Labour Demand, Firm Growth and the Evolution of Industries

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Abstract

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This paper examines labour demand using insights from Industrial Organization. On the one hand employment behaviour by firms is characterized by decisive heterogeneity: the simultaneous appearance of firms demanding labour and firms destroying jobs throughout the business cycle is observed. On the other hand, firm size, firm age and industry type can say a lot for the creation and destruction of jobs. Based upon work testing Gibrat's Legacy, this paper shows how the relation between employment behaviour and firm and/or industry characteristics can be explained. Moreover, various contributions are made to the literature of firm growth and industry evolution. Although a recent wave of empirical studies counteracts Gibrat's Law of Proportionate Effects, evidence is found that Gibrat's insights do prevail in servicing as well as in part of manufacturing industries. So, employment behaviour by firms seems to differ between and within industries.

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Introduction

Ever since the emanation of economy-wide macro data sets during the first half of the 20th century, labour economists have been examining aggregate net employment changes. Only recently their attention has turned to study the simultaneity of job creation and destruction in labour markets, due to the emergence of large micro data sets containing firm level observations. Consequently, in the early '90's a new research domain came forth, known today as "the study of gross job flows". This new approach partly outweighs the traditional focus on the aggregate employment stock and its (net) changes over time. Analysing gross job flows is a more detailed way of analysing labour demand or employment behaviour by firms. This paper scrutinises gross job flows in Belgium.

Section I acquaints the reader with the concepts of gross job flows in general and its estimates for Belgium in particular. For the latter, a unique data set is used covering the 1986-1995 time span, representing all firm size categories (small as well as large firms) and all sectors (manufacturing as well as services) in the economy. Stylised facts come about when examining gross job flows by year, by firm employment level and firm age. Industry differences are also subject to scrutiny.

In order to elucidate the stylised facts of Section I theoretically as well as empirically, Section II focuses to recent developments in the Industrial Organisation literature examining the life cycle of firms and the evolution of industries. Based upon work testing Gibrat's Legacy, Section II supplies some theoretical background and a statistical model by which the stylised facts of Section I can be clarified. Therefore, studying the process of firm entry, survival and exit contributes to our understanding of gross job flows and the demand for labour.

Before deliberating on the estimates for Belgium in Section IV, Section III gives some summary statistics and specifies the econometric approach. The sample considered in Sections III and IV is a subset of the observations used in Section II. In particular, a cohort of more than 600 starters in 1986 is followed throughout the sampling period. When regressing firm growth on firm size and age, a possible sample selection bias is accounted for by transforming the statistical model into a Generalised Tobit framework (or, following the quotation of Amemiya (1994), a "Tobit II" model). Estimated coefficients are the optimal outcomes of the Heckman two-step estimator combined with a full information maximum likelihood procedure.

Finally Section IV yields regression results and makes various contributions to the literature of firm growth and as such sheds some fresh light on the decision to employ. Section IV consists of two subsections. First, firm growth and survival are examined for both the manufacturing and servicing sector jointly. Overall estimates show that small and young firms grow at the highest rates, but at the same time it seems that small companies have the poorest foresight of survival. Hence, Gibrat's Law is refuted for Belgian firms when looking at the overall economy. The second subsection goes into two recent studies of sector differences in employment behaviour and their consequences with regard to industry evolution. First, Audretsch, Klomp and Thurik (1997) used Dutch firm level data to show that the decision to employ differs strikingly between the manufacturing and the servicing sector. In particular, they argue Gibrat's Law to be restored for studying hotel and retail industries. Their results are uphold by referring to post-entry firm performance. Results using observations for the entire Belgian servicing fortifies their insights. Second, Walsh (1999) argued that relative establishment growth is independent of its size for small manufacturing Irish plants that subcontract into R&D sectors. His argument is sustained by pre-entry decision making of plants and the nature of sunk costs to market accession. An application to Belgian manufacturing empowers different employment behaviour to exist among manufacturers.

I Gross job flows in Belgium: the facts to be explained

In this study, a job is an employment opportunity filled by a worker and changes in the number of jobs indicate firm-level changes in employment positions. Analysing gross job flows is therefore to be considered as a detailed way of examining labour demand. This section first provides the definitions used in this paper to measure job creation and destruction and second, estimates for Belgium are shown.

Definitions

Suppose employment in firm *i* at time *t* is given by n_{it}. The size of firm *i* at time *t*, x_{it} is then defined as

$$x_{it} = [n_{it} - n_{it-1}]/2 \qquad (1)$$

and employment growth is given by

$$g_{it} = [n_{it} - n_{it-1}]/x_{it} \qquad (2).$$

The above measure of employment growth g_{it} is somewhat different compared to conventional growth estimates since x_{it} instead of n_{it-1} appears in the denominator of equation (2). Using g_{it} instead of its more conventional expression can be argumented as follows. First, g_{it} is monotonically related to the conventional growth rate measure and they are approximately equal for small growth rates. Second, g_{it} is symmetric about zero and lies in the closed interval [-2,2] with firm deaths (births) corresponding to the left (right) endpoint of the distribution (Davis and Haltiwanger (1992)).

Suppose the employment growth rate of an individual firm i at time t has a density function $f(g_{it})$, defined by its mean $\overline{g}_t$ and the higher moments of the distribution. In the traditional aggregate analysis of net employment changes, the attention is concentrated on the mean. However, insight in the higher moments of the employment growth distribution is important since gross measures of job flows are defined as weighted means of different truncations of the distribution $f(g_{it})$, as is shown below.

According to Davis and Haltiwanger (1992), the gross job creation rate in sector s at time t, jc_{st} is calculated as follows:

$$jc_{st} = \sum_{i \in I_{st} \cap g_{it} > 0} g_{it} \left[\frac{x_{it}}{x_{st}} \right] \tag{3}$$

with I_{st} the set of all firms in sector s at time t. Note that the sectoral specification can be any meaningful categorisation of firms like industry type, region, firm size or firm age. If $s=i$ for all i, each individual firm is dealt with separately.

Similarly, gross job destruction in sector s at time t, jd_{st} is defined as

$$jd_{st} = \sum_{i \in I_{st} \cap g_{it} < 0} \left| g_{it} \right| \left[\frac{x_{it}}{x_{st}} \right] \qquad (4).$$

From equations (3) and (4) it follows that the gross job creation rate in sector *s* is derived from the sum of employment gains of new and expanding firms within the sector, while gross job destruction is constructed as the sum of job losses in dying or contracting establishments. Gross job destruction is expressed as a positive number. Also note that the expressions in (3) and (4) reflect the reallocation of employment positions or jobs and not the reallocation of workers.[1]

The gross job reallocation rate is the sum of gross job creation and destruction. Hence we can write

$$jr_{st} = jc_{st} + jd_{st} \tag{5}$$

The difference between gross job creation and destruction is the net employment growth in sector *s* and is defined as

$$ng_{st} = jc_{st} - jd_{st} \quad (6).$$

Finally, the excess job reallocation rate in sector *s* at time *t*, $excess_{st}$, measures the amount of market turnover that exists in excess of the minimum market turbulence that is required to accommodate the net change in the number of jobs (Davis and Haltiwanger (1992)) and is defined as

$$excess_{st} = jr_{st} - |ng_{st}| \quad (7).$$

In other words, the excess job reallocation rate is a yardstick to the simultaneity of job creation and –destruction appearing in sector *s*. The excess job reallocation rate is often used if one is after measuring structural changes in the economy.

[1] For a discussion of the difference between job flows and worker flows, see Konings (1995a).

It is worthwhile to note that the sample used can be considered as a random draw over all sectors (manufacturing as well as non-manufacturing), all regions and all firms (small as well as big firms) in Flanders.[2] The sampling period is the interval 1985-1995 and the number of firms observed during this time span equals 123 737. The remainder of this section only highlights the process of gross job creation and destruction 1) for all firms and each year, 2) for different employment levels or firm size categories, 3) for different firm age classes and 4) for different industries. Exactly these estimates will proof to be useful for the analyses in the following sections (in fact, this statement twists reality: the analyses in the following sections are based on the findings here.)

Table 1: Gross job flows in Flanders

Year	*jc*	*jcs*	*jd*	*jds*	*ng*	*jr*	*excess*
1986	0.085	0.294	0.071	0.225	0.015	0.156	0.141
1987	0.087	0.264	0.047	0.390	0.040	0.134	0.094
1988	0.107	0.280	0.038	0.459	0.069	0.146	0.076
1989	0.129	0.264	0.038	0.549	0.091	0.167	0.076
1990	0.122	0.295	0.043	0.483	0.079	0.165	0.086
1991	0.120	0.291	0.044	0.447	0.076	0.164	0.088
1992	0.094	0.330	0.050	0.424	0.052	0.153	0.092
1993	0.078	0.321	0.060	0.353	0.034	0.154	0.104
1994	0.111	0.297	0.067	0.328	0.011	0.145	0.167
1995	0.089	0.213	0.069	0.349	0.042	0.181	0.116
Average	0.103	0.285	0.058	0.400	0.045	0.162	0.104
Stand. Dev.	0.019	0.033	0.012	0.092	0.027	0.017	0.029

Note: jc=job creation rate, jcs=job creation share of new firms (number of jobs created by entrants as % of total job creation), jd=job destruction rate, jds=job destruction share of exiting firms (number of jobs destroyed by exiting firms as % of total job destruction), ng=net employment growth (=jc-jd), jr=job reallocation rate (=jc+jd), excess=excess job reallocation rate (jr-|ng|). A firm reporting more

[2] Politically Belgium is divided in a Dutch speaking part, Flanders, a French speaking part, Walloon and a German speaking minority. Flanders can crudely be defined as the northern half of Belgium.

than 50 employees for the first time, is not considered as an entrant in the analysis. Firm exit does not include the disappearance of a company because of a take over or a split-up. The averages are unweighted.

Besides its longitudinal character, the used data set can yield additional information if job creation and destruction rates are estimated by employment size categories. This entails a firm being labelled a size category each year and according to its reported employment level. Table 2 represents the estimates for the different employment size classes. The highest job creation and destruction rates are found for firms with the lowest employment levels. The smaller the firm (said differently: the lower the firm's employment level), the more dynamic its labour market seems to be. Among the smallest firms, the importance of market entrants is as high as 55.9 % of total job creation. A firm reporting more than 50 employees for the first time is not considered an entrant in the analysis. Also concerning firm exiting, the data were cleaned from unreal market disappearance, like the take over or splitting-up of establishments. Firm exit peaks within the smallest employment categories. Net employment growth is higher for smaller firms. The highest growth rates are observed for firms employing less than 21 workers. Note also that the maximum net employment growth is taken down by the smallest but one size class and amounts to 7.6 %. The job reallocation and excess reallocation rate are considerably higher for the smallest employment class and decreases continuously as size classes contain larger firms. So, smaller firms are marked by more flexible labour markets and restructuring. However, some caution is recommended before one jumps to conclusions too easily.

Davis, Haltiwanger and Schuh (1996) pointed out the often misleading and fallacious results that give rise to the above conventional wisdom. In particular, the prowess of small firms is shown to be possibly exaggerated in either of three cases. First when the longitudinal data are not able to track the path of a single firm over time, estimates might be subject to the so called "size distribution fallacy". Since the used data are longitudinal at the firm level (and used as such), this fallacy is easily avoided. Second, "netting out of reality" is present if, for a given year the pools of establishments creating jobs and establishments destroying jobs are not disjoint. Referring to definitions (3) and (4), the use of side conditions over the summation dodges this statistical pitfall. Finally, if short-term transitory movements in firm employment occur in the data, the regression fallacy might bias insights drawn from firm level data. Categorising a firm according to the average employment level within two subsequent years or even within the entire sampling period easily controls for regression-to-the-mean bias. Since employment size classes in Table 2 are based on average employment levels within two subsequent years, the regression fallacy is likely to occur only if transitory employment fluctuations require more than one year to reverse themselves.[3]

Table 2: Gross job flows by firm-level employment size in Flanders

class	*jc*	*jcs*	*jd*	*jds*	*ng*	*jr*	*excess*
0-10	0.179	0.559	0.115	0.459	0.064	0.294	0.230
11-20	0.125	0.337	0.049	0.444	0.076	0.174	0.098
21-50	0.102	0.295	0.044	0.428	0.058	0.146	0.088
51-100	0.098	-	0.046	0.401	0.052	0.144	0.092
101-500	0.081	-	0.043	0.335	0.038	0.124	0.086
>500	0.054	-	0.023	0.143	0.031	0.077	0.046
Average	0.104	0.280	0.054	0.399	0.050	0.158	0.108
Standard.Dev.	0.042	0.142	0.031	0.120	0.003	0.016	0.013

Note: class=discrete distribution of firms by employment level, jc=job creation rate, jcs=job creation share of new entrants (number of jobs created by new firms as a % of total job creation), jd=job

[3] Only for firm entry (exit) the first (last) reported employment level is used as the classifying device instead of the average between zero and the first (last) reported employment level. This labelling however does not interfere with the regression fallacy since the process of entry and exit is non-transitory.

destruction rate, jds=job destruction share of exiting firms (number of jobs lost by exiting firms as a % of total job destruction), ng=net employment growth (=jc-jd), jr=job reallocation rate (=jc+jd), excess=excess job reallocation rate (jr-|ng|). A firm reporting more than 50 employees for the first time, is not considered as an entrant in the analysis. Firm exit does not include the disappearance of a company because of a take over or a split-up. The averages are weighted.

To conclude, from Table 2 it follows that employment size can say a lot for net employment growth, labour market turnover and structural adjustment in Flanders. Relative high measures of net employment growth, job - and excess reallocation typify the smaller establishment. Only a limited number of studies are able to examine exhaustively the behaviour of small versus large firms in the economy. If so, higher labour market volatility for smaller firms follows. Moreover, the smaller the size category the more important the process of market entry and exit becomes.

The analysis of gross job flows by establishment age is shown in Table 3. The age measure reflects the date of the firm's construction and the year of observation in the sample. Firms are broken down in seven detailed age categories. The job creation rate is highest for the youngest incumbents (28 %), drops as establishments age and touches bottom for the group of oldest firms (3.9 %). The same holds for job destruction, however to a lesser degree. Consequently, the job reallocation rate diminishes for classes containing older firms. The same holds for net employment growth even yielding a negative estimate for the oldest age class. Restructuring among employment positions seems to be most relevant for medium aged corporations. The evidence of Table 3 therefore suggests that higher market flexibility characterises younger firms. Job market turnover due to restructuring between firms becomes more important if firms grow older, reaches a record level of 13.8 % between the age of 6 and 10 years and fades away thereafter. The role of market failure in the process of job destruction becomes less important if firms age. Independent of the job destruction rate, the job destruction share of firm exit by establishment age claims market failure to appear less frequent for a group of older firms in Flanders: it ranges from 58.5 % for the youngest to 31.5 % for the oldest firms.

Table 3: Gross job flows by firm age in Flanders

class	*jc*	*jd*	*jds*	*ng*	*jr*	*excess*
1	1	0	-	1	1	0
2	0.280	0.061	0.585	0.219	0.341	0.122
3	0.234	0.061	0.519	0.173	0.295	0.122
4-5	0.114	0.061	0.499	0.053	0.175	0.122
6-10	0.090	0.069	0.417	0.021	0.159	0.138
11-14	0.055	0.049	0.395	0.006	0.104	0.098
>14	0.039	0.048	0.315	-0.009	0.087	0.078
Average	0.104	0.054	0.399	0.043	0.147	0.094
Standard.Dev.	0.700	0.144	0.045	0.010	0.014	0.015

Note: class=discrete distribution of firms by age, jc=job creation rate, jcs=job creation share of new entrants (number of jobs created by new firms as a % of total job creation), jd=job destruction rate, jds=job destruction share of exiting firms (number of jobs lost by exiting firms as a % of total job destruction), ng=net employment growth (=jc-jd), jr=job reallocation rate (=jc+jd), excess=excess job reallocation rate (jr-|ng|). Firm exit does not include the disappearance of a company because of a take over or a split-up. The averages are weighted.

Finally, industry-type might matter. Therefore, firms are segmented by disposition of their activities. In particular, a crude distinction is made between manufacturing and non-manufacturing industries. Table 4 represents the results. Both job creation and destruction are higher for non-manufacturing firms relative to their employment levels. On the same lines, the process of market entry and exit seems to be more important in non-manufacturing. Net growth in the manufacturing sector is outweighed by measures for the non-manufacturing industries. A greater part of job turnover is dedicated to restructuring in non-manufacturing firms. Table 4 thus reveals differences in gross job flows by industry-type. Higher labour market turnover, restructuring and market entry and exit seems to be typical of non-manufacturing.

Table 4: Gross job flows by industry in Flanders

class	*jc*	*jcs*	*jd*	*jds*	*ng*	*jr*	*excess*
manufac-turing	0.083	0.216	0.048	0.265	0.035	0.131	0.096
non-manu-facturing	0.118	0.318	0.063	0.339	0.055	0.181	0.126
Average	0.100	0.274	0.055	0.305	0.044	0.156	0.111
Standard.Dev.	0.010	0.028	0.006	0.033	0.004	0.016	0.012

Note: class=discrete distribution of firms by industry, jc=job creation rate, jcs=job creation share of new entrants (number of jobs created by new firms as a % of total job creation), jd=job destruction rate, jds=job destruction share of exiting firms (number of jobs lost by exiting firms as a % of total job destruction), ng=net employment growth (=jc-jd), jr=job reallocation rate (=jc+jd), excess=excess job reallocation rate (jr-|ng|). Firm exit does not include the disappearance of a company because of a take over or a split-up. Public establishments are excluded from the analysis. The averages are weighted.

Mapping measures of gross job flows is a straightforward and technical exercise if one has access to good data. A challenge then becomes putting the different pieces together into a sound economic model, making predictions and testing them. To do the trick, we will link arms with recent developments in Industrial Organisation examining the life cycle of firms and the evolution of industries.

II Gross job flows in Belgium: an explanation using IO-models

The simplest version of a growth model is one in which growth rates are independent of firm size (measured by the number of employees). In other words, this growth model predicts an equal growth rate for firms employing a different number of workers, ceteris paribus. This is known as Gibrat’s Law of Proportionate Effects: each firm in each employment size category has the same probability of proportional growth. Said differently, corporate growth is optimally modelled by a random walk since growth rates are erratic and thus unpredictable. This was already analysed empirically in the 50's by Hart and Prais (1956) and Simon and Bonini (1958) among others. Since the work of Evans (1987a,b), Dunne, Roberts and Samuelson (1989) and Hall (1987), the legacy of Gibrat's law was questioned. These papers found that firm growth did depend on firm size and moreover, on the firm's age.

Recently, a wave of empirical studies has looked at the dynamic evolution of firm size and age and its implications for industry evolution, which has led to a number of "stylized" facts about firm dynamics and industry evolution (for overviews e.g. Audretsch, 1995a; Sutton, 1997; Caves, 1998). These can be summarized as follows. First, employment start-up size of the firm and firm age are negatively related to net employment growth at the firm level and the probability of firm exit (Evans, 1987a,b). Second, the conditions of technology underlying the industry can explain why survival rates vary considerably across industries (e.g. Audretsch, 1991), and finally at all times there exist high entry rates of new firms, but also high exit rates. Likewise, at all times there are expanding firms and contracting firms, which leads to simultaneous creation and destruction of jobs in narrowly defined sectors and regions (e.g. Baldwin and Gorecki, 1987; Davis and Haltiwanger, 1992; Konings, 1995a,b; Konings, Roodhooft and Van De Gucht, 1996).

Empirical models of firm growth

The observation that Gibrat's law failed to hold in US manufacturing was consistent with a number of recent theoretical models of firm growth. Two examples are the passive learning model of Jovanovic (1982) and the active learning model of Pakes and Erickson (1989). Both models predict a negative relationship between firm growth and firm size or age. Moreover, both models incorporate the process of firm entry and exit. Note that these predictions are a sufficient condition to get the estimates shown in Tables 2 and 3 of the foregoing section. However, the assumptions of both models are by no means necessary to explain firm growth or the evolution of industries.

The active and passive learning model can be considered as part of a larger family of IO-models all being tested among the same empirical line, designed as follows.[4] Assume that the firm growth relationship is given by

$$\frac{\ln x_{it} - \ln x_{it'}}{d} = a_0 + a_1 \ln x_{it'} + a_2 \ln a_{it'} + e_{it} \tag{8}$$

where x stands for employment (as a measure of firm-size) and a indicates the firm's age. Subscript i stands for firm i, subscripts t and t' indicate time such that $d = (t - t') > 0$ and ε is (asymptotically) normally distributed and supposed to have mean zero and a constant variance s^2. If $\alpha_0 = \alpha_1 = \alpha_2 = 0$ shocks are idiosyncratic and corporate growth can hardly be thought of as a process composed of a deterministic trend with some noise superimposed on it. If both α_0 and α_1 are different from 0 and $\alpha_2 = 0$ then the observation that $\alpha_1 < 0$ is taken to indicate the existence of "mean reversion", i.e. the proposition that larger firms grow relatively slower than smaller firms. If reversion to the mean is likely to be present, (8) can be rewritten as a transitional process of

[4] For an overview, see Geroski (1999).

convergence (a partial adjustment model) towards a steady state firm size x^* such that $\ln x^* = -(\alpha_0 / \alpha_1)$.

The following extension of (8) allows for elasticities to differ according to the sample's observations:

$$\frac{\ln x_{it} - \ln x_{it'}}{d} = a_0 + a_1 \ln x_{it'} + a_2 \ln a_{it'} + a_3 (\ln x_{it'})^2 + a_4 (\ln a_{it'})^2 + a_5 \ln x_{it'} \ln a_{it'} + e_{it}$$

(8)'.

Equations (8) and (8)' are referred to as the linear and non-linear "growth equation" respectively and both will serve as the bedrock of our empirical tests. First, we test equations (8) and (8)' for the entire sample. Apart from including firm age and firm size we will also include sector dummies (among regional and year dummies) to control for unobserved exogenous sector effects. Hence Gibrat's Law is field-tested. Second, the coefficients of equations (8) and (8)' are estimated for the non-manufacturing sector, checking up for differences in employment behaviour by industry-type. Finally, the paper works out an alternative assumption of industry evolution. In doing so, only the manufacturing firms are concerned and the work explicitly distinguishes between manufacturing firms that are subject to endogenous sunk costs of market entry compared to firms being faced with exogenous start-up sunk costs. This might have important implications for the dynamics of firm growth and the equilibrium market structure as shown by Sutton (1991).

III Econometric Approach

This section examines yearly average firm growth during the period 1986-1995. Information on a cohort of over 600 new start-ups in 1986 is subject to estimation.

Yearly growth rates for surviving firms are calculated according to the expression on the left- hand side of equations (8) or (8)'. By reporting missing values for firm growth, this procedure reveals which firms although reporting in the previous year dropped out before the expiration of the subsequent annum. As will become clear below, this enables to control for sample selection bias when estimating the determinants of employment growth at the corporate level. Before turning to more technical issues, a quick look is cast on the data under examination. Understanding the configuration of the used cohort will make the econometric procedure explained subsequently more comprehensive.

Figures 1 and 2 show the distribution of the logarithm of employment in 1987 and 1995 respectively and Figure 3 graphs the average corporate growth rate of survivors. The distribution of log employment is skewed to the right in 1987, indicating the abundance of small firms. Small establishments still abound in 1995, however to a lesser degree. The comparison of Figure 1 to Figure 2 clearly displays a shift of firm size towards larger employment classes during the sampling period. Survivors being small in 1987 have grown by 1995. The average employment level in the cohort increased by 3.02 workers, from 5.39 to 8.41. Figure 3 plots the observed firm growth rates between –25 % and +25 %. Comparatively, a normal distribution with mean 0.056 and standard deviation 0.330 is fitted over the growth histogram in Figure 3. Symmetry suggests as many firms with a positive growth rate in the economy to be present compared to shrinking establishments. This reflects firm heterogeneity: at all times firms creating and firms destroying jobs coexist, yielding considerable estimates of excess job reallocation in the economy as was inferred from Table 1 of Section II.

Figure 1: Distribution of firm employment in 1987

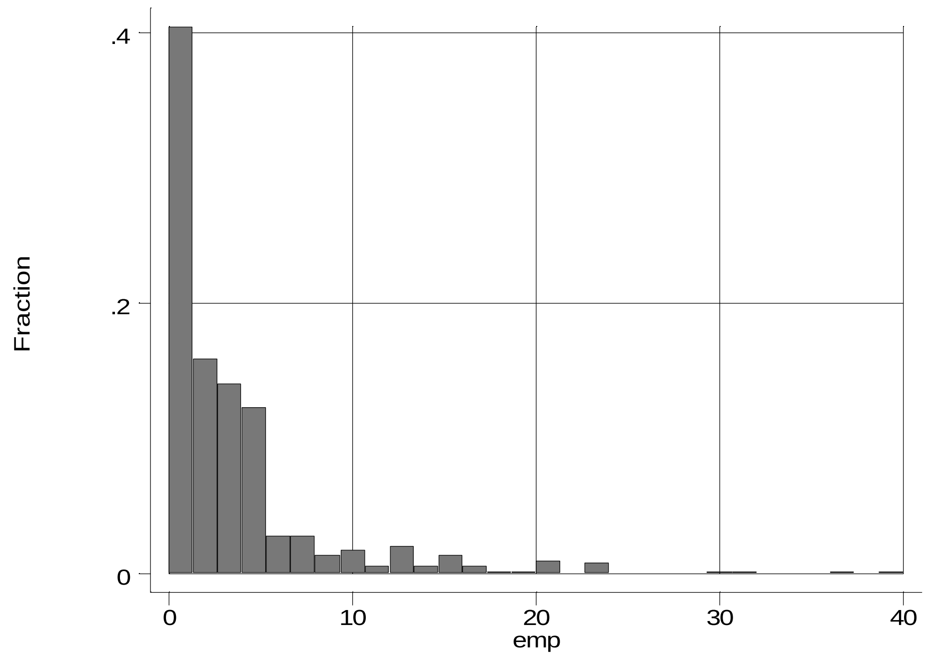


Figure 2: Distribution of firm employment in 1995

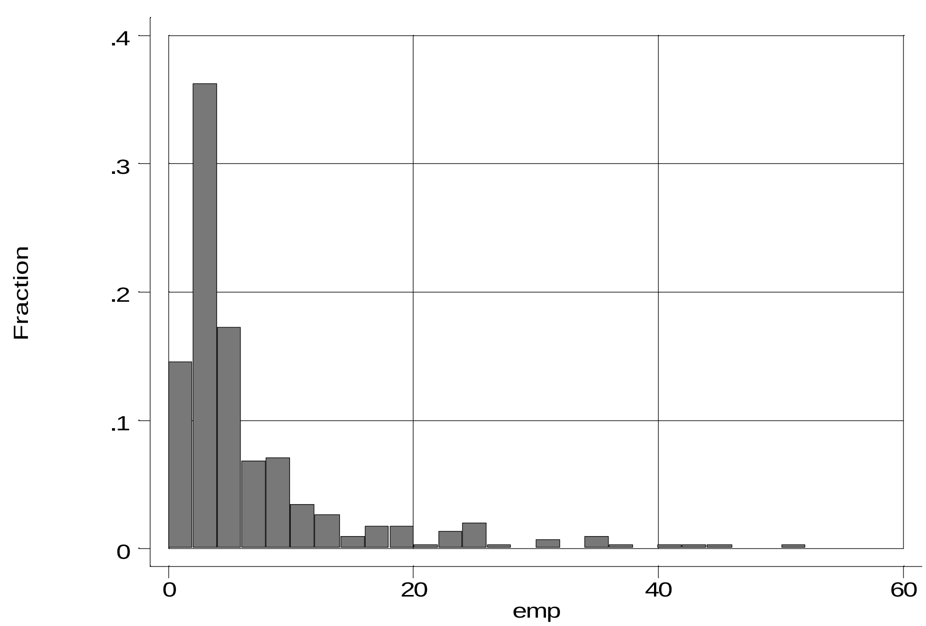
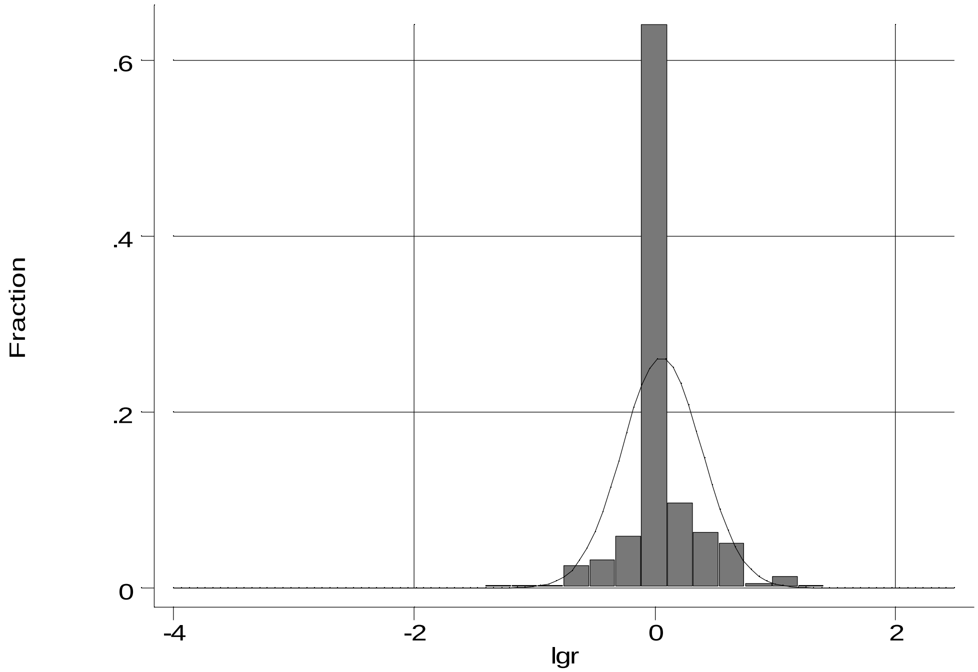


Figure 3: Distribution of percentage firm growth



To estimate equations (8) and (8)' accurately, a potential sample selection bias must be allowed for. Sample selection occurs if the observations in the regression equation are sampled through an unobserved selecting process. In particular, firm growth is only observed if the firm stayed in business between two subsequent years. Using ordinary least squares to estimate the coefficients in the growth equation would only compare survivors. However, the growth equation fails to explain why these firms survived in the first place. It is straightforward that the reasons of firm survival should be taken into account when discussing the model's economic implications. Moreover, the estimates using ordinary least squares in the presence of a selection bias are inconsistent (Greene (1999)). To get around this econometric pitfall, a number of alternative estimators can be called upon. This paper uses a mix of two parametric methods, the Heckman two-step estimator (also called the HECKIT estimator) and a full information conditional maximum likelihood estimation procedure (or the FIML estimator). Of course, both estimators appeal to all observations, i.e. take into account survivors as well as dyers. In particular, the first step of the estimation consists of applying the Heckman two-step estimator due to Heckman (1976). The second step of the estimation uses the Heckman two-step estimates as initial values in the maximum likelihood estimator, hinging upon the usual normality assumptions. The application of the FIML estimator is required since the Heckman two-step estimates are possibly governed by multicollinearity (Amemiya (1984)).

The relevant Tobit model assumes firm *i* having an observed growth rate at time *t* if

$$Z_{it'}^{'} g + u_{1it} > 0\,, \tag{9}$$

where u_{1it} is an independent draw from a standard normal distribution and (9) can be referred to as "the survival equation".[5] The (column) vector $Z_{ti'}$ contains the variables determining the firm's survival. Notation is slightly abused since all variables in Z_i either will hold at the penultimate year *t' = t - 1* (e.g. size and age) or are assumed to be independent of time (e.g. sector and regional dummies). The zero on the right hand side of the inequality comes in as the appropriate reservation level to observe the firm's success or failure over time. Simultaneously, there is another equation, namely "the growth equation" and which is given by

$$y_{it} = X_{it'}^{'} a + s u_{2it} \tag{10}$$

where the (column) vector $X_{it'}$ contains all the variables determining growth of firm *i* at time *t*. Again, the time index is used somewhat cavalier since for the data

[5] Given the inequality sign in (9), it might seem strange to quote this expression as an "equation". Nevertheless we can do this since (9) is analytically transformed into a probit equation where the dependent variable equals 1 if the left-hand side of (9) is strictly positive.

considered, t - t' is fixed to unity or independent of time. The error term u_{2it} has a standard normal distribution, but is potentially correlated with the error term of the first equation, with a coefficient of correlation equal to r. Significant correlation between the errors of (9) and (10) underpins the existence of an unobserved selecting process and indicates sample selectivity. Technically, a sample selection bias occurs if (u_{1it},u_{2it}) are independent draws from a bivariate incidentally truncated normal distribution where the marginal distribution of u_{1it} is truncated from below and shifting the marginal normal distribution of u_{2it} to the right.[6] As mentioned earlier, if this is the case, standard regression techniques applied to the second equation (which in our case is equation (8) or (8)') yield biased results. The next section displays both, estimates of the growth and the survival equation.

IV Results

This section consists of two subsections. The first subsection entails firm growth averaged over all sectors of the economy. By estimation, tests for Gibrat's Law are performed. The second subsection seeks for sector peculiarities and the consequences for the firm growth/survival - firm size/age relationship.

Overall firm growth

Table 5 shows the results of estimating the growth and survival function for all sectors in Flanders, notational equation (10) and (9) respectively. The first column shows the

[6] See Greene (1999) for a preliminary discussion. Amemiya (1994) for Tobit models in general and Vella (1998) for sample selection models in particular offer a more extensive support.

results of estimating constant elasticities by approximation of firm growth with respect to firm size and age. Column (1) thus gives estimates of the parameters in the growth function given by equation (8) earlier. Column (2) represents optimal coefficients of the survival equation, controlling the estimates in column (1) for a possible sample selection bias. Likewise, in column (3) the growth equation is regressed but non-constant elasticities are allowed for within the sample (previously quoted as equation (8)') and in column (4) the corresponding survival equation controls for incidental truncation.

Table 5: Estimated elasticities of firm growth and determinants of firm survival for the entire sample: constant and non- constant elasticities

	(1)	(2)	(3)	(4)
$\ln x_{it'}$	-0.041** (0.007)	0.671** (0.067)	-0.144** (0.020)	0.679** (0.164)
$\ln a_{it'}$	-0.032** (0.012)	-0.089 (0.082)	-0.013 (0.034)	-0.181 (0.097)
$(\ln x_{it'})^2$	-	-	0.023** (0.004)	-0.140** (0.037)
$(\ln a_{it'})^2$	-	-	-0.018 (0.015)	-
$\ln x_{it'} * \ln a_{it'}$	-	-	0.011 (0.009)	0.222** (0.083)
Number of observations	2506		2506	
λ	0.070* (0.032)		0.021 (0.041)	

Note: Columns (1)/(3) and (2)/(4) show the estimates of the growth and the survival equation of the linear statistical specification respectively. In brackets are standard *errors, ** indicates significance at 1 % level and * significance at 5 % level. The fourth estimate of column (4) drops out due to strong multicollinearity. During estimation sector, regional and time dummies are included.*

From column (1) in Table 5 we can note that initial firm size and age are negatively related to firm growth at the 1 % significance level. A 10 % increase in employment leads to a 0.41 % decrease in the growth rate of the average firm. The same reasoning holds for a 10 % increase in the firm's age, resulting in a 0.32 % decrease in the average firm growth rate. Small and young firms therefore tend to grow faster.

Evidence for Belgian firms thus underpins recent models contrasting Gibrat's Law. A negative relationship between firm growth and firm size and age is found, corroborating the (stylised) facts from Tables 2 and 3 of Section II. Column (1) reveals that sample selection might bias OLS results since the test statistic λ is significant at conventional levels. From column (2) it is learned that initial firm size is positively related to firm survival, or said differently, smaller firms are more likely to fail market requirements. This bears out the result found in Table 2: the job destruction share of firm exit diminishes, as firms become larger (the average is 0.399 with a standard deviation of 0.120). A bit of a surprising result is the observation that elderly firms are more likely to fail than their younger counterparts. However, one can not reject the null that the effect on firm growth with respect to firm age is zero.

Although Table 3 suggests firm exit to be less for older firms with a weighted average job destruction rate by firm exit of 0.399, its standard deviation only amounts to 0.045. Heretofore it can be summarised from columns (1) and (2) that small and young firms grow at the highest rates, but at the same time it seems that small companies have the poorest foresight of staying in business.

Columns (3) and (4) of Table 5 allow for non-constant elasticities within the sample. The growth-size relationship is convex with a minimum for employment equal to 23. Given the log size-distribution of employment in Figure 1, it is straightforward that a negative growth-initial size relationship holds for more than 95 % of all firms in the cohort. Examining the effects of increasing age on the firm's growth rate, it follows from column (3) that no age effect is significant. Column (4) teaches an inverted u-shape relationship to exist between firm survival and firm employment size. In general we can conclude from Table 5 that evidence exist for Flanders counteracting Gibrat's theoretical predictions: firm growth is negatively related to firm size. Moreover, smaller firms (like most new entrants) are growing considerably but the probability of survival only decreases if establishments grow (and only up to a critical point). Speaking of gross job flows, small firms (relatively) create but also destroy most job opportunities, a far from surprising result. If evidence for an age-effect is found, it is estimated to induce a negative relationship between firm growth and the establishment's age. So, if at all, elderly firms are earmarked by less growth, a result also found in Table 3 of Section II. Note that using a non-linear growth specification mitigates the effects of a sample selection bias as can be deduced from the insignificance of λ. Other research as well (e.g. Evans, 1987) finds an unobserved selection process being absent.

Firm growth and the evolution of industries

Table 4 of Section IV established different gross job flows for the manufacturing and non-manufacturing Flemish industries. Audretsch, Klomp and Thurik (1997) have shown employment behaviour for part of Dutch services to be different from manufacturing (Audretsch, Klomp, Thurik (1997)). In contrast to the Stylised Results reported by Geroski (1995) based on the manufacturing sector, Audretsch et al. find that firm growth in retailing and hotel industries is not systematically related to either size or age. In particular, Gibrat's Law is restored for all but the smallest firms in part of Dutch services, suggesting firm growth being independent of firm size. Elucidation is given by that the impact of size and age on growth should be low or even non-existent for firms that have attained the minimum efficient scale (MES) level of output. Furthermore, an important characteristic of Dutch retailing and hospitality is the absence of significant scale economies and the profusion of small firms in these industries. Upon entry, does this (stylised) result also hold for the entire Flemish servicing?

Following Audretsch, Klomp and Thurik (1997), the servicing sector is decomposed by firm employment levels using a crude classification of employment size below and above 5. Columns (1) and (2) of Table 6 give the estimated parameter values for the growth and the survival equation respectively for servicing firms employing less than (or equal to) 5 individuals. Columns (3) and (4) redo the exercise for the complement of larger market incumbents. Straightforwardly from columns (3) and (4) it is concluded that Gibrat's Law holds for larger firms in servicing. These results are in line with estimates of (part of) the Dutch servicing industries. Since firms in the manufacturing sector face significant cost disadvantages, a negative relationship between firm growth and size remains, even for establishments employing over 5 workers. For the latter subset of larger manufacturers only, the constant elasticity of firm growth with respect to firm size is –0.138 with a standard deviation of 0.026. Servicing firms stabilise earlier at a lower employment level, not subject to the pushing forces of any scale economies. Employer's behaviour thus differs among types of industries. The key insight is the presence of significant economies to scale in manufacturing and its lacking in servicing sectors. The absence of any cost disadvantage in the servicing sector spurs on the decision to entry ex ante. However, by the same reasoning market failure is most likely if economies of scales are non-existent. This is exactly what emerged from Table 4 of Section II.

Table 6: Estimated constant elasticities of firm growth and determinants of firm survival in the servicing sector: less than 5 employees (columns (1) and (2)) versus more than 5 employees (columns (3) and (4))

	(1)	(2)	(3)	(4)
ln $x_{it'}$	-0.108** (0.195)	0.784** (0.099)	-0.018 (0.022)	-1.572 (0.834)
ln $a_{it'}$	-0.030* (0.013)	-0.145 (0.093)	-0.032 (0.022)	0.382 (0.642)
Number of observations	1437		428	
λ	0.159* (0.063)		-0.021 (0.262)	

*Note: Columns (1)/(2) and (3)/(4) show the estimates of the growth and the survival equation of services with employment <=5 and >5 respectively. In brackets are standard errors, ** indicates significance at 1 % level and * significance at 5 % level. During estimation sector, regional and time dummies are included.*

Walsh (1999) has modelled the growth and failure of small Irish plants and showed Gibrat's Law to hold for plants that subcontract into R&D sectors and to fail in traditional industries. The author builds up his argument in analysing pre-entry considerations of potential market entry. Starting from scratch, entrepreneurs have to bear in mind the sunk costs of start-up. Even more, possible market entrants have to consider the nature of these costs upon entry. Exogenous sunk costs of entry are attendant when fixed costs are due only upon industry accession. In particular, exogenous sunk costs do not require any post-entry information. They only need to be endured as to become a market incumbent. Once born in a market, exogenous sunk costs no longer interfere the firm's decision making. In contrast to exogenous sunk costs, endogenous sunk costs of entry influence post-entry market performance of the firm. Pre-entry considerations of potential market players require post-entry information on the firm's prosperity in case sunk costs are endogenous. It goes without saying that R&D or advertising can be good examples of endogenous sunk costs of entry.

Why would Gibrat's predictions be verified in industries earmarked by endogenous sunk costs and be offset otherwise? Since endogenous sunk costs request information on post-entry performance ex ante, firms need to know their efficiency (cost) levels before market participation. If not, uncertainty makes the decision to bear down endogenous sunk costs an undertaking too risky. If sunk costs are exogenous however, uncertainty about post-entry progress might be mastered by learning-from-doing. In line with Irish manufacturing, do we find evidence for Flemish firms?

Table 7 reports results for the manufacturing sector only. Columns (1) and (2) consider sectors that face exogenous sunk costs, while columns (3) and (4) show the results for the sub-sample of sectors facing endogenous sunk costs of entry. The assignment of the nature of sunk costs is taken from Davies and Lyons (1996) and is done by looking at R&D and advertising expenditures. Endogenous sunk cost sectors are characterised by intensive R&D and/or advertising expenditures. The residual sectors are those characterised by exogenous sunk costs of entry. This used classification method is not a trivial one.[7]

Table 7: Estimated constant elasticities of firm growth and determinants of firm survival in the manufacturing sector: exogenous sunk costs of entry (columns (1) and (2)) versus endogenous sunk costs of entry (columns (3) and (4))

	(1)	(2)	(3)	(4)
ln $x_{it'}$	-0.024* (0.010)	0.715** (0.194)	-0.020 (0.035)	-0.196 (0.408)
ln $a_{it'}$	-0.062** (0.020)	0.029 (0.222)	-0.149 (0.079)	0.828 (0.645)
Number of observations	570		71	
λ	0.056 (0.111)		-0.015 (0.121)	

*Note: Columns (1)/(2) and (3)/(4) show the estimates of the growth and the survival equation of exogenous and endogenous sunk cost industries in manufacturing respectively. In brackets are standard errors, ** indicates significance at 1 % level and * significance at 5 % level. During estimation sector, regional and time dummies are included.*

The results in Table 7 are forthright. Gibrat's Law hold for industries characterised by endogenous sunk costs while the opposite is true with respect to exogenous sunk cost industries. The growth and survival equation for the latter are given in columns (1) and (2) while estimates for the former are given by columns (3) and (4) respectively. The firm growth-size relationship is no longer pertinent for establishments that engage

[7] In the classification used, an industry that does not have high R&D and/or advertising expenditures is labelled as an "exogenous sunk cost industry". We can abstract from the *level* of exogenous sunk costs since it is shown by Sutton not to influence the decision to entry.

in considerable R&D or advertising activities. Hitherto, one can conclude that no firm growth-size relationship exists for manufacturing firms facing endogenous sunk costs of entry. Hence there seem to be differences in employment behaviour not only between sectors (see the foregoing section) but also within sectors.

For one thing the low number of growth observations in R&D and advertising intensive industries can questionmark the found results. Yet, few observations for endogenous sunk cost industries copes with what theory would suggest since endogenous sunk cost sectors are typified by that in equilibrium a lower bound to concentration exists (Sutton, 1991). Endogenous sunk cost sectors are characterised by products with some 'vertical' attribute, i.e. with some degree of vertical product differentiation. If so, it can be shown that the Limit Theorem, i.e. as the size of the market increases the equilibrium concentration level will diminish, fails to hold. The intuition is straightforward. Suppose that all firms are producing products of the same 'perceived' level of quality and hence there exists a uniform price in the market. In this setting it is optimal for at least one firm to increase its advertising expenditures (i.e. endogenous sunk costs) thereby increasing the 'perceived' level of quality of its product, which results in a positive increase of its market share given the price asked for the product is equal to the marginal cost of production, which is the same for all firms and independent of any fixed cost components. In this setting all customers will buy the quality product which is strictly preferred over the low quality product at the given price. It is this mechanism which leads to a bounded number of firms in the market. The implication for the growth-size relationship is that we expect that the effects of initial size and age are lower, if not absent. Endogenous sunk costs can raise barriers to entry, which leads to less market inauguration and less "entry mistakes".

Which knowledge did Section IV impart? Gibrat's Law seems to be re-established in either of two cases. First, scarce evidence comparing servicing and manufacturing propounds employment behaviour by firms to differ between crude sectoral classifications. While a negative firm growth-size relationship occurs in overall manufacturing, this is not necessarily true for services. Explanations can be found looking at the presence of scale economies facing market incumbents. Second, within manufacturing Gibrat's Law is contained for R&D and/or advertising intensive industries. The stakeholder's explanation is found in pre-entry considerations and the consequences of bearing the costs of entry. Firms will only engage in high levels of R&D or advertising upon entry if they know their market efficiency levels ex ante. Moreover, endogenous sunk cost industries are subject to a lower bound of market concentration.

Conclusions

References

-Amemiya, T. (1984), “Tobit Models: a Survey”, Journal of Econometrics, Vol. 24, pp. 3-61, Elsevier Science Publishers.

-Audretsch, D. (1991), “New-Firm Survival and the Technological Regime”, Review of Economics and Statistics, 73:3, pp. 441-450.

-Audretsch, D. (1995a), “Innovation and Industry Evolution”, MIT Press, 205 p.

-Audretsch, D. (1995b), “Innovation, Growth and Survival”, International Journal of Industrial Organisation, 13:4, pp. 441-457.

-Audretsch, D., Klomp, Thurik, A., (1997), “Do services differ from manufacturing? The post-entry performance of firms in Dutch services”, Centre for Economic Policy Research, Discussion Paper Series 1718, Centre for Economic Policy Research, London, 25 p.

-Baldwin, R.J. (1995), “The Dynamics of Industrial Competition: a North American Perspective”, Cambridge University Press.

-Baldwin, R.J., Gorecki, (1987), “Plant Creation versus Plant Acquisition: the Entry Process in Canadian Manufacturing”, International Journal of Industrial Organisation, 5:1, pp. 27-41.

-Caves, R. (1998), “Industrial Organisation and New Findings on the Turnover and Mobility of Firms”, Journal of Economic Literature, Vol. XXXVI, pp. 1947-1982.

-Davis, S.J., Haltiwanger, J. (1992), “Gross Job Creation, Gross Job Destruction and Employment Reallocation”, Quarterly Journal of Economics, 107:3, pp. 819-63.

-Davis, S.J., Haltiwanger, J. (1999), “Gross Job Flows”, in: Ashenfelter, O. & Card, D, editors, Handbook of Labour Economics, Vol. 3 and 4, Amsterdam, North-Holland.

-Davis, J.S., Haltiwanger J.C., Schuh, S. (1996), “Job Creation and Destruction”, MIT Press, 253 p.

-Davies, S., Lyons, B. (1996), “Industrial Organisation in the European Union”, Clarendon Press, Oxford, 283 p.

-Dunne, T., Roberts, M., Samuelson, L. (1989), “Patterns of Firm Entry and Exit in US Manufacturing Industries”, Rand Journal of Economics, 19:4, pp. 495-515.

-Evans, D.S. (1987a), “Test of Alternative Theories of Firm Growth”, Journal of Political Economy, Vol. 95 (4), pp. 657-674.

-Evans, D.S. (1987b), "The Relationship Between Firm Growth, Size and Age: Estimates for 100 Manufacturing Industries", Journal of Industrial Economics, Vol. 35, pp. 567-581.

-Garibaldi, P., Konings, J., Pissarides, C. (1997), "Gross Job Reallocation and Labour Market Policy", in: Snower, D.J. & de la Dehesa G., editors, Unemployment Policy: Government Options for the Labour Market, New York: Cambridge University Press.

-Geroski, P. (1999), "The Growth of Firms in Theory and in Practice", CEPR DP 2092, march 1999, pp. 30.

-Geroski, P. (1995), "What do we know about entry?", International Journal of Industrial Organisation, Vol. 13, p. 421-440.

-Goos, M., Konings, J. (1999), "Firm Growth in Belgium", Tijdschrift voor Economie en Management, Katholieke Universiteit Leuven, forthcoming.

-Greene, W.H. (1999), "Econometric Analysis", Fourth Edition, Prentice Hall, New York.

-Heckman, J. (1976), "The Common Structure of Statistical Models of Truncation, Sample Selection and Limited Dependent Variables and a Simple Estimator for Such Models", Anals of Economic and Social Measurement, vol. 5, pp. 475-492.

-Hall, B. (1987), "The Relationship between Firm Size and Firm Growth in the US Manufacturing Sector", Journal of Industrial Economics, 35:4, pp. 583-600.

-Hart, P.E., Prais, S.J. (1956), "The analyis of business concentration: a statistical approach", Journal of the Royal Statistical Society, A, vol. 119, pp. 150-191.

-Jovanovic, B. (1982), "Selection and the Evolution of Industry", Econometrica, Vol. 50 (3), pp. 649-670.

-Konings, J. (1995a), "Gross Job Creation and Destruction in the UK Manufacturing Sector", Oxford Bulletin of Economics and Statistics, 57(1), 1-20.

-Konings, J. (1995b), "Gross Job Flows and the Evolution of Size in U.K. Establishments", Small Business Economics, Vol. 7: 1-8, Kluwer Academic Publishers.

-Konings, J., Roodhooft, F., Van De Gucht, L. (1998), "Startende ondernemingen in Vlaanderen: hun levenscyclus en invloed op jobcreatie en jobdestructie", Maandschrift Economie, Vol. 62, p. 239-253.

-Konings, J., Mommaerts, G., Seldeslachts, J., Veugelers, R. (1999), "Schepping en vernietiging van banen: de invloed van O&O-actieve bedrijven", Economisch en Sociaal Tijdschrift, Vol. 53 (1), pp. 79-109.

-Leonard, J.S., Van Audenrode, M. (1993), “Corporatism run amok: job stability and industrial policy in Belgium and the United States”, Economic Policy, October 1993, p. 356-400.

-Leonard, J.S. (1999), “Bringing the firm back in”, Labour Economics: an International Journal, Vol. 6, p. 43-51.

-Lyons, B., Matraves, C., Moffat, P. (1999), “Industrial Concentration and Market Integration in the European Union”, mimeo, School of Economic and Social Studies, University of East Anglia, Norwhich.

-Pakes, A., Ericson, R. (1989),”Empirical Implication of Alternative Models of Firm Dynamics”, Working Paper, Yale University.

-Simon, H.A., Bonini, C.P. (1958), “The size distribution of business firms”, American Economic Review, vol. 48, pp. 607-617.

-Sutton, J. (1991), “Sunk Costs and Market Structure”, MIT Press, 577p.

-Sutton, J. (1997), “Gibrat’s Legacy”, Journal of Economic Literature, Vol. XXXV, pp. 40-59.

-Sutton, J. (1998), “Technology and Market Structure: Theory and History”, MIT Press, 676 p.

-Vella, F. (1998), “Estimating Models with Sample Selection Bias: A Survey”, The Journal of Human Resources, vol. XXXIII, pp. 127-169.

-Walsh, P.P. (1999), “Sunk Costs and the Growth and Failure of de novo Irish Manufacturing Plants”, mimeo LICOS Centre for Transition Economics.