Economics Bulletin

Volume 45, Issue 1

Good vs. bad jobs over the business cycle

Dennis Wesselbaum
University of Otago

Abstract

This paper estimates a search and matching model of the U.S. labor market with on-the-job search. Using Bayesian methods we find that the model generates different dynamics compared to the standard search and matching model. Furthermore, our parameter estimates vary sizably across good and bad jobs. Job-specific shocks have different effects and create interesting spillover effects. We find that shocks to good jobs matter more than shocks to bad jobs.

Citation: Dennis Wesselbaum, (2025) "Good vs. bad jobs over the business cycle", *Economics Bulletin*, Volume 45, Issue 1, pages 150-165
Contact: Dennis Wesselbaum - dennis.wesselbaum@otago.ac.nz.
Submitted: April 04, 2023. **Published:** March 30, 2025.

1 Introduction

The U.S. labor market is characterized by sizable and volatile job flow rates.[1] A significant share of those flows are explained by continuous reallocations across sectors and firms: workers move between employment and unemployment as well as across employers.

Fallick and Fleischman (2004), using the Current Population Survey, measure employment-to-employment (EE, for short), or job-to-job, flows. They find that 2.6 percent of employed workers move across employers within an average month. Menzio and Shi (2011), using longer time series, find a value of 2.9 percent per month.[2] They also document the relationship of EE flows with the dynamics of unemployment and vacancies over the business cycle. They find a positive, negative correlation of EE flows with vacancies, unemployment respectively in line with the result by Shimer (2005).[3]

Strong evidence for the importance of EE transitions over the business cycle can be found in Nagypál (2008). She shows that EE transitions account for 49 % of all separations and finds that the increase in the incidence of unemployment during the 2001 recession can be explained by a shift in the composition of separations away from employer-to-employer to employment-to-unemployment transitions. Further, changes in the EE transition probability affect unemployment volatility much more than changes in the job-finding probability.

This paper contributes to the on-the-job search literature and, more broadly, to the literature estimating search and matching models. To the best of our knowledge, this is the first paper that estimates an on-the-job search DSGE model with job-specific shocks. The canonical model has been estimated, for example, by Gertler et al. (2008), Lubik (2009), Di Pace and Villa (2013), and Furlanetto and Groshenny (2012). Since EE flows appear to be important over the cycle, estimating on-the-job-search models able to replicate these flows is a natural extension to the "standard" estimations of search and matching models without EE flows. This is important in order to see whether the implications for aggregate variables from a standard search and matching model are supported by the on-the-job-search model.

The canonical search and matching model does not allow for employment-to-employment transitions and therefore ignores this important adjustment margin. Exceptions are the papers by Krause and Lubik (2006), Nagypál (2007), Tasci (2007), Van Zandweghe (2010), Tüzemen (2012), and Martin and Pierrard (2014). Those papers allow for on-the-job search which generates employment-to-employment transitions over the business cycle. The crucial difference to the canonical search and matching model is that workers also search for jobs when they are employed rather than restricting search to when they are unemployed. Those studies focus on the dynamic properties of the on-the-job search model relative to the canonical search and matching model stressing the role for the ability of the model to match observed second moments and persistence. The on-the-job search model generates realistic

[1]See Davis and Haltiwanger (1999) and Davis et al. (2006) for an overview.

[2]Bjelland et al. (2008) show that EE flows represent four percent of employment, 30 percent of separations each quarter, and are procyclical.

[3]Other paper studying EE transitions include Bell and Smith (2002) and Gomes (2009) for the UK. Earlier papers include Black (1981), Kahn and Low (1984), and Pissarides and Wadsworth (1994). Topel and Ward (1992) show that EE transitions explain a sizable share of earnings growth over the lifetime of a worker.

worker reallocation dynamics. It fosters the reallocation from bad to good jobs which occurs mainly in booms. Barlevy (2002), for example, finds that on-the-job search matters for the reallocation of resources over the business cycle. Further, when a worker moves from a bad to a good job, she increases the marginal revenue of labor in the bad job firm. This creates incentives for the bad firm to post new vacancies. The consequence is a vacancy chain (Akerlof et al. (1988)). Fujita (2010), using the Labour Force Survey in the UK, finds that four percent of the working age population engaged in on-the-job search. His study shows that the main reasons for searching on-the-job is being unsatisfied with the current job and the fear of loosing the job.

The main findings can be summarized as follows. Compared to the canonical search and matching model, we find a higher value of the worker's bargaining power and a lower job separation rate in the on-the-job search model. Further, the difference in vacancy posting costs across good and bad jobs is smaller as usually assumed in calibrated models. Further, in the on-the-job search model separation rate shocks, especially to good jobs, are a much more important driving force of total variations in key variables compared to the canonical search and matching model. The differences across good and bad type of jobs is significant and ignored in the standard search and matching model.

2 Model Overview

We build a Real Business Cycle model with search and matching frictions and job heterogeneity. The model is an otherwise standard model taken from Krause and Lubik (2006), Van Zandweghe (2010), Tüzemen (2012), and Martin and Pierrard (2014). Those authors build upon the work by Pissarides (1994, 2000) and Acemoglu (2001) on on-the-job-search and, particularly, the existence of "good" (high-wage) and "bad" (low-wage) jobs. Given that the model is standard, the full derivations are relegated to the appendix.

The model works as follows. The economy is populated by a continuum of infinitely-lived, risk neutral, and identical households, composed of homogeneous workers, and heterogeneous, risk neutral firms. There exist two types of firms offering good and bad jobs. Heterogeneity across firms is generated by different job creation costs. Those different job creation costs imply that every match generates a rent, but also leads to wage differentials across good and bad jobs. In addition, workers in good and bad jobs produce different goods with different prices. It follows that all workers in bad jobs search on-the-job for good jobs. Furthermore, it is assumed that workers' search is directed: employed workers search only for good jobs, while unemployed workers search for good and bad jobs.

3 Estimation Details

In this section we present our calibration and the choice of priors for the set of estimated parameters. We follow the related literature (Krause and Lubik, 2006; Van Zandweghe, 2010; Tüzemen, 2012; and Martin and Pierrard, 2014) in choosing the calibration and priors.

We begin with the parameters describing household behavior. We assume a discount factor of $\beta = 0.98$. Relative risk aversion is set to 2. As in Krause and Lubik (2006) we assume $h = 0$ such that there is no utility loss due to working. This assumption would mainly affect welfare analysis but does not affect our results, as there is no intensive labor margin in the model.

Along the firm side of the economy we assume the following values. We assume that the final good production function is Cobb-Douglas and set $\tau = 0$. Technology in steady state is normalized to one. We choose the following values for labor market parameters. Equilibrium unemployment is set to 10 percent. This higher than observed value of steady state unemployment pays tribute the shortcoming of the unemployment rate namely the non-conformity of effective searchers and unemployed workers (cf. Cole and Rogerson, 1999). Following Krause and Lubik (2007), we assume a steady state job separation rate of 10 percent. This value includes exogenous and endogenous job separations as well as EE transitions and out-of-labor force transitions and is in line with the empirical evidence on the U.S. job separation rate.

In contrast to standard search and matching models, we need to fix values for the cost of on-the-job-search. Giving the restrictions imposed on F, we follow Krause and Lubik (2006) and assume $F(S_t) = \kappa S_t^{\sigma}$, and set $\kappa = 0.04$ and $\sigma = 1.1$. The number of new matches for both types of jobs is assumed to be 0.6. This value implies that, in steady state, the job finding probabilities are 0.77 for good jobs and 0.63 for bad jobs. Unemployment benefits are set to 0.4 as in Krause and Lubik (2006).

We estimate nine structural parameters and all shock parameters. In the following, we describe for each estimated parameter to which distribution family it belongs and which prior mean and standard deviation we assume. For both types of jobs, we assume that the job separation rate belongs to the Beta family with mean 0.1 and standard error 0.02. The worker's bargaining power for both jobs is set to 50 percent with standard deviation 0.1 and is normally distributed. Therefore, we assume symmetric bargaining in the first place. The elasticity of the matching function w.r.t. unemployment, μ^x, is set to 0.4 with a standard deviation of 0.15 and follows a Beta distribution.

A crucial assumption in the model is the difference in vacancy posting costs across jobs. This leads to different rents and equilibrium wages. We assume that vacancy posting costs are three times higher for good jobs compared to bad jobs and set the prior to 0.15, 0.05 respectively. Both follow Gamma distributions with standard deviation of 0.05, 0.2 respectively.

We estimate α, the relative weight of the two input goods and assume that it follows a Beta prior distribution with mean 0.4 and standard deviation 0.15. We assume that the good input good is relatively more important in the production of the final good, therefore has a higher productivity. This is a consequence from assuming that prices across the two goods are roughly equal and that wages in good jobs are higher than wages in bad jobs (cf. Krause and Lubik, 2006).

Finally, the shock processes are estimated assuming that the autocorrelation parameters are Beta distributed with mean 0.5 and standard deviation 0.2, while the standard deviations of the shocks are Inverse-Gamma distributed with mean 0.1 and a standard deviation of 2.

All time series are taken from the St. Louis FED's online system FRED. Our sample covers the period from 1964:Q1 to 2017:Q2, which gives us 214 observations. We use the following six time series: output, employment, and wages across good and bad jobs. The "good" sector in the model is the service sector in the data. The "bad" sector in the model corresponds to data from the manufacturing sector in the data. The manufacturing sector is characterized by low and falling wages and productivity, while the service sector has increasing wages and productivity.

Output is measured by the real gross domestic product in both sectors. Wages are measured by the monthly, seasonally adjusted average hourly earnings (Real US Dollars per hour) of production and non-supervisory employees in both sectors. Finally, employment is the seasonally adjusted number of all employees in both sectors. All time series are written in logarithmic scale and are detrended using a first-difference filter.

4 Discussion

In this section we present our baseline estimation results of the on-the-job search model (*OTJS*, for short) and compare them to a *standard* search and matching model without on-the-job-search. The model is estimated using Bayesian methods (Herbst and Schorfheide, 2015) with six shocks (technology, match efficiency, and separation rate for good and bad jobs) and the following observed time series: output, employment, and wages. To obtain our results, we use five MCMC chains with 250.000 draws each.

4.1 Parameter Estimates

We begin by discussing the posterior estimates and the implications for labor market dynamics.[4] Table 1 and 2 present the posterior estimates as well as the 95 percent confidence bands for the estimated deep parameters and the parameters describing the exogenous processes. In addition, in the table we also present the calibrated values taken from Krause and Lubik (2006). The posterior values are significantly shifted away from their respective priors which, given that all parameters are tightly estimated, indicates that the data is informative and parameters are identified.

The posterior mean for the bargaining power for good jobs in the OTJS model is 0.82 and 0.42 for bad jobs. This result is intuitive, as workers in good jobs, generating a larger surplus (higher price), should have a higher bargaining power relative to workers in bad jobs. To allow comparison, we also estimate a standard search and matching model without on-the-job search. Here, we find that our result is different to the value obtained in the standard search model: the mean is 0.04. This low value is in line with the finding by Lubik (2009) who reports a value of 0.03. This difference has major implications for vacancy postings. While in the standard model almost the entire surplus goes to the firm, in the OTJS model workers in good jobs receive 82 percent of the surplus of the match, while workers in bad jobs only receive 42 percent. Hence, firms in the standard model have larger incentives to post vacancies. Therefore, we can expect vacancy postings in the OTJS model to be less volatile over the business cycle.

The posterior mean of the separation rate is 0.03 in the OTJS model for both type of jobs and 0.26 in the standard search and matching model. The estimated value by Lubik

[4]The codes and data set are available upon request from the author.

Table 1: Posterior estimates for the baseline model (with on-the-job-search), the standard search and matching model (without on-the-job search), and the model with stigma.

	Prior	OTJS	Standard	Krause and Lubik (2006)
η^g Bargaining power, Good	0.5 Normal-0.1	0.82 (0.76,0.90)	0.04 (0.03,0.05)	0.5
η^b Bargaining power, Bad	0.5 Normal-0.1	0.42 (0.37,0.46)	-	0.5
μ^g El. of match. fct., Good	0.4 Beta-0.15	0.10 (0.02,0.20)	0.02 (0.003,0.03)	0.4
μ^b El. of match. fct., Bad	0.4 Beta-0.15	0.76 (0.69,0.91)	-	0.4
ρ^g Separation rate, Good	0.1 Beta-0.02	0.028 (0.02,0.04)	0.26 (0.25,0.27)	0.1
ρ^b Separation rate, Bad	0.1 Beta-0.02	0.03 (0.02,0.04)	-	0.1
c^g Vacancy posting costs	0.15 Gamma-0.05	0.04 (0.03,0.05)	0.77 (0.75,0.79)	0.16
c^b Vacancy posting costs	0.05 Gamma-0.02	0.02 (0.01,0.02)	–	0.04
α Weight on Goods	0.4 Beta-0.15	0.58 (0.51,0.66)	–	0.4

(2009) of 0.12 is an intermediate value of those two extremes. Further, the job separation rate shock for bad jobs is higher (0.72) while the autocorrelation for good jobs is lower (0.42) relative to the standard search model (0.63). Along this line, the shock to the bad separation rate is five times larger compared to the separation shocks to good jobs. The value in the standard model is 0.02 and closer to the good job value. We can draw several conclusions. First, there is sizable heterogeneity across good and bad jobs not captured in the standard model. Second, separations are much higher in the standard model and shocks to the separation rate will have more persistent effects compared to the average across the two types of separation shocks. The intuition for this result is related to the bargaining power of workers. A high share of the match surplus going to firms encourages vacancy postings. Hence, firms in the standard model post more vacancies compared to firms in the OTJS model. In order to match the observed time series the standard model requires a high separation rate to explain, for example, aggregate unemployment over the business cycle.

In the search and matching models at hand, flows out of unemployment are driven by the creation of new matches. This creation is mainly influenced by the elasticity parameter μ. For the standard model we obtain a mean value of 0.02. The elasticity of the matching function w.r.t. unemployment for good jobs is 0.1 and 0.76 for bad jobs. The latter value is in line with the estimated value by Lubik (2009) of 0.74. As a consequence of the low rate for good jobs, the finding rate reacts more elastically to changes in labor market tightness. This implies two things for good jobs. First, the finding rate reacts stronger to changes in the labor market. Second, the matching rate is less sensitive to changes in labor market conditions and firms vacancy posting decisions (via the job creation condition) are less affected by swings in labor market tightness over the business cycle. The opposite hold for bad jobs.

Finally, we discuss the estimates for vacancy posting costs. In the OTJS model, the key assumption is the presence of a wage differential derived from differences in vacancy posting costs across jobs. Hence, it is not surprising to find a higher vacancy posting cost for good jobs compared to bad jobs. Interestingly, the difference is smaller as usually assumed in the literature (0.04 vs. 0.02). For example, Krause and Lubik (2006) assume that vacancy posting costs are four times as large (0.16 vs. 0.04) as the costs for posting a bad job. Those values are hard to compare to the findings by Lubik (2009) as he estimates non-linear vacancy posting costs. His findings show that vacancy posting costs exhibit increasing returns to scale. The standard search and matching model finds an unrealistic high value of the vacancy posting costs of 0.77. This value, again, is related to the fact that the model tries to match the observed time series with a low value of the bargaining power and a high separation rate. With a volatile exit margin, the model's likelihood is maximized by a stable entry margin. To achieve this, the model requires a large disincentive for firms (high vacancy posting costs) to balance the strong, positive incentives to post vacancies (low worker bargaining power). Hence, the high value of the vacancy posting costs can be understood as the desire of the model to balance the effects along the entry side. The final column shows the calibration assumed in Krause and Lubik (2006). The take-away from the comparison is that there is no difference in most of the parameters except vacancy posting costs and that our priors are set to match the calibrated values.

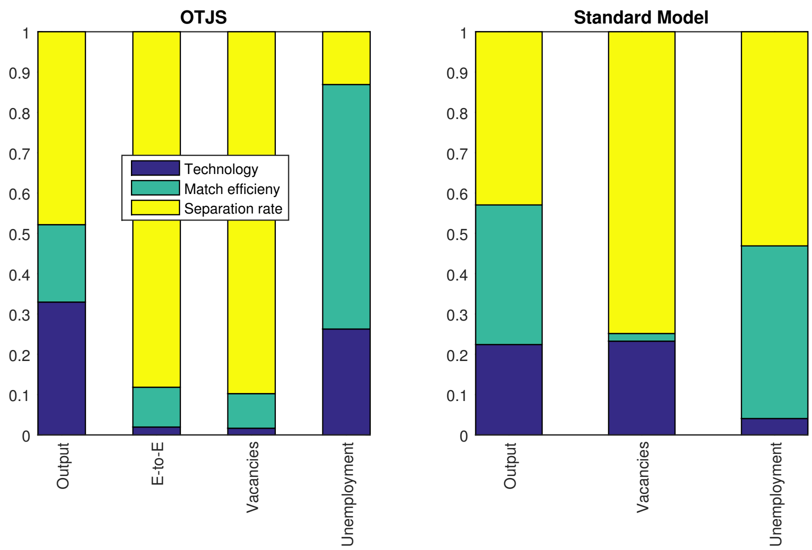
Table 2: Posterior estimates for the shock parameters across all models.

	Prior	OTJS	Standard
ρ_{Z^g} AR: Technology, Good	0.5 0.2	0.75 (0.58,0.91)	0.41 (0.28,0.54)
ρ_{Z^b} AR: Technology, Good	0.5 0.2	0.74 (0.61,0.89)	–
ρ_{M^g}, AR: Match eff., Good	0.5 0.2	0.32 (0.20,0.43)	0.89 (0.84,0.93)
ρ_{M^b}, AR: Match eff., Bad	0.5 0.2	0.69 (0.63,0.76)	–
ρ_{ρ^g} AR: Separation, Good	0.5 0.2	0.42 (0.13,0.73)	0.63 (0.55,0.71)
ρ_{ρ^g} AR: Separation, Bad	0.5 0.2	0.72 (0.65,0.78)	–
σ_{Z^g} Std: Technology, Good	0.1 2	0.01 (0.01,0.01)	0.01 (0.01,0.01)
σ_{Z^b} Std: Technology, Bad	0.1 2	0.04 (0.03,0.05)	–
σ_{M^g} Std: Match eff., Good	0.1 2	0.03 (0.03,0.04)	0.02 (0.01,0.02)
σ_{M^b} Std: Match eff., Bad	0.1 2	0.11 (0.07,0.15)	–
σ_{ρ^g} Std: Separation, Good	0.1 2	0.01 (0.01,0.01)	0.02 (0.02,0.02)
σ_{ρ^b} Std: Separation, Bad	0.1 2	0.05 (0.04,0.06)	–

4.2 Variance Decomposition

Having discussed the posterior estimates, we want to focus on the underlying driving forces of variations in key variables across the standard model and the model with on-the-job-search. Figure 1 presents an unconditional variance decomposition for the OTJS and the standard search and matching model.

Figure 1: Unconditional Variance Decomposition - Part 1.



Notes: Unconditional variance decomposition for the on-the-job search model and the standard search and matching model without on-the-job search.

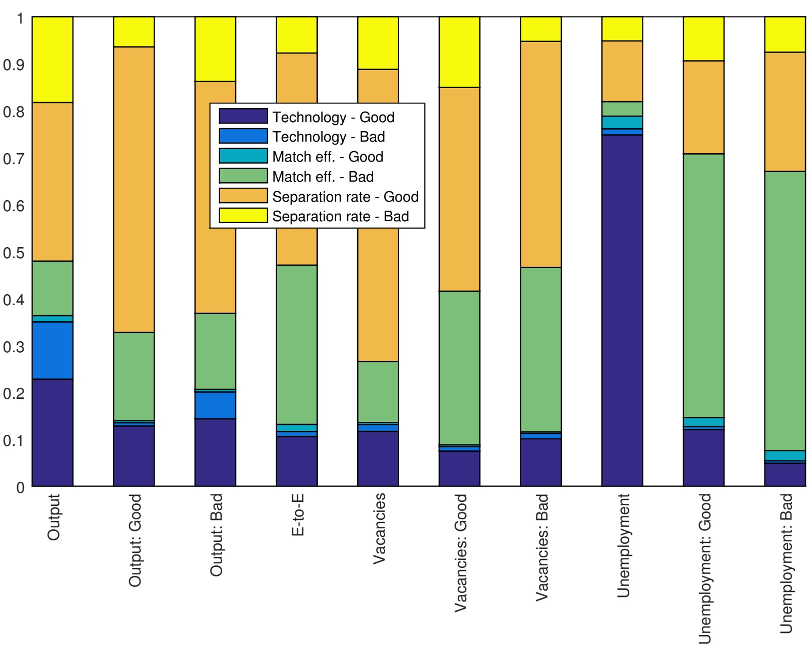
For output we find that dynamics are mainly driven the separation rate shock which explains about 50 percent of total variations. This value is similar to the one obtained for the standard search and matching model. However, in the OTJS model the technology is more important as it explains roughly 30 percent of total variations in output (only 20 percent in the standard model). Consequently, the match efficiency shock is less important in the OTJS model.

Variations in vacancies across the two models are mainly driven by innovations to the job separation rate. In the standard model, they explain roughly 70 percent of the variation, while they explain 90 percent in the OTJS model.

The most significant difference in the driving forces is obtained for unemployment. In the standard search and matching model dynamics are mainly driven by the job separation shock (50 percent of total variations). Another 45 percent are explained by the match efficiency shock, while the technology shock explains the remaining five percent. In contrast, in the OTJS model the match efficiency shock explains roughly 60 percent of the variation in unemployment. The technology shock adds another 25 percent and the job separation rate shock only explains the missing 15 percent. What is the intuition for those differences in vacancies and unemployment? As explained in the previous section, the models feature very different parameter estimates regarding to bargaining power, separation rate, and vacancy posting costs. In the standard model the level of job separations is higher and, hence, innovations to this level will have larger effects on unemployment dynamics. The opposite holds for the OTJS model. Further, in the OTJS model, technology shocks will generate smaller incentives to create vacancies because the worker's share of the match surplus is larger. Therefore, the technology shock explains more of the variation in vacancies in the standard model.

Finally, variations in employment-to-employment transitions are mainly driven by innovations to the job separation rate. This finding should be intuitive given that search intensity is mainly influenced by the good job finding probability and the vacancy filling probabilities. Those probabilities mainly depend on matches and vacancies posted. As in the OTJS model separation rate shocks are more important for vacancy dynamics, this also holds for EE transitions.

Figure 2: Unconditional Variance Decomposition - Part 2.



Notes: Unconditional variance decomposition for the on-the-job search model.

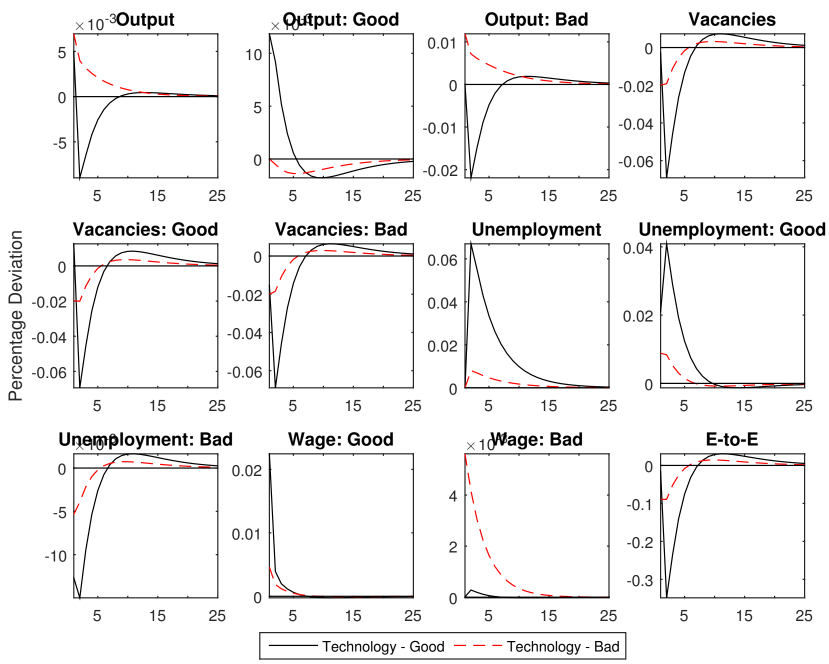
Figure 2 presents the results from estimating the OTJS model with six shocks. We find that innovations to the job separation rate of good jobs is the main driver of variations in almost all variables. The only exceptions are unemployment, where technology shocks to good jobs dominate, unemployment of good (main driver is match efficiency of bad jobs), and unemployment of bad jobs (main driver is match efficiency of bad jobs). The second and third most important drivers of variations are the match efficiency shock to bad jobs and the technology shock to good jobs. Also the separation rate shock to bad jobs plays a non-negligible role.

Overall, we can conclude that shocks to good jobs (technology and separation) explain most of the variation in the data. This finding is in line with our discussion in the previous section about the estimated parameters in the OTJS model. Separation rates are similar across jobs, but good jobs are more expansive to create and good workers demand a larger share of the match rent. Hence, shocks to the separation margin do create large adjustments.

4.3 Model Dynamics

We begin by discussing the dynamics generated by the technology shocks to good (black, solid line) and bad (red, dashed line) jobs as shown in figure 3.

Figure 3: Estimated Impulse Response Functions - Technology Shock.



Notes: Estimated impulse response functions for a technology shock in the on-the-job search model.

As in the standard search and matching literature, a positive productivity shock shifts the production frontier outside and, hence, firms are able to produce more output with the same amount of workers. We start by discussing the shock to bad jobs. Here, we find the effects we would expect from a standard search and matching model. Output of bad jobs increases which creates an incentive for firms to reduce vacancy posting for bad jobs. Employment in bad jobs nevertheless increases because employment-to-employment transitions decrease. This is a consequence of the smaller wage gap between good and bad jobs. This gap is mainly decreased by the raise in the wage for bad jobs: higher productivity creates a larger rent which is shared between firm and worker. We also observe a sectoral spillover effect that reduces employment in the good job sector. Labor market tightness for both types of jobs increases in response to the shock. Overall, we find that unemployment increases but output increases as well, although output in good jobs decreases slightly.

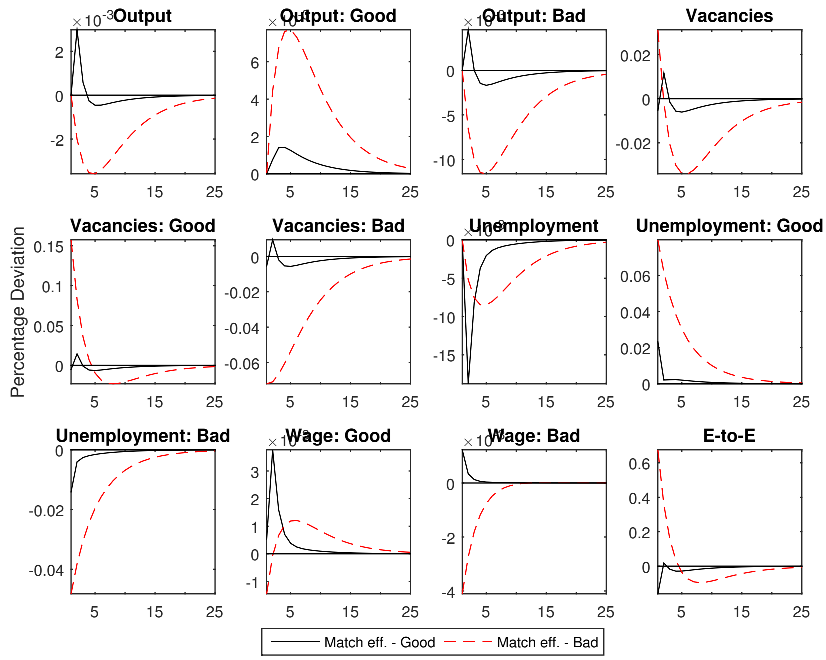
Next, we discuss the effects of a technology shock to good jobs. Here, the results are very different. Output produced by good jobs increases but, because output produced by bad jobs decreases even more, total output falls. Vacancies for good jobs decrease because firms can produce the same amount of output with less workers (labor market tightness is generally higher for both types of jobs). Hence, unemployment in good jobs increases. This is also driven by higher wages for good jobs, as the estimated bargaining power for good jobs is much higher compared to bad jobs. E-to-E transitions fall because of the drop in employment in the good job sector, implying less chances to find a good job. The spillover effect towards bad jobs is large. While unemployment falls in bad jobs (due to lower E-to-E flows), it increases in good jobs. Further, total unemployment increases, because the effect on good jobs is larger than the effect on bad jobs as the shock originates in the good job sector.

In conclusion, the job-specific technology shocks create interesting spillover effects. The effects on total output, employment, and vacancy posting also depend on the relative size of the two sectors. Finally, if we would hit the model with a technology shock that affects both types of workers equally (not shown here), we would find more standard effects: total output, vacancies, and employment increase. The sectoral effects are such that we observe a shift towards good jobs, where unemployment in bad jobs increases. Importantly, we observe an increase in E-to-E transitions, which is different to the sectoral shocks discussed above. The strong response of wages in this OTJS model is driven by the employment-to-employment flows which are absent in the standard search and matching model and add to the standard productivity effect on wages by changing job filling probabilities (and, therefore, vacancy posting costs).

Figure 4 presents the estimated impulse response functions to positive match efficiency shocks.

We begin with the response of the model to a bad match efficiency shock (red, dashed line). Furlanetto and Groshenny (2012) show that an increase in match efficiency - via the matching function - increases the number of new matches. Intuitively, an increase in match efficiency will increase the job filling rate. As a consequence, firms are able to increase employment. The generated model dynamics in the on-the-job search model are surprising and appear counterintuitive at a first glance. The increase in match efficiency for bad jobs increases the number of new bad matches. This reduces unemployment in bad jobs. Given that firms have to post less vacancies to obtain the same number of matches, vacancy posting in bad firms is reduced. Wages in bad jobs decrease mainly because the output in bad jobs decreases. This decrease in bad wages increases the gap between good and bad wages and EE transitions increase as workers increase the search effort. The increase in EE transitions creates an important spillover towards the good job labor market. The rise in EE transitions decreases the vacancy filling probability for good jobs. Further, good job output increases and leads to more vacancy posting in good job firms. Given the low estimate of μ^g the consequence of higher vacancy posting is that matches react even stronger than vacancies leading to an increase in the job finding probability q^g. Then, this increase explains the initial drop in good job wages. Over the cycle good firms start to post much more vacancies relative to bad firms and employment in good firms start to increase again. This increases good output. However output in bad jobs reacts stronger than output in good jobs and total

Figure 4: Estimated Impulse Response Functions - Match Efficiency Shock.



Notes: Estimated impulse response functions for the match efficiency shocks in the on-the-job search model.

output is reduced. The result is a quite perverse effect: good firms benefit while bad firms suffer from lower output. Again, we find a strong redistribution mechanism from bad to good type of jobs and firms.

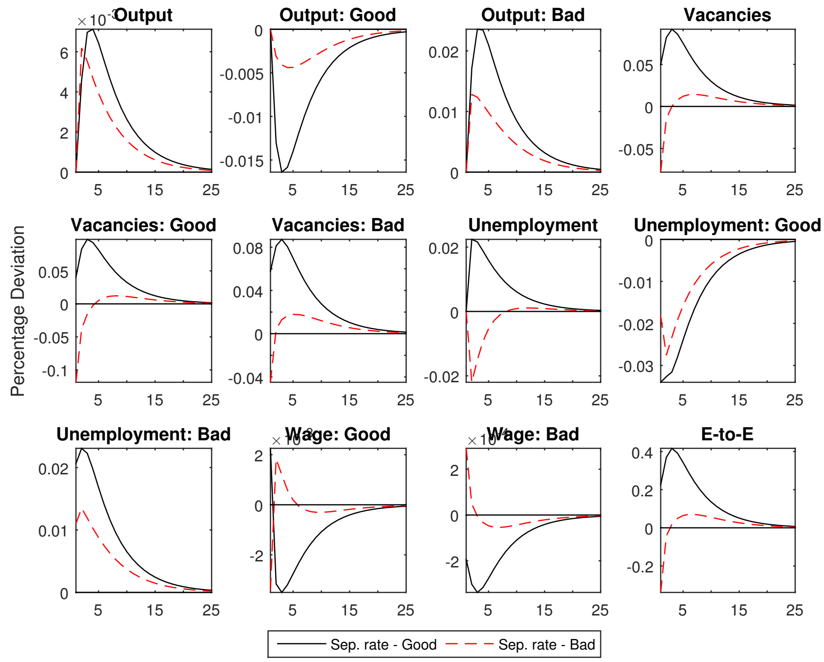
Next, we discuss the good job match efficiency shock. Figure 4 presents the estimated impulse responses for this shock (black, solid lines). The increase in match efficiency for good jobs increases employment - via increased match creation - in good job firms. However, in our general equilibrium model other effects occur at the same time. Higher match efficiency reduces the incentive for firms to post vacancies for good jobs. Further, the reduction in the wage gap and the fall in employment in good jobs, reduce E-to-E flows. Therefore, we observe a increase in unemployment in good jobs. The spillover effect towards the bad job firms is positive. Unemployment in bad jobs decreases because of a drop in E-to-E flows and higher output produced (increasing vacancy posting incentives).

In conclusion, allowing for job-specific match efficiency shocks appears to be important as the model generates sizable different dynamic responses. Further, we find a strong redistribution channel from bad to good type of jobs and firms.

Finally, we discuss the estimated impulse response functions to positive separation rate shocks (see Figure 5). The response to a separation rate shock in good jobs is plotted in solid, black lines, while the response to the shock in bad jobs is plotted in red, dashed lines.

In response to the increased job separation rate, unemployment increases because firms are not able to increase hiring as it takes one period until new matches become effective.

Figure 5: Estimated Impulse Response Functions - Separation Rate Shock.



Notes: Estimated impulse response functions for the separation rate shocks in the on-the-job search model.

Hence, employment falls which reduces production and output as well as consumption fall. Vacancy postings decrease because (i) the higher separation rate reduces the expected, discounted value of a worker and (ii) the marginal product of labor decreases. Lower vacancy posting and higher unemployment lead to a reduction in labor market tightness. But, because the increase in unemployment is larger compared to the decrease in vacancies more matches are created. This, in turn, increases the job filling rate. Wages in the good sector decrease due to the drop in the marginal product of labor and the lower labor market tightness. For the bad job firms the opposite holds true. This implies a smaller wage gap between good and bad type of jobs. Hence, workers in bad type of jobs spend less time and effort searching for good jobs. Therefore, EE transitions fall. This implies that employment in bad firms increases. With more labor bad firms are able to produce more output. This creates a negative redistribution effect for the good firms. Output in good firms falls four time as much as final output does.

The response of our model economy to a separation rate shock for good type of jobs (black, solid lines) creates similar dynamics to the job separation rate shock that affects both types of jobs. The main difference is that with a constant job separation rate of bad jobs, the positive effects towards the bad firms become stronger mainly because there is no negative effect on vacancies. In contrast, the job separation rate specific to the bad jobs (red, dashed lines) generates different dynamics. The reason is that the bad job separation rate shock decreases wages for bad jobs and, therefore, increases EE transitions. This implies more match creation for good jobs. This puts upward pressure on good wages which further opens the wage gap and strengthens incentives for workers to move across jobs. Hence, employment in good firms increases allowing them to produce more output. The consequence is an increase in final output which is in contrast to the two other considered separation rate shocks. Intuitively, with increased separations only for bad jobs, the positive labor market spillover effects benefit the good firms leading to more output being produced.

5 Conclusion

Previous research has shown that the U.S. labor market is characterized by sizable and volatile job flow rates. Within those flow rates, employment-to-employment reallocations play an important role. Fallick and Fleischman (2004), Shimer (2005), Nagypál (2008), and Menzio and Shi (2011) show that about three percent of employed workers move across employers within an average month, are negatively correlated with unemployment, and account for 49 percent of all separations.

These EE transitions are ignored in the canonical search and matching model of the labor market. This paper contributes to the on-the-job search literature by estimating an on-the-job search DSGE model. Compared to the canonical search and matching model, we find a higher value of the worker's bargaining power and a lower job separation rate in the on-the-job search model. Further, the difference in vacancy posting costs across good and bad jobs is smaller as usually assumed in calibrated models. In the on-the-job search model separation rate shocks, especially to good jobs, are a more important driving force of total variations in key variables compared to the canonical model.

A References

Acemoglu, D., 2001. Good Jobs versus Bad Jobs. *Journal of Labor Economics,* **19**(1): 1-21.

Akerlof, G., Rose, A., and Yellen, J., 1988. Job Switching and Job Satisfaction in the U.S. Labor Market. *Brooking Papers on Economic Activity*, **2**: 495-594.

Barlevy, G., 2002. The Sullying Effect of Recessions. *Review of Economic Studies*, **69**(1): 65-96.

Barnichon, R., 2010. Building a Composite Help-Wanted Index. *Economics Letters*, **109**(3): 175-178.

Bell, B. and Smith, J., 2002. On Gross Worker Flows in the United Kingdom: Evidence from the Labour Force Survey. Bank of England Working Paper, July.

Bjelland, M., Fallick, B., Haltiwanger, J., and McEntarfer, E., 2008. Employer-to-Employer Flows in the United States: Estimates Using Linked Employer-to-Employee Data. NBER Working Paper, No. 13867.

Black, M., 1981. An Empirical Test of the Theory of On-the-Job Search. *Journal of Human Resources*, **16**: 129-140.

Cole, H. L. and Rogerson, R., 1999. Can the Mortensen-Pissarides Model Match the Business Cycle Facts? *International Economic Review*, **40**(4): 933-960.

Davis, S. J. and Haltiwanger, J., 1999. Gross Job Flows. In: Ashenfelter, O. and D. Card (eds.). *Handbook of Labour Economic*, **3**: 2711-2797.

Davis, S. J., Faberman, R. J., and Haltiwanger, J., 2006. The Flow Approach to Labor Markets: New Data Sources and Micro-Macro Links. *Journal of Economics Perspectives*, **20**(3): 3-26.

Di Pace, F. and Villa, S., 2013. Redistributive Effects and Labour Market Dynamics. Center for Economic Studies - Discussion Papers, ces13.23.

Fallick, B. and Fleischman, C., 2004. Employer-to-Employer Flows in the U.S. Labor Market: The Complete Picture of Gross Worker Flows. Board of Governors of the Federal Reserve System, Finance and Economics Discussion Series, 2004-34.

Fujita, S., 2010. Reality of on-the-job search. Philadelphia FED Working Paper, No. 10-34.

Furlanetto, F. and Groshenny, N., 2012. Matching Efficiency and Business Cycle Fluctuations. Norges Bank Working Paper 2012/07.

Gertler, M., Sala, L., and Trigari, A., 2008. An Estimated Monetary DSGE Model with Unemployment and Staggered Nominal Wage Bargaining. *Journal of Money, Credit, and Banking*, **40**(8):1713-1764.

Gomes, P., 2009. Labour Market Flows: Facts from the United Kingdom. Mimeo.

Herbt, E. and Schorfheide, F., 2015. Bayesian Estimation of DSGE Models. Princeton University Press.

Kahn, L., and Low, S., 1984. An Empirical Model of Employed Search, Unemployed Search, and Nonsearch. *Journal of Human Resources*, **19**: 104-117.

Krause, M. and Lubik, T., 2006. The Cyclical Upgrading of Labor and On-the-Job Search.

Labour Economics, **13**: 459-477.

Lubik, T., 2009. Estimating a Search and Matching Model of the Aggregate Labour Market. *Federal Reserve Bank of Richmond Economic Quarterly*, **95**(2): 101-120.

Martin, D. and Pierrard, O., 2014. On-the-Job Search and Cyclical Unemployment: Crowding Out vs. Vacancy Effects. *Journal of Economic Dynamics & Control*, **44**: 235-250.

Menzio, G. and Shi, S., 2011. Efficient Search on the Job and the Business Cycle. *Journal of Political Economy*, **119**(3): 468-510.

Merz, M., 1995. Search in the Labour Market and the Real Business Cycle. *Journal of Monetary Economics*, **36**: 269-300.

Nagypál, E., 2007. Labor-Market Fluctuations and On-the-job Search. Mimeo.

Nagypál, E., 2008. Worker Reallocation over the Business Cycle: The Importance of Employer-to-Employer Transitions. Mimeo.

Pissarides, C., 1994. Search Unemployment with on the Job Search. *Review of Economic Studies*, **61**: 457-476.

Pissarides, C., 2000. Equilibrium Unemployment Theory. Second edition, MIT Press.

Pissarides, C. and Wadsworth, J., 1994. On-the-Job Seach - Some Empirical Evidence from Britain. *European Economic Review*, **38**: 385-401.

Shimer, R., 2005. The Cyclicality of Hires, Separations, and Job-to-Job Transitions. St. Louis FED, **87**(4): 493-507.

Shimer, R., 2006. On-the-job search and strategic bargaining. *European Economic Review*, **50**: 811-830.

Topel, R. and Ward, M., 1992. Job Mobility and the Careers of Young Men. *Quarterly Journal of Economics*, **107**: 439-479.

Tüzemen, D., 2012. Labor Market Dynamics with Endogenous Labor Force Participation and On-the-Job Search. Kansas City FED Working Paper, No. 12-07.

Van Zandweghe, W., 2010. On-the-Job Search, Sticky Prices, and Persistence. *Journal of Economic Dynamics & Control*, **34**: 437-455.