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Abstract

In this paper, I investigate the conditional contributions of the ins and outs of unemployment from both empirical and theoretical perspectives. Based on a New Keynesian DSGE theoretical framework, I estimate a sign restriction VAR using French data. To identify the origins of unemployment dynamics in terms of worker transition rates, I simulate two shocks: one on the supply side (technology) and one on the demand side (monetary). The VAR model reveals that the contributions of transition rates in explaining unemployment differ across shocks. After a technology shock, unemployment fluctuations are mainly explained by the job finding process, while the contributions of the two margins are more balanced for the monetary shock. The theoretical model is not able to reproduce the underlying mechanisms inducing unemployment. In particular, the conditional contributions of the job separation margin are overestimated each time. For instance, after a technology shock, 60% of unemployment changes are generated by this margin, while the data suggest a contribution of 28%. The paper strongly indicates that, in its standard formulation, a search and matching DSGE model featuring endogenous job separations is not able to replicate the dominating influence of the outflow process.

Keywords: Unemployment variations, transition rates, sign restrictions, DSGE models

JEL classifications: J60, E24

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1 Introduction

Conditional on structural shocks, what drives French labour market fluctuations in terms of worker flows into and out of unemployment? This question is at the heart of an active debate because empirical works are still inconclusive. When Shimer (2012) (for the U.S.) or Hairault et al. (2015) and Fontaine (2016) (for France) claim that outflows from unemployment win[1], Elsby et al. (2009) and Fujita and Ramey (2009) conclude that there is no winner because both inflows/outflows contribute equally to unemployment variations. From a theoretical point of view, such a question joins the literature, initiated by Shimer (2005), which is aimed at gauging the ability of the search and matching framework in replicating observed co-movements. Since that paper, many articles have modified the model environment to eliminate the puzzle. To the best of my knowledge, very few papers have examined whether the conditional responses of the transition rates unveiled by the model are in line with their empirical counterparts.

To explore the conditional ins and outs of French unemployment[2], two aggregate shocks are studied: a (neutral technology) supply shock and a (monetary) demand shock. The macroeconomic effects of these two shocks have been studied extensively. Since the seminal contribution of Kydland and Prescott (1982), technology shocks are often seen as one of the main sources of economic fluctuation. Furthermore, by devoting attention to monetary non-neutrality, a parallel stream of the literature argues that monetary shocks have significant effects on the real side of the economy (e.g., Bernanke and Blinder (1992), Walsh (2005), Trigari (2009) or Galí (2010)). In this paper, I investigate how these two shocks interact with the labour market and especially worker flows. More specifically, do technology and monetary shocks imply the same worker reallocation process?

[1] For short, in the rest of the paper, I use the single word "outflows" to refer to outflows *from* unemployment. Consequently, the single word "inflows" designates inflows *to* unemployment.

[2] The French case is interesting because its labour market differs from the U.S. labour market. For instance, its Employment Protection Legislation index is among the highest in OECD countries. This feature could have important implications for the responses of the aggregate labour market variables to macroeconomic shocks.

The theoretical framework used as a guide for the empirical analysis is a New Keynesian model enriched by a frictional labour market and an endogenous job separation margin. Such a framework is particularly relevant for my study since price stickiness gives rise to monetary non-neutrality and frictions on the labour market introduce an extensive margin of unemployment. In the model, both shocks modify the equilibrium conditions governing transition rates. A monetary shock is likely to reduce current and future expected profits of a match, such that firms are likely to respond by opening fewer vacancies, which in turn reduces the job finding rate, and by increasing job separations. In contrast, the responses of labour market variables after a technology shock are the consequence of two opposite channels. On the one hand, the productivity increase is likely to push unemployment down by lowering the job separation rate and by increasing the job finding rate. On the other hand, as price rigidities prevent final demand from reacting strongly, firms are likely to take advantage of the productivity improvement by reducing labour inputs. The simulation of the model allows me to provide evidence about which forces drive unemployment after the two aggregate shocks. In this respect, the present paper follows Balleer (2012) and proposes a reappraisal of the performance of the matching model based on co-movements conditional on structural shocks.

The empirical conditional responses of transition rates are estimated within a VAR containing five quarterly French time series: the growth rate of labour productivity, the inflation rate, the interest rate and the two main transition rates. Along the lines of Uhlig (2005), I disentangle the shocks of interest by means of sign restrictions directly imposed on the impulse response functions[3]. This framework has a number of practical advantages. It is convenient to identify shocks of different nature. Moreover, its flexibility allows for the identification of structural shocks without imposing any restrictions on the behaviour of transition rates.

[3]Other related studies use sign restrictions to identify the impact of aggregate shocks on the labour market. In this respect, Foroni et al. (2018) aim to disentangle labour supply shocks from wage bargaining shocks. Mumtaz and Zanetti (2012) explore how labour input responds to neutral technology shocks. In the same spirit, but with a time-varying parameter VAR model, Mumtaz and Zanetti (2015) show that the responses of labor market variables to technology shocks vary over the U.S. post-war period.

By doing so, I remain agnostic about transition rate responses, solely the data shape worker reallocation patterns conditional on aggregate shocks. Finally, using sign restrictions allows me to eliminate the concern about the inability of long-run restrictions *à la* Gali (1999) in generating permanent effects of technology shocks[4].

After an empirical technology shock, the labour market turnover is reduced since both transition rates decline. However, the decrease in job finding is stronger, leading ultimately to an increase in unemployment. For the monetary demand shock, transition rates move in opposite directions, and the combined effect leads to an unambiguous rise in unemployment. Taken together, both shocks are followed by an impact increase in unemployment but worker reallocation patterns are quite different. Conditional on a technology shock, French unemployment is explained mainly by cyclical fluctuations in the job finding process. For the monetary policy shock, the influence of the two transition rates is balanced.

Two main results emerge from the comparison between data and model outputs. First, some parameters should be carefully chosen because they are keys to retrieving reliable volatility of labour market variables. Specifically, when the model incorporates the standard share of endogenous separations, the value of total vacancy posting cost is of prime importance. When it is set to a high value, as in Shimer (2005), the model yields excessive volatility of vacancies and job separations. By contrast, a low value of vacancy posting cost implies much more realistic theoretical moments. Second, even with such a careful calibration, the conditional ins and outs of the model are not totally in line with those unveiled by the empirical VAR model. In particular, conditional on a technology shock, the model predicts that around 60% of unemployment variations are generated by the job separation rate. In the data, only 28% of unemployment fluctuations are explained by this margin. The finding is very similar for the monetary shock, and in the model, the separation margin explains a larger proportion of unemployment dynamics. My general results hold for several perturbations of the empirical and theoretical models.

[4] For more detail, see Faust and Leeper (1997) and Chari et al. (2008).

My paper is related to several empirical works examining the conditional dynamics of transition rates. However, it is the only one to study whether conditional responses emerging from a model are consistent with their empirical counterparts. Canova et al. (2013) address this empirical issue with U.S. data. Following technology shocks, they show that most U.S. unemployment variations are due to the response of the job separation rate[5]. As I find that the job finding matters more, my empirical evidence for France is at odds with theirs. Hairault and Zhutova (2018) find that conditional variations of French unemployment are generated mainly by the outflow process. My empirical findings are broadly in line with theirs. However, my paper extends their work in at least two respects. First, I study two different aggregate shocks (one arising from the supply side and the other one arising from the demand side), while they focus mainly on shocks originating from the labour market. Second, this paper complements their evidence by showing that, in its standard formulation, a search and matching DSGE model is not able to reproduce the dominating influence of the outflow process. The paper of Rahn and Weber (2017) investigates the ins and outs of German unemployment, conditional on technology and two demand shocks. Their empirical model unveils that the response of the job finding is positive after a technology shock, while the response of job separation is barely significant. Using French data, I find that the opposite is true, suggesting that conditional unemployment variations could be very different between two neighbouring European countries. Finally, by comparing the ability of the model to match conditional moments, my paper is closely related to Balleer (2012). However, she does not take into account an endogenous separation margin, while I do so explicitly in this paper.

The remainder of this paper is structured as follows. Section 2 develops the model economy, its calibration and its business cycle properties. Section 3 discusses the data, the empirical framework and the identification scheme chosen to recover the structural shocks. Section 4 presents the impulse response functions and studies the contribution of transition rates to

[5]Focusing on an aggregate shock, Fujita (2011) finds that the role of the job separation margin cannot be ignored because it is equally important as job finding.

unemployment variations. Section 5 discusses the results. Finally, section 6 concludes.

2 Theoretical framework

2.1 Model

This subsection presents the New Keynesian DSGE model used in this paper. The model builds on the work of Trigari (2009) and incorporates a frictional labour market with an endogenous job separation margin. In spirit, such a theoretical framework is close to those developed by Fujita and Ramey (2012), Walsh (2005), Thomas and Zanetti (2009) and Pizzinelli et al. (2018) (among others). However, I adapt the reference framework of Trigari (2009) to my own purposes by simplifying it in several aspects. First, as one of the areas of focus of this research is to study the influence of technology shocks on worker flow dynamics, such a disturbance is added in the production function. Second, "backward-looking" retailers are not taken into account because I am not interested in explaining inflation inertia. Finally, the model is calibrated to replicate the cyclical properties of the French economy instead of the U.S. ones. As a result, the contribution of the paper does not rely on the technical development of the model. Instead, my objective is to focus on an understudied property of that model: its ability to replicate the volatility and the responses of transition rates conditional on aggregate shocks.

2.1.1 The representative household

Each household is composed of a continuum of members indexed by i on the unit interval, so each of them could be viewed as a large extended family. Household members could be either in employment or in unemployment. To avoid fluctuations in consumption due to its position on the labour market, it is assumed, as in Thomas and Zanetti (2009) and Zanetti (2011), that each member pools its income and insures each other. The representative utility function is as follows:

$$E_t \sum_{t=0}^{\infty} \beta^t \left(\ln(c_t - ec_{t-1}) - \kappa_h \frac{h_t^{1+\phi}}{1+\phi} - \chi_t a_t \right) \tag{1}$$

where the parameter e captures habit persistence in consumption c_t. The parameter β is the subjective discount factor. The disutility of supplying hours is represented by the last two members of (1), where κ_h is a scalar parameter, h_t the number of hours worked, ϕ the inverse of the Frisch elasticity and χ_t a binary indicating if the member is employed or unemployed. Finally, a_t is the idiosyncratic i.i.d preference shock used for the modelling of endogenous separations. It is assumed that it follows a log-normal distribution with cumulative distribution function $F(a_t)$. Households are firm owners, and they maximize lifetime utility under the following budget constraint:

$$c_t + \frac{B_t}{p_t r_t^n} = d_t + \frac{B_{t-1}}{p_t} \tag{2}$$

with d_t being a compact term representing all households' revenues[6], r_t^n the nominal interest rate and p_t the level of prices. The derivation of the Euler equation is standard.

2.1.2 The labour market

The labour market is frictional, and intermediate firms and workers cannot match instantaneously. Before production begins, both engage in a costly search process. The number of new job matches during period t is given by the following Cobb-Douglas matching technology:

$$m_t = \varrho u_t^{\alpha} v_t^{1-\alpha}, \text{ with } 0 < \alpha < 1 \tag{3}$$

Here, v_t is the number of job vacancies posted by intermediate firms, u_t is the number of searching workers and α is the elasticity of the matching function relative to searchers. The

[6]Households' revenues are wages, unemployment benefits, and profits from firm minus government lump-sum tax used to finance unemployment benefit.

scalar parameter ϱ reflects the efficiency of the matching technology. It is convenient to derive some aggregate variables related to the matching framework. Thus, $s_t = \frac{m_t}{u_t}$ is the job finding rate of workers, $q_t = \frac{m_t}{v_t}$ is the job filling rate of vacancies and $\theta_t = \frac{v_t}{u_t} = \frac{s_t}{q_t}$ is the labor market tightness. If θ_t is above (below) 1, then the labor market is tighten from the firms' (workers') side.

There are two sources of job separation in the model. At the beginning of each period, a fraction ψ^x of existing matches is broken for some exogenous reasons. The second source of separation is due to the idiosyncratic shock of disutility a_t. If the realization of the shock is greater than a threshold $\underline{a}_t$, the employment relationship becomes unprofitable for the firm/worker pair, and the match is severed. The endogenous job separation probability is $\psi_t^n = Pr(a_t > \underline{a}_t) = 1 - F(a_t)$, implying an overall job separation rate equal to $\psi_t = \psi^x + (1 - \psi^x)\psi_t^n$. Whenever a job separation takes place, there is no production. Given this framework, employment evolves as $n_t = (1 - \psi_{t-1})n_{t-1} + m_{t-1}$, with n_t the level of employment in period t. The participation decision is not taken into account and the labor force is normalized to one.

2.1.3 Wages and hours bargaining

The matching framework ensures that a job generates an economic surplus. The instrument used to split it is the wage. The latter is derived following the standard Nash bargaining solution, which maximizes the weighted product of the workers and firms net value [7]:

$$w_t = \text{argmax}(W_t(a_t) - U_t)^{\eta}(J_t(a_t) - V_t)^{1-\eta} \tag{4}$$

with $0 < \eta < 1$ being the relative bargaining power of the worker. Appendix A details the presentation of each term of the right-hand side of equation (5). It should be mentioned that U_t and V_t correspond to the labor market outside options of workers and firms, whereas

[7] With the Nash bargaining solution, it is implicitly assumed that wages are renegotiated at each period. Furthermore, a consequence of the Nash bargaining scheme is that wages are closely related to the level of aggregate productivity.

$W_t(a_t)$ and $J_t(a_t)$ are the value attributed by those agents when they are within a match pair. In equilibrium, free entry must hold, and the value of an open vacancy V_t for the firm is zero. The individual wage satisfies the following optimality condition:

$$\eta J_t(a_t) = (1-\eta)(W_t(a_t) - U_t) \tag{5}$$

Therefore, using (16)-(19) and the free entry condition, we obtain the wage rate $w_t(a_t)h_t$:

$$w_t(a_t)h_t = \eta\left(x_t f(h_t) + \kappa\theta_t\right) + (1-\eta)\left(\frac{\kappa_h h_t^{1+\phi}}{(1+\phi)\lambda_t} + \frac{a_t}{\lambda_t} + b\right) \tag{6}$$

with x_t being the relative price of the intermediate good which coincides with the real marginal cost, $f(h_t)$ being the production function, κ being the vacancy posting cost and λ_t being the marginal utility of consumption. The negotiation is not simply on wages but also on hours worked. The hours of work chosen by a pair satisfy:

$$x_t z_t = \frac{\kappa_h h_t^{\phi}}{\lambda_t} \tag{7}$$

In the event that a firm and a worker succeed in forming a matched pair and that the job is not separated, production begins, and its output is given by the following production function: $f(h_t) = y_t = z_t h_t$. The productivity disturbance z_t follows the autoregressive process $\ln(z_t) = \rho_z \ln(z_{t-1}) + \varepsilon_t^z$.

2.1.4 Retailers and prices

There is a continuum of retailers indexed by j operating on a monopolistic competitive market[8]. Retailer j produces $y_t(j)$ units of final goods by disaggregating intermediate goods

[8] I do not replicate the exact structure of price stickiness of Trigari (2009). Specifically, as explaining inflation inertia is not the subject of this paper, I do not take into account "backward-looking" retailers. In general, such modelling introduces a lagged inflation term in the Phillips curve.

according to the following CES technology:

$$y_t = \left(\int_0^1 y_t(j)^{\frac{\epsilon-1}{\epsilon}} dj\right)^{\frac{\epsilon}{\epsilon-1}} \tag{8}$$

where ϵ is the elasticity of demand for each intermediate good. Retailers sell their final goods directly to the household at the nominal prices $P_t(j)$. They are confronted with the following demand function:

$$y_t(j) = \left(\frac{p_t(j)}{p_t}\right)^{-\epsilon} y_t \tag{9}$$

with $p_t = \left(\int_0^1 p_t(j)^{1-\epsilon} dj\right)^{\frac{1}{1-\epsilon}}$ being the aggregate price level. Price stickiness occurs at this level. In particular, retail firms are not free to adjust their own prices but reset them following the scheme proposed by Calvo (1983). In each period, only a proportion $1-\xi$ of retail firms is able to reset their prices. The other proportion ξ is stuck and charges the price prevailing in the previous period. Therefore, retailers choose their prices to maximize their expected profit by integrating that they may be stuck with a price during s periods:

$$\max E_t \sum_{s=0}^{\infty} \xi^s \beta^s \frac{\lambda_{t+s}}{\lambda_t} \left(\frac{p_t(j)}{p_{t+s}} - x_{t+s}\right) \left(\frac{p_t(j)}{p_{t+s}}\right)^{-\epsilon} y_{t+s} \tag{10}$$

Finally, the evolution of the aggregate price is given by the following:

$$p_t = \left[(1-\xi)(p_t^o)^{1-\epsilon} + \xi p_{t-1}^{1-\epsilon}\right]^{\frac{1}{1-\epsilon}} \tag{11}$$

where p_t^o is the optimal price charged by retail firms that can reset the price.

2.1.5 Monetary authority and market clearing

The monetary authority controls the level of interest rate by following a standard Taylor rule. Consecutive to some deviations of output and inflation from their steady state levels, the nominal interest rate is adjusted as follows:

$$\frac{r_t^n}{(r^n)^*} = \left(\frac{r_{t-1}^n}{(r^n)^*}\right)^{\rho_m} \left(\frac{\pi_t}{\pi^*}\right)^{\gamma_\pi(1-\rho_m)} \left(\frac{y_t}{y^*}\right)^{\gamma_y(1-\rho_m)} \nu_t \tag{12}$$

with π_t being the inflation rate, ρ_m being the degree of interest rate smoothing, γ_y being the reaction coefficient to output deviations and γ_π being the one for inflation deviations[9]. In (12), ν_t corresponds to the i.i.d monetary shock, and it follows an autoregressive process $\ln(\nu_t) = \rho_m \ln(\nu_{t-1}) + \varepsilon_t^m$.

Market clearing is achieved by imposing that all output is consumed and therefore $y_t = c_t$. Finally, output in the retail sector is given by $y_t = n_t(1-\psi_t)h_t$. The dynamics of the model are then approximated by log-linearizing the equilibrium conditions around the deterministic steady state with no inflation.

2.2 Worker flows in the model

Job creation is governed by the free-entry condition. As long as the value of a vacancy is positive, firms open new vacancies. At equilibrium, $V_t = 0$, and the vacancy posting condition can be written as follows:

$$\frac{\kappa}{q_t} = E_t \beta_{t,t+1}(1-\psi_{t+1}) \left(x_{t+1} z_{t+1} h_{t+1} - w_{t+1} h_{t+1} + \frac{\kappa}{q_{t+1}}\right) \tag{13}$$

with $\beta_{t,t+1} = \frac{\beta\lambda_{t+1}}{\lambda_t}$ being the discount factor[10] and $w_{t+1} = \int_0^{\underline{a}_{t+1}} w_{t+1}(a_{t+1}) \frac{dF(a_{t+1})}{F(\underline{a}_{t+1})}$ being the aggregate wage. The vacancy posting condition states that a fall in the sum of expected profits (the right-hand side of (13)) should be associated with a rise in $q_t = \frac{m_t}{v_t}$. In a model with endogenous separations, an increase in q_t can be the result of either an increase in unemployment or a fall in vacancies (or a combination of the two effects), which in turn decreases the job finding probability.

[9]The superscript * denotes the steady-state value.

[10]This discount factor evaluates profits in terms of values attached to them by the households who hold firms in the model.

Endogenous separations take place when the realization of the preference shock implies a negative or a zero value for the joint surplus $S_t(a_t) = J_t(a_t) + W_t(a_t) - U_t$. Using the free-entry condition and equation (5), the condition governing endogenous separations is as follows:

$$x_t z_t h_t - \frac{\kappa_h h_t^{1+\phi}}{\lambda_t(1+\phi)} - \frac{\underline{a}_t}{\lambda_t} - b + \frac{1-\eta s_t}{1-\eta}\frac{\kappa}{q_t} = 0 \tag{14}$$

Regarding the threshold above which a job match is severed, the latter equation shows that any changes in the expected future joint payment from continuing the match (the last term of the left hand side) should be compensated by an opposite variation of the current pay-off. Aggregate shocks will affect worker flows in the model by the combination of these two mechanisms.

A consequence of price stickiness is that an increase in the nominal interest rate induces an increase in the real interest rate. The latter increase changes household behaviour by lowering current and future demand for final goods. As the production sectors produce to meet demand, current and future expected profits of intermediate firms fall. In the vacancy posting condition, the fall in future profits requires an increase in q_t. It can be obtained by more unemployed and/or fewer vacancies. In the job destruction condition, the decrease in current and expected profits requires a diminution of the threshold $\underline{a}_t$. The threshold being lower, job destruction unambiguously increases.

After a technology shock, the disentangling of worker flows responses is less straightforward. Observe that it enters directly the two equations governing worker flows. All else being equal, an unexpected shock on z_t is likely to increase current and future expected profits obtained from a match pair. In contrast to a monetary shock, this implies a fall in q_t and an increase in the threshold at which a job is destroyed. However, it should be noted that the above mechanism does not take into account the demand channel. Indeed, as firms are not able to change their prices, the demand for final goods changes only slightly. Given the productivity increase, firms are able to produce the same amount of goods with less labour inputs. As a result, the job finding rate and the job separation rate are likely to move such

	Variable	Data	(I)	(II)	(III)	Benchmark
Standard deviations relative to output						
σ_z/σ_y	Productivity	0.69	1.01	0.97	0.91	0.85
σ_u/σ_y	Unemployment	5.83	1.15	3.96	12.86	6.48
σ_s/σ_y	JFR	4.07	0.82	3.27	2.72	4.11
σ_ψ/σ_y	JSR	5.86	1.20	1.49	13.43	5.73
σ_v/σ_y	Vacancies	5.81	1.67	6.70	10.52	7.61
Autocorrelations						
y_t	Real GDP	0.887	0.104	0.720	0.853	0.888
z_t	Productivity	0.827	0.068	0.661	0.707	0.724
u_t	Unemployment	0.915	0.420	0.505	0.536	0.624
s_t	JFR	0.533	0.346	0.509	0.507	0.487
ψ_t	JSR	0.574	0.124	0.553	0.601	0.473
v_t	Vacancies	0.803	0.206	0.408	0.795	0.752
Cross-correlations						
ρ_{y_t,u_t}	Real GDP, Unemployment	-0.847	-0.359	-0.083	-0.466	-0.499
ρ_{y_t,s_t}	Real GDP, JFR	0.661	0.360	0.321	0.401	0.399
ρ_{y_t,ψ_t}	Real GDP, JSR	-0.381	-0.356	-0.843	-0.625	-0.593
ρ_{y_t,v_t}	Real GDP, Vacancies	0.8055	0.124	0.136	0.862	0.461
ρ_{u_t,v_t}	Unemployment, Vacancies	-0.603	-0.183	0.208	0.343	-0.213
	Separation	–	*Low*	*Low*	*High*	*High*
	Vacancy posting cost	–	*High*	*High*	*High*	*Low*
	Price stickiness	–	*No*	*Yes*	*Yes*	*Yes*

Table 1: Second-moment properties.

Sources: For transition rates and unemployment: Hairault et al. (2015) for real GDP and French National Institute of Statistic and Economic Studies for vacancies. Simulated and observed time series are logged and HP filtered with a smoothing parameter equal to 1,600. Simulated figures are computed from a sample of 2,000 observations.

Notes: Model (I) is calibrated in the spirit of Shimer (2005). Model (II) adds price stickiness and habit persistence to Model (I). Model (III) is Model (II) with a share of endogenous separation equal to 1/3. The column Benchmark displays the benchmark model with 1/3 of endogenous separations, low vacancy posting costs and nominal rigidities on prices.

JFR corresponds to the job finding rate, and JSR corresponds to the job separation rate.

that unemployment increases.

2.3 The benchmark calibration

The model economy is calibrated to replicate the structural features of the French economy. Time length is quarterly. As is commonly done in the DSGE literature, the quarterly discount factor rate β is set to 0.99. I follow Le Barbanchon et al. (2011) by assuming that the parameter governing the degree of habit persistence e is equal to 0.7. For the probability that firms cannot reset their prices, I select the value of 0.9. This value is slightly higher than the one proposed in Christoffel et al. (2009) or Trigari (2009), but it is in line with Le Barbanchon et al. (2011). The microeconomic and macroeconomic estimates do not converge, and there is a debate on how to calibrate the inverse of the intertemporal elasticity of substitution of leisure. Consistent with Trigari (2009), I set ϕ equal to 10, which implies a low elasticity of intertemporal substitution. I choose the conventional value of 10% for the price mark-up, implying an elasticity of demand $\epsilon = 11$.

Let me now turn to the calibration of labour market parameters and steady states. The steady-state values of worker transition rates are based on the average empirical estimates of Hairault et al. (2015). Therefore, the quarterly job finding rate s^* is set to 0.226, and the quarterly job separation ψ^* rate to 0.036. These two values imply a steady state unemployment rate of 0.136[11]. It is difficult to have solid empirical evidence about the proportion of endogenous separations. Following den Haan et al. (2000) and Zanetti (2011), I assume that one-third of separations are endogenous[12]. The mean of the log-normal distribution of the idiosyncratic shock is normalized to 0. There is no empirical counterpart for the calibration of the standard deviation of the log-normal distribution of $\underline{a}_t$. To do so, this standard deviation is chosen such that the theoretical volatility of the overall job separation matches, as close as possible, the empirical volatility of the job separation rate. As a consequence, in the benchmark, it is set to 0.60, and it implies a threshold $\underline{a}$ of 3.88. Little evidence exists about the quarterly job filling rate on the French labour market. Here, I follow Christoffel et al. (2009), who calibrate this steady state for the Euro area by fixing q^* to 0.7. Burda and Wyplosz (1994) find that the elasticity of the matching function with respect to unemploy-

[11] It should be noted that the measure of unemployment used in Hairault et al. (2015) is not based on the ILO's definitions. Instead, it is based on an individual's own declarations. That is why the average level of unemployment is higher than the one provided by the official figures.

[12] Subsection 2.4 shows that the share of endogenous separations has important implications for the properties of the model.

ment is equal to 0.7 in France. In their survey, Petrongolo and Pissarides (2001) conclude that a plausible value for this elasticity is between 0.5 and 0.7. I target α to 0.55, which is close to the lower bound suggested by the latter interval. The bargaining power is set to 0.5, a standard value in this literature. To choose a value for the parameter κ, I follow a strategy similar to Abowd and Kramarz (2003), Chéron and Langot (2004), or Blanchard and Galí (2010). More specifically, the total vacancy expenditure is targeted to represent 1% of model output[13].

Concerning the Taylor rule parameters, ρ_m the degree of interest rate smoothing is fixed at 0.85, and γ_π the interest rate response to inflation is set to 1.5, while γ_y the interest rate response to output is set to 0.5.

Finally, I calibrate the two stochastic shocks of the model. The standard deviation of the productivity disturbance is set to reproduce the empirical volatility of French real GDP. After taking log and HP filtered the observed time series of output for the French economy, I fix σ_t^z the standard deviations of the productivity shock to 0.00964. The serial correlation of the productivity shock is also based on this approximation, and it is set to 0.9. The calibration of the monetary policy shock follows standard practice of the New Keynesian literature (e.g., Christoffel et al. (2009), or Zanetti (2011)). Its standard deviation is set to 0.001, and its first -order autocorrelation to 0.85[14].

2.4 Business cycle properties

Table 1 compares empirical moments of labour market variables with their counterfactual values obtained from different calibrations of the model. The data on real GDP and vacancies come from the French National Institute of Statistic and Economic Studies, while transition rates (and the associated unemployment rate) are taken from Hairault et al. (2015). In the data, unemployment volatility is approximately 5.5 times greater than that of real GDP.

[13] For the calibration of her model, Trigari (2009) chooses a vacancy cost to output ratio equal to 5%, which is quite close to the value used by Shimer (2005). As suggested by Pizzo (2017), such a calibration strategy implies a measure of total vacancy posting costs largely above what empirical evidence suggests.

[14] Changing the persistence of the monetary policy shock has no effect on the main message of the paper.

Among transition rates, the job separation rate is more volatile. Three parameters are keys in reproducing unconditional observed moments: the share of endogenous separation in total separations, the total cost spent for vacancies governed by the scalar parameter κ and the incorporation of price rigidities. Column (I) reports business cycle statistics for a calibration close to Shimer (2005), i.e., without habit persistence and price rigidities but with almost no endogenous job separation[15] and a high value of κ. Such a model yields unrealistic volatility of labour market variables and mirrors the "Shimer puzzle". Specifically, unemployment is 5 times less volatile than in the data. Adding price stickiness and habit persistence (column (II)) into the model improves its ability to match with empirical moments. However, such a specification is inconsistent for at least two reasons. First, variations in the job separation margin are not relevant. Indeed, the latter is mainly exogenous, and its correlation with output is close to -0.8. The same statistic amounts to -0.38 in the data. Second, the volatility of unemployment remains too weak comparatively to what it is in the data. In the last two columns of Table 1, the endogenous share of separation is set to the standard value of one-third. In those models, the calibration of vacancy posting cost is non-trivial. A model with the same amount of vacancy expenditures as in Shimer (2005) (4.5% of total output) implies unrealistic volatility of the job separation rate and vacancies (column III). In particular, the job separation rate is 13 times more volatile than output. It also gives rise to a positive correlation between unemployment and vacancies. This can be rationalized by the fact that, hiring being costly, the separation margin becomes the easiest way to adjust the employment level. The benchmark model yields a better match between theoretical and empirical moments. As in the data, unemployment is approximately 6 times more volatile than output. Such a good match of unemployment volatility is also accompanied by a very good match of transition rates standard deviations. In the benchmark model, the job separation rate and unemployment are countercyclical, while the job finding rate and vacancies are procyclical. Given the properties of other models, especially their difficulty in

[15] In Table 1, models with low endogenous job separation include 95% of exogenous separations.

reproducing unemployment volatility, the benchmark model appears to be a good basis for studying labour market dynamics over business cycles.

3 Empirical methodology

3.1 Data

My benchmark specification contains five endogenous variables included in the vector $X_t = (\Delta z_t, \Delta\pi_t, r_t^n, \psi_t, s_t)'$, where Δ is the difference operator. All these variables are in logarithm. Labour productivity z_t is defined as output per employee. The inflation rate $\Delta\pi_t$ is calculated from the Consumer Price Index (CPI) provided by the Federal Reserve Bank of St. Louis. The interest rate is based on a 3-month interbank interest rate, also available on the FRED database. I introduce the inflation rate to have a solid identification of the monetary shock because the interaction between them are well known in the literature.

The job separation rate ψ_t and the job finding rate s_t are taken from Hairault et al. (2015). These transition rates are calculated from the retrospective calendar of the French Labour Force Survey (FLFS). In this calendar, each individual interviewed for the first time recall his/her labour market status during the last twelve months. This measure of French labour market flows provides relatively long series since the retrospective calendar is available since 1990. However, because of a redesign of the FLFS in 2003 [16], worker flows for the years 2003 and 2004 could not be calculated. For my purpose, this lack of observation is problematic because the VAR cannot be estimated with this kind of blank. To address this issue, I fill the gap by estimating automatically via the TRAMO procedure, and the ARIMA model relied on each time series[17]. The time series of transition rates used in this study are corrected for temporal aggregation bias by applying the pioneered method proposed by Shimer (2012). Observe that the transition rates are simply quarterly averages of monthly data. The VAR

[16] Before 2003, the survey was annual. Since 2003, the survey has been quarterly.

[17] The method used is based on the TRAMO (Time series Regression with ARIMA noise, Missing values, and Outliers). Appendix B shows that estimated series are very close to the observed ones.

is estimated with quarterly series over the period 1990Q1-2010Q3 avoiding the problem of the zero lower bound of the interest rate[18].

3.2 Bayesian VAR framework

Let $A(L)X_t = \nu_t$ be the VAR representation of the process[19]. Under the stability assumption, the Wold theorem implies that the VAR can be expressed as an infinite vector moving average $VMA(\infty)$: $X_t = A(L)^{-1}\nu_t = C(L)\nu_t$, with $C(L)$ a matrix of polynomials in the lag operator L. There is a consensus about the estimation of VAR models, and ordinary least squares are largely used. However, disagreements appear when structural shocks have to be recovered. Indeed, the residual terms ν_t of the reduced form has no reason to be uncorrelated implying that its variance-covariance matrix Σ has also no reason to be diagonal. The purpose is to find a mapping that allows for the retrieving of structural shocks from the reduced form shocks. The reduced form disturbance ν_t and the structural disturbances ϑ_t are related by $\nu_t = D\vartheta_t$, where the latter are mutually independent with a variance normalized to 1, and so, $E(\vartheta_t\vartheta_t^{'}) = I$. In general, to achieve the identification of structural disturbances, the matrix D is computed, such that $\Sigma = E(\nu_t\nu_t^{'}) = DE(\vartheta_t\vartheta_t^{'})D^{'} = DD^{'}$, where D is the Cholesky factor of Σ. Here, to find the matrix D, I follow Uhlig (2005), who observed that a candidate for the decomposition of Σ can also be $\Sigma = \tilde{D}\tilde{D}^{'}$, where $\tilde{D} = DQ^{'}$ and Q denotes some orthogonal matrix. Both D and $\tilde{D}$ provide a candidate for the decomposition of Σ $\left(\Sigma = \tilde{D}\tilde{D}' = (DQ^{'})(QD^{'}) = DID^{'} = DD'\right)$. The objective is to choose Q to retrieve the five shocks of the system. Nonetheless, the matrix Q, which allows for the full characterization of the model, is not unique, and it is necessary to examine a large number of candidates. To take the uncertainty about the multiplicity of Q and VAR parameters into account, I proceed using a Bayesian framework. The general procedure is as follows:

1. I perform a Bayesian estimation of $A(L)$ and Σ by imposing a prior and a posterior to

[18] The choice of the period is also restricted by the availability of transition rate series

[19] With L the lag operator, A the coefficient matrix and ν_t the $(n, 1)$ matrix of residuals.

belong to the Normal-Wishart family.

2. From the posterior distribution, I take n number of draws of $A(\hat{L})$ and $\hat{\Sigma}$. For each of these draws I evaluate m rotation matrix Q.

3. For each joint draw, I construct impulse responses functions and check whether sign restrictions are satisfied. If all imposed conditions are met, I save the draw. However, if one or more restrictions are not satisfied, I discard the pair, and it receives zero prior weight.

The inference is based on the median response together with the 16th and 84th percentile confidence intervals. In the baseline model, I fix n and m to 5,000 and 25 million candidates examined, respectively.

3.3 Sign restriction justification

Compared to traditional identification schemes that employ short-run or long-run neutrality restrictions, the sign restriction approach offers a more flexible framework. For instance, when shocks of different nature have to be identified, it is not easy to justify them jointly with the traditional approach. Furthermore, in many works, the use of long run restrictions in identifying technology shocks from finite samples has been criticized[20]. Nonetheless, the sign restriction approach requires solid theoretical support. In this respect, I base the isolation of structural shocks on the theoretical model developed in the previous section. More specifically, I depart from my benchmark calibration, and I assume that some key parameters of the model are uniformly and independently distributed over a selected range. Appendix C presents and discusses the choice of parameter ranges. I then randomly draw 1,000 sets of parameters. For each of them, the model is run, and I compute the impact responses of some variables. Distributions of the impact responses of key variables are then displayed.

[20] When Faust and Leeper (1997) show that long-run (and permanent) effects could not be precisely estimated in finite samples, Chari et al. (2008) demonstrate that researchers need extremely long time series to infer reliable long run effects of technology shocks. In practice, such long time series are not available.

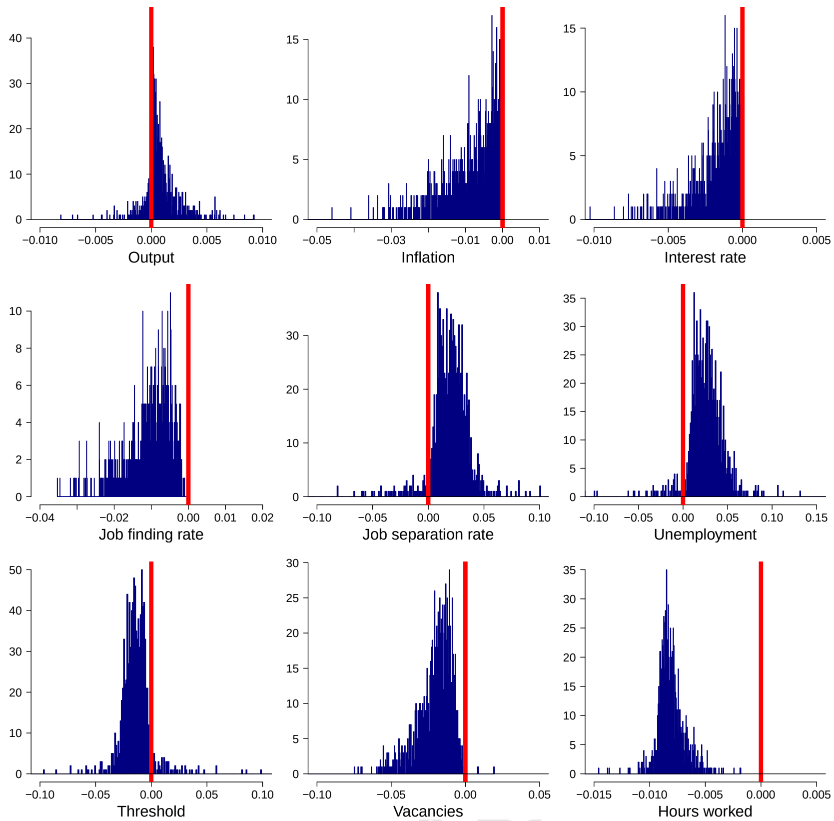

Figure 1: Distribution of theoretical impulse response to technology shocks.
Sources: Author's calculations.

Their shapes serve as a guide for the identification[21]. This strategy has been already used by Peersman and Straub (2009), Pappa (2009) and Foroni et al. (2018) (among others).

3.3.1 The technology shock

Figure 1 displays the distributions of impact responses after 1,000 simulations of the model. In a New Keynesian economy, firms are not able to set their own prices at each period. They will take advantage of the technology improvement by reducing their demand for labour. In the model, employment adjustment may occur at both margins. Firms open fewer vacancies and the job finding rate decreases. Moreover, the real marginal cost and labour market tightness fall, the threshold at which a job match is severed diminishes. A direct consequence

[21]It should be noted that, in this subsection, I focus on the two shocks of interest. In Appendix D, I present the so-called "multiple shock" problem associated with the sign restriction framework and the identification of the other shocks of the VAR.

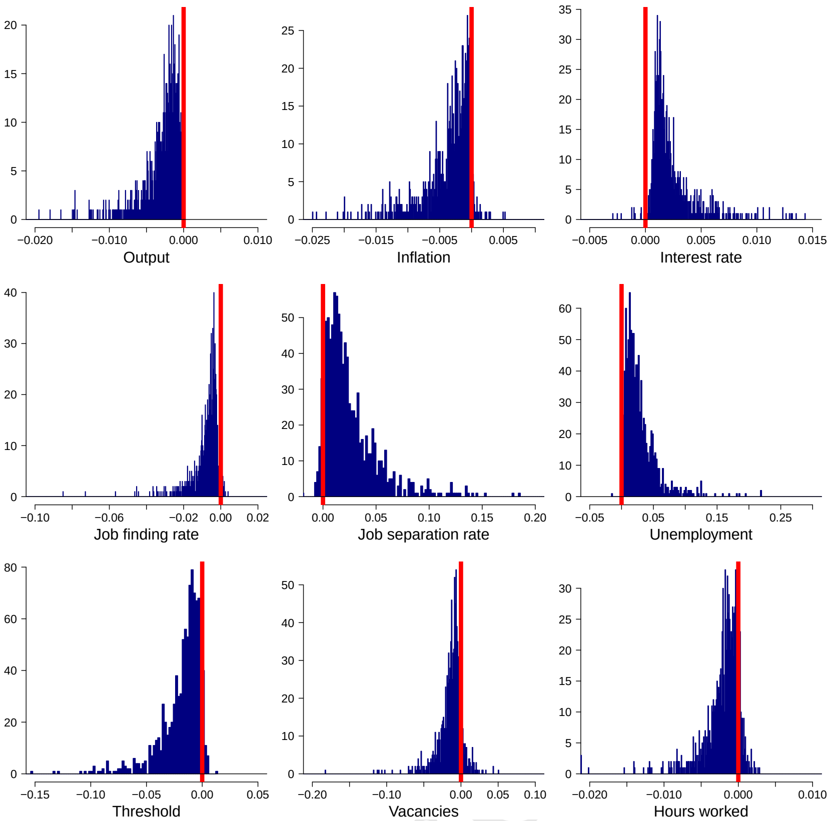

Figure 2: Distribution of theoretical impulse response to monetary shocks.
Sources: Author's calculations.

is a spike in the overall level of job separation. In the model, unemployment unambiguously increases. Thomas (2011) shows that the incorporation of labour market frictions in a New Keynesian model is key to explain the negative and sluggish response of inflation empirically observed. As shown in the figure, the responses of interest rate and inflation are mainly negative. Consequently, to isolate the technology improvement, I choose a mix approach. I give up the long-run sign restrictions on the labour productivity for a shorter restrictions. In particular, I restrict the response of labour productivity to be positive during 4 quarters. Otherwise, the responses of inflation and interest rate are negatively restricted in the impact period. I keep free the responses of transition rates.

	Δy_t	$\Delta \pi_t$	r_t	ψ_t	s_t
Technology shock	+4	-1	-1	–	–
Monetary shock	–	-4	+1	–	–

Table 2: Sign restrictions imposed on the impulse responses.
Notes: + for ≥ 0, - for ≤ 0, – for unrestricted, numbers next to the signs indicate the horizon of restrictions.

3.3.2 The monetary shock

Figure 2 presents the distributions of impact responses after monetary shocks. Unsurprisingly, an increase in the interest rate acts as a negative demand shock. It decreases inflation and output. These results are robust to the parameter range. On the labour market, the distributions of the job finding rate and vacancies appear to be more sensitive to the set of parameters. However, as the threshold of endogenous separations is sharply negative, the unemployment response is positive. The reader should note that, in my favourite calibration (Subsection 2.3), both the job finding rate and vacancy posting decrease. This indicates that the fall in profits induces firms to post fewer vacancies leading to higher unemployment. In this context, the fall in expected profit also decreases the threshold of endogenous separations. To identify the negative monetary shock, I impose the interest rate to be positive one period after the shock, and I force the response of inflation to not be positive during 4 quarters.

4 Results

This section lays out the main findings of the paper. The impulse responses of transition rates and unemployment are described. Then, unemployment variations are decomposed in terms of underlying worker flows. Finally, a battery of robustness checks follow.

4.1 Empirical impulse responses

Figures 3 and 4, respectively, display the impulse response functions of labour market variables conditional on technology and monetary shocks. Each time, the first row reports

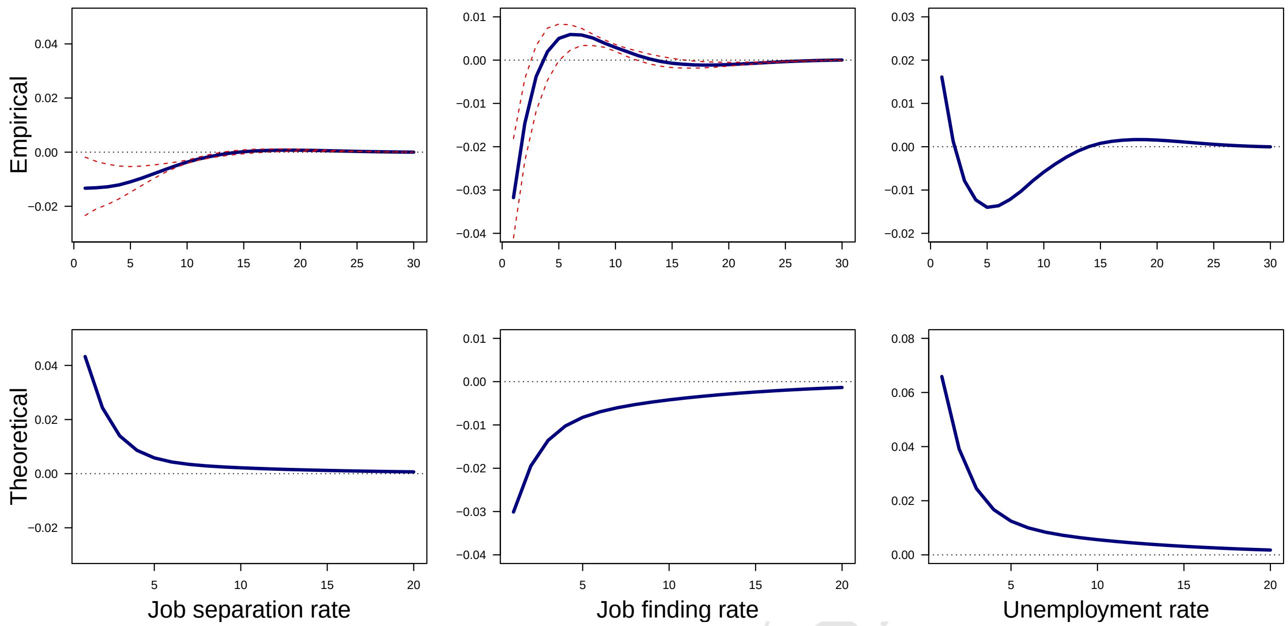

Figure 3: Impulse response functions to a positive technology shock.
Sources: Author's calculations.
Notes: Impulse responses to a one-standard-deviation shock are reported. In the first row, solid blue lines represent the median impulses responses obtained with the VAR. Dashed lines correspond to the 64% of the posterior distribution. In the second row, blue lines correspond to the impulse responses obtained with the model.

responses obtained from the baseline VAR, while the second row reports those obtained from the benchmark model.

Following an empirical technology shock, labour market turnover, approximated by the sum of the two transition rates, is reduced. In particular, a positive technology shock implies an immediate fall in the job finding rate of about 3% relative to its steady state. This fall in the job finding takes between 4 or 5 quarters to regain its steady state level. As Balleer (2012), I find a negative co-movement between the job finding rate and labour productivity. The dynamic path followed by the job separation rate is quite surprising since it is weak and negative. In this respect, it is totally at odds with the U.S. evidence of Canova et al. (2013), who find an increase in job separations after a neutral technology shock. My French evidence does not support the view that neutral technology shocks have "Schumpetarian" features[22]. The concomitant decrease in the job finding rate and the job separation rate leads to a positive rise in unemployment in the first period after the impact. However, the response of unemployment is U-shaped and takes between 3 or 4 quarters to become negative before definitively reaching its steady state. Using French data, the initial co-movement between labour productivity and unemployment is positive. It should be observed that the initial increase in unemployment observed with French data is not a common feature of European economies. For example, when Rahn and Weber (2017) identifies a technology shock from German data, they find that it leads to an increase in the job finding rate, together with a decrease in the job separation rate, inducing ultimately a fall in unemployment. Concerning the model, it predicts the good response of the job finding at impact. However, the response of the job separation rate is stronger and positive. As both margins move in opposite directions, unemployment unambiguously increases.

Following a monetary shock (Figure 4), the job separation rate significantly increases. This rise is relatively persistent since it takes approximately 8 quarters to go back to its steady-state value. At impact, the response of the job finding rate is non-significant. However, after 2 quarters, it becomes significantly negative. As a consequence of these cyclical behaviours of worker flows, the tightening in monetary policy causes a significant and relatively persistent raise in unemployment with a peak at the impact. In contrast to the technology shock, the model provides a better match of the worker reallocation pattern. As in the data, the job separation rate increases, and the job finding rate decreases, leading ultimately to higher unemployment.

4.2 Decomposing unemployment fluctuations

To shed more light on the underlying mechanism driving unemployment, I decompose its fluctuations in contributions attributable to inflows and outflows. The starting point of the exercise is the conditional responses of transition rates. For each shock, I use impulse

[22] "Schumpetarian" features mean that technology shocks yield more job separations and more return to jobs.

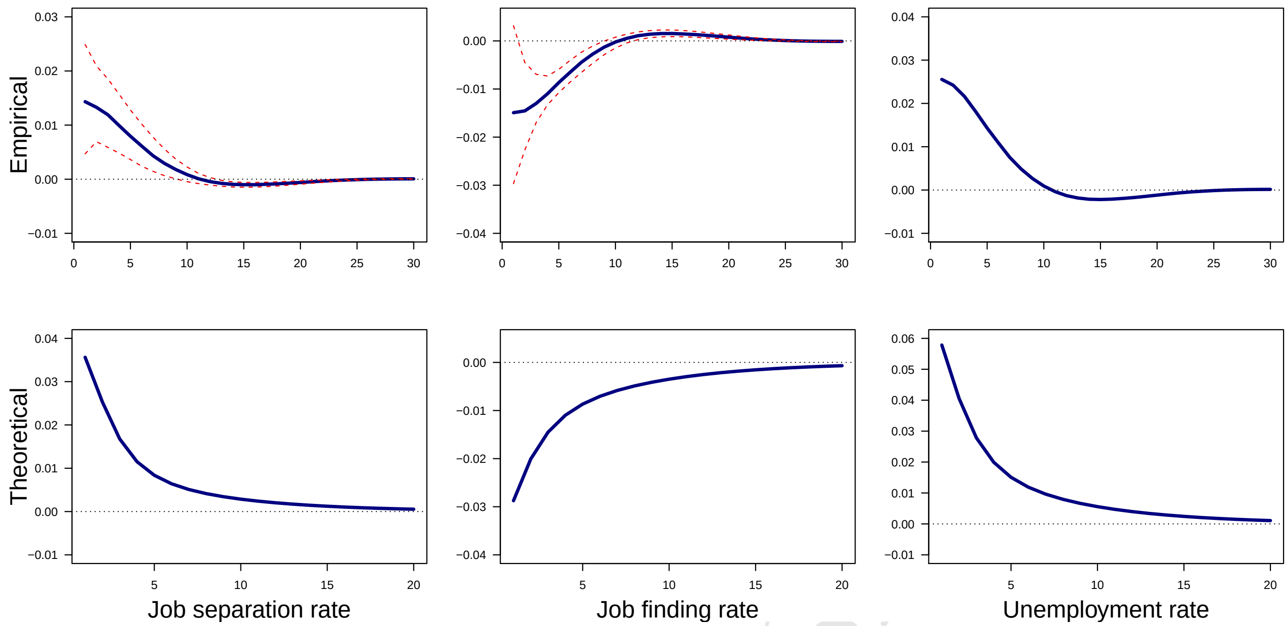

Figure 4: Impulse response functions to a negative monetary shock.
Sources: Author's calculations.
Notes: Impulse responses to a one-standard-deviation shock are reported. In the first row, solid blue lines represent the median impulses responses obtained with the VAR. Dashed lines correspond to the 64% of the posterior distribution. In the second row, blue lines correspond to the impulse responses obtained with the model.

response functions to deduce two "fictional" series of job separation and job finding rates. With these two hypothetical series in hand, I compute the steady-state unemployment rate. Then, following Elsby et al. (2013), I decompose unemployment variations with a logarithm differentiation of u_t^*:

$$\Delta \ln u_t^* \approx ((1 - u_t^*)(\Delta \ln(\psi_t) - \Delta \ln(s_t))$$

$$\Delta \ln u_t^* \approx \underbrace{(1 - u_t^*)\Delta \ln(\psi_t)}_{C^*_{\psi_t}} - \underbrace{(1 - u_t^*)\Delta \ln(s_t)}_{C^*_{s_t}} \tag{15}$$

As emphasized by Fujita and Ramey (2009), equation (15) can lead to an exact decomposition of variance of $\ln u_t^*$, so I compute "beta values" as follows:

$$\beta^k = \frac{cov(\Delta \ln u_t^*, C^*_{k_t})}{var(\Delta \ln u_t^*)} \text{ with } k \in \{\psi, s\}$$

	Technology shock		Monetary shock	
	β^{ψ}	β^{s}	β^{ψ}	β^{s}
Empirical decomposition of $\ln u_t^*$	0.28	0.72	0.48	0.52
Theoretical decomposition of $\ln u_t^*$	0.59	0.41	0.56	0.44

Table 3: Unemployment decomposition conditionally to technology and monetary shocks.
Sources: Author's calculations.
Notes: "Betas" are defined as the contribution of changes in transition rates to the variance of steady-state unemployment. ψ is the job separation rate, and s the job finding rate.

These "beta values" can be interpreted as the proportion of steady-state unemployment u_t^* generated by the transition considered.

Table 3 reports the relative contributions of both transition rates in generating the variance of "fictional" unemployment rates. Inspections of this table leads to two main comments. The first one is related to the contribution of transition rates among shocks. The job finding is at the origin of 72% of cyclical changes in unemployment for the empirical technology shock against 52% for the empirical monetary shock. The second one is the divergent message delivered by the theoretical and the empirical models. In the model, after a technology shock, the job separation rate accounts for approximately 60% of unemployment rate variance. Empirically, its contribution is sharply lower since it amounts to 28%. The same finding operates for the monetary shock since in the model this margin explains 58% of unemployment variance against 48% empirically. Taken together, unemployment decompositions indicate that, in its basic formulation, the search and matching DSGE model developed in Section 2 is not able to reproduce the dominating role of the job finding rate in shaping unemployment. This is especially true for the technology shock.

4.3 Robustness analysis

4.3.1 Empirics

Identification scheme An important robustness check is to establish whether the results are similar across different structural identification schemes. In this respect, I estimate suc-

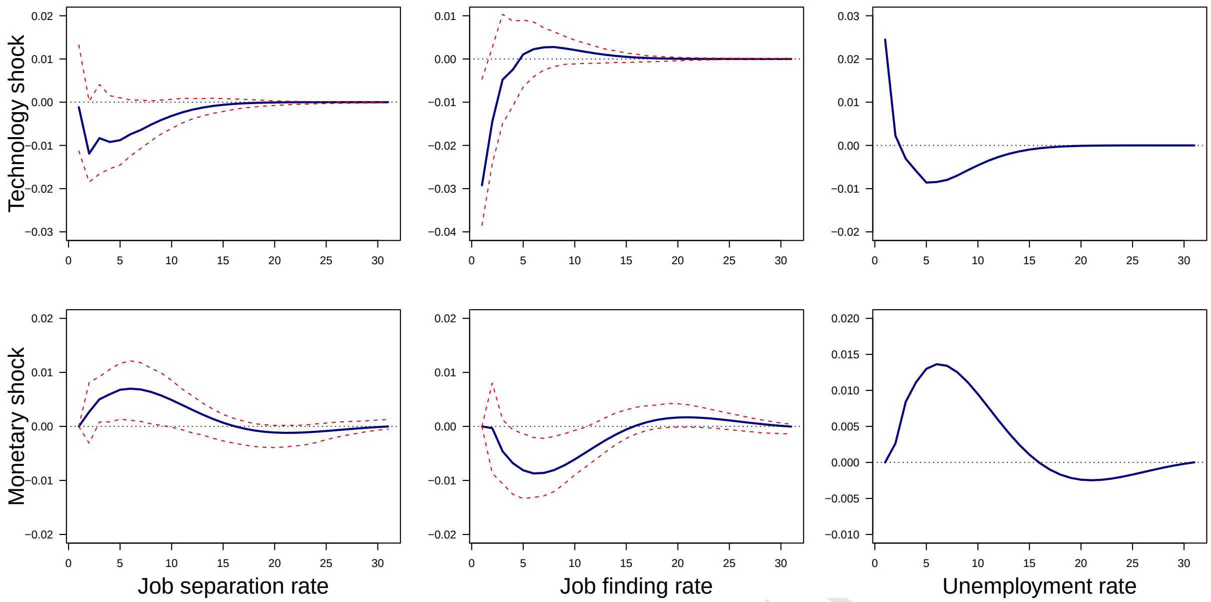

Figure 5: Impulse responses with "standard" identifying restrictions.
Sources: Author's calculations.
Notes: The first row corresponds to the impulse responses to technology shocks identified with long-run restrictions in the spirit of Gali (1999). The second row corresponds to the impulse responses to monetary shocks identified with a Cholesky decomposition and the interest rate ordered last in the VAR as in Bernanke and Blinder (1992). Solid blue lines represent the median impulses responses. Dotted lines are 5th and 95th quantiles of the distribution of responses simulated by bootstrapping 1,000 times the residuals of the VAR. Responses are expressed as log deviations from the steady-state levels.

cessively two "more classical" SVAR models. The first one considers an identification of technology shocks based on long-run restrictions *à la* Gali (1999). It consists in a trivariate VAR including the log-difference of labour productivity and the log of the two transition rates. It is then assumed that the only shock affecting labour productivity in the long run is the technology shock. The second SVAR considers an identification of monetary shocks in line with Bernanke and Blinder (1992). Another trivariate VAR with the log of the two main transition rates and the interest rate is estimated. Monetary policy shocks are identified by applying a Cholesky decomposition of the covariance matrix. The interest rate being ordered last, this implies that other variables do not react contemporaneously to monetary shocks. The obtained impulse responses are reported in Figure 5. Table 4 provides the relative contributions of inflows and outflows in generating unemployment.

After a technology shock, the shapes of impulse responses are very close to those obtained

Robustness to...	Shocks	β^{ψ}	β^{s}
... Identification scheme	Technology shocks *à la* Gali (1999)	0.21	0.79
	Monetary shocks *à la* Bernanke and Blinder (1992)	0.54	0.46
... Productivity variable	Technology	0.24	0.75
	Monetary	0.48	0.52
... lag length	Technology	0.46	0.55
	Monetary	0.31	0.69
... Restriction length	Technology	0.15	0.85
	Monetary	0.55	0.45
... a VAR including hours	Technology	0.42	0.58
	Monetary	0.64	0.36

Table 4: Robustness - Empirical unemployment decomposition under various perturbations.
Sources: Author's calculations.
Notes: "Betas" are defined as the contribution of changes in transition rates to the variance of steady-state unemployment. ψ is the job separation rate, and s the job finding rate.

with sign restrictions since both transition rates decrease. The response of the job separation rate is however non-significant. The decline in both transition rates leads to higher unemployment. The unemployment decomposition of Table 4 suggests that more than three-quarters of unemployment fluctuations are generated by the job finding rate, conditional to a technology shock.

The second row of Figure 5 displays the impulse responses to an unexpected increase in monetary policy rate. A direct consequence of the identifying assumption is that the paths of impulse responses look different across the two applications. Indeed, as transition rates are not able to respond immediately in this framework, the response of the job separation rate is positive and hump-shaped, while the one for the job finding rate is negative and U-shaped. This difference should not disturb the reader since I am more interested by worker flows' contributions to unemployment variations. In line with my benchmark results, Table 4 indicates that, conditional on a monetary shock, both transition rates contribute almost equally to unemployment changes.

Productivity per hour In the baseline model, labour productivity is defined as output per employee. However, in the literature, productivity is often defined as output per hour. To check the robustness of my results, I re-estimate the VAR model with the Eurostat measure of output per hour. As shown in Table 4, the results are nearly the same.

Lag length In the baseline model, the number of lags included in the VAR follow the Hannan-Quinn criterion. As the Aikake criterion suggest the inclusion of more lags, I estimate the corresponding model. The relative contribution implied by this model is reported in the third row of Table 4. The qualitative result is preserved. Conditional on a technology shock, the dominant influence of the job finding margin is weaker. By contrast, it explains a higher share of unemployment variations after a monetary shock.

Restriction length To ensure that the results hold under perturbations to my medium-lived identification procedure, I reduce the maximum length of sign restrictions to 2 periods. Again, I find that results of the baseline model remain qualitatively unaffected. More specifically, the job finding margin is dominant conditional on a technology shock, while the relative contributions are balanced conditional on a monetary shock.

Adding hours worked to the VAR To explore whether the results may be driven by the non-inclusion of some labour market variables, the model is re-estimated by augmenting it with a measure of hours worked per workers. The latter measure is obtained from the database provided by Ohanian and Raffo (2012). In doing such an exercise, the analysis deals with both the extensive margin (the number of people at work or unemployed) and the intensive margin (the number of hours worked in the economy). To save some space, the corresponding IRFs are reported in Figure 7 of Appendix E. They suggest that my main results are qualitatively unaltered and largely quantitatively unchanged. Furthermore, in line with my benchmark model, the response is weak, positive, hump-shaped and barely significant after a technology shock. The exact opposite is true after a monetary shock. The

	Technology shock		Monetary shock	
	β^{ψ}	β^{s}	β^{ψ}	β^{s}
Benchmark (1)	0.59	0.41	0.56	0.44
Flexible prices (2)	0.80	0.20	–	–
(1) without habit	0.61	0.39	0.59	0.41
(2) without habit	0.85	0.15	–	–
(1) with $\eta = 0.9$	0.77	0.23	0.88	0.12
(1) with $\phi = 5$	0.54	0.46	0.52	0.48
(1) with κ as in Trigari (2009)	0.80	0.20	0.95	0.05

Table 5: Robustness - Theoretical unemployment decomposition with parameter changes.
Sources: Author's calculations.
Notes: "Betas" are defined as the contribution of changes in transition rates to the variance of steady-state unemployment.

unemployment decompositions of Table 4 also indicate the robustness of my findings. In particular, the job finding rate is still the main driver of cyclical changes in unemployment after a technology shock.

4.3.2 Calibration of the theoretical model

To establish that the theoretical contributions of transition rates are insensitive to the calibration of parameters, I make several model simulations by changing each time one parameter. The results are displayed in Table 5. Overall, it appears that the job separation rate dominates in explaining unemployment variations, conditional on both technology and monetary shocks. Thus, when prices are flexible, the separation margin accounts for more than 70% of unemployment variations. This contribution is even higher when habit persistence is shut off. In all models incorporating sticky prices, the contribution of outflows is always weaker than the contribution of inflows, ranging from 20% to 46%. Furthermore, the relative contribution of the job separation margin is always higher for the monetary shock than the technology shock. The main finding is also insensitive to changes in important parameters of the matching environment such that the vacancy posting cost κ and the bargaining power of firms η.

To further check the robustness to the calibration strategy, Figure 8 of Appendix F represents the entire distribution of "beta values" obtained for the 1,000 simulations of Subsection 3.3. It confirms that the job separation margin has a greater influence in generating theoretical unemployment variations. Conditional on a technology (resp. monetary) shock, the median value of β^{ψ} is equal to 70% (resp. 72%)[23]. Such a finding indicates that my benchmark calibration does not exaggerate the main message of the paper. It also strongly reinforces the idea that a DSGE model incorporating a frictional labour market and an endogenous separation tends to attribute too much influence to the latter margin.

5 Interpreting the evidence

5.1 A French specificity: job finding matters more

The exercises conducted in Section 4 illustrate important stylized facts about French unemployment dynamics. First, the origin of unemployment depends on the type of the economic shock. This finding is at odds with that of Fujita (2011), who finds that U.S. labour market dynamics are the same whatever the aggregate shocks. The diversity in unemployment driving forces should be kept in mind for the design of economic policies. Secondly, it appears that the dominant role of the job finding is a striking feature of the French labour market. In this respect, my finding reinforces the result provided by previous French studies. Hairault et al. (2015) demonstrate that—during the 2004-2010 period—the job finding rate explained 60% of unemployment changes[24]. Furthermore, Hairault and Zhutova (2018), with a conditional study, show that changes in unemployment are mainly dictated by the job finding margin. Unconditional and conditional studies converge to the same result: none of the transition rates can be ignored, but job finding remains more important. In this respect, French unemployment dynamics stands out from U.S. ones for which unconditional and conditional studies are at odds.

[23]The average values of β^{ψ} are respectively equal to 71% and 62%.

[24]In a reappraisal of this finding, Fontaine (2016) finds that the split between the job finding rate and the job separation rate is of 70:30.

5.2 On the Shimer puzzle

The inability of the search and matching framework to replicate observed stylized facts is based on the comparison of unconditional standard deviations. Shimer (2005) also notes that labour market variables move almost one to one with productivity. Thus, after a technological improvement, wages increase and absorb most of the productivity gain. In contrast to Shimer (2005), Balleer (2012) gauges the performance of the search and matching framework through the lens of standard deviations and correlations that are conditional on structural shocks. She finds that the Shimer critique does not hold when the analysis is conditional. However, the weakness of internal propagation is barely mitigated since the job finding moves in the same direction of labour productivity while her VAR shows the opposite. Surprisingly, although her empirical study integrates the job separation rate, her theoretical model considers that this margin is constant over time. Here, the benchmark model with endogenous job separations provides a realistic picture of unconditional moments. However, it fares poorly in replicating the sources of unemployment variations in terms of transition rates. In particular, it is unable to attribute a prevailing influence on the job finding margin. This finding can be seen as a refinement of the "job finding puzzle" of Balleer (2012). A frictional labour market embedding into an otherwise New Keynesian DSGE model is able to replicate the negative co-movement between the job finding rate and labour productivity. However, the response of the job separation margin remains exaggerated in the model.

5.3 Should we model the job separation margin in a matching framework?

From a purely theoretical point of view, the incorporation of an endogenous job separation margin in a matching model is due to Mortensen and Pissarides (1994). In their model, the job separation margin is important for unemployment fluctuations, especially because it has more volatile dynamics than the job finding process. After the Great Recession of 2008-09, the economic literature aims at quantifying the role of financial markets on labour market variables. In this respect, Zanetti (2017) shows that financial frictions distort firms' hiring decisions. However, in such a context, the role attributable to the job separation rate is far from being marginal.

Using U.S. data, Shimer (2012) computes the unconditional contributions of transition rates in explaining unemployment variations. He finds that the job separation margin has only a minor contribution to unemployment changes[25]. Based on this kind of evidence, Shimer concludes that one does not need to model the separation margin in matching models. Several papers argued that such a conclusion was premature (Fujita and Ramey (2009), Elsby et al. (2009) among others). Canova et al. (2013) indicate that Shimer's conclusion does not hold when the respective contributions of the ins and outs are computed conditional on technology shocks. After neutral technology shocks, they find that 90% of unemployment variations are explained by the job separation rate. Although my conditional analysis indicates that in France, job finding rate matters more—as in Shimer (2012)—I do not share the idea that the abstraction of the separation margin is an acceptable approximation. At least two arguments support my view. First, the introduction of an endogenous job separation, combined with a careful calibration of some parameters, allows to get rid of the Shimer critique. Second, the abstraction of the separation margin may be misleading because my empirical evidence suggests that unemployment driving forces vary with the origins of structural shocks. Therefore, a model with two margins is desirable, but it is necessary to reduce the relative role of job separations in explaining unemployment variability.

To achieve this goal in the French context, the inclusion of particular labour market institutions seems promising. It is well known that the French labour market is characterized by a strong employment protection legislation materialized by important firing costs[26]. In the benchmark model, the hiring decisions of firms are costly while their separation decisions are

[25] For instance, table 1 in Shimer (2012) indicates that, during the 1987-2010 period, 90% of U.S. unemployment variations are dictated by changes in the job finding rate.

[26] The term firing cost should be understood as all administrative and procedural cost accompanying a separation.

left free. Consequently, the separation margin is the easiest way to adjust the employment level. This could be a possible explanation to justify its larger role for unemployment fluctuations. One can conjecture that the inclusion of firing costs could create some counterweight leading to a more balanced contribution of the two margins. However, doing so is beyond the scope of my analysis.

6 Conclusion

In this paper, I have studied the responses of French labour market transition rates consecutive to two aggregate economic shocks. I calibrate a New Keynesian model incorporating labour market frictions and an endogenous job separation margin. I then estimate a VAR including the labour productivity, the inflation rate, the interest rate, the job separation rate and the job finding rate. To isolate structural meaningful economic shocks, I adopt the strategy of Uhlig (2005) by imposing sign restrictions directly on the impulse response functions.

The empirical technology shock induces a decrease in both margins. The combined effects lead to a positive raise in unemployment in the short run. The aggregate monetary shock appears to be recessionary for the labour market by increasing unemployment. Then, I assess the conditional contributions of the ins and outs of unemployment. Two insights appear. First, depending on the origins of the shock, the unemployment driving forces are not the same. Both transition rates contribute equally to unemployment variations after a monetary shock, while the job finding rate is largely dominant after a technology shock. Second, the model and the data do not reveal the same underlying mechanism leading to unemployment variations for a technology shock. The model tends to attribute an exaggerated importance to the job separation margin.

The empirical evidence emerging from this paper sheds light on the plurality of mechanisms governing changes in the French unemployment rate. These patterns seem to be specific to the French economy and are different to those highlighted with U.S. data. Furthermore, the theoretical application suggests that a simple benchmark is not sufficient to reproduce the underlying mechanism governing unemployment variations. This is especially true when the economy is hit by a technology shock. This indicates that other features, e.g., the institutions of the labour market as firing costs or unemployment benefits, may be possible candidates in explaining the determinant role of the job finding. These further theoretical investigations are left for future research.

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Appendices

A Bellman equations

Let $J_t(a_t)$, V_t, $W_t(a_t)$ and U_t be the present-discounted value of expected income from a filled job, a vacancy, employment and unemployment, respectively. The Bellman equation for a filled job can be written as follows:

$$J_t(a_t) = x_t f(h_t) - w_t(a_t)h_t + E_t\beta_{t,t+1}(1-\psi_{t+1})\int_0^{\underline{a}_{t+1}} J_{t+1}(a_{t+1})\frac{dF(a_{t+1})}{F(\underline{a}_{t+1})} \tag{16}$$

This equation states that for a filled job, a firm receives a net return $x_t f(h_t) - w_t(a_t)h_t$ plus the continuation value. In the following period, the match is not discontinued with a probability $1-\psi_{t+1}$, and the firm enjoys the expected value of a job. It is important to note that, with probability ψ_{t+1}, the match is severed, and the firm is left with nothing. Analogously, the asset value of a vacancy is as follows:

$$V_t = -\kappa + E_t\beta_{t,t+1}\left[q_t(1-\psi_{t+1})\int_0^{\underline{a}_{t+1}} J_{t+1}(a_{t+1})\frac{dF(a_{t+1})}{F(\underline{a}_{t+1})} + (1-q_t)V_{t+1}\right] \tag{17}$$

with $-\kappa$ the cost of posting. An open vacancy yields a current negative return equal to κ. In the future period, a vacancy is filled (and not destroyed in the same time) with probability $q_t(1-\psi_{t+1})$, and the firm obtains the future value of a job. In contrast, with probability $(1-q_t)$ the vacancy remains unfilled, and the firm obtain the future value V_{t+1}.

The present-discounted value of an employed worker is as follows:

$$W_t(a_t) = w_t(a_t)h_t - \frac{\kappa_h h_t^{1+\phi}}{(1+\phi)\lambda_t} - \frac{a_t}{\lambda_t} + E_t\beta_{t,t+1}\left[(1-\psi_{t+1})\int_0^{\underline{a}_{t+1}}(W_{t+1}(a_{t+1}) - U_{t+1})\frac{dF(a_{t+1})}{F(\underline{a}_{t+1})} + U_{t+1}\right] \tag{18}$$

This equation indicates that the value of a match yields, for an employed worker, a current net return equal to the wage minus the disutility of supplying work, plus the continuation value due to a possible change in its labour market position. Finally, the present-discounted value of unemployment is as follows:

$$U_t = b + E_t \beta_{t,t+1} \left[s_t(1-\psi_{t+1}) \int_0^{\underline{a}_{t+1}} (W_{t+1}(a_{t+1}) - U_{t+1}) \frac{dF(a_{t+1})}{F(\underline{a}_{t+1})} + U_{t+1} \right] \tag{19}$$

The unemployed worker enjoys the net return b from non-labour market activities (unemployment benefit, home production etc.) and expects to find and keep a job with probability $s_t(1-\psi_{t+1})$. In the opposite case, the worker receives the future value of unemployment.

B Original transition rate series vs TRAMO series

Figure 6 compares initial data and time series estimated by the TRAMO process. The estimated series track very well the initial data. Thus, I consider that the data obtained for the years 2003 and 2004 with the estimated model are also close to the unknown initial data.

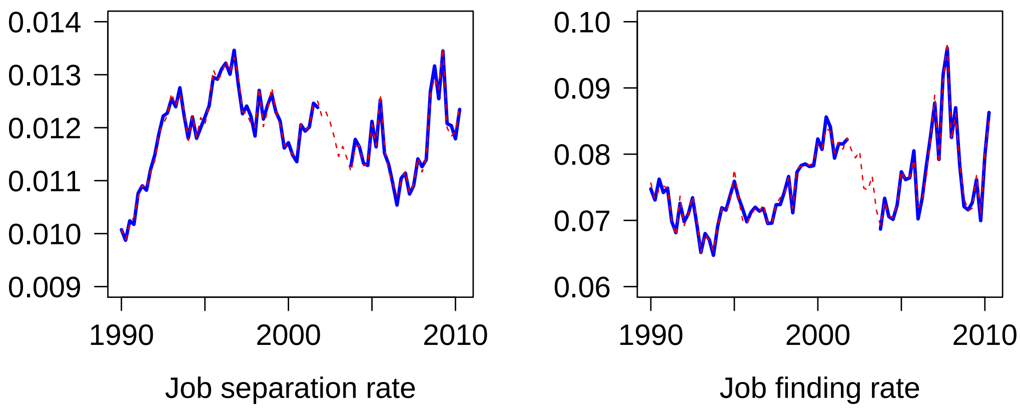

Figure 6: Comparison between the initial series of transition rates (solid blue lines) with the series obtained by TRAMO (dashed red lines).
Sources: Hairault et al. (2015), author's calculations.

C Parameter ranges

Empirical studies and the posterior distributions of structural parameters from estimated medium-scale DSGE models serve as a guide in choosing the parameter ranges. Table 6 provides a summary of the parameter ranges.

	Variable	Range
e	Degree of habit persistence	[0.1 ; 0.9]
ϕ	Inverse of Frisch elasticity	[1 ; 10]
γ_π	Reaction of interest rate to inflation	[1.1 ; 2.5]
γ_π	Reaction of interest rate to output	[0 ; 1]
ξ	Probability of price stickiness	[0.6 ; 0.95]
α	Elasticity of matching function	[0.5 ; 0.7]
κ_h	Scalar of disutility	[0.1 ; 0.95]
η	Bargaining power of firms	[0.2 ; 0.9]
ρ_m	Persistence of monetary shock	[0.65 ; 0.9]
ρ_z	Persistence of technology shock	[0.6 ; 0.95]
$\frac{\kappa v^*}{y*}$	Total vacancy posting cost in %	[0.5 ; 5]

Table 6: Ranges of varying parameters.

In their survey of the estimation of the matching functions, Petrongolo and Pissarides (2001) suggest that the elasticity of matches with respect to unemployment is comprised between 0.5 and 0.7. I follow this suggestion. The parameter indicating the bargaining power of firms is allowed to vary in the interval [0.2 ; 0.9]. Such an interval allows me to test very different specifications: from models with a low firm bargaining power to those with very high firm bargaining power, as in Hagedorn and Manovskii (2008). The parameter e governing the amount of habit persistence is assumed to lie in the interval [0.1 ; 0.9]. Such an interval integrates Smets and Wouters (2005) 95% estimated posterior distribution. Given the divergent evidence about the probability of price stickiness ξ, I restrict it to fluctuate between [0.6 ; 0.95], allowing me to include values chosen by Thomas and Zanetti (2009), Christoffel et al. (2009) and the interval of Smets and Wouters (2005). The calibration of the Frisch elasticity has been challenging. When macroeconomists often rely on an elasticity equal to 1 or above, most microeconomic studies estimate it to be small and not higher than 0.5. To allow for both cases, the inverse of Frisch elasticity is assumed to vary in the interval [1 ; 10]. The total expenditure spent in vacancies ranges between [0.5 ; 5], allowing me to explore models with low (as in my benchmark calibration) but also models with high value of vacancy posting cost, as in Shimer (2005) or Trigari (2009). Following Foroni et al. (2018), the parameters governing the monetary policy rule lie in intervals discussed in the macroeconomic literature. The inflation response is comprised between [1.1 ; 2.5] and the output response between [0 ; 1]. Finally, the range for the persistence of shocks is based on a survey of the literature.

D The other shocks of the VAR system

In his empirical framework, Uhlig (2005) imposes sign restrictions to isolate a unique monetary policy shock. However, the strategy consisting in the identification of a single shock in a sign restriction framework has been criticized in many works, as in Fry and Pagan (2011). Consistently, with the so-called multiple shock problem, I identify not only a single disturbance but also all disturbances of the system. More specifically, I identify the demand shock relative to the inflation rate and the two other shocks affecting the transition rates.

D.1 The demand shock

In the NK literature, a demand shock is a perturbation on the utility of consumption and affects the household inter-temporal decisions. A positive demand shock induces an unexpected rise in consumption, which creates some positive pressure on inflation. This expansion of inflation coincides with an increase in output, and, contrary to the monetary shock, pushes up the interest rate. To recover a demand shock in my empirical model, I impose that the last one is required to increase the inflation rate for at least 4 quarters. Fujita (2011), Braun et al. (2007) and Peersman (2005) also use similar restrictions. Again, I do not restrict the responses of the job separation rate and the job finding rate, and I let the data tell me how unemployment reacts consecutive to the shock.

D.2 Labour market shocks

In a NK economy characterized by nominal rigidities on prices, a shock on the job separation lowers the expected value of a job for firms, which react by opening fewer vacancies. This decrease in the number of vacancies posted reduces the chances for a worker to find a job. Not surprisingly, these patterns of transition rates lead to higher unemployment. I translate these theoretical mechanisms by imposing the job separation to rise during 4 quarters and the job finding to decrease one quarter after the shock. Finally, I isolate a job search shock. A job search shock affects the efficiency of the matching process. It refers to all characteristics facilitating the meeting between firms and workers. Theoretically, this perturbation increases the probability of a worker finding a job and pushes up the job separation rate. The channel is as follows: a matching efficiency shock increases the job finding rate but also the value of unemployment spells. Since the value of unemployment for a worker increases, it becomes more costly for the workers to supply labour. All else equal the threshold at which endogenous job separation takes place diminishes, and the overall job separation rate increases. These movements of transition rates reduce unemployment because the first effect dominates the second. Empirically, I impose that following the search shock, the job finding increases during four quarters. The response of the job separation is required to be positive during the impact period. The fact that the two transition rates move in the same direction is essential for the identification of the job search shock. Other evidence justifying why the job search shock leads to positive co-movements between the job separation rate and the job finding rate can be found in Hairault and Zhutova (2018).

E What about the intensive margin?

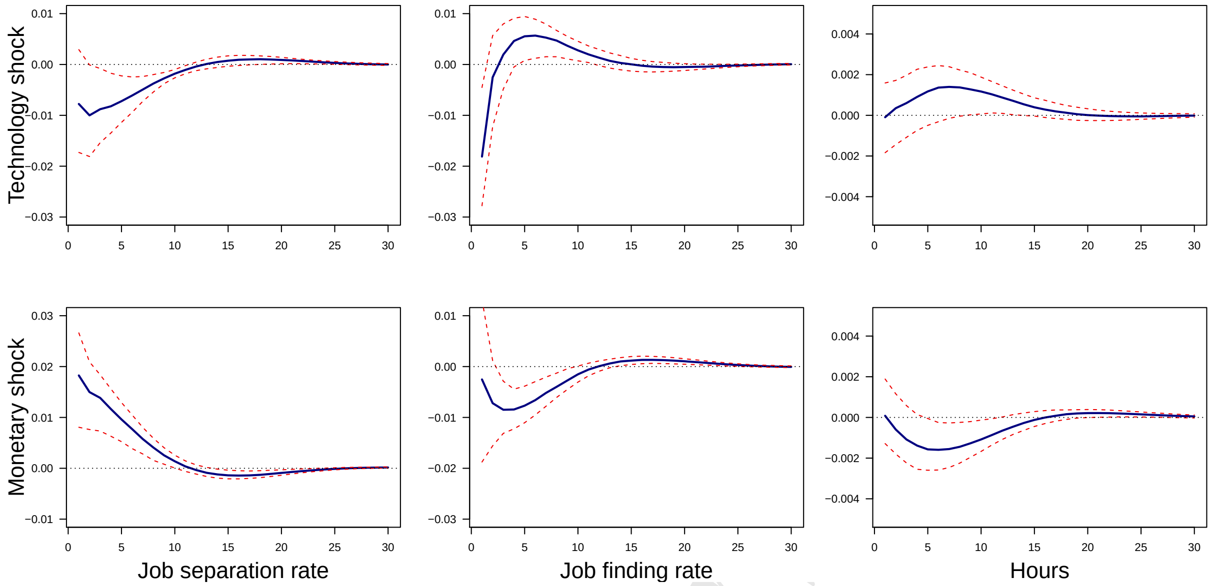

Figure 7: Impulse responses in an empirical framework containing hours
Sources: Author's calculations.
Notes: Shocks are identified as detailed in Section 3. Impulse responses to a one-standard-deviation shock are reported. Solid blue lines represent the median impulses responses obtained with the VAR. Dashed lines correspond to the 64% of the posterior distribution.

F Relative contributions in the model

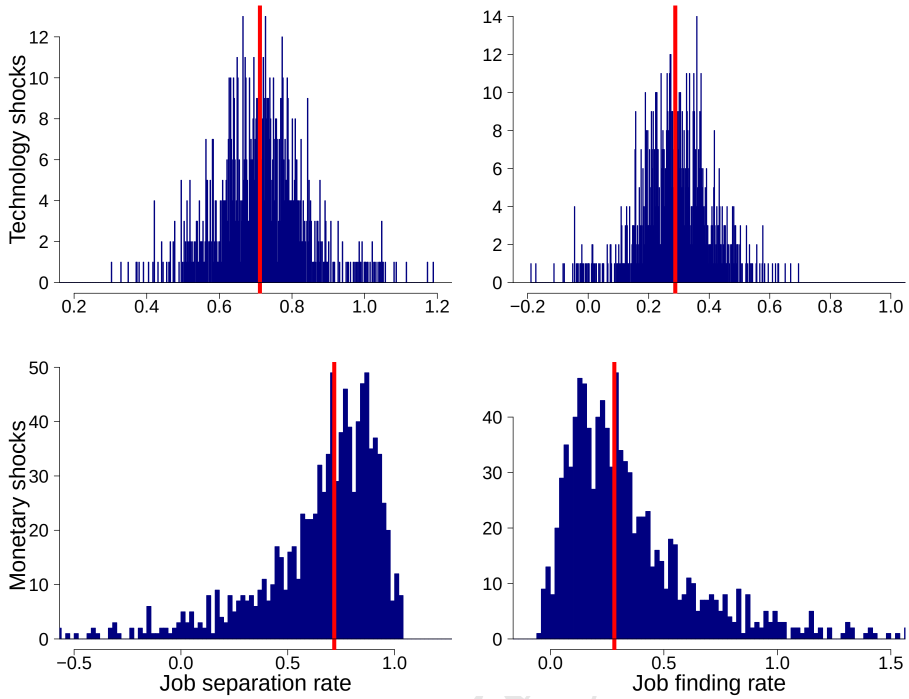

Figure 8: Distributions of "beta" values obtained after 1,000 simulations of the model.
Sources: Author's calculation.
Notes: Red vertical lines are the median of the distributions