

New evidence, old puzzles: Technology shocks and labor market dynamics

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Can the standard search-and-matching labor market model replicate the business cycle fluctuations of the job finding rate and the unemployment rate? In the model, these fluctuations are driven by movements in productivity. This paper investigates the sources of productivity fluctuations that are commonly interpreted as technology shocks. I estimate different types of technology shocks from structural vector autoregressions and reassess the empirical performance of the standard model based on second moments that are conditional on technology and nontechnology (preference) shocks. Most prominently, the model is able to replicate the conditional volatilities of job finding and unemployment. However, it fails to replicate the correlation of productivity with unemployment and job finding that is conditional on both technology and nontechnology shocks.

KEYWORDS. Labor market dynamics, technology shocks, structural VAR, search and matching, business cycle.

JEL CLASSIFICATION. E24, E32, O33.

1. INTRODUCTION

How well can the standard search-and-matching framework explain the large movements into and out of employment that we observe in U.S. business cycles? This question has been one of the most controversially discussed issues in the recent macro-labor literature. Fueled by [Shimer \(2005\)](#), the debate has centered around the ability of the search-and-matching model to propagate shocks to labor productivity such that the model can replicate the high volatilities of the job finding rate and the unemployment rate that are observed in the data.

Against this background, this paper investigates the sources of fluctuations in labor productivity and how these relate to the volatility and co-movements of the labor market variables over the business cycle. In the view of the standard search-and-matching model, “a change in labor productivity is most easily interpreted as a technology or supply shock” (as [Shimer \(2005\)](#) phrases it). In fact, the dynamics in the baseline Mortensen–Pissarides model and its many extensions that allow for risk aversion,

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capital accumulation, or an explicit production technology stand in the tradition of the real-business-cycle (RBC) literature.¹ Next to technology shocks, other structural disturbances, generally referred to as nontechnology or demand shocks, have been advocated to play an important role for the business cycle fluctuations of labor market variables. Hall (1997), for example, documented the importance of preference shocks, that is, shocks that change the marginal rate of substitution between consumption and leisure, for the cyclical fluctuations of hours worked.

Here, I readdress the empirical performance of the search-and-matching model based on standard deviations and correlations that are conditional on structural shocks rather than on the overall unconditional sample moments. For this purpose, I compare the second moments from a model that allows for both technology and nontechnology shocks to their conditional equivalents in the data. The latter are estimated using a structural vector autoregression (VAR) with long-run restrictions. As in Galí (1999), the main assumption that is used to separate technology shocks from nontechnology shocks is that they are the only shocks that affect labor productivity in the long run. This assumption holds in a large class of models including RBC and New Keynesian setups. It should be noted that this aggregate concept of technology shocks both theoretically and empirically may encompass phenomena not directly related to technological progress such as permanent demand shifts between sectors.

The structural VAR is estimated on quarterly U.S. data incorporating the worker flow data calculated by Shimer from the Current Population Survey (CPS). Conditional standard deviations enable us to investigate whether the model sufficiently propagates the respective shocks, how the conditional volatilities translate into the overall volatility of productivity and the labor market variables, and, hence, whether this provides new information with respect to the Shimer debate. More importantly, the conditional correlations between productivity and the labor market variables reveal potentially different and counteracting dynamics that are generated by the different shocks and that are encompassed by the unconditional correlations. In fact, I show that since conditional and unconditional moments substantially differ in this case, a judgement of the model that is based on unconditional moments only may be very misleading.

A simple version of a search-and-matching model provides the benchmark moments to which the empirical conditional and unconditional moments will be compared. This model nests search-and-matching in a real-business cycle and growth setup with frictions on the labor market as in Merz (1995) or Andolfatto (1996). Hence, it is not identical to the original setup introduced by Mortensen and Pissarides (1994) and used by Shimer (2005), but designed to be comparable to the output from the structural VAR. Growth in this model is driven by permanent technology shocks, modeled as a random walk with drift. These shocks then satisfy the long-run restrictions in the structural VAR. Driven by technology shocks only, this model reflects similar problems with respect to the propagation of these shocks as the standard model that is discussed in Shimer. Over the business cycle, the model allows for different sources of variation in

¹Well known examples that use search and matching in an RBC context include Merz (1995), Andolfatto (1996), and den Haan, Ramey, and Watson (2000).

labor productivity and hence labor market variables, here both technology and preferences shocks.

Comparing the output from the model to the conditional and unconditional moments in the data, 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 only. Consequently, the Shimer critique of the model with respect to its lack of volatility does not apply when the empirical performance is based on moments that are conditional on technology shocks. To replicate the unconditional moments in the data, the standard model should, therefore, be augmented by additional nontechnological sources of fluctuations rather than with respect to a better propagation of technology shocks as suggested in the literature (see [Hall \(2005\)](#), [Shimer \(2005\)](#), [Hagedorn and Manovskii \(2008\)](#), and many others). I show that preference shocks work well in this respect.

As an additional result, job separations significantly move after both types of estimated structural shocks. This means that it is not reasonable to assume that the job separation rate is constant over the business cycle (as has been done by many contributions to the literature).

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. From the viewpoint of the standard model, this result constitutes a “job finding puzzle” 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 is Shimer’s “volatility in unemployment puzzle”. Hence, this result supports models that are able to incorporate these effects. Since the correlations of these two variables with productivity that is conditional on technology shocks are of opposite sign to the respective unconditional moments, nontechnology shocks are once more necessary to fully describe the overall dynamics in the data. I show that preference shocks are not suitable to explain the remaining variation in the data.

The use of long-run restrictions to identify technology shocks and the empirical dynamics that are induced by these shocks has been harshly criticized, most prominently by [Chari, Kehoe, and McGrattan \(2008\)](#). I address their critique in various ways. First, I account for the “lag-truncation bias,” the fact that a VAR cannot be estimated with an infinite number of lags as would correspond to the inverted solution of the respective model. For this, I estimate the VAR with a Minnesota prior, adjusting the weight of the

lags such that I can incorporate more past information (as suggested by [Canova, Lopez-Salido, and Michelacci \(2010\)](#)). Second, I simulate data from the baseline model and show that my structural identification can reveal the theoretical impulse responses of the technology and nontechnology shocks. Third, I compare the results driven by the estimated technology shocks to the dynamics induced by an alternative measure from [Basu, Fernald, and Kimball \(2006\)](#) and document robustness of my results in this respect.

The results are robust when allowing for investment-specific technology shocks. [Fisher \(2006\)](#) motivated the separate identification of investment-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 also have a negative long-run effect on the price of investment goods relative to consumption goods. In line with Fisher, investment-specific technology shocks are identified in the data through the assumption that, in the long run, they affect the relative price of investment negatively and labor productivity positively and in a certain ratio to the effect of neutral shocks on this variable. I document that both in the model and in the data, investment-specific technology shocks behave similar to neutral technology shocks.

I am not the first investigator to address conditional moments with respect to labor market dynamics. [Michelacci and Lopez-Salido \(2007\)](#), [Ravn and Simonelli \(2008\)](#) or [Canova, Lopez-Salido, and Michelacci \(2007\)](#) and [Barnichon \(2012\)](#) have also used long-run restrictions in structural VARs to investigate the effect of different shocks on either job flows, worker flows, or vacancies and unemployment. Different from these contributions, this paper uses these conditional moments to address the empirical validity of the baseline search-and-matching model. By investigating the sources of fluctuations in labor productivity and thereby highlighting the discrepancies between conditional and unconditional moments, this paper seeks to shed new light on ongoing debates like the Shimer puzzle. This involves not only the role of technology shocks, but also preference shocks as proposed by [Hall \(1997\)](#). It is important to document that labor market fluctuations are not only driven by different shocks, but also that these different shocks induce counteracting dynamics on the labor market. Furthermore, this paper is the first that actually tests whether the structural VAR correctly addresses the empirical performance of the baseline model through the simulation exercise mentioned above.

Complementary to these studies, there exist many contributions in the literature that estimate medium or large scale dynamic stochastic general equilibrium (DSGE) models that incorporate search-and-matching in the labor market.² Here, technology shocks are usually identified based on a combination of short-run sign restrictions as in [Fujita \(2011\)](#) or [Braun, De Bock, and DiCecio \(2006\)](#). 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.

²See, for example, [Mandelman and Zanetti \(2008\)](#).

The remainder of this paper is organized as follows. Section 2 presents the model that is used as a benchmark for the unconditional and conditional moments. The baseline identification of technology shocks, and details on the specification and estimation results are documented in Section 3. Section 3 also discussed some robustness of the results, while most details regarding robustness along various dimensions are provided in the Appendices B and C. Section 4 concludes.

2. A STANDARD LABOR MARKET MODEL

2.1 The model

The standard labor market framework referred to in the following discussion nests search-and-matching on the labor market within a real-business-cycle (RBC) and growth model as in Merz (1995).³ The model comprises the subsequent equations

$$\max_{\{C_t, N_{t+1}, V_t, K_{t+1}\}_{t=0}^{\infty}} E_0 \sum_{t=0}^{\infty} \beta^t \left(\chi \ln(C_t) - \frac{N_t^{1+\phi}}{1+\phi} \right)$$

subject to

$$A_t K_t^\alpha N_t^{1-\alpha} \geq C_t + X_t + a V_t Z_t,$$

$$K_{t+1} \leq (1 - \delta) K_t + I_t X_t,$$

$$N_{t+1} = (1 - \psi) N_t + \mu V_t^{1-\eta} (1 - N_t)^\eta.$$

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. Merz (1995) has shown that the social planner representation is equivalent to a decentralized problem in which workers and firms bargain over the wage if the Hosios condition holds. In order to generate results that are comparable with most studies in the literature (Merz (1995), Shimer (2005), Mortensen and Nagypal (2007)), I assume the Hosios condition, that is the bargaining weight is implicitly set equal to the matching elasticity in this setup.

Growth and business cycle fluctuations originate in the following exogenous process for the general purpose technology A_t :

$$A_t = \exp(\gamma + \varepsilon_{at}) A_{t-1}.$$

³Note that this model uses a version of Merz's model without endogenous search effort and therefore abstracts from labor adjustment along an additional margin. It is therefore better comparable to the model presented in Shimer (2005). Furthermore, unlike the model with endogenous effort, it replicates the Beveridge curve relationship, that is a negative correlation between unemployment and vacancies.

Shocks to A_t will be called neutral technology shocks in the following. Neutral technology shocks have permanent effects and, hence, output, consumption, the capital stock, investment and labor productivity grow at the rate $\frac{\gamma}{1-\alpha}$ along a balanced growth path. The long-run effect of technology shocks on labor productivity will serve as the identifying restriction in the estimation in Section 3. The variable I_t measures the price of new investment goods relative to consumption goods and is assumed to be constant. This assumption will be relaxed in Section 3.2.3 when we allow for permanent investment-specific technology shocks. Employment, unemployment and vacancies are stationary.⁴

Over the business cycle, positive neutral technology shocks increase labor productivity and, hence, the incentive of firms to post vacancies. As a consequence, the job finding rate rises after a positive technology shock, while unemployment falls. It is further straightforward to add any other, nonpermanent nontechnological 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. Hall (1997) suggested preference shocks as an important driving force of labor market fluctuations. I consider preference shocks as shocks to the marginal rate of substitution between consumption and leisure. This means that the parameter χ is replaced by a stochastic process of the form $\ln(x_t) = \rho_x \ln(x_{t-1}) + \varepsilon_{x,t}$. As agents want to consume more the higher is x_t , they save less, and capital and output fall. At the same time, agents would like to work more. Within a search-and-matching context, this intuitively means that agents would accept a lower wage to become employed, which increases the incentives for firms to post vacancies and increases employment. As a consequence, labor productivity falls after a preference shock of this sort.

The labor market model outlined above differs in many respects from the standard Mortensen and Pissarides (1994) model. Utility is not linear, but follows the standard assumptions in the RBC literature. In addition, due to the explicit modeling 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. Moreover, the identifying assumptions that I use in the empirical assessment are fulfilled in this framework. While the original Mortensen–Pissarides model potentially accounts for permanent productivity (or neutral) technology shocks, it does not allow for investment-specific technology shocks or other, potentially counteracting, sources of variation in labor productivity. When addressing issues like the Shimer debate on volatility, features like risk aversion and the possibility of saving will increase the model-generated volatility compared to the version in Shimer. In that sense, an RBC setup enhances the performance of the model when viewing Shimer’s productivity shocks as technology shocks. Different to Shimer, the central question here is not whether a model with technology shocks can replicate the overall unconditional moments. Instead, I want to investigate whether the model can match the empirical moments that are conditional on different structural shocks and how this can help to replicate the overall unconditional moments as well.

⁴Hence, vacancies are multiplied by $Z_t = A_t^{1/(1-\alpha)} I_t^{\alpha/(1-\alpha)}$ in the budget constraint.

2.2 Calibration and simulation

To motivate the empirical assessment based on conditional moments, I start by considering the empirical performance based on unconditional moments. If we believe that productivity shocks are (mainly) technology shocks, these shocks should, in fact, be able to generate both the conditional and the unconditional data moments. For this, I calibrate the model and generate artificial time series from the model, compute the respective second moments, and compare them to the empirical moments. I use quarterly time series data for the United States from 1955:1 to 2004:4, which is also used in the empirical specification below. The job finding and separation rates are taken from the worker flow data produced by Robert Shimer.⁵ Labor productivity (output per hours of all persons) is the standard nonfarm business measure provided by the U.S. Bureau of Labor Statistics.

The baseline calibration is shown in Table 1. I set the capital share $\alpha = 0.36$ in order to match a labor share of 64% as in Hansen (1985) and McGrattan and Prescott (2010). The value of α and a technology growth rate of 0.33% replicate the mean growth rate of labor productivity in my sample which is 0.52%. Given these values, the time discount factor $\beta = 0.9952$ then generates an annual real interest rate of 4.1% in the model, which is in line with McGrattan and Prescott (2005). For a comparable sample, Ríos-Rull and Santaaulàlia-Llopis (2010) provide annual values for the ratios of capital and consumption to output, which I use to calibrate the quarterly depreciation rate of capital to $\delta = 0.0217$.

In the utility function, I set $\chi = 1$ in order to formulate preferences in line with Merz (1995). This will also be the mean value of the stochastic process in the specification with preference shocks. The parameter $\phi = 0.5$ imposes a Frisch elasticity of 2 in the baseline model. This number is regarded as the consensus macro estimate of this elasticity according to Chetty, Guren, Manoli, and Weber (2011). In line with Mortensen and Nagypal (2007), the elasticity of the matching function with respect to unemployment is

TABLE 1. Baseline calibration of the model.

Parameter		Calibration Target
Capital share in production	$\alpha = 0.36$	Labor share of 64%
Growth rate technology shock	$\gamma = 0.0033$	Qtly. mean prod. growth rate of 0.52%
Discount factor	$\beta = 0.9952$	SS annual interest rate of 4.1%
Capital depreciation	$\delta = 0.0217$	Annual SS ratios $\frac{k}{y} = 2.31$ and $\frac{c}{y} = 0.75$
Parameter in utility function	$\chi = 1$	Corresponding to Merz (1995)
Parameter in utility function	$\phi = 0.5$	Frisch elasticity of 2
Matching function elasticity	$\eta = 0.46$	Mortensen and Nagypal (2007)
Constant in matching function	$\mu = 1.79$	Mtly mean job finding rate of 59%
Separation rate	$\psi = 0.11$	Mtly mean job separation rate of 3.57%
Vacancy posting cost	$a = 0.02$	SS labor market tightness $\theta = 1$

⁵This is the worker flow data officially posted on the website of Robert Shimer and documented in Shimer (2012). For additional details, see <http://home.uchicago.edu/~shimer/data/flows>.

set to $\eta = 0.46$. Based on this, the constant of the matching function ($\mu = 1.79$) 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 corresponds to the mean monthly job finding rate of 59.6% in the worker flow data over my sample. The same data delivers a mean monthly job separation rate of 3.4% which corresponds to $\psi = 0.11$.

Under the assumption of homogenous workers and a constant labor force, [Shimer \(2012\)](#) showed that the unemployment rate can be approximated by the steady state unemployment rate $\tilde{u} = \frac{js}{js+jf}$. Using the values described above, this means that the model generates a steady-state unemployment rate of 5.79%. Here, in line with [Shimer \(2005\)](#), it is assumed that the job separation rate does not move over the cycle and, therefore, does not play a role for fluctuations. This has been criticized by [Fujita and Ramey \(2009\)](#), among others. For now, I calculate unemployment rate fluctuations by setting the job separation rate equal to its sample mean. Addressing the criticism, I separately consider fluctuations in the job separation rate and the resulting movements of the unemployment rate later on.

The first column of Table 2 (model I) compares the second moments that are generated from the model driven by neutral shocks only to those in the data. Hence, $\varepsilon_{it} =$

TABLE 2. Model simulation.^a

Model Shocks	I Techn. Shocks	II Techn. Shocks	III Pref. Shocks	IV Both Shocks
A: Standard Deviations				
JFinding	0.0756	0.0576	0.1593	0.1330
data	0.1542	(0.04, 0.08)	(0.10, 0.14)	0.1542
Unemployment	0.0739	0.0563	0.1601	0.1311
data	0.1542	(0.04, 0.08)	(0.10, 0.14)	0.1542
Productivity	0.0156	0.0116	0.0166	0.0156
data	0.0156	0.0116	0.0166	0.0156
B: Autocorrelations				
JFinding	0.9175	0.9177	0.8491	0.8662
data	0.9128	(0.85, 0.95)	(0.86, 0.90)	0.9128
Unemployment	0.8424	0.8452	0.7039	0.7139
data	0.9128	(0.85, 0.95)	(0.86, 0.90)	0.9128
Productivity	0.8640	0.8628	0.9069	0.8767
data	0.8507	(0.86, 0.92)	(0.90, 0.94)	0.8507
C: Cross-Correlations				
JFind., Prod.	0.8355	0.8450	-0.8053	-0.2084
data	0.0567	(-0.66, -0.10)	(0.52, 0.77)	0.0567
Unemp., Prod.	-0.7565	-0.7663	0.8963	0.2911
data	-0.0567	(0.10, 0.66)	(-0.77, -0.52)	-0.0567

^aAll figures are obtained from data simulated from the model with the baseline calibration and shocks that are calibrated such that the respective empirical standard deviation of productivity is matched. All series are detrended with the smooth HP-filter as in [Shimer \(2005\)](#). Model I matches the overall unconditional standard deviation of productivity. Model II, driven by technology shocks only, and model III, driven by preference shocks only, match the respective conditional standard deviation of labor productivity. In model IV, the technology shock matches the conditional standard deviation of productivity and the preference shock is then calibrated such that both shocks match the overall unconditional standard deviation of productivity.

$\varepsilon_{xt} = 0$. The standard deviation of the neutral technology shock ε_{at} is then calibrated to match the standard deviation of labor productivity. Both the artificial and the actual data series are detrended with a very smooth Hodrick–Prescott (HP) filter ($\lambda = 10^5$) as in Shimer so as to relate my results directly to his. In the actual data, the standard deviation of the job finding rate and unemployment are about 10 times as large as that in labor productivity. All series are highly autocorrelated in the first lag. The job finding and unemployment rates are hardly correlated with productivity in the data.

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 less than half of those in the data. Second, the correlation of unemployment and job finding with productivity is too high in the model compared to the data. Shimer concluded that no internal propagation mechanism of labor productivity shocks exists in the model, since the real wage strongly reacts to labor productivity shocks and, hence, weakens the incentives for firms to post vacancies. To improve its empirical performance, Shimer and also Hall (2005) proposed to introduce rigid wages into the standard framework.

Note that the volatility that the model generates with respect to the labor market variables is higher than in the original model in Shimer (2005). This is partly due to the choice of certain parameters. A lower Frisch elasticity, closer to a value of 0.5 as in the micro data, and a higher cost of posting a vacancy generate smaller volatilities also in this model. The same is true when increasing the value of the matching elasticity to $\eta = 0.72$ as promoted by Shimer. In contrast, many other authors have argued that Shimer's volatility in unemployment puzzle disappears for a different calibration of the model. Hagedorn and Manovskii (2008), for example, have argued in favor of a different calibration of the outside option of the workers in combination with a lower weight of the workers in the wage bargaining. It would be straightforward to implement this calibration in a decentralized version of the model which departs from the Hosios condition. However, the calibration here serves two purposes: First, it should be relatively standard. Second, it should reflect the Shimer critique. The next section will then show that this critique vanishes once the model output is compared to conditional rather than unconditional moments.

3. MOMENTS CONDITIONAL ON TECHNOLOGY SHOCKS

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 nontechnology 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.⁶ It has to be noted that many structural disturbances other than technological innovations can affect labor productivity in the short and the medium run, but that technology shocks can be distinguished from nontechnology 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.⁷

All identification alternatives presented in the following discussion are based on the same reduced-form VAR, which contains labor productivity, the job finding rate, and the 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, Lopez-Salido, and Michelacci \(2007\)](#). The Minnesota prior incorporates a unit root in the levels of the variables included in the VAR and a fixed residual variance that 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. outlined. This addresses an often cited criticism of the VAR approach (e.g., by [Chari, Kehoe, and McGrattan \(2008\)](#)) that states that in theory one should employ a VAR with an infinite number of lags (here eight lags are employed) so as to correctly identify technology shocks using long-run restrictions. Except for the decay, I use a relatively loose prior in the estimation.⁸

Furthermore, the VAR is estimated with a trend as suggested by [Fernald \(2007\)](#) and [Canova, Lopez-Salido, and Michelacci \(2010\)](#). 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 they replicate the turning points in the job separation rate and unemployment series.⁹

The baseline specification is estimated using quarterly time series data for the United States over the sample 1955:1–2004:4. Apart from the data described in Section 2.2, the real price of investment is included in the analysis and will become important later on when we consider the effects of investment-specific technology shocks. This series consists of a price index for equipment and software, and a consumption

⁶See Appendix A.1 for further details.

⁷It does not hold in endogenous growth frameworks.

⁸The prior variance of the coefficients depends on three hyperparameters, $\phi_1 = 0.2$, $\phi_2 = 0.5$, 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 $d = 7$.

⁹See [Fernald \(2007\)](#) for empirical evidence on the trend breaks. Appendix C 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.

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 for not taking 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.¹⁰ Labor productivity and the relative price of investment are included in growth rates in the VAR, while the job finding and separation rates are included in levels. Unemployment is then deducted from the dynamics of the job finding rate and the separation rate, respectively.

3.2 Results

3.2.1 The Shimer puzzle Table 3 depicts the historical decomposition of the actual time series into the technology and nontechnology (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

TABLE 3. Historical decomposition of baseline identification.^a

	Unconditional Sample	Conditional Moments	
		Technology	Residual
A. Standard Deviations			
JFind. and Unemp.	0.1542	0.0548 (0.04, 0.08)	0.1229 (0.10, 0.14)
Productivity	0.0156	0.0116 (0.01, 0.02)	0.0166 (0.01, 0.02)
B. Autocorrelations			
JFind. and Unemp.	0.9128	0.9189 (0.85, 0.95)	0.8869 (0.86, 0.90)
Productivity	0.8507	0.8927 (0.86, 0.92)	0.9208 (0.90, 0.94)
C. Cross-Correlations			
JFind., Prod.	0.0567	-0.4360 (-0.66, -0.10)	0.6739 (0.52, 0.77)
Unemp., Prod.	-0.0567	0.4360 (0.10, 0.66)	-0.6739 (-0.77, -0.52)

^aAll series are detrended with the smooth HP filter as in [Shimer \(2005\)](#). 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.

¹⁰The series by Jonas Fisher was extended by Ricardo DiCecio. I thank both for making their data available to me.

exactly those moments in the data that have been used for judging the empirical performance of the model.¹¹

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 (model II in Table 2), the standard deviation of the job finding rate and the unemployment rate generated in the model is close to and lies within the confidence bands of the standard deviation that is conditional on technology shocks. As a result, conditional on technology shocks, the model works well to replicate the volatilities in these two central variables and, consequently, the Shimer critique does not apply.

While the technology-shock-driven 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 is still unexplained in the “residual” disturbances as depicted in the last column of Table 3. As they are important for the overall dynamics, nontechnology sources of volatility, generally referred to as demand shocks, should consequently be incorporated into the standard model.

Hall (1997) proposed a candidate for these residual shocks, namely preference shocks or shocks to the marginal rate of substitution between consumption and leisure. Hall decomposed 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, but does not use structural VAR techniques for his analysis. He shows that preference shocks account for most of the fluctuations in hours worked. Here, I investigate the extent to which these shocks can enhance the performance of the labor market model. Note that labeling the residual shocks as preference shocks potentially sums up a lot of different “demand-type” shocks, including shocks to government spending or monetary shocks.¹²

Model III of Table 2 exhibits the second moments from a model that is driven by preference shocks only and in which the law of motion of the shock is calibrated to match the standard deviation of labor productivity that is conditional on nontechnology shocks in the data (this involves $\rho_x = 0.15$ and a very high $\sigma_x = 0.31$). Hence, very large preference shifts are needed to explain this residual nontechnological variation. These shocks generate a substantial volatility in the job finding rate and unemployment that is close to the conditional standard deviation in the data. Working together, both technology and preference shocks do improve the model with respect to the overall volatility in the labor market variables as shown in model IV in Table 2.

Table 4 exhibits the full set of results, including the job separation rate and its effect on the unemployment rate. The estimated standard deviation of the job separation rate that is conditional on both technology shocks and nontechnology shocks is significantly

¹¹Note that since all data series are detrended with the HP filter, the conditional variances corresponding to the standard deviations in Table 3 do not add up to the unconditional variance.

¹²Barnichon (2012) argued that these remaining shocks are monetary policy shocks. A direct estimate of monetary policy shocks has, however, been shown to have only little influence on labor market variables that reflect the extensive margin such as worker flows or vacancies (see Ravn and Simonelli (2008)).

TABLE 4. Historical decomposition with job separation rate.^a

	Unconditional Sample	Conditional Moments	
		Technology	Residual
A. Standard Deviations			
JSeparation	0.062	0.0503 (0.04, 0.06)	0.056 (0.05, 0.06)
Unemployment	0.1786	0.0881 (0.06, 0.12)	0.1409 (0.12, 0.16)
B. Autocorrelations			
JSeparation	0.6336	0.9256 (0.89, 0.95)	0.6158 (0.59, 0.66)
Unemployment	0.9218	0.9131 (0.88, 0.93)	0.9109 (0.90, 0.92)
C. Cross-Correlations			
JSep., Prod.	−0.4392	0.3544 (0.11, 0.48)	−0.6703 (−0.74, −0.59)
Unemp., Prod.	−0.1858	0.4613 (0.17, 0.63)	−0.8014 (−0.88, −0.70)
JSep., Unemp.	0.6845	0.885 (0.80, 0.92)	0.6302 (0.56, 0.69)
JFind., JSep.	−0.4404	−0.596 (−0.76, −0.19)	−0.3167 (−0.40, −0.19)

^aAll series are detrended with the smooth HP filter as in [Shimer \(2005\)](#). 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.

positive. In addition, it contributes to a large extent to the volatility of the unemployment rate, which is substantially higher now. 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 exogenous job separation as in [den Haan, Ramey, and Watson \(2000\)](#).¹³

3.2.2 The “job finding puzzle” The conditional co-movement of the variables is depicted in panel C of Table 3 and also in the impulse responses to a 1 standard deviation technology shock in Figure 1.¹⁴ 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 those in the overall sample and are the exact contrary to what

¹³Note also that all results discussed also hold for HP-filtered data using the standard parameter $\lambda = 1600$. This is documented in Table 7 in the [Appendix](#).

¹⁴The 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.

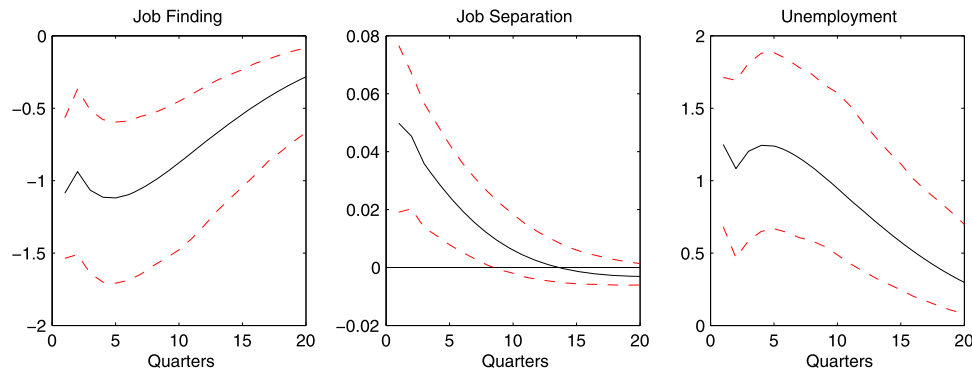


FIGURE 1. Impulse responses to Galí technology shocks. Responses are in percentage points to a positive 1 standard deviation shock. Confidence intervals are 68% Bayesian bands.

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.

This result raises three issues that are addressed subsequently. First, how important are technology shocks to explain the overall business cycle dynamics of the labor market variables. Second, can we be sure that the structural VAR recovers the correct dynamics from the actual data. Third, if technology shocks turn out to be important for the dynamics and the VAR works well to detect the conditional moments in the data, how do we explain the puzzling correlation conditional on technology shocks. Moreover, regardless of the mechanism that explains the correlations conditional on technology shocks, a model driven by these shocks is not suitable to explain the overall correlations in the data: other sources of labor market fluctuations should be taken into account.

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 nontechnology shocks, technology shocks explain up to 17% of the business cycle variance of job finding and over 20% of the variance of unemployment.¹⁵ Hence, an appropriate model should take technology-shock-driven dynamics into account.

The use of structural VARs has been widely disputed in the literature. Most prominently, Chari, Kehoe, and McGrattan (2008) argued that to trust the results from the VAR, it should be able to replicate the dynamics of the model it refers to when applied to simulated data. I do this exercise with the model presented in Section 2, allowing for the presence of both neutral technology and preference shocks. Note that here, the job finding rate increases after a positive technology shock and labor productivity falls after a preference shock, opposite to the dynamics estimated in the actual data. Nicely, the VAR

¹⁵See Table 8 for the full variance decomposition.

can reproduce the true impulse response to both shocks in the model as documented in Appendix B. To my knowledge, I am the first to actually test the use of structural VARs in the context of the search-and-matching model.

Another concern that is often raised in combination with the use of long-run restrictions in a structural VAR is the question whether we believe that these restrictions actually discover shocks that may be interpreted as technology shocks. To address this, I use an alternative data series that was carefully constructed by [Basu, Fernald, and Kimball \(2006\)](#) as a measure of “purified technology.” I use this measure instead of labor productivity in the structural VAR and show that the results are very similar to the ones documented above. I also regress lags of this series on the job finding and separation rates, the results of which support the negative effect of technology on the job finding rate. See Appendix B for details and results of this exercise.

Galí explained the drop in hours worked within a sticky price New Keynesian framework. The obvious question to ask is, therefore, whether the natural extension of this framework, including search-and-matching on the labor market, can equally explain the drop in the job 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 \(2010\)](#) documented that unemployment increases after a positive productivity shock. Here, labor market tightness and, hence, the job finding rate move together with unemployment. [Barnichon \(2012\)](#) used a similar reasoning to generate the fall in labor market tightness that he documents in a structural VAR framework similar to the one presented here. In both cases, the model is, however, not able to generate such a large and persistent fall in labor market tightness (and, consequently, the job finding rate) and respective increase in unemployment as documented here. Moreover, if agents are allowed to adjust along both the intensive and the extensive margin, short-run adjustment most likely happens through hours worked rather than employment, contradictory to the evidence provided here.

There are explanations for this empirical finding that are different from a New Keynesian setup. [Balleer and van Rens \(forthcoming\)](#) documented that the shocks that have been identified as neutral technology shocks in the Galí identification are, in fact, positively biased toward 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. Depending on the elasticity of labor supply and the degree of substitutability, 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 workers is greater 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, nontechnology shocks are

needed 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 to explain the empirical correlation of labor productivity with hours.¹⁶ 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 nontechnology 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, which induces a negative correlation of this variable with the job finding rate and a positive correlation with unemployment. Hence, preference shocks are not suitable to explain the conditional correlations within this setup.

When allowing for a more general production function with a certain degree of substitutability between different types of skilled labor, preference shocks can indeed generate a positive correlation between the job finding rate and productivity. As outlined above, capital falls after a positive preference shock. If capital and high-skilled labor are substitutes in production, the employment of high skilled workers will increase and, as they are more productive, so will labor productivity. Balleer and van Rens (forthcoming) provided evidence for capital–skill substitutability over the business cycle.

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 is specific to existing vintages. Canova, Lopez-Salido, and Michelacci (2007) employed a vintage human capital to model “Schumpeterian creative destruction” after a neutral technology shock. As is documented in greater detail in Appendix C, the sign of the job separation effect is not robust, however, in particular neither when considering different subsamples nor to the inclusion or exclusion of a trend in the estimation.

3.2.3 Robustness Based on Greenwood, Hercowitz, and Krusell (1997), Fisher (2006) 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 that these shocks are factor-neutral. Fisher proposed a strategy to separately estimate neutral and investment-specific technology shocks, and documents that the latter contribute to a larger extent 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 Mortensen and Pissarides framework, it is not possible to distinguish between these two sources of variation in labor productivity, whereas the model in Section 2 can differentiate between these two shocks. Similar to Fisher (2006), I_t can

¹⁶See, for example, Bencivenga (1992) on the Dunlop–Tarshis observation.

be referred to as investment-specific technology which makes new investment goods cheaper relative to consumption goods and consequently drives the real price of new investments down.¹⁷ As A_t , I_t follows a random walk with drift according to

$$I_t = \exp(\nu + \varepsilon_{it})I_{t-1}.$$

Through capital accumulation, investment-specific technology favors new investments, leads to new capital formation and hence has a positive effect on output and labor productivity. Just like after positive neutral technology shocks, the job finding rate increases and unemployment falls after a positive investment-specific technology shock. 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. Furthermore, the correlation between the job finding rate and productivity is less than in the model with neutral shocks only. However, these effects are not large enough to replicate the unconditional data moments.¹⁸

I estimate the effects of both neutral and investment-specific technology shocks on the labor market dynamics using the identification strategy in Fisher (2006): Only investment-specific technology shocks affect the investment price in the long run and only technology shocks (both investment-specific and neutral) may be sources of long-run fluctuations in labor productivity. In addition, the long-run effect of investment-specific technology shocks on labor productivity is equal to $\frac{\alpha}{1-\alpha}$, which is consistent with a Cobb–Douglas production function with capital share α . All of these identifying assumptions hold in the model with investment-specific technological progress.

As outlined in more detail in Appendix C, the results for the Fisher identification support all results from the baseline identification documented above: Technology shocks generate standard deviations in the job finding rate and unemployment that are close to the one produced within the model, but that are a lot smaller than the unconditional volatilities. In addition, positive investment-specific technology shocks induce a fall in the job finding rate and an increase in the unemployment rate. Over and above this assessment, Appendix C also provides the robustness of the results to changes in the specification of the reduced form VAR, such as prior, lag length or trend, as well as to the use of alternative measures of labor market dynamics in the estimation.

4. CONCLUSION

Starting from the recent ongoing debate on the empirical performance of the Mortensen–Pissarides search-and-matching model, this study provides an important contri-

¹⁷This can also be described as $\frac{1}{P_t}$. Greenwood, Hercowitz, and Krusell (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.

¹⁸When simulating 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 $\frac{1}{1-\alpha}\gamma + \frac{\alpha}{1-\alpha}\nu$. Please contact the author for a table of the model moments.

bution to the debate, as it judges the empirical performance of the model on the 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 rate and unemployment rate into the contributions of technology and non-technology shocks. These shocks are identified within a structural VAR 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 nontechnology or demand shock. To mirror the overall volatility in the data, the model should be augmented with an additional nontechnological source of volatility rather than with respect to the propagation of technology shocks as proposed by Shimer. Here, I investigate an idea from [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. I show that these shocks add a lot of volatility to the model when matching their respective conditional moments.

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. Furthermore, additional non-technological disturbances are needed to replicate the unconditional correlation between productivity, the job finding rate, and unemployment.

Both the fall in the job finding rate after technology shocks and the importance of non-technology shocks point to the fact that a more general production function is needed to understand the empirical labor market dynamics, both on a conditional and an unconditional level. A potential candidate is a production function in which high and low skilled labor are substitutes. If technology shocks as identified by the Galí identification are skill-biased as documented by [Balleer and van Rens \(forthcoming\)](#), then the substitution of low-skilled in favor of high-skilled workers can explain the drop in the total job finding rate. In addition, this type of production function could replicate the empirical labor market dynamics generated by preference shocks.

APPENDIX A: IDENTIFICATION AND ESTIMATION

A.1 *Standard Long-Run Identification*

Identification involves finding a mapping A of the residuals from a reduced form VAR into so-called structural residuals such that these can be interpreted as technology shocks. More precisely, name v_t the residuals from a reduced form VAR with n variables

and $E[v_t v_t'] = \Omega$. The relationship between the structural and the reduced form residuals is then $e_t = A v_t$, which induces $A \Sigma_e A' = \Omega$. The remaining assumptions necessary to pin down A then need to come from restrictions on the matrix of long-run effects. These assumptions can be incorporated as zero restrictions in the matrix of long-run effects $C \equiv \sum_{i=0}^{\infty} \Phi_i A$, where Φ_i are the impulse-response coefficients.

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

$$\text{MSE}(k) = \left(\sum_{i=0}^k \Phi_i \right) \Omega \left(\sum_{i=0}^k \Phi_i \right)'.^{19}$$

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

The reduced form VAR for all baseline specifications is estimated in a Bayesian framework in the main application. More precisely, I obtain 1000 draws of the posterior distribution of the reduced form coefficients and then apply the identification procedure to each of them to produce draws of the distribution of the structural coefficients.²⁰ The point estimates exhibited then correspond to the median and the confidence intervals to the 16th and 84th percentiles of the posterior distribution.

A.2 Fisher identification

In the Fisher identification, I impose the identifying assumption for neutral and investment-specific technology shocks as in [Fisher \(2006\)](#): Only investment-specific technology shocks affect the investment price in the long run and only technology shocks (both investment-specific and neutral) may be sources of long-run fluctuations in labor productivity. In addition, a third restriction imposes that the long-run effect of investment-specific technology shocks on labor productivity is equal to $\frac{\alpha}{1-\alpha}$, which is consistent with investment-specific random walk shocks and a Cobb–Douglas production function with capital share α , such as in the model presented in Section 2.

¹⁹See, for example, [Uhlig \(2004\)](#). Note that the variables important for identification, here labor productivity, need to enter in first differences in the VAR for this equation to hold.

²⁰This approach goes back to [Canova \(1991\)](#) and [Gordon and Leeper \(1994\)](#), and is feasible if the system is just identified, that is, if a unique mapping exists between draws of the residual variance–covariance matrix and draws of the identification matrix A .

I implement these restrictions using a decomposition of the matrix of long-run effects, similar to the Galí identification.²¹ First, if the real investment price is ordered first and labor productivity is ordered second in the VAR, the matrix of long-run effects may be lower triangular so as to impose the first two restrictions. In addition, the third restriction implies that $\frac{c_{21}}{c_{11}} = \frac{\alpha}{1-\alpha}$, where c_{ii} are the respective elements of the matrix of long-run effects C .

Since the lower triangular structure already imposes the sufficient number of conditions for the identification of A , I need to relax one of the other assumptions to maintain exact identification. Here, the third restriction results in a positive correlation between neutral and investment-specific technology shocks. Hence, Σ_e is no longer diagonal, but rather

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

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

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

With $b = (\frac{\alpha}{1-\alpha}\lambda_{11} - \lambda_{21})/\lambda_{22}$, with λ_{ii} being the elements of Λ . I set $\alpha = \frac{1}{3}$ as in the model calibration. The correlation between the two technology shocks is pinned down as $\rho = \frac{-b}{\sqrt{(1+b)^2}}$.

APPENDIX B: ROBUSTNESS—ARE THE ESTIMATED SHOCKS REALLY TECHNOLOGY SHOCKS?

B.1 Using artificial data from the model

As Galí (1999) documented, the result that hours worked fall after a positive technology shock challenges the empirical validity of the technology-shock-driven RBC model. In one of the most well known contributions to the debate on the hours puzzle, the use of long-run restrictions in structural VARs and its application to test the validity of macroeconomics models has been harshly criticized by Chari, Kehoe, and McGrattan (2008). Chari et al. simulated data from the baseline RBC model and used it in a simple VAR containing labor productivity and hours worked as in Galí. They compared the resulting impulse responses to the “true” ones from the model. With their calibration and specification, the VAR is not able to replicate the theoretical increase in hours worked after a positive technology shock.

²¹Note that Fisher imposed his restrictions in an instrumental variable framework similar to Shapiro and Watson (1988). I thank Fabio Canova for the solution of the implementation of the Fisher restrictions as explained here.

To address these concerns, I test the validity of the structural VAR as employed in Section 3 with artificial data generated from the model presented in Section 2. I generate 1000 simulations of labor productivity and the job finding rate of 184 quarters, the length of the actual sample. For this, I use the version of the model that is driven by both technology and preference shocks. Chari et al. argued that the VAR performs badly in the presence of nontechnology shocks that do not only play a minor role. Here, the preference shock plays a substantial role for the business cycle variation, as can be seen from the model simulation in Table 2.

I then apply the baseline VAR to this artificial data. More precisely, the VAR is estimated using a Minnesota prior with 8 lags and a decay of 7 in the specification. Note that this is a key difference to the specification in Chari, Kehoe, and McGrattan (2008). With this procedure, we can impose a much longer lag structure onto the VAR, which is consequently less prone to “lag-truncation bias” as Chari et al. phrased it. Unlike in the baseline specification, there is no trend (or broken dummy) used here as, clearly, there are no such trends in either the productivity or the job finding series. As documented below, the trend does, however, not change the results in the actual data.

Figure 2 exhibits the estimated impulse responses using both the artificial data and the theoretical responses from the model. The confidence bands for the estimated responses are 2 standard deviations of the sample means from the 1000 simulations. Most importantly, the VAR generates an increase in the job finding rate after both the tech-

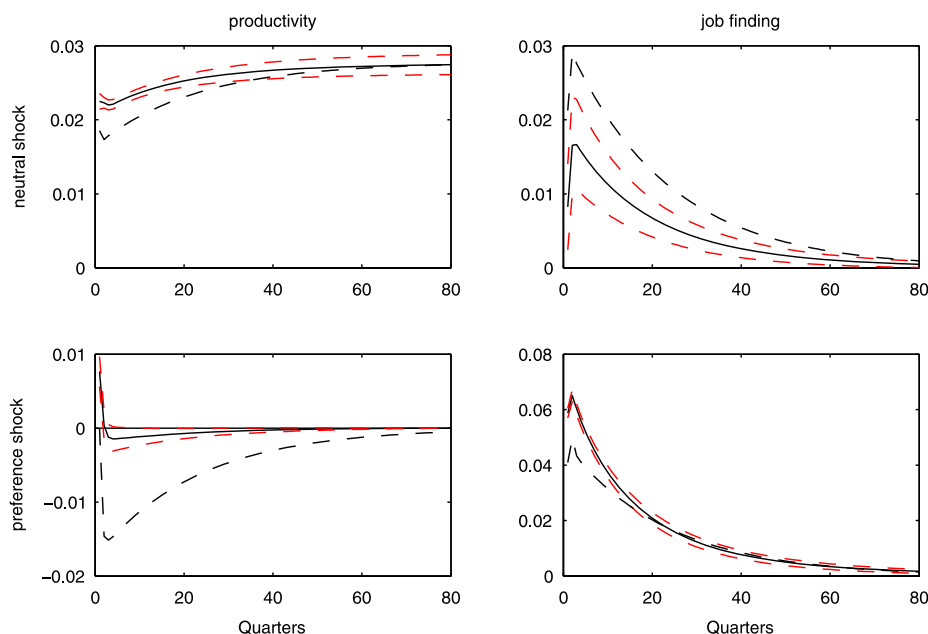


FIGURE 2. Impulse responses with simulated data. Dashed lines are model responses to 1 standard deviation technology and preference shocks; solid lines are estimated responses from simulated data. Confidence bands are 2 standard deviations from 1000 simulations.

nology and the preference shock, as implied by the model. Overall, the estimated responses are quite close to the theoretical responses. This supports the assertion that the structural VAR used here can be used to verify the validity of the model in the actual data.

B.2 Comparison to an alternative measure of technology

A recent contribution from [Basu, Fernald, and Kimball \(2006\)](#) (BFK) further supports the findings from [Galí \(1999\)](#). These authors provided a measure of technological progress—derived as a “sophisticated” Solow residual from a very different exercise than the one in Galí—that also induces a contractionary effect on hours worked. Here, I use this measure to support the effect of technology on the job finding and separation rates from my estimation in two different ways. First, I incorporate their measure of total factor productivity (TFP) instead of labor productivity into my structural VAR with long-run restrictions. Neutral technology shocks are then the only shocks that move TFP in the long run. As depicted in Figure 3, the effects of these shocks on the job finding rate, the job separation rate, and unemployment are very similar to the effects from the estimation with labor productivity.

Second, as suggested by [Basu, Fernald, and Kimball \(2006\)](#), 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 5 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.

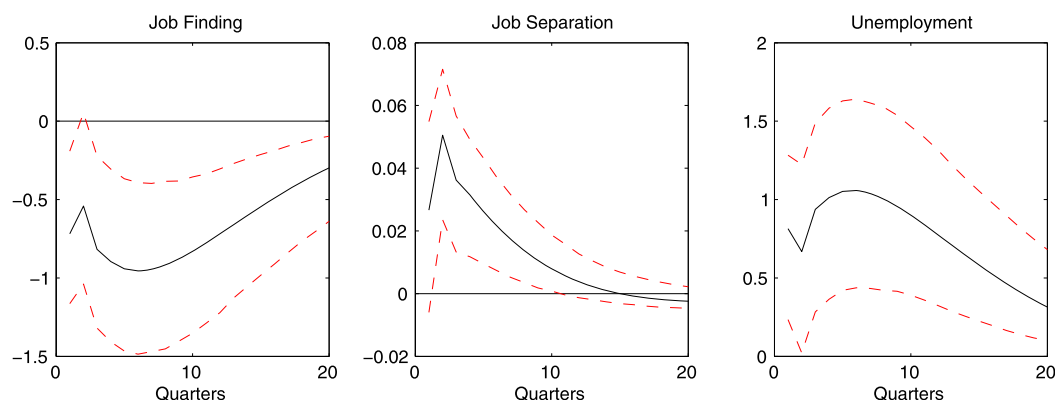


FIGURE 3. Impulse responses to BFK technology shocks. Responses in percentage points to a positive 1 standard deviation shock. Confidence intervals are 68% Bayesian bands.

TABLE 5. Regression on BFK measure.^a

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

^aThe asterisk (*) denotes significance based on 1 standard error bands.

APPENDIX C: ROBUSTNESS—INVESTMENT-SPECIFIC TECHNOLOGY SHOCKS, DATA, AND SPECIFICATION

C.1 *Investment-specific technology shocks*

As pointed out by Fisher (2006), fluctuations in labor productivity might be generated not only by factor-neutral technological progress, but also by investment-specific technological innovations. This section investigates whether the results from our baseline specification with neutral technology shocks are robust to separately estimating the effect of neutral and investment-specific technology shocks on the job finding rate and unemployment. In order to identify the two shocks, we implement the assumptions from Fisher (2006) as described in Section A.2.

The historical decomposition for the Fisher identification supports the results from the baseline identification documented above. 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 those produced from the model (with both shocks). Once more, sources other than technology are necessary to understand the unconditional volatility in the data.²²

As described in Section A.2, neutral and investment-specific technology shocks are correlated in the Fisher identification due to the third restriction on the effect of investment-specific technology shocks on labor productivity. Hence, their effects on the labor market variables are similar, that is the job finding rate falls and the unemployment rate increases after a positive investment-specific technology shock. However, these effects are not as strong as after a neutral technology shock. Job separation does not react significantly to an investment-specific technology shock. In the Fisher identification, investment-specific shocks explain about 13% of the business cycle variation of labor productivity and over 15% on impact and at least 6% in the subsequent quarters of the business cycle variation in the job finding rate and unemployment. Neutral shocks play a much larger role for the variation of these three variables, however.²³

²²Table 6 depicts the conditional standard deviation of both shocks. A full table for the historical decomposition of the Fisher identification can be provided by the author upon request. 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.

²³A figure with the impulse responses and a table for the variance decomposition can be provided by the author upon request.

TABLE 6. Robustness of the restricted Fisher identification.^a

	Conditional Standard Deviation				Impulse Response	
	Job Finding		Unemployment		Job Finding	
	i-Shock	n-Shock	i-Shock	n-Shock	i-Shock ^b	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 ^c	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.

^aHere, –;+ indicates initial drop, then hump-shaped increase.^bDescribes the effect on impact.^cKadiyala and Karlsson prior with Minnesota structure, same parameters as in baseline specification.

Note that the Galí and the Fisher identification strategies perform two different decompositions of the long-run variance matrix of the investment price, productivity and hours worked, due to the different ordering. This means that, by construction, the Fisher identification does not deliver technology shocks that induce the same effect on price and productivity as the Galí identification. Thus, the Fisher identification does not provide a decomposition of the Galí technology shocks. The estimated neutral technology shocks from the Fisher identification deliver very similar results to the neutral shocks from the Galí identification, however.

The third restriction of the Fisher identification plays an important role for the estimated dynamics that follow from an investment-specific technology shock. In particular, the dynamics of the job finding and unemployment rate that follow from an investment-specific technology shock are substantially different when including the additional restriction or not. Without the restriction, the job finding rate increases and unemployment falls after an investment-specific technology shock. This explains why studies with a similar focus as that of this paper, such as [Canova, Lopez-Salido, and Michelacci \(2010\)](#) or [Ravn and Simonelli \(2008\)](#) who do not add this third restriction, document different responses of labor market variables to investment-specific technology shocks. However, without the third restriction, the effect of the investment-specific

shocks on labor productivity is negative. Consequently, these shocks neither can be interpreted as technology shocks in the tradition of Galí nor do they correspond to labor productivity shocks that drive the labor market dynamics in the search-and-matching model. It is puzzling that the literature has not paid any attention to this while strongly debating the response of hours worked to both shocks.

C.2 Specification

This section investigates the robustness of the two main results: the low standard deviation conditional on technology shocks in job finding and unemployment, and the drop in the job finding rate after positive innovations of technology. Since the neutral shocks from the Fisher identification are very similar to those from the Galí identification, I document the results for the Fisher identification only. Table 6 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 ordinary least squares (OLS) specification with 2–4 lags in the VAR. In the Minnesota 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 does not deliver significant results.

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 second set of robustness checks addresses the presence of trends in the data. The baseline specification includes a broken dummy trend in the specification that is controversial. In fact, the question of whether 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 they are specified in first differences or are HP-filtered, hours worked fall after a positive Galí-type technology shock, while they increase after the same type of shock when specified in levels (see Galí (1999) and Christiano, Eichenbaum, and Vigfusson (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. A trend like the one applied in the baseline removes slow-moving components from the series and is, therefore, related to taking first differences of the labor market variables. Canova, Lopez-Salido, and Michelacci (2010) argued 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 to explain business cycles fluctuations.

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 robust to

including or not including a trend in the specification. Note further that job separation now falls significantly after both shocks. In fact, it falls by such a large extent 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, but the results are robust to an inclusion of trend breaks as in the baseline specification. 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.

C.3 Data

The worker flow data of Shimer and the respective business cycle facts are not without controversy in the literature. Fujita and Ramey (2009) also calculated worker flows from the CPS. The Fujita and Ramey data set does not encompass the same sample used by Shimer; it ranges from 1976:3 to 2004:4.²⁴ As stated by the authors, the standard deviation of the job separation rate is higher and that of job finding is lower in their data series compared to Shimer. With respect to the dynamics of unemployment, this suggests a larger role for the first series. Job separation is also more persistent, and the correlations of the job finding and separation rates with productivity are much lower than in the Shimer series. Figure 4 shows that the responses to technology shocks in both data sets are quite similar. Note that job separation decreases after a positive technology shock, which is mainly due to the difference in the sample rather than to the difference in the measurement of the data.



FIGURE 4. Shimer versus Fujita–Ramey. Solid lines depict Shimer data, broken lines show Fujita and Ramey data. Responses are in percentage points to a positive 1 standard deviation shock. Confidence intervals are 68% Bayesian bands.

²⁴I thank Shigeru Fujita for making the data available to me.

APPENDIX D: ADDITIONAL TABLES

TABLE 7. Model simulation with $\lambda = 1600$.^a

Model Shocks	I Techn. Shocks	II Techn. Shocks	III Pref. Shocks	IV Both Shocks
A: Standard Deviations				
JFinding	0.0516	0.0339	0.1061	0.1045
data	0.1011	(0.02, 0.05)	(0.07, 0.10)	0.1011
Unemployment	0.0532	0.0349	0.1156	0.1134
data	0.1011	(0.02, 0.05)	(0.07, 0.10)	0.1011
Productivity	0.0105	0.0065	0.0089	0.0105
data	0.0105	0.0065	0.0089	0.0105
B: Autocorrelations				
JFinding	0.8185	0.8207	0.7365	0.7377
data	0.8112	(0.68, 0.87)	(0.71, 0.80)	0.8112
Unemployment	0.6577	0.6645	0.4883	0.5020
data	0.8112	(0.68, 0.87)	(0.71, 0.80)	0.9128
Productivity	0.6357	0.6326	0.7827	0.7291
data	0.6917	(0.63, 0.80)	(0.70, 0.75)	0.6917
C: Cross-Correlations				
JFind., Prod.	0.9090	0.9032	-0.6984	-0.3758
data	0.139	(-0.87, -0.46)	(0.45, 0.73)	0.139
Unemp., Prod.	-0.6673	-0.6648	0.8567	0.5455
data	-0.139	(0.45, 0.87)	(-0.73, -0.45)	-0.139

^aAll figures are obtained from data simulated from the model with the baseline calibration and shocks that are calibrated such that the respective empirical standard deviation of productivity is matched. All series are detrended with a HP-filter with $\lambda = 1600$. Model I matches the overall unconditional standard deviation of productivity. Model II, driven by technology shocks only, and model III, driven by preference shocks only, match the respective conditional standard deviation of labor productivity. In model IV, the technology shock matched the conditional standard deviation of productivity and the preference shock is then calibrated such that both shocks match the overall unconditional standard deviation of productivity.

TABLE 8. Contribution of neutral shocks to variance.^a

Quarters	1	8	16	32
Productivity	35.84 (15.98, 58.11)	55.72 (36.87, 72.97)	74.67 (62.21, 84.67)	88.29 (82.73, 92.33)
Investment price	11.90 (4.60, 21.08)	14.30 (5.39, 25.84)	14.10 (5.01, 27.10)	12.86 (4.02, 27.07)
Job finding	12.87 (3.78, 28.18)	17.03 (4.29, 35.45)	18.47 (5.13, 38.13)	18.54 (5.12, 38.71)
Job separation	10.97 (1.97, 24.74)	12.20 (2.66, 28.16)	11.85 (2.74, 27.47)	11.95 (2.85, 27.38)
Unemployment	15.52 (5.01, 31.79)	18.04 (4.57, 36.70)	19.16 (5.38, 39.50)	19.36 (5.48, 39.87)

^aThe values for the displayed shocks 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 in percent.

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