E c o n o m i c s B u l l e t i n

Asymmetric Adjustment Costs and Aggregate Job Flows: Specification, Estimation and Testing with French Data

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Abstract

This paper aims to study whether a simple asymmetric adjustment costs model with tractable heterogeneity can account for the observed distribution of French aggregate job flows. Each firm chooses endogenously its level of hiring or firing depending on the level of a specific technology shock. These policy rules allows, via aggregation, to account for dynamics in aggregate job flows. The deep parameters of the model are then estimated using the Simulated Method of Moments. We then show that the model is able to match some key features of the French aggregate job flows, but the results appears sensitive to the level of heterogeneity.

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Introduction

In most industrial countries, the aggregate dynamics of labor market can be characterized by the following stylized facts (see Davis and Haltiwanger [2000]): *(i)* aggregate job flows are large within the business cycle, *(ii)* the destruction rate is more volatile than the creation rate, *(iii)* destruction and creation rates are negatively correlated.

Several structural models are potentially able to account for these stylized facts: search model with endogenous separation (Mortensen [1994], Andolfato [1997] , den Hann, Ramey and Watson [2000] and Collard, Fève, Langot and Perraudin [2002]), multi–sectors economy (see e.g., Greenwood, MacDonald and Zhang [1996]), so–called (s, S) rule approach (see e.g., Bentolila and Bertola [1990]) or asymmetric adjustment costs models (Pfann and Palm [1993] and Fève [2002]). These models provides a good way to understand the labor market dynamics, but most of them was not subjected to a formal quantitative evaluation. As underline by Cole and Rogerson [1999], there has been little systematic work to evaluate their quantitative properties with regard to labor market flows over the business cycle. Some exceptions concern the papers of Pfann and Palm [1993] and Collard et al. [2002], among others. The aim of this paper is precisely to study whether a simple asymmetric adjustment costs model extended to firms heterogeneity is able to match some key features of aggregate job flows[1].

At a theoretical level, two essential dimensions must be taken into account. First, the time series behavior of creation and destruction rates (see Davis, Haltiwanger and Schuh [1996]) suggests to distinguish hiring behavior from firing behavior at the firm level. This is achieved, in our model, by the specification of separate adjustment costs functions on hirings and firings. Second, creation and destruction co–exist at aggregate level. This is achieved *via* the existence of many firms, each of them experiences specific technology shock. It turns out that this is essential to match the distribution of creation and destruction within the business cycle (Caballero, Engel and Haltiwanger [1997]). Given the non–linear structure of the model and given that the specific technology shock has no observable counterpart, the structural parameters of the model are estimated using a simulation-based estimation method (see e.g., Ingram and Lee [1991]). Our results indicates that a simple model with asymmetric adjustment costs is able to match the selected moments computed using quarterly data on creation and destruction rate in the French economy.

The paper proceeds as follows. Section 1 presents the model and its closed form solution.

[1]Karamé and Perraudin [1999] provide empirical evidence on asymmetric behavior of aggregate gross job flows in France and United States.

Section 2 discusses the specification choices and the econometric methodology. The estimation and testing results are reported in section 3. A last section offers some concluding remarks.

1 A Simple Model of the Labor Demand

We consider an economy that consists in many firms, indexed by $j = 1, ..., S$. Each firm j has access to the constant returns-to-scale production function given by:

$$Y_{j,t} = (1 + \kappa)(\overline{a} + \eta_{j,t})N_{j,t} \tag{1}$$

where $\kappa, \overline{a} \geq 0$ are scale parameters. $N_{j,t}$ denotes the employment level involved in the production process. The instantaneous operating profits of firm j at time t is given by:

$$\Pi_{j,t} = Y_{j,t} - w_{j,t}N_{j,t}$$

where $w_{j,t}$ denotes the real wage. We assume for simplicity that the real wage is indexed on productivity

$$w_{j,t} = \kappa(\overline{a} + \eta_{j,t})$$

such that $w_{j,t}$ cancels in the expression of operating profits:

$$\Pi_{j,t} = (\overline{a} + \eta_{j,t})N_{j,t} \tag{2}$$

Despite its simplicity, the constant returns–to–scale hypothesis turns out to be a central assumption to get an analytical and tractable solution to individual policy rules. Each firm is characterized by a specific technology shock $\eta_{j,t}$ which is assumed to follow a covariance stationary AR(1) process:

$$\eta_{j,t} = \rho\eta_{j,t-1} + \sigma\nu_{j,t} \tag{3}$$

where $|\rho| < 1$ and $\nu_{j,t}$ is a zero mean, unit variance Gaussian white noise. Each firm controls its hiring policy through $H_{j,t}$ and its firing policy through $F_{j,t}$. The cost functions, $\phi_x(.)$ – for $x = \{h, f\}$ – associated to hirings and firings , satisfy the following conditions: *i)* $\phi_x(.) \geq 0$ for any $x \geq 0$, *ii)* $\phi_x'(.) > 0$, *iii)* $\phi_x''(.) > 0$ and *iv)* $\phi_x(0) = 0$. In each firm and in every period t, the number of employment outflows has two components: *i)* an "exogenous" separation, given by the product of the separation rate, s, with the current number of employees $N_{j,t}$ and *ii)* an active firing policy, denoted by $F_{j,t}$. Employment evolves according to the following law of motion:

$$N_{j,t+1} = (1 - s)N_{j,t} + H_{j,t} - F_{j,t} \tag{4}$$

Thus, hirings or firings at time t affects productive employment at time $t + 1$. The dynamic problem of the firm j is then to choose the number of hirings $H_{j,t}$ and firings $F_{j,t}$

to maximize the expected discounted sum of profit flows:

$$\max_{\{H_{j,t+\tau},F_{j,t+\tau}\}_{\tau=0}^{\infty}} E_t \left\{ \sum_{\tau=0}^{\infty} (1+r)^{-\tau} \left[\Pi_{j,t+\tau} - \phi_h(H_{j,t+\tau}) - \phi_f(F_{j,t+\tau}) \right] \right\}$$

$$s.t. \left\{ \begin{array}{rcll} N_{j,t+1} & = & (1-s)N_{j,t} + H_{j,t} - F_{j,t} & (X_{j,t}) \\ H_{j,t} & \geq & 0 & (\lambda_{j,t}) \\ F_{j,t} & \geq & 0 & (\mu_{j,t}) \end{array} \right.$$

where $(1+r)^{-1}$ denotes the firm's discount factor, $r \in (0,1)$. $\lambda_{j,t}$ and $\mu_{j,t}$ are the Lagrange multipliers associated to the positivity constraints on respectively hirings and firings. $X_{j,t}$ is the marginal value of employment. The first–order conditions for a firm j shows that firm hires up to the point where the marginal value of employment is equal to the marginal costs of hirings, given the positivity constraint:

$$-\phi'_h(H_{j,t}) + X_{j,t} + \lambda_{j,t} = 0 \tag{5}$$

An analogous condition holds for firings:

$$-\phi'_f(F_{j,t}) - X_{j,t} + \mu_{j,t} = 0 \tag{6}$$

We also have the two additional conditions:

$$\lambda_{j,t} H_{j,t} = 0 \tag{7}$$

$$\mu_{j,t} F_{j,t} = 0 \tag{8}$$

From the first order conditions (5)–(6) and the two conditions (7)–(8), for any given value of $X_{j,t}$, we get the following property.

Proposition 1 *A firm will not fire when it has positive hirings. Conversely, a firm will not hire when it fires.*

According to equations (5)–(6) and proposition 1, the model displays three regimes. In a first regime, a firm hires and does not fire when the expected marginal value of employment is strictly positive. Further, in the second regime, the firm does not hire but fires when the expected marginal value of employment is strictly negative. Finally, there exists a third regime in which firms are totally inactive. It occurs when $X_t = 0$. As our economy display constant returns to scale, the marginal value of employment is exogenous. We have:

$$X_{j,t} = \frac{1}{1+r} E_t \left[\overline{a} + \eta_{j,t+1} + (1-s) X_{j,t+1} \right] \tag{9}$$

$$N_{j,t+1} = (1-s)N_{j,t} + H_{j,t} - F_{j,t} \tag{10}$$

$$\phi'_h(H_{j,t}) = X_{j,t} \quad \text{if } X_{j,t} > 0 \tag{11}$$

$$\phi'_f(F_{j,t}) = -X_{j,t} \quad \text{if } X_{j,t} < 0 \tag{12}$$

Equation (11) gives the level of hiring, while equation (12) provides the firing level both in terms of $X_{j,t}$. The shift from one regime to another is driven by the shocks, as implied by the exogenous marginal value of employment (9).

2 Specification, Estimation and Testing

In order to evaluate the quantitative implications of the model, we must first specify the adjustment cost functions. The costs of hirings and firings are given by:

$$\phi_h(H_{j,t}) = \frac{H_{j,t}^{\varphi_h}}{\varphi_h} \quad \text{and} \quad \phi_f(F_{j,t}) = \frac{F_{j,t}^{\varphi_f}}{\varphi_f}$$

where the parameters $\varphi_h, \varphi_f > 1$ and are not restricted to be equal. We depart here from the usual quadratic adjustment costs. This is because they introduce severe identification problems between the adjustment cost parameters, which allows to smooth the decision variables in response to the exogenous marginal value of employment, and the volatility of the shock. Our specification choice has thus two interesting features: *i)* they can be viewed as a generalization of the quadratic adjustment costs, which constitutes a second order approximation of our costs function, *ii)* they allow to potentially avoid the identification problems through non-linear rules for hirings and firings. Given the process of the shock (3), the dynamics of individual employment can be summarized as

$$\begin{aligned} N_{j,t+1} &= (1-s)N_{j,t} + (\mathbb{1}_{[X_{j,t}>0]}X_{j,t})^{\frac{1}{\varphi_f - 1}} - (-\mathbb{1}_{[X_{j,t}<0]}X_{j,t})^{\frac{1}{\varphi_f - 1}} \\ X_{j,t} &= \alpha_0 + \alpha_1 \eta_{j,t} \end{aligned} \tag{13}$$

where $\alpha_0 = \bar{a}/(r+s)$ and $\alpha_1 = \rho_\eta(1+r-(1-s)\rho_\eta)^{-1}.\mathbb{1}_{[z]} = 1$ when z is true, 0 otherwise. Employment dynamics is thus characterized by the presence of dynamic latent variables, that determine the shift between regimes within the business cycle.

We are interested in the aggregate implications of our structural model. Complexity occur from various sources: both creation and destruction levels are non–linear policy functions (see (13)), these series are aggregated over firms and we compute gross job creation and destruction rate deflated by the average of begin and end of period stocks. This normalization is performed to insure compatibility of aggregate data. These various elements lead also to complicated reduced forms for aggregate creation and destruction rates, denoted c_t and d_t respectively. In order to circumvent these difficulties, we implement the Simulated method of Moments (SMM hereafter). This procedure can be easily implemented even when the likelihood function is intractable or when the moments cannot be computed using direct integration methods.[2]

The choice of moments is a crucial step for this estimation method. It should not be driven by the specification of our model, but it should encompass as many features of the data as possible, therefore avoiding any arbitrary choice and reducing biases in estimation (see Michaelides and Ng [2000]), We thus select a set of moments that describes as much

[2]See the appendix for a presentation of the implementation of SMM and Collard et al. [2002] for more details concerning the implementation of this method in the case of a similar labor demand model with tractable heterogeneity and endogenous separation.

as possible the joint distribution of aggregate data, although our selection of particular moments is admittedly *ad-hoc*. The selected moments are the following:

$$\psi_t = \{m_1(x_t), \mu_i(x_t), \rho_p(x_t), corr(c_t, d_{t-k})\}$$

where $x_t = \{c_t, d_t\}$, $m_1(x_t) = E(x_t)$ and $\mu_i(x_t) = E[(x_t - m_1(x_t))^i]$, $i = 2, \cdots, 4$, $\rho_p(x_t)$ are the first and second order autocorrelation ($p = 1, 2$). The first moments are rather conventional, that is the sample mean ($m_1(.)$) and variance ($\mu_2(.) = \sigma.^2$) of the data. We introduce higher order moments in order to fully capture the properties of both the model and the data. The normality assumption implies that the third moments are zero and a linear relationship between even order moments. In order to complete our description of the data, we introduce the linear correlation between gross creation and destruction rate ($corr(c_t, d_{t-k})$) from one lag to and one lead($k = -1, 0, 1$) and autocorrelations. We thus use 15 auxiliary parameters in order to estimate the unknown structural parameters of the model $\theta = \{r, s, \bar{a}, \rho, \sigma\, \varphi_h, \varphi_f\}$ and to conduct some specification tests.
The basic idea of SMM is to find values of the structural parameters which minimize the following loss function:

$$J(\theta) = g'_{T,N} W_T\, g_{T,N}$$

where $g_{T,N} = \left(\widehat{\psi}_T - \frac{1}{N}\sum_{i=1}^{N} \widetilde{\psi}_T^i(\theta)\right)$ and W_T is a symmetric non-negative weighting matrix defining the metric that depends on the actual data.[3] N denotes the number of simulations used for estimation. $\widehat{\psi}_T$ corresponds to the estimated moments from actual data $\{c_t, d_t\}_{t=1}^T$, whereas $\widetilde{\psi}_T^i(\theta)$ corresponds to the estimated moments from the simulated data $\{\widetilde{c}_t^i, \widetilde{d}_t^i\}_{t=1}^T$ for $i = 1, \cdots, N$ for a given value of θ.
Identifying conditions impose that the number of moments exceeds the number of structural parameters. Thus, one may conduct a global specification test, denoted $J - stat = TNJ(\theta)/(1 + N)$ at convergence. This statistic is distributed as a chi–square, with a degree of freedom equal to the number of over–identifying conditions. We further use a simple diagnostic test, in the lines of Gallant, Hsieh and Tauchen [1997] and Collard, Fève and Perraudin [2000]. This test allows to locate some failures in the structural model. The main idea is that each element of $g_{T,N}$ measures the discrepancy between the moments computed from the data and from model simulations. Each element thus contains a diagnostic information assessing the ability of the model to match the moments. A small value for some elements indicates that the structural model is able to well explain some features of the data, while large values may reveal some failures.

3 Empirical Results

This section first presents the data, before turning to the exposition of empirical results.

[3] It corresponds to the inverse of the covariance matrix of the moments, which is obtained from actual data.

3.1 Basic Data

The data on job creation and destruction rates are obtained from the "Déclarations des mouvements de main d'oeuvre " database (DMMO).[4] Our attention is restricted to aggregate creation and destruction rates. The sample runs from the first quarter of 1987 to the fourth quarter of 1994. It is worth noting that French data do not incorporate flows concerning small establishment (less than 50 workers). It follows that French job flows cannot be directly compared to the US ones, which concern smaller establishment (see Davis et al. [1996]).

Table 1: Selected Moments on French Job Flows (annual rate)

	Creation rate	Destruction rate
$m_1(x_t)$	3.21	4.43
	(0.16)	(0.19)
$\mu_2(x_t)^{1/2}$	0.86	1.00
	(0.09)	(0.10)
$\mu_3(x_t)$	7.98	20.07
	(28.36)	(46.40)
$\mu_4(x_t)$	12.08	21.63
	(3.37)	(7.54)
$\rho_1(x_t)$	0.9332	0.8614
	(0.1959)	(0.1809)
$\rho_2(x_t)$	0.7914	0.6468
	(0.1753)	(0.1545)
$corr(c_t, d_{t-1})$	-0.8143	
	(0.1752)	
$corr(c_t, d_t)$	-0.9187	
	(0.1974)	
$corr(c_t, d_{t+1})$	-0.8670	
	(0.1960)	

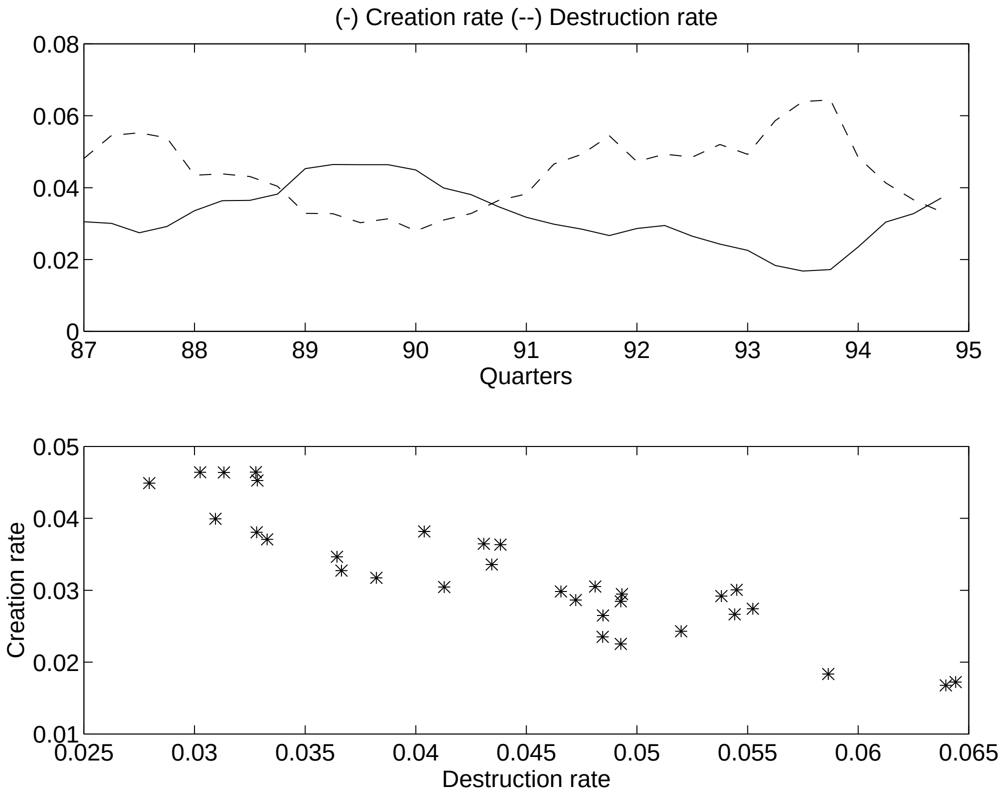
Note: All moments, except correlations, are multiplied by 100. Estimates are robust to both heteroskedasticity and serial correlation, using a Parzen window with bandwidth parameter set to 10.

First of all, the gross creation rate is lower on average than gross destruction rate, indicating that the French economy rather destroyed jobs than it created on average. The destruction rate is 16% more volatile than the creation rate. Both creation and destruction do not display that much asymmetries. Smoothness and persistence will constitute another feature of the data. Finally, the bottom of table 1 provides some insights on the joint behavior of job flows within the business cycle. More specifically, creations and

[4]The DMMO database is jointly managed by INSEE and the French Ministry of Labor.

destructions are strongly negatively correlated. They are thus in opposite phase within the business cycle. Indeed, as it is now well–known, job creation is procyclical whereas job destruction is strongly countercyclical. Plots of job creation and destruction rates illustrate these features (see figure 1).

Figure 1: French Aggregate Job Flows (annual rate)



3.2 Estimation Results

We do not estimate all the structural parameters. The discount factor is constrained at 1% per quarter. We will thus estimate the parameters for *(i)* the technology ($\bar{a}$, ρ, σ), *(ii)* the adjustment costs (φ_h, φ_f) and *(iii)* the quit rate (s). We only consider what Caballero and Engel [1991] call *stochastic heterogeneity* rather than *structural heterogeneity* which would amount to consider specific firm behavior. Despite its simplicity, this approach allows to model heterogeneity without introducing a large number of parameters. An important issue is then the number of firms S which is *a priori* unknown. Table 2 reports the p-value of the global specification test for different numbers of firms. There is actually no need for a high heterogeneity in the model, as it appears that 4 firms are sufficient to match the data at near 5% level. The model performs better when the number of firms is set around 8. Further, increasing too much heterogeneity seems to introduce too much noise in the model, which is then performing worse while being not rejected by the data. Too much firms leads to reduce significantly the correlation between creation and destruction rates. Conversely, a low level of heterogeneity induces a strong negative correlation, but reduces the ability of the model to match a large set of other moments.

Table 2: Parameter estimates

S	2	4	6	8	10	12
ρ	0.7167	0.7807	0.8134	0.8202	0.7959	0.8278
	(0.3944)	(0.1331)	(0.1154)	(0.0191)	(0.0180)	(0.0271)
σ	0.0113	0.0251	0.0265	0.0388	0.0420	0.0415
	(0.3913)	(0.0623)	(0.2308)	(0.0028)	(0.0034)	(0.0042)
$\overline{a}$	0.0036	0.0086	0.0097	0.0091	0.0077	0.0080
	(0.1189)	(0.0125)	(0.0791)	(0.1e-3)	(0.1e-3)	(0.1e-4)
s	0.0378	0.0344	0.0327	0.0273	0.0257	0.0242
	(0.5e-3)	(0.11e-2)	(0.8e-3)	(0.15e-2)	(0.16e-2)	(0.17e-2)
φ_h	16.8983	7.6595	6.3411	5.8609	4.4538	6.0887
	(27.26)	(11.78)	(14.52)	(3.63)	(2.00)	(4.21)
φ_f	41.8624	17.7024	17.5800	15.6547	16.9300	18.3409
	(511.39)	(29.26)	(119.37)	(21.67)	(30.10)	(24.09)
J–stat	28.1243	17.0133	16.085	13.7504	15.6956	15.7286
	[0.09]	[4.85]	[6.486]	[13.15]	[7.35]	[7.28]

Note: standard errors in parentheses, p-values (%) into brackets

Parameter estimates are precisely estimated when the number of firms is sufficiently high, except for the adjustment cost parameter on firings. The quit rate is sensitive to the number of firms. It also appears that its point estimate decreases as the number of sector increases. As the model incorporates endogenous firings, the exogenous quit rate only accounts for part of the separation process. Indeed, as heterogeneity diminishes, the model rarely enters the firing regime, so that the exogenous quit rate has to be high enough to account for the mean of destruction rate. In the case of a 2 firms, endogenous firings explain, in average, 15% of total destruction rate, whereas it can account for more than 35% in a 8 firms economy.

Beyond the estimated values of the structural parameters, one may look at the diagnostic test, in order to locate where the model performs well or fails. For illustrative purposes, table 3 reports the diagnostic test for 2 and 8 firms economies. In accordance with global specification tests, we can see that the model matches well each moment in the 8 firms economy, except for the one lead and lag cross–correlation. In the case of a 2 firms economy, the model fails to match especially moments on destruction rate. Indeed, the economy rarely enters the firing regime and thus cannot account for the observed volatility of the destruction rate.

Table 3: Diagnostic Test (annual rate)

Moments	Data	Model		Diagnostic Test	
		S=2	S=8	S=2	S=8
$m_1(c)$	3.21	3.91	3.87	1.85	1.73
$m_1(d)$	4.43	3.92	3.81	-1.30	-1.56
$m_2^{1/2}(c)$	0.86	0.55	0.81	-1.94	-0.32
$m_2^{1/2}(d)$	1.00	0.58	0.88	-3.08	-0.85
$m_3(c)$	7.98	-32.59	-2.03	-0.69	-0.17
$m_3(d)$	20.07	85.25	52.11	0.78	0.38
$m_4(c)$	12.08	11.35	11.29	-0.14	-0.14
$m_4(d)$	21.63	25.64	19.82	0.38	-0.17
$\rho_1(c)$	0.93	0.49	0.76	-1.27	-0.54
$\rho_1(d)$	0.86	0.43	0.67	-1.66	-0.80
$\rho_2(c)$	0.79	0.37	0.64	-1.32	-0.46
$\rho_2(d)$	0.65	0.34	0.55	-1.26	-0.40
$corr(c_t, d_{t-1})$	-0.81	-0.24	-0.20	2.15	2.29
$corr(c_t, d_t)$	-0.92	-0.82	-0.51	0.36	1.42
$corr(c_t, d_{t+1})$	-0.87	-0.35	-0.33	1.78	2.02

Note: All moments, except correlations, are multiplied by 100. A positive value of the statistics indicate an over–estimation, whereas a negative value indicates an under–estimation. The statistics is distributed as a standard normal.

4 Concluding remarks

This paper is an attempt to show that a simple asymmetric adjustment costs model can account for the observed distribution of French aggregate job flows. Each firm chooses endogenously its level of hiring or firing depending on the level of a specific shocks. Introducing tractable heterogeneity allows to obtain both positive creation and destruction at the aggregate level. The parameters of the model are then estimated using a simulation-based estimation method. A test of the model then reveals its ability to mimic the data. However, several extensions would provide a better modelling of French aggregate job flows by either allowing for structural heterogeneity and/or introducing other specifications of the hiring and firing costs.

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Appendix

A Proof of Proposition 1

These results can be directly deduced from the two optimality conditions (5) and (6) . Consider the case of a firm that both fires and hires , *i.e.* $H_{j,t} > 0$ ($\lambda_{j,t} = 0$) and $F_{j,t} > 0$ ($\mu_{j,t} = 0$). Then, the optimality condition on vacancies implies $X_{j,t} = \phi'_h(H_{j,t}) > 0$ whereas the optimality condition on firings implies $X_{j,t} = -\phi'_f(F_{j,t}) < 0$. These two conditions are mutually inconsistent. We thus have: either $H_{j,t} > 0$ and $F_{j,t} = 0$, which implies $\lambda_{j,t} = 0$ and $\mu_{j,t} = \phi'_h(H_{j,t}) \geq 0$; either $H_{j,t} = 0$ and $F_{j,t} > 0$, which implies $\lambda_{j,t} = \phi'_h(F_{j,t}) \geq 0$ and $\mu_{j,t} = 0$; or $H_{j,t} = 0$ and $F_{j,t} = 0$, which implies $X_t = \lambda_{j,t} = \mu_{j,t} = 0$.

B Implementation of SMM

The minimization of the simulated criterion function is carried out using a simplex method for minimization provided in the *Optim* MATLAB numerical optimization toolbox. We prefer this method to more traditional optimizers that use local gradient search methods, as they fail to converge in our experiments. The estimation is time consuming, despite the small number of parameters to be estimated. This is because the simplex method requires a large number of function evaluations, which implies for each function evaluation two steps : *i)* the computation of simulated paths for creation and destruction for each sector, given the policy function , *ii)* the aggregation over the sector and the computation of associated statistics. We use 20 simulations for a sample size equals to 67. We use the same trial for all the values of θ. These simulated values are redrawn from the same seed values. Simulation experiments of Michaelides and Ng [2000] indicates that efficiency gain becomes negligible when the number of simulations exceeds ten. The loss of efficiency using $N = 20$ is less than 5% as $T \to \infty$. In order to reduce the effects of initial conditions, simulated samples includes 250 initial points which are subsequently discarded in the estimation. The initial condition corresponds to the firms'steady–state value of employment.