)	(0.04,0.06)	(0.05,0.06)
Unemp.	0.1786	0.0708	0.0658	0.0996	0.088	0.1434
		(0.0657)	(0.05,0.09)	(0.06,0.14)	(0.07,0.12)	(0.12,0.17)
Prod.	0.0156	0.0156	0.0185	0.0184	0.0129	0.016
		(0.0129)	(0.01,0.02)	(0.02,0.02)	(0.01,0.01)	(0.01,0.02)
B: Autocorrelations						
Find.	0.9128	0.8655	0.7116	0.8182	0.8771	0.9009
		(0.8671)	(0.62,0.82)	(0.69,0.89)	(0.81,0.92)	(0.87,0.92)
Sep.	0.6336		0.9245	0.8984	0.8757	0.6389
			(0.85,0.96)	(0.83,0.95)	(0.82,0.92)	(0.59,0.70)
Unemp.	0.9218	0.8607	0.7692	0.8326	0.9045	0.9143
		(0.8632)	(0.67,0.88)	(0.74,0.88)	(0.87,0.93)	(0.90,0.92)
Prod.	0.8507	0.8482	0.9055	0.8597	0.8909	0.9253
		(0.855)	(0.85,0.95)	(0.80,0.91)	(0.87,0.92)	(0.91,0.94)
C: Cross-Correlations						
JF,P	0.0567	0.5141	-0.1674	-0.5569	-0.3274	0.6979
		(0.4087)	(-0.38,0.11)	(-0.29,-0.70)	(-0.55,0.01)	(0.57,0.79)
JS,P	-0.4392		-0.4355	0.2757	0.2059	-0.6298
			(-0.61,-0.21)	(0.03,0.46)	(-0.02,0.38)	(-0.73,-0.53)
U,P	-0.1858	-0.4427	-0.0838	0.5323	0.3431	-0.821
		(-0.3506)	(-0.44,0.19)	(0.27,0.67)	(0.03,0.55)	(-0.89,-0.72)
JF,U	-0.9558	-0.8718	-0.8394	-0.9147	-0.8606	-0.9409
		(-0.8749)	(-0.92,-0.72)	(-0.79,-0.97)	(-0.94,-0.75)	(-0.91,-0.95)
JS,U	0.6845		0.3897	0.794	0.7584	0.5997
			(0.06,0.65)	(0.60,0.88)	(0.58,0.85)	(0.51,0.66)
JF,JS	-0.4404		0.2296	-0.4877	-0.3075	-0.2893
			(-0.12,0.52)	(-0.17,-0.69)	(-0.58,0.11)	(-0.17,-0.38)

Notes: All series are detrended with the smooth HP-filter as in Shimer (2005a). The point estimate is the median, the confidence intervals are 68% Bayesian bands from the posterior distribution. The model is calibrated to match the unconditional standard deviation of labor productivity and the same figure that is conditional on both technology shocks (in brackets).

Table 9: Variance Decomposition in Fisher Identification - Job Flows

	Investment-specific Shock				Neutral Shock			
Quarters	1	8	16	32	1	8	16	32
Price	76.39	92.80	96.60	98.39	4.44	0.91	0.42	0.20
	(54,90)	(82,98)	(91,99)	(96,100)	(0,19)	(0,5)	(0,2)	(0,1)
Productivity	12.15	11.94	11.01	10.50	80.46	85.85	87.87	88.94
	(9,15)	(11,13)	(10,12)	(10,11)	(73,85)	(84,88)	(87,89)	(88,89)
JCreation	6.32	6.84	7.04	7.05	3.93	10.19	10.45	10.45
	(1,14)	(3,13)	(3,12)	(3,12)	(0,15)	(3,24)	(3,24)	(3,24)
JDestruction	1.37	4.60	4.66	4.66	15.77	11.79	11.81	11.81
	(0,5)	(2,12)	(2,12)	(2,12)	(2,40)	(4,31)	(4,31)	(4,31)
Unemployment	1.35	6.12	6.12	6.12	8.20	9.11	9.28	9.27
	(0,6)	(2,13)	(2,13)	(2,13)	(1,26)	(3,21)	(3,22)	(3,22)

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. The point estimate is the median, the confidence intervals are 68% Bayesian bands from the posterior distribution. All numbers are percent.

Table 10: Variance Decomposition in Sign Identification

	Investment-specific Shock				Investment-unspecific Shock			
Quarters	1	8	16	32	1	8	16	32
Productivity	24.66	28.25	29.67	31.68	46.85	59.75	63.89	65.10
	(2,59)	(3,67)	(3,70)	(3,74)	(18,77)	(23,86)	(24,91)	(24,93)
Price	27.75	35.71	38.80	37.82	11.45	24.53	39.06	51.75
	(7,52)	(10,61)	(9,68)	(8,74)	(1,36)	(4,53)	(9,69)	(16,82)
JFinding	16.86	6.44	6.00	5.90	3.54	9.88	12.93	13.42
	(4,33)	(2,18)	(2,17)	(2,17)	(0,14)	(3,28)	(4,31)	(4,31)
JSeparation	2.69	2.98	3.06	3.10	17.87	15.26	14.50	14.51
	(0,13)	(1,12)	(1,12)	(1,12)	(6,36)	(5,34)	(5,33)	(5,32)
Unemployment	16.38	6.35	5.91	5.83	4.09	10.62	13.61	14.00
	(4,34)	(2,18)	(2,17)	(2,17)	(0,16)	(3,30)	(4,32)	(4,32)

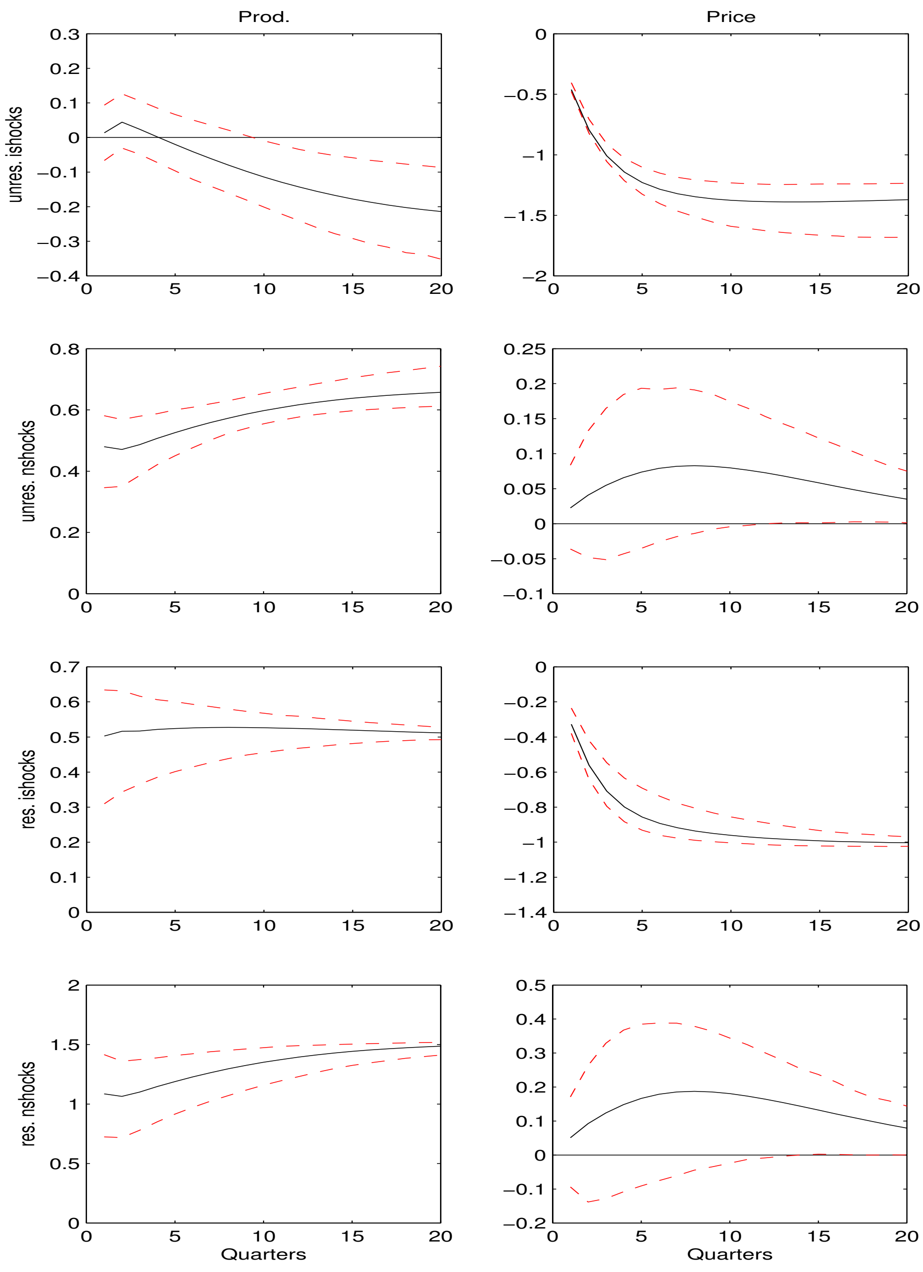
The values for the investment-specific shock, the investment-unspecific shock and the (omitted) residual disturbances add up to 100 for each variable at each time horizon. The point estimate is the median, the confidence intervals are 68% Bayesian bands from the posterior distribution. All numbers are percent.

Table 11: Historical Decomposition of Sign Identification

	Uncond. Sample	Conditional Moments I-Specific	I-Unspecific	Both Shocks	Residual
A: Standard Deviations					
Find.	0.1542	0.0456	0.051	0.0643	0.1242
		(0.04,0.07)	(0.04,0.07)	(0.05,0.09)	(0.10,0.15)
Sep.	0.062	0.0408	0.0499	0.0527	0.0535
		(0.03,0.05)	(0.04,0.06)	(0.04,0.06)	(0.05,0.06)
Unemp.	0.1786	0.0538	0.0742	0.088	0.139
		(0.04,0.08)	(0.05,0.10)	(0.07,0.11)	(0.12,0.16)
Prod.	0.0156	0.0122	0.0109	0.0127	0.0156
		(0.01,0.01)	(0.01,0.01)	(0.01,0.01)	(0.01,0.02)
B: Autocorrelations					
Find.	0.9128	0.8091	0.9436	0.8653	0.9028
		(0.70,0.91)	(0.90,0.96)	(0.79,0.91)	(0.87,0.92)
Sep.	0.6336	0.9374	0.8886	0.8634	0.6507
		(0.88,0.96)	(0.83,0.94)	(0.80,0.92)	(0.59,0.71)
Unemp.	0.9218	0.897	0.9185	0.8992	0.9137
		(0.83,0.95)	(0.89,0.95)	(0.87,0.92)	(0.90,0.92)
Prod.	0.8507	0.92	0.9381	0.8929	0.9225
		(0.88,0.97)	(0.89,0.98)	(0.87,0.92)	(0.90,0.94)
C: Cross-Correlations					
JF,P	0.0567	0.003	-0.0897	-0.3597	0.7118
		(-0.46,0.29)	(-0.47,0.21)	(-0.53,-0.04)	(0.58,0.80)
JS,P	-0.4392	-0.1501	-0.1297	0.235	-0.6269
		(-0.58,0.33)	(-0.51,0.30)	(-0.02,0.40)	(-0.73,-0.54)
U,P	-0.1858	-0.1624	-0.0406	0.3822	-0.8218
		(-0.65,0.46)	(-0.48,0.44)	(0.05,0.56)	(-0.91,-0.76)
JF,U	-0.9558	-0.7386	-0.8048	-0.8396	-0.9408
		(-0.90,-0.55)	(-0.92,-0.61)	(-0.93,-0.70)	(-0.95,-0.91)
JS,U	0.6845	0.6339	0.7937	0.7583	0.5913
		(0.33,0.86)	(0.64,0.88)	(0.64,0.86)	(0.51,0.66)
JF,JS	-0.4404	0.1652	-0.2492	-0.2512	-0.2781
		(-0.46,0.47)	(-0.59,0.19)	(-0.57,0.04)	(-0.38,-0.15)

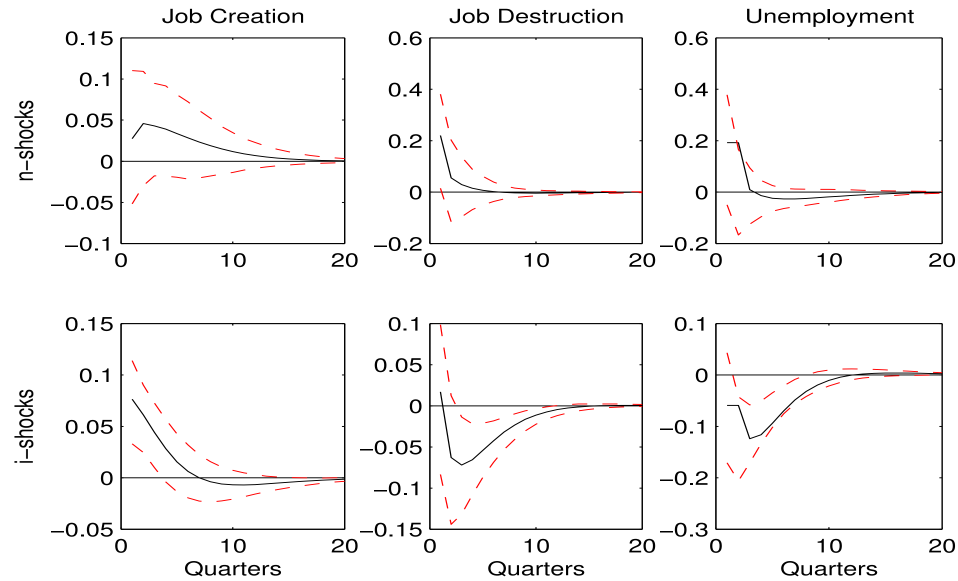
Notes: All series are detrended with the smooth HP-filter as in Shimer (2005a). The point estimate is the median, the confidence intervals are 68% Bayesian bands from the posterior distribution.

Figure 6: Restricted and unrestricted Fisher Identification



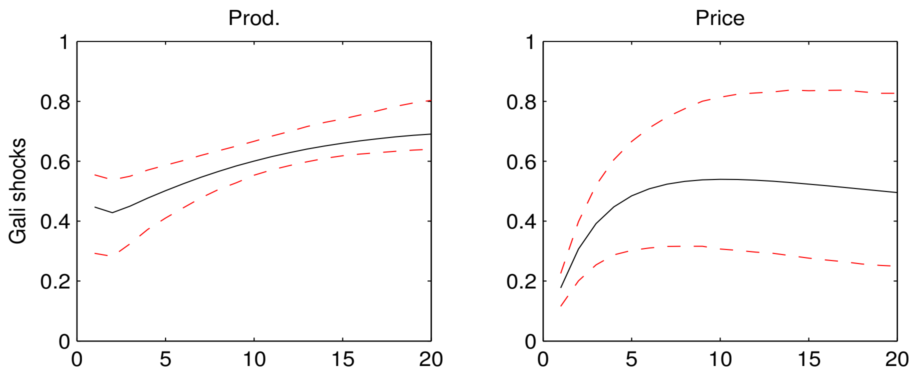
Notes: Responses in percent to a positive one-standard-deviation shock.
Confidence intervals are 68% Bayesian bands.

Figure 7: Job Flow Responses to Fisher Technology Shocks



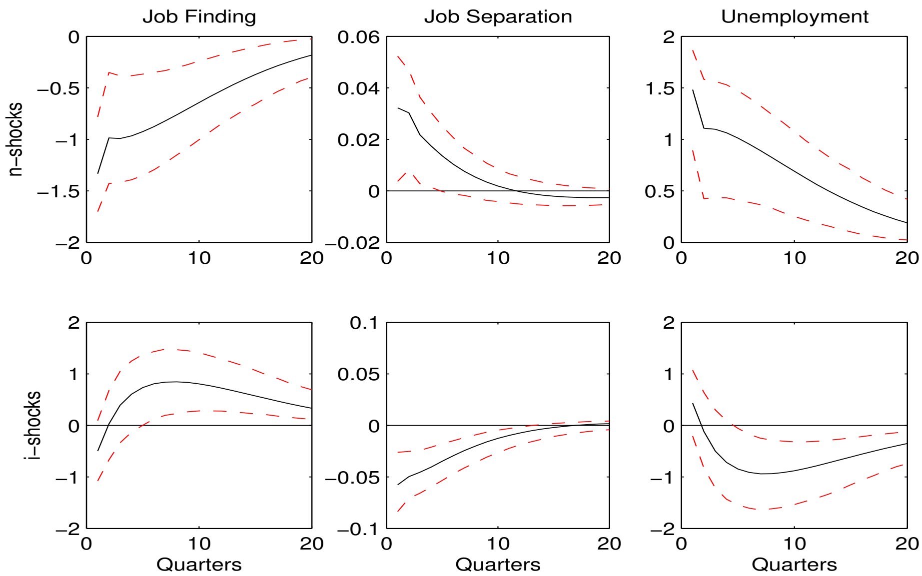
Notes: Percentage responses to a positive one-standard-deviation shock.
Confidence intervals are 68% Bayesian bands.

Figure 8: Impulse-Responses to Galí Technology Shocks



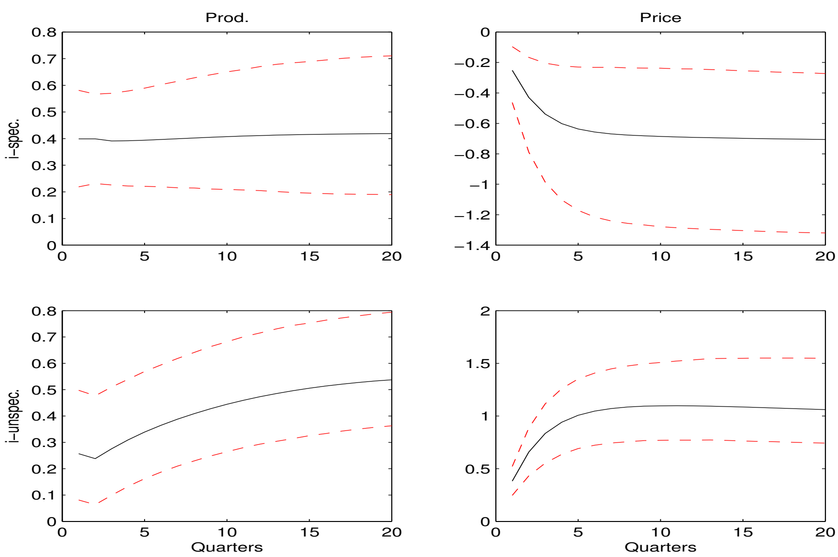
Notes: Percent responses to a positive one-standard-deviation shock.
Confidence intervals are 68% Bayesian bands.

Figure 9: Unrestricted Fisher Technology Shocks



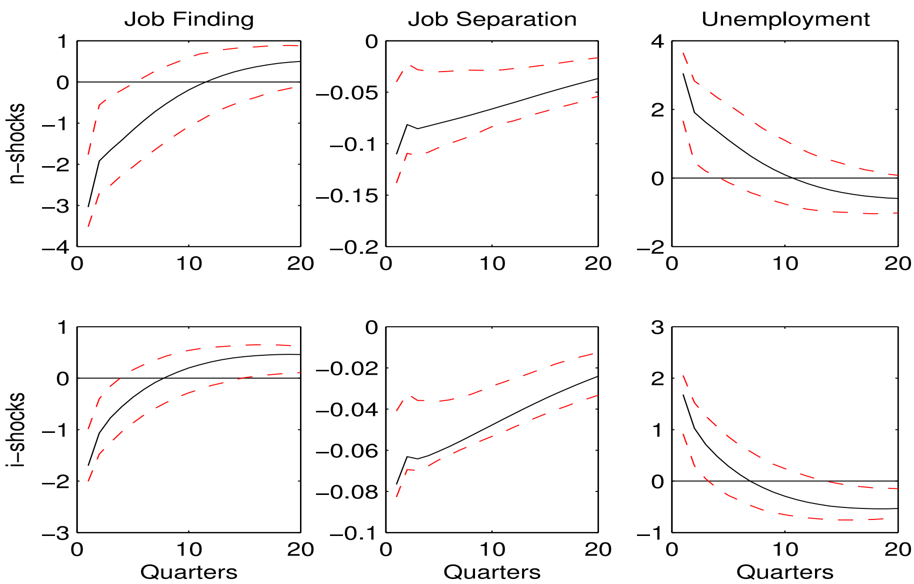
Notes: Percentage responses to a positive one-standard-deviation shock. Confidence intervals are 68% Bayesian bands.

Figure 10: Sign Identification - Price and Productivity



Notes: Responses in percentage points to a one-standard deviation shock. Confidence intervals are 68% Bayesian bands.

Figure 11: Fisher Technology Shocks - No Trend



Notes: Percentage responses to a positive one-standard-deviation shock. Confidence intervals are 68% Bayesian bands.