Business Cycles and Labor Market Flows with Skill Heterogeneity in a Monetary Policy Model*

Federico Ravenna† and Carl E. Walsh‡

October 2011

Abstract

We construct a model in which screening of heterogeneous workers by employers plays a central role in determining both the flows into and out of unemployment. Following a negative productivity shock, the share of low-skill workers in the pool of unemployed rises, and this composition effect reduces the incentive of firms to post vacancy falls, lowering job opportunities for *all* workers. Skill heterogeneity amplifies unemployment fluctuations in economies with small gross labor flows, or during a persistent fall in demand. The model provides a rich environment to study the implications of labor market structure for real and monetary disturbances.

JEL: E52, E58, J64

1 Introduction

We construct a business cycle model in which the average skill distribution across employed and unemployed workers is endogenous. We assume a worker's skill level is unobservable ex-ante by firms and job search is non-directed. By interviewing an unemployed worker, firms can observe the worker's skill level. Workers with low productivity may be interviewed but not hired as firms screen these workers out during the interview process.

*This research was supported by the Fondation Banque de France grant on "European Labor Market Institutions and their Consequences for Monetary Policy".

†HEC Montreal, Institute of Applied Economics. Email: federico.ravenna@hec.ca.

‡Department of Economics, University of California, Santa Cruz. Email: walshc@ucsc.edu.

We show that screening amplifies the volatility of the exit rate from unemployment, capturing the idea that firms become more selective in a recession, reducing the vacancy yield falls relative to a model with homogeneous skills. Following a negative productivity shock, the share of low-skill workers in the pool of unemployed rises, and this composition effect lowers the average productivity of the unemployed relative to the employed. As the share of low-skill workers increases, the incentive to post vacancy falls, lowering job opportunities for *all* workers.

The composition effect in our model can act as a powerful mechanism for amplifying the relative volatility of unemployment to output. Separations at the beginning of a recession disproportionately affect low-skill workers, and the decline in the job finding probability is larger for low relative to high skill workers. Thus the composition effect makes the average TFP of unemployed workers more volatile than the TFP of the overall labor force. In fact, measured labor productivity of those who remain employed will *increase* if the recession is driven by a demand shock. We show that a strong amplification effect can obtain even if low-skill workers represent a small share of the total labor force.

It has long been recognized that the impact of business cycle fluctuations on employment and total hours worked differs across subgroups of the population. Clark and Summers (1981) find that while teenagers comprise less than 10% of the US population, they account for more than a fourth of cyclical employment fluctuations. Elsby, Hobijn and Sahin (2010) find that younger, less educated workers and individuals from ethnic minorities experienced steeper increases in joblessness during all of the last six US recessions, mainly because of a larger fall in the exit rate from unemployment.

These observations suggest time-varying heterogeneity in the skill level of the unemployed, as measured by observable characteristics, could have a strong impact on the volatility of aggregate labor market variables. This hypothesis has received only mixed support in empirical studies. Yet a worker's productivity may also depend on unobservable characteristics, and many theoretical frameworks imply that separations disproportionately hit low-productivity workers. In fact, a large literature has documented large wage differentials among observationally equivalent workers, and unexplained wage differentials are often found to be of the order of 70% of total wage inequality (Mortensen, 2003).

While skill-heterogeneity in our model helps in explaining several observed stylized facts, such as higher unemployment volatility among low-skill workers, negative duration dependence of unemployment exit rates and re-employment wage, a key contribution of our paper is to show under what conditions the composition effect is relevant.

First, skill heterogeneity by itself is not sufficient to generate amplification of productivity shocks on the unemployment rate. In an economy with large steady state flows between employment and unemployment, a change in the employment level can be achieved with relatively small changes in separations and hiring. This implies the skill composition of the unemployed does not change much over the business cycle and the composition effect will contribute little to the volatility of unemployment. Thus, the larger labor flows that characterize the US relative to many European economies imply a weaker composition effect and less volatility of unemployment in the US. Pries and Rogerson (2005) report evidence that worker turnover is between two and three times larger in US than in Europe. We show that parameterizations consistent with labor data from the EU and US leads indeed to a much weaker composition effect in the US.

Second, our model implies that recessions originating from long-lived shocks result in much larger increases in unemployment for a given fall in output. Thus the composition effect may be relevant and contribute to a slow recovery of employment during severe and long lasting recessions even in economies with large gross labor flows. In our basic parameterization, the composition effect result in a sluggish increase in unemployment following a contractionary shock, peaking six quarters after the initial fall in demand.

Third, the impact of a fall in productivity that affects disproportionately low skill workers relative to high skill workers greatly amplifies the composition effect and the volatility of unemployment. Such a skill-biased technology shock can lower average productivity of the pool of unemployed workers, reduce vacancy posting, and lower the vacancy yield. In turn, this leads to a fall in the exit rate from unemployment for all workers, leading to higher economy-wide unemployment. If the notion of labor heterogeneity in our model is interpreted more broadly, it might help account for the empirical evidence for the recent US experience which indicates the shortfall in employment has been especially hard in specific sectors (construction and manufacturing sectors) while vacancy yields have been below expectations across all the sectors during the recovery (Daly, Hobijn and Valletta 2011).

We use our model to compare the effectiveness of alternative monetary policy rules. Following a fall in productivity, policy rules that are more output-stabilizing are effective at reducing the fall in output only in the initial periods, while after a year the improvement in output and unemployment is more limited. Moreover, stabilizing output and unemployment comes at a great cost in terms of inflation. Skill-biased productivity shocks pose even more of a conundrum to the policy maker, since the gain in employment and output obtained with a more output-stabilizing policy is even more modest after one year.

Our modeling framework is related to several contribution in the literature. We include nominal rigidities in a model with unemployment, as do Blanchard and Galí (2007, 2010), Gertler, Sala and Trigari (2008), Gertler and Trigari (2009), Ravenna and Walsh (2008, 2011a, 2011b), Walsh (2003, 2005), and Galí (2011). However, these contributions with the exception of Walsh (2003, 2005) assume an exogenous separation rate, and all these previous papers assume homogenous workers.

Worker and match heterogeneity play a key role in several models in the search and matching literature, among which Guerrieri (2007), Nagypal (2007), Nagypal and Mortensen (2007), and models with job-to-job transitions, as Krause and Lubik (2010) and Tasci (2007). Our model includes endogenous separations, as Den Haan, Ramey, and Watson (2000). Contrary to their model, we assume a portion of the match-productivity is worker-specific rather than match-specific. Bils, Chang and Kim (2009) and Mueller (2011) study the implications of skill heterogeneity for wages and labor market flows over the business cycle, but assume segmented labor markets and only consider productivity shocks.

Our approach is closer to the models of Rogerson and Pries (2005) and Pries (2008). In Rogerson and Pries (2005), matches have persistent job-specific productivity, and firms screen for workers based on limited information on their productivity. As the match productivity is revealed over time, separations take place. Contrary to our approach, the average productivity of unemployed workers is not state-dependent, and the authors focus on steady state results rather than on the dynamics of labor market variables over the business cycle. Pries (2008) shows in a model with heterogeneous skills and exogenous separation rates that the composition effect has a large impact on the cyclical value of vacancies and thus on the behavior of employment flows. While the framework we propose is closely related, and relies on a similar mechanism in affecting incentives to post vacancies, we relate the composition effect to the size of gross labor flows, the persistence of shocks, the possibility of skill-biased TFP changes, and we provide a framework with nominal rigidities that allows alternative monetary policies to be analyzed. In addition, Pries sets the relative covariance of separation rates for high and low skilled workers exogenously, this covariance is endogenous in our model and can vary depending on the nature of the shock processes.

The paper is organized as follows. In section 2, we review some of the empirical evidence on worker heterogeneity and labor market dynamics. Our model is presented in section 3. The role of skill heterogeneity and the composition effect is investigated in a calibrated version of the model in section 4, while the impact of monetary shocks and alternative policy rules for monetary policy are studied in section 5. Finally, conclusions are discussed in the final section.

2 Empirical Evidence

2.1 Skill Heterogeneity and Aggregate Labor Market Dynamics

The hypothesis that changing heterogeneity in the pool of unemployed may drive in part the correlation between aggregate labor market variables and the business cycle has a long history. Darby, Haltiwanger and Plant (1985) advanced the heterogeneity hypothesis to explain the strong countercyclicality of average unemployment duration: if the composition of job-losers changes systematically over the business cycle, and groups that experience longer durations enter unemployment in proportionally greater numbers during a recession, the average spell will be countercyclical even if individual spells are acyclical.

Most empirical studies of the heterogeneity hypothesis have relied on observable heterogeneity. Baker (1992) finds no support for the heterogeneity hypothesis in unemployment duration when selecting groups by demographics or reason for joblessness, and similar results are obtained for unemployment exit rates by Abbring, van den Berg and van Ours (2002) and van den Berg and van der Klaauw (2001) using French data. One observable characteristic that has received much attention in the literature as a potential driver of time-varying heterogeneity in the unemployment pool is the reason for joblessness. Davis, Haltiwanger and Schuh (1996) provide evidence supporting the hypothesis that a disproportionate part of unemployment inflows during a recession consists of laid-off workers, and stress the countercyclical behavior of layoffs, as opposed to the procyclical behavior of quits (which reflect in large part job-to-job transitions). The recent literature has stressed that the separation rate is rather acyclical in recent US business cycle, but the data show that increased inflows into unemployment during a recession can be traced to a shift in separations towards layoffs (Elsby, Hobijn, Sahin, 2008). Our model is consistent with this evidence, since the share of endogenous separation is procyclical, leading to low-skill workers being over-represented in the group flowing into unemployment during a recession. Davis (2005) cites several studies finding that layoffs are associated with greater unemployment incidence and longer unemployment spells than quits, and workers experiencing layoffs also experience a large and persistent decline in earnings.

Using CPS data from 1976 to 2007, Shimer (2007) reports that, while the change in the share of laid-off workers is correlated with the business cycle, it explains a small portion of the overall variation in the job-finding probability. Similarly, the data in Elsby, Hobijn, Sahin (2010) show that the bulk of the large differences in the level of unemployment across demographics subgroups are driven by differences in each group's inflow rate. Outflow rates from unemployment are remarkably more similar than inflow rates by age, education, ethnicity. We provide a theoretical framework that is partly consistent with this evidence by allowing both high and low skill workers to compete in the same labor market. Thus, while we assume inflows into unemployment increases only for low-skill workers, the outflow rate endogenously falls for all workers - though proportionally more for low skill workers - as the composition effect reduces the incentive of firms to post vacancies.

Barnichon and Figura (2011) provide evidence in support of the heterogeneity hypothesis. They examine the role of heterogeneity in explaining changes in matching efficiency for a matching function estimated using CPS data for the 1976-2009 sample. Their estimates support the finding that most of the shifts in the matching function up to 2006, and half of the decline in matching efficiency over the 2007-2009 period, are due to changes in the composition of the pool of unemployed.

The model we propose relies on unobserved heterogeneity, as workers with heterogeneous skills cannot be sorted according to observable characteristics before being interviewed by a firm. Thus, empirical studies that examine the heterogeneity hypothesis relying on demographic data for age or education, or looking at sectorial data, do not provide direct support for our assumptions. Unobserved heterogeneity and its relation with the behavior of aggregate labor market variables over the business cycle has been considered by some authors. Many labor economists have documented that most of the wage differentials across workers cannot be explained by observable characteristics[1]. Education and experience are often badly measured and do not fully capture the effectiveness of a worker. Indeed, Villena-Roldan (1997) reports evidence from the National Employer

[1] See Mortensen, (2003). A substantial literature examines the behaviour of wages over the business cycle, and has considered the heterogeneity hypothesis (see for example Solon, Barski and Parker, 1994).

Survey 1997 that firms interview a median of 5 applicants per vacancy and spend and average \$4200 on recruiting activities per recruited worker. Pries (2008) observes that skill-heterogeneity is hard to measure, both because a worker's productivity is only partially accounted for by observable characteristics and because workers can differ in the value of their outside option relative to employment. Abbring, van der Berg and van Ours (2002) find using French data that unemployment duration dependence over the first five quarters is explained by unobserved heterogeneity.

Mueller (2011) provides some direct evidence related to our assumption of unobserved heterogeneity. Using CPS data, he shows that separation and job-finding rates are more cyclical for high-residual wage workers as opposed to low-residual wage ones. If we attribute the above-median wage-residual to a higher skill level, the evidence points towards a reverse impact of heterogeneity than the one assumed in our model. However, our model can match his evidence on the procyclicality of wages for workers flowing into the pool of unemployed, since it implies that in the beginning of a recession the productivity of low-skill workers entering unemployment is higher than average, and the average wage for unemployment entrants does not need to fall. Bils, Chang and Kim (2009) find results opposite to Mueller (2011) using SIPP data. They conclude that low-wage, low-hours workers (which they identify with workers having a low comparative advantage on the labor market in comparison to non-market activities) have separation and job finding rates substantially more sensitive to the business cycle than high-wage, high-hours workers.

2.2 Cross-country Evidence on Labor Flows

A very extensive literature has documented the differences in labor flows between US and large European economies. Elsby, Hobijn, and Sahin (2008) find that unemployment inflow and outflow rates are positively correlated, with continental European countries characterized by low rates of both inflow and outflow. The average of the inflow and outflow rates in France, Germany, Italy, Portugal, and Spain ranged from 4.8% (Italy) to 10.2% (Spain). By way of contrast, the rate averaged 40% in the US. The estimated rate of outflow from unemployment for Spain was 1% while rates for France, Germany, Italy, and Portugal were even lower. For the US, the comparable figure was estimated to be 3.6%. Elsby, Hobijn, and Sahin (2008) argue that inflows contribute only about 20% of the time series variation of unemployment rates in Anglo-Saxon and Nordic countries, a finding consistent with Shimer (2005). However, the corresponding figure for continental

European economies is 50%, suggesting a much larger relative role is played by variations in the inflow to unemployment in accounting for fluctuations in European unemployment.

The important role played by fluctuations in the rate of inflow into unemployment in European economies is inconsistent with the standard assumption of most recent monetary models with search and matching in the labor market, which typically assume a constant and exogenous separation rate (e.g., Ravenna and Walsh 2008, 2011a, 2011b, Gertler, Sala and Trigari 2008, Gertler and Trigari 2009, Blanchard and Galí, 2010).

Jung and Kuhn (2011) provide additional evidence on cross-country differences in employment dynamics using US and German data. While the average German job finding and firing rate are respectively 1/5 and 1/4 of the US one, the firing rate is 2.5 times more volatile in Germany than in the US. Firing contribute between 60 and 70% to the German unemployment volatility. The authors report evidence supportive of an important role for workers' skill heterogeneity: 75% of all firings happen for matches with tenure less than two years, and the majority of jobs destroyed falls at the lower end of the earnings distribution.

3 A Model with Skill-heterogeneity and Non-directed Search

The model consists of households, wholesale and retail firms, and a monetary authority. Wholesale firms produce an homogenous good which is sold in a competitive market to retail firms, of which there are a continuum of mass one. Retail firms sell differentiated goods to households, and the retail sector is characterized by monopolistic competition and price stickiness as in standard new Keynesian models.

3.1 Overview of the labor market and labor flows

Workers are assumed to be heterogeneous with respect to skill; for simplicity, we assume workers are of two types, either high (h) or low (l) skill. Firms post vacancies to which unemployed workers apply. Firms must interview applicants to determine the worker skill type. Thus, the job search and recruitment process involves both interviewing and screening. The aggregate number of interviews per period is determined through random matching as in standard matching models of the labor market. We assume all job seekers have identical interview-finding probability regardless of skill level. At the interview, the job applicant is screened. Not all interviews result in hires. We assume that if the skill level is revealed in the interview to be h, the worker is hired and produces with probability equal to one. That is, we assume the firm is able to identify a high-skill worker in the interview and the productivity of an h worker is high enough that it guarantees a positive surplus in all states.[2]

The productivity of low-skill workers is assumed to be stochastic. Each period, regardless of whether employed or unemployed, each low-skill worker i receives a new idiosyncratic stochastic productivity level $a_{i,t}$. We assume $a_{i,t}$ is serially uncorrelated and drawn from a distribution with support (0 1]. While productivity is randomly drawn in each period for a low-skill worker, the worker's skill-type, h or l, is permanently assigned.[3] While all high-skill unemployed workers who are interviewed are subsequently hired, only low-skill unemployment workers with $a_{i,t} > \bar{a}_t$ will be hired, where $\bar{a}_t$ is an endogenously determined threshold level of productivity that will be shown to depend on an aggregate productivity shock and on the markup of retail over wholesale prices. In the absence of direct hiring and firing costs, $\bar{a}_t$ will also be the cut off value for determining whether an existing employed low-skill worker is retained by the firm. That is, from the perspective of the firm, the decision to retain or fire an existing low-skill worker with productivity $a_{i,t}$ is the same as the decision to screen out or hire a newly interviewed low-skill worker with productivity $a_{i,t}$.

In addition to idiosyncratic productivity shocks, all employed workers are subject to an aggregate productivity shock z_t. We also allow for skill-biased productivity shocks z_t^h, z_t^l. Hence, the total productivity of a low-skilled worker-hour i at t is $z_t z_t^l a_{i,t}$ while that of a high-skilled worker-hour is $z_t z_t^h$.

We neglect labor force participation decisions and normalize the total workforce to equal one:

$$L^l + L^h = L = 1,$$

where L^j denotes the labor force of type j, $j = h, l$. Let $\bar{\gamma} = L^l/L$ be the (fixed) fraction of the total labor force that is low skilled. Let S^j be the number of type j workers who are seeking jobs, and let N^j be the number of type j workers who are employed. Then

[2] This assumption is for simplicity as it will imply that endogenous separations and interviews that do not lead to hires only involve low skilled workers.

[3] We could assume match productivity is also random for high skill workers. If the support of the distribution is such that high-skill workers productivity for the least productive match is sufficiently higher then low-skill workers productivity for the least productive match, the basic results of our model would be unchanged.

the probability a worker drawn from the pool of unemployed job seekers is low skill is

$$\gamma_t = \frac{S_t^l}{S_t^l + S_t^h},$$

while the share of employed workers of skill l is

$$\xi_t = \frac{N_t^l}{N_t^l + N_t^h}.$$

The timing of activities is as follows. The stock of producing matches (filled jobs) in period t is N_t of which $1 - \xi_t$ are quality h and ξ_t are quality l. At the start of each period, there is an exogenous separation probability, denoted by ρ^x, that affects all employed workers, regardless of skill level. Workers who are not in a match at the start of the period, or who do not survive the exogenous separation hazard, are unemployed and seek new interviews. There are

$$S_t = 1 - (1 - \rho^x) N_{t-1}$$

such job seekers. We define the end-of-period number of unemployed workers as

$$U_t = 1 - N_t.$$

The two measures of unemployment can differ as some job seekers find employment (and produce) during the period. In search models based on a monthly period of observation, it is more common to assume workers hired in period t do not produce until period $t+1$. In this case, the number of job seekers in period t plus the number of employed workers adds to the total work force. Because we base our model on a quarterly frequency, we allow for some workers seeking jobs to find jobs and produce within the same period.

After exogenous separation occurs, all aggregate shocks are realized and observed. This allows firms to determine $\bar{a}_t$, the cutoff point for low-skill productive that will determine hiring and retention.[4]

Firms post vacancies V_t. The number of vacancies, together with the number of job seekers, determine the number of interviews I_t via a standard matching function. The probability a job seeker gets an interview is $k_t^w \equiv I_t/S_t$. Firms interview $k_t^f V_t$ workers

[4] We show below that $\bar{a}_t$ is the same for all firms.

in the aggregate, where k_t^f is the probability a given vacancy receives an applicant to interview.

The time t idiosyncratic productivity shocks $a_{j,t}$ associated with employed low-skill workers and low-skill workers who are interviewed are observed. A fraction $1-\rho_t^n$ type l workers receive productivity levels $a_{i,t} > \bar{a}_t$. So new hires H_t are given by the number of interviewees who are of high skill, all of whom are hired, plus the number of interviewees who are of low skill times the fraction of these with productivity levels that exceed $\bar{a}_t$:

$$H_t = (1-\gamma_t)k_t^w S_t + (1-\rho_t^n)\gamma_t k_t^w S_t = (1-\rho_t^n\gamma_t)\, k_t^w S_t.$$

Note that fewer workers are hired than are interviewed: $H_t = (1-\gamma_t\rho_t^n)\, k_t^w S_t < k_t^w S_t$. The probability a randomly selected unemployed worker is screened out in the interview process (i.e., actually gets interviewed with a firm, is of low skill but has a $a_{i,t} < \bar{a}_t$ and so is not hired) is $\gamma_t \rho_t^n$. In standard matching models, new hires equal $k_t^w S_t$. Screening implies new hires are less than this level and depend on the average skill quality of the pool of unemployed workers γ_t and the aggregate productivity level which we show below will affect ρ_t^n.

Low-skill workers employed in existing matches that survived the exogenous separation hazard also receive a new productivity shock and are retained if and only if $a_{i,t} > \bar{a}_t$. Thus, actual employment in period t is equal to

$$\begin{aligned} N_t &= (1-\rho^x)\left[\left(1-\xi_{t-1}\right) + \xi_{t-1}(1-\rho_t^n)\right] N_{t-1} + H_t \\ &= (1-\rho^x)\left(1-\xi_{t-1}\rho_t^n\right) N_{t-1} + H_t \end{aligned}$$

The total separation rate is $(1-\rho^x)\left(1-\xi_{t-1}\rho_t^n\right)$ and depends on the exogenous hazard ρ^x, the endogenous hazard for low-skill workers ρ_t^n, and the average skill-quality of beginning-of-period matches ξ_{t-1}. The share of low skill employed workers evolves according to

$$\xi_t = (1-\rho_t^n)\left[\frac{(1-\rho^x)\xi_{t-1}N_{t-1} + \gamma_t k_t^w S_t}{N_t}\right]. \tag{1}$$

Job seekers at t who are of quality l equal the total number of low-skilled workers minus the number of matches of quality l that survive the exogenous separation hazard. Hence,

$$\gamma_t = \frac{L^l - (1-\rho^x)\xi_{t-1}N_{t-1}}{S_t}. \tag{2}$$

In deriving (1) and (2) we assume workers who suffer exogenous separations can search within the same period, while those who experience endogenous separation, which occurs after shocks are realized during the period, cannot search until the following period.[5]

Since $a_{i,t}$ is *i.i.d.*, the model does not generate any endogenous distribution of skill-related productivity (each l worker may be more or less productive in every period), and an l worker can become less productive even if already in a match. But the share of low-skill workers in the unemployment pool, γ_t, is endogenous, so the skill-weighted productivity of both the workforce and the pool of unemployed changes over time. In particular, a burst of separations raises the average productivity of surviving matches and lowers the average skill level of the pool of unemployed job seekers.

3.2 The labor and goods markets

3.2.1 The wholesale sector

Wholesale firms post vacancies, interview and screen applicants, make hiring and retention decisions, and produce a homogenous output. Let h_t^h denote hours worked by an employed high-skill workers and let $h_{i,t}^l$ be hours worked by employed low-skill worker i. All type h workers will work the same hours since they have the same productivity, but the hours of low-skill workers will depend on their idiosyncratic productivity realizations. Output of wholesale goods is obtained by aggregating over the output produced by employed high-skill workers and the output produced by employed low-skill workers (i.e., those with idiosyncratic productivity levels greater than $\bar{a}_t$):

$$\begin{aligned} Q_t &= z_t z_t^l N_t^l \left[\frac{\int_{\bar{a}_t}^1 a_{i,t} h_{i,t}^l dF(a_i)}{1 - F(\bar{a}_t)} \right] + z_t z_t^h h_t^h N_t^h \\ &= \left\{ z_t^l \xi_t \left[\frac{\int_{\bar{a}_t}^1 a_{i,t} h_{i,t}^l dF(a_i)}{1 - F(\bar{a}_t)} \right] + (1 - \xi_t) z_t^h h_t^h \right\} z_t N_t \end{aligned} \tag{3}$$

where z_t^j is aggregate productivity for all workers of skill level $j = [l, h]$ and $F(a)$ is the c.d.f. of the idiosyncratic productivity shocks. We assume the productivity of a match depends on a common productivity disturbance z_t, with the productivity z_t^l of l workers

[5] Combining eqs. (1) and (2), it can be seen that job seekers at t who are of quality l arise from three sources: low-skilled workers who were searching for jobs in $t-1$ and failed to be hired; those employed in $t-2$ who survived the exogenous separation hazard but were endogenously terminated; and those employed in $t-1$ but who suffer the exogenous hazard at the start of period t.

equal to z_t, and the productivity of h workers equal to $z_t^h = z^h z_t$. The constant z^h is used to parameterize the relative average productivity of l and h workers. Since $F(\bar{a})$ is the probability $a_{i,t} \leq \bar{a}_t$, $F(\bar{a}) = \rho_t^n$ is also the endogenous separation and screening rate.

The homogenous output of wholesale firms is sold to retail firms in a competitive goods market. The price of the wholesale good is P_t^w; the aggregate price index for retail goods is P_t. We define $\mu_t = P_t/P_t^w$ as the retail-price markup.

Expressed in terms of final retail goods, the current surplus of a firm-worker match involving a high-skill worker is

$$s_t^h = \left(\frac{z_t z_t^h h_t^h}{\mu_t}\right) - \frac{v(h_t^h)}{\lambda_t} - w_t^{u,h} + q_t^h, \tag{4}$$

where h_t^h is chosen optimally to maximize the match surplus, $v(h_t^h)$ is the disutility of hours worked, λ_t is the marginal utility of consumption, $w_t^{u,h}$ is the value of an unmatched high-skilled worker's outside opportunity, and q_t^h is the continuation value of a match with a high-skill worker. Since all type h workers have the same productivity, they will all work the same number of hours and generate the same surplus.

The surplus of a match involving a low-skill worker is

$$s_{i,t}^l = \left(\frac{a_{i,t} z_t z_t^l h_{i,t}^l}{\mu_t}\right) - \frac{v(h_{i,t}^l)}{\lambda_t} - w_t^{u,l} + q_t^l, \tag{5}$$

This differs from the expression for high-skill worker/firm matches because of the idiosyncratic productivity disturbance and the non-degenerate distribution of hours worked among low-skill workers. As is common in the literature on unemployment, we assume complete consumption risk sharing, so λ_t is the same for all workers.

Because the idiosyncratic productivity shocks are assumed to be serially uncorrelated, q_t^j depends on the skill-type of the worker in a match but is the same for all matches of the same skill-type. Let $f(a_i)$ be the density function for $a_{i,t}$. The continuation values are therefore given by

$$q_t^h = \beta \mathrm{E}_t \left(\frac{\lambda_{t+1}}{\lambda_t}\right) \left[(1-\rho^x) s_{t+1}^h + w_{t+1}^{u,h}\right]. \tag{6}$$

and

$$
\begin{aligned}
q_t^l &= \beta \mathrm{E}_t \left(\frac{\lambda_{t+1}}{\lambda_t} \right) \left[(1-\rho^x)(1-\rho_{t+1}^n) E_t(s_{i,t+1}^l | a_{i,t} > \overline{a}_{i,t}) + w_{t+1}^{u,l} \right] \\
&= \beta \mathrm{E}_t \left(\frac{\lambda_{t+1}}{\lambda_t} \right) \left[(1-\rho^x) \int_{\bar{a}_{t+1}}^{1} s_{i,t+1}^l f(a_i) da_i + w_{t+1}^{u,l} \right]. \qquad (7)
\end{aligned}
$$

To determine $w_t^{u,j}$, we assume that w^u is the value of time spent unemployed (home production or an unemployment benefit) and that wages are determined by Nash bargaining with the worker receiving a constant share η of the match surplus. Then the value of unemployment is equal to w^u plus the expected probability of being employed and receiving the surplus share ηs_{t+1}^j plus the expected value of remaining unemployed. For a high-skilled worker this is

$$
w_t^{u,h} = w^u + \beta \mathrm{E}_t \left(\frac{\lambda_{t+1}}{\lambda_t} \right) \left(k_{t+1}^w \eta s_{t+1}^h + w_{t+1}^{u,h} \right), \qquad (8)
$$

while for a low-skilled worker it is

$$
\begin{aligned}
w_t^{u,l} &= w^u + \beta \mathrm{E}_t \left(\frac{\lambda_{t+1}}{\lambda_t} \right) \left[k_{t+1}^w \eta (1-\rho_{t+1}^n) E_t(s_{i,t+1}^l | a_{i,t} > \overline{a}_{i,t}) + w_{t+1}^{u,l} \right] \\
&= w^u + \beta \mathrm{E}_t \left(\frac{\lambda_{t+1}}{\lambda_t} \right) \left[k_{t+1}^w \eta \int_{\bar{a}_t+1}^{1} s_{i,t+1}^l f(a) da + w_{t+1}^{u,l} \right]. \qquad (9)
\end{aligned}
$$

If a low-skilled worker's productivity is too low, the surplus will be negative, leading to endogenous separation (or screening in the case of an interviewed job seeker). From (5), the cutoff value of worker productivity at which the surplus produced by a low-skill worker equals zero is

$$
\bar{a}_t = \frac{\mu_t \left(w_t^{u,l} + \frac{v(\hat{h}_t^l)}{\lambda_t} - q_t^l \right)}{z_t z_t^l \hat{h}_t^l},
$$

where $\hat{h}_t^l$ maximizes the surplus and satisfies

$$
v_h(\hat{h}_t^l) \equiv \frac{\partial v(\hat{h}_t^l)}{\partial \hat{h}_t^l} = \left(\frac{\bar{a}_t z_t z_t^l}{\mu_t} \right) \lambda_t.
$$

That is, hours $\hat{h}_t^l$ maximizes the joint surplus in a match with a low-skill worker of productivity $\bar{a}_t$.

Matches of low-skill workers separate endogenously if $a_{i,t} < \bar{a}_t$. As claimed previously, $\bar{a}_t$ is the same for all firm considering the retention or hire of a low–skill worker. The probability of endogenous separation for a low-skilled worker/firm match is

$$\rho_t^n = F(\bar{a}_t).$$

This is also the probability a low-skill worker who receives an interview is not hired. If the aggregate productivity shock is low, $\bar{a}_t$ will rise, lowering the fraction of low-skill unemployed that receive job offers and increasing the endogenous separation rate of already employed low skill workers. Low skill workers become a larger fraction of the unemployed pool, since the probability of separation is always higher than for high skill workers. Also, after a positive aggregate shock (even *i.i.d.*) the average duration of unemployment increases, as the low skill workers lose jobs faster and have a harder time finding new employment since they are more likely to be screened out during the interview process.

3.2.2 Hours

Hours maximize the joint surplus in a match s_t^h, $s_{i,t}^l$. For a high-skill worker, this implies

$$v_h(h_t^h) = \left(\frac{z_t z_t^h}{\mu_t}\right)\lambda_t$$

For a low-skill worker of productivity $a_{i,t}$, this implies

$$v_h(h^l) = \left(\frac{a_{i,t} z_t z_t^l}{\mu_t}\right)\lambda_t;\ a_{i,t} \geq \bar{a}_t.$$

3.2.3 Vacancies

Wholesale firms post vacancies after observing aggregate variables, so their decisions are conditional on $\bar{a}_t$. If κ is the cost of posting a vacancy, expressed in terms of final goods, and firms receive a share $1-\eta$ of the surplus from a match, the job posting condition is

$$k_t^f(1-\eta)\left[(1-\gamma_t)s_t^h + \gamma_t \int_{\bar{a}_t}^1 s_{i,t}^l f(a_i)da_i\right] = \kappa, \tag{10}$$

since with probability $(1-\gamma_t)$ the firm interviews (and hires) a high-skill worker and with probability γ_t it interviews a low-skilled worker. This condition can also be expressed as

$$k_t^f(1-\eta)\left[s_t^h - \gamma_t\left(s_t^h - \int_{\bar{a}_t}^1 s_{i,t}^l f(a_i)da_i\right)\right] = \kappa.$$

Since the surplus from a high skill worker is greater than that from an employed low skill worker, a fall in the quality of the unemployment pool (a rise in γ_t) reduces the incentive to post vacancies.

Given the pool of job seekers S_t and the number of vacancies V_t posted by firms, the number of new interviews is determined by a standard matching function $m(S_t, V_t)$. This is taken to be Cobb-Douglas with constant returns to scale:[6]

$$m(S_t, V_t) = \psi S_t^\alpha V_t^{1-\alpha} = \psi\theta_t^{1-\alpha} S_t, \qquad 0 < \alpha < 1,\, \psi > 0, \tag{11}$$

where $\theta_t \equiv V_t/S_t$ is the standard measure of labor market tightness. Because of worker heterogeneity, the probabilities of being interviewed and being hired will differ by the worker's skill level. The probability an unemployed worker obtains an interview, k_t^w, is

$$k_t^w = \frac{m(S_t, V_t)}{S_t} = \psi\theta_t^{1-\alpha}. \tag{12}$$

This is the same for all job seekers. Similarly, the probability a firm with a posted vacancy finds an applicant, k_t^f, is

$$k_t^f = \frac{m(S_t, V_t)}{V_t} = \psi\theta_t^{-\alpha}. \tag{13}$$

Compared to the standard single-skill setup, k_t^w is the probability a firm obtains an interview, and k_t^f is the probability an interview slot will not go unfilled. The job finding probability is identical to the interview rate for high-skill workers, while it is lower, and equal to

$$k_t^{w,l} = k_t^w\,(1-\rho_t^n) < k_t^w$$

for low-skill workers. The overall job finding probability can be defined as $\gamma_t k_t^{w,l} + (1-\gamma_t)k_t^w$. With heterogeneous worker skills, a job opening that would be filled and lead to production if a high-skill applicant is interviewed may go unfilled if a low-skill worker is

[6] Constant returns to scale is consistent with the empirical evidence when applied to new hires; see Petrongolo and Pissarides (2001).

interviewed.

3.3 Households

The representative household purchases consumption goods, holds bonds, and supplies labor. Since some workers will be matched while others will not be, and workers differ in their productivity and hours worked, distributional issues arise. To avoid these issues, we follow the literature in assuming households pool consumption by viewing the household as consisting of a continuum of members of various skill levels, some of whom will be employed, others unemployed.[7] Households are also the owners of all firms in the economy.

Households maximize

$$\mathrm{E}_t \sum_{i=0}^{\infty} \beta^i \left[D_t \frac{\mathcal{C}_{t+i}^{1-\sigma}}{1-\sigma} - v(h_{t+i}^h)(1-\xi_{t+i})N_{t+i} - \xi_{t+i} N_{t+i} \int_{\bar{a}_t}^{1} v(h_{i,t+i}^l) f(a) da \right], \tag{14}$$

where $\sigma > 0$ is the coefficient of relative risk aversion, D_t is an aggregate preference shock, $\mathcal{C}_t$ is the sum of a market-purchased composite consumption good C_t and home produced consumption by unemployed workers $C_t^u = (1 - N_t)w^u$.

Market consumption C_t is a Dixit-Stiglitz composite good consisting of the differentiated products produced by retail firms and is defined as

$$C_t = \left[\int_0^1 c_{kt}^{\frac{\theta-1}{\theta}} dk \right]^{\frac{\theta}{\theta-1}} \qquad \theta > 0.$$

Given prices p_{kt} for the final goods, this preference specification implies the household's demand for good j is

$$c_{kt} = \left(\frac{p_{kt}}{P_t} \right)^{-\theta} C_t, \tag{15}$$

where the aggregate retail price index P_t is defined as

$$P_t = \left[\int_0^1 p_{kt}^{1-\theta} dj \right]^{\frac{1}{1-\theta}}.$$

[7] This assumption is common in search and matching models of the labor market (see for example den Haan, Ramey, and Watson, 2000).

In (14), the term

$$v(h^h_{t+i})(1-\xi_{t+i})N_{t+i} - \xi_{t+i}N_{t+i}\int_{\bar{a}_t}^1 v(h^l_{i,t+i})f(a)da$$

is the disutility to the household of having N_t members working, where hours worked depends on type and the idiosyncratic productivity shocks. We assume $v(h_{t+i}) = \ell h_{t+i}^{1+\chi}/(1+\chi)$.

If i_t is the nominal rate of interest. the representative household's first order conditions imply the following must hold in equilibrium:

$$\lambda_t = \beta(1+i_t)\mathrm{E}_t\left(\frac{P_t}{P_{t+1}}\right)\lambda_{t+1}, \tag{16}$$

where λ_t denotes the total marginal utility of consumption at time t.

3.4 Retail firms

Each retail firm purchases wholesale output which it then converts into a differentiated final good that is sold to households and wholesale firms. Retail firms maximize profits subject to a CRS technology for converting wholesale goods into final goods, the demand functions (15), and a restriction on the frequency with which they can adjust their price.

Retail firms adjust prices according to the Calvo updating model. Each period a firm can adjust its price with probability $1-\omega$. The real marginal cost for retail firms is the price of the wholesale good relative to the price of final output, P^w_t/P_t. This is just the inverse of the markup of retail over wholesale goods.

A retail firm k that can adjust its price in period t chooses $P_t(k)$ to maximize

$$\sum_{s=0}^{\infty}(\omega\beta)^s\,\mathrm{E}_t\left[\left(\frac{\lambda_{t+s}}{\lambda_t}\right)\left(\frac{P_t(k)-P^w_{t+s}}{P_{t+s}}\right)Y_{t+s}(k)\right],$$

subject to

$$Y_{t+s}(k) = Y^d_{t+s}(k) = \left[\frac{P_t(k)}{P_{t+s}}\right]^{-\varepsilon}Y^d_{t+s}, \tag{17}$$

where Y^d_t is aggregate demand for the basket of final goods. The first order condition for those firms adjusting their price in period t is

$$P_t(k)\mathrm{E}_t\sum_{s=0}^{\infty}(\omega\beta)^s\left(\frac{\lambda_{t+s}}{\lambda_t}\right)\left[\frac{P_t(k)}{P_{t+s}}\right]^{1-\varepsilon}Y_{t+s}=\left(\frac{\varepsilon}{\varepsilon-1}\right)\mathrm{E}_t\sum_{s=0}^{\infty}(\omega\beta)^s\left(\frac{\lambda_{t+s}}{\lambda_t}\right)\left(\frac{1}{\mu_{t+s}}\right)\left[\frac{P_t(k)}{P_{t+s}}\right]^{1-\varepsilon}Y_{t+s}.$$

When linearized around a zero-inflation steady state, these conditions yield a new Keynesian Phillips curve in which the retail price markup

$$\mu_t \equiv \frac{P_t}{P_t^w}$$

is the driving force for inflation. As in a standard Phillips curve, the elasticity of inflation with respect to real marginal costs will be $\delta \equiv (1-\omega)(1-\beta\omega)/\omega$.

3.5 Monetary policy

We assume that the monetary authority in this economy implements monetary policy through a simple Taylor-type instrument rule with inertia of the form

$$\ln(1+i_t) = -\ln\beta + \chi_i \ln(1+i_{t-1}) + (1-\chi_i)\left[\omega_\pi \pi_t + \omega_y\left(\ln Y_t - \ln \overline{Y}\right)\right] + \varepsilon_t. \tag{18}$$

where ε_t is an i.i.d. policy shock. As a baseline policy we assume $\omega_\pi = 1.5$, $\omega_y = 0$ and $\chi = 0.8$.

3.6 Market clearing

Goods market clearing requires that household consumption of market produced goods equals the output of the retail sector minus final goods purchased by wholesale firms to cover the costs of posting job vacancies Hence, goods market equilibrium takes the form

$$Y_t = C_t + \kappa V_t. \tag{19}$$

4 The Impact of Skill Heterogeneity on Unemployment Dynamics

The impact of the change in the composition of the unemployment pool on the unemployment rate in a recession works through two channels: first, by changing the relative quantity of low to high-skill workers searching for a match (the direct composition effect), and second, by changing the incentive of firms and applicants to form matches (the indirect incentive effect). As the matches with the least productive workers separate in a downturn, their share in the unemployment pool increases. As a consequence, the average productivity of the unemployed falls by more than the average productivity of the labor force, and the outflow rate from unemployment decreases by more than it would in a model with homogeneous skills.

The direct composition effect can be illustrated through the equation defining the unconditional outflow rate. For a randomly chosen unemployed worker, the job-finding probability is the weighted average of the job finding probability for l and h workers:

$$k_t^{job,w} = \gamma_t k_t^w \Pr(s_{i,t}^l > 0) + (1-\gamma_t) k_t^w \tag{20}$$

The probability of finding a job for a l worker depends on the interviewing rate k_t^w and on the probability that the idiosyncratic productivity shock yields a positive match surplus. Both will fall in a recession; thus the job finding probability falls by more for the l workers than for the h workers. With heterogeneous skills, the larger the increases in the share γ_t of l workers, the larger the amplification in the fall of the unconditional job finding probability.

The indirect effect of the change in the composition of the unemployment pool occurs through the change in the value of a vacancy. Equations (10) and (13) imply the vacancy posting condition can be written as:

$$\frac{V_t}{S_t} = \left\{ \frac{\psi}{\kappa}(1-\eta) \left[\gamma_t \int_{\bar{a}_t}^1 s_{i,t}^l f(a_i) da_i + (1-\gamma_t) s_t^h \right] \right\}^{1/\alpha} \tag{21}$$

The right-hand side of (21) depends on the expected surplus from a match. Since the surplus from a high skill worker is higher than the expected surplus from a low skill worker, a worsening of the unemployment pool skill-level (an increase in γ_t) reduces the expected surplus and thereby reduces the incentive to post vacancies. Thus, the larger the increases in the share γ_t of l workers, the larger the fall in the number of vacancies per searching worker, and the larger the fall in the interview rate. Since search is non-directed, an increase in the share of low skill workers worsens the probability of exiting unemployment for *all* workers.

Finally, firms also become more selective in a recession. For a given number of posted vacancies, an increase in γ_t implies the chance that a randomly interviewed worker will be hired is lower. The impact of γ_t on the hiring probability can be described by the screening rate, that is, the unconditional rate at which an interviewee is screened out:

$$scr_t = \gamma_t \rho_t^n = \gamma_t [1 - \Pr(s_{i,t}^l > 0)]. \tag{22}$$

Ceteris paribus, in a recession the screening rate increases for two reasons. First, as in any search model of the labor market with endogenous separation, the separation rate ρ_t^n increases. Second, the likelihood that an interviewee is a low skill worker γ_t also increases.

In summary, any shock that results in an increase in the low-skill unemployed share worsens labor opportunities for all workers. Since low and high skill workers compete for the same vacancies, the incentive for firms to open positions falls. From the perspective of the job applicants, the chance of exiting unemployment falls since fewer vacancies are posted. The average worker has a higher likelihood of being drawn from the low skill pool and when interviewed, low skill workers have a lower likelihood of being hired.

To evaluate the dynamic behavior of the model economy, we adopt a baseline calibration based on characteristics of the EU. The model is very parsimonious and contains a limited number of parameters. The value of home production w^u, the coefficient ℓ scaling the disutility of labor hours, the cost of vacancy posting κ, the productivity of the matching technology ψ, the relative steady state productivity of high to low skill workers $z_{ss}^h / \left(z_{ss}^l \int_0^1 a_i dF(a_i) \right)$ and the labor force share of low skill workers $\bar{\gamma}$ are chosen to match the steady-state values for six variables with average aggregate data. Table 1 reports the matched steady state values, together with the additional parameters used in the numerical simulations.

The steady state unemployment rate is the average quarterly rate for the EU15 group of countries, over the sample 1993:1 to 2010:4. Since we do not have data for skill-based unemployment rates for workers competing for the same position, we distinguish among h and l-skill workers by using unemployment data by age. The l-skill workers' unemployment rate is the rate for the 16 to 24 age group, while the h-skill unemployment rate is the rate for the 25 to 74 age group, reported in the Labor Force Survey compiled by Eurostat. The steady state hours per worker h_{ss}^{av} and the probability of a match between an applicant and a vacancy k_{ss}^f are parameterized to standard values in the labor search literature. The share of output devoted to hiring activities is in line with empirical evidence reported in Ravenna and Walsh (2008).

The steady state aggregate separation rate is set according to available average separation data (Blanchard and Galí, 2010). Our parameterization strategy takes as given a value for the exogenous separation rate, but the aggregate separation rate turns out to be close in value to the exogenous rate. The choice for the remaining parameters follows the recent literature on business cycle models with search unemployment and nominal rigidities. [8]

The parameterization implies that the share of l workers $\bar{\gamma}$ in the labor force L is 13.4%. Because the separation rate of l workers is about twice as large as the overall separation rate, their share γ_{ss} in the pool of job seekers is 22.6%, while their share ξ_{ss} in the employment pool is 11.8%. Thus, low skill workers are over-represented in the pool of unemployed.

To illustrate the relevance of the size of average labor flows, we compare our baseline parameterization to an alternative economy, with the same steady state level of output and unemployment, but with larger steady state flows. To achieve a larger steady state separation rate, we assume the alternative economy draws on a labor force where high skill workers are more productive, and low skill workers less productive, relative to the baseline. Table 2 shows that in this economy the average productivity of high relative to low skill workers is higher, while the average productivity of the labor force is very similar. To obtain an alternative economy with identical unemployment rate and output as the baseline, we also assume a higher productivity ψ of the matching function and a lower vacancy-posting cost κ. In this way, the steady state outflow from unemployment is large enough to balance the higher steady state inflow at the same level of steady state unemployment.

When the relative productivity of high to low skill workers increases, the endogenous separation rate ρ^n_{ss} for low skill workers increases to 51%, while it is only 3.9% in the baseline parameterization. The overall separation rate increases by a smaller amount, since the share of low skill workers in the labor force is unchanged relative to the baseline, and equal to 13.4%. The increase in the separation rate implies the share of low skill workers in the unemployed pool rises from 23% in the baseline to 66% in the alternative parameterization. This implies that in a recession the percent increase in the separation rate, and in the share of low skill unemployed, required to achieve the equilibrium change

[8] The only exception is given by η, the workers' share of surplus, which given our choice of α implies the Hosios condition is not met. The value of $\eta = 0.35$ was chosen to be as close as possible to the Hosios condition, while ensuring determinacy of the equilibrium.

in employment is smaller relative to the baseline parameterization. Finally, the larger size of gross labor flows implies that, while the unemployment rate is identical across the two economies, the unemployment duration is about 60% longer in the baseline parameterization.

4.1 Gross Labor Flows and the Relevance of the Composition Effect

In this section, we evaluate the role the composition effect plays in contributing to the response of unemployment to a negative aggregate productivity shock and to a persistent preference shock that reduces output demand.

4.1.1 The Impact of a Fall in Total Factor Productivity

Figure 1 shows the impact of a persistent fall in total factor productivity (TFP) on the aggregate unemployment rate and the unemployment rates for the two types of workers. To highlight the impact of skill heterogeneity, the shock is scaled across the two parameterizations so that output falls on impact by 1% in both economies (this implies the size of the shock is 1% in the baseline parameterization and 1.1% in the large labor flows parameterization). The plot is scaled in terms of percentage points of the overall labor force and of the labor force for each group of workers.

The change in the unemployment rate for the low-skill workers is about 20 times as large as for the high-skill workers in the baseline parameterization and about four times as large in the alternative one. Low-skill workers experience higher volatility in both job-finding probability and unemployment duration. The effect on the overall unemployment rate is relatively small in the parameterization with large labor flows, a feature that is common to search models of the labor market with Nash bargaining. In the baseline parameterization, the impact of the TFP shock is significantly amplified. The unconditional volatility of employment relative to output σ_n/σ_y is equal to 0.65 in the baseline parameterization and only 0.14 in the alternative one. Note that this amplification is obtained with a steady-state share of low skill workers in the employment pool of only 11.8% and in the labor force of only 13.4%.

An implication of a strong composition effect is a considerable delay in the response of unemployment to a fall in productivity and its subsequent sluggish recovery. The peak response in overall unemployment occurs after 6 quarters in the baseline case, and 4 quarters in the alternative one. The lag depends on the progressive buildup of a larger share of low skill workers in the unemployed pool (who have a lower outflow rate from unemployment) and the reduction in the incentive to post vacancies.

Figure 2 shows the log-deviation of selected variables in response to a negative productivity shock. The increase in the separation rate - driven entirely by the firing of low skill workers - raises the share of less productive workers in the unemployment pool by over 15% in the baseline economy. Since the composition effect amplifies the fall in the average productivity of the jobless, the unconditional job finding probability falls sharply. In the alternative parameterization, the response of the separation rate is muted; thus the composition of employment shifts in favor of h workers, but the skill-composition of the unemployment pool hardly changes. This implies that the average fall in productivity among the unemployed is nearly identical to the fall in aggregate TFP.

To single out the role of the composition effect in reducing the flow out of unemployment, figure 3 compares the behavior of different variables to the counterfactual built from (21) under the assumption that γ_t remains constant. The first panel of figure 3 shows that as the average skill-level of the pool of unemployed worsens, the fall in productivity among the unemployed more than doubles relative to an economy with homogeneous workers. Moreover, since low-skill workers accumulate in the unemployment pool, the fall in TFP for the average unemployed worker peaks nearly a year and half later than aggregate TFP. Skill-heterogeneity amplifies unemployment volatility because the fall in productivity of the overall unemployment pool is much more severe than for the labor force overall or for those workers who remain employed.

The top right panel of figure 3 compares the behavior of the log-change in vacancies per unemployed worker to the counterfactual in which γ_t remains constant. Virtually all the fall in the incentive to post vacancies originates from the change in the skill-composition of the unemployed. Additionally, the composition effect increases the likelihood that any firm that posts a vacancy will end up interviewing a low-skill worker, so the probability an interview actually results in a hire decreases as more interviewees will be screened out. The lower left panel of figure 3 compares the screening rate defined in (22) to the counterfactual assuming γ_t is constant. The composition effect increases the screening rate by up to 40%.

The bottom right panel of figure 3 shows the behavior of the unconditional outflow rates for low and high skill workers. The unconditional rate falls in part because both k_t^w and $k_t^{w,l}$ fall, but it also falls because the weight on $k_t^{w,l}$ increases in the overall average job finding rate.

Table 3 exploits the log-linear approximation to (20) to compute the contribution to the change in the outflow rate originating from the change in the separation rate for new matches ρ_t^n, the share of low skill unemployed γ_t (the direct composition effect), and the probability of an interview k_t^w (the indirect incentive effect). When the composition effect is at work, the change in the job finding rate that is driven by the increase in the separation rate for new matches falls by half relative to the economy without composition effect, from 31% to 15%. Most of the difference is explained by the larger fall in the probability of an interview taking place.[9]

In summary, in an economy with large steady-state labor flows between employment and unemployment, a change in the employment level can be achieved with a relatively small change in separations and hiring. This implies that the skill composition of the unemployment pool does not change much in a business cycle, the change in productivity among unemployed workers is not amplified, and neither is the outflow rate from unemployment. An economy with smaller gross labor flows – even with an identical unemployment rate in steady state – will experience a sharper increase in separations during a recession, a significant worsening of the unemployment pool skill level, and a larger fall in the outflow rate from unemployment. This ultimately leads to a slower recovery, as the skill composition of the unemployment pool slowly reverts to its steady state.

4.1.2 The Impact of a Persistent Fall in Demand

We next examine the impact of a negative preference shock D_t in (14). Since a demand shock does not affect TFP, the experiment offers the means to measure the change in TFP among the unemployed caused only by a change in the skill composition of the unemployed. In addition, since the strength of the composition effect depends on the rate at which unemployed low-skill workers can be reabsorbed in the economy after a shock, we examine the consequences for unemployment of a long-lived shock.

Figure 4 shows the impact of a fall in demand driven by a preference shock with AR(1) coefficient equal to 0.95. The size of the shock is scaled to produce a 1% fall in output on impact. While aggregate TFP is unchanged, the average unemployed worker's TFP falls by about 0.8% after four quarters. This effect in turn has a much stronger effect on unemployment than on output, since the productivity of the employed workers

[9] The change in γ_t plays a similar, and small, role in the fall in the job finding probability. This depends on the fact that the share of low-skill workers is small among the unemployed in the baseline parameterization, while it is large but unresponsive to the productivity shock, in the alternative parameterization.

- the majority in the economy - has not changed. In our calibration, a 5% change in the low-skill unemployment share corresponds to about a one percentage point increase of the low-skill unemployment share, from 22.6% to 23.6%. Since the extra percentage point of low-skill workers has replaced high-skill workers whose productivity is 50% higher, TFP among the unemployed falls by roughly 0.5%. Note that while our calibration implies that low skill workers are substantially less productive than high-skill workers, they represent only 13.4% of the labor force. Thus the average TFP of the employed worker-hour is only 4.5% higher than the average TFP for the unemployed.

Figure 4 also shows the effects of less persistent fall in demand, one with an AR(1) coefficient of 0.75. The less persistent shock implies a smaller fall in employment, a smaller composition effect, and a smaller fall in average TFP among the unemployed. However, output falls on impact by a larger amount due to a decline in hours-worked by high-skill workers, but both output and the unemployment rate rebound quickly. In a recession driven by a long lasting shock, the composition effect leads to a percent cumulative fall in employment over the 10 years following a shock equal to 0.65 for each 1% of fall in output. This 'sacrifice ratio' is equal to only 0.3 in the case of a less persistent shock since the composition effect plays a smaller role.

4.2 The Composition Effect: a Comparison of the EU and US Calibrations

In this section we compare the impact of a productivity shock for the baseline parameterization, obtained using data for the EU15 group of countries, and a parameterization based on US data. The US steady state values are obtained averaging BLS quarterly data over 1948:1 to 2010:1. We identify unemployment rates for low and high skill workers with rates for age 16 to 24 and over-24 workers. While the US has lower unemployment rates across all groups, the ratio of the skill-specific to the aggregate unemployment rates is similar to the EU case. Table 4 shows the two sets of steady state values matched under the two parameterizations. The steady state aggregate separation rate is about twice as large in the US calibration, consistent with available average separation data (Shimer, 2005).

Our parameters imply that the steady-state share of l workers in the labor force is 16% in the US and 13.4% in the EU. The share of l workers in the pool of job seekers is similar across the two parameterizations, equal to 22.6% for the EU and 22.8% for the

US calibration. Unemployment duration is half as long in the US case, where it is equal to 1.71 quarters, relative to the EU case, where it is equal to 3.36 quarters.

Gross labor flows are larger in the US case. We parameterized the model so that the higher separation rate is primarily the result of a higher rate of exogenous separations, consistently with empirical evidence showing that the volatility of unemployment in the US is largely explained by volatility in the outflow rate from unemployment. Thus the implied endogenous separation rate is similar across parameterizations (ρ_{ss}^{n} is equal to 3.9% for the EU and 4.6% for the US). Despite the fact that the difference in average labor flows across the two parameterizations originates from exogenous rather than endogenous separations (and thus also affects high skill workers, contrary to our earlier experiment), the composition effect still turns out to be much smaller for the US case. Figure 5 shows that the impact of a fall in TFP the reduces output 1% on impact. The rise in unemployment in the EU case is less than half as large as in the US, but it peaks earlier in the US parameterization. The unemployment rate among low-skill workers increases by about 20 times the high-skill one in the EU case, and only by about 10 times in the US case. If we identify the low-skill workers with young workers, Table 5 shows that this behavior is consistent with the dynamics of unemployment rates over the period 1983-2007 for which youth unemployment data is available. Volatility of youth and long term unemployment is much higher in Euro area countries. The volatility of the youth unemployment rate is 200% higher than that of the aggregate unemployment rate in the EU-27 data, and only 32% higher in the US data.

Figure 6 shows that the log-increase in the unemployed share of low skill workers peaks at 5%, about a third of its increase in the EU case, limiting the relevance of the composition effect for unemployment volatility. Low-skill workers experience a pronounced fall in average hours relative to high skill workers, a result consistent with the empirical evidence in Bils et. al. (2009) and Hines, Hoynes and Krueger (2001) that the an important fraction of the fall in wage earnings for workers with below-average wages during a recession comes from a fall in hours worked.

4.3 The Impact of a Skill-biased Productivity Shock

We next consider the impact of a fall in productivity that disproportionately affects low skill workers. For this experiment we use the US parameterization to show that, even in an economy with large steady state labor reallocation, a skill-biased productivity shock can substantially amplify unemployment volatility. The shock results in a large surge of low skill workers into unemployment and a large increase in the low-skill share of unemployment which then takes a long time to revert to its steady state value.

We compare a 1% fall in aggregate TFP for the US parameterization with a TFP shock affecting predominantly the low skill labor force. We scale this skill-biased shock so that the initial decline in output is the same obtained in response to the aggregate TFP shock. This is achieved with a 0.5% decline in productivity of the high-skill workers, and a decline that is 5 times as large for the low-skill workers. While this may seem a large bias in the TFP shock, recall that the share of l workers in the labor force is only 16%, so the large fall in TFP is affecting a small fraction of workers.[10]

Even though the skill-based shock generates a similar fall in output as the aggregate TFP shock, the top left panel of figure 7 shows that it generates a rise in unemployment about 3.5 times larger than an aggregate shock. The unemployment increase is also greatly amplified for high-skill workers even though they experience a fall in TFP equal to about one half of the fall in the case of an aggregate productivity shock. This amplification is due entirely to the impact of the productivity decline of low-skill workers on aggregate variables. While the difference in output is small across the aggregate and skill-biased shocks - since the bulk of employed workers belong to the high-skill group - the impact on unemployment is radically different.

Figure 8 illustrates the channels through which the large amplification in unemployment is obtained: the separation rate increases sharply, raising the share of low skill unemployed in the jobless pool by 24% relative to the steady state These workers, in turn, face a smaller chance of exiting unemployment, keeping the unemployment rate high for a prolonged period. Low skill workers who remain employed also optimally lower their hours worked, although this fall in hours plays a small role in the fall in output, given the small share of low skill workers in productive matches.

Finally, the upper left panel of figure 9 plots the vacancy yield normalized by the number of unemployed workers. The distance between the two impulse responses is a measure of the shortfall in vacancy yield when the TFP shock is skill-biased. The shortfall in the aggregate vacancy yield has been documented in the recent US recession by Daly,

[10] Residual wage inequality, which can be interpreted as reflecting unmeasured differences in productivity, has been documented to be very large. Hornstein, Krusell and Violante (2007) use 1990 US Census data to show that the ratio of the mean wage to the 10th percentile is 1.83 even conditioning on low-skill occupations and a set of workers with less than 10 years of experience.

Hobijn, Valletta (2011). Skill-heterogeneity amplifies the fall in vacancy yield by a factor of 6.

5 Monetary Shocks and the Policy Rule

5.1 Monetary Policy Shocks

The presence of nominal rigidities affects the dynamic adjustment of output, inflation, and labor market variables. It also allows us to investigate the effects of monetary shocks. We consider an i.i.d. shock to the baseline monetary policy rule equivalent to a 1% increase in the annualized nominal interest. An interest rate shock has standard effects on consumption through the Euler condition (16). A interest rate increases that reduces demand reduces wholesale prices (which are flexible) relative to retail prices (which are sticky), leading to an increase in the markup μ_t. In addition, the real interest rate affects the discounted continuation value of labor matches and the markup both affect the cutoff productivity level $\bar{a}_t$ that governs separations. The choice of hours is also affected. Figure 10 shows for the US and EU calibrations the effect of a 1% increase in the annualized nominal interest. It is useful to compare Figure 10 to Figure 5, which showed the effects of a productivity shock on the same variables. The two types of shocks produce quite different dynamic responses in unemployment. For the EU, overall unemployment and the unemployment rates of both low-skill and high-skill workers are more persistent than for the US.

The unemployment rate for high-skill workers is much less volatile than low-skill unemployment under either calibration. For the US calibration, however, the immediate impact of the policy shock on unemployment among high-skill workers is larger than in the EU case, but it is also much less persistent, consistent with the perception that labor flows adjust quickly in the US.

5.2 Policy Rules that Respond to Output

In our baseline calibration, the nominal interest rate responded only to its lagged value and to inflation. Standard Taylor-type rules also incorporate a response to a measure of real economic activity. To investigate the role of responding to output, we compare the effects of various shocks for our baseline parameterization (where policy is described by an inflation targeting instrument-rule and a feedback coefficient on output of $\omega_y = 0$ in 18) to the case of a policy rule that puts a weight of $\omega_y = 0.3$ on output.

Figure 11 (upper left panel) shows that a policy that reduces the interest rate as output falls can reduce the immediate fall in output due to a negative aggregate TFP shock by over 95%. As prices adjust, however, the paths under the two policy rules display greater similarity. Most of the smaller initial drop in output is the result of a large increase in hours of high-skill workers in response to the fall in consumption, while a smaller contribution is explained by a fall in separations and a gain in the job-finding probability for the unemployed. Figure 12 shows that by responding to output, monetary policy is able to reduce unemployment by about a third over the course of the downturn, and the reduction is proportionally distributed across the skill-groups.

Part of the reduction in employment volatility when $\omega_y > 0$ comes from the smaller composition effect: with low-skill unemployment in total unemployment rising by about a third less, this translates into a smaller drop in TFP for the average unemployed worker. The greater stability of output and employment is achieved at a large cost in terms of inflation, however, which jumps on impact from about 0.5% to 4.5%, and after two years is still 2.5% above steady state (see the upper right panel of figure 12).

The effects of responding to output are more muted when the shock is a persistent fall in demand arising from a preference shock. Using our baseline parameterization, figure 13 and 14 show that the policy with $\omega_y = 0.3$ reduces the initial fall in output in the face of the negative demand shock by only 50%, but the policy maker faces a much more favorable trade-off. Inflation rises only to 1.3%, and relative to its peak it falls by about one-half of a percentage point within a year. Similarly to the case of an aggregate TFP shock, the policy with $\omega_y = 0.3$ is effective in reducing unemployment. Since a demand shock lowers output by calling for a sharp fall in hours, rather than employment, the more activist policy yields smaller gains in terms of the unemployment rate.

Finally, consider the skill-biased productivity shock. The policy with $\omega_y = 0.3$ is effective in reducing the fall in output (see figure 15, upper left panel). This gain is attained mainly by making it optimal for high-skill workers to provide additional hours. The impact on the unemployment rate is small (figure 16). Low-skill workers – who are suffering the bulk of the increase in unemployment – see their unemployment rate fall by only half a percentage point, down to 5%, relative to the baseline policy. Since the policy with $\omega_y = 0.3$ has little impact on the low-skill unemployment share, the TFP fall for the average unemployed worker does not differ much under the alternative policies. In turn, while the employment gain is small, the policy with $\omega_y = 0.3$ is very inflationary (see figure 15, upper right panel).

6 Conclusions and Extensions

We have developed a parsimonious model of worker heterogeneity that incorporates endogenous separations. Heterogeneity causes the composition of the pool of unemployed workers to vary over the business cycle in ways that cannot occur in standard models with homogenous labor. A negative productivity shock reduces output and employment, but it also lowers the average quality of the unemployed, as low-skill workers experience a greater inflow into unemployment. This compositional effect reduces the incentive for firms to post vacancies, as they are less likely to find a worker who is sufficiently productive to generate a positive surplus if hired. As a consequence, the exit rate from unemployment falls for all workers relative to a model with homogeneous labor.

As den Haan, Ramey and Watson (2000) had previously shown, endogenous separation can contribute to both the amplitude of employment responses to productivity shocks and the persistence generated by such shocks. We find that these effects are further strengthened by compositional affects that arise with heterogeneous workers. Despite the introduction of only two worker types, the model generates a rich set of implications for unemployment inflows and outflows. Skill heterogeneity amplifies unemployment fluctuations in economies with small gross labor flows, or during a persistent fall in demand, and lowers the vacancy yield during recessions. The model provides a platform on which to investigate the role of labor market dynamics in affecting the transmission of monetary policy, and the effects of macroeconomic fluctuations on unemployment flows in different countries or global regions characterized by different labor market structures.

There are a number of extensions that could be pursued using the framework developed in this paper. One simplifying assumption of the model is that the same critical productivity level determines whether existing employed low-skill workers would be retained and whether a low-skill job seeker would be hired. Hiring and firing costs would drive a wedge between the productivity level that determines if an existing worker is retained and the level sufficient to justify hiring a new low-skill worker. Introducing these costs would imply that for some productivity levels, a firm would be willing to retain an existing worker while simultaneously be unwilling to hire an identical job seeker.[11]

We believe models with workers heterogeneity raise very important questions for monetary policy. We considered the impact on unemployment stabilization of two simple rules for monetary policy. However, as discussed in Ravenna and Walsh (2011a), in search and matching models unemployment stabilization is not an optimal policy. As is well know, a form of congestion externality is present in search and matching models; a firm that posts a vacancy reduces the probability other firms are able to fill their vacancies. With worker heterogeneity and endogenous separations, an additional externality arises. When a firm fails to retain a low-skill worker, the average skill-quality of the pool of job seekers is lowered, thus making it less likely a firm with a vacancy will make a hire. And as firms hire high-skill workers, they increase the probability that other firms will end up with a low-skill worker. The impact of these externalities on optimal monetary policy is left open for future research.

References

[1] Abbring, J., van den Berg, G. and van Ours, J., "The anatomy of unemployment dynamics", *European Economic Review* 46, 1785-1824, 2002.

[2] Barnichon, R. and Figura, R., "What drives matching efficiency? A tale of composition and dispersion", mimeo, 2011.

[3] Baker, M., "Unemployment Duration:compositional effects and cyclical variability", *American Economic Review* 82, 315-321, 1992.

[4] Bils, M., Chang, Y. and Kim, S., "Comparative advantage and unemployment", NBER Working Paper 15030, 2009.

[5] Blanchard, O. J. and Jordi Galí, "Real wage rigidity and the new Keynesian model," *Journal of Money, Credit and Banking*, 39 (1), 2007.

[6] - , "A New Keynesian Model with Unemployment," *American Economic Journal: Macroeconomics,* vol. 2 n^{o}2, 1-30, 2010.

[7] Clark, K. and Summers, L., "The Demographic Composition of Cyclical Employment Variations," *Journal of Human Resources*, Vol. XVI, pp. 61-79, 1981.

[11] See Lechthaler, Merkl, and Snower (2010).

[8] Daly, M., Hobijn, B. and Valletta, R., "The recent evolution of the natural rate of unemployment", FRB San Francisco Working Paper 2011-05, 2011.

[9] Darby, M., Haltiwanger, J. and Plant, M., "Unemployment rate dynamics and persistent unemployment under rational expectations", *American Economic Review* 75, 614-637, 1985

[10] Davis, S., "Job Loss, Job Finding, and Unemployment in the U.S. Economy over the Past Fifty Years. Comment" in NBER Macroeconomics Annual, Vol. 20 (2005), pp. 139-157.

[11] - , John C. Haltiwanger, and Scott Schuh, *Job Creation and Job Destruction*, Cambridge, MA: The MIT Press, 1996.

[12] den Haan, W. J., G. Ramey, and J. Watson, "Job destruction and Propagation of Shocks," *American Economic Review*, June 2000, 90 (3), 482-498.

[13] Elsby, M., B. Hobiijn, and A. Sahin, "Unemployment dynamics in the OECD," NBER Working Paper No. 14617, Dec. 2008.

[14] - , "The labor market in the great recession", NBER Working Paper No. 15979, 2010.

[15] Galí, J. *Unemployment Fluctuations and Stabilization Policies: A New Keynesian Perspective.* MIT Press: Cambridge, MA, 2011.

[16] Gertler, M. and Antonella Trigari, "Unemployment Fluctuations with Staggered Nash Wage Bargaining", *Journal of Polictical Economy,*117 (1), pp. 38-86, 2009.

[17] Gertler, M., Sala, L. and Antonella Trigari, "An Estimated Monetary DSGE Model with Unemployment and Staggered Nominal Wage Bargaining", *Journal of Money, Credit and Banking* 40-8, pages 1713-1764, 2008.

[18] Guerrieri, V., "Heterogeneity and Unemployment Volatility", *Scandinavian Journal of Economics*, 2007, 109, No. 4, 667-693

[19] Hines, J., Hoynes, H. and Krueger, A., "Another look at whether a rising tide lifts all boats", in Krueger, A. and Solow, R., eds., The roaring nineties: Can full employment be sustained?, New York, Russel Sage Foundation, 2001.

[20] Hornstein, A., Krusell, P. and Violante, G., "Frictional wage dispersion in search models: a quantitative assessment", Federal Reserve Bank of Richmond Working Paper, 2007.

[21] Krause, M. and Lubik, T., "On-the-Job Search and the Cyclical Dynamics of the Labor Market", FRB Richmod Discussion Paper 10-12, 2010.

[22] Jung, P. and Kuhn, M., "Labor market rigidity and business cycle volatility", mimeo, 2011.

[23] Lechthaler, W., C. Merkl, and D. Snower, "Monetary persistence and the labor market: a new perspective," *Journal of Economic Dynamics and Control* 34 (2010): 968-983.

[24] Mortensen, D. T., Wage Dispersion: Why are Similar People Paid Differently. MIT Press, 2003.

[25] Mueller, A., "Separations, Sorting and Cyclcal Unemployment", mimeo, 2011.

[26] Nagypal, E., "Learning-by-Doing Versus Learning About Match Quality: Can We Tell Them Apart?", *Review of Economic Studies*, 74 (2), pp. 537-566, 2007.

[27] Nagypal, E. and Mortensen, D. T., "Labor-market Volatility in Matching Models with Endogenous Separations," *Scandinavian Journal of Economics*, Vol. 109, No. 4., pp. 645-665, 2007.

[28] Petrongolo, B. and Pissarides, C., "Looking into the Black Box: A Survey of the Matching Function," *Journal of Economic Literature*, vol. 39(2), pages 390-431, 2001.

[29] Pries, M., "Worker heterogeneity and labor market volatility in matching models", *Review of Economic Dynamics,* 11, 644-687, 2008.

[30] - , and Rogerson, R., "Hiring policies, labor market institutions, and labor market flows", *Journal of Political Economy,* 113(4), 2005.

[31] Ravenna, F. and C. E. Walsh, "Vacancies, Unemployment, and the Phillips Curve," *European Economic Review*, Vol. 52, November 2008.

[32] - , “Welfare-based optimal monetary policy with unemployment and sticky prices: A linear-quadratic framework,” *American Economic Journal: Macroeconomics*, Vol 3(2), 2011a.

[33] - , "The welfare consequences of monetary policy and the role of the labor market: a tax interpretation,” mimeo, 2011b.

[34] Shimer, Robert, “The Cyclical Behavior of Equilibrium Unemployment and Vacancies,” *American Economic Review*, 2005, 95(1), 25-49.

[35] - , "Reassessing the ins and outs of unemployment", mimeo, 2007.

[36] Solon, G., Barski, R. and Parker, J., "Measuring the cyclicality of real wages: how important is composition bias?", *Quarterly Journal of Economics,* February 1994, pp. 1-28.

[37] Tasci, M., "On the job search and labor market reallocation", *Federal Reserve Bank of Cleveland Working paper* 7-25, 2007.

[38] van den Berg, G. and van der Klaauw, B., "Combining micro and macro unemployment duration data", *Journal of Econometrics* 102, 271-309, 2001.

[39] Villena-Roldan, B., "Aggregate implications of employer search and recruiting selection", mimeo, 2008.

[40] Walsh, C. E., “Labor market search and monetary shocks,” in *Elements of Dynamic Macroeconomic Analysis*, S. Altuĝ, J. Chadha, and C. Nolan (eds.), Cambridge: Cambridge University Press, 2003, 451-486.

[41] - , “Labor market search, sticky prices, and interest rate policies,” *Review of Economic Dynamics*, 8(4), Oct. 2005, 829-849.

Table 1: Baseline Parameterization		
Steady State Values		
Unemployment rate	u_{ss}	8.7%
Unemployment rate - $l-skill$ labor	u_{ss}^{l}	17.7%
Unemployment rate - $h-skill$ labor	u_{ss}^{h}	7.4%
Average hours per worker	h_{ss}^{av}	0.25
Vacancy posting cost share of output	$\frac{\kappa V_{ss}}{Y_{ss}}$	0.05
Probability of vacancy matched with applicant	k_{ss}^{f}	0.7
Parameters		
Vacancy elasticity of matches	α	0.6
Discount factor	β	0.99
Inverse of labor hours supply elasticity	χ	2.5
Relative risk aversion	σ	1
Steady state inflation rate	π_{ss}	1
Workers' share of surplus	η	0.35
Exogenous separation rate	ρ^{x}	3.4%
Implied steady state separation rate	ρ_{ss}	3.8%
AR(1) parameter for technology shock z_t	ρ_z	0.95
Calvo pricing parameter values		
Price elasticity of retail goods demand	ε	6
Average retail price duration (quarters)	$\frac{1}{1-\omega}$	3.33
Steady state markup	μ	1

Note: Baseline parameterization based on EU15 data. The policy rule for the baseline parameterization is described by eq. (18) with coefficients $\omega_{\pi} = 1.5$, $\omega_{y} = 0$, $\chi = 0.8$.

Table 2: Steady State Labor Flows with Alternative Parameterizations

		Baseline	Large labor flows
Parameters	Average productivity of high-skill workers	0.76	0.76
	Average productivity of low-skill workers	0.5	0.40
	Relative productivity of high/low skill workers	1.53	1.90
	Average productivity labor force	0.73	0.71
	ψ	0.42	0.80
	κ	0.16	0.05
Steady State	ρ_{ss}	0.038	0.062
	ρ_{ss}^n	0.039	0.51
	γ_{ss}	0.23	0.66
	ξ_{ss}	0.12	0.06
	Unemployment duration (quarters)	3.36	2.10

Note: Average productivity of high and low-skill worker-hours is given by z_{ss}^h and $z_{ss}^l \int_0^1 a_i dF(a_i)$. The two parameterizations have identical steady state output and unemployment

Table 3: Percent Contribution to Log-change in Job Finding Rate

	ρ_t^n	γ_t	k_t^w
Baseline	15%	5%	80%
Large Labor Flows	31%	4%	65%

Note: Contribution to cumulative log-change of unconditional job finding rate $k_t^{job,w}$ over 20 quarters following a TFP shock.

Table 4: Parameterization for EU and US			
Steady State Values		US	EU
Unemployment rate	u_{ss}	5.7%	8.7%
Unemployment rate - $l-skill$ labor	u_{ss}^{l}	11.6%	17.7%
Unemployment rate - $h-skill$ labor	u_{ss}^{h}	4.4%	7.4%
Average hours per worker	h_{ss}^{av}	0.33	0.25
Exogenous separation rate	ρ^{x}	6.8%	3.4%
Implied steady state separation rate	ρ_{ss}	7.4%	3.8%

Table 5: Unemployment rate, 1983-2007

		Average	Standard deviation
Euro area	Unemployment (% labor force)	10.11%	1.33
	Unemployment - youth (% labor force age 15-24)	22.16%	4.06
	Unemployment - long term (% total unemployment)	48.74%	4.11
France			
	Unemployment (% labor force)	9.98%	1.36
	Unemployment - youth (% labor force age 15-24)	22.32%	3.16
	Unemployment - long term (% total unemployment)	40.47%	3.14
US			
	Unemployment (% labor force)	5.84%	1.28
	Unemployment - youth (% labor force age 15-24)	12.03%	1.69
	Unemployment - long term (% total unemployment)	9.25%	2.40

Note: Annual data. Source: World Development Indicators (2009).

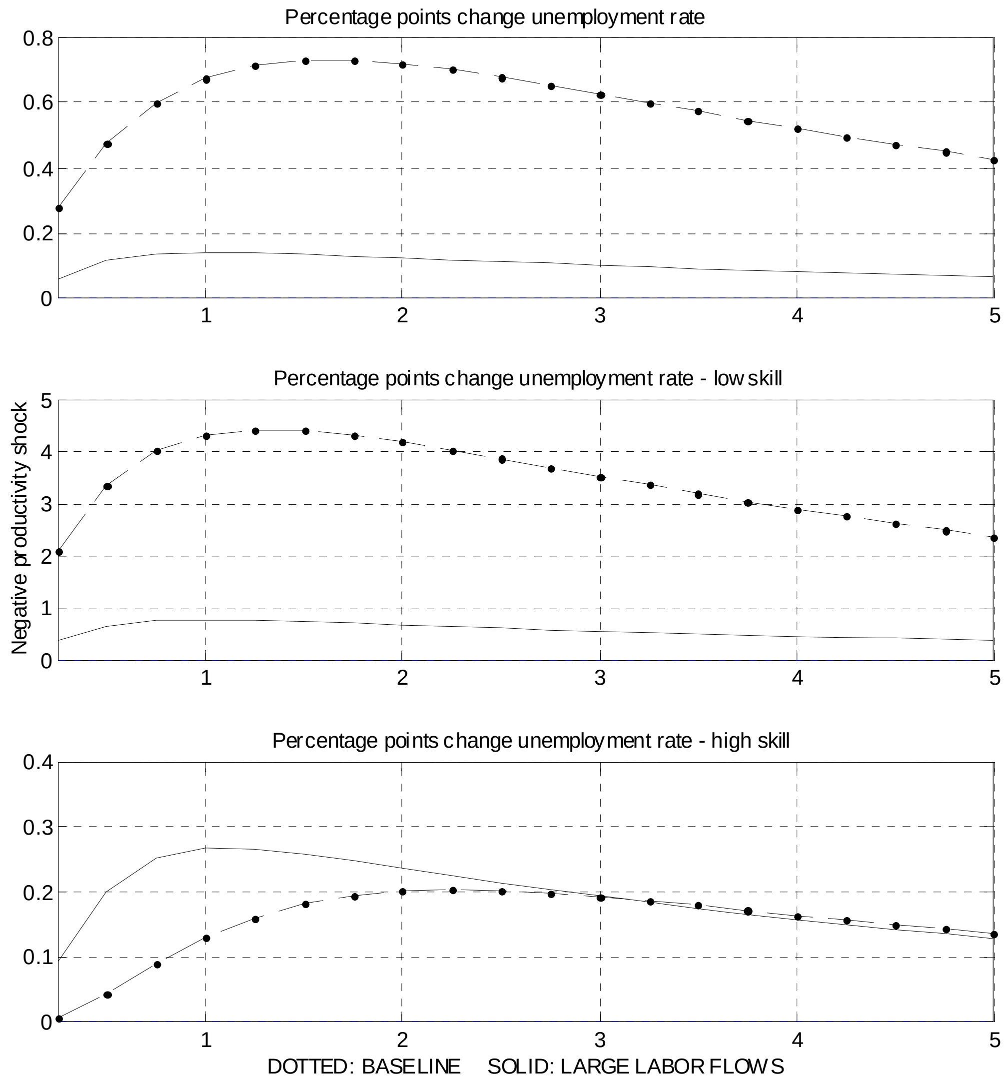

Figure 1: Impulse response to a negative TFP shock z_t under the baseline parameterization and the steady-state large labor flows parameterization described in Table 2. AR(1) coefficient of TFP shock $\rho_{z_t} = 0.95$. Shock is scaled to deliver a 1% fall in output in the initial period under each parameterization. Change in unemployment rate for total, low-skill and high-skill population scaled in percentage points of the labor force L, L^l, L^h of each group.

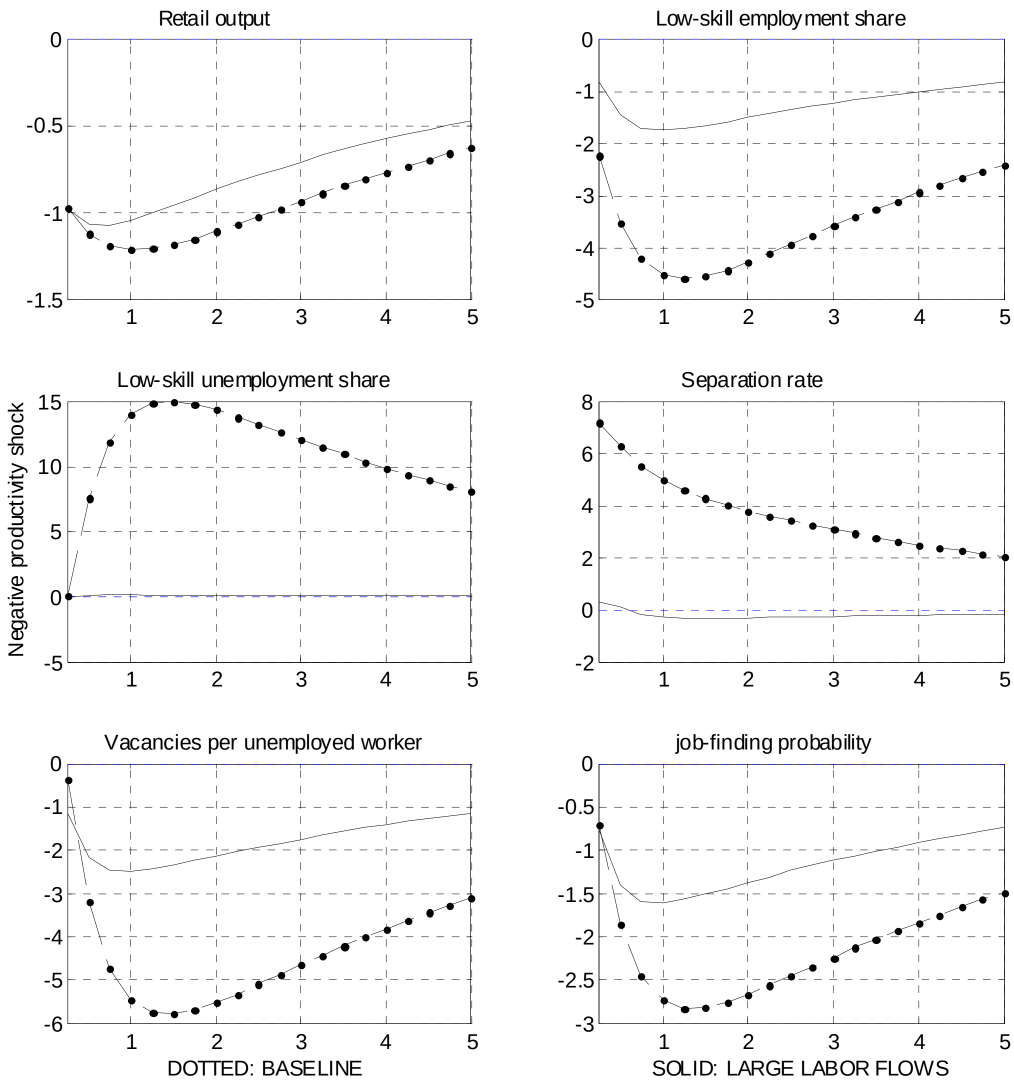

Figure 2: Impulse response to a negative TFP shock z_t under the baseline parameterization and the steady-state large labor flows parameterization described in Table 2. AR(1) coefficient of TFP shock $\rho_{z_t} = 0.95$. Shock is scaled to deliver a 1% fall in output in the initial period under each parameterization. Scaling in percent.

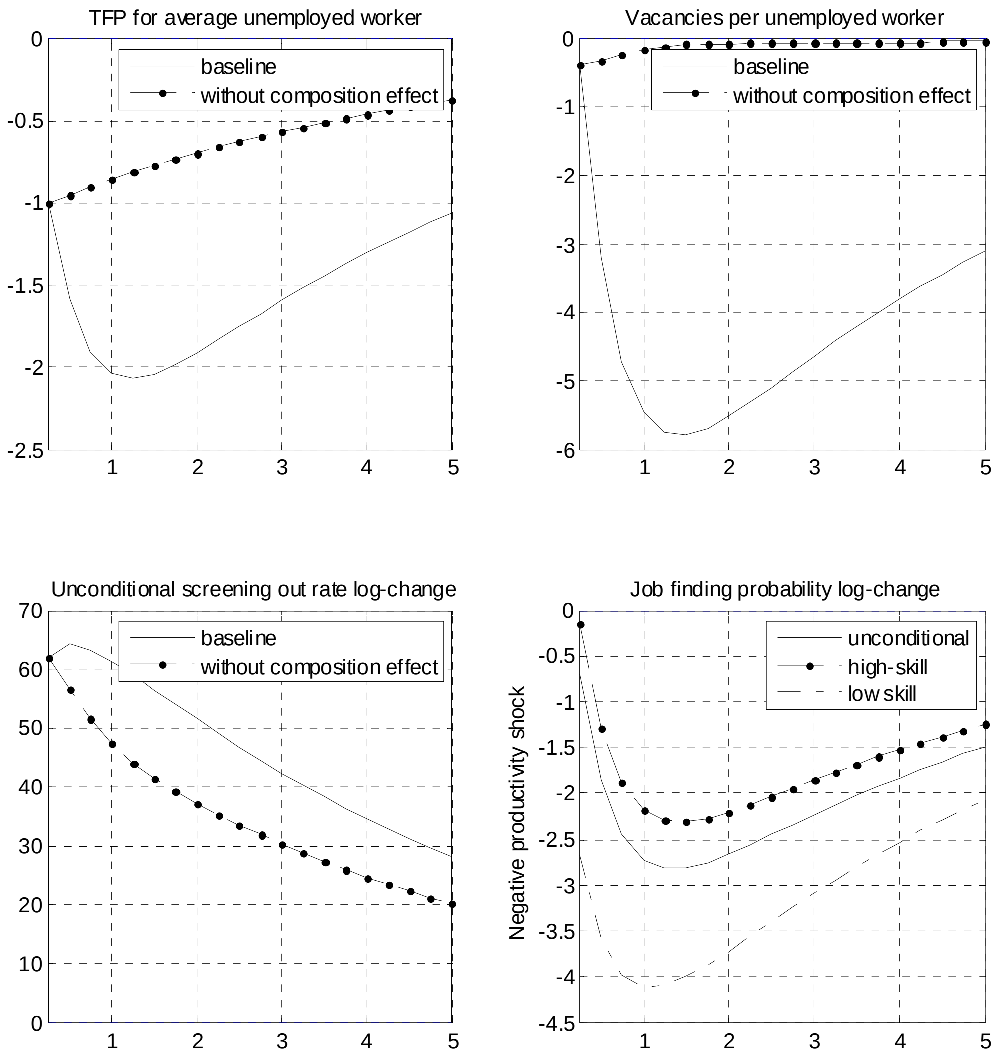

Figure 3: Impulse response to a negative TFP shock z_t under the baseline parameterization (Table 1). AR(1) coefficient of TFP shock $\rho_{z_t} = 0.95$. Shock is scaled to deliver a 1% fall in output in the initial period. Scaling in percent. Impulse responses without composition effect assume share of low-skill unemployed is constant at $\gamma_t = \gamma_{ss}$.

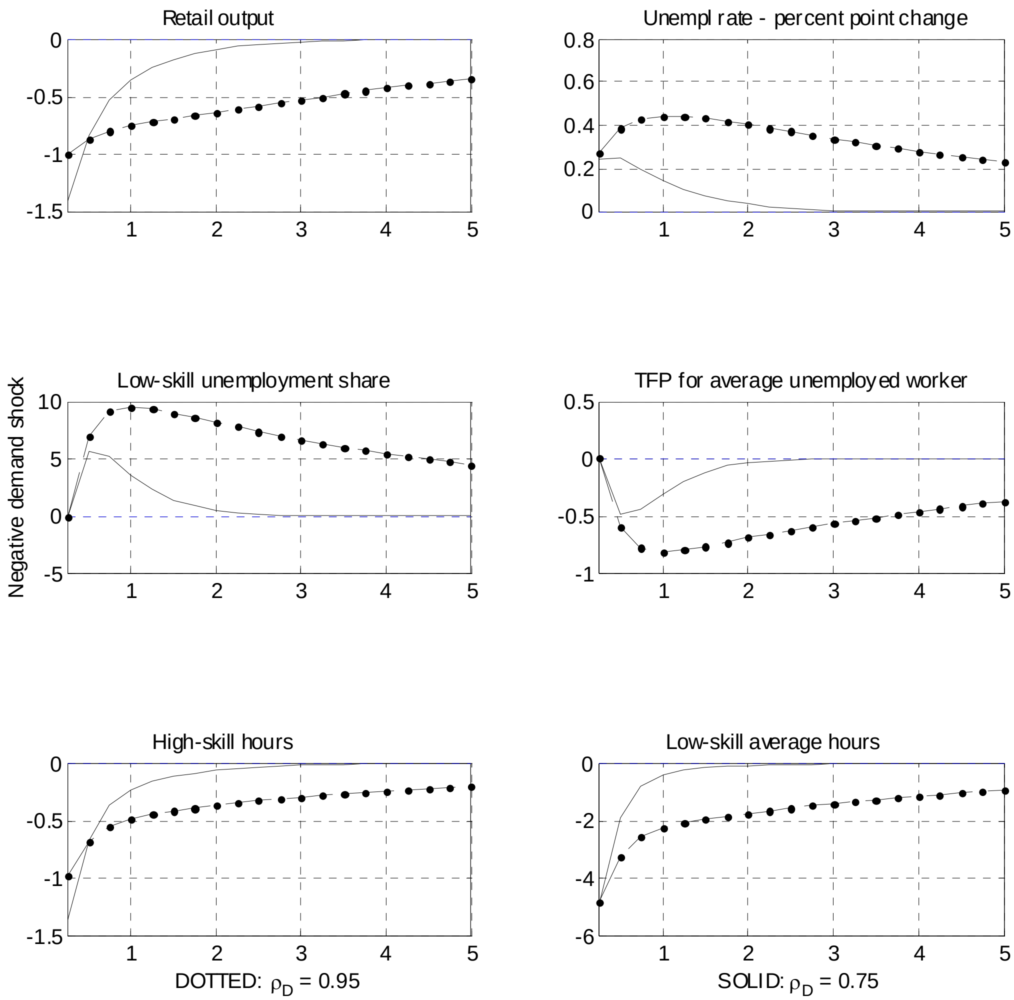

Figure 4: Impulse response to a negative preference shock D_t under the baseline parameterization (Table 1) for alternative values of the AR(1) coefficient ρ_{D_t} in the shock stochastic process. Shock is scaled to deliver a 1% fall in output in the initial period under the $\rho_{D_t} = 0.95$ parameterization. Scaling in percent.

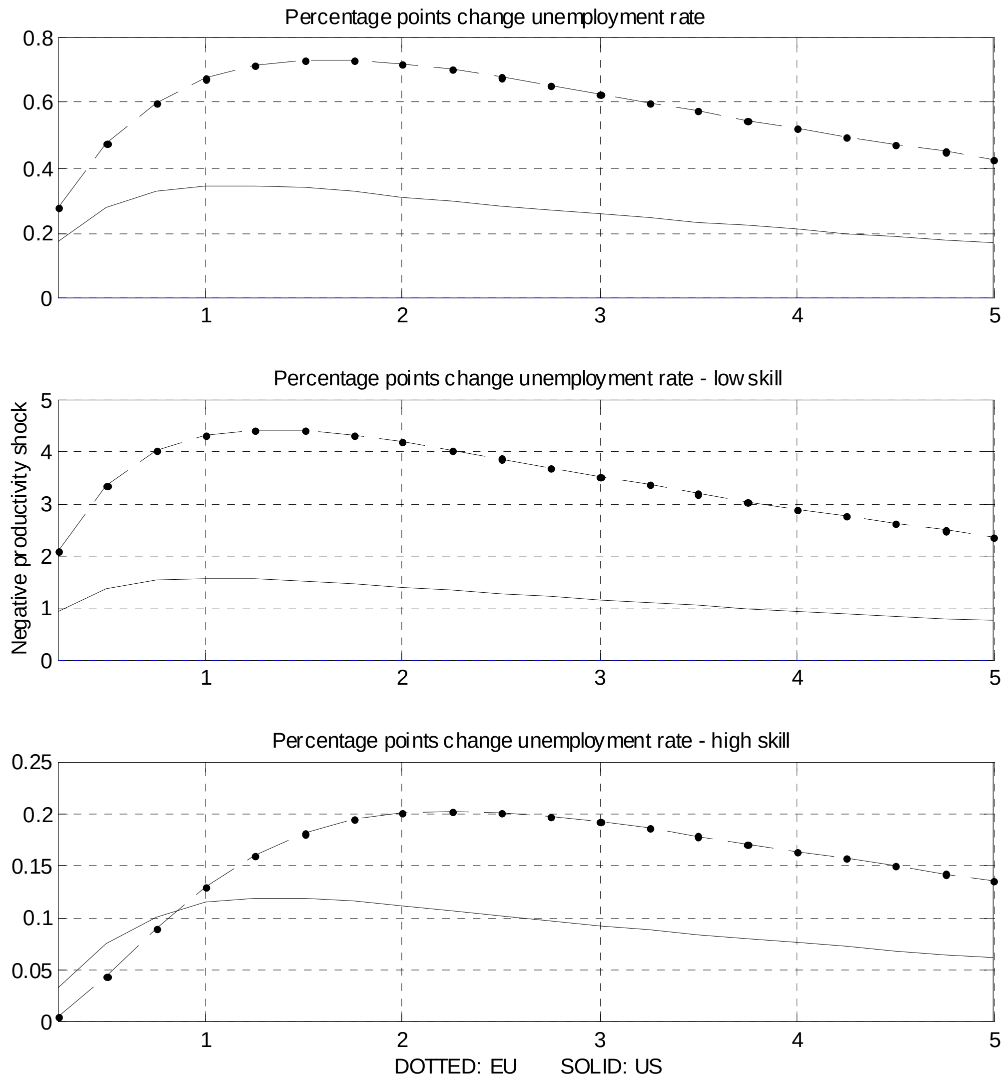

Figure 5: Impulse response to a negative TFP shock z_t under the baseline parameterization (EU) and a parameterization matching US data, described in Table 4. AR(1) coefficient of TFP shock $\rho_{z_t} = 0.95$. Shock is scaled to deliver a 1% fall in output in the initial period under each parameterization. Change in unemployment rate for total, low-skill and high-skill population scaled in percentage points of the labor force L, L^l, L^h of each group.

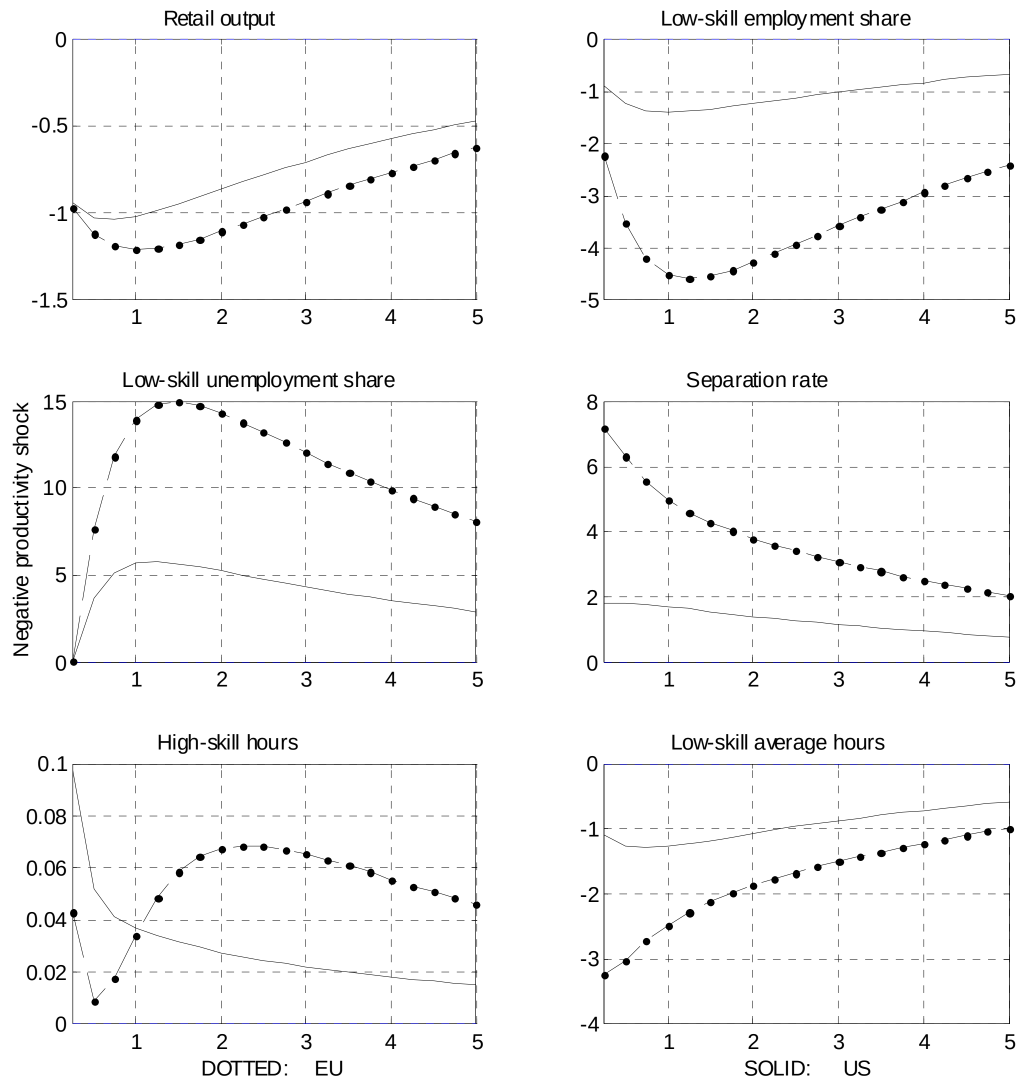

Figure 6: Impulse response to a negative TFP shock z_t under the baseline parameterization (EU) and a parameterization matching US data, described in Table 4. AR(1) coefficient of TFP shock $\rho_{z_t} = 0.95$. Shock is scaled to deliver a 1% fall in output in the initial period under each parameterization. Scaling in percent.

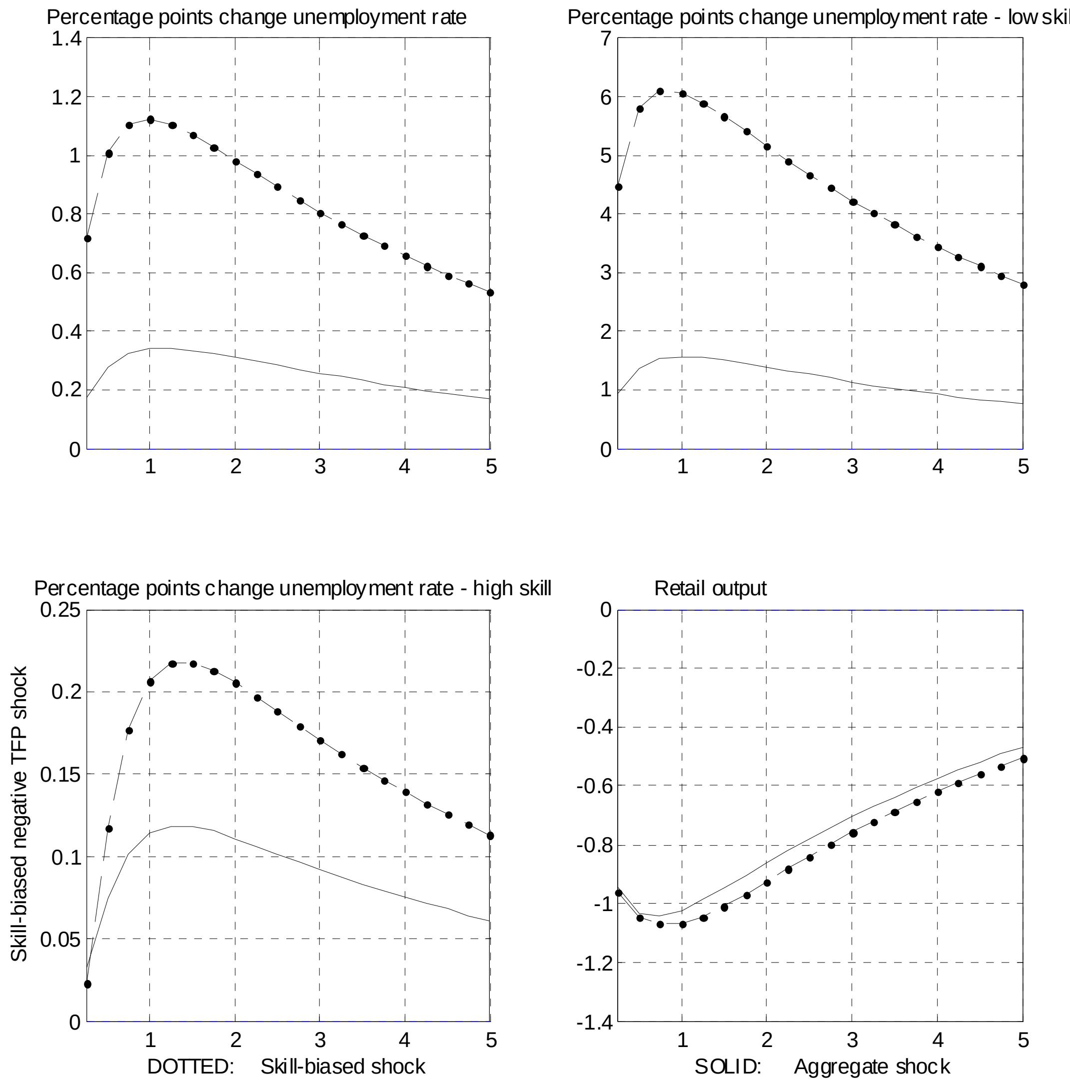

Figure 7: Impulse response to a skill-biased negative TFP shock z_t under the parameterization matching US data, described in Table 4.. AR(1) coefficient of TFP shock $\rho_{z_t} = 0.95$. TFP innovation is equal to -0.5% for high-skill workers, and -2.5% for low-skill workers. For the case of an aggregate TFP shock, innovation is equal to -1%. Change in unemployment rate for total, low-skill and high-skill population scaled in percentage points of the labor force L, L^l, L^h of each group.

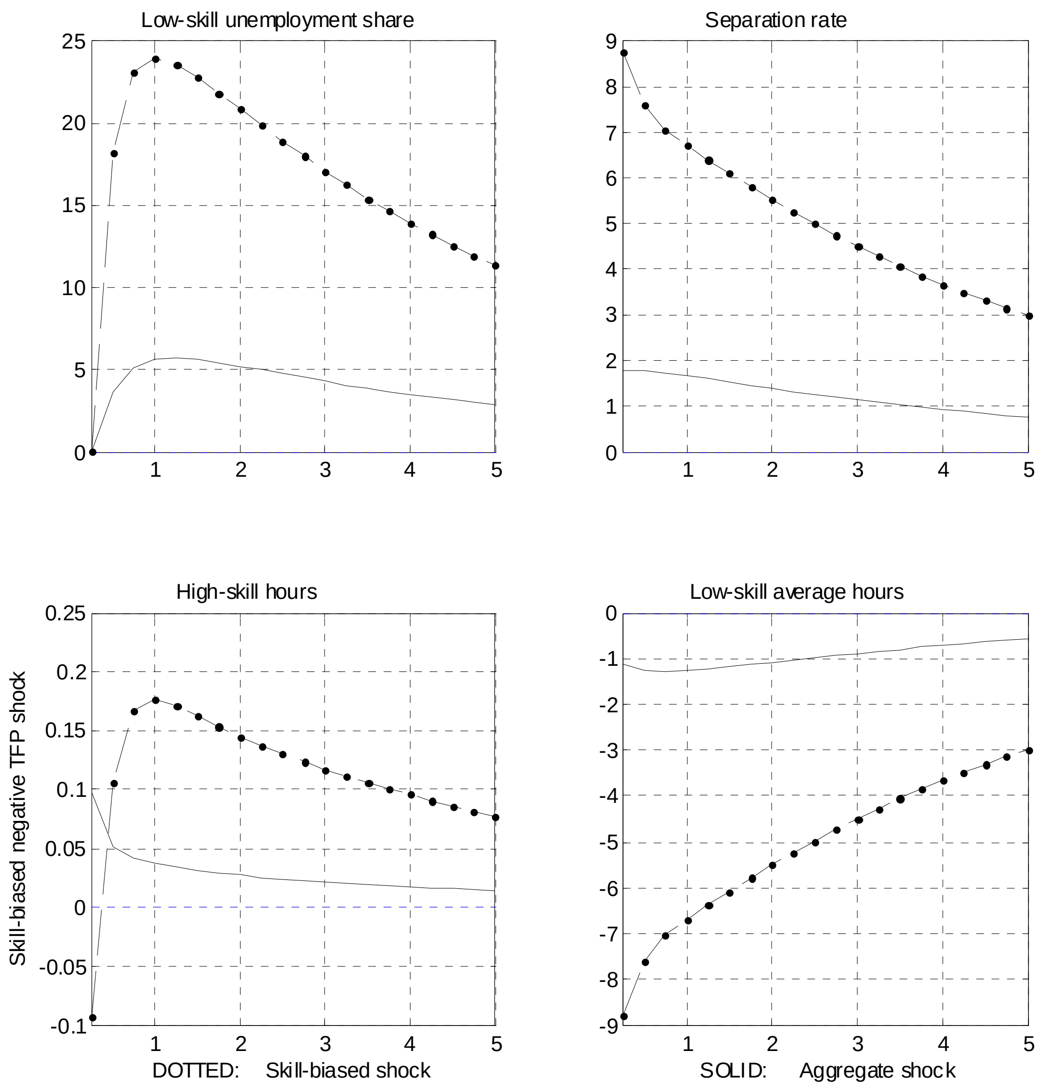

Figure 8: Impulse response to a skill-biased negative TFP shock z_t under the parameterization matching US data, described in Table 4.. AR(1) coefficient of TFP shock $\rho_{z_t} = 0.95$. TFP innovation is equal to -0.5% for high-skill workers, and -2.5% for low-skill workers. For the case of an aggregate TFP shock, innovation is equal to -1%. Scaling in percent.

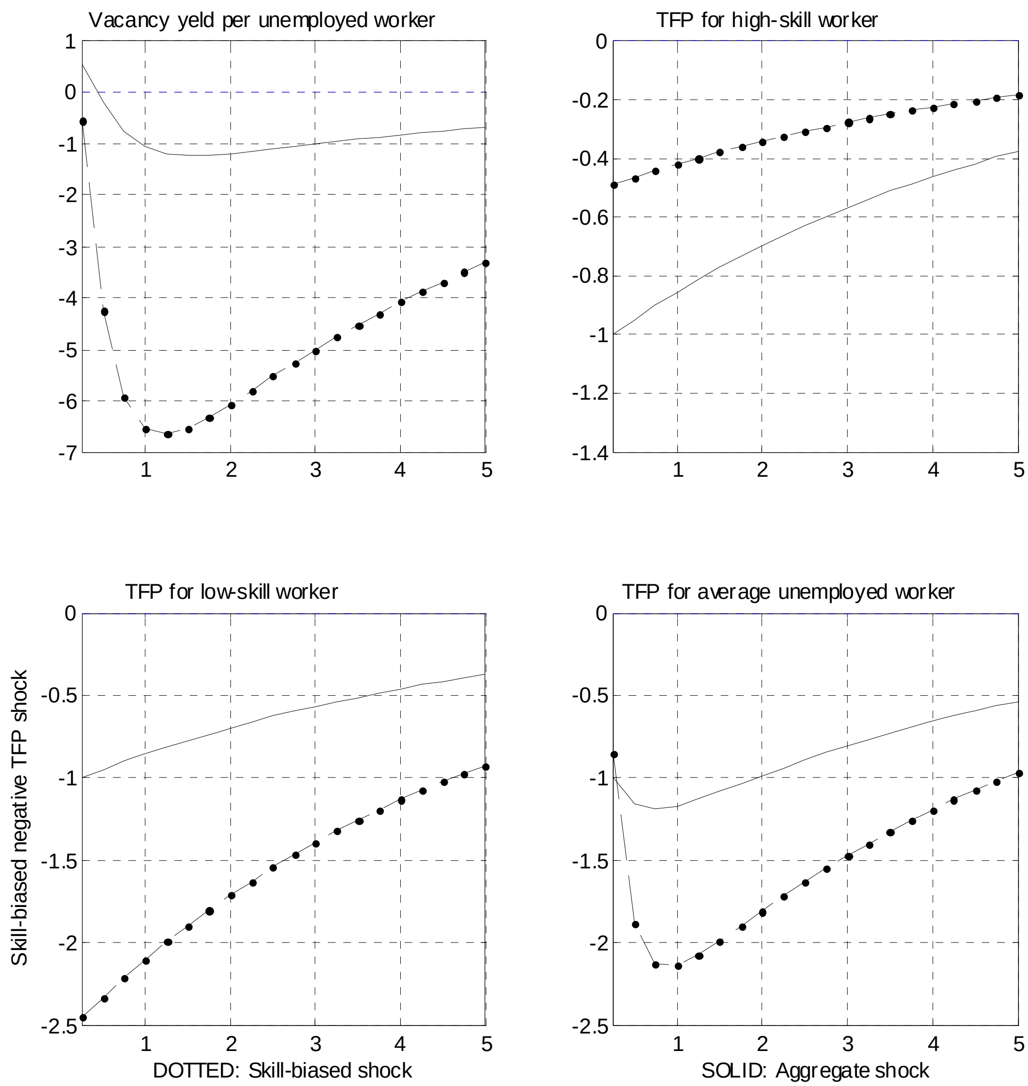

Figure 9: Impulse response to a skill-biased negative TFP shock z_t under the parameterization matching US data, described in Table 4.. AR(1) coefficient of TFP shock $\rho_{z_t} = 0.95$. TFP innovation is equal to -0.5% for high-skill workers, and -2.5% for low-skill workers. For the case of an aggregate TFP shock, innovation is equal to -1%. Scaling in percent.

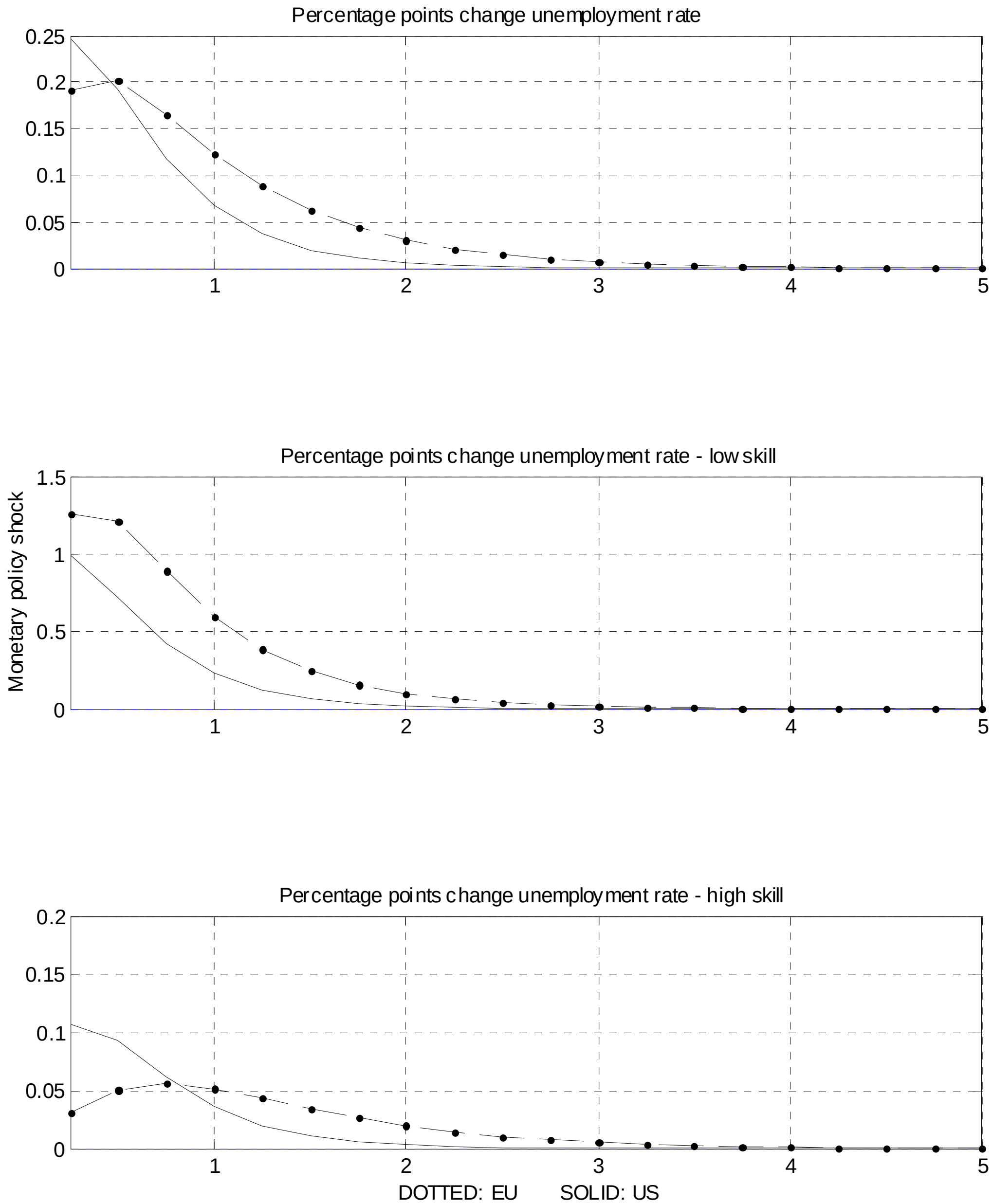

Figure 10: Impulse response to an interest rate i.i.d innovation ε_t equal to 1% at annual rate, under the baseline parameterization (EU) and a parameterization matching US data, described in Table 4. The policy rule, eq. (18), assumes $\omega_\pi = 1.5$, $\omega_y = 0$, $\chi = 0.8$. Change in unemployment rate for total, low-skill and high-skill population scaled in percentage points of the labor force L, L^l, L^h of each group.

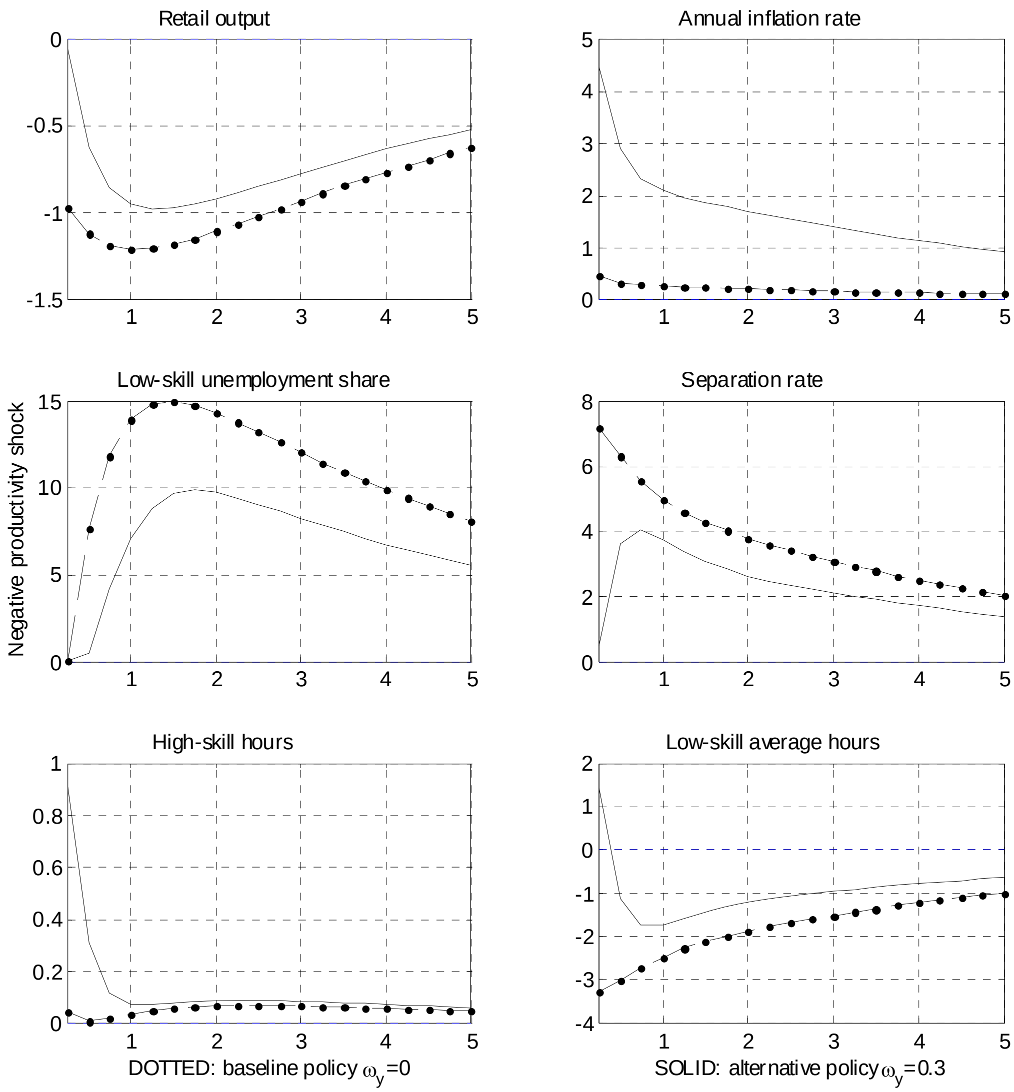

Figure 11: Impulse response to a negative TFP shock z_t under the baseline parameterization (EU) for alternative policies. The policy rule is described in eq. (18), and assumes $\omega_\pi = 1.5,\ \chi = 0.8$. AR(1) coefficient of TFP shock $\rho_{z_t} = 0.95$. Shock is scaled to deliver a 1% fall in output in the initial period under the baseline policy.

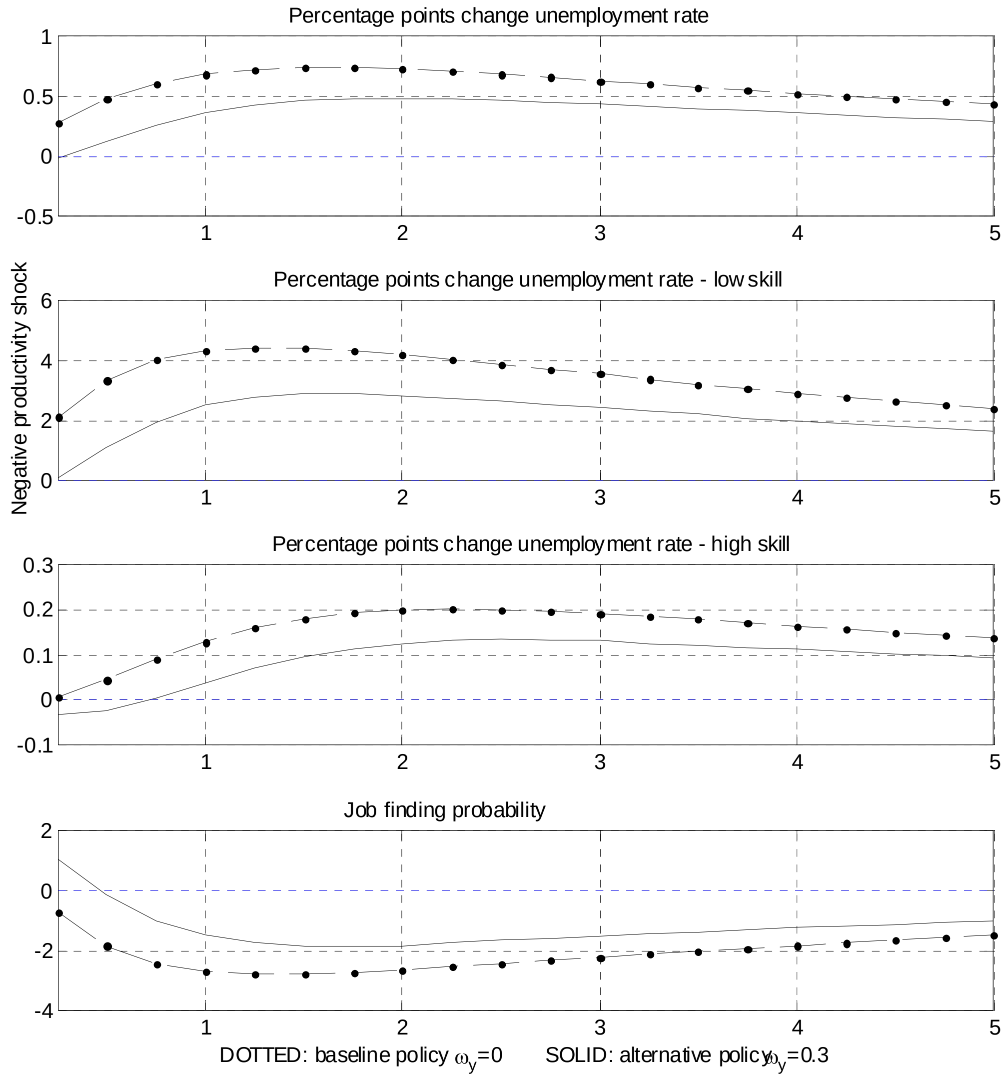

Figure 12: Impulse response to a negative TFP shock z_t under the baseline parameterization (EU) for alternative policies. The policy rule is described in eq. (18), and assumes $\omega_\pi = 1.5,\ \chi = 0.8$. AR(1) coefficient of TFP shock $\rho_{z_t} = 0.95$. Shock is scaled to deliver a 1% fall in output in the initial period under the baseline policy.

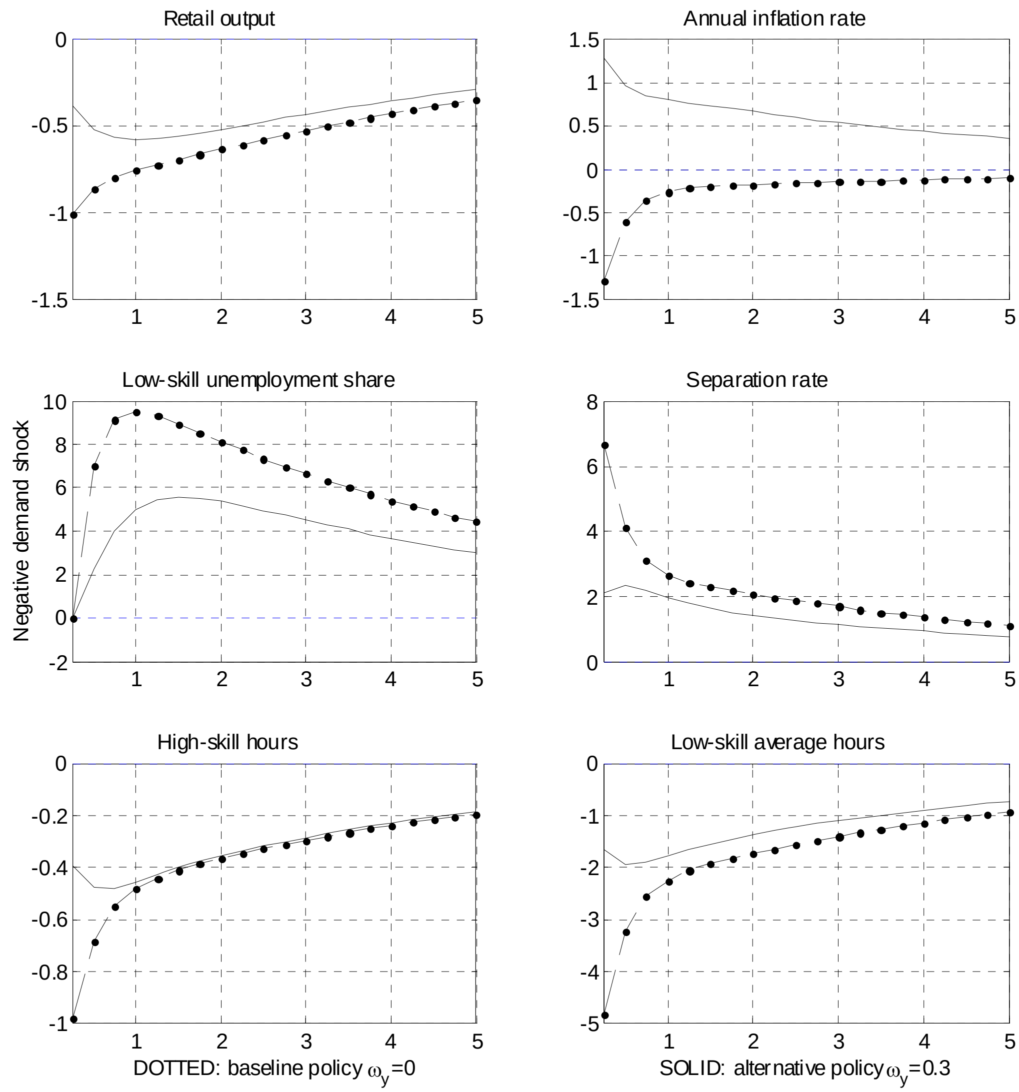

Figure 13: Impulse response to a negative preference shock D_t under the baseline parameterization (EU) for alternative policies. The policy rule is described in eq. (18), and assumes $\omega_\pi = 1.5$, $\chi = 0.8$. AR(1) coefficient of preference shock $\rho_{D_t} = 0.95$. Shock is scaled to deliver a 1% fall in output in the initial period under the baseline policy.

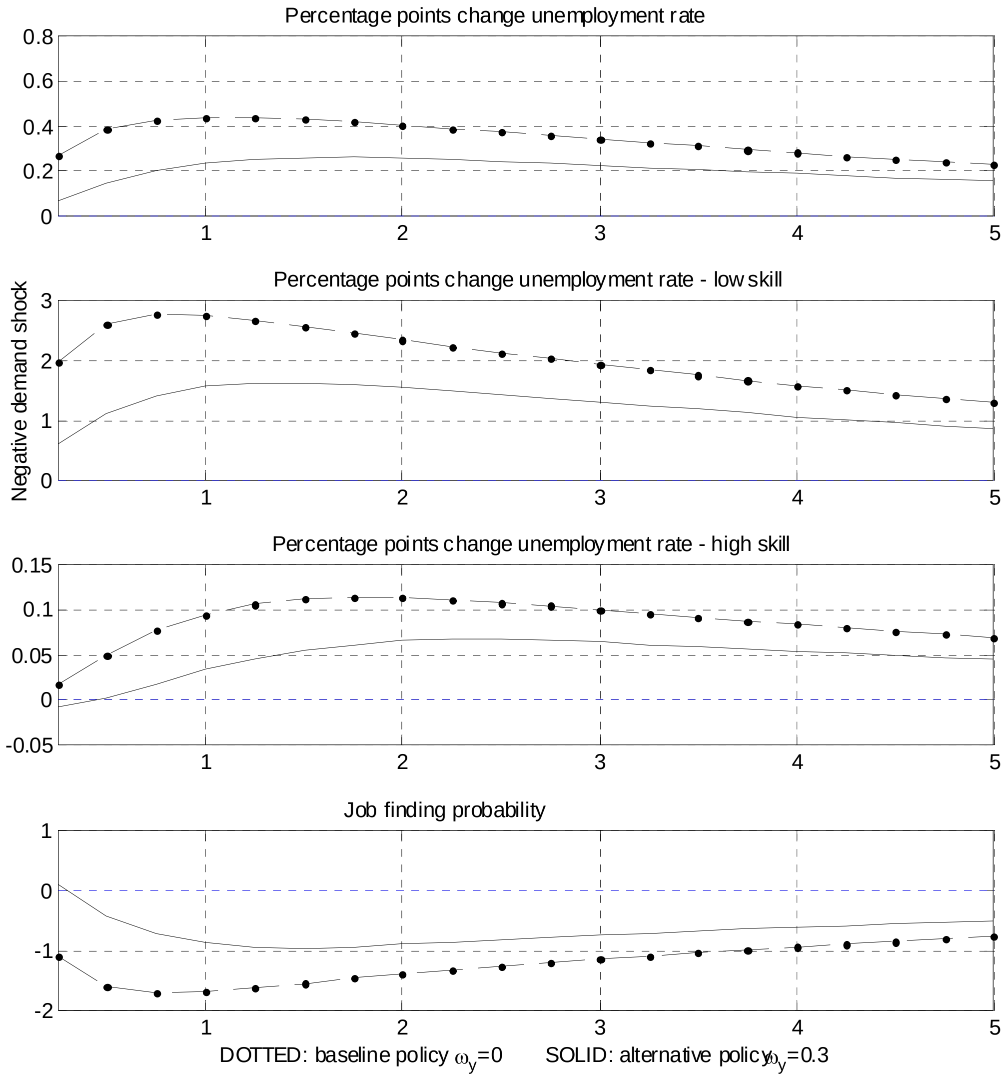

Figure 14: Impulse response to a negative preference shock D_t under the baseline parameterization (EU) for alternative policies. The policy rule is described in eq. (18), and assumes $\omega_\pi = 1.5$, $\chi = 0.8$. AR(1) coefficient of preference shock $\rho_{D_t} = 0.95$. Shock is scaled to deliver a 1% fall in output in the initial period under the baseline policy.

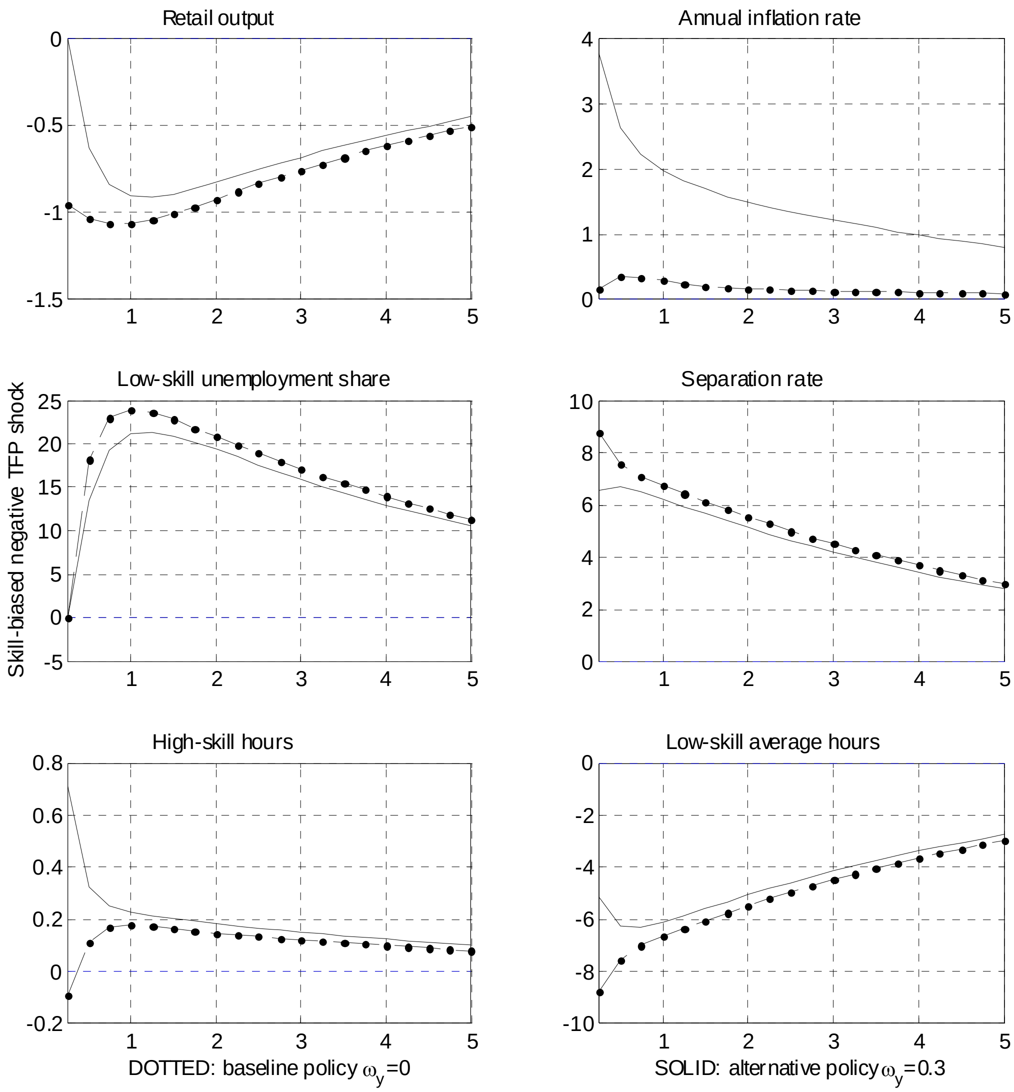

Figure 15: Impulse response to a skill-biased negative TFP shock z_t under the parameterization matching US data, described in Table 4, for alternative policy rules. The policy rule is described in eq. (18), and assumes $\omega_\pi = 1.5$, $\chi = 0.8$. AR(1) coefficient of TFP shock $\rho_{z_t} = 0.95$. TFP innovation is equal to -0.5% for high-skill workers, and -2.5% for low-skill workers.

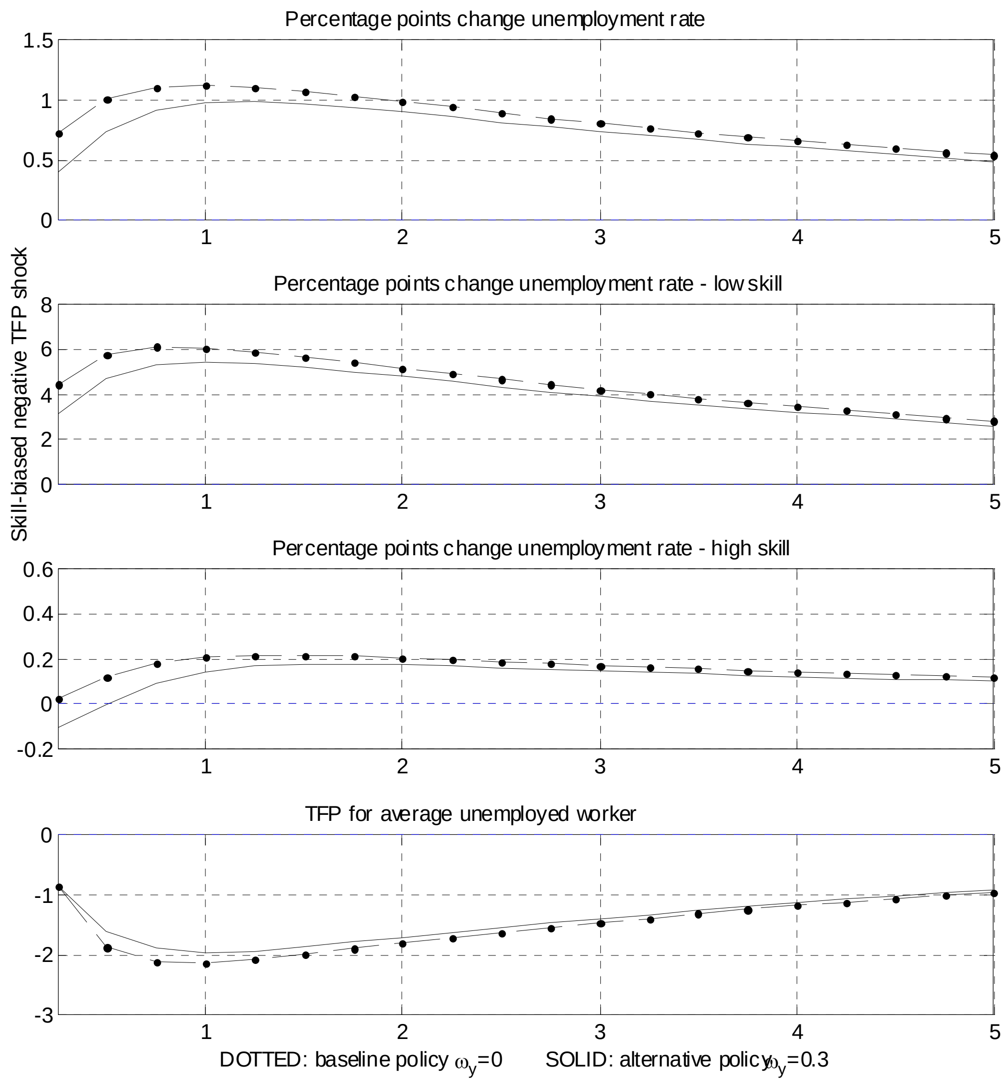

Figure 16: Impulse response to a skill-biased negative TFP shock z_t under the parameterization matching US data, described in Table 4, for alternative policy rules. The policy rule is described in eq. (18), and assumes $\omega_\pi = 1.5$, $\chi = 0.8$. AR(1) coefficient of TFP shock $\rho_{z_t} = 0.95$. TFP innovation is equal to -0.5% for high-skill workers, and -2.5% for low-skill workers.