What Drives Labor Market Dynamics in the US and Germany?

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Abstract

This paper explores the differences in labor market volatilities between Germany and the U.S. Employing a structural VAR with long-run restrictions, we analyze the role of technology and demand shocks. We therefore address the empirical performance of the standard labor market model based on conditional rather than unconditional moments. Our results show that positive technology shocks lead to strikingly different dynamics in the two countries. Most importantly, the job separation rate falls in the US, while it increases in Germany. Further, demand shocks are especially important to understand the dynamics of the job finding rate over the cycle. We discuss the shortcomings of the standard model as well as possible extensions in order to account for these features in the data.

JEL codes: E24, E32, J64
Key Words: worker flows, technology shocks, structural VAR, search and matching, business cycle

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1 Introduction

How well does the standard Mortensen-Pissarides model explain the business-cycle fluctuations of unemployment and vacancies? Recent studies on the U.S. labor market have addressed the so-called "volatility in unemployment puzzle" documented by Shimer (2005). In his paper, Shimer showed that the standard search-and-matching model is not able to replicate the high volatility in the job finding rate and unemployment that can be observed in the data. He argued that this is mostly due to the fact that productivity shocks are absorbed by variation in wages, which are determined by Nash bargaining and hence are very flexible.

Shimer's contribution has fueled a controversial debate on various issues, including the calibration of the model, the validity of assuming rigid wages in the model, the importance and cyclicality of job separations and the role of different kinds of shocks for labor market fluctuations. This ongoing debate has major implications not only for understanding the functioning of the labor market, but also for labor market policy. Against this background, comparable evidence from other countries with different institutional settings is likely to provide additional insights into the major driving forces underlying the current discussion.

In this respect, this paper presents evidence on labor market dynamics in Germany and compare the results to the case of the US. As there are no official figures on German labor market dynamics available, we construct the relevant time series for worker flows (e.g. job finding and separation rates) from a process-induced, administrative data set, the IABS. Two other studies for Germany also use the IAB employment sample in order to assess labor market dynamics in Germany: Gartner et al. (2009) and Jung and Kuhn (2009).[1] Contrary to these studies, we focus on one particular question in the context of the volatility in unemployment puzzle, namely the role and importance of different shocks to labor productivity for labor market dynamics. 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" (Shimer, 2005). In fact, the dynamics in the baseline Mortensen-Pissarides model and its many extensions stand in the tradition of the real-business-cycle (RBC) literature.[2] Next to technology shocks, other structural disturbances, generally referred to as non-technology or demand shocks, have been advocated to play an important role for the business cycle fluctuations of labor market variables. Hall (1997) has for example documented the importance of preference shocks, i.e. shocks that change the marginal rate of substitution between consumption and leisure, for the cyclical fluctuations of hours worked.

Balleer (2009) has addressed the differences between the labor market dynamics induced by these two shocks for the US. In her paper, the empirical per-

[1] We discuss similarities and differences that are related to the construction of the series of interest in section 2.

[2] Well-known examples which use search-and-matching in an RBC context include Merz (1995), Andolfatto (1996) or denHaan et al. (2000).

formance of the search-and-matching model is addressed based on standard deviations and correlations that are conditional on structural shocks rather than on the overall unconditional sample moments. More precisely, the second moments from a model which allows for both technology and non-technology shocks are compared 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 non-technology 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 'true' technological progress, but also dynamics at the disaggregated level such as permanent demand shifts between sectors. This measure of technology shocks hence suits the definition of productivity shocks in the baseline Mortensen-Pissarides setup quite well.

Conducting a conditional analysis for both Germany and the US, we find striking differences in labor market dynamics between the two countries. After a positive technology shock, job finding drops in both countries (even though increasing in the medium term in the US). This finding is parallel to the so-called 'hours-puzzle', i.e. the fall in hours worked after a positive technology shock, as documented by Galí (1999). This effect strongly contradicts the dynamics generated within a standard labor market model that is driven by one type of shocks, i.e. productivity or supply shocks. Further, non-technology shocks, which drive job finding up, are necessary to understand the overall procyclical dynamics of this variable. In addition, job separation strongly increases after a positive technology shock in Germany, while it falls in the US. While the US response may be explained in a setup with endogenous job separation in the flavor or denHaan et al. (2000), this setup does not suffice to explain the German dynamics.

The remainder of the paper is organized as follows: Section 2 describes the data set used as well as our methodology to obtain job finding and separation rates for Germany. Section 3 introduces, solves and calibrates a version of the standard model that is especially suited for our empirical exercise which is described in section 4. Section 5 presents and discusses the results and section 6 concludes.

2 Data and business cycle facts for Germany

2.1 Data and measurement

The following analysis uses an administrative data set provided by the Institute for Employment Research (IAB), the IAB Employment Sample (IABS), in order to calculate gross worker flows. The basis of the data set is the *Employment Statistics Register*, an administrative panel data set of the employment history of all individuals in Germany who worked in an employment covered by social security between 1975 and 2006.[3] For 1995, this data source contains the employee history of nearly 79.4% of all employed persons in Western Germany, and 86.2% of all employed persons in Eastern Germany. The basis of the employee history is the integrated notification procedure for health insurance, the statutory pension scheme, and unemployment insurance. At the beginning and at the end of any employment spell, employers have to notify the social security agencies. This information is exact to the day. For spells spanning more than one calendar year, an annual report for each employee registered within the social insurance system is compulsory, and provides an update on, for example, the qualification and the current occupation of the employee. Further worker characteristics included are the year of birth, sex, marital status, and nationality.[4]

The IAB Employment Sample (IABS), is a 2% sample of the Employment Statistics Register for the time period 1975-2004. The IABS is representative for all dependent-status workers, and contains information on all employment and unemployment spells of the workers covered. Given the relatively long time span of the data set, we are able to observe two full business cycles. From this sample, we exclude observations on apprentices, trainees, homeworkers, part-time workers, and individuals older than 65. This results in a sample with 1.05 million individual workers. Two other studies for Germany also use the IAB employment sample in order to assess labor market dynamics in Germany: Gartner et al. (2009) and Jung and Kuhn (2009). Unlike the other papers, we consider flows for total Germany, not just West Germany (which we use for a robustness check of the results).

The IABS is representative regarding employment covered by the social security system but not regarding unemployment. Only those unemployed who are entitled to transfer payments are covered. Given these definitions, we can derive three labor market states at each point in time: employment (E) covered by social security, unemployment (U), if the worker is receiving transfer payments, and non-participation (N).[5] Non-participants are those individuals not recorded in the data sets. Therefore, this state includes those workers out of the labor market, as well as workers not covered by social security legislation, e.g. civil servants and self-employed workers. Because of the way the data are collected, both firms' reports of a new employee and individuals' notifications of moving into or out of unemployment are not exactly consistent with the actual change of labor market state. For example, a workers might report to the unemployment office only a few days after having been laid off. The latter potential measurement error is taken into account in the following way: If the time lag between two employment

[3]This data base has been used, among others, by Bender and von Wachter (2006) and Dustmann and Meghir (2005).

[4]A detailed description of the Employment Statistics Register and the notification procedure is given by Bender et al. (2000).

[5]In the IABS data, the record on unemployment benefit recipients are unreliably measured before 1980. As we can therefore not use the worker flows to and from unemployment for the time period 1975-1979, we start our analysis in 1980.

or unemployment notifications does not exceed 30 days, it is defined as a direct transition between the two states recorded. We count it as an intervening spell of non-participation if the time interval between the two records is larger than 30 days. Stocks and flows are computed by using the employment and unemployment spells in order to identify for each individual the labor market state (employment, unemployment, non-participation) which in terms of working days prevailed during a given month.

This study has two main objectives, first, to assess the empirical performance of the standard search-and-matching labor market model in Germany and, second, to compare the respective results to those for the US labor market. Studies on the US, such as Shimer (2005), use time series that are calculated from the Current Population Survey (CPS) conducted by the Bureau of Labor Statistics. More precisely, the performance of the model is assessed on the bases of job finding and separation rates, i.e. the probabilities with which unemployed persons move into employment and employed persons separate from their existing jobs and become unemployed. We follow this approach as closely as possible to make our results comparable to Shimer and other studies on the US (such as Canova et al., 2007, or Balleer, 2009).

Similarly to Shimer, we calculate the job finding rate from the flows out of unemployment into employment relative to the unemployment stock, and the separation rate from the flows out of employment into unemployment relative to the stock of employment. Here we assume a constant labor force as is standard in the macro labor literature. The unemployment rate is approximated from the dynamics of the job finding and separation rate according to $u_t = \frac{s_t}{s_t+f_t}$. We calculate quarterly rates as averages of monthly rates. All series are seasonally adjusted using the X12-ARIMA method. As we exclusively focus on employment and unemployment in our analysis, we make these stocks consistent with flows into and out of non-participation as a robustness measure.

2.2 Business cycle facts of the German labor market

Figure 1 shows plots of the job finding, job separation and unemployment rates for Germany and the United States for the period 1980 - 2004. In Germany, the job finding rate has substantially fallen over time, while it has on average remained stable in the US. In Germany, job separation and unemployment rates have increased, while they have decreased in the US (mildly so in the case of the unemployment rate). Unlike in Germany, the US time series appear to follow a slow-moving trend as job separation first in- and then decreases and unemployment falls and then stabilizes[6]. Germany exhibits a structural break in the separation rate and unemployment series around 1991:4. While the trends appear strikingly different in both countries, the question at hand is whether this is also the case for the business cycle.

[6]Canova et al. (2007) describe this statistically.

Table 1 compares the business cycle moments in terms of standard deviations and correlations for Germany and the US (first column labeled unconditional moments respectively). The moments here are calculated as in Shimer, i.e. the business cycle is measured as the deviation from trend which is derived from the HP filter with a smoothing parameter of $\lambda = 10^5$. The table shows that while the standard deviations for the job finding rate is similar in both countries, the German unemployment rate is much more volatile than its US counterpart. Also labor productivity is more volatile in Germany. Further, job separation is much more volatile in Germany than in the US. As can also be seen in the correlations of job finding and separation rates with unemployment, this implies that separations are much more important for unemployment dynamics in Germany than in the US. Interestingly, job finding and separation rates are positively correlated in Germany, while they are negatively correlated in the US.

3 The model

The model we present in the following serves two main purposes. First, it provides a baseline setup which incorporates search-and-matching on the labor market and is designed to analyze labor market dynamics such as the job finding and separation rate in response to labor productivity shocks, here technology and demand shocks. Second, it motivates the empirical identification strategy that is used to separate technology from demand shocks in the data. Comparing the estimated impulse responses to these two shocks to the one from the model therefore shed light on the empirical performance of this 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 following 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

$$\begin{aligned} A_t K_t^{\alpha} N_t^{1-\alpha} &\geq C_t + X_t + a V_t Z_t \\ K_{t+1} &\leq (1-\delta) K_t + X_t \\ N_{t+1} &= (1-\psi) N_t + \mu V_t^{1-\eta} (1-N_t)^{\eta}. \end{aligned}$$

The posting of vacancies (V) creates a cost a and thereby search frictions. Employment (N) 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.

A_t represents general purpose technology in the production function and follows

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

Due to the positive effect on labor productivity, job finding rises after a positive technology shock, while unemployment falls. Figure 2 in the appendix exhibits these dynamics. In the following, the theoretical impulse-responses will be compared to the ones estimated from a structural VAR.[7] As the model is based on the neoclassical growth model, technology shocks have permanent effects and due to them, output, consumption, investment and labor productivity grow with the same rate along a balanced growth path, while employment, unemployment and vacancies are stationary. The permanent effect of these shocks on labor productivity will serve as the identifying restriction in the estimation.

In this setup, 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. As Hall (1997) suggested preference shocks as an important driving force of labor market fluctuations, we will consider shocks to the marginal rate of substitution between consumption and leisure in this model. In the framework presented above, this means that the parameter χ will be replaced by a stochastic process of the form $\ln(x_t) = \rho_x \ln(x_{t-1}) + \varepsilon_{xt}$. As agents like to consume more, 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 in order 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. 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. Moreover, the identifying assumptions that we will use in the empirical assessment are fulfilled in this framework. While the origi-

[7] The responses in the figure are generated from a calibration for the US similar to Balleer (2009). Clearly, the calibration for Germany will need to be different. Qualitatively, these results are valid even for Germany however.

nal Mortensen-Pissarides model potentially accounts for permanent productivity (or broadly speaking neutral technology shocks), it does not allow for other, potentially counteracting, sources of variation in labor productivity such as demand shocks.

In order to address issues like the Shimer debate on volatility for Germany, we calibrate and simulate the model outlined above. In a first step, we then compare the moments that are generated with the model driven by technology shocks in order to generate moments conditional on technology and preference shocks. For the calibration, we pick standard parameters for the capital share in production $\alpha = \frac{1}{3}$, time discounting $\beta = 0.99$, capital depreciation $\delta = 0.02$, the Frisch elasticity of labor supply $\phi = 1$ and the mean preference shift $\chi = 1$. We further set the elasticity in the matching function to $\eta = 0.5$ and calibrate the cost of posting a vacancy $a = 0.12$ such that labor market tightness is one in steady state. We then match the mean job finding rate with $\mu = 0.2$ and the mean job separation rate with $\psi = 0.02$ in order to match their empirical counterparts. Finally, γ is set to match the standard deviation of labor productivity in the data.

Table 2 shows the results in the first column for model and data respectively. It is evident that the model with the standard calibration inherits the problems Shimer describes in the sense that it is not able to generate the high volatility in the job finding and unemployment rate that we see in the data. Differently to Shimer, the central question in this study is not whether a model with technology shocks can replicate the overall unconditional moments. Instead, we aim at investigating whether the model can match the empirical moments that are conditional on different structural shocks and how this can help to understand and replicate the overall unconditional moments as well. This will be addressed below.

4 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. It has to be noted that many structural disturbances other than technological innovations can affect labor productivity in the short and medium run, but that technology shocks can be distinguished from non-technology shocks with respect to their long-run effects on this variable.

With this approach, we do not exactly estimate the model outlined above. Rather, the conditional moments obtained should hold for a broad class of different model specifications that fulfill the identifying assumptions. The long-run assumption about the nature of technology shocks holds in the model presented as well as in many other models, such as the neoclassical growth model or the New Keynesian model.[8]

In order to obtain the conditional moments, we estimate a reduced-form VAR in the flavor of Galí which contains the job finding and separation rates instead of hours worked, i.e. the extensive rather than the intensive margin of labor. 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, we will use a relatively loose prior in the estimation.[9] Furthermore, the VAR is estimated with a structural break in 1991:4 as is detected from a Chow test.

5 Results

Conducting a conditional analysis for both Germany and the US, we document two sets of results, impulse-responses as well as a decomposition of the business cycle variances of the key variables conditional on the technology and non-technology (demand) shock. We find striking differences in labor market dynamics between the two countries. Figure 3 compares the impulse responses to a technology shocks for Germany and the US. After a positive technology shock, job finding drops in both countries (even though increasing in the medium term in the US).[10] This effect strongly contradicts the dynamics generated within a standard labor market model that is driven by one type of shocks, i.e. productivity or supply shocks. In the standard setup, an increase in technology increases

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

[9] 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 $d = 7$.

[10] Figure 4 addresses robustness of the German responses to various specifications.

the surplus from a job match and hence the incentives for firms to post vacancies.

There exist some attempts to explain this apparent contradiction between evidence and theory within a New Keynesian framework (Barnichon, 2008) or with changes in relative demand for skilled and unskilled labor (Balleer and van Rens, 2008). Even though this appears to be less of a problem in Germany as the job finding rate increases on impact, it is clear that the unemployment response is driven by the separation, not the finding rate. As a complementary result, non-technology shocks, which drive job finding up, are necessary to understand the overall procyclical dynamics of this variable.[11]

In addition to the evidence on the job finding rate, the job separation rate strongly increases after a positive technology shock in Germany, while it falls in the US. Shimer (2005) has motivated the theoretical setup in his study by the fact that the separation rate can be assumed to be constant in the standard model. Clearly, this is not the case neither for Germany nor the US. It is thus reasonable to extend the standard setup to allow for endogenous separations, such as e.g. in denHaan et al. (2000). Here, separations are efficient and are linked to the surplus falling below a certain profitability cutoff. Hence, an increase in the surplus due to a technology shock reduces job separations. In turn, this setup fails to explain the German dynamics. It thus remains to be shown in what sense their model provides a sensible framework for either Germany or the US and along which lines the important differences with respect to the separation rate can be explained.

Table 1 shows the historical decomposition for both countries. Here, the actual time series are decomposed 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 individual shocks to replicate exactly those moments in the data that have been used for judging the empirical performance of the model.[12]

Volatility is measured by the standard deviation in panel A. The most important thing to note is that both shocks generate substantial volatility in the labor market variables. This indicates that shocks other than technology shocks play an important role when understanding the business cycle dynamics as well. A model that is driven by technology shocks should consequently be compared to the moments that are conditional on these shocks rather than on overall unconditional moments. Conditional on technology shocks, the job finding rate

[11]Table 3 shows the variance decomposition for technology shocks in both countries. This table documents that in fact both shocks are important for the business cycle variance of the labor market variables.

[12]Note that since these are standard deviations and the data are detrended, the second moments resulting from these series do not add up to the respective unconditional moment.

and unemployment are less volatile than in the overall sample in both countries. Hence, addressing the Shimer puzzle, it may be easier to generate these moments within a standard model. Panel B exhibits the correlations that are conditional on technology and non-technology shocks respectively. This part of the table replicates the results in the impulse-responses. More precisely, it documents the opposite sign of the correlation between the job finding rate, the job separation rate and unemployment with productivity conditional on a technology shock compared to the overall sample in Germany. Further, the US dynamics evolve exactly opposite to the German ones.

Table 2 compares conditional moments for technology shocks and preference shocks for the model and the data. It is evident that in the case of Germany, the model can neither generate the unconditional nor the conditional moments in the data.

6 Conclusion

In a conditional analysis of the labor market effects of business cycle shocks, we document that both technology and non-technology shocks play an important role for the variation in the job finding rate, the job separation rate and unemployment. This result holds for both the US and Germany. We further find striking differences in labor market dynamics between the two countries. After a positive technology shock, job finding drops in both countries (even though increasing in the medium term in the US). This effect strongly contradicts the dynamics generated within a standard labor market model that is driven by one type of shocks, i.e. productivity or supply shocks.

We plan to explore whether a theoretical framework with a two tier labor market can explain the dynamics in both countries. The intuition works as follows. Consider two types of workers, with and without tenured jobs. As firms face higher firing costs for the tenured workers, this reduces the separation probability of this group of workers and increases the value of tenured jobs relative to the value of non-tenured jobs. We conjecture that most of the dynamics in the German labor market originate in dynamics of non-tenured workers in recessions and tenured workers in booms. Intuitively, German workers are willing to take on non-tenured positions in recession, while looking for tenured positions in booms. Firms would also like to hire tenured workers in booms in order to provide incentives to employ the best possible candidates. Hence, non-tenured workers quit employment in booms in order to sort themselves into the unemployment pool searching for tenured jobs, increasing the job separation rate and decreasing the job finding rate of non-tenured workers. In the US, all workers are the same with respect to firing costs. The induced labor market dynamics therefore very much resemble the familiar dynamics described in the standard model with endogenous job separation.

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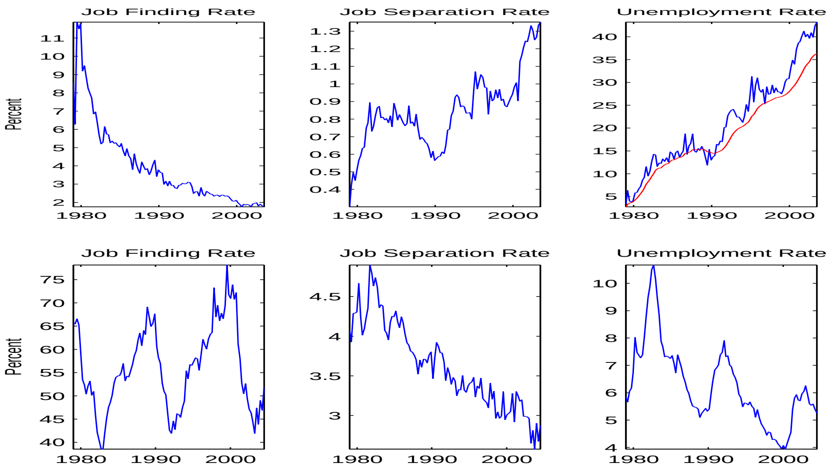
7 Figures and Tables

Figure 1: Worker flows in Germany and the US



Notes: The first row shows logs of the respective rates for Germany, the second row for the US. The red line plots the approximated unemployment rate using $u = \frac{js}{js+jf}$.

Figure 2: Impulse responses from the standard model

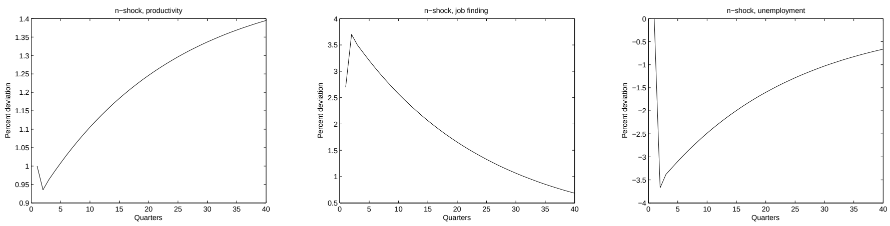
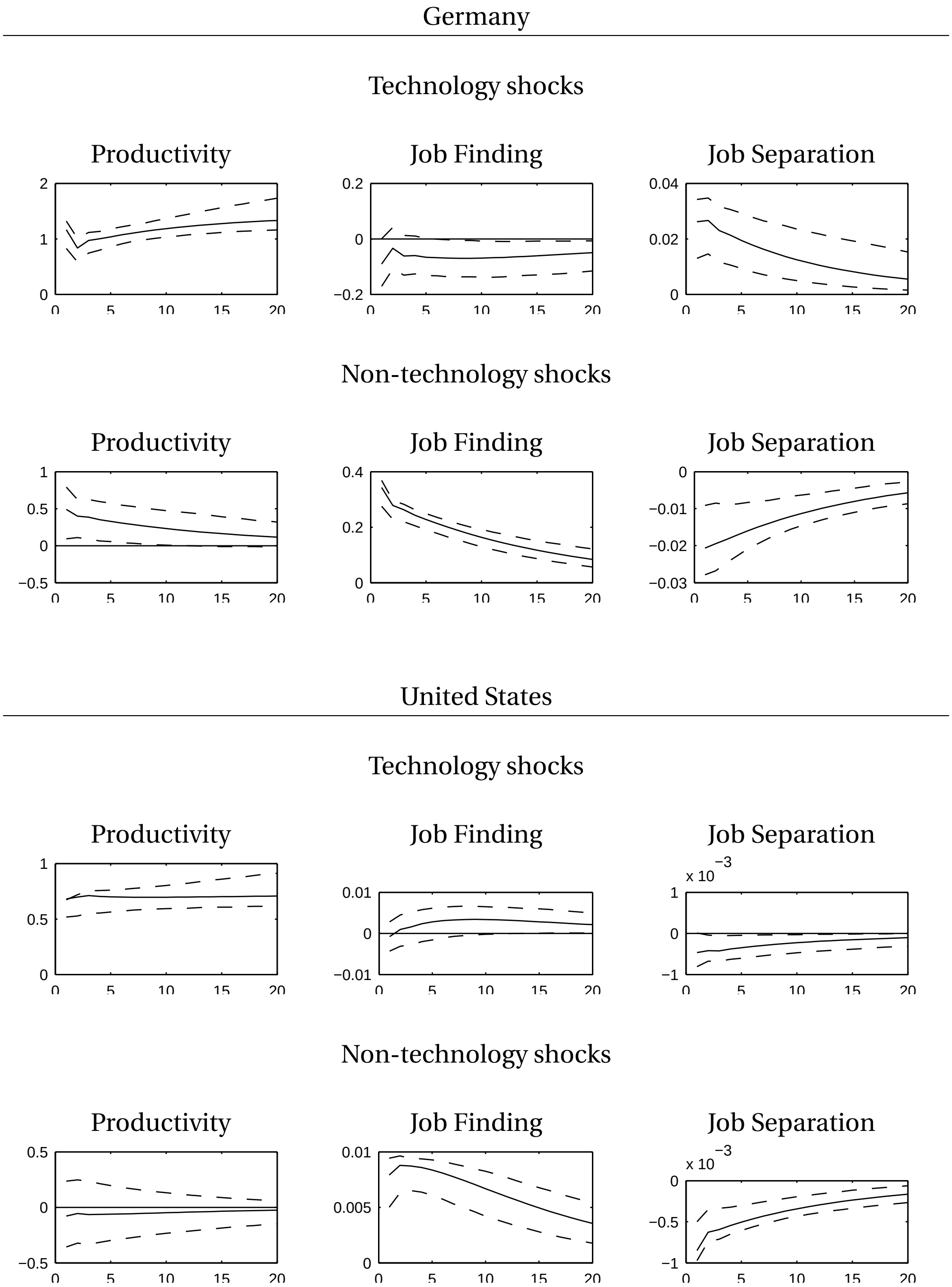
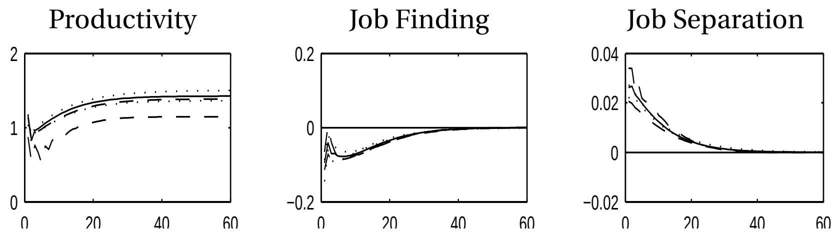


Figure 3: Estimated Impulse Responses



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

Figure 4: Robustness for German responses
Technology shocks



Notes: Percent responses to a positive one-standard-deviation shock. Confidence intervals are 68 % Bayesian bands.
Baseline specification: black solid line.
Additional variables output, investment and hours worked: black dashed line.
Flat prior, OLS equivalent with four lags: red solid line.
Shorter sample starting 1982:3: red dashed line.

Table 1: Historical Decompositions

	Germany			US		
	Uncond.	Conditional Moments		Uncond.	Conditional Moments	
		Technology	Residual		Technology	Residual
A: Standard deviations						
JFind.	0.103	0.0659	0.0995	0.1129	0.0317	0.1078
		(0.05,0.08)	(0.08,0.11)		(0.02,0.05)	(0.09,0.11)
JSep.	0.1522	0.0798	0.1127	0.0656	0.0394	0.0642
		(0.06,0.10)	(0.07,0.14)		(0.02,0.06)	(0.05,0.07)
Unemp.	0.2151	0.1239	0.1769	0.1458	0.0534	0.1419
		(0.10,0.15)	(0.13,0.21)		(0.03,0.09)	(0.11,0.15)
Prod.	0.0217	0.0187	0.0145	0.0142	0.0127	0.0057
		(0.02,0.02)	(0.01,0.02)		(0.01,0.02)	(0.00,0.01)
B: Cross-correlations						
JF,P	0.2039	-0.3997	0.5303	-0.3254	0.5075	-0.8539
		(-0.57,-0.14)	(0.26,0.77)		(-0.36,0.79)	(0.51,-0.96)
JS,P	-0.1388	0.6062	-0.8971	-0.1395	-0.7836	0.6492
		(0.44,0.71)	(-0.65,-0.97)		(-0.89,-0.50)	(0.27,0.90)
U,P	-0.1796	0.5346	-0.816	0.1849	-0.8395	0.9089
		(0.37,0.66)	(-0.47,-0.95)		(-0.92,-0.09)	(0.57,0.98)
JF,U	-0.8768	-0.9101	-0.8853	-0.9327	-0.8146	-0.933
		(-0.97,-0.82)	(-0.84,-0.92)		(-0.94,-0.53)	(-0.91,-0.94)
JS,U	0.9472	0.9415	0.9211	0.7764	0.8724	0.7823
		(0.90,0.97)	(0.84,0.94)		(0.66,0.9)	(0.63,0.84)
JF,JS	-0.6776	-0.7112	-0.6355	-0.4972	-0.3661	-0.5105
		(-0.87,-0.48)	(0.45,-0.71)		(-0.72,0.23)	(-0.31,-0.61)

Notes: All series detrended with the smooth HP-filter with $\lambda = 10^5$. Brackets: Bayesian 68% confidence intervals from the posterior distribution.

Table 2: Model Performance for Germany

	Data			Model		
	Uncond.	Conditional Moments		Technology Shocks		Preference
		Technology	Residual			Shocks
Standard Deviations						
JFind.	0.103	0.0659	0.0995	0.0173	0.0194	0.0113
		(0.05,0.08)	(0.08,0.11)			
Unemp.	0.2151	0.1239	0.1769	0.0255	0.0142	0.0289
		(0.10,0.15)	(0.13,0.21)			
Prod.	0.0217	0.0187	0.0145	0.0217	0.0187	0.0145
		(0.02,0.02)	(0.01,0.02)			
Correlations						
JF,P	0.2039	-0.3997	0.5303	0.8654	0.8639	-0.5729
		(-0.57,-0.14)	(0.26,0.77)			
U,P	-0.1796	0.5346	-0.816	-0.8107	-0.7870	0.9961
		(0.37,0.66)	(-0.47,-0.95)			

Notes: All series detrended with the smooth HP-filter with $\lambda = 10^5$. Brackets: Bayesian 68% confidence intervals from the posterior distribution.

Table 3: Variance Decomposition for Technology Shocks

	Germany				US			
	Quarters				Quarters			
	1	8	16	32	1	8	16	32
Prod.	63.61	77.72	87.77	94.24	84.19	91.04	94.41	96.93
	(33,89)	(53,93)	(72,96)	(87,98)	(57,97)	(70,98)	(78,99)	(89,100)
Find.	5.28	7.82	10.99	12.79	3.61	11.85	15.77	16.90
	(1,20)	(2,24)	(2,32)	(2,38)	(0,16)	(3,36)	(4,45)	(5,51)
Sep.	38.63	42.64	42.78	42.72	16.74	24.53	24.94	25.24
	(11,70)	(13,74)	(13,75)	(13,75)	(2,52)	(4,63)	(4,64)	(4,64)
Unemp	26.40	27.92	28.86	29.67	12.40	19.91	22.08	22.59
	(7,54)	(7,59)	(8,62)	(8,64)	(2,47)	(3,58)	(4,61)	(4,62)

Brackets: Bayesian 68% confidence intervals from the posterior distribution.