Discount factor shocks and labor market dynamics

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Abstract

In this paper we investigate the labor market dynamics in a matching model where fluctuations are driven by movements in the discount factor. A comparison with the standard productivity shock is provided. Movements in the discount factor can be used as a proxy for variations in financial risks, especially the expected payoff from hiring workers. It is shown that the canonical matching model under a very standard calibration is able to generate an important volatility of unemployment and vacancies with respect to output. We estimate the structural model with the two shocks and using the Bayesian methodology. The bulk of variations in unemployment and vacancies is mainly explained by disturbances pertaining to the discount factor. Productivity shocks account for most of the historical output variations but the discount factor plays a more important role over the last two decades.

Keywords: Search and matching, discount factor shock, Bayesian estimation, unemployment volatility puzzle.

JEL Classification: E3, J6

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1 Introduction

The ability of the search and matching model (Mortensen-Pissarides, 1994) to reproduce the cyclical behavior of key labor market variables has received an important attention. Shimer (2005) and Hall (2005) argued that the model, in its standard form, is clearly unable to generate substantial fluctuations in unemployment, vacancies and the labor market tightness as compared to the data. They are 9,10 and 17 times more volatile than output respectively. The reason is that wages absorb most of the variations coming from productivity shocks.

This puzzle has led to an important literature trying to modify the matching model using wage rigidities (Shimer (2005), Hall (2005), Gertler et al. (2008), Hall & Milgrom (2008)), small surplus calibration (Hagedorn & Manovskii (2008)), workers and jobs heterogeneity (Krause & Lubik (2006), Chassamboulli (2013)), alternative forms of hiring costs (Yashiv (2006), Fujita & Ramey (2007), Rotemberg (2008), Pissarides (2009)) counter-cyclical payroll taxes (Burda & Weder (2010), etc. The list is far from being exhaustive. All the aforementioned specifications have attempted, directly or indirectly, to prevent wages from adjusting rapidly. A notable exception is a study by Di Pace & Faccini (2012) that introduced deep habits in the matching model. They show that this produces endogenous countercyclical mark-ups and generates amplification in the response of labor market variables to technology shocks. Most of these studies[1] assumed that labor market fluctuations are solely driven by the popular productivity shock. However, many economists and institutions have cast some doubts on the movements of productivity as a main driver for business cycle fluctuations, especially over the last three recessions in the US. In this paper we study the labor market dynamics but we consider an alternative source of business cycle fluctuations: variations in the discount factor. We argue that disturbances to the discount factor provide an important source of propagation. The relative volatility of unemployment and vacancies is well reproduced.

The discount rate expresses the difference between the remuneration of the risk free bonds and risky bonds also know as the risk premium. In a paper closely related to ours, Hall (2014) wonders what force depresses the payoff to job creation in recession. He noticed that a rise in the discount rate has similar effects to an increase in financial risks. It makes employers less prone to invest in any type of investments, including job creation. A rise in the risk premium reduces the expected payoff from hiring a new worker because the real interest rate is simply the rate at which firms discount their future profit streams. The

[1] With few exceptions like Rotemberg (2008) who uses changes in market power as a source of business fluctuations but it still make real wages less procyclical. Faccini & Ortigueira (2010) assume that investment-specific technology fuel up the cycles and found that is helps to solve the unemployment volatility puzzle.

fall in the expected value of a filled job lowers firms' jobs openings which, in turn, increases aggregate unemployment. An adverse shock on the discount factor can then be viewed as a proxy for the financial market turmoil since it impacts the interest rate in a way that mimic the Great Recession.

Most of the studies on the dynamics of the DMP model assumed that TFP shocks track labor market fluctuations. Figure 1 and **??** show the cyclical component of the labor market tightness against that of discount rate[2] and that of productivity. While the movements in productivity seems to provide a rational explanation for the labor market dynamics until 1982, the path of productivity and tightness do not really support this view over the last three decades. The first panel of Figure 3 shows that the correlation between the two was maximal with a three lag periods in the tightness over 1952-1984. It falls short over 1985-2012 and the maximum correlation calls for a unrealistic number of lags. On the other side, the labor market tightness seems to be highly correlated with the discount rate, particularly over the last two decades. The second panel of Figure 3 shows that the maximum correlation between the discount factor and the tightness is higher than in the previous case. In the pre-1984 sample the contemporaneous correlation is the highest one can obtained while a one-lag period is needed in the post-1984 sample.

The role of disturbances pertaining to the discount factor must be questioned. We do not explain what exacerbates the uncertainty on financial markets. There is an abundant literature on this topic. We simply assume that a shock on the discount rate is a simple proxy for frictions in financial markets. We try to understand how the risk translates in the labor market and how firms react to changes in future flow of profits. Our analysis goes one step further than Hall (2014) since we focus on the volatility puzzle rather than the interactions between labor and financial market. We investigate the respective role of the two shocks for unemployment, vacancies and output dynamics in an estimated model. In addition we document how change in the business cycle can be explained by an increasing contribution of the discount factor shock.

Our results are as follows. The two shocks are needed to match empirical moments. The productivity shock injects large fluctuations in output but has difficulties to reproduce the relative[3] standard deviation of labor market under a plausible calibration. The discount factor shock reaches the opposite conclusions. It implies a very large relative volatility in unemployment, vacancies and the labor market tightness but its variation must be extremely important to generate a consistent absolute volatility.

The small surplus calibration *a la* Hagedorn & Manovskii (2008) is not rejected by our estimations but the bulk of variations in unemployment and va-

[2]See appendix A for data description and methodology

[3]By relative standard deviation we mean the volatility of the variable X divided by the volatility of output.

cancies is mainly explained by disturbances pertaining to the discount factor. The productivity shock accounts for half of the output variations. However, the discount factor has gained an increasingly role over time, especially over the last two decades. We argue that the introduction of the discount factor shock to proxy financial risk in a very simple way is key to improve the fit of the canonical search and matching model.

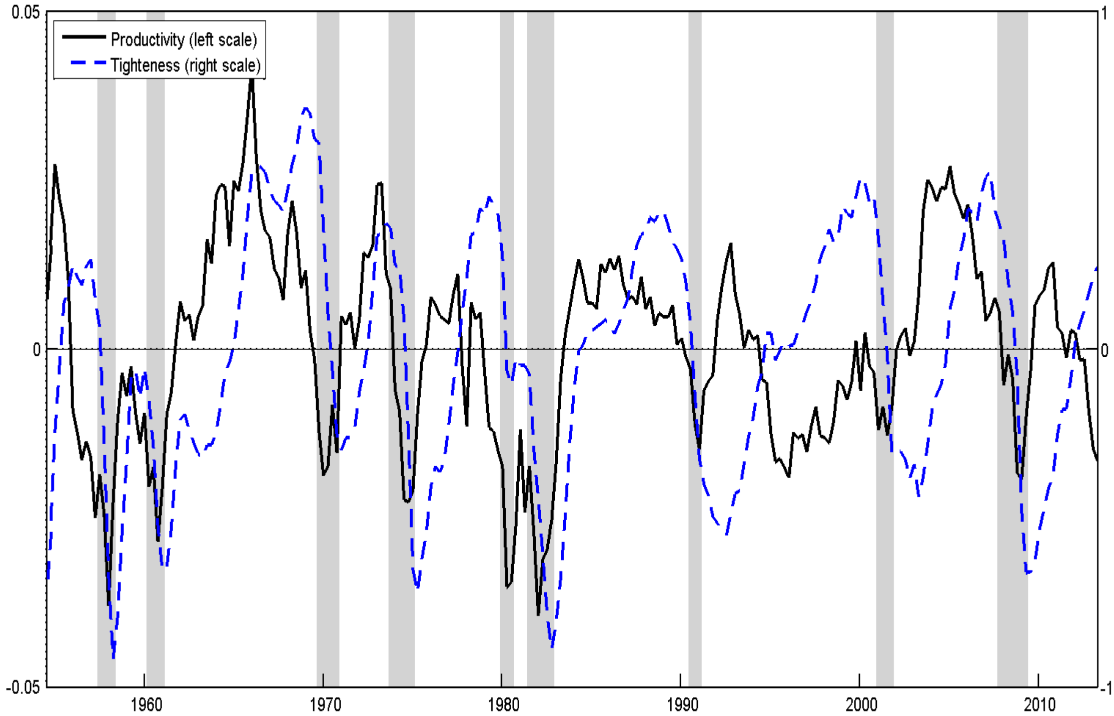

Figure 1: ***Cyclical component of Productivity and the labor market tightness.***

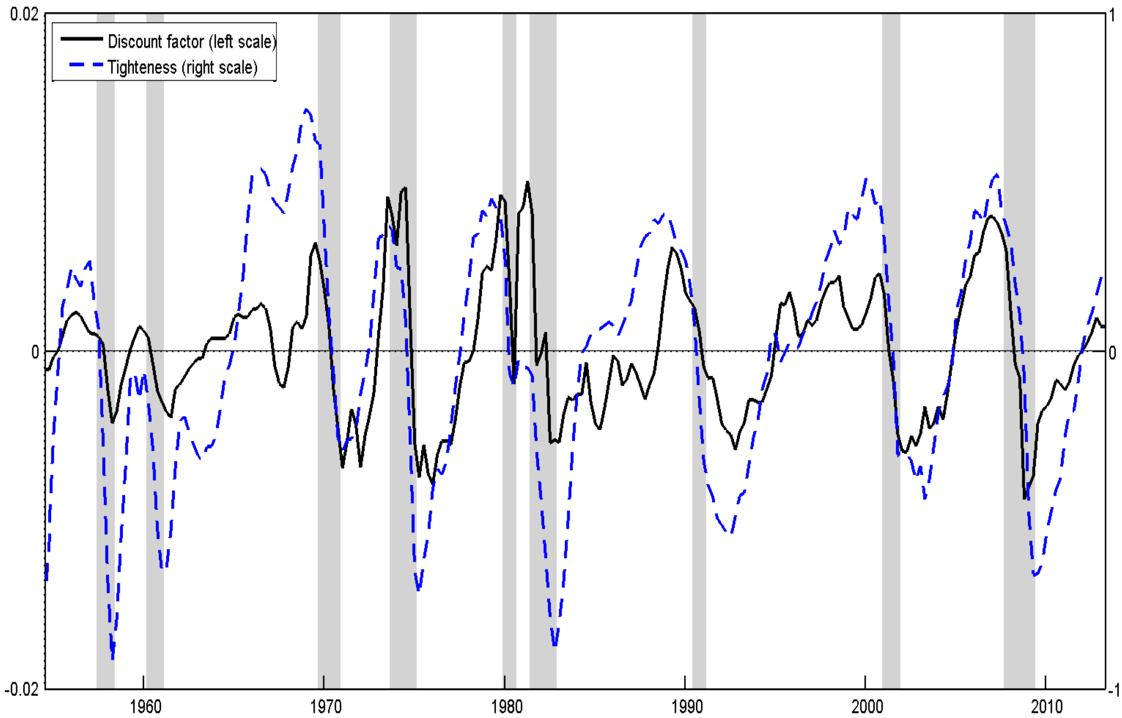

Figure 2: ***Cyclical component of Real interest rate and the labor market tightness.***

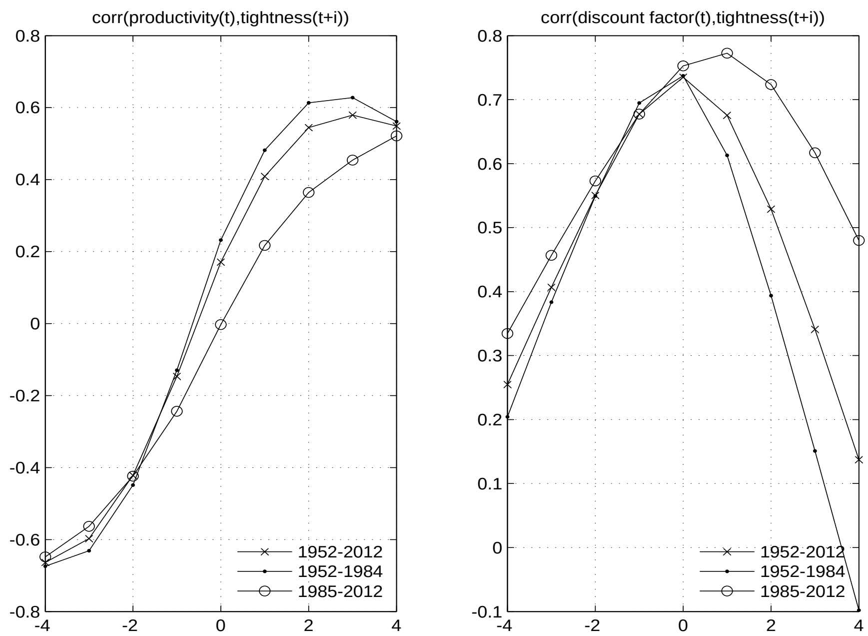

Figure 3: ***Correlations.***

The rest of the paper is organized as follows. Section 2 is devoted to the presentation of the dynamic matching model. Section 3 addresses calibration, simulations and the estimation of the structural model using Bayesian methodology. Section 5 concludes.

2 The model

We use a discrete time version of the standard matching model. Separations are exogenous. Labor is the only input into the production process and it may be adjusted through the extensive margin (employment). Wages are set according to a Nash bargaining process.

2.1 Matching

A job may either be filled and productive, or unfilled and unproductive. Workers are identical and they may either be employed or unemployed. The number of matches, m_t, is given by the following Cobb-Douglas matching function:

$$m_t \quad = \quad \chi j_t^{\gamma} v_t^{1-\gamma} \leq \min(j_t, v_t) \tag{1}$$

where $v_t \geq 0$ denotes the mass of vacancies, $j_t \geq 0$ represents the mass of searching workers. The matching function (1) is increasing and concave in its two arguments and homogenous of degree 1. A vacancy is filled with probability $q_t = m_t / v_t$ and the job finding probability is $f_t = m_t / j_t$. Total employment is n_t and the number of job seekers is defined by $j_t = 1 - (1-s)n_{t-1}$. The labor force is assumed equal to one such that end-of-period unemployment is $u_t = 1 - n_t$. The employment law of motion is given by:

$$n_t = (1-s)n_{t-1} + m_t \tag{2}$$

which implies that hirings are immediately productive[4].

2.2 Representative household

The representative household maximizes aggregate consumption[5] c_t:

$$\max_{\Omega_t^H} E_0 \sum_{t=0}^{\infty} \left(\prod_{k=0}^{t} \beta_k \right) c_t \tag{3}$$

subject to (i) the budget constraint:

$$c_t = w_t n_t + u_t b + \Pi_t + T_t \tag{4}$$

[4]It should be noticed that our results remain unchanged with an employment law of motion that is entirely backward: $n_t = (1-s)n_{t-1} + m_{t-1}$, $m_t = f_t u_t$ or $m_t = f_t j_t$

[5]For the sake of clarity, we consider a linear utility function. Results are robust to a more standard CRRA utility function.

(ii) the job seekers j_t definition and (iii) the law of motion of employment:

$$n_t = (1-s)n_{t-1} + f_t j_t \tag{5}$$

β_t represents a discount factor shock with $\beta_0 = \beta$. w_t is the wage level. Π_t represents profits from holding shares in firms and T_t is a lump-sum tax. The representative household derives a constant utility b from unemployment (unemployment benefits and home production). Prices are normalized to 1. The program consists of choosing the set of processes $\Omega_t^H = \{c_t, n_t\}_{t=0}^{\infty}$ taking as given the set of processes $\{w_t, f_t\}_{t=0}^{\infty}$ so as to maximize their intertemporal utility. The optimality conditions of the household's problem defines the marginal value of employment for a worker:

$$\varphi_t = (w_t - b) + E_t \beta_{t+1}(1-s)(1-f_{t+1})\varphi_{t+1} \tag{6}$$

2.3 Firms

The optimization problem of the firm consists of choosing the set of processes $\Omega_t^F = \{v_t, n_t\}_{t=0}^{\infty}$ taking as given the set of processes $\{w_t, q_t\}_{t=0}^{\infty}$ so as to maximize the following intertemporal profit function:

$$\max_{\Omega_t^F} E_0 \sum_{t=0}^{\infty} \left(\prod_{k=0}^{t} \beta_k \right) (y_t - w_t n_t - \kappa v_t) \tag{7}$$

subject to the production function and the law of motion of employment:

$$\begin{aligned} y_t &= z_t n_t \\ n_t &= (1-s)n_{t-1} + q_t v_t \end{aligned}$$

Hiring is costly and incurs a cost κ per vacancy posted. z_t is an aggregate productivity shock. The optimality conditions of the above problem gives the job creation condition which equal expected surplus from a filled job μ_t to the expected cost of search:

$$\frac{\kappa}{q_t} = \mu_t \tag{8}$$

$$\mu_t = z_t - w_t + (1-s)E_t \beta_{t+1} \mu_{t+1} \tag{9}$$

Combining the two gives the job creation condition:

$$\frac{\kappa}{q_t} = z_t - w_t + (1-s)E_t \beta_{t+1} \frac{\kappa}{q_{t+1}} \tag{10}$$

2.4 Wages

The wage is determined every period through an individual Nash bargaining process between each worker and the large firm, who share the total surplus of the match. The standard optimality condition of the above problem is given by: $\xi\mu_t = (1-\xi)\varphi_t$ where $\xi \in [0,1]$ and $1-\xi$ denote the workers and firms bargaining power respectively. Using equation (6), (8) and (9), one has:

$$w_t = \xi\left(z_t + E_t\beta_{t+1}(1-s)\kappa\theta_{t+1}\right) + (1-\xi)b \tag{11}$$

To close the model we define profits as $\Pi_t = y_t - w_t n_t - \kappa v_t$ which, combined with the household budget constraint (4) and the government budget constraint $T_t = j_t b$, yields the following market clearing condition: $c_t = y_t - \kappa v_t$. The discount factor shock and the productivity shock follow an autoregressive process with mean β and z respectively:

$$\log\beta_{t+1} = \rho_\beta \log(\beta_t) + (1-\rho_\beta)\log(\beta) + \varepsilon^\beta_{t+1} \quad \text{With } \varepsilon^\beta \sim \mathcal{N}(0,\sigma^2_\beta) \tag{12}$$

$$\log z_{t+1} = \rho_z \log(z_t) + (1-\rho_z)\log(z) + \varepsilon^z_{t+1} \quad \text{With } \varepsilon^z \sim \mathcal{N}(0,\sigma^2_z) \tag{13}$$

2.5 Model calibration

We adopt a very standard calibration based on US data and quarterly frequencies (See Table 1).

Labor market, stocks and flows: We set the steady state discount factor to 0.99 which gives an annual real interest rate of 4%. The US unemployment rate u is about 6% on average over several decades. We set the probability of being unemployed s to 10% which corresponds to the BLS monthly data of 3.35%. At the steady state, the number of matches must be equal to the number of separations: $m = sn$ with $n = 1 - u = 0.94$. We get the number of job seekers from the definition $j = 1 - (1-s)n$ and the job finding rate from $f = m/j \simeq 50\%$. Following den Haan et al. (2000), the rate at which a firm fills a vacancy is about 0.71. Then, we deduce $v = m/q$ and set χ in such a way that $m = \chi j^\gamma v^{1-\gamma}$. As in Hagedorn & Manovskii (2008) the cost of posting vacancy κ is set at 0.58. The elasticity of the matching function w.r.t. the number of job seekers is equal to 0.5, in line with Pissarides & Petrongolo (2001).

Calibration of ξ and b: Shimer (2005) shows that in the DMP model the standard calibration implies a high sensitivity of wages which offsets the impact of productivity shocks. Two key parameters govern the volatility of wages: ξ and b. Our strategy is to calibrate the model in order to reproduce the elasticity of the labor market tightness w.r.t. the productivity shock. We focus on this elasticity in order to make a comparison with previous studies in which the productivity shock is the driver of business cycle fluctuations. Basically, the following equations give the elasticities of the tightness to productivity:

$$\varepsilon_{\theta,z} = \frac{1}{\gamma}\frac{z-\varepsilon_{w,z}w}{z-w} \tag{14}$$

$$\varepsilon_{w,z}w = \xi(z+\beta(1-s)\kappa\theta\varepsilon_{\theta,z}) \tag{15}$$

and to discount rate:

$$\varepsilon_{\theta,\beta} = \frac{1}{\gamma}\left[\frac{\beta(1-s)}{1-(1-s)\beta} - \frac{(1-(1-s)\beta)\varepsilon_{w,\beta}w}{z-w}\right] \tag{16}$$

$$\varepsilon_{w,\beta}w = \xi\beta\kappa(1-s)\theta\left(1+\varepsilon_{\theta,\beta}\right) \tag{17}$$

The empirical counterpart corresponds to the ratio of the volatility of the tightness over the volatility of the productivity: $\frac{\sigma_\theta}{\sigma_z}$. From 1951-2003 it is equal to 28.27. However, as underlined by Pissarides (2009), we should modify this ratio. He said that this should be the target if there were no measurement or other random errors in the two variables and if no other shocks influenced tightness. When considering an additional shock one has to includes the correlation between the two variables: $\varepsilon^{data}_{\theta,z} = \frac{\sigma_\theta}{\sigma_z}corr(\theta,z)$. Using the data this correlation is equal to 0.16 which involves $\varepsilon^{data}_{\theta,z} = 4.65$. Pissarides (2009) found a value of 7.5 using Shimer's data which cover the periods 1951-2003. Two reasons explain this discrepancy. First, the time period that we consider also cover the period 2003-2013. This period is marked by a negative correlation between the tightness and the productivity, which reduces the elasticity. Second, we use a more traditional value for the smoothing parameter of the HP-filter (1600) while they consider a value of 10^5. Their value amplifies the cyclical component of the tightness relative to the productivity. In a robustness analysis, we calibrate the model and set the prior's value by imposing the elasticity to be equal to 7.5 and recalculate ξ and b accordingly. We found that estimated parameters and shocks series remain virtually unchanged.

We proceed as follow. We plug $\varepsilon(w,z)w$ in Equation (14) and get the steady state value of the wage from Equation (10). We defined ξ from Equation (11) as being equal to $(w-b)/(z+\beta(1-s)\kappa\theta-b)$. We replace ξ in Equation (14) in order to pin down b. The resulting values for the workers' bargaining power and the utility when unemployed are 0.32 and 0.73 respectively. The low ability of workers to get a share of the surplus combined with a high outside option reduces the sensitivity of wages to variation in productivity. The implied elasticity of wages is 0.79. Furthermore, it implies a wage rate w equal to 93% of the productivity. Albeit a little bit lower, this value is typical from small surplus calibration *a la* Hagedorn & Manovskii (2008). This calibration results in an elasticity of the v/u ratio w.r.t. the discount rate of 5.82. It is worth noting that rigid wages are likely to raise the responsiveness of the tightness to a variation in the discount factor. However, all other things being equal, the small surplus calibration ($z - w$ low) increase the elasticity of θ w.r.t β.

Shocks: We calculate the series of productivity by dividing the real GDP by the total employment. The discount factor is calculated by differentiating the BAA corporate bonds rate with the federal fund rate at quarterly rate. We use an HP-filter with smoothing parameter $\lambda = 1600$ on the logarithm of the series and estimate an AR(1) process. We obtain a persistence coefficient of 0.85 for the productivity shock and 0.84 for the discount factor shock. The corresponding volatility are equal to 0.009 and 0.002 respectively.

Variables	Symbol	Value	Source
Discount factor	β	0.99	4% annual real interest rate
Separation rate	s	0.1	BLS, SIPP
Utility when unemployed	b	0.82	Target: $\varepsilon_{\theta,\beta} = 4.65$
Worker bargaining power	ξ	0.16	Deduced
Elast. matching w.r.t u	γ	0.5	Hall and Milgrom (2008)
Vacancy posting cost	c	0.58	Hagedorn and Manovskii (2008)
Matching efficiency	χ	0.74	Deduced
Autocorrelation coefficient	ρ_β	0.84	Estimated with AR(1)
Std. of β shock	σ_β	0.002	Estimated with AR(1)
Autocorr. coefficient z_t	ρ_z	0.85	Estimated with AR(1)
Std. of z_t shock	σ_z	0.009	Estimated with AR(1)

Table 1: **PARAMETERS**

3 Results

3.1 Simulations

In a first step, we use the calibration described in Table 1 and simulate the model to highlight the intuition. Table 2 describes the unconditional empirical moments for U.S. data. Unemployment and vacancies are about 8 and 10 times more volatile than output respectively. Both are strongly correlated. The labor market tightness is about 17 times more volatile than output. As shown by Shimer (2005), the wage volatility is low and weakly correlated with unemployment. All variables are highly persistent.

Variables	u	v	θ	w	y
Data					
Absolute std.	14.90	15.06	26.60	0.71	1.55
Relative std.	9.61	9.72	17.16	0.46	1.00
Autocorrelation	0.93	0.93	0.93	0.92	0.88
Correlation with u	1.00	-0.94	-0.98	-0.12	-0.87
Model: Productivity shock only					
Absolute std.	10.58	6.58	16.61	0.96	2.29
Relative std.	4.61	2.87	7.25	0.42	1.00
Autocorrelation	0.92	0.65	0.85	0.85	0.87
Correlation with u	1.00	-0.87	-0.98	-0.98	-0.99
Model: Discount factor shock only					
Absolute std.	1.09	0.69	1.72	0.08	0.07
Relative std.	15.64	9.88	24.68	1.18	1.00
Autocorrelation	0.92	0.63	0.84	0.84	0.92
Correlation with u	1.00	-0.86	-0.98	-0.98	-1.00
Model: Both shocks					
Absolute std.	10.71	6.64	16.81	0.97	2.31
Relative std.	4.63	2.88	7.28	0.42	1.00
Autocorrelation	0.92	0.65	0.85	0.85	0.88
Correlation with u	1.00	-0.87	-0.98	-0.98	-0.99

Table 2: **LABOR MARKET STATISTICS - DATA VS MODEL.** *All moments in the data are reported in logs as deviations from an HP trend with smoothing parameter* 1600.

The simulated moments show that the two shocks involve similar patterns regarding the correlations and the persistence of the variables. They both reproduce a consistent Beveridge curve and enough persistence of the variables. The major differences between the two concern the absolute and relative volatility of the labor market. Thanks to our calibration strategy, the absolute volatilities of labor market quantities is large when the productivity shock fuel up the cycle. We match the targeted relative volatility of the tightness of 7.3. By raising this value in the calibration exercise one can easily match the absolute volatility of the tightness. However, this target should not be considered in a multiple shock enthronement. The weak workers' bargaining power make the volatility of wages broadly consistent with the data. Except for wage the relative volatilities are too low. Unemployment relative volatility is about one half of the target while the model clearly fails to produce enough variations in vacancies. The productivity shock has no difficulties to generate the observed fluctuations in output.

The discount factor shock is the opposite. It generates too much volatility in unemployment and vacancies w.r.t. output but requires a large standard deviation of the shock to match the output volatility[6]. The mechanism behind the discount factor shock lies in the movements of the expected hiring costs (the last term on the RHS in Equation (10)). It directly impacts the payoff to job creation. As firms experience drastic variations in the expected payoff from hiring a new worker they adjust job openings very sharply. The productivity shock increases the job productivity but also the wage rate due to the Nash bargaining. The latter effect offsets the former which implies less variations in the expected gain from hiring a new worker. On the other side, the discount factor produces a strong volatility in wages due to the expectations term in Equation (11).

One may naturally wonder whether combining the two shocks will result in more realistic moments. The previous results are conditional on the parametrization of the shocks and the calibration. But how large is the standard deviation and the persistence of each shock? Which one mainly governs the fluctuations in unemployment, vacancies and output? Does the model predict a change in the source of business cycle fluctuations over time? This we investigate now more formally.

3.2 Estimation

3.2.1 Parameter estimates

We use Bayesian techniques to estimate the model's parameters and shock variances. The posterior density is evaluated using a random-walk Metropolis-Hastings algorithm, for which we generate 2 000 000 draws and we target an acceptance ratio of 0.3. We log-linearize the model around the deterministic steady state and apply the Kalman filter to evaluate the likelihood function. We combine the likelihood function with the prior distribution of the model parameters to obtain the posterior distribution in line with Lubik & Schorfheide (2005), An & Schorfheide (2007) and Lubik (2009).

We set β to 0.99 and estimate the rest of the parameters. We adopt relatively loose priors for the model parameters except for the separation rate[7] (see Table 3). We assume a beta-distribution for share parameters defined on unit intervals and a gamma-distribution for positive-valued parameters. The mean of the prior is always set to the value reported in Table 3. Finally, the priors for the standard deviations of shocks follow an inverse-gamma distribution with infinite standard deviation. Our data set runs from 1948Q1 to 2014Q1. We have two observable variables: the unemployment rate and the real gross do-

[6]Increasing the volatility of the shock does not impact the relative standard deviation $\sigma_x/\sigma_y, x = u, v, \theta, w$ of the variables. This result holds using the non-linear version of the model and a perturbation method of order 2 and 3.

[7]Due to an identification problem of this parameter we restrict the standard deviation to be equal to 0.01.

mestic product. We take log and use an HP-filter with smoothing parameter 1600 as in An & Schorfheide (2007).

One of our major goal is to check whether the model predicts a change in the source of business cycle fluctuations. To evaluate if such a change happened we perform our various numerical experiments on different subperiods. The vanishing procyclicality of labor productivity starts after the 1982 recession. We label by *Sample I* the sample from 1948Q1 to 1984Q4[8] and by *Sample II* the sample from 1985Q1 to 2014Q1. In line with Lubik (2013), we also consider a shorter and more recent episode of economic cycle: 2000Q4-2014Q1 which only includes the last two recessions.

Variables	Symbol	Prior density	Posterior		
			Sample I	Sample II	Full sample
Separation rate	s	$\beta(0.10, 0.01)$	0.089 [0.07, 0.10]	0.092 [0.08, 0.11]	0.082 [0.07, 0.09]
Worker bargaining power	ξ	$\beta(0.20, 0.15)$	0.16 [0.00, 0.31]	0.13 [0.00, 0.26]	0.16 [0.00, 0.31]
Elast. matching w.r.t u	γ	$\beta(0.50, 0.20)$	0.51 [0.32, 0.71]	0.66 [0.48, 0.84]	0.53 [0.36, 0.72]
Utility when unemployed	b	$\Gamma(0.82, 0.10)$	0.78 [0.67, 0.90]	0.76 [0.65, 0.88]	0.77 [0.66, 0.89]
Vacancy posting cost	κ	$\Gamma(0.58, 0.20)$	0.66 [0.36, 0.96]	0.65 [0.34, 0.95]	0.67 [0.36, 0.98]
Matching efficiency	χ	$\Gamma(0.74, 0.20)$	0.57 [0.38, 0.76]	0.53 [0.38, 0.68]	0.53 [0.36, 0.71]
Discount persistence	ρ_β	$\beta(0.84, 0.10)$	0.79 [0.70, 0.88]	0.90 [0.84, 0.96]	0.80 [0.74, 0.87]
Productivity persistence	ρ_z	$\beta(0.85, 0.10)$	0.73 [0.63, 0.82]	0.73 [0.62, 0.84]	0.71 [0.64, 0.79]
Discount Std.	σ_β	$\Gamma^{-1}(0.002, \text{inf})$	0.046 [0.01, 0.08]	0.022 [0.00, 0.04]	0.040 [0.01, 0.07]
Productivity Std.	σ_z	$\Gamma^{-1}(0.009, \text{inf})$	0.007 [0.01, 0.01]	0.004 [0.00, 0.00]	0.006 [0.01, 0.01]

Table 3: **ESTIMATION RESULTS**

Table 3 reports posterior means of the estimated parameters and the 90% confidence intervals. The posterior mean of the workers' bargaining power is lower than its prior level (0.2) but not as low as the in Hagedorn & Manovskii (2008) for which they assign a value of 0.052. However, the posterior density does not rule out this value. It follows that firms get most of the total surplus

[8] We decide to not split the 1982 recession. This is why we cut the sample in 1984 instead of 1982.

from a match, giving to the workers not really more than their outside option.

The posterior mean of the utility derived from unemployment is slightly lower than its prior mean. It gives support to Hall & Milgrom (2008) calibration ($b = 0.71$) but reject Hagedorn & Manovskii (2008) value. Indeed the posterior density assigns zero probability to $b = 0.955$ over the three samples. Recall that b is an overall measure of benefits, leisure, home production and disutility of work. Then b corresponds to the entire outside option. We argue that a low value of workers bargaining power and a high value of the utility when unemployed is needed. This result holds and remains fairly stable of the two samples.

The posterior mean of the cost of posting a vacancy is a bit higher than the prior mean but roughly constant over the two samples. The elasticity of the matching function with respect to unemployment is in the range of the most standard values (Pissarides & Petrongolo (2001)). It turns out to be 20% larger in the post-1984 sample. The Hosios condition, $\xi = 1 - \gamma$, is unlikely to be satisfied.

The standard deviation of the discount factor shock (0.04) is larger than that of the productivity shock and way more larger that the one we get from the data (0.002). However, in Sample II, only half of the volatility is required compare to Sample I. The volatility of the productivity shock does not move away from its prior in Sample I but experiences a brutal decline after 1984. While the persistence of the productivity shock remains stable over the two samples, the discount factor shock is more persistent after 1984.

3.2.2 Moments

Variables	u	v	θ	w	y
Data					
Absolute std.	14.90	15.06	26.60	0.71	1.55
Relative std.	9.61	9.72	17.16	0.46	1.00
Autocorrelation	0.93	0.93	0.93	0.92	0.88
Correlation with u	1.00	-0.94	-0.98	-0.12	-0.87
Model: mode of the parameter estimate					
Absolute std.	16.89	17.16	32.52	2.16	1.73
Relative std.	9.75	9.90	18.77	1.25	1.00
Autocorrelation	0.92	0.62	0.80	0.80	0.86
Correlation with u	1.00	-0.82	-0.95	-0.96	-0.87

Table 4: **LABOR MARKET STATISTICS - DATA VS MODEL.** *All moments in the data are reported in logs as deviations from an HP trend with smoothing parameter* 1600.

We report the moments of the simulated variables using the mode of the posterior distribution for parameters' values (see Table 4). We consider the estimation on the full sample. It is shown that the canonical search and matching model generates large fluctuations in the labor market when the two shocks are considered. The absolute and relative volatility of unemployment, vacancies and the tightness are well reproduced despite the high volatility of wages. Indeed, wages are more than two times more volatile than in the data. The reason comes from the impact of the discount factor shock. It discounts the expected cost of posting vacancies in the wage equation (11) and in the job creation condition (10). As a consequence, it generates movements in the tightness but also in wages. The presence of the discount factor shock in the wage equation is inherited from the contemporaneous hirings assumption. Within the same period, firms pay the cost κ, post v_t vacancies and hire m_t new workers that are immediately productive. Since wages are bargained at the end of the period, workers can not use the job posting cost already paid by the firm as a threat point[9] to get an higher share of the surplus. They can only bargain on the next period job posting costs. With hirings not immediately productive, the employment law of motion is entirely backward and wage are negotiated before the payment of hiring expenditures. In this environment, the discount factor does not enter the wage equation. We relax the contemporaneous hirings assumption in the robustness analysis.

The slope of the Beveridge curve is a little bit lower but still broadly consistent with the data. Except for vacancies, the model provides enough persistence of the variables. Furthermore, the presence of the two shocks breaks the perfect negative correlation between unemployment and output that is obtained in a single shock setup. The same result holds for vacancies and the tightness. Except for wages, the correlation of the variables with unemployment is well reproduced.

3.2.3 Shock decomposition

In this section, our objective is to understand which shock is the main driver for unemployment, vacancies and output. What can explain the change in business cycle fluctuations? Is it cyclical or structural? The estimations show that the only structural parameter that has change between the two samples is the elasticity of the matching function with respect to the number of job seekers, the rest belongs to the shock processes. To disentangle the two we perform a shock decomposition with and without considering a change in the structural parameters. We analyze the variance decomposition over different subperiods and different specifications. We label by **case 1** the case where the model's parameters are re-estimated on each subperiod. The **case 2** cor-

[9]The first term on the right-hand side of Equation ((11)).

responds to the estimation of the model over the full sample but we split the shock decomposition over the different subperiods. The major difference between the two lies in the value of the parameters that are re estimated in the first case but not in the second case. This allows to disentangle the structural effects from the cyclical effects. Indeed, if the shocks decomposition varies over time but not between case 1 and case 2, the cyclical effects (change in the shocks) are more likely to explain the shifts in business cycles. On the opposite, a difference between case 1 and 2 calls for a change in the propagation of shocks.

An inspection of Table 5 makes it clear that the bulk of variation in unemployment and vacancy is mainly governed by the disturbances pertaining to the discount factor. About 80% of labor market fluctuations are explained by this shock. Only a small fraction of the fluctuations are generated by the productivity shock during the different subperiods. On the other side, the two shocks equally contribute to the variations in output.

The contribution of the discount factor is larger after 1984. Case 1 and 2 support this tendency, albeit the first one is more striking during 1985-2014. The subperiod 2000-2014 highlights the important role played by the discount factor during the last two recessions, especially for output. Its contribution increased by around 30%. For unemployment, vacancies and the tightness the decline in the contribution of the productivity shock between pre-84 and post-84 is about 13% in case 1 and 1% in case 2. Between pre-84 and post-2000 the decline is about 11% in case 1 and 6% in case 2. We argue that the changes in the nature of the cycle have been driven by a change in the contribution of shocks rather than a change in the propagation of shocks

Variables	Symbol	1948Q1 1984Q4	1985Q1 2014Q1	1960Q1 1984Q4	2000Q4 2014Q1	Full sample
		Case 1				
Output	y	51	54	53	62	54
Unemployment	u	79	87	82	86	82
Vacancies	v	75	86	80	86	80
Tightness	θ	77	87	82	85	81
		Case 2				
Output	y	53	55	48	64	54
Unemployment	u	82	82	80	87	82
Vacancies	v	79	82	77	85	80
Tightness	θ	81	81	80	85	81

Table 5: **SHOCK DECOMPOSITION.** *Contribution of the discount factor shock to the variance of the variables (in percentage). The contribution of the productivity shock is 100 minus the values. Case 1: estimated parameters are different (see Table 3). Case 2: estimated parameters are identical, the shock decomposition is split into the subperiods.*

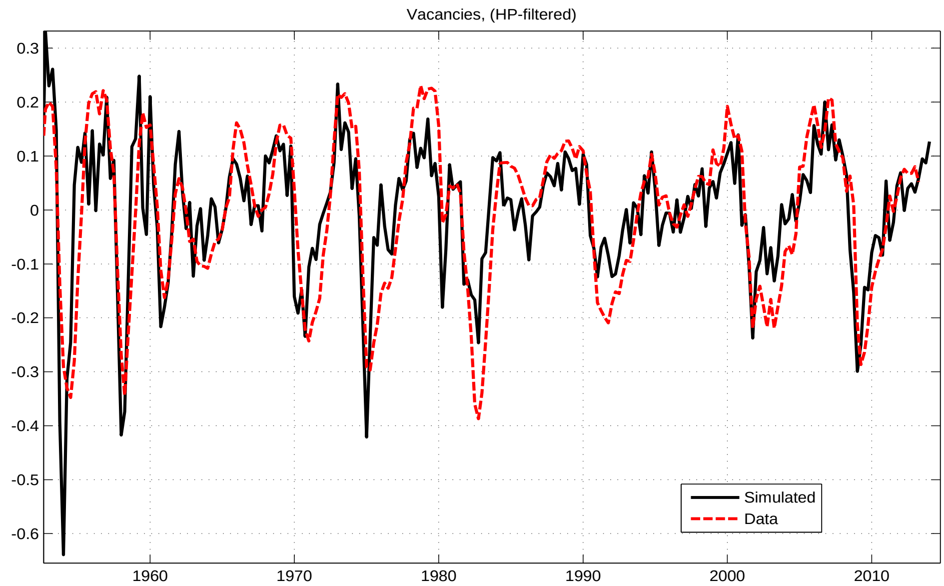

Figure 4: ***Vacancies path***.

3.2.4 Shock dynamics

Last but not least, we analyze the extent to which the sequence of shocks estimated departs from the one in the data[10]. We display the productivity and the discount factor shock obtained by Bayesian estimation against those from the data (see Figure 5 and 6). The fit of the productivity shock is very good, especially between 1960 and 1990. After 1990, the co-movements between the two series are not as pronounced as before. The volatility of the productivity shock exhibits a clear decline since the end of the 1982 recession in both cases.

The correlation between the two series for the discount factor shock is surprisingly good. Since 1990, movements in the series from the Bayesian estimation are extremely close to our proxy for the discount factor. However, the shocks needed to reproduce the observable variables (unemployment and output) is very volatile. Indeed, the shock is ten times more volatile than the one in the data. One may naturally question the model's ability to fit the data or the proxy we used for the discount factor. In the first case, it is reasonable to think that our basic model lacks of internal propagation mechanisms. Medium and large scale DSGE models with capital, a financial sector and other rigidities could be likely to reduce the requirements in terms of shocks. This issue is very ambitious and we leave it for future research. The second issue concerns what β_t is. So far, we have assumed that the discount factor can be measure using a ratio of BAA corporate bonds over the federal fund rate[11]. Is it a sat-

[10]We use an HP-filter with smoothing parameter 1600

[11]See appendix for details.

isfying assumption? In a similar approach, Hall (2014) considers instead the SP500 as a proxy for the job value (our μ_t). He compares the job value produced by the model to the one calculated using asset prices of the SP500 and dividends. He shows that they co-move remarkably well. By computing the discount rate for the SP stock-price index he found that the standard deviation is large, way more larger than that of the BAA measure. The obtained volatility is even larger than the one we get from our Bayesian estimation.

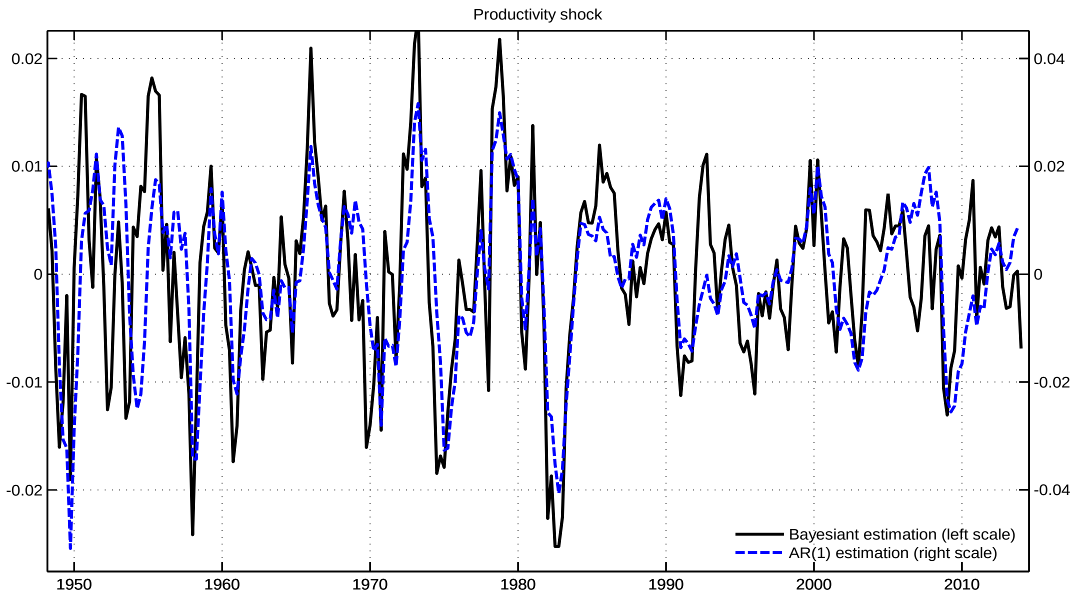

Figure 5: ***Productivity shock***.

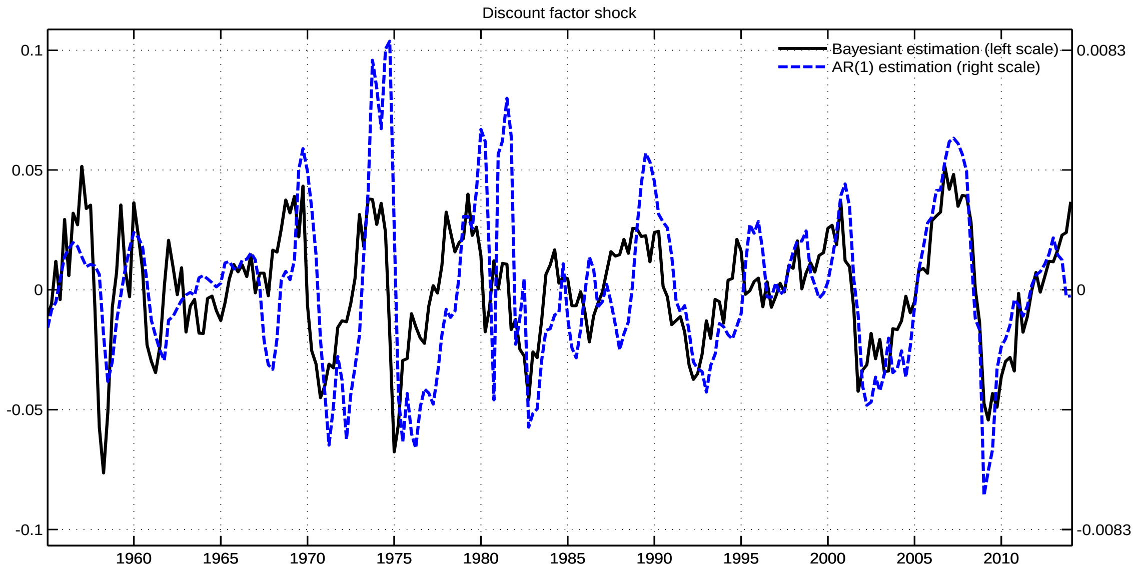

Figure 6: ***Discount factor shock***.

3.3 Robustness of results

We check the robustness of the previous analysis. We focus on key assumptions which we consider important for our results: the timing of events and the response of wages.

4 Conclusion

Most of the literature on the labor market volatility puzzle has assumed that changes in productivity are the main, and sometimes only, source of business cycle fluctuations. The Nash bargaining structure in the search and matching theory is such that wages reduce the propagation of the productivity shock which translate little into job creation and unemployment.

In contrast, we argue that the canonical search and matching model is able to generate enough volatility in unemployment and vacancies if the fluctuations are not solely driven by the standard productivity shock. The discount factor shock impacts the expected hiring costs in such a way that firms adjust vacancies more sharply. An estimation of the model reveals that the discount factor shock is more likely to explain labor market fluctuations than the productivity alone. The bulk of variations in unemployment and vacancies is mainly explained by disturbances pertaining to the discount factor. Furthermore, we show a significant change in business cycles sources since the 1982 recession. The productivity shock is no longer correlated with the labor market tightness. The discount factor shock is the opposite and is likely to explain several moments in the data. Our general conclusion is that the model alternative sources of uncertainty like the one coming from the discount factor should be considered for future research.

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Variables	Type	Source	Code
Output	Quantities, s.a, Index numbers, 2005=100	Bureau of Economic Analysis (BEA)	Table 1.1.3
Unemployment	level, s.a, 16 years and over	Bureau of Labor Statistics (BLS)	LNS13000000
Vacancies	level, s.a, Job openings Total nonfarm and Help-wanted index.	Bureau of Labor statistics and Barnichon (2010)	JTS00000000JOL
Real wages	Average Hourly Earnings in \$, s.a, Private divided GDP Deflator, s.a, 2009=100	FRED BEA	$\frac{\text{AHETPI}}{\text{GDPDEF}}$
Risky rate	Moody's baa corporate bonds yield.	FRED	BAA
Risk free rate	Federal fund rate	FRED	FEDFUNDS

Table 6: ***Data source and definitions.***

Data used to compute the moments cover the periods 1964Q1-2013Q2. We use the cyclical component of real GDP and unemployment over 1948Q1-2014Q2 for the estimation. All data are taken or built at quarterly frequencies using average over months if necessary. Vacancies in level are built using the job opening rate ($jo_t = v_t/(v_t + n_t)$) and the vacancy index from Barnichon (2010) which is specified as a base 1998=100. We rescale Barnichon' series to get a longer job opening rate series using the first observation of job opening rate (2001Q1). Then, using employment in level, s.a. we recover vacancies in level $v_t = jo_t n_t/(1 - jo_t)$. The tightness is simply equal to vacancies in level divided by unemployment in level. The discount factor is calculated in the following manner:

$$R = \frac{1 + risky\ \ rate}{1 + Risk\ \ free\ \ rate}$$

$$\beta = \frac{1}{R}$$