Industrial and Corporate Change, Volume 17, Number 4, pp. 753–777
doi:10.1093/icc/dtn025
Advance Access published July 8, 2008

Market selection along the firm life cycle

Flora Bellone, Patrick Musso, Lionel Nesta and Michel Quéré

This article analyses market selection in French manufacturing in the nineties. It argues that the determinants of firm survival have different effects depending on firm age. Results show that exiting firms display low levels of profitability and productivity. This selection process is more severe for young firms because industry structures favor the survival of mature firms. Concerning the latter, markets select against persistent bad performers, not against temporary losses of efficiency. These results reveal the presence of barriers to firm growth—not to entry—as an important driver of industry dynamics.

1. Introduction

Since less productive firms quit the market, selection is thought to contribute positively to aggregate economic growth. This simple but robust stylized fact has been documented in a large number of countries.[1] This should not conceal the fact that market selection mechanisms (MSM) may work more or less efficiently across countries, industries and over time, depending on a potentially large host of factors.[2] For example, the work of Bartelsman *et al.* (2004, 2005), comparing firm turnover to aggregate productivity growth in 10 OECD countries, argues that the regulatory frameworks in Europe, and especially in France, have been less efficient than the one in the United States at promoting the growth of new firms. The authors claim that higher entry and labor-adjustment costs in France both discourage entrepreneurship

[1]Evidence of this market selection mechanism has been found in a large variety of countries. A non-exhaustive list of contributions includes Baily *et al.* (1992), Haltiwanger (1997), Foster *et al.* (2001) for the United States, Griliches and Regev (1995) for Israel, Aw *et al.* (2001) for South Korea and Taiwan, among others. A notable exception is the paper by Nishimura *et al.* (2005) which advocates that selection mechanisms no longer work in severe recessions. The authors show that over a decade of a recessive Japanese economy, mature unproductive Japanese firms remained in the market while younger efficient ones exited.

[2]For instance, Scarpetta *et al.* (2002) argue that, on average, firms tend to exit with better relative productivity levels in periods of downturn and in mature and/or restructuring industries. Aw *et al.* (2001) compare data for Taiwan and South Korea from 1983 to 1993, a period of rapid economic expansion for both those economies. They conclude that, institutions in Taiwan were more effective at supporting the market selection process acting against unproductive firms.

and depress firm growth. These findings suggest that firms cope with MSM which may be highly country specific.

Generally endowed with more modern technologies, young firms play a crucial role in promoting economic growth. Hence a better understanding of the determinants of life duration of young firms—as distinct from mature firms—is much needed. To our knowledge, our research is the first to consider explicitly that the determinants of firm duration may change along the firm life cycle. The intuition is straightforward. Contrary to established companies, young firms cope with imperfect competition on both the product market (e.g., no reputation, absence of distribution channels) and factor market (e.g., access to financial resources) which renders them more fragile. We address this issue by examining firm survival using a large scale dataset on French manufacturing during the nineties. We document how the determinants of firm duration—in terms of firm performance and industry characteristics—act differently according to the age of the firm. Our research relates to three streams of literature.

First, our research follows the empirical literature by focusing on the determinants of firm survival (Audretsch, 1991; Mata and Portugal, 1994). Firm level determinants are essentially age, size and profitability, and industry level determinants are generally concentration, minimum efficient scale (MES), market size, and some measures of industry turbulence (firm turnover, size of entrants, and growth in overall sales, among others). The observed vector of parameter estimates associated with industry level variables is then interpreted as the result of competition between firms in imperfect markets. It also reflects the fact that MSM do not operate equally over uniform industries, so that industry structures matter in shaping the survival of firms. Two important innovations of this article are to relax the implicit assumption that MSM apply uniformly and to document that firms of different ages within one single industry cope with different MSM. By doing so, we are more in line with the literature that emphasizes the distinction between small and large firms (Audretsch *et al.*, 1999).

Second, our research is linked to the theoretical literature on industrial dynamics, which relates the firm's decision to exit to its profitability. The seminal papers by Jovanovic (1982) and Hopenhayn (1992) have made explicit the link between firm heterogeneity and industrial dynamics. In this framework, firms are endowed at birth with a time invariant profitability parameter, which determines the distribution of their future profit stream. A new firm does not know its relative efficiency but discovers it gradually by observing its actual post-entry profit realizations. Consequently, young firms have higher probabilities of failures and more volatile growth rates. This basic model replicates interesting patterns of industry dynamics: the overall stability of firm-size distributions conceals numerous entry and exit of firms and substantial changes of market shares between established companies. In Ericson and Pakes (1995), firms know about their relative profitability, but the latter changes over time as a result of stochastic outcomes of firms' own investments.

Successful investments lead firms to earn more profit, whereas unsuccessful investments lead to a deterioration of profit and eventually to exit. Overall, this family of models predicts that the rate of firm turnover is negatively related to entry costs and that, in turn, a low firm turnover rate is associated with large profitability gaps between exiting and surviving firms.

Finally, our research relates to the work of Gort and Klepper (1982), which triggered a series of theoretical and empirical investigations concerning the so-called industry life cycle. The theoretical models of Klepper (1996, 2002a) and repeated empirical investigation by Klepper (2002a), Klepper and Simmons (2005), and Argawal and Audretsch (1995) imply that the dynamics of product markets are likely to affect firm exit. The stylized facts predict that in the early stages of an industry, competition is mainly based on product innovation. Both firm entry and firm exit are frequent, although entry dominates over exit. At this stage, product competition is the rule, so that there is no decisive advantage in implementing large scale production. As the industry matures, process innovation dominates so that price competition plays a major role in dictating firm exit. At this stage, there is a natural advantage for large, generally older, firms in that they can spread unit cost reductions across larger scales of production. It follows that beyond and above the major role of firm profitability in accurately predicting firm exit, one should also consider market structures and industry turbulence as potential determinants of the fates of firms.

The article is organized as followed. Section 2 describes the dataset and the methodology used to estimate productive efficiency. It also provides descriptive statistics on turnover by industry and captures post-entry performance of young firms. Section 3 focuses on the market selection process throughout the life cycle of the firm by means of duration models. Section 4 summarizes our main findings and provides some conclusions.

2. Firm turnover and productivity in French manufacturing industries

2.1 Data and measurement

The empirical investigation uses the French Manufacturing Census (EAE) collected by the French Ministry of Industry (SESSI), which gathers information from the financial statements and balance sheets of all individual manufacturing firms with at least 20 employees, from 1990 to 2002.[3] Unlike most of the existing literature, the surveyed unit is the legal unit (the firm), not the production unit (the establishment). This avoids spurious exits when assessing the role of efficiency and market selection in determining firm survival: a plant closure may be the result of internal restructuring

[3]While this total of 23,000 firms represents 25% of all manufacturing firms in France, it accounts for 75% of employment and 80% of value added in French manufacturing.

Table 1 Entry and exit by year

year	Entrants	Continuing	Exits	Turnover rate
1990	1887	19,351	1738	18.7
1991	2130	19,181	2057	21.8
1992	1683	18,896	2415	21.7
1993	1157	18,295	2284	18.8
1994	1961	17,785	1667	20.4
1995	1511	17,816	1930	19.3
1996	1644	17,679	1648	18.6
1997	1626	17,828	1495	17.5
1998	1374	18,007	1447	15.7
1999	1304	17,911	1470	15.5
2000	1345	17,758	1457	15.8
2001	1464	17,617	1486	16.7

Note: Figures indicate firm counts, except the last column which reports yearly turnover rates, defined as the sum of entrants and exits relative to continuing firms.

rather than mere market selection.[4] To assess the contribution of market selection to productivity growth, firm rather than plant level datasets are at need.

Each firm is identified by a unique number used to track the firm over time and to compute entry and exit flows. This does not allow us to discriminate neither between true entry/exit nor mergers and acquisitions.[5] This limitation is common to most of the micro datasets used in the literature, and consistently with Bartelsman *et al.* (2005), we rely on the following standard definitions of entrant, continuing, and exiting firms. An entrant is an identification number that exists in the reference year t, but not in $t-1$; an exiting firm is an identification number that exists in year t, but not in $t+1$. A continuing firm is an identification number that exists in years t, $t+1$, and $t-1$. When applied to our dataset, these definitions induce some re-entry phenomena, due essentially to the +20 employee threshold effect. In what follows, we correct for this bias by discarding re-entering firms from our sample.

Table 1 shows that firms' entry and exit rates average about 9 and 10%, respectively. The turnover rate, defined as the sum of the entry and the exit rates,

[4]A firm may decide to close a plant for reasons other than relative efficiency or pure selection. The decision will draw primarily on the ability of the firm to restructure and monitor its scope of activities across several plants.

[5]In EAE, an acquisition results in the disappearance of the identification number of the acquired unit and persistence of the identification number of the acquiring unit. A merger can result either in the disappearance of the identification numbers of both firms and in the creation of a new one, or the disappearance of one of the identification numbers and the persistence of the other.

Table 2 Sectoral turnover rates, firm counts, and employment weighted

Industry	Number of firms			Employment		
	Entry	Exit	Sum	Entry	Exit	Sum
Clothing and footwear	9.2	15.2	24.4	5.1	9.3	14.4
Printing and publishing	9.2	11.0	20.1	5.4	6.6	12.1
Pharmaceuticals	8.1	8.4	16.6	4.3	6.2	10.5
House equipment and furnishings	8.3	10.4	18.8	4.8	5.9	10.7
Automobile	7.3	7.1	14.4	7.2	6.6	13.8
Transportation machinery	8.9	9.4	18.2	5.5	3.5	9.1
Machinery and mechanical equipment	9.7	9.8	19.5	5.0	5.5	10.6
Electrical and electronic equipment	11.9	12.4	24.2	5.4	5.4	10.8
Mineral industries	7.6	8.6	16.2	3.9	4.7	8.6
Textile	7.6	10.0	17.6	4.7	6.5	11.3
Wood and paper	8.0	9.0	17.1	4.8	5.8	10.6
Chemicals	8.1	7.1	15.2	3.9	3.8	7.8
Metallurgy (Iron and steel)	8.0	7.9	15.9	6.1	5.2	11.3
Electric and Electronic components	9.5	8.9	18.4	5.2	5.7	10.9

Note: The turnover rate is defined as the sum of entrants and exitors relative to continuing firms.

averages 18% per annum, displaying a slightly decreasing trend over the period. These numbers are slightly lower than those reported by Bartelsman *et al.* (2005) for France. However, they show that France has a relatively high turnover rate as compared to other OECD countries.

Another feature is cross sectoral heterogeneity in terms of overall turnover rates, firms' entry and exit rates (Table 2). The most turbulent sectors are *clothing and footwear*, *printing and publishing*, and *electrical and electronic equipment*, while the least turbulent ones are *automobile*, *chemicals*, *mineral industries*, and *metallurgy*. These observed cross-industry differences conceal differences in entry costs across industries (Hopenhayn, 1992), differences in market size (Asplund and Nocke, 2003), or differences in rate of technological progress (Jovanovic and Tse, 2006).

What do these turnover rates tell us about MSM? The preferred way to assess the well-functioning of MSM is to compute measures of productive efficiency at the firm level in order to compute the mean productive efficiency of both entering and exiting firms. We do this by applying two complementary indicators, namely labor productivity (LP) and total factor productivity (TFP). *LP* is defined as the log-ratio of real value added on labor:

$$\ln LP_{it} = \ln\left(\frac{V_{it}}{L_{it}}\right) \tag{1}$$

where V denotes the value added of firm i at time t deflated by the sectoral price indexes published by INSEE (French System of National Accounts), and L is the number of hours worked. Furthermore, we compute *TFP* using the so-called *multilateral productivity index* first introduced by Caves *et al.* (1982) and extended by Good *et al.* (1997). This methodology consists of computing the TFP index for firm i at time t as follows:

$$\ln TFP_{it} = \ln Y_{it} - \overline{\ln Y_t} + \sum_{\tau=2}^{t}\left(\overline{\ln Y_\tau} - \overline{\ln Y_{\tau-1}}\right) - \left[\begin{array}{l} \sum_{n=1}^{N} \frac{1}{2}\left(S_{nit} + \overline{S_{nt}}\right)\left(\ln X_{nit} - \overline{\ln X_{nt}}\right) \\ + \sum_{\tau=2}^{t}\sum_{n=1}^{N} \frac{1}{2}\left(\overline{S_{n\tau}} + \overline{S_{n\tau-1}}\right)\left(\overline{\ln X_{n\tau}} - \overline{\ln X_{n\tau-1}}\right) \end{array}\right] \quad (2)$$

where Y denotes the real gross output using the set of N inputs X, where input X is alternatively capital stocks (K), labor in terms of hours worked (L), and intermediate inputs (M). Variable S is the cost share of input X in the total cost (see Appendix A for a full description of the variables). Subscripts τ and n are indices for time and inputs, respectively, and upper bars denote sample means.[6] Importantly, this index is its transitive, which allows the comparison of any two firm-year observations. Applied to our dataset, the multilateral index reveals strong cross-sectoral variations in productivity growth over the period. Average TFP growth rates range from around 3% per annum in the fastest growing industries, to <0.3% per annum in the slowest growing industries. In the remainder of this work, we trimmed the dataset by screening out observations located in the top 1% and the bottom 1% of the TFP distributions, in order to control for the presence of outliers which could alter the results of the subsequent calculations.

2.2 Characteristics of entrants and post-entry performance

Before investigating the determinants of firm exit, it is necessary to depict the post-entry performance of entrants. Examination of their (unreported) survival rates shows that entrants in our dataset suffer from high rates of infant mortality (18% in the first year) which declines steeply with age to stabilize at 5–7% after the age of 10. Only half of a given cohort managed to survive beyond their sixth year. These preliminary statistics are consistent with most empirical analyses of firm demography (Caves, 1998; Bartelsman *et al.*, 2005).

[6]Note that Equation (2) implies that reference points $\overline{\ln Y}$ and $\overline{\ln X}$ are the geometric means of the firm's output and input quantities, respectively, whereas the cost shares of inputs for the representative firms $\overline{S}$ are computed as the arithmetic means of the cost shares for all firms in the dataset.

Table 3 Relative TFP distributions

Quintile	Age = 1		Age = 13	
	Survivors	Exitors	Survivors	Exitors
1	22.02	23.36	20.02	35.03
2	18.32	19.42	21.48	21.66
3	18.48	18.15	20.71	15.29
4	19.52	18.19	20.34	15.92
5	21.67	20.87	17.45	12.10
	100	100	100	100

Note: See text for computational details.

Because productive efficiency is traditionally considered a major determinant of firm survival, we estimate post-entry TFP performance by computing for a given year t the TFP of each firm i *relative* to all firms with a different age in the industry:

$$\ln TFP^{ri}_{it,a} = \ln TFP^{S}_{it,a} - \ln \overline{TFP}^{S}_{t} \tag{3}$$

where $\ln \overline{TFP}^{S}_{t}$ is the arithmetic mean of the TFP of the firms in sector S at period t:

$$\ln \overline{TFP}^{S}_{t} = \frac{1}{n}\sum_{i\in S}^{n} \ln TFP^{S}_{it,b\neq a}$$

and a and b stand for age. The first two columns in Table 3 show these relative productivity distributions over the quintiles for two categories of entrants: those surviving at least one year (*Survivors*), and those exiting after only one year (*Exitors*). It is interesting that the two distributions are similar, suggesting that technical efficiency is not a crucial determinant of young firms' survival. Mature firms (age = 13) exhibit sharper differences, since exitors are clearly concentrated in the lowest part of the productivity distribution (Quintile 1): for mature firms, productivity is closely associated with survival. This is preliminary evidence to support the hypothesis that the determinants of survival change with firm age, allowing for a potentially inefficient market selection process affecting young firms. We return to this aspect in Section 3.

Another interesting result is that, the relative productivity indexes of entrants are almost uniformly distributed across quintiles. This contradicts the basic vintage theory that the entrants are more productive because they embody up-to-date technologies. To shed more light on this, we follow the TFP dynamics of firms after entry. Figure 1 displays two sorts of TFP dynamics: the dotted line depicts the dynamics of firms' TFP relative to the sector average ($\ln TFP^{ri}_{it,a}$);

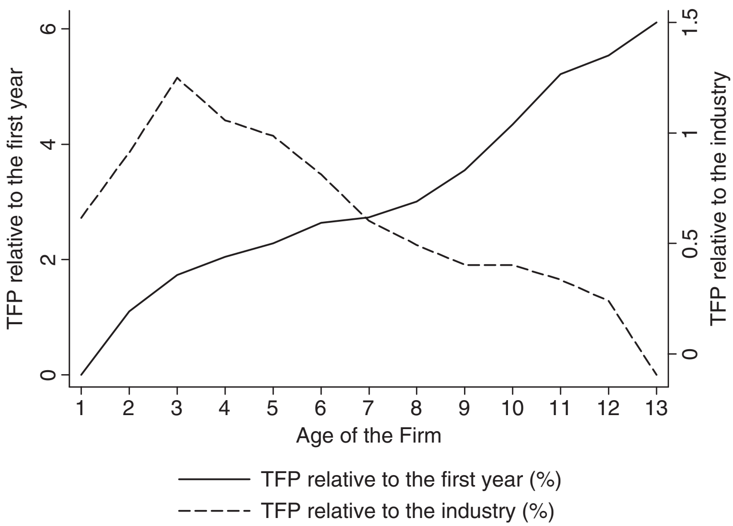

Figure 1 Post-entry TFP performance (%).

the plain line represents the dynamics of firm TFP relative to its year of entry. Formally:

$$\ln TFP_{it}^{re} = \ln TFP_{it,a} - \ln TFP_{it,a=1} \tag{4}$$

where $\ln TFP_{it,a=1}$ is the TFP of firm i in year t at time of entry.[7] Figure 1 shows that conditional on survival, the representative firm enjoys continuous productivity gains. Moreover, entrants have a significant productivity advantage over incumbents of around 0.6%. Conditional on survival, this relative advantage increases to 1.25% to then converge monotonically over the next decade toward the industry average.

The initial rise of TFP relative to the industry is puzzling: it may result from a selection effect, i.e., only the most productive firms survive, or a learning effect, i.e., firms TFP increases over the course of their productive activities. In order to discriminate between these effects, we concentrate on successful entrants, defined as firms that survive for a substantial period of time. Should the selection effect dominate over the learning effect, the peak at age 3 should simply vanish, implying that the observed increase in relative TFP is the result of an efficient MSM. Should the learning effect dominate, the general pattern would remain unchanged.

Figure 2 displays measures $\ln TFP_{it,a}^{ri}$ for four types of entrants: all entrants; entrants surviving at least 3 years; entrants surviving at least 5 years; entrants surviving at least 10 years. It shows that the general pattern is robust to entrant types. The initial increase persists until age 3 over all life durations, implying that

[7]Note that Figures 1 and 2 and Table 4 report mean differences expressed as percentages.

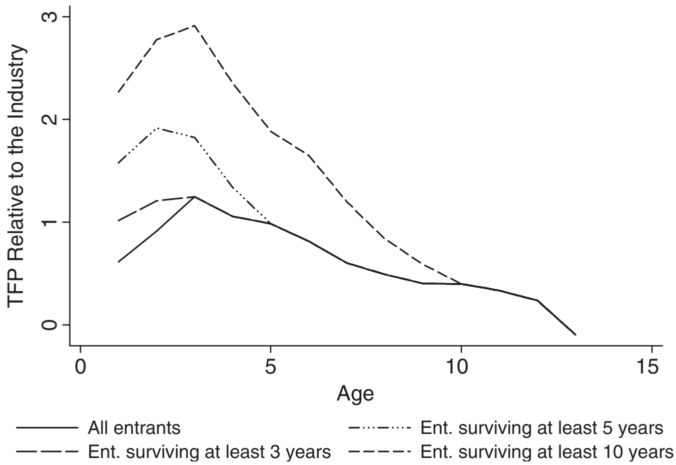

Figure 2 Post-entry TFP performance, by life duration (%).

the learning effect dominates over the vintage effect, at least for infant firms.[8] Moreover, the initial TFP advantage of entrants is positively associated with life duration, suggesting that successful entrants enjoy a greater productive advantage from birth onwards. This also underlines the importance of initial conditions in shaping the fate of firms. Altogether, the data militate in favor of a model of industry dynamics in which a learning effect dominates when firms are young and a vintage effect dominates when firms become mature. Importantly, the presence of both effects is suggestive that both interact to drive aggregate productivity growth (Baldwin and Rafiquzzaman, 1995).

To complete the picture, Table 4 provides information on the dynamics of TFP, LP, employment (L), and capital intensity (K/L) after entry.[9] We observe a well-documented result (Caves, 1998) where entrants are significantly smaller than incumbents (37%) and dramatically less capital-intensive (50%). This lack of productive capital translates into a significant disadvantage in labor productivity (−6.2%) despite the relative advantage in TFP previously mentioned. But conditional on firm survival, young firms double their capital-labor ratio within eight years and converge rapidly toward the average level of labor productivity.

[8]The persistence of year 3 as the peak year is very puzzling. The fact that the learning effect is bounded to such a short period of time suggests that firms learn to use a vintage technology without updating it. Obviously, this question is beyond the scope of this article.

[9]Again, values relative to the rest of the industry are computed as the log difference between the observed value of firms of a given age, and the sectoral mean value of firms of a different age $x^{ri}_{it,a} = x_{it,a} - \overline{x_{it,b \neq a}}$. Values relative to the year of entry are computed as $\ln x^{re}_{it} = \ln x_{it,a} - \ln x_{it,a=1}$.

Table 4 Post entry performance of firms, by age (%)

Age	Relative to industry average					Relative to firm year of entry				
	n	TFP	LP	L	K/L	*n*	TFP	LP	L	K/L
1	15,695	0.62	−6.02	−36.68	−50.83	15,695	*0.00*	*0.00*	*0.00*	*0.00*
2	13,630	0.91	−4.21	−30.43	−42.62	12,951	1.10	3.64	3.82	20.94
3	12,188	1.25	−2.30	−25.11	−33.97	10,158	1.73	6.09	8.38	36.92
4	11,359	1.06	−1.49	−21.99	−26.53	8257	2.05	8.49	12.16	50.89
5	10,540	0.99	*−0.59*	−18.47	−20.16	6797	2.28	10.69	16.29	64.28
6	9742	0.81	*−0.21*	−15.86	−13.96	5656	2.64	12.86	20.22	75.98
7	8942	0.60	*0.54*	−12.41	−8.10	4573	2.73	14.28	23.60	88.39
8	7542	0.49	*0.34*	−10.03	−4.45	3626	3.01	16.50	26.74	100.85
9	6400	0.40	*0.91*	−7.70	*−0.94*	2852	3.55	20.11	28.66	116.31
10	5347	0.40	*1.33*	−4.41	2.83	2077	4.34	23.12	29.95	132.81
11	4653	0.33	*0.26*	−3.94	5.95	1620	5.22	27.23	31.99	148.22
12	3841	*0.24*	1.55	*−1.59*	9.20	1032	5.54	30.05	33.07	174.41
13	3085	*−0.10*	2.12	*0.92*	14.44	459	6.11	33.37	32.10	185.92

Note: Mean values $\overline{x^{ri}_{it,a}}$ and $\overline{x^{re}_{it,a}}$ reported. Significant differences are indicated in italics. See text for computational details of $x^{ri}_{it,a}$ and $x^{re}_{it,a}$. *n*: number of observations.

3. Market selection along the firm life cycle

3.1 Econometric models

This section develops an empirical model of the determinants of the hazard rate of exit. It is based on a discrete time duration model for grouped data following the approach introduced by Prentice and Gloeckler (1978). Suppose there are firms $i = 1, \ldots, N$, that enter the industry at time $t = 0$. The hazard rate function is defined as the probability of failure in interval t and $t + 1$ divided by the probability of surviving at least until t. The hazard rate function for firm i at time $t > 0$ and $t = 1, \ldots, T$ is assumed to take the proportional hazard form: $\theta_{it} = \theta(t) \cdot X'_{it}\beta$, where θ_{it} is the baseline hazard function and X_{it} is a series of time-varying covariates summarizing observed differences among firms. The discrete time formulation of the hazard of exit for firm i in time interval t is given by a complementary log logistic function such as:

$$h_t(X_{it}) = 1 - \exp\{-\exp(X'_{it}\beta + \theta(t))\} \tag{5}$$

where $\theta(t)$ is the baseline hazard function relating the hazard rate $h_t(X_{it})$ at the t-th interval to the spell duration (Jenkins, 1995). This model can be extended to account for unobserved but systematic differences across firms.

Suppose that unobserved heterogeneity is described by a random variable μ_i independent of X_{it}. The proportional hazards form with unobserved heterogeneity can be written as:

$$h_t(X_{it}) = 1 - \exp\{-\exp(X'_{it}\beta + \theta(t)) + \mu_i\} \quad (6)$$

where μ_i is an unobserved individual-specific error term with zero mean, uncorrelated with the Xs. Model (6) can be estimated using standard random effects panel data methods for a binary dependent variable, under the assumption that some distribution is provided for the unobserved term. In this article, we assume that μ_i is distributed normal.[10] Also, we perform a likelihood ratio (LR) test for the unrestricted (with unobserved heterogeneity) and the restricted models (without unobserved heterogeneity). The reported estimates are chosen from the LR test.

We expect the hazard of exit to depend primarily on firm performance in terms of profitability and productivity. Profitability is the ratio of operating cash flow over assets.[11] Because operating cash flow can be negative, and values in log will be entered as regressors, we transform the variable by adding to it its minimum value plus 1. Moreover, we control for negative profits by adding to the vector of independent variables a dummy variable set to unity if the firm has negative profitability, 0 otherwise.[12] We expect profitability to be the main explanation for firm survival, and to impact negatively on the hazard rate of exit. The reason for this is that profitability is the chief objective if firms are to survive and expand their activities. Productivity should play a similar role, albeit in a more subtle way. Productivity impacts on profitability: higher productive efficiency means lower unit costs, positively boosting firm operating income in the short-run. Thus the inclusion of both profitability and productivity as explanatory variables in estimating firm survival, dictates that both be independent. In order to account for this, we extract the profitability residual of P as follows:

$$\ln P_{it}^{u|tfp} = \ln P_{it} - \ln \hat{P}_{it} \quad (7)$$

[10]See Chapters 17 and 18 of Cameron and Trivedi (2005) for a discussion on the appropriate choice of distribution for the parameter of unobserved heterogeneity.

[11]Operating cash flow is defined as earnings before interest, taxes, depreciation and amortization, derived from the company's income statement. Firm assets are defined as a company's common stock equity, i.e. total assets, from which are subtracted liabilities, preferred stock, and intangible assets.

[12]To do this, we do not set the threshold value of profits to its accounting value, in other words, operating cash flow must be above zero. We define the indicator variable on negative profit to be equal to unity if the operating cash flow does not outweigh the interest charged on debts, and 0 otherwise. This dummy variable is designed to grasp more accurately the short-run, break-even condition that price covers average variable costs.

where

$$\ln \hat{P}_{it} = E[\ln P_{it} | \ln TFP_{it}] = \hat{\beta} \times \ln TFP_{it}$$

and

$$\hat{\beta} = \frac{\ln P_{it} - \left(\alpha + \sum_{jt} \delta_{jt} \times (S_j \cdot D_t) + \mu_i + \varepsilon_{i,t} \right)}{\ln TFP_{it}}$$

where profitability P is defined as the ratio of operating income over assets, and both S and D are indicator variables for sector j and year t, respectively. Depending on their age, we would not expect all performance variables to have a similar effect. As documented in Section 2, entrants suffer from significantly higher hazard rates of exit. The reasons could be related to firm-level characteristics, such as smaller sizes of young firms, structure of ownership (Audretsch and Mahmood, 1995), access to financial resources (Aghion *et al.*, 2006), or to industry characteristics such as MES, nature of the technological regime (Audretsch, 1991), and stage in the industry life cycle (Argawal and Audretsch, 1995). Therefore, we expect productivity to be a deterrent to firm exit for incumbents more than for entrants.

We follow Mata and Portugal (1994) and Mata *et al.* (1995), and include a set of variables controlling for market structures and turbulence that may steer firm exit beyond and above the presumably chief role of firm performance. To do so, we define the industries at the 3-digit level, decomposing French manufacturing into 53 classes. The reason for not using broader classes is to define markets around more homogeneous product classes. Although this remains far from a fully fledged product definition, as in Klepper (2002b) for example, this finer level of industry definition should prove more satisfactory than the 2-digit level.

We define market structures by measuring the size of the market (computed as the sum of firm sales for firms belonging to the 4-digit industry) and the Herfindahl concentration index (defined as the sum of the squared market shares). Interpreting these measures as an indirect measure of industry maturity, we expect both to relate negatively to firm exit. We also provide an *ex ante* measure of barriers to entry by computing the MES—following the methodology defined by Lyons (1980).[13] The characteristics of industry dynamics indicate the turbulence of an industry. We define market growth as the growth rate in the industry sales. The assumption here is that higher growth rates should equate with more frequent market opportunities. We also control for the number and average size of entrants. First, entry represents a threat—an increase in competition—for incumbents; therefore, in industries with high entry rates, we would expect firm lifetimes to be shorter, i.e., we would expect a

[13]In simple terms, MES is defined as the logarithm of one half of the average size of the firms that, on average, operate 1.5 establishments within an industry.

Table 5 Persistency in variables

	β	N	R^2
Profitability (log)	0.769	174,416	0.57
Residual of profitability (log)	0.773	174,416	0.58
TFP (log)	0.764	174,416	0.57
LP (log)	0.912	174,416	0.83
Herfindahl (log)	0.869	583	0.83
MES (log)	0.607	583	0.37
Market size (log)	1.011	583	0.99
Market growth (log)	0.158	583	0.03
Mean size of entrants (log)	0.374	583	0.14
Number of entrants (log)	0.873	538	0.75

Note: Ordinary least squares on the value of variables lagged 1 year.

positive sign on firm exit. The average size of entrants, in terms of sales, indicates demand attributable to entrants.[14] We expect a negative sign for the average size of entrants on *young* firm hazard rates.

Before discussing the results, we look at the persistency of all variables by regressing the explanatory variables on themselves. In order for a firm to decide to withdraw from the market, observation of their current performance must provide them with reliable information on the stream of expected future profits. In order for these variables to be economically meaningful, we start by revealing their persistency (Table 5). We see that the variables characterizing firm performance are all very persistent, notably $\ln P_{it}^{u|tfp}$ and TFP. Concerning the latter, persistency had to be expected, since productivity is conditional on the firm's workforce, capital stock, and a vector of unobserved but persistent characteristics such as the organization of productive tasks, the presence of a labor union and management practices.

3.2 Results

Table 6 reports the results for different specifications, introducing all explanatory variables sequentially. All models initially control for unobserved heterogeneity as specified above. Looking at the LR test for $\rho = 0$, the unrestricted model accounting for unobserved heterogeneity is preferred over the restricted specification without

[14]Note that inclusion of both number and average size of entrants is tantamount to jointly introducing the number and total size of entrants and to adding a constraint to the parameter estimate associated with the number of entrants.

Table 6 Sequential regressions for firm hazard rates

	(1)	(2)	(3)	(4)	(5)
Profit (log)	−0.137***	−0.101***			
	(0.025)	(0.025)			
Profit < 0 (Dummy)	0.660***	0.633***	0.881***	0.891***	0.895***
	(0.018)	(0.018)	(0.071)	(0.071)	(0.071)
TFP (log)		−0.396***	−0.577***	−0.543***	−0.498***
		(0.058)	(0.063)	(0.064)	(0.064)
Res. of profit (log) (>0)			−0.061	−0.058	−0.045
			(0.026)**	(0.026)**	(0.026)*
Res. of profit (log) (<0)			−0.319***	−0.323***	−0.322***
			(0.069)	(0.069)	(0.069)
Herfindahl (log)				−0.019**	0.056***
				(0.007)	(0.011)
MES (log)				−0.141***	−0.100***
				(0.017)	(0.018)
Market size (log)				−0.046***	−0.086***
				(0.012)	(0.014)
Market growth (log)					−0.723***
					(0.151)
Mean size of ent. (log)					−0.095***
					(0.011)
Number of ent. (log)					0.114***
					(0.014)
Observations	209,005	209,005	209,005	209,005	208,535
Number of firms	34,589	34,589	34,589	34,589	34,585
Log likelihood	−57,825.3	−57,802.0	−57,797.3	−57,755.3	−57,543.2
LR test[a]	1807.4***[b]	46.6***	9.4***	84.0***	424.3***
ρ	0.066	0.066	0.066	0.065	0.061
LR test for $\rho = 0$	57.5***	60.4***	60.5***	59.8***	53.9***

Note: Link function: complementary log–log with unobserved heterogeneity. Non-parametric baseline hazard Function. All models include a full vector of time dummies, year dummies, age at entry, and an indicator variable for the firm's presence in the database starting year 1984. Standard errors in brackets.

*Significant at 10%; **significant at 5%; ***significant at 1%.

[a]LR test on previous column.

[b]LR test on model without profitability variables.

unobserved heterogeneity. For the sake of clarity, we report marginal effects.[15] We start by introducing profitability as the sole explanatory variable, together with the indicator variable pointing firms recording a negative operating income. We find that profitability boosts firm survival in two ways. First, profitable firms are more likely to remain in the market (−0.137). In terms of marginal effect, a negative departure of 1 SD from the sample mean of profitability raises the probability of exit by a considerable 40%. Most importantly, the hazard rate of exit rises significantly if profits are negative (+0.660), increasing the probability of exit by 88% relative to firms with positive operating cash flows. Looking at the full specification (Column 5), the marginal effect reaches 134%. Hence profitability significantly affects the hazard rate of exit in the expected direction and magnitude.

In Column (2), we introduce TFP as a supplementary explanatory variable. The inclusion of productivity adds significant information, as shown in the LR test. We find all variables to be significant, with productivity negatively affecting the hazard rate of exit. Textbook economics tells us that this had to be expected, since the implication is that more efficient firms are more likely to survive and remain on the market. However, as stressed earlier, the introduction of both profitability and productivity makes it difficult to separate the effects of productive efficiency and profitability, irrespective of TFP. Therefore, in Column (3), we amend the model in two ways. First, we introduce net profitability of the contribution of TFP, as specified in Equation (7). Second, we distinguish between positive and negative profitability (net of TFP) by interacting the indicator variable on negative profits with $\ln P_{it}^{u|tfp}$. We do this to account for the possible non-linearity of the impact of profitability on the hazard rate of exit. Whereas, we would expect negative profitability to depend largely on *how negative they are*, the effect of positive profitability on firm survival should be less strict as once profits are positive, the remuneration of all production factors is secured.

From Column (3) we see that, the new specification adds significant information (LR = 9.4) and all variables are significant. TFP impacts negatively on the probability of exit (−0.577), implying that markets select against less efficient firms. A 1 SD move above the representative firm decreases the probability of exit by 7.5%. Interestingly, we find the effect of negative profits to be far more dramatic than recording positive ones. A 1 SD below the average value of negative profit is associated with a 13% increase in the probability of exit, whereas 1 SD above the average value of positive profit is associated with a 3.5% decrease in the

[15]Marginal effects are computed as the percentage difference between the probability of exit of the representative firm with mean age and for the mean year ($h^{\bar{x}}$) with the probability of exit adding 1 SD to the average value of the considered explanatory variable $h^{\bar{x}+\sigma_x}$, holding all other explanatory variables at their average value. For the qualitative variable indicating negative profits, the difference is computed between probabilities with null or unit values.

probability of exit.[16] Altogether, it appears that the overall effect of profitability is far larger than that of productivity, the overall effect of negative profit being to increase the probability of firm exit by 143%. These results should come as no surprise: profitable firms ought to remain in the market, whereas variations in firm profitability due to micro-, meso-, and macro-economic shocks may have dramatic consequences for firm survival. These results hold strongly across alternative specifications displayed in subsequent columns.

Column (4) includes all the variables describing market structures: (the log of) the size of the industry; (the log of) the Herfindahl index; (the log of) the MES. First with a versatile sign in both columns (4) and (5), the role of market concentration (Herfindahl) is hard to grasp. In fact, concentrated industries, in a traditional sense, are imperfect markets, which should boost the survival of incumbents with strong market power, and increase the probability of exit for firms with weak market power. Thus the effect of market concentration mitigates these two opposing forces, which may in turn produces instability in the role of concentration. Second, we find that, the MES boosts the survival of incumbent firms (−0.141): in industries where MES is 1 SD higher than the representative industry, the probability of firm exit decreases by a significant 6%. In fact, as a measure of barriers to entry, MES must be a hindrance to the threat of new firms to incumbents.

Industry size has a similar effect (−0.046), implying that in industries with a total industry sales value 1 SD higher than the representative industry, the probability of firm exit decreases by a significant 3%. There are two alternative, perhaps opposite, interpretations. First, large sectors (in terms of sales) offer a wide range of unexplored and unexploited, but available market opportunities. This allows all types of firms to benefit from first mover advantage in these unexplored niches. It is not clear whether incumbents or entrants are better able to seize such opportunities as this depends on initial sunk costs, barriers to entry, minimum efficient scale, and the technological competencies needed to enter these niches. Second, industry size acts as a proxy for the maturity of industry. With little or no room for additional entrants, all incumbent firms operate near or at equilibrium, such that the rate of industry turnover is low. Thus the observed coefficient could also indicate industry maturity. It is not easy to say which effect dominates, and we will come back to this issue when we investigate the stability of selection mechanisms by distinguishing entrants from mature firms. Note that, the impact of industry size doubles in our preferred specification, where the probability of exit diminishes by almost 6%.

To further our analysis of the influence of industry characteristics on market selection, Column (5) introduces variables to describe industry turbulence in terms of market growth rate, and number and mean size of entrants. Rapidly expanding industries offer numerous niche opportunities, which in turn increase firm survival.

[16]Note that, as we introduce more explanatory variables into subsequent regressions, the parameter estimate for positive profitability becomes decreasingly significant.

A 1 SD move above the average market growth rate decreases the probability of exit by 4.7%. Large entrants are also associated with a lower probability of exit of 6.8%. The largest marginal effect is found for number of entrants (+11%): industries with numerous entrants have equally numerous firm exits. This result confirms other findings that entry and exit rates are tightly correlated (Caves, 1998). Note that effect of the Herfindahl index on the hazard of exit is both significant and positive. This suggests that concentrated industries boost the selection of firms: processes of industrial concentration translate into a lower number of firms by boosting firm exit.

Taken together, our results suggest that the chief factor in firm selection is profitability. If firms are profitable to the point where they can remunerate their production factors, they will enjoy significantly higher chances of survival. If we look only at the role of productivity, we find that markets select according to what the theory tells us, i.e., markets select out less efficient firms. Market structures and industry turbulence also have an effect. Imperfect markets, in terms of industry size and barriers to entry, equate with higher firm survival for incumbents. Industry growth and firm entry also influence the hazard rate of exit, albeit in opposite directions. Lastly, we find that the effect of market concentration depends on the econometric specification. Notably, the fact that control for industry turbulence modifies its effect is suggestive that market concentration has a differentiated effect on firms, depending on their market power. Firms with high market power should benefit from concentration in terms of survival. Firms with a low market power, typically young firms, should suffer from market concentration, which will reduce their probability of making it to the next period.

To address this issue directly, we decompose the population of firms into age classes: from ages 1 to 3, from ages 4 to 9, and 10 years or more in order to investigate whether market selection forces operate equally over different age classes. Table 7 displays the results for the whole population of firms (Column 5, replicated from Table 6) and for different age classes. Because it is hard to compare the parameter estimates *per se*, we computed the marginal effects of each variable on the hazard rate of exit, displayed in Table 8.

First, we looked at the effects of firm performance on the hazard of exit. The most immediate observation is that the chief reason for firm exit, across all types of firms, is a negative operating cash flow. On average, a negative operating cash flow more than doubles the probability of exit (+134.0%, which equates with a multiplication of the probability of exit by a factor of 2.34). Importantly, this effect becomes more dramatic with firm age. Whereas, the fact of having negative profit almost doubles the hazard rate of young firms (+86.1%), it triples that of old firms (+200.8%). These figures may seem unduly large, but their economic meaning is crystal clear. The decision to exit is first and foremost determined by the capacity of firms to generate profit, and this condition becomes more critical as firms grow. The second observation is that if global manufacturing markets screen out less efficient firms,

Table 7 Market selection along the firm life cycle

Age	(5) All	(6) [1; 3]	(7) [4; 9]	(8) [10; +[
Profit < 0 (Dummy)	0.895***	0.682***	0.861***	1.145***
	(0.071)	(0.108)	(0.117)	(0.150)
TFP (log)	−0.498***	−0.125	−0.573***	−0.974***
	(0.064)	(0.097)	(0.104)	(0.135)
Res. of profit (log) (>0)	−0.045*	−0.043	−0.045	−0.116**
	(0.026)	(0.040)	(0.043)	(0.055)
Res. of profit (log) (<0)	−0.322***	−0.252**	−0.283**	−0.560***
	(0.069)	(0.104)	(0.114)	(0.148)
Herfindahl (log)	0.056***	0.068***	0.070***	0.026
	(0.011)	(0.018)	(0.019)	(0.023)
MES (log)	−0.100***	−0.122***	−0.105***	−0.057*
	(0.018)	(0.030)	(0.030)	(0.031)
Market size (log)	−0.086***	−0.111***	−0.111***	−0.010
	(0.014)	(0.023)	(0.022)	(0.026)
Market growth (log)	−0.723***	−0.987***	−0.108	−1.205***
	(0.151)	(0.251)	(0.230)	(0.321)
Mean size of ent. (log)	−0.095***	−0.108***	−0.082***	−0.072***
	(0.011)	(0.019)	(0.018)	(0.022)
Number of ent. (log)	0.114***	0.170***	0.124***	0.033
	(0.014)	(0.025)	(0.023)	(0.027)
Observations	208,535	43,364	84,244	80,927
Number of firms	34,585	20,217	24,905	13,887
Log likelihood	−57,543.2	−17,662.4	−19,833.2	−17,000.7
ρ	0.061	0.044	0.017	0.041
LR test for $\rho=0$	53.9***	114.7***	5401.3***	114.6***

Note: See previous table footnote.

the consequence of a negative productive efficiency gap on firm survival increases with age. For old firms, productivity is negatively associated with the hazard of exit, suggesting that a move away from productive efficiency is particularly painful and may translate into lower profitability, and eventually into exit from the market. For young firms, TFP has no particular effect.

These results suggest that firm performance, in terms of either profitability or productivity, becomes gradually more critical for firm survival as the firm grows. We can interpret this in two ways. First, it reflects the opportunity costs of remaining in the market, that is, the difference between the economic definition of profit, which includes opportunity costs, and the accounting definition of profits. Clearly,

Table 8 Marginal effects of firm performance and industry structure on the hazard rate of exit

Age	All	[1; 3]	[4; 9]	[10; +[
Profit < 0 (Dummy)	134.0	86.1	126.6	200.8
TFP	−6.5	*−1.7*	−7.4	−12.0
Res. of Profit.(log) (>0)	*−2.5*	*−2.4*	*−2.5*	−6.4
Res. of Profit. (log) (<0)	−11.8	−9.4	−10.4	−19.8
Herfindahl	6.2	7.6	7.9	2.8
MES	−4.2	−4.7	−4.2	*−2.7*
Market Size	−5.7	−6.8	−7.1	*−0.7*
Market Growth	−4.5	−6.1	*−0.7*	−6.7
Mean Size of entrants	−6.8	−7.3	−5.7	−5.5
Number of entrants	11.6	16.3	12.6	*3.3*

Note: Percent Change in the Probability of Exit. Figures in italics mean non significance at 5% level. See text for computational details.

our results suggest that the opportunity costs of remaining in the market grow with firm age, moving the cursor from the minimum level of profitability to the right of the distribution. Second, the difference simply reflects the fact that young firms are more exposed to market selection, so that the relationship between firm performance and survival becomes looser. In other words, the micro-economic determinants of markets selection of young firms lie elsewhere, perhaps in firm size (Audretsch and Mahmood, 1995) and, again, credit constraints (Aghion *et al.*, 2006).

Turning to the effects of market structure on firm survival, there are two main results. Overall, we find that market structures impact mainly on young firms rather than on mature firms. Market concentration impacts positively on the probability of young and middle-aged firms exiting. Old firms are immune to it. This reflects both the positive correlation between firm age and firm size, and the positive association between firm size and survival rates. Since older firms are generally larger, they contribute positively to industry concentration, while they are hard to market contest. The puzzle lies in the minimum efficient scale. We would expect MES to have a negative influence on the survival rates of young firms. Such newly established companies generally operate at suboptimal scale, dragging profitability downwards. This somewhat surprising result is reminiscent of Audretsch's study (1991), which argues that since high MES industries are usually associated with high price-cost margins, firms operating at the optimal scale of production may in the short-run benefit from them. Finally, industry size is negatively associated with the hazard rate of exit of young firms. This argues in favor of the idea that large sectors offer a wide range of unexplored market opportunities principally for entrants, boosting their survival rate.

Second, the most important effect of industry characteristics on firm survival lies not in the static dimensions (concentration, scale and size), but in the dynamic features. The greatest effect is observed for the number of entrants, where 1 SD above the average value for number of entrants increases the probability of exit by 16% for young firms and by 12% for middle-aged firms. Large firms are not statistically influenced by the number of entrants. In fact, this result simply echoes the observation that entry and exit rates are highly correlated. Thus, young and middle-aged firms, not old firms, find it hard to survive in turbulent industries.

High market growth exerts a positive influence on young and old firms, but not on middle-aged firms. This result may be the replication of the Schumpeterian debate on the inverted U-shape relationship between firm size and innovation, provided that age and market opportunities can be considered acceptable proxies for firm size and technological opportunity, respectively. In our case, young firms benefit from flexibility and reactivity, allowing them to occupy strategic niches, whereas large firms may enjoy some size advantage in terms of higher internal economies of variety. This suggests that, both young and old firms succeed in seizing market opportunities, but in rapidly growing industries, the critical age remains the middle area where firms need to scale up their operations without the benefit of either flexibility or economies of variety.

These findings suggest the existence of a two-tier market structure. The first layer is comprised of rather stable large firms, i.e., incumbents, for which competition is mainly based on price competition, implying that a departure from productive efficiency may be harmful. Such firms are not very sensitive to market structures because they themselves define the bulk of the industry. Competition relies heavily on productive efficiency, profitability and competition, and the players are fairly stable and well identified. In this case, market selection operates according to textbook economics, and persistent less efficient firms are driven out of the market. This first stable layer differs from the second, more turbulent, layer, where competition concerns both incumbents and new entrants. It is unbalanced with failing entrants being on average more efficient than surviving incumbents. Entrants are subjugated to market structures, since with the exception of number of entrants all industry characteristics have a significant effect on their fate.

4. Conclusion

We have analyzed market selection in French manufacturing markets for the period 1990–2002. Our investigation was based on the hypothesis that the competitive challenges that firms face may change along their life cycle. Our empirical investigation led to the following results. First, conditional on survival, firms experience continuous productivity gains as they grow older. In the first few years of existence, their productivity growth is higher than that of the industry average but then decreases continuously to finally converge toward the industry average. This militates for a model of industry dynamics in which a learning effect dominates when firms are young and a vintage effect dominates when firms become mature. Second, profitability is by far the chief reason for firm exit, since firms with negative profit are twice as likely to exit the industry. Third, firm performance, in terms of either profitability or productivity, becomes gradually more critical for firm survival over time. Conversely, the selection effect of industry characteristics—both in terms of industry concentration and turbulence—is much larger on young than on old firms. These findings suggest the existence of a two-tier market structure, where old and rather stable firms compete in productive efficiency and profitability while young firms evolve in a more turbulent environment where productive efficiency has less influence on selection.

These findings support the recent theoretical industrial dynamics literature insofar as exiting firms display below-average productivity levels and are smaller than their surviving counterparts. Thus, micro data on French manufacturing industries are consistent with the common view that market selection favors the most efficient firms. Our results also point to a need for a deeper examination of the institutional differences among countries, which could explain why MSM may impact differently on firms of different ages, within a given industry. The French case suggests that the effect of institutions that help markets to operate this selection process appropriately, could be more severe for young firms than for mature ones. Young firms are challenged not because of their relative efficiency—they reveal themselves more efficient than old firms—but because industry structures favor the survival of mature firms. This is not to say that mature firms are free from competition. Rather, mature firms face the challenge to continuously renew their productive efficiency and economic profitability, since those that persistently fail to do so will eventually be forced to quit the market.

Addresses for correspondence

Flora Bellone, Université de Nice Sophia-Antipolis, avenue Doyen Trotabas, 06050 NICE Cedex 1, France, and CNRS-GREDEG, 250 rue Albert Einstein, Valbonne – Sophia Antipolis, 06560 France. e-mail: flora.bellone@gredeg.cnrs.fr

Patrick Musso, Université de Nice Sophia-Antipolis, avenue Doyen Trotabas, 06050 NICE Cedex 1, France, and CNRS-GREDEG, 250 rue Albert Einstein, Valbonne – Sophia Antipolis, 06560 France. e-mail: patrick.musso@gredeg.cnrs.fr

Lionel Nesta, Observatoire Français des Conjonctures Economiques, Département de Recherche sur l'Innovation et la Concurrence, 250, rue Albert Einstein, Valbonne – Sophia Antipolis, 06560 France. e-mail: lionel.nesta@ofce.sciences-po.fr

Michel Quéré, CEREQ, Marseille, France. e-mail: michel.quere@cereq.fr

References

Aghion, P., T. Fally and S. Scarpetta (2006), 'Credit constraints as a barrier to the entry and post-entry growth of firms: lessons from firm-level cross country panel data,' Working Paper, Mimeo, 23 pp.

Argawal, R. and D. Audretsch (1995), 'The two views of small firms in industry dynamics: a reconciliation,' *Review of Economics and Statistics*, **1**, 97–103.

Asplund, M. and V. Nocke (2003), 'Imperfect competition, market size and firm turnover,' CEPR. Discussion Paper DP 2625, Centre for Economic Policy Research, www.cepr.org/pubs/dps/DP2625.asp.

Audretsch, D. (1991), 'New-firm survival and the technological regime,' *Review of Economics and Statistics*, **3**, 441–450.

Audretsch, D. and T. Mahmood (1995), 'New firm survival: new results using a hazard function,' *Review of Economics and Statistics*, **1**, 97–103.

Audretsch, D., Y. Prince and A. R. Thurik (1999), 'Do small firms compete with large firms?,' *Atlantic Economic Journal*, **2**, 201–209.

Aw, B. Y., X. Chen and M. J. Roberts (2001), 'Firm-level evidence on productivity differentials and turnover in taiwanese manufacturing,' *Journal of Development Economics*, **1**, 51–86.

Baily, M. N., C. Hulten and D. Campbell (1992), 'Productivity dynamics in manufacturing plants,' *Brookings Papers on Economic Activity*, **1992**, 187–249.

Baldwin, J. R. and M. Rafiquzzaman (1995), 'Selection versus evolutionary adaptation: learning and post-entry performance,' *International Journal Of Industrial Organization*, **13**, 501–522.

Bartelsman, E., J. C. Haltiwanger and S. Scarpetta (2004), 'Microeconomic evidence of creative destruction in industrial and developing countries,' The World Bank, Policy Research Working Paper Series: 3464, Washington, DC, USA.

Bartelsman, E., S. Scarpetta and F. Schivardi (2005), 'Comparative analysis of firm demographics and survival: evidence from micro-level sources in OECD countries,' *Industrial and Corporate Change*, **3**, 365–391.

Cameron, A. and P. Trivedi (2005), *Microeconometrics: Methods and Applications*. Cambridge University Press: Cambridge, New York, USA.

Caves, D. W., L. R. Christensen and W. E. Diewert (1982), 'Multilateral comparisons of output, input, and productivity using superlative index numbers,' *Economic Journal*, **365**, 73–86.

Caves, R. E. (1998), 'Industrial organization and new findings on the turnover and mobility of firms,' *Journal of Economic Literature*, **4**, 1947–1982.

Ericson, R. and A. Pakes (1995), 'Markov-perfect industry dynamics: a framework for empirical work,' *Review of Economic Studies*, **62**, 53–82.

Foster, L., J. Haltiwanger, C. J. Krizan, C. R. Hulten, E. R. Dean and M. J. Harper (2001), 'Aggregate productivity growth: lessons from microeconomic evidence,' in 'New developments in productivity analysis,' in C. R. Hulten, E. R. Dean and M. J. Harper (eds), *NBER Studies in Income and Wealth*, Vol. 63, University of Chicago Press: Chicago and London, pp. 303–363.

Good, D. H., M. I. Nadiri and R. Sickles (1997), 'Index number and factor demand approaches to the estimation of productivity,' in M. H. Pesaran and P. Schmidt (eds), *Handbook of applied econometrics: microeconometrics*. Blackwell: Oxford.

Gort, M. and S. Klepper (1982), 'Time paths in the diffusion of product innovations,' *Economic Journal*, **3**, 630–653.

Griliches, Z. and H. Regev (1995), 'Firm productivity in Israeli industry 1979–1988,' *Journal of Econometrics*, **1**, 175–203.

Hall, R. (1988), 'The relation between price and marginal cost in U.S. industry,' *Journal of Political Economy*, **96**(5), 921–947.

Haltiwanger, J. C. (1997), 'Measuring and analyzing aggregate fluctuations: the importance of building from microeconomic evidence,' *Federal Reserve Bank of St. Louis Review*, **3**, 55–77.

Hopenhayn, H. A. (1992), 'Entry, exit, and firm dynamics in long run equilibrium,' *Econometrica*, **5**, 1127–1150.

Jenkins, S. (1995), 'Easy ways to estimate discrete time duration models,' *Oxford Bulletin of Economics and Statistics*, **57**, 129–138.

Jovanovic, B. (1982), 'Selection and the evolution of industry,' *Econometrica*, **50**, 649–670.

Jovanovic, B. and C.-Y. Tse (2006), 'Creative destruction in industries,' *Mimeo*.

Klepper, S. (1996), 'Entry, exit, growth, and innovation over the product life cycle,' *American Economic Review*, **3**, 562–583.

Klepper, S. (2002a), 'The capabilities of new firms and the evolution of the US automobile industry,' *Industrial and Corporate Change*, **4**, 645–666.

Klepper, S. (2002b), 'Firm survival and the evolution of oligopoly,' *Rand Journal of Economics*, **1**, 37–61.

Klepper, S. and K. Simmons (2005), 'Industry shakeouts and technological change,' *International Journal of Industrial Organization*, **23**, 23–43.

Lyons, B. (1980), 'A new measure of minimum efficient plant size in UK manufacturing industry,' *Economica*, **47**, 19–34.

Mata, J. and P. Portugal (1994), 'Life duration of new firms,' *The Journal of Industrial Economics*, **42**, 227–245.

Mata, J., P. Portugal and P. Guimaraes (1995), 'The survival of new plants: start-up conditions and post-entry evolution,' *International Journal of Industrial Organization*, **13**, 469–481.

Nishimura, K. G., T. Nakajima and K. Kiyota (2005), 'Does the natural selection mechanism still work in severe recessions? Examination of the Japanese economy in the 1990s,' *Journal of Economic Behavior and Organization*, **1**, 53–78.

Prentice, R. and L. Gloeckler (1978), 'Regression analysis of grouped survival data with application to breast cancer data,' *Biometrics*, **34**, 57–67.

Scarpetta, S., P. Hemmings, T. Tressel and J. Woo (2002), 'The role of policy and institutions for productivity and firm dynamics: evidence from micro and industry data,' OECD Economics Department Working Papers 329, OECD Publishing, doi:10.1787/547061627526.

Appendix

A1. Main variables used in TFP computation

All nominal output and input variables are available at firm level. Industry level data are used for price indexes, hours worked and depreciation rates.

A1.1 Output

Output is defined as gross output deflated using sectoral price indexes published by INSEE.

A1.2 Labor

Labor input is obtained by multiplying the number of effective workers (i.e., number of employees plus number of outsourced workers minus workers taken from other firms) by the average hours worked. The annual series for hours worked are available at the 2-digit industry level and provided by INSEE. A large drop in hours worked occurs from 1999 onwards because of the 35 h policy: worked hours fell from 38.39 h in 1999 to 36.87 h in 2000.

A1.3 Capital input

Capital stocks are computed from investment and book values of tangible assets following the traditional perpetual inventory method (PIM):

$$K_t = (1 - \delta_{t-1})K_{t-1} + I_t \qquad (A1)$$

where δ_t is the depreciation rate and I_t is real investment (deflated nominal investment). Both investment price indexes and depreciation rates are available at the 2-digit industrial classification from INSEE data series.

A1.4 Intermediate inputs

Intermediate inputs are defined as purchases of materials and merchandize, transport and travel, and miscellaneous expenses. They are deflated using sectoral price indexes for intermediate inputs published by INSEE.

A1.5 Input cost shares

With w, c, and m representing wage rate, user cost of capital, and price index, respectively for intermediate inputs $CT_{it} = w_{it}L_{it} + c_{It}K_{it} + m_{It}M_{it}$ represents the total cost of production of firm i at time t. Labor, capital and intermediate inputs cost shares are then respectively given by

$$S_{Lit} = \frac{w_{it}L_{it}}{CT_{it}}; \quad S_{Kit} = \frac{c_{It}K_{it}}{CT_{it}}; \quad S_{Mit} = \frac{m_{It}M_{it}}{CT_{it}} \tag{A2}$$

To compute labor cost share, we rely on the variable labor compensation provided by the EAE survey. This value includes total wages paid to salaries plus income tax withholding, and is used to approximate the theoretical variable $w_{it}L_{it}$. To compute the intermediate inputs cost share, we use variables for intermediate goods consumption in the EAE survey and the price index for intermediate inputs in industry I provided by INSEE.

We computed the user cost of capital using Hall's methodology (1988) in which the user cost of capital (i.e., the rental price of capital) in the presence of a proportional tax on business income and of a fiscal depreciation formula, is given by

$$c_{It} = \left(r_t + \delta_{It} - \pi_t^e\right)\left(\frac{1 - \tau_t z_I}{1 - \tau_t}\right)p_{Iit} \tag{A3}$$

where π_t^e is the expected inflation rate for investment computed as a 3-periods moving average of the past inflation rate in investment price index. τ_t is the business income tax in period t and z_I denotes the present value of the depreciation deduction on one nominal unit investment in industry I. Complex depreciation formulae can be employed for tax purposes in France. To simplify this, we chose to rely on the following depreciation formula

$$z_I = \sum_{t=1}^{n} \frac{(1 - \bar{\delta}_I)^{t-1}\delta}{(1 + \bar{r})^{t-1}}$$

where $\bar{\delta}_I$ is a mean of the industrial depreciation rates for the period 1984–2002 and $\bar{r}$ is the mean of the nominal interest rate on the period 1990–2002.