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Inter-firm rivalry and firm growth: is there any evidence of direct competition between firms?

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Inter-firm competition has received much attention in the theoretical literature, but recent empirical work suggests that the growth rates of rival firms are uncorrelated. We begin by investigating the correlations of the growth rates of competing firms (i.e. the largest and second-largest firms in the same industry) and observe that, surprisingly, the growth of these firms can be taken as uncorrelated. Nevertheless, peer-effect regressions, that take into account the simultaneous interdependence of growth rates of rival firms, are able to identify significant negative effects of rivals' growth on a firm's growth.

JEL classification: L25: L22: L11

> The businessman feels himself to be in a competitive situation even if he is alone in his field or if though not alone, he holds a position such that investigating government experts fail to see any effective competition between him and any other firms in the same or a neighboring field and in consequence conclude that his talk, under examination, about his competitive sorrows is all make-believe.
>
> Schumpeter (1942: 85)

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1. Introduction

A central concept in economic development is the issue of inter-firm competition. For example, John Stuart Mill wrote that "only through the principle of competition has political economy any pretension to the character of a science" (1984: 147). For a subject of its importance, therefore, inter-firm competition seems to be poorly understood and relatively under-researched. "Competition seems very well in practice, but it is not so clear how it works in theory," according to Vickers (1995: 1). Unfortunately, though, we suggest that inter-firm competition does not seem to be well-understood even in practice. Some recent empirical investigations into inter-firm competition have failed to find strong evidence of inter-firm competition, because the growth of rival firms appears to be uncorrelated. At the same time, however, management scholars continue to emphasize the crucial role of inter-firm competition, and have even coined new expressions such as "hypercompetition" (See e.g. D'Aveni, 1994; Wiggins and Ruefli, 2005). Furthermore, the phenomenon of "industrial espionage" certainly indicates that some firms consider that competitive pressure is not only a vague industry-wide force but also that there are strong sources of direct competition coming from specific rivals [for a survey of industrial espionage, see Crane (2005)].

The aim of this article is to complement the sparse literature by providing new empirical evidence on the matter. We begin with investigations of direct competition at the firm-dyad level of analysis [following Sutton (2007) on Japanese data], focusing on the correlations of growth rates of the largest versus second largest firms in specific sectors. Afterwards, we relate the growth of firms to the growth of rivals in the same sector, by taking advantage of recent developments in peer-effects econometrics. Among the main contributions of this article is the use of peer-effects econometrics to investigate inter-firm competition.

The structure of the article is the following. The next section briefly summarizes the relevant literature. Section 3 presents the database and Sections 4 and 5 contain the analysis. In Section 4, we focus on correlations between the largest and second largest firm in each sector, while Section 5 contains our regression results. The final section (Section 6) draws the conclusions, discussing the results and suggesting future research directions.

2. Literature review

2.1 Theoretical literature

Theoretical models of inter-firm competition have generally suggested that the growth of one firm is negatively correlated with the growth of its rival. "[C]ompetitors are typically seen as being in an ongoing, zero-sum battle with each other for customers, resources, and other rewards" (Crane, 2005: 234).

For example, the "islands" models of firm growth (Ijiri and Simon, 1977; Sutton, 1998; Bottazzi and Secchi, 2006a) hold that firms compete for a limited number of growth opportunities. The introduction of game theory into the industrial organization literature has had the effect of further emphasizing the importance of considerations of competitive interactions between firms.[1] By way of an illustration, consider the case of the reaction of incumbents to the entry of new firms. The game-theoretic literature frames this situation as a one-on-one strategic game, whereby entrants take market share from incumbents, and incumbents make strategic investments in capacity to deter potential entrants from entering [see e.g. Salop (1979) and Dixit (1980)]. This vision of the relationship between incumbents and entrants is not entirely realistic, however (Geroski, 1995). In reality, entrants are often far too small to be of any threat, their growth is too slow, their exit hazard too high, and their arrival is too erratic. Furthermore, in the unlikely event that incumbents are genuinely concerned about defending their market share from entrants, the available evidence suggests that they are unlikely to do so by investing in additional capacity, but rather through the use of strategies such as advertising or licensing deals (Geroski, 1995). As such, some predictions emerging from the theoretical literature do not closely correspond to the actual workings of the economy.

The resource-partitioning model in Carroll (1985) discusses an ecology of heterogeneous organizations that follow either generalist or specialist market strategies. Generalist organizations (which would correspond to large firms) compete in a variety of domains simultaneously, while specialist organizations (which would correspond to small firms) focus on a small number of niche markets. Large firms can engage in "inter-generalist rivalry" between themselves that need not necessarily have an adverse effect on specialist firms.

More recently, theoretical contributions on the topic of inter-firm competition have emphasized that competitive behaviour might be dampened by multi-market contact between rivals, and the threat of retaliation (Evans and Kessides, 1994; Baum and Korn, 1996). Inter-firm competition may also be dampened if one considers that the opportunity sets available to growing firms are limited by the idiosyncratic nature of a firm's existing resource configurations, managerial perception of the attractiveness of different growth strategies, and also different degrees of managerial creativity and audacity (Penrose, 1959).

To complicate things further, it has also been suggested in the management literature that rival firms should simultaneously compete and cooperate with each other (Hamel *et al.*, 1989; Bengtsson and Kock, 2000). There are indeed many ways in which one firm may *benefit* from the growth of a supposed rival firm. This could occur, for example, if there is some complementary nature of the

[1]For example, Carl Shapiro's confidently titled survey article, "The theory of business strategy" (Shapiro, 1989), is little more than a survey of applications of game-theoretic interactions between two players in the field of industrial organization.

goods produced, if there are spillovers through generic aspects of advertising or lobbying, or if firms benefit from a better negotiating position with suppliers and distributors, and so on. Rival firms can also benefit from each other's successes by imitating each other.

As a result, theoretical work does not yield very clear predictions for expected inter-firm competitive dynamics (in terms of the growth rates of rivals), and it seems that empirical work can help to elucidate this matter.

2.2 Empirical literature

The early empirical research on inter-firm competition often measured competition as an industry-wide pressure (of unspecified origin), rather than a competitive pressure emanating from any single competitor. In this early literature, competition was usually measured in terms of industry concentration, or rents obtained by incumbents. However, it has been shown that these variables are poor indicators of actual inter-firm competition (Boone *et al.*, 2007). As a result, other measures of inter-firm competition have been investigated, such as questionnaire responses on perceived competition (e.g. Nickell, 1996), import penetration (e.g. Haskel *et al.*, 2007; Kato and Honjo, 2009) and the "profit elasticity" indicator used in Boone *et al.* (2007).

While we acknowledge that there are difficulties in measuring competition, nonetheless we argue that efforts should be made to measure competition bearing in mind the importance attributed to this topic. Empirical investigations into the matter have often failed to find any significant statistical evidence of inter-firm competition, however. Storey (1994: 144, 152) provides a survey of four empirical papers and observes that none of these four papers can find any statistically significant impact of competition on firm growth. More recently, Geroski and Gugler (2004) consider the impact of the growth of rival firms on a firm's employment growth, using a database on several thousand of the largest firms in 14 European countries.[2] In their main regression results (see their Table 2), they are unable to detect any significant effect of rival's growth on firm growth, although they do find a significant negative effect in specific industries (i.e. differentiated good industries and advertising intensive industries).

Empirical work focusing on specific, narrowly defined markets has in some cases been able to identify competitive interactions between firms. In the airline industry, Goolsbee and Syverson (2008) identify a significant effect of threat of entry on incumbent price levels, where threat of entry on an airline route A–B is measured relative to the time when Southwest Airlines operates from airports A and B (but not from A to B). In the pharmaceutical industry, there is a sudden increase in

[2]Rival firms are defined as other firms in the same three-digit industry.

competitive pressure (including the *threat* of entry even if no entry actually occurs) when a patent expires. In this situation, empirical work focusing on the prices of individual drugs has identified significant effects of inter-firm competition (Bergman and Rudholm, 2003). Chen *et al.* (2005) detect a significant negative wealth effect of a firm's new product introduction on its rivals, when considering the few days surrounding the product announcement. McGahan and Silverman (2006) consider the effect of competitor patenting on firm value, and their results support both market-stealing and spillover effects of innovation. Fosfuri and Giarratana (2009) focus on the competitive interactions between Coca-Cola and Pepsi, and observe significant effects of rivals on a firm's market value: rival product innovation has a negative impact on a firm's financial market value, while interestingly enough a rival's new advertising has a positive effect. These effects are observed to be statistically significant, although when the event window is enlarged by a few days the significance fades. However, we want to go beyond this seemingly narrowly defined evidence relating to certain peculiar submarkets, and find some general properties of competition at the more aggregated firm-level.

Questionnaire evidence on subjectively perceived competition suggests that small business managers do feel competitive pressure. Hay and Kamshad (1994) observe that intensity of competition is ranked as the most important constraint, by far, to the growth of small and medium sized firms in the UK. Similarly, Robson and Obeng (2008) report that 49.3% of entrepreneurs report "too many competing firms" as an important, or crucial limitation to these firms in achieving their objectives (see their Table 1). Vos *et al.* (2007, Table 5) report that perceived competition is the second most important issue affecting SMEs in their sample, far above the issue of financing. Nevertheless, we argue that subjective attitudes towards inter-firm competition are no substitute for objective statistical evidence on the matter. As illustrated by our opening quote, subjectively perceived competitive pressure may plague the imaginations of businessmen even if they are alone in their field. Indeed, the idea that inter-firm competition may reside in the minds of businessmen without leaving a detectable statistical trail is implied by phrases such as "the specter of competition" (Aboulnasr *et al.*, 2008: 94), "Schumpeter's ghost" (Wiggins and Ruefli, 2005), or that "the warfare must be perceived as a continuing battle without blood" (Fosfuri and Giarratana, 2009: 184).

An interesting contribution to the empirical literature can be found in Sutton (2007). Sutton analyzes the dynamics of market shares of leading Japanese firms. While many studies view "competitive pressure" as a rather vague, broadly defined, industry-wide variable affecting all firms but originating from no individual firm, Sutton looks for evidence of direct competition between specific firms. Given that market shares add to unity by construction, shocks to different firms market shares can be expected to be interdependent. It is rather surprising, therefore, to see that the changes in market share of the first and second largest firms in any industry are,

Table 1 Descriptive statistics for Spanish manufacturing firms with 250 workers or more in 2000

	Mean (SD)	Skewness	Kurtosis	10%	25%	Median	75%	90%	Obs.
2000									
Empl	577 (835)	9.6	117.4	268	299	380	588	908	579
Sales	161510.1 (425501.7)	11.6	164.2	27440.5	43630.18	72846.9	149369.8	267613.9	579
VA	34713.3 (62704.8)	8.9	110.4	4557.8	10117.5	18171.1	37616.9	66667.0	579
2006									
Empl	570 (939)	7.8	79.2	184	268	363	592	917	436
Sales	170179.4 (471125.7)	8.7	89.1	18062.0	35823.8	72632.8	153729.8	277325.3	447
VA	32205.4 (60729.2)	6.0	49.1	7214.9	12022.1	18697.6	34321.4	60726.2	452

in all but a few exceptional circumstances,[3] uncorrelated. Sutton uses this finding to justify his model of independent shocks.

2.3 The locus of competition

Empirical investigations into inter-firm competition should consider where evidence of competition is most likely to be found. For example, are competitive forces stronger for small firms or large firms?

Small firms are often too small to engage in direct competition, and tend to thrive in specific niches or "interstices" (Penrose, 1959). Wiklund (2007) also writes that small firms tend to avoid taking a competitive stance vis-à-vis their rivals.[4] Larger firms, in contrast, are less sheltered, more visible, and their behavior is likely to have some influence on their business environment. Evidence presented in Boone *et al.* (2007) suggests that forces of competition are more significant for larger firms than for smaller firms. Audretsch *et al.* (1999) do not find any evidence of direct competition between large firms and small firms (more specifically, they suggest that small-firm profits are independent of large-firm profits). In contrast, Nickell (1996) is able to detect evidence of inter-firm competition on productivity growth in his analysis of large UK manufacturing firms. Of greater relevance to our present investigation is the size disaggregation exercise in Geroski and Gugler (2004: 612), where significant (negative) effects of rival growth on firm growth can only be found for the "very large firms" category.

In this article, we take the view that inter-firm rivalry is not at its strongest between small firms, or between small and large firms, but we expect the strongest rivalry effects to be between large firms. Therefore, in our analysis we either focus on the two largest firms in specific four-digit industries (Section 4) or on relatively large firms with 250 employees or more (i.e. corresponding to the standard EU definition of a large firm) in Section 5.

3. Database

This study uses the Spanish Mercantile Register through the System of Analysis of Iberian Balance Sheets (SABI database) compiled by Bureau van Dijk. This database offers exhaustive information from balance sheets and financial sources for a large number of firms. In our regression analysis, our main sample database focuses on large manufacturing firms with 250 or more employees in 2000, and we observe their

[3]That is, when the combined market share of these two firms is >80%.

[4]Wiklund 2007 writes that: "Firms grow foremost through an increase in demand in their market niche and not through taking market share from their competitors. That is, growing small firms prefer to find new market niches than fight for market share in existing markets" (2007: 145).

evolution until 2006 (both years included).[5] In our robustness analyses, however, we will sometimes include all firms with 100 or more, or 200 or more employees in 2000.[6] Our sample is unbalanced (entries and exits may occur during the period) and contains 579 firms in the year 2000.[7]

The period 2000–2006 was characterized by an economic expansion that increased the overall number of active Spanish firms, although the share of firms in manufacturing decreased from 18.4% in 2000 to 14.3% in 2006. When looking at the evolution of the economic variables of manufacturing firms, the average annual growth rate of the manufacturing sector was equal to 5.79% for sales, while the growth was equal to 4.78% for value added. In terms of employment, however, manufacturing grew by only 0.28% every year. During this period, the industrial structure remained stable. In line, the international evidence in Bartelsman *et al.* (2005: 373), the percentage of Spanish manufacturing firms with less than 20 employees has remained equal to around 80%.

Firm growth is measured using three different indicators: employees, sales, and value added. Each indicator taken individually has its own idiosyncratic drawbacks, but in our analysis we observe that the different indicators give broadly similar results. Measuring size and growth in terms of employees avoids controversies related to the choice of deflators. Previous work has identified inter-firm competition on the labour market (Sorensen, 2004), and also the migration of workers into rival firms (e.g. Almeida and Kogut, 1999; Franco and Filson, 2006), which justifies our interest in employment growth. However, one problem is that the number of employees often does not change from one year to the next (i.e. growth = 0.00).[8] Furthermore, a focus on a headcount of employees does not take into account different skill levels of a firm's employees. Alternatively, Sales and Profits can be used to measure firm growth. A drawback of these variables is that they must be deflated. Nevertheless, these are the most common variables used to measure firm size and market power (sales in particular). The variable "Profits" (measured here as total income – operating expenditures) is also a key variable in antitrust investigations by

[5]In keeping with previous work on this database, we have excluded two sectors due to the scarce number of firms: NACE16 (Tobacco industry) and NACE23 (Petroleum industry). More information on the Spanish manufacturing sectors (number of firms, employees, and some main economic variables) can be found at the following webpage of the Spanish Statistical Institute: www.ine.es/jaxiBD/menu.do?divi=EIE&his=0&type=db&L=1. This webpage provides information related to the Encuesta Industrial (Manufacturing survey).

[6]As a result of our focus on large firms, however, we should be aware that some industries containing mostly small firms will be under-represented.

[7]One drawback of this database is that micro firms are not well represented. However, this is no cause for concern here given that we focus on large firms.

[8]We should also remark that the variable *Employees* is not a compulsory reporting requirement for some firms. As a consequence, we may lose some observations when analyzing this variable.

Table 2 Correlation matrix of size levels in 2006 for Spanish manufacturing firms

	Empl	Sales	VA	Profits
Empl	1			
P-value				
obs	436			
Sales	0.8337	1		
P-value	0.0000			
obs	436	447		
VA	0.9029	0.8519	1	
P-value	0.0000	0.0000		
obs	436	447	452	
Profits	0.3360	0.2336	0.5784	1
P-value	0.0000	0.0000	0.0000	
obs	436	447	452	452

competition authorities (Geroski and Griffith, 2004). However, we have many negative values for profits, which implies that we cannot calculate growth rates for many observations. Hence, we use *value added*, which contains information on both firm size and also relative financial performance (cf the correlation matrix in Table 2). Finally, we should mention that sales and value added have been deflated using sector-specific deflators at the four-digit industry level.

Unlike Sutton (2007), we focus on firm growth rather than the dynamics of market shares. Normalizing firm growth into market share growth, by dividing firm growth by industry growth, can be seen as an artificial way of introducing endogeneity and interdependence between firms, and we suggest that this is not necessary for the purposes of our present analysis. It is interesting to consider that Sutton (2007) observes that the growth of rival firms can be seen as uncorrelated, even when their growth is measured in terms of market share dynamics. We can therefore anticipate, *a fortiori*, that our investigations of firm growth (measured in terms of employees, sales and value added) will show that the growth of rival firms is uncorrelated.

With respect to the classification of firms to a sector, in Spain firms declare their sector of main activity (according to the NACE classification scheme) and other "secondary activities." Here, we classify firms to one sector in accordance with their main activity. Hence, we do not consider the possibility that a firm may be operating in similar or completely different sectors simultaneously. Details on the industry classification scheme can be found online.[9]

[9]For more information, see www.ine.es/jaxiBD/menu.do?divi=EIE&his=0&type=db&L=1.

Table 3 Firm age and C_{20}^{4} ratios for Spanish manufacturing firms in 2006, for young firms (<10 years), medium firms (10–19 years) and old firms ($\geqslant$20 years)

Firm age	Obs.	Mean	Median (sd)
Young	50	7.58	7.5 (0.99)
Medium-aged	116	14.96	15 (2.97)
Old	291	40.83	38 (16.28)
Total	457	30.63	27 (18.92)
C_{20}^{4} four-digits			
Young	20	0.53	0.55 (0.21)
Medium-aged	30	0.60	0.61 (0.21)
Old	73	0.60	0.59 (0.22)
Total	123	0.59	0.59 (0.21)
C_{20}^{4} three-digits			
Young	8	0.41	0.40 (0.16)
Medium-aged	19	0.52	0.50 (0.14)
Old	36	0.53	0.45 (0.21)
Total	63	0.51	0.46 (0.19)

C_{20}^{4} ratios are disaggregated by age according to the age of the largest firm in the sector.

Table 1 shows the descriptive statistics of main variables for the years 2000 and 2006. First, the average firm size is 570 employees. Second, at the end of the period of observation we observe a slightly smaller size measured in employees and sales among smaller firms (10%, 25%, and 50% quantiles), while there is an increase of the values for the largest firms (see the 75% and 90% quantiles). Conversely, value added has increased in 2006 for firms in the smallest percentiles, while for firms belonging to the largest percentiles value added decreased during the same period.

Table 2 shows the correlation matrices for levels of employees, sales, value added, and profits. All of these variables are significantly positively related to each other, although the correlations between profit levels and levels of the other variables are smaller in magnitude. Value added is better correlated with each of the other variables. Hence, we can consider that it is a good indicator of size, and it is also also strongly related to financial performance.

Table 3 shows descriptive statistics for firm age and C_{20}^{4} ratios in 2006 (where the C_{20}^{4} ratio is calculated as the cumulative market share of the four largest firms divided by the cumulative market share of the 20 largest firms in a sector). In this case, we have also classified firms according to whether they are young (<10 years), medium-aged (between 10 and 19 years), or old ($\geqslant$20 years). Our results show that

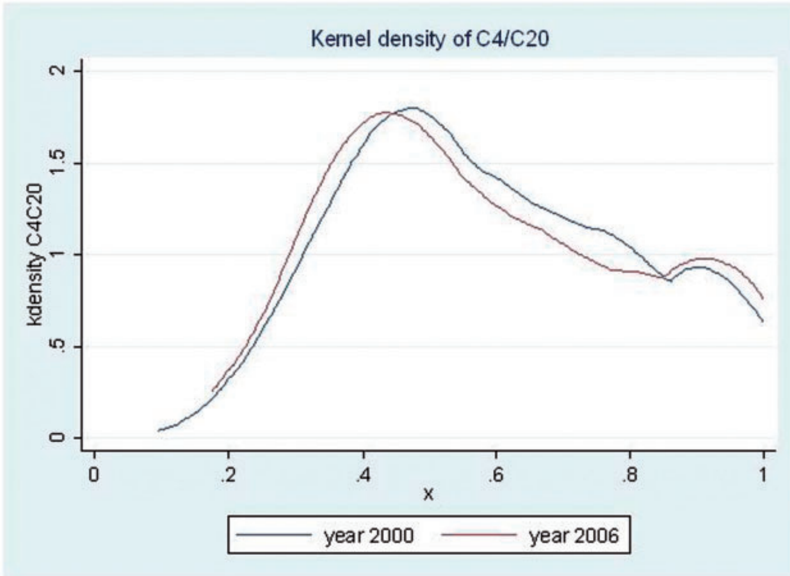

Figure 1 Distribution of the C_{20}^{4} for four-digit industries.

the majority of firms which are large have been operating in the market for $\geqslant 20$ years. Furthermore, for old firms the average age is 41 years. Hence, the evidence for Spanish large manufacturing firms is that they are rather old. Table 3 also contains information on how C_{20}^{4} ratios vary with respect to the age of the sector's largest firm. We have 159 industries at four-digit industry level, where the mean C_{20}^{4} ratio takes values between 0.53 and 0.60. If we consider the C_{20}^{4} ratio at the level of three-digit industries, the concentration ratio diminishes. We also observe that sectors in which the largest firm is younger tend to be less concentrated.

Figure 1 shows the distribution of C_{20}^{4} concentration ratios at four digit industry-level sectors. Values of C_{20}^{4} must lie within an upper bound at 1.00 and a lower bound of 0.20, by construction. Therefore, as we can observe, the empirical distribution covers most of the available support, but with higher density on the value interval between about 0.40 and 0.60.

Figure 2 shows the distribution of the ratio of the size of the largest to the second largest firm classified at four-digit industries. The lower limit at 1.00 corresponds to the case where the leader is almost the same size as the second largest firm. In most cases, the leader is not much more than twice as large as the second largest firm, although in some cases the leader can be 10 times larger, or even more.

Growth rates g are calculated by taking log-differences of size levels:

$$g_{i,t} = log(X_{i,t}) - log(X_{i,t-1}) \tag{1}$$

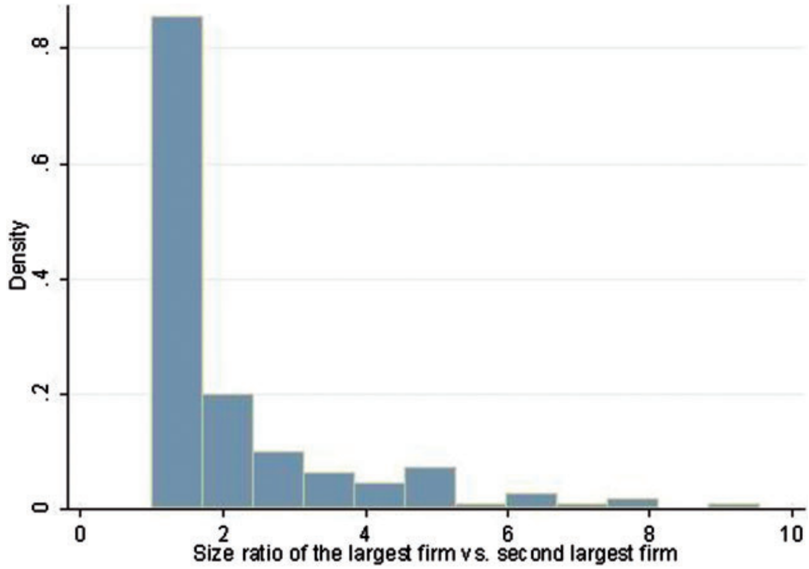

Figure 2 Size ratios of the largest firm versus second largest firm in four-digit industries, for the year 2006. Firm size measured in terms of number of employees. Size ratios are restricted to taking values of at least one, by construction.

where X is a measure of firm size ($X \in \{Sales, Employment, Value\ Added\}$) for firm i at time t.[10]

4. Leader–follower correlations

4.1 Scatterplots

We begin our analysis with some correlations, following Sutton (2007). Figure 3 shows the correlations of the growth rates of the largest and second largest firms that are in the same sectors, where the sector is defined alternatively on a three-digit and four-digit industry level of aggregation. Growth is defined in terms of employment, sales or value added, and growth is measured over a 1-year period or a 7-year period. The most striking finding is that the growth of one firm appears to be uncorrelated with the growth of its rival, in each case. We also introduced a year lag between the growth of the largest and second-largest firm, but obtained similar results. Our investigations into inter-firm competition do not appear to have made a good start and find results similar to Sutton (2007).

[10]This way of calculating growth rates is the preferred choice according to Tornqvist *et al.* (1985).

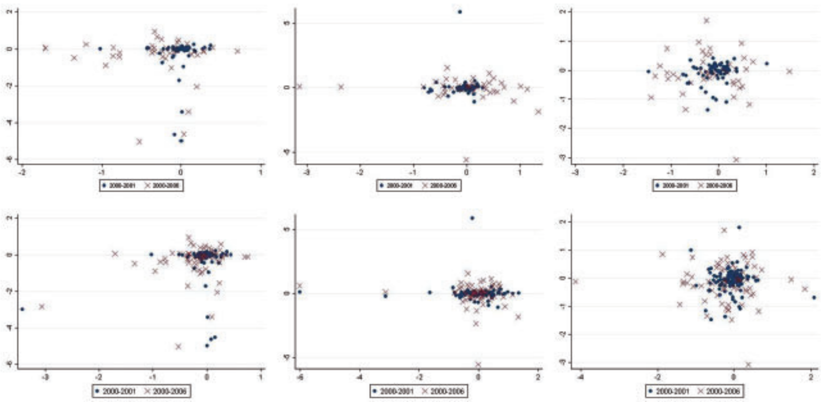

Figure 3 Scatterplots of the growth (2000–2001) of the largest versus second largest firm in each sector. Three-digit industries are shown on the top row, and four-digit industries are shown on the bottom row. Growth is measured in terms of employees (A), sales (B), or value added (C). Leader's growth plotted on the vertical axis, follower's growth plotted on the horizontal axis.

Data constraints prevent us from taking a finer level of disaggregation beyond the four-digit industry level. It should be mentioned, however, that even at the four-digit industry level, in a number of cases the largest firm in its four-digit industry is relatively small and would not qualify as a "large firm" according to any standard definition.

4.2 Correlated growth profiles

We pursue our investigation of inter-firm competition by focusing on one industry at a time, and within this industry focusing on the correlation between the annual growth rates of the two largest firms. For each industry j we calculate the correlation coefficient ρ_j relating the growth of the largest firm (firm A) to the growth of the second largest (firm B), according to the following formula:

$$\rho_j = \frac{\sum_{t=2000}^{2006}(g_{A,t} - \overline{g_A})(g_{B,t} - \overline{g_B})}{\sigma_A \sigma_B} \tag{2}$$

Figures 4 and 5 show the distributions of the correlation coefficients, ρ_j, at the level of three-digit and four-digit industries, respectively. Sutton (2007: 226) shows that negative correlation is more likely to be found in the market share dynamics of the two largest firms in the case of industries that are essentially duopolies. In our analysis we observe both negative and positive correlations between the growth profiles of the two largest firms in the same industry. In contrast to what we would expect if growth of rival firms was merely random, the mode of the

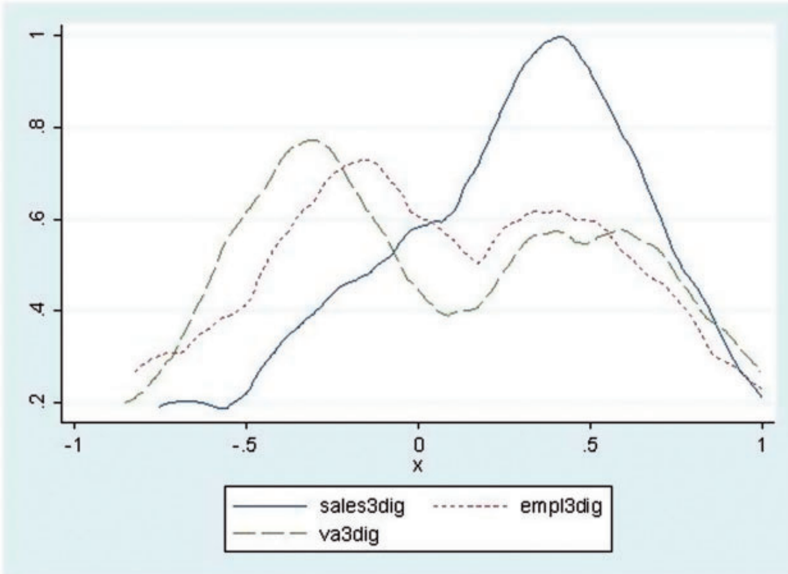

Figure 4 Kernel density showing the correlations between the annual growth rates of the leader and second-largest firm in those thre-digit industries for which at least five data points exist (i.e. at least five annual growth rates for leader versus follower for the period 2000–2006) for the whole database. In other words, this figure shows the distribution of the ρ_j coefficients obtained from equation (2). We restrict ourselves to industries in which the largest firm is not more than 10 times larger than the second largest firm in the year 2000. Annual growth rates are measured in terms of Sales (32 obs), Employment (32 obs), or value added (30 obs). Kernel bandwidth = 0.15. Tests for multimodality, following Silverman (1981) and Hall and York (2001) (using gbutils 5.2) cannot convincingly reject the hypothesis that the distribution is unimodal the *P*-values are 0.330 (Sales), 0.215 (Employment) and 0.051 (VA).

distribution of ρ_j does not appear to be located around zero. This could signal that there might be some structure in the growth profiles of the largest versus second largest firms. In some cases, such as value-added growth at the three-digit industry level, the distribution of ρ_j appears to be bimodal.[11] Formal multimodality tests do

[11]Bimodality in the distribution of ρ_j would suggest that there are two competitive regimes at work in our data set. In some cases, firms in the same industry may share the same fate (positive correlation in growth rates). In other cases, there may be a negative correlation such that sales growth of one firm is associated with a decline of sales for the other firm. One could summarize this structure of interactions between firms by using catchphrases such as “love me or hate me, but nothing in between.” Significant bimodality in the distribution of ρ_j was found for French data in an earlier investigation in Coad and Valente (2011).

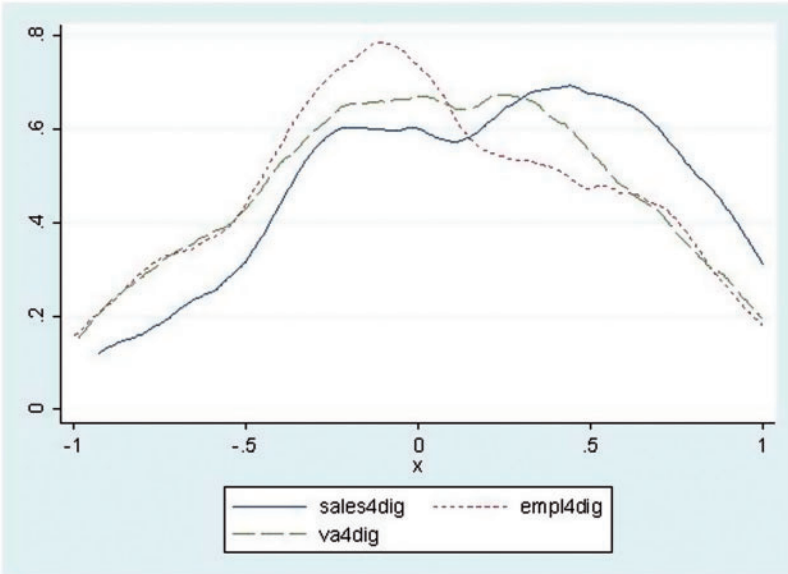

Figure 5 Kernel density showing the correlations between the annual growth rates of the leader and second largest firms in those four-digit industries for which at least five data points exist (i.e. at least five annual growth rates for leader versus follower for the period 2000–2006) for the whole database. In other words, this figure shows the distribution of the ρ_j coefficients obtained from equation (2). We restrict ourselves to industries in which the largest firm is not more than 10 times larger than the second largest firm in the year 2000. Annual growth rates are measured in terms of Sales (85 obs), Employment (83 obs), or value added (79 obs). Kernel bandwidth = 0.15. Tests for multimodality, following Silverman (1981) and Hall and York (2001) (using gbutils 5.2) cannot convincingly reject the hypothesis that the distribution is unimodal the *P*-values are 0.116 (Sales), 0.466 (Employment), and 0.124 (VA).

not suggest that this bimodality is statistically significant at conventional levels, however (see the figure captions for the *P*-values).

4.3 Discussion

So far, our analysis seems to provide justification for theoretical and empirical models that assume that the growth rates of different firms can be modeled as being independent.[12] For example, our results provide some support for Gibrat's model of firm growth, which "explains" growth in terms of stochastic multiplicative

[12]Strictly speaking, however, we must acknowledge that an absence of correlation is not a sufficient condition for statistical independence. Instead, full statistical independence requires that the joint probability density of a pair of variables equals the product of its marginals, i.e. $P(\eta_1, \eta_2) = P(\eta_1) \cdot P(\eta_2)$ (Moneta *et al.*, 2010).

shocks, that are independent across firms. Even when analyzing the growth of rival firms, the following statement still appears to hold: "The most elementary 'fact' about corporate growth thrown up by econometric work on both large and small firms is that firm size follows a random walk" (Geroski, 2000: 169).

Our failure to find interdependencies in the growth rates of firms in the same industries may perhaps be explained by arguing that firms are multiproduct entities that are diversified into many submarkets (with competition taking place at the submarket level), and that industry classification schemes (such as the three-digit to four-digit industry levels analyzed here) are too broadly defined to be able to detect significant competitive interactions. Although it is well known that large firms often diversify into several lines of business (Bottazzi and Secchi, 2006b), however, it has nonetheless been shown that firms in the same industries often have similar diversification patterns (Teece *et al.*, 1994), such that large firms with the same sector of principal activity are likely to have some degree of "multi-market contact" with their rivals even if they are diversified into more than one market. It has also been observed that European firms are more focused than their US counterparts (Geroski and Gugler, 2004: 603).

It seems to us that if competition cannot be detected at the firm level, nor even at the level of rival firms in the same sectors, then competition is a concept that is only relevant at finely disaggregated levels of analysis, and that, as a consequence, we could take the extreme view that it is not relevant to mention competition effects in discussions of *firm*-level performance. In other words, our results seem to suggest that firms can be modeled "as if" they are independent from each other. Antitrust investigations take the "relevant market", defined as narrowly as possible, as the starting point for investigations of inter-firm competition (Geroski and Griffith, 2004). However, these "relevant markets" are extremely difficult to define, and the boundaries of these markets can change from year to year (Geroski and Griffith, 2004). While we consider that competitive interdependence is a useful concept at the level of antitrust "relevant markets", it is far less useful at the firm level.[13] Large firms can be seen as aggregated entities, being active in several different sectors, and being diversified into numerous lines of business in different geographical markets. Perhaps there might be some kind of "law of large numbers" at work, according to which the evidence of inter-firm rivalry tends to disappear with aggregation. While direct competition may sometimes have visible effects at the level of finely disaggregated

[13]There is (by definition) nothing that we can do to resolve the tautology that competition only exists once "relevant markets" have been properly delineated, and that relevant markets are by definition composed of competing firms. Therefore, a sceptic might point out that we fail to find evidence of competitive interdependence because we have failed to properly delineate the relevant markets. However, we would reply that competitive interdependence does not appear to be a relevant concept at the *firm level*.

markets, statistical aggregation effects may wash away evidence of competition as one takes a more aggregated level of analysis.

Although our correlation analysis did not yield evidence of inter-firm competition, we pursue our analysis in the context of multivariate regressions, controlling for other influences and also accounting for the endogeneity of the growth rates of interdependent firms by applying peer-effects econometrics. With regard to our correlation analysis, it might be argued that our focus on the two largest firms in each industry is misplaced, because these giants may avoid competing with each other but instead engage in fierce competition with other common rivals (such as the third or fourth-largest firms). We therefore complement our correlation analysis with regressions that include the growth of other large rivals.

5. Multivariate regressions

5.1 Standard regressions

Equation 3 shows the regression equation.

$$g_{i,t} = c + \beta RivGr_{i,t} + \gamma CTRL_{i,t} + \varepsilon_{i,t} \tag{3}$$

where $RivGr_{i,t}$ corresponds to the growth of rivals, and is defined as $RivGr_{i,t} = \left(\sum_{j\neq i}^{m_r} g_{j,t}\right)/(m_r - 1)$ where m_r corresponds to the number m of firms in sector r. c is a constant term and $\varepsilon_{i,t}$ is the usual error term. $CTRL_{i,t}$ corresponds to a set of control variables, i.e. lagged size, lagged growth, age, three-digit industry growth and also industry and year dummies.[14] These control variables have been shown in previous work to have an effect on firm growth (Coad, 2009), and so they are included here.

Regression results of OLS, Least Absolute Deviation (LAD), and Weighted Least Squares (WLS) are presented in Table 4. Following Geroski and Gugler (2004), our OLS estimations show that rival growth appears to have a significant *positive* impact on firm growth, regardless of whether we consider competition at the level of three- or four-digit industries. Our estimates for the impact of rival growth are not significant, however, when analogous regressions are performed using LAD regressions [also known as "median regressions," which are better suited to the case of

[14]Note that we include a lagged-dependent variable, which could be a source of Nickell-bias in a model with time-invariant-fixed effects and strong autocorrelation. In our particular case, however, the evidence suggests that fixed effects are not a major concern for firm growth rates, because there is more variation in the time series of a single firm's growth rates, than there is across different firms. In other words, the within component of growth rate variance is larger than the between component (Geroski and Gugler, 2004). Furthermore, autocorrelation of growth rates is often rather small in magnitude, and indeed we observe it to be small in our data set. We conclude that Nickell-bias can be expected to be especially small in the present context.

Table 4 Regression results from estimation of Equation (3) for Spanish manufacturing firms with 250 workers or more

	OLS			LAD			WLS		
	Labour	Sales	VA	Labour	Sales	VA	Labour	Sales	VA
four-digit rivalry									
RivGr(t)	**2.0690**	**3.5792**	**2.4987**	0.1533	**1.1219**	0.3425	**1.8481**	**3.5699**	**2.3659**
t-stat	3.26	5.93	4.49	0.68	2.39	1.34	2.96	5.77	4.31
Size	**−0.1513**	**−0.0707**	**−0.1261**	**−0.0132**	−0.0015	**−0.0205**	**−0.0647**	**−0.0485**	**−0.1007**
t-stat	−4.62	−3.88	−5.28	2.91	−0.39	−3.59	−3.63	−3.42	−5.97
Age	−0.0123	−0.01428	−0.0146	−0.0031	−0.0048	−0.0031	−0.0108	−0.0095	−0.0099
t-stat	−1.37	−1.23	−1.19	−1.19	1.21	−0.55	−1.39	−0.94	−0.89
$g_{i,t-1}$	**−0.3023**	**−0.2363**	**−0.2136**	−0.0006	−0.0106	−0.0752	**−0.1927**	**−0.1298**	**−0.1382**
t-stat	−4.43	−3.32	−3.96	−0.04	−0.65	−1.74	−2.58	−2.20	−3.35
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector growth	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.3286	0.3273	0.2741	0.0423	0.0512	0.0431	0.2196	0.2609	0.2107
Obs.	3125	3214	3179	3125	3214	3179	3124	3214	3179
three-digit rivalry									
RivGr(t)	0.0802	−0.0727	0.1085	0.0068	0.0013	0.0028	0.0731	−0.0662	0.1052
t-stat	0.65	−0.55	0.69	0.66	0.02	0.09	0.65	−0.45	0.73
Size	**−0.1556**	**−0.0859**	**−0.1287**	**−0.0149**	−0.0041	**−0.0243**	**−0.0654**	**−0.0622**	**−0.1022**
t-stat	−4.74	−5.21	−5.82	−4.26	−1.18	−4.27	−3.71	−4.64	−6.44
Age	−0.0104	−0.0138	−0.0098	−0.0036	−0.0047	−0.0009	−0.0080	−0.0108	−0.0051
t-stat	−1.15	−1.19	−0.79	−1.54	−1.42	−0.19	−1.09	−1.07	−0.47
$g_{i,t-1}$	**−0.3561**	**−0.3303**	**−0.2534**	−0.0067	−0.0074	−0.0652	**−0.2203**	**−0.1894**	**−0.1563**
t-stat	−4.97	−4.25	−4.19	−0.44	−0.52	−1.65	−2.85	−2.84	−3.44
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector growth	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.2429	0.1789	0.1823	0.0311	0.0333	0.0321	0.1268	0.1016	0.1217
Obs.	3125	3214	3179	3124	3214	3179	3124	3214	3179

LAD regression results are taken after 50 bootstrap replications.
Coefficients significant at the 1% level appear in bold.

non-Gaussian growth rate distributions (Coad 2010)]. WLS regressions (where firms are weighted by lagged size in order to account for the different importance of firms of different sizes) also yield positive and significant estimates for the coefficient of rival growth on firm growth.

Concerning the other coefficients, our results are in line with the previous literature. On the one hand, firm size shows a significant negative impact on firm growth. This is an interesting feature given that our results would reject Gibrat's Law even for large firms (for a survey of the Gibrat's Law literature, see Coad, 2009, Chapter 4). In line with previous findings, firm age has a negative impact on firm growth, although this effect is not always significant. We should also mention the relatively high explanatory power of the regressions, especially for the OLS regressions at the four-digit industry level.

In a further robustness analysis, we split our sample into subsamples of growing or declining industries, to investigate whether inter-firm rivalry becomes more fierce in declining markets, as firms fight for limited resources. In this supplementary analysis, however, we did not find any clear patterns in our results. For example, there is no clear evidence of a negative dependence on rival's growth on a firm's growth that is stronger in declining industries. An additional line of analysis we pursued was to repeat our analysis on subsamples of industries with many subclasses (corresponding to differentiated product markets) and industries with few subclasses (corresponding to relatively homogeneous product markets).[15] Interestingly enough, this analysis seems to tentatively suggest that the effects of inter-firm rivalry appear to be more negative in industries with few subclasses (where differentiation is presumably lower).

A drawback of the estimates reported in Table 4, however, is that problems of endogenous growth of rival firms make the resulting coefficient estimates unreliable. Despite this endogeneity, we consider it worthwhile to present these initial results for two reasons. First, our results can now be compared to previous work. Second, our results can shed light on the associations between the variables without addressing issues of causality. Nevertheless, in the next section we will take issues of endogenous regressors into account.

5.2 *Peer-effects econometrics*

In this section, we apply a peer-effects estimator to analyze firm growth rates, in the hope of finding evidence of inter-firm competition. In previous work, peer-effects econometrics has been applied many times to the analysis of neighborhood effects, substance use among teenagers, and peer-group effects among university room-mates (see Soetevent, 2006 for a survey). In our context, peer-effects econometrics can be used to see how a firm is affected by the behaviour of its rivals. Oberhofer and Pfaffermayr (2010) investigate the growth of multinational groups, and observe positive externalities within vertically organized multinational networks, although horizontally organized networks display negative growth spillovers.

[15]We are grateful to an anonymous referee for this idea.

We follow the methodology used in Oberhofer and Pfaffermayr (2010) and use the instrumental-variable estimator proposed by Lee (2007) (see also Bramoullé *et al.*, 2009). As stressed by Davezies *et al.* (2009), Lee's (2007) identification strategy crucially requires knowledge of peer group sizes, with at least three groups having a different size. With this in mind, we define a firm's "peer group" in terms of the other firms that are above a certain size threshold (100+, 200+, 250+ employees in the initial time period) in the same three-digit or four-digit industry in the same year. In our regressions, identification of the growth spillover effects depends crucially on variation in group size. Given that the firm size distribution varies considerably across sectors (with some sectors having more large firms than others), it is reasonable to assume that we have sufficient variation in group size to ensure identification.
Consider the following regression equation:

$$g_{ir} = \lambda \cdot \left(\frac{\Sigma_{j \neq i}^{m_r} g_{jr}}{m_r - 1} \right) + \gamma X_{ir} + \mu_r + \epsilon_{ir} \tag{4}$$

where X_{ir} corresponds to a set of exogenous control variables [cf. the control variables in Equation (3)]: lagged size, firm age, and industry growth. In this case, the parameter of interest is λ, which indicates how a firm's growth is influenced by the growth of its rivals. m_r corresponds to the number m of firms in sector r. μ_r is a group-specific fixed effect.

The econometric issue is that the growth of rival firms may simultaneously affect each other—a firm's growth may be limited by the growth of its rival, at the same time as the rival's growth is affected by the growth of the first firm. This problem has been called the "reflection problem" by Manski (1993), because "the problem is similar to that of interpreting the almost simultaneous movements of a person and his reflection in a mirror" (Manski, 1993: 532).
Equation (4) can be rewritten as:

$$g_{ir} = \frac{\lambda}{m_r - 1} (m_r \bar{g}_r - g_{ir}) + \gamma X_{ir} + \mu_r + \epsilon_{ir} \tag{5}$$

Taking averages across groups, we obtain the between-group equation:

$$\bar{g}_r = \frac{\lambda}{m_r - 1} (m_r \bar{g}_r - \bar{g}_r) + \gamma \bar{X}_r + \mu_r + \bar{\epsilon}_r \tag{6}$$

which can be rearranged to yield:

$$\bar{g}_r = \frac{1}{1 - \lambda} (\gamma \bar{X}_r + \mu_r + \bar{\epsilon}_r) \tag{7}$$

Subtracting (7) from (5) we obtain:

$$(g_{ir} - \bar{g}_r) = -\lambda \frac{(g_{ir} - \bar{g}_r)}{(m_r - 1)} + \gamma (X_{ir} - \bar{X}_r) + (\epsilon_{ir} - \bar{\epsilon}_r) \tag{8}$$

Equation (8) corresponds to the within-group equation, in which an individual firm's growth is related to the average growth of the rival firms in the same sector. As emphasized by Oberhofer and Pfaffermayr (2010), the peer-effect parameter λ cannot be identified in the between-group equation (6), but instead it must be identified using the within-group equation (8).

Note that the dependent variable is the term $(g_{ir} - \bar{g}_r)$, which is different from the dependent variable in our regression equation in Section 5.1 and implies that our regression estimates cannot be directly compared to each other. The first term on the right-hand side is clearly endogenous—g_{it} has an influence on g_{jt}, but g_{jt} also influences g_{it}. To deal with this endogeneity, we apply instrumental-variable (IV) techniques (following Oberhofer and Pfaffermayr, 2010), which involves two iterative instances of instrumental variable (IV) estimation. First, we use the exogenous variables multiplied by $(1)/(m_r - 1)$ as instruments in a two-stage least squares (2SLS) regression of Equation (8) to obtain a consistent initial estimator of λ. Our IV diagnostics for the first-stage regressions pertain to this regression. Second, we use this estimate of λ (i.e. $\widetilde{\lambda}$, where the tilde $\sim$ denotes an estimated value) to derive an improved instrument, that we use in another 2SLS estimation of equation (8).[16]

Bearing in mind that $(g_{ir} - \bar{g}_r)/(m_r - 1)$ can be rearranged to yield $((g_{ir} - \bar{g}_r) + \lambda \frac{(g_{ir}-\bar{g}_r)}{m_r-1})/(m_r - 1 + \lambda)$, we use our first-stage IV estimates (that is, the predicted values) to instrument $(g_{ir} - \bar{g}_r)/(m_r - 1)$ by the following term:

$$\frac{(g_{ir} \widetilde{-} \bar{g}_r) + \widetilde{\lambda} \frac{(g_{ir}-\bar{g}_r)}{m_r-1}}{(m_r - 1 + \widetilde{\lambda})} \tag{9}$$

Table 5 contains the estimation results using the labour, sales, and value-added growth rates as dependent variables. Our results are also differentiated according with three different firm sizes: 100, 200, and 250 workers or more. The estimated impact of rival growth on firm growth is always negative, and statistically significant in most cases. In the case of employment growth, the coefficient of rival growth is only significant for the subsample that includes all firms with 100 or more employees. For value-added growth, however, negative and significant effects of rival growth can be found in all samples.

The results concerning the firm size and firm age are in line with the estimations obtained in Table 4. On the one hand, firm size has a negative impact on firm growth, regardless the variable. Hence, our results controlling for endogenous peer-group effects would still reject Gibrat's Law. With respect to firm age, our results show that there is a stable negative impact on firm growth. In general, this

[16]See Lee (2007: 345).

Table 5 Pooled regression results from peer-effects estimations for Spanish manufacturing firms according with firm size: IV estimation of Equation (8)

	⩾100 employees			⩾200 employees			⩾250 employees		
	Empl	Sales	VA	Empl	Sales	VA	Empl	Sales	VA
Rival group at four-digit industry level									
RivGr	**−0.361**	−0.282	−0.295	−0.229	−0.267	**−0.537**	**−0.336**	−0.194	**−0.553**
SE	0.134	0.239	0.188	0.124	0.269	0.107	0.086	0.255	0.082
P-value	0.007	0.239	0.117	0.065	0.321	0.000	0.000	0.447	0.000
Empl	**−0.070**	**−0.023**	**−0.064**	**−0.073**	**−0.021**	**−0.053**	**−0.045**	**−0.023**	**−0.038**
SE	0.005	0.004	0.005	0.008	0.006	0.007	0.009	0.008	0.008
P-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.005	0.000
Age	**−0.013**	**−0.021**	**−0.020**	**−0.018**	**−0.017**	**−0.018**	−0.010	−0.016	−0.013
SE	0.004	0.005	0.005	0.006	0.007	0.007	0.006	0.008	0.008
P-value	0.001	0.000	0.000	0.003	0.014	0.006	0.108	0.052	0.086
$\mathbf{g_{i,t-1}}$	**−0.259**	**−0.258**	**−0.215**	**−0.234**	**−0.182**	**−0.139**	**−0.248**	**−0.174**	**−0.147**
SE	0.010	0.014	0.011	0.017	0.024	0.014	0.021	0.034	0.016
P-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Obs	11533	11969	11776	4400	4538	4483	2977	3067	3029
R^2 1st stage	0.1583	0.1086	0.1102	0.1334	0.0803	0.1671	0.1800	0.1049	0.1772
Angrist–Pischke	443.29	226.12	262.84	121.89	56.79	178.09	125.08	49.71	136.65
P-value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Anderson LM	1192.93	642.29	739.39	338.04	164.40	477.94	333.84	142.49	361.71
P-value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Anderson-Rubin	7.43	3.80	8.48	8.52	5.86	29.77	7.31	12.89	21.36
P-value	0.0001	0.0098	0.0000	0.0000	0.0005	0.0000	0.0001	0.0000	0.0000
Rival group at three-digit industry level									
RivGr	**−1.356**	**−10.994**	−1.016	−0.110	−0.213	**−0.392**	−0.123	**−2.393**	**−0.330**
SE	0.341	5.469	0.545	0.124	0.295	0.145	0.129	0.288	0.164
P-value	0.000	0.044	0.063	0.374	0.471	0.007	0.340	0.000	0.044
Empl	**−0.068**	−0.008	**−0.064**	**−0.091**	**−0.029**	**−0.062**	**−0.073**	−0.009	**−0.053**
SE	0.005	0.009	0.005	0.008	0.006	0.007	0.010	0.006	0.008
P-value	0.000	0.359	0.000	0.000	0.000	0.000	0.000	0.111	0.000
Age	**−0.014**	−0.004	**−0.020**	**−0.017**	**−0.015**	**−0.018**	−0.010	**−0.010**	−0.013
SE	0.004	0.009	0.005	0.007	0.007	0.007	0.007	0.006	0.008
P-value	0.000	0.627	0.000	0.007	0.043	0.013	0.171	0.081	0.120
$\mathbf{g_{i,t-1}}$	**−0.253**	−0.030	**−0.211**	**−0.284**	**−0.231**	**−0.190**	**−0.309**	**−0.063**	**−0.199**
SE	0.011	0.123	0.013	0.015	0.020	0.014	0.019	0.022	0.018
P-value	0.000	0.808	0.000	0.000	0.000	0.000	0.000	0.004	0.000
Obs	11788	12229	12040	4712	4862	4799	3287	3381	3337
R^2 1st stage	0.1404	0.0939	0.1177	0.1918	0.1153	0.2150	0.1878	0.0815	0.1853
Angrist-Pischke	929.88	395.92	281.43	272.78	113.26	313.00	168.12	30.44	161.99
P-value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

(continued)

Table 5 Continued

	⩾100 employees			⩾200 employees			⩾250 employees		
	Empl	Sales	VA	Empl	Sales	VA	Empl	Sales	VA
Anderson LM	861.89	383.51	789.34	698.01	317.95	786.17	437.97	89.08	424.86
P-value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Anderson-Rubin	8.56	4.7	8.84	2.97	6.29	25.86	3.35	7.73	16.54
P-value	0.0000	0.0028	0.0000	0.0308	0.0003	0.0000	0.0182	0.0000	0.0000

IV diagnostics include the first-stage R^2, the Angrist–Pischke multivariate *F*-test of excluded instruments, the Anderson canonical correlation LM statistic (whether the equation is identified, i.e. whether the excluded instruments are relevant), and the Anderson–Rubin Wald test (significance of the endogenous regressors). Coefficients significant at the 1% level appear in bold.

coefficient is significant. However, for firms with 250 workers or more the coefficient is only significant in the sales growth equation.

Lagged firm growth also shows a significant and negative impact on current firm growth. We observe that firms with 250 or more workers are more affected by the negative impact of previous employment growth, firms with 200 or more workers show a stronger negative autocorrelation for sales growth and firms with 100 or more workers present a larger coefficient the past value added growth. Hence, there is some tentative evidence that growth rate autocorrelation has different effects on the growth of firms of different sizes.[17]

Finally, we also check for differences over time. Table 6 shows the evolution across years of the impact of rival growth for our three variables, and for different firm size subsamples. In the majority of cases, our estimates of the coefficient of rival growth tend to be negative and significant. Furthermore, we may observe that firms with 100 or more workers display a higher negative impact of rivalry than their counterparts.

6. Conclusion

Theoretical work into inter-firm competition has taken many different views on the nature of rivalry, ranging from predictions of zero-sum games, to tacit collusion in settings of multimarket contact, and even to cooperation between competitors.

[17]However, we do not wish to unduly emphasize the magnitudes of the autocorrelation coefficients here, since it has been shown that least-squares estimation of firm growth rate autocorrelation coefficient magnitudes is strongly affected by the non-Gaussian nature of firm growth rate distributions (Bottazzi *et al.*, 2011, Table 3).

Table 6 Regression results from peer-effects estimations for Spanish manufacturing firms according with firm size: IV estimation of the coefficient λ in Equation (8)

		2000	2001	2002	2003	2004	2005	2006
Employees								
⩾100 Empl	**RivGr**	−**1.055**	−**0.880**	0.387	−**4.760**	−13.474	−**3.572**	−0.042
	SE	0.453	0.383	3.779	0.539	17.313	0.886	1.299
	Obs	1656	1803	1858	1793	1710	1542	1426
⩾200 Empl	**RivGr**	−**0.342**	0.485	−1.216	−**0.477**	−**1.022**	−**1.072**	−**3.262**
	SE	0.135	0.268	2.514	0.242	0.162	0.048	1.278
	Obs	668	720	743	712	676	616	577
⩾250 Empl	**RivGr**	−**0.372**	**1.112**	−0.222	10.688	−**0.5460**	−**1.048**	15.988
	SE	0.150	0.405	3.525	20.801	0.267	0.048	90.802
	Obs	474	502	515	492	470	428	406
Sales								
⩾100 Empl	**RivGr**	1.604	−**3.964**	−33.741	−**8.533**	−5.411	−**2.242**	1.955
	SE	9.208	1.237	99.773	2.140	5.928	0.281	8.726
	Obs	1879	1881	1885	1820	1741	1565	1458
⩾200 Empl	**RivGr**	−**0.862**	−**8.766**	−0.927	−**1.229**	−**1.011**	−**0.619**	−**1.220**
	SE	0.195	1.709	2.124	0.177	0.250	0.130	0.518
	Obs	745	746	751	720	685	625	590
⩾250 Empl	**RivGr**	−**0.859**	−**6.908**	−**6.703**	−**1.072**	−0.848	−**0.6750**	−4.910
	SE	0.193	1.309	1.466	0.287	0.762	0.102	5.76
	Obs	517	520	521	497	476	434	416
VA								
⩾100 Empl	**RivGr**	−1.295	−2.906	45.222	−**6.570**	−**2.223**	−1.412	7.996
	SE	1.030	1.731	241.753	1.428	0.784	0.852	17.203
	Obs	1864	1865	1860	1786	1702	1535	1428
⩾200 Empl	**RivGr**	−**0.793**	3.568	−1.422	−**1.207**	−**0.901**	−**0.810**	**1.691**
	SE	0.139	8.229	2.016	0.169	0.139	0.087	0.733
	Obs	740	742	743	706	673	615	580
⩾250 Empl	**RivGr**	−**0.749**	4.522	−3.329	−**1.296**	−0.569	−**0.837**	**1.951**
	SE	0.160	10.834	6.015	0.182	0.525	0.092	0.792
	Obs	514	516	515	488	468	428	408

Control variables are lagged size, age, lagged growth, sector growth, and sector and year dummies are included in the regressions but not reported here. Coefficients significant at the 1% level appear in bold.

The general assumption, though, is that a firm's growth will be negatively affected by the growth of its rivals. Empirical work into the matter has not always found any evidence of inter-firm competition on firm growth, however. We measure growth in terms of employment, sales, and value added in our analysis of Spanish firms during the period 2000–2006. To begin with, we focus on correlations between the growth rates of the largest and second largest firms within the same industry, and are not able to reject the hypothesis that the growth of these rival firms shows no interdependence.

Our analysis looks for evidence of competition by applying two different approaches. At first, we focus on firm-dyad pairs, investigating whether competitive pressure emanates from a single identifiable rival. Looking at scatterplots of the growth performance of the largest versus second largest firms in the same industry, nonetheless we are not able to reject the hypothesis that the growth of the largest firm is independent of the growth of the second largest. However, the effects of competition might not be so clear-cut as a zero-sum game between two rivals—instead competition might be a more amorphous force emanating from no particular individual, but from a group of rival firms taken together as a whole. Therefore, we also seek evidence for competition in multivariate regressions where the growth of one firm is seen to depend on the growth of a group of rivals (other large firms in the same industry), rather than any specific individual firm.

Standard multivariate regressions show that, if anything, the growth of rival firms is positively associated with each other. However, standard regressions are beset by endogeneity problems—the growth of firm i depends on the growth of firm j, which simultaneously depends on the growth of firm i. Applying a peer-effects estimator to deal with this endogeneity allows us to find significant negative effects of rivals' growth on a firm's growth. Unless we control for issues of endogeneity due to rival firms' growth affecting each other simultaneously, using our peer-effects estimator, we are unable to detect the expected negative effects of rivals' growth on firm growth. This seems to suggest that the negative effects of competition, at the firm-level, are not strong enough to counteract the bias introduced by endogeneity. A skeptic might consider that we need to "torture the data" pretty hard before it confesses to the expected negative effect. This latter might be so difficult to find because, in many cases, rivals can be expected to have a *positive* association with a firm's performance, for a number of reasons such as spillovers (from e.g. R&D or advertising), imitation, "Red Queen" effects (e.g. interacting aspiration levels), or exogenous industry-level trends. The differences between our results for standard regressions and peer-effects regressions also emphasize that, when comparing results in the literature, we should keep in mind the econometric methodology applied and also the size and number of firms analyzed, and the degree of sectoral aggregation.

We also suggest that future empirical work on inter-firm interdependence might fruitfully explore the significance of network effects (e.g. innovation networks and regional industry clusters) on firm performance using peer-effects estimators.

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References

Aboulnasr, K., O. Narasimhan, E. Blair and R. Chandy (2008), 'Competitive response to radical product innovations,' *Journal of Marketing*, **72**, 94–110.

Almeida, P. and B. Kogut (1999), 'Localization of knowledge and the mobility of engineers in regional networks,' *Management Science*, **45**(7), 905–917.

Audretsch, D. B., Y. M. Prince and A. R. Thurik (1999), 'Do small firms compete with large firms?' *Atlantic Economic Journal*, **27**(2), 201–209.

Bartelsman, E., S. Scarpetta and F. Schivardi (2005), 'Comparative analysis from demographics and survival: evidence from micro-level sources in OECD countries,' *Industrial and Corporate Change*, **14**(3), 365–391.

Baum, J. and H. Korn (1996), 'Competitive dynamics of interfirm rivalry,' *Academy of Management Journal*, **39**(2), 255–291.

Bengtsson, M. and S. Kock (2000), '"Coopetition" in business networks – to cooperate and compete simultaneously,' *Industrial Marketing Management*, **29**(5), 411–426.

Bergman, M. and N. Rudholm (2003), 'The relative importance of actual and potential competition: empirical evidence from the pharmaceuticals market,' *Journal of Industrial Economics*, **LI**(4), 455–467.

Boone, J., J. C. van Ours and H. van der Weil (2007), 'How (not) to measure competition,' CEPR discussion paper 6275, Centre for Economic Policy Research, London, UK.

Bottazzi, G., A. Coad, N. Jacoby and A. Secchi (2011), 'Corporate growth and industrial dynamics: evidence from French manufacturing,' *Applied Economics*, **43**(1), 103–116.

Bottazzi, G. and A. Secchi (2006a), 'Explaining the distribution of firms growth rates,' *Rand Journal of Economics*, **37**, 234–263.

Bottazzi, G. and A. Secchi (2006b), 'Gibrat's law and diversification,' *Industrial and Corporate Change*, **37**(2), 235–256.

Bramoullé, Y., H. Djebbari and B. Fortin (2009), 'Identification of peer effects through social networks,' *Journal of Econometrics*, **150**(1), 41–55.

Carroll, G. R. (1985), 'Concentration and specialization: Dynamics of niche width in populations of organizations,' *American Journal of Sociology*, **90**, 1262–1283.

Chen, S., K. W. Ho and K. H. Ik (2005), 'The wealth effect of new product introductions on industry rivals,' *Journal of Business*, **78**(3), 969–996.

Coad, A. (2009), *The Growth of Firms: A Survey of Theories and Empirical Evidence*. Edward Elgar: Cheltenham, UK.

Coad, A. (2010), 'Exploring the processes of firm growth: evidence from a vector autoregression,' *Industrial and Corporate Change*, **19**(6), 1677–1703.

Coad, A. and M. Valente (2011), 'Hunting for a bogeyman? In search of statistical evidence of direct competition between firms,' *Evolutionary and Institutional Economics Review*, **8**(1), 65–85.

Crane, A. (2005), 'In the company of spies: When competitive intelligence gathering becomes industrial espionage,' *Business Horizons*, **48**(3), 233–240.

D'Aveni, R. (1994), *Hypercompetition: Managing the Dynamics of Strategic Maneuvering*. Free Press: New York.

Davezies, L., X. D'Haultfoeuille and D. Fougère (2009), 'Identification of peer effects using group size variation,' *Econometrics Journal*, **12**(3), 397–413.

Dixit, A. (1980), 'The role of investment in entry-deterrence,' *Economic Journal*, **90**(357), 95–106.

Evans, W. and I. Kessides (1994), 'Living by the "Golden Rule": Multimarket contact in the US airline industry,' *Quarterly Journal of Economics*, **109**(2), 341–366.

Fosfuri, A. and M. S. Giarratana (2009), 'Masters of war: rivals' product innovation and new advertising in mature product markets,' *Management Science*, **55**(2), 181–191.

Franco, A. M. and D. Filson (2006), 'Spin-outs: knowledge diffusion through employee mobility,' *Rand Journal of Economics*, **37**(4), 841–860.

Geroski, P. A. (1995), 'What do we know about entry?' *International Journal of Industrial Organization*, **13**, 421–440.

Geroski, P. A. (2000), 'The growth of firms in theory and practice,' in N. Foss and V. Mahnke (eds), *Competence, Governance, and Entrepreneurship*. Oxford University Press: Oxford, UK.

Geroski, P. A. and R. Griffith (2004), 'Identifying antitrust markets,' in M. Neumann and J. Weigand (eds), *The International Handbook of Competition*. Edward Elgar: Cheltenham, pp. 290–305 . Chapter 8.

Geroski, P. A. and K. Gugler (2004), 'Corporate growth convergence in Europe,' *Oxford Economic Papers*, **56**, 597–620.

Goolsbee, A. and C. Syverson (2008), 'How do incumbents respond to the threat of entry? Evidence from the major airlines,' *Quarterly Journal of Economics*, **123**(4), 1611–1633.

Hamel, G., Y. Doz and C. Prahalad (1989), 'Collaborate with your competitors and win,' *Harvard Business Review*, **67**(1), 133–139.

Haskel, J. E., S. C. Pereira and M. J. Slaughter (2007), 'Does inward foreign direct investment boost the productivity of domestic firms?' *Review of Economics and Statistics*, **89**(3), 482–496.

Hay, M. and K. Kamshad (1994), 'Small firm growth: intentions, implementation and impediments,' *Business Strategy Review*, **5**(3), 49–68.

Ijiri, Y. and H. A. Simon (1977), *Skew Distributions and the Sizes of Business Firms*. North Holland: Amsterdam.

Kato, M. and Y. Honjo (2009), 'The persistence of market leadership: evidence from Japan,' *Industrial and Corporate Change*, **18**(6), 1107–1133.

Lee, L. (2007), 'Identification and estimation of econometric models with group interactions, contextual factors and fixed effects,' *Journal of Econometrics*, **140**(2), 333–374.

Manski, C. (1993), 'Identification of endogenous social effects: The reflection problem,' *Review of Economic Studies*, **60**(3), 531–542.

McGahan, A. M. and B. S. Silverman (2006), 'Profiting from technological innovation by others: the effect of competitor patenting on firm value,' *Research Policy*, **35**, 1222–1242.

Mill, J. S. (1984), *Principles of Political Economy*. Longmans: London.

Moneta, A., D. Entner, P. Hoyer and A. Coad (2010), 'Causal inference by independent component analysis with applications to micro- and macroeconomic data,' Jena Economic Research Papers in Economics, Friedrich-Schiller-University Jena, Max-Planck-Institute of Economics.

Nickell, S. (1996), 'Competition and corporate performance,' *Journal of Political Economy*, **104**(4), 724–746.

Oberhofer, H. and M. Pfaffermayr (2010), 'Firm growth in multinational corporate groups,' Working Paper no. 2010-07, University of Salzburg.

Penrose, E. T. (1959), *The Theory of the Growth of the Firm*. Basil Blackwell: Oxford.

Robson, P. and B. Obeng (2008), 'The barriers to growth in Ghana,' *Small Business Economics*, **30**(4), 385–403.

Salop, S. C. (1979), 'Strategic entry deterrence,' *American Economic Review Papers and Proceedings*, **69**(2), 335–338.

Schumpeter, J. (1942), *Capitalism, Socialism and Democracy*. Harper: New York.

Shapiro, C. (1989), 'The theory of business strategy,' *Rand Journal of Economics*, **20**(1), 125–137.

Soetevent, A. (2006), 'Empirics of the identification of social interactions; an evaluation of the approaches and their results,' *Journal of Economic Surveys*, **20**(2), 193–228.

Sorensen, J. B. (2004), 'Recruitment-based competition between industries: a community ecology,' *Industrial and Corporate Change*, **13**(1), 149–170.

Storey, D. (1994), *Understanding the Small Business Sector*. Thomson: London, UK.

Sutton, J. (1998), *Technology and Market Structure: Theory and History*. MIT Press: Cambridge, MA.

Sutton, J. (2007), 'Market share dynamics and the 'persistence of leadership' debate,' *American Economic Review*, **97**(1), 222–241.

Teece, D., R. Rumelt, G. Dosi and S. Winter (1994), 'Understanding corporate coherence: theory and evidence,' *Journal of Economic Behavior and Organization*, **23**(1), 1–30.

Tornqvist, L., P. Vartia and Y. Vartia (1985), 'How should relative changes be measured?' *American Statistician*, **39**(1), 43–46.

Vickers, J. (1995), 'Concepts of competition,' *Oxford Economic Papers*, **47**(1), 1–23.

Vos, E., A. J. Yeh, S. Carter and S. Tagg (2007), 'The happy story of small business financing,' *Journal of Banking and Finance*, **31**, 2648–2672.

Wiggins, R. and T. Ruefli (2005), 'Schumpeter's ghost: is hypercompetition making the best of times shorter?' *Strategic Management Journal*, **26**(10), 887–911.

Wiklund, J. (2007), 'Small firm growth strategies,' in A. Zackarakis and S. Spinelli (eds), *Entrepreneurship and Growth: The Engine of Growth*. 2nd edn. Praeger: Westport, Connecticut, pp. 135–154. Chapter 7.