Spatial agglomeration and firm exit: a spatial dynamic analysis for Italian provinces

Giulio Cainelli

Department of Economics and Management, University of Padua, via del Santo 33, 35122 Padua, Italy, Phone: +39 049 8274227, Fax: +39 049 8274211 & CERIS-CNR Milan, Italy

Sandro Montresor

Department of Economics, University of Bologna, Strada Maggiore 45, 40125 Bologna, Italy, Phone: +39 051 2092651, Fax: +39 051 2092670 & JRC-IPTS, European Commission Seville, Spain

Giuseppe Vittucci Marzetti*

Department of Sociology ad Social Research, University of Milano-Bicocca, via Bicocca degli Arcimboldi 8, 20126 Milan, Italy

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Abstract

The paper investigates the effect of spatial agglomeration on firm exit in a dynamic framework. Using a large dataset at the industry-province level for Italy (1998-2007), we estimate a spatial dynamic panel model via a GMM estimator and analyze the short-run impact of specialization and variety on firm exit. Specialization negatively affects firm exit rates in the short-run. The effect is particularly significant for low-tech firms. The impact of variety on firm mortality rates at the industry level is instead less clear, although still negative and significant for low-tech firms.

Key words: Firm exit, Localization, Spatial agglomeration, Specialization, Variety.

JEL Classification: R11, R12, L11, G20

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*Corresponding author: Department of Sociology ad Social Research, University of Milano-Bicocca, via Bicocca degli Arcimboldi 8, 20126 Milan, Italy Phone: +39 0264487457, Fax: +39 0264487561

Email addresses: `g.cainelli@ceris.cnr.it` (Giulio Cainelli), `sandro.montresor@unibo.it` (Sandro Montresor), `giuseppe.vittucci@unimib.it` (Giuseppe Vittucci Marzetti)

1. Introduction

The importance of spatial agglomeration for economic activities is nowadays undisputed. With an increasing intensity in the last twenty years, its effects have been extensively investigated from different perspectives. Growth, industrial and innovation studies have added flesh to the bones of the issue in urban and regional economics.

The bulk of the literature focuses on the externalities that spatial agglomeration creates, both in the short and in the long-run. In the short-run, geographically clustered firms are able to save on the variable production costs that are linked to their distance: typically, transportation and logistic costs. There are also factors related with labor market pooling, home market effects, urban consumption opportunities, and rent-seeking (for a survey on the theoretical microfoundations of agglomeration economies, see, for instance, Duranton and Puga, 2004). Furthermore, geographical proximity enables firms to exchange among them tacit knowledge, which requires face-to-face interaction and allows them to build up mutual trust relationships. Static and dynamic transaction costs get thus also reduced by agglomerating (Boschma, 2005; Langlois, 1992). As time passes, through repeated interactions, spatial agglomeration can also generate knowledge spillovers and learning-by-interacting among co-located industries (e.g. Bathelt, 2010).[1]

Nearly all of the studies debating about the role and the extent of agglomeration economies examine their impact on measures of productivity (labor productivity and TFP), innovativeness, real wages and employment growth (Rosenthal and Strange, 2004; Beaudry and Schiffauerova, 2009).

The role of agglomeration economies with respect to industrial demography indicators—e.g. firm entry and exit—has been instead less investigated and asymmetrically. On the one hand, firm-entry has received some attention. The set-up of new establishments has been analyzed, for example by Carlton (1983) and Rosenthal and Strange (2003), to indirectly estimate the impact of agglomeration economies. Furthermore, the importance of local industrial conditions for the start-up of new entrepreneurial activities has been attracting new interest (e.g. Glaeser and Kerr, 2009; Jofre-Monseny et al., 2011; Fritsch and Schroeter, 2011), also with respect to multinational enterprises (Mariotti et al., 2010). On the other hand, the attention for firm-exit has been scanty. With few exceptions (e.g. Staber, 2001; Carree et al., 2011), the analysis of firm exit/survival has been focused on the role of firm- and sector-specific factors (e.g. Evans, 1987; Geroski, 1995; Yasuda, 2005), while location- and region-specific ones have been only partly studied. Short vs. long-run exit effects have

[1] Some authors distinguish between static and dynamic externalities (e.g. Glaeser et al., 1992; Henderson et al., 1995; Henderson, 2003). Static externalities are one-time efficiency gains produced by spatial concentration. As such, they can account for spatial agglomeration in a homogeneous space, but not for long-run growth differentials between regions. Dynamic externalities are instead within- and across-industry knowledge spillovers able to explain sustained differentials in regional growth rates.

also found limited attention. This is quite unfortunate, since there are some important local/regional specificities of the issue at stake.

First, in different kinds of local production systems (e.g. industrial districts vs. Porterian clusters), agglomeration economies combine with different kinds of socio-economic features (Becattini, 1990; Dei Ottati, 1994), which provide firms with "idiosyncratic" survival mechanisms in the short-run (Storper and Christopherson, 1987). Second, in the long-run, agglomeration patterns have also appeared to interfere with the impact of the business cycle on firm mortality: enhancing local growth and firm entry during expansions, but possibly increasing firm exit and employment decline at the local level during recessions (see, for instance Bugamelli et al. (2009) and CENSIS (2010) for empirical evidence on Italy, and Cainelli et al. (2012) for a theoretical analysis). In both respects, reconciling regional and urban studies with industrial organization in the analysis of firm survival appears thus an important research priority.

In trying to fill this gap, in the paper we bring the interlink of industry- and location- specific determinants of firm exit to the front in a dynamic setting. Our aim is to investigate the extent to which spatial agglomeration affects firm exit at the local-industry level. Using a large panel dataset for the Italian economy at industry-province level, covering 13 years (from 1998 to 2007), we estimate spatial dynamic panel data models to analyze the impact of industry specialization and variety on firm exit.

With respect to the extant literature, our work introduces important elements of originality. First of all, the impact of agglomeration on firm exit is addressed consistently, by retaining the possible presence of spatial and serial correlations in firm exit rates. Second, rather than with time-invariant, lagged agglomeration indicators—mainly used when specialization and variety are considered structural features of a local economy—we account for time-specific effects with short-term indicators: i.e., yearly variations of specialization and variety measurements. Since these measurements are closer, in their meaning, to short-run spillovers occurring in the labour market and in the market of other inputs, rather than to long-run knowledge spillovers, the findings of this work are not necessarily consistent with those obtained using long-run measurements (e.g. Martin et al., 2011). Last, but not least, the role of spatial agglomeration on firm exit is for the first time directly disentangled with a specific indicator of variety, based on the idea of Jacobs' (1969) externalities.

The paper is organized as follows. Section 2 reviews the relevant literature on firm exit, and integrates it with predictions that emerge by focusing on agglomeration economies. Section 3 presents the dataset and the empirical estimation strategy. In Section 4 we discuss the main results. Section 5 concludes.

2. Background literature

The theoretical and empirical literature on the determinants of firm exit is abundant (for a recent survey see Schindele et al., 2011). However, agglomeration economies do not find much scope in it.

The bulk of the results refer to firm- and sector-specific factors, usually taken in isolation from the geographical and socio-economic context firms are located and embedded in. As for the firm-specific factors, a battery of "liability" hypotheses have been tested, supporting the role of age and size of firm start-ups in affecting firm exit.[2] As for the industry-specific factors, the start-up rate of an industry (both current and lagged) (Honjo, 2000; Johnson and Parker, 1994; Audretsch, 1995) and its unit labor costs (Patch, 1995) have emerged among the most significant antecedents of firm exit. The industry growth rate (Ilmakunnas and Topi, 1999; Bradburd and Caves, 1982) and its technological intensity (Licht and Nerlinger, 1998; Cefis and Marsili, 2006; Jensen et al., 2008) have instead appeared to have less ambiguous effects.

Although less investigated, spatial agglomeration can be argued to affect firm exit on the ground of different theoretical interpretations and with the support of different empirical evidence. Once more, as for the case of firm entry, the specific kind of externalities that spatial agglomeration of firms is expected to nurture is a crucial aspect to address.

2.1. Specialization and firm exit

Specialization is at the core of the emergence of agglomeration economies. Its effects has been mainly linked to the scale of activity of an industry in a certain region. Indeed, as stressed by Rosenthal and Strange (2004), "explicit theories of the microfoundations of agglomeration economies have nearly always been based on the idea that an increase in the *absolute* scale of activity has a positive effect... [While models] do not make direct predictions regarding the impact of the industry's share of employment in a particular city or regarding the city's share in the industry relative to other cites" (p.2135, emphasis ours).[3]

With this meaning, regional specialization can increase input-sharing among firms and produce a better matching between employers and employees (Rosenthal and Strange, 2004). Being their workers specialized in similar activities,

[2]With respect to age, the most debated are the "liability" of "newness" (Stinchcombe, 1965; Geroski, 1995), "aging" (Hannan, 1998), "obsolescence", "senescence" (Barron et al., 1994), and "adolescence" (Schindele et al., 2011). With respect to size, the most investigated is the so-called liability of "smallness" (Aldrich and Auster, 1986; Geroski, 1995; Honjo, 2000).

[3]The widespread use the extant literature makes of the location quotient as an indicator of localization economies comes from the seminal studies by Glaeser et al. (1992) and Henderson et al. (1995), which somehow re-initiated this literature. However, Glaeser et al. (1992), who first express the idea that the location quotient can better capture the potential for Marshall-Arrow-Romer (MAR) externalities, do not provide a clear theoretical justification for this. In fact, it seems that Glaeser et al. (1992) and Henderson et al. (1995) use the location quotient only because the size-based indicator (the level of own industry employment) could not be used, as it was already included in the specification to account for mean reversion processes in the employment dynamics. This is explicitly, although incidentally, acknowledged also by Henderson (2003), who uses the number of own industry plants to proxy localization economies and observes that "it is difficult to disentangle dynamic externalities from mean reversion processes—both typically involve the same quantity, measures of past own industry employment" (p.4).

local firms can benefit from a larger labor pool and a higher workers' mobility, precisely in the way Marshall originally put it and subsequent endogenous growth theories assumed: for this reasons, specialization economies are also called Marshall-Arrow-Romer (MAR) externalities.

The impact of specialization economies at the local level appears confirmed by the empirical evidence (Beaudry and Schiffauerova, 2009; Breitenecker and Schwarz, 2011), although as a manifold process. At the regional level, specialization concurs to provide firms with a cognitive kind of proximity (in terms of mastering a common knowledge), which can either complement or substitute their geographical and social one (Boschma, 2005), depending on the specific technological regime and sectoral system (Malerba, 2002) and on the relevant formal and informal institutional set-up (Evangelista et al., 2002).[4]

The absolute size of an industry in a certain region can also increase productivity via spatial sorting and firm selection. On the one side, assuming complementarity between firm productivity and density, and endogenous location choices, more productive firms might choose, ex-ante, denser areas to locate (for the application of this argument to the issue of wage premium, see Combes et al., 2008; Andersson et al., 2013; Eeckhout et al., 2013). On the other side, tougher competition in denser regions allows only the most productive firms to survive and left-truncates the distribution of firm productivity, thus increasing its average value (on this point see Combes et al., 2012, who develop a formal test of this hypothesis using French establishment-level data, showing that firm selection cannot explain spatial productivity differences).

All in all, via the positive effects exerted on firm productivity, specialization is expected to negatively impact on firm exit rates. However, given its effects in terms of tougher competition (Combes et al., 2012), higher costs for commuting and for recruiting local production inputs (Tabuchi, 1998; Higano and Shibusawa, 1999), not to say of lower resilience—for example, because of more costly employment reallocation across sectors in front of industrial shocks (Cingano and Schivardi, 2004)—the net impact of specialization on firm mortality rates could be positive.

Out of the few studies that analyze the effect of specialization on the probability of firm exit (Schindele et al., 2011), nearly all find support of the second, positive effect (i.e. increasing firm-exit). Staber (2001), in particular, finds that belonging to a specialized industrial district (the knitwear district of Baden-Württemberg, Germany) reduces firm survival, because of competition effects on local resources. However, this could still be consistent with a positive effect, via labor productivity, when short and long-run effects are distinguished. In our view, this can be investigated by calculating the variation of specialization over time, and its current impact on firm exit, rather than a structurally fixed

[4] The role of the production and technological capabilities of the local firms is hard to disentangle from that of the regional ones, as the latter are not simply additive with respect to the former. On this point, see, for instance, Iammarino et al. (2012) and Simonen and McCann (2008).

measure of it, and its lagged impact, as in the extant literature.

2.2. Variety and firm exit

Unlike that of specialization, the impact of variety on firm exit has not received attention yet, at least in systematic empirical studies. Given the theoretical relevance of the related externalities – following his seminal work Jacobs (1969) on them, called Jacobs externalities – and the evidence that regional studies have found for them, this research gap is somehow surprising. Its filling thus represents another valued added of this paper.

From a theoretical point of view, a variegated business environment is expected to reduce firm exit. This could be argued by considering how variety counterbalances the problems of an excessive specialization (i.e. inflexibilities and rigidities) we have identified above. In particular, regions marked by technological variety can be claimed to be less vulnerable to lock-in effects than specialized ones, being more permeable to fresh knowledge from outside. Furthermore, they can be expected to be more capable to adjust to exogenous changes, especially the negative ones brought about by recessions (Combes, 2000; Frenken et al., 2007).

Moreover, Jacobs externalities are expected to induce higher innovation outcomes than MAR externalities (Duranton and Puga, 2000). This is due to the importance of knowledge spillovers across sectors, in allowing for the recombination and cross-fertilization of ideas, although under the constraints posed by the firms technological proximity and shared common knowledge (Cohen and Levinthal, 1989; Feldman and Audretsch, 1999). The higher survival rate firms are found to have because of their higher innovation profile (Licht and Nerlinger, 1998; Cefis and Marsili, 2006; Jensen et al., 2008) closes the causal link between variety and firm exit.

However, it should be noted that the available empirical evidence provides only partial empirical support of the latter effect. Jacobs externalities tend to emerge conditionally on the industry aggregation level and the adopted geographical unit (Beaudry and Schiffauerova, 2009; Breitenecker and Schwarz, 2011). In brief, for the higher impact of variety on productivity and innovation to emerge, a finely grained industrial aggregation (at least 3-digit) seems to be required, while aggregated results provide a slight, counterintuitive supremacy to MAR ones. Furthermore, a similar bias seems to be introduced by taking a firm level of analysis, rather than a regional one: "firm level studies have a tendency to inflate MAR externalities while regional level studies would tend to inflate diversity externalities" (Breitenecker and Schwarz, 2011, p.333).

This last set of specifications suggests us to be cautious in looking for an eventual role of variety on firm exit (mainly through the role of innovation). Furthermore, a more substantial argument makes us refrain from expecting a clear impact of Jacobs externalities on firm survival, that is: the relevant temporal focus. By looking at short-run variations of variety as well as specialization indicators, our analysis actually clashes with the fact that the former kind of economies, unlike the latter, take place over a longer time period. In other words, our research strategy, as the one adopted by Martin et al. (2011) with respect to firm entry "may hardly capture technological/knowledge spillovers, since a long time is probably needed for new ideas to circulate and be implemented in neighboring firms" (p. 185).

3. Empirical application

3.1. Data

Our analysis refers to the Italian economy as one of the most popular for agglomeration phenomena.[5] Accordingly, Italy seems a suitable field of investigation to test for their impact on firm exit.

For this analysis we made use of the Movimprese archive, collected by the Italian Chamber of Commerce (www.infocamere.it), and drew yearly data on the number of dead, born and active firms for 23 manufacturing industries (2-digit ISTAT-ATECO 2007 classification) in 103 Italian provinces (equivalent to NUTS3 in the EU classification) over the period 1998-2007.[6] Using these data, we built up a first raw, balanced panel of 23,690 observations at the industry-province level ($23 \times 103 \times 10$). Some data cleaning was then carried out. First, we controlled for the "cancellations of firms" due to administrative reasons: a piece of information provided for some years by Movimprese.[7]

Second, we dropped the tobacco industry, since the relative firm-stock resulted nearly systematically null. Finally, in order to avoid artificially high exit rates, we dropped all the observations (i.e. industry-provinces and/or periods) for which the firm-stock was lower than 7 (the 10^{th} percentile of the stock-firm variable), with the great majority of the drops satisfying this bounding condition in all the years of investigation.[8]

After these trimming procedures, we obtained a nearly balanced panel dataset of 22,660 observations, referring to the firm exit exhibited by 22 manufacturing industries located in 103 Italian provinces.[9] Our units of analysis are thus industries in provinces, for which information about heterogeneity among firms is not available. Although this kind of data prevents us from distinguishing location- and sector-specific determinants from firm-specific ones in an explicit way, suffering from the so-called problem of "geo-ecological fallacy" (e.g. Kramer, 1983;

[5] Italy is actually the country where Marshallian industrial districts, theorized by Becattini (1990), have received the largest attention, both in the academic research and in the policy analysis.

[6] Data availability prevented us from investigating to what extent the 2007 crisis affected firm exit in Italy. Although with a different econometric strategy, on this issue see Amendola et al. (2010).

[7] Among the other things, this control enabled us to reduce the incidence of possible operations of Mergers and Acquisitions (M&A) on the actual exit of firms from the market.

[8] As a robustness check, estimates have been also run by dropping the 20^{th} percentile of the variable, referring to observations with less then 16 firms. As they remain substantially unchanged, these estimates will be not reported in the following and are available upon request.

[9] As our focus is on the impact of spatial agglomeration on firm mortality in manufacturing as a whole, we differentiate from Carree et al. (2011), who use different sectoral panels for different manufacturing industries.

Schwartz, 1994), we can however draw from them interesting insights on the role of agglomeration economies for firm exit.

3.2. Variables

The dependent variable of our econometric specification is the firm exit rate of sector i, in province s and year t, E_{ist}, defined as:

$$E_{ist} = \frac{EX_{ist}}{\frac{A_{ist}+A_{is,t+1}}{2}} \tag{1}$$

where EX_{ist} is the number of exits during t and A_{ist} is the estimated stock of active firms at the beginning of the period. More precisely, A has been estimated recursively from the firm-stock of 1995, by using yearly data on exits and start-ups. In doing that, rates are calculated with respect to the estimated mid-year stock, as it is common in demographic studies.

The key regressors refer to location-specific factors and are two measurements of specialization and variety, respectively. As far as the former is concerned, the way we measure specialization falls in the category of the so-called size indicators of localization economies (Beaudry and Schiffauerova, 2009; Breitenecker and Schwarz, 2011) and refers to the number of active firms in each industry-province. As we have argued in Section 2.1, this choice is motivated by the fact that the economies accounted by localization are more genuinely related to the absolute, rather than relative, size of an industry and to the existence of companies *per se*, rather than to their average employment (Henderson, 2003). According to this argument, we have computed the specialization index as the number of active firms per Km^2 in the sector for a certain province at the beginning of the year:[10]

$$C_{ist} = \frac{A_{ist}}{\mathrm{Km}_s^2} \tag{2}$$

As far as variety is concerned, for each industry i, province s and period t, we calculated an entropy index of the shares of the firms belonging to the sectors other than i in the same province s (P_{jst}):

$$D_{ist} = -\sum_{j \neq i} P_{jst} \log_2(P_{jst}) \tag{3}$$

where $P_{jst} = A_{jst} / \sum_{m \neq i} A_{mst}$.

[10]It is worth stressing that the indicator, as such, is not able to account for the level of industrial concentration of the sector or for other factors related with the average size of the firms belonging to a certain sector (on the interconnections between industrial and spatial concentration see Ellison and Glaeser, 1997; Rosenthal and Strange, 2001). Indeed, the number of firms per Km^2 in a certain sector-province tends to be lower for the sectors characterized by structurally higher industrial concentration. Nonetheless, we account somehow for these factors controlling for the unobserved time-invariant heterogeneity in the econometric specification.

By calculating the external entropy index of an industry-province, rather than a simple pool of a certain variable (typically employment) in all industrial sectors other than it, we are able to capture variety as such, rather than the simple size of the relative urbanization economies.[11]

It should be noted that, differently from the extant literature, both the spatial agglomeration indicators we use are short-run indicators: i.e., yearly measurements of specialization and variety (C_{ist} and D_{ist}). As we said, since these measurements are closer to labor and input market spillovers, rather than to knowledge spillovers, our findings do not need to be, and actually should be not, consistent with those obtained using long-run measurements (Martin et al., 2011).

Of course, agglomeration economies are not the only determinant of firm exit. In affecting it, location-specific factors intertwine with firm- and industry-specific ones, to which the literature has paid most of the attention. As far as the former are concerned, we refer to the inner micro-dynamics of exit rates represented by the liability of *newness* – younger firms likely survive less than older ones (Stinchcombe, 1965; Geroski, 1995) – and of *smallness*– larger firms survive more than smaller ones (Geroski, 1995; Honjo, 2000). As our application is based on sectoral data, we try to proxy these micro phenomena by introducing in the estimates the (current and lagged) start-up rates at the industry-province level:

$$S_{ist} = \frac{SU_{ist}}{\frac{A_{ist}+A_{is,t+1}}{2}} \tag{4}$$

where SU is the number of start-ups and A is defined as in Equation (1) (Table 1 reports the summary statistics of all the variables). If, for example, we retain plausible that a high entry rate in one year will increase the weight of young firms in the firm population the year(s) after, we could point to evidence about the "liability of newness" in a positive relationship between $S_{is,t-1}$ and E_{ist}. Similarly, retaining presumable that new firms have a smaller efficient scale than the established ones, a positive partial correlation between $S_{is,t-1}$ and E_{ist} would provide hints about the "liability of smallness" too.

As micro-studies reveal (e.g. Cefis and Marsili, 2006), firm exit could be affected by the level of firms' technological development and innovations. Once again, with the data at hand, we try to capture this aspect with the (OECD-Eurostat) classification of firms into high-, medium- and low-tech industries. It should be noticed that, as the recent research stream on the so called "Young Innovative Companies" show, the last set of firm-specific features interact among them (see Pellegrino et al. (2012)), possibly also in the affecting the dynamics of firm exit. Although the dataset we use does not provide us with sufficiently

[11] We use the entropy index instead of the log of the (inverse) Herfindahl index to measure variety, as it does not require any further transformation (it is already a weighted average of logs) and as it is becoming a more standard measure of it, given its decomposability property (see, for instance, Frenken et al., 2007). The index is in fact what Frenken et al. (2007) call "unrelated variety".

Table 1: Summary statistics

		Mean	Min	Max	Std. Dev.
E	overall	0.068	0.000	1.000	0.068
	between		0.000	0.350	0.035
	within		-0.240	0.902	0.058
S	overall	0.056	0.000	1.200	0.069
	between		0.000	0.379	0.038
	within		-0.307	0.956	0.058
C	overall	0.125	0.000	13.78	0.365
	between		0.000	10.53	0.360
	within		-2.925	3.423	0.060
D	overall	3.334	1.729	3.861	0.233
	between		1.280	3.853	0.230
	within		3.116	3.484	0.052

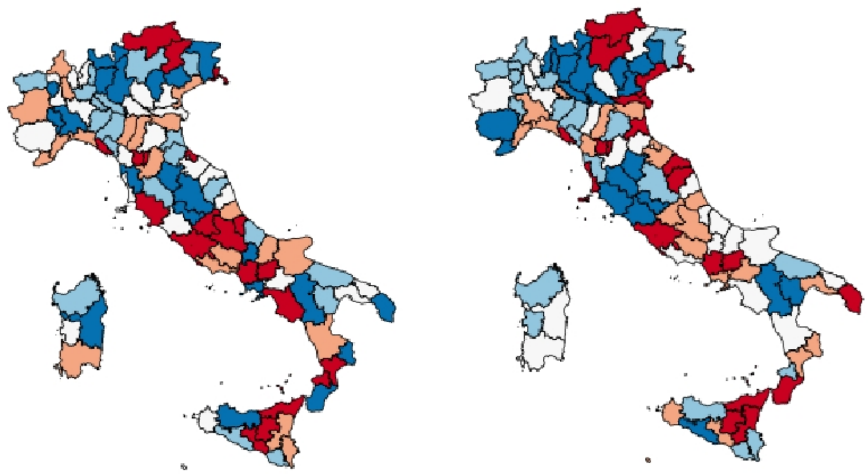
significant evidence of these companies in industry-province units of analysis, this is for sure an important extension to be explored with additional sources of data.

Finally, in order to analyze how agglomeration forces interact with the firms' technological level, we estimate separate specifications for, respectively, low-tech, mid-tech and high-tech firms.

3.3. Modeling strategy

In order to estimate the impact of spatial agglomeration on firm exit rates, we need to properly account for the complex temporal and spatial patterns exhibited by our dependent variable. As has been shown in previous empirical studies (e.g. Carree et al., 2011; Martin and Sunley, 2006), firm exit is generally affected by both its lagged values, and by the current and lagged values of start-up rates. As for the former, a "multiplier effect" is expected as the closing down of the actor of one industry (especially an important one) will presumably reverberate on other firms – connected (competitively and/or along the supply chain) to it in the same industry – the following periods (Dejardin, 2004). As for the latter, instead, new entries might either "displace" incumbent firms by making them less efficient, or generate exits among the entrants, given their short life-expectancy ("revolving door effect") (Audretsch, 1995).

A less commonly addressed issue we need to account for is that firm entry and exit could take place on the territory in a non-uniform way. On the contrary, the industrial demography effects at word are expected to primarily diffuse along the provinces that surround a certain one. In brief, current firm exit and start-up rates could be expected to be spatially correlated, even in front of localized shocks. This is particularly so in the case of the local production systems that characterize Italy (Cingano and Schivardi, 2004), in which business value chains and other techno-economic relationships usually span across the boundaries of



(a) 1999 (b) 2007

Figure 1: Quartile distribution of exit rates by province

different administrative provinces.[12]

The need of addressing this issue is shown by Figure 1, which reports the quartile distribution of exit rates by province in the first and last year of our sample: exit rates exhibit both temporal and spatial autocorrelation (and a similar figure emerge with respect to start-up rates). These hints are confirmed in Table 2, which reports the correlation between actual and (temporally and spatially) lagged exit rates and start-up rates. In particular, the spatial lags of the exit rates have been calculated using a row-standardized contiguity weight matrix (**W**) (LeSage and Pace, 2009) at the province level, assuming that the sectors in the same province were neighbors.[13]

Finally, in order to analyze the effects of local-specific determinants on firm exit we need to model the dynamic structure of firm demography accounting for the possible endogeneity of the regressors. In this respect, dynamic panel models can accommodate two important aspects, that is: i) the serial dependence between the observations of each unit in time; ii) the presence of unobservable time-invariant specific factors. However, they cannot accommodate other two crucial issues, that is: iii) the spatial dependence at each point in time; iv) the

[12]The case of industrial districts is particularly illustrative. Their identification through the popular "Sforzi approach" and the "Iuzzolino approach" (Boccella et al., 2005; Sforzi, 2009) actually show them to be very often trans-provincial.

[13]Both the correlations and all the subsequent specifications have been estimated also using (Euclidean) distance-based matrices with threshold cut-off equal to: 75 Km (critical cut-off, i.e. min cutoff so that each province has got at least one neighbor); 100 Km; 200 Km; 300 Km; 400 Km. Results do not significantly differ and are available at request.

Table 2: Autocorrelation matrix

E_t	E_{t-1}	E_{t-2}	S_t	S_{t-1}	S_{t-2}	$\mathbf{W}E_t$	$\mathbf{W}E_{t-1}$	$\mathbf{W}E_{t-2}$	
1.000	0.209	0.304	0.206	0.150	0.138	0.121	0.096	0.102	E_t
	1.000	0.181	0.249	0.209	0.151	0.083	0.107	0.087	E_{t-1}
		1.000	0.248	0.239	0.174	0.072	0.076	0.114	E_{t-2}
			1.000	0.243	0.265	0.015	0.026	0.042	S_t
				1.000	0.243	−0.005	0.019	0.034	S_{t-1}
					1.000	−0.015	0.0003	0.021	S_{t-2}
						1.000	0.429	0.481	$\mathbf{W}E_t$
							1.000	0.423	$\mathbf{W}E_{t-1}$
								1.000	$\mathbf{W}E_{t-2}$

5% critical value (two-tailed) = 0.0130 for n = 22660

unobservable effects specific to space and time periods.

Given that these latter effects are important in the present application, as a further value added of it, we suggest to make use of a Spatial Dynamic Panel Data (SDPD) model (e.g. Elhorst, 2005; Su and Yang, 2007; Yu et al., 2008; Lee and Yu, 2010a,c,b; Kukenova and Monteiro, 2009; Bouayad-Agha and Vedrine, 2010) (for a recent survey see Elhorst, 2010). In particular, we estimate the following "time-space dynamic" specification (Anselin et al., 2008; Bouayad-Agha and Vedrine, 2010):

$$\begin{aligned}\mathbf{E}_t = \lambda \mathbf{W}\mathbf{E}_t + \sum_{l=1}^{L_e} \gamma_l \mathbf{E}_{t-l} + \sum_{l=1}^{L_e} \rho_l \mathbf{W}\mathbf{E}_{t-l} + \sum_{l=0}^{L_s} \delta_l \mathbf{S}_{t-l} + \tau_t \mathbf{I} + \boldsymbol{\mu} + \\ + \beta_c \mathbf{C}_t + \beta_d \mathbf{D}_t + \boldsymbol{\nu}_t\end{aligned} \tag{5}$$

where, in addition to our focal variables (C_{ist} and D_{ist}), the exit rate of industry i in province s at time t (E_{ist}) is regressed against its lagged values ($E_{is,t-l},\ l = 1, \ldots, L_e$), the current and lagged values of the start-up rate ($S_{is,t-l},\ l = 0, \ldots, L_s$), the current spatial lag of the exit rate ($\mathbf{WE}_t$), the spatial-time lags ($\mathbf{WE}_{t-l}$, $l = 0, \ldots, L_e$), time (τ_t) and unit (μ_{is}) dummies, and the usual independently distributed error (ν_{ist}).

In Equation (5), λ is the *spatial autoregressive coefficient* of the Spatial Auto-Regressive (SAR) model (LeSage and Pace, 2009), γ_l are the *autoregressive coefficients* of the Auto-Regressive (AR) models, and ρ_l captures the spatial-time effects. The value of the dependent variable is thus modeled as the result of complex interactions of a bunch of things: all the present and past values of the regressors and of the exogenous shocks (like in ARDL models); the simultaneous spatial spillovers (like in SAR models); the lagged spatial spillovers. Quite interestingly, this creates cross-section, cross-temporal effects like those analyzed in VAR models.[14]

[14]This specification is a generalization of that analyzed, among the others, by Lee and Yu (2010c), where there is only one time lag and one spatial-time lag ($L_e = 1$). Lee and Yu (2010c) work out the sufficient and necessary stability conditions for the model with only one

In the model that we use, the short-run Average Total Impact (ATI) of our focal variables (i.e. specialization and variety) is defined as the sum of direct and indirect effects produced by a marginal increase of them in all the cross-sectional units, averaged across all the units, and is simply given by:

$$\frac{\beta_k}{1-\lambda} \tag{6}$$

$k \in \{c, d\}$, like in the SAR model (LeSage and Pace, 2009, p.38), whereas the long-term ATI (at the steady state) for these two variables is given by (see Appendix A for the derivation):

$$\frac{\beta_k}{1-\lambda-\sum_{l=1}^{L_e}(\gamma_l+\rho_l)} \tag{7}$$

In general, SDPD models like the one we are using are estimated via (Quasi) Maximum Likelihood (e.g. Elhorst, 2005; Su and Yang, 2007; Yu et al., 2008; Lee and Yu, 2010a,c,b). However, this method cannot correct for the potential endogeneity of the explanatory variables in addition to the endogeneity of the spatially lagged dependent variable. In order to cope with these other potential endogeneity problems, an alternative method is to rely on GMM estimators (Arellano and Bond, 1991), as has been done in some recent papers (Kukenova and Monteiro, 2009; Bouayad-Agha and Vedrine, 2010).

Following the GMM logic, the spatial lag ($\mathbf{WE}_t$) is a strictly endogenous variable; the first time lag ($\mathbf{E}_{t-1}$) and the first spatial-time lag ($\mathbf{WE}_{t-1}$) are predetermined variables, whereas all the (spatial-) time lags higher than the first one ($\mathbf{E}_{t-l}$ and $\mathbf{WE}_{t-l}$, $l = 2, \ldots, L_e$) are strictly exogenous variables. Accordingly, we can use the following moment conditions (for definitions and details see, for instance, Bond, 2002):

$$\mathrm{E}\Big(\widehat{\mathbf{WE}}_s\ \Delta(\boldsymbol{\mu}+\boldsymbol{\nu}_t)\Big)=\mathbf{0}; \qquad s=1,...,t-2; \quad t=3,...,T$$

$$\mathrm{E}\Big(\widehat{\mathbf{E}}_s\ \Delta(\boldsymbol{\mu}+\boldsymbol{\nu}_t)\Big)=\mathbf{0}; \qquad s=1,...,t-2; \quad t=3,...,T$$

where the hat stands for the diagonalized vector of cross-sectional observations.

Assuming that both the start-up rates ($\mathbf{S}_t$), the specialization indexes ($\mathbf{C}_t$) and the variety indexes ($\mathbf{D}_t$) are all strictly endogenous variables, for the estimation we can use also the following moment conditions:

$$\mathrm{E}\Big(\widehat{\mathbf{S}}_s\ \Delta(\boldsymbol{\mu}+\boldsymbol{\nu}_t)\Big)=\mathbf{0}; \qquad s=1,...,t-2; \quad t=3,...,T$$

$$\mathrm{E}\Big(\widehat{\mathbf{C}}_s\ \Delta(\boldsymbol{\mu}+\boldsymbol{\nu}_t)\Big)=\mathbf{0}; \qquad s=1,...,t-2; \quad t=3,...,T$$

time lag and one spatial-time lag. The sufficient and necessary stability conditions for the more general model in (5) have not yet been worked out.

$$\mathrm{E}\Big(\widehat{\mathbf{D}}_s\ \Delta(\boldsymbol{\mu}+\boldsymbol{\nu}_t)\Big)=\mathbf{0}; \qquad s=1,...,t-2; \quad t=3,...,T$$

Finally, under the assumption that the series satisfy mean stationarity conditions, one can also use lagged differences of endogenous regressors as valid instruments for equations in levels via a system GMM (SYS-GMM) estimator (Blundell and Bond, 1998, 2000).

3.4. Empirical estimation

As we have detailed in the previous section, model (5) is estimated by means of a two-step SYS-GMM. Standard errors are computed using the finite-sample correction suggested by Windmeijer (2005).

As far as the spatial weights matrix ($\mathbf{W}$) is concerned, both contiguity weights matrix and (Euclidean) distance-based matrix with different threshold cut-off have been used.[15] However, as the estimates obtained by using the latter are not significantly different, all the results reported are based on the row-standardized contiguity weights matrix.

As the specification at stake (in terms of exit and start-up rates) experienced problems, when the stock of firms in the industry-province is very small, the units for which the stock of firms is within the 10-percentile of the sample have been dropped. That amounts to 2,244 observations (industry-provinces and periods), in which the total number of active firms at the beginning of the relevant period was less than 7. As many as 1,720 among them refer to units for which the value was less than 7 in all the periods.[16]

Finally, in order to analyze how agglomeration forces interact with the technological level of the sectors in which firms operate, we also estimate separate equations for, respectively, high-tech, mid-tech and low-tech industries.

4. Results

Through the iterative elimination of non-significant variables and the analysis of information criteria, we ended-up with a SDPD model with two time and spatial-time lags ($L_e = 2$), and without a simultaneous spatial lag.[17] Table 3 summarizes the results for the estimation carried out on the whole sample, whereas Table 4 reports the results for separate industries classified according to their technological level (low-tech, mid-tech and high-tech).

A first finding, which delineates the empirical background in which agglomeration economies affect firm exit, is represented by its actual dynamic and

[15] Once again, the following cut-offs have been considered: 75 Km (critical cut-off, i.e. min cutoff, so that each province has got at least one neighbor); 100 Km; 200 Km; 300 Km; 400 Km. Industries in the same province have always been considered neighbors.

[16] We estimate all the specifications also by dropping the 20-percentile (units-periods with less than 16 firms) and the results, available on request, do not significantly differ.

[17] In order to check for economic opportunities and business cycle conditions affecting firm exit, which were not already captured by our spatial-time lags, we have also tried to include in the specification the growth rate of the GDP at the NUTS-3. However, and as expected, it turned out not significant and has therefore been omitted.

Table 3: Estimation results

	(I)	(II)	(III)	(IV)
$E_{is,t-1}$	0.291	0.418***	0.351**	0.347**
	(0.186)	(0.151)	(0.160)	(0.161)
$E_{is,t-2}$	0.695***	0.552***	0.619***	0.601***
	(0.192)	(0.149)	(0.157)	(0.164)
$\mathbf{W}E_{t-1}$	-0.395**	-0.155	-0.066	-0.049
	(0.155)	(0.168)	(0.121)	(0.157)
$\mathbf{W}E_{t-2}$	-0.186	0.0263	-0.244*	-0.190
	(0.174)	(0.223)	(0.147)	(0.173)
$S_{is,t-1}$	0.043	0.070**	0.079***	0.047
	(0.030)	(0.032)	(0.028)	(0.033)
C_{ist}		-0.001*		-0.003*
		(0.000)		(0.002)
D_{ist}			0.002	-0.020
			(0.003)	(0.014)
Mid-tech$_i$	-0.001	-0.001***	-0.001	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)
High-tech$_i$	-0.005***	-0.005***	-0.005***	-0.004***
	(0.001)	(0.001)	(0.001)	(0.001)
N. obs.	15994	15994	15994	15994
N. instruments	47	59	51	49
AR(1) (p-value)	-1.78 (0.074)	-2.56 (0.010)	-2.25 (0.025)	-2.14 (0.032)
AR(2) (p-value)	-1.04 (0.298)	-0.43 (0.664)	-0.80 (0.425)	-1.08 (0.282)
Hansen test (p-value)	40.15 (0.153)	52.42 (0.154)	41.18 (0.218)	35.16 (0.321)

Not reported constant and time dummies. 2044 cross-sectional units. Standard errors in parentheses. *** significant at 1%; ** significant at 5%; * significant at 10%.

Table 4: Estimation results by technological specialization

	Low-tech	Mid-tech	High-tech
$E_{is,t-1}$	0.396***	0.470***	-0.327
	(1.141)	(0.160)	(0.254)
$E_{is,t-2}$	0.686***	0.402***	0.782**
	(0.147	(0.146)	(0.271)
$\mathbf{W}E_{t-1}$	-0.069	-0.008	0.589*
	(0.224)	(0.246)	(0.333)
$\mathbf{W}E_{t-2}$	0.004	-0.266	0.181
	(0.289)	(0.224)	(0.441)
$S_{is,t-1}$	0.084	0.090	0.209**
	(0.078)	(0.084)	(0.102)
C_{ist}	-0.010***	-0.001	-0.009*
	(0.003)	(0.002)	(0.004)
D_{ist}	-0.080***	0.008	-0.041
	(0.027)	(0.018)	(0.039)
N. obs.	6,815	6,159	3,020
N. instruments	40	41	36
AR(1) (p-value)	-2.56 (0.011)	-3.00 (0.000)	-1.94 (0.050)
AR(2) (p-value)	-1.20 (0.231)	0.56 (0.574)	-2.29 (0.022)
Hansen test (p-value)	41.31 (0.021)	52.34 (0.002)	24.51 (0.321)

Not reported constant and time dummies. Standard errors in parentheses. *** significant at 1%; ** significant at 5%; * significant at 10%.

spatial nature. Firm exit at the industry-province level shows a quite strong path-dependence. A mortality increase of the firms in one local industry significantly increases that of both the following first ($E_{is,t-1}$) and second year ($E_{is,t-2}$). From a different perspective, it seems that in local industries negative shocks take time to be absorbed, maintaining their firms in a recession climate for more than a while. This is an interesting finding, which is somehow consistent with the (although impure) hysteresis Italian regional economies have been recognized in terms of unemployment (e.g. Lanzafame, 2010, 2012). As we said, this "multiplier effect" has already been detected in empirical studies at the firm-industry level (Dejardin, 2004), and interpreted by considering the induced effects of the death of an important business partner along the industry supply chain. As we also said, the adoption of a local-industry perspective reinforces these effects, by filtering out the most important business partnerships in the territory.

The (weak) evidence of the negative impact exerted by the lagged exit rates in neighbor provinces ($WE_{is,t-1}$ and $WE_{is,t-2}$), although apparently counterintuitive, could be tentatively taken to further specify the previous result. The (Italian) territory actually seems bounding in making firm exit a path-dependent treat of one industry. This seems to be so the case that closer provinces of the same industry could exit from a recession earlier and (possibly) at the expenses of the province where it has originated. Interestingly enough, however, the effect is significantly reversed for firms in high-tech industries (Table 4), where the propagation of a shock in terms of firm exit does occur along contiguous provinces. The less space-constrained linkages among the firms of these sectors, which are based on a more codified kind of knowledge, could explain why firm exit does not remain limited to the originating province as for the whole sample.

The dynamic picture is completed by the significant impact that firm entry has on firm exit in the same industry-province, although after one period ($S_{is,t-1}$).[18] Both the hypotheses of a "displacement" and a "revolving-door" effect can thus be put forward by looking at the Italian local production systems (e.g. Audretsch, 1995). This result, which is consistent with previous studies on Italian industries (e.g. Carree et al., 2011), does not seem to support the theoretical idea according to which, localities would facilitate entrepreneurship, by inhibiting "entry mistakes" and inefficient start-ups (Santarelli and Vivarelli, 2007). A qualified kind of social embeddedness and a dedicated institutional set-up (e.g. local banks, business associations, and so on), such as the ones granted by the presence of an industrial district, might be required for that to happen: a research line which is on our future research agenda (Cainelli et al., 2012).

Out of the other "standard" antecedents of firm exit, the technological intensity of an industry is confirmed to have an hindering effect on it (Cefis and Marsili, 2006). This is also an interesting result with respect to the Italian context, very well-known for its traditional specialization model. Local industries with a higher innovative vocation seems to have higher opportunities of firm survival. A result which has been also found to lower firm exit over the recent crisis (Amendola et al., 2010).

Coming to the core issue of the paper, first of all our analysis provides evidence of the effect that specialization economies (C_{ist}) exert in reducing firm exit at the local level. This effect turns out to be significantly negative already in the short-run and is particularly interesting. Indeed, the structure of the Italian economic systems seems able to more than compensate the diseconomies – e.g. in terms of tougher competition and/or pressures on the cost of local inputs — that could interfere with the productivity advantages that specialization normally grants them as time passes. Indeed, this productivity effect appears available to them since agglomeration occurs.

As a confirmation of this general result, it should be noticed that the effect of specialization in reducing firm exit turns out to be particularly strong in low-tech industries (Table 4). In fact, the peculiarities of the Italian production system, in terms of the great presence of SMEs operating in traditional sectors, seem to be *per se* more conducive to "interaction-induced externalities of the Marshall type" (Beaudry and Schiffauerova, 2009, p.328), as already argued, for example, by Cingano and Schivardi (2004).

As far as variety is concerned, the effect of Jacobs externalities on firm exit is less clear-cut at the investigated local level. The coefficient of D_{ist} is, for the

[18] Given the absence of a simultaneous spatial lag ($\lambda = 0$) in the estimated specification, the short-run ATI coincides with the coefficient attached to the variable.

whole sample, not significant and sometimes even shows a positive sign. Given the short-run perspective we have adopted, and given that the positive externalities that variety generates take time to emerge, this non-significance result is not completely unexpected. An increasing agglomeration with other heterogeneous industries does not make the industry of one province immediately more prone to benefit from their knowledge spillovers: the impact of the latter on the firm's survival rate of the former usually occurs through innovation and risk diversification phenomena that take time. To be sure, our evidence shows that this could exceptionally occur in the short-run for low-tech industries (Table 4), for which the impact of the cross-sectoral fertilization of knowledge could be more visible, given their technological-gap, and/or more urgent to exploit.

In spite of these considerations, further analysis is needed to properly account for the non-significant impact of variety. On the one hand, given the theoretical premises we have reviewed, the result might be partially due to the disaggregation level we have adopted to classify industries and regions: further analysis at a more disaggregated level are thus in need, and awaits for newly available data. On the other hand, some extra work, and actually an extra-dataset (possibly containing a finely grained disaggregation for each of our 2 digit sector), would be required to investigate whether, unlike our own indicator, other variety indicators are able to attenuate firm-exit since the short-run.[19]

As a general final insight, it should be noted that, looking at the long-run ATI (Equation (7)) of the variables, the point estimates are quite high: they are all 3.4 times higher than the short-run impacts because of the spatial and time feedbacks. The calculated confidence intervals are nonetheless quite large and the point estimates therefore only indicative of the actual long-run impact.

5. Conclusions

Although nearly systematically relegated to industrial organization, the analysis of firm exit has important potentialities in urban and regional studies. Both variety and specialization can have different effects on firm exit in local production systems, as well as different are their expected effects on firm survival over time.

In spite of these important research opportunities, spatial agglomeration and firm exit have so far remained quite separated issues, as very few empirical studies have attempted to provide empirical evidence on their interaction. Firm-specific determinants seem to attract greater interest than industry- and location-specific ones. Furthermore, the simultaneous analysis of the spatial and temporal correlation of the phenomenon is complex at the econometric level and quite cumbersome for the construction of time-specific indicators of agglomeration economies.

[19]The first candidate would be what Frenken et al. (2007) call "related variety", as distinguished from the variety indicator that we used, which correspond to the "unrelated" one in their framework.

To the best of our knowledge, this paper is the first attempt at filling this gap. Using a large panel dataset at the industry-province level and estimating a GMM spatial dynamic panel data model, we investigated the impact of short-run measurements of specialization and variety on firm exit.

Our results are quite interesting. First, in local industries firm exit reveals strong path-dependence, as the micro-evidence on multiplier effects would suggest. Second, also at the industry-province level, firm exit shows traces of displacement and replacement effects. To be sure, local specificities make this temporal path-dependence territorially bounded. Third, and as expected, specialization appears to significantly affect firm exit in the short-run, and the effect is particularly strong for low-tech firms. As for variety, the evidence is less clear-cut, although some evidence of a negative impact of variety on firm exit rates seems to emerge at least for low-tech industries.

Further analysis is required to integrate some important aspects that the dataset at hand did not allow us to retain. Among these, the analysis of firm exit that provinces reveal at thinner levels of industry disaggregation, although only possible with a different dataset and econometric strategy than that of this paper, represents the most direct extension of it. On our future research agenda is also the investigation of whether and how, at the investigated level of analysis, the exit rate of Young-Innovative-Companies (YIC) differ from that of the other firms. Finally, the specification that the phenomenon shows in industrial districts will also be addressed by making use of new data sources that we are currently acquiring.

However, the results we obtained have already some interesting policy implications. First of all, they show how strengthening the specialization of local production systems—for example, by pushing regional firms to keep on along their revealed comparative advantages—could provide positive economic performances in terms of industrial dynamics already in the short-run. Second, our analysis also shows that a policy strategy to foster variety at the regional level should be a long-run one, whose fruits are not immediately visible in the short-run, at least in terms of industrial demography.

A. Long-run steady state Average Total Impact

Looking at the steady state relation of Equation (5) we have:

$$\bar{\mathbf{E}} = \lambda \mathbf{W}\bar{\mathbf{E}} + \sum_{l=1}^{L_e} \gamma_l \bar{\mathbf{E}} + \sum_{l=1}^{L_e} \rho_l \mathbf{W}\bar{\mathbf{E}} + \sum_{l=0}^{L_s} \delta_l \bar{\mathbf{S}} + \boldsymbol{\mu} + \bar{\mathbf{X}}\boldsymbol{\beta}$$

where $\boldsymbol{\beta} = (\beta_c, \beta_d)'$ and $\bar{\mathbf{X}} = (\bar{\mathbf{C}}, \bar{\mathbf{D}})$.

$$\left(\left(1 - \sum_{l=1}^{L_e} \gamma_l\right)\mathbf{I} - \left(\lambda + \sum_{l=1}^{L_e} \rho_l\right)\mathbf{W}\right)\bar{\mathbf{E}} = \sum_{l=0}^{L_s} \delta_l \bar{\mathbf{S}} + \boldsymbol{\mu} + \bar{\mathbf{X}}\boldsymbol{\beta}$$

$$\bar{\mathbf{E}} = \mathbf{B}(\lambda, \boldsymbol{\gamma}, \boldsymbol{\rho}) \sum_{l=0}^{L_s} \delta_l \bar{\mathbf{S}} + \mathbf{B}(\lambda, \boldsymbol{\gamma}, \boldsymbol{\rho})\boldsymbol{\mu} + \mathbf{B}(\lambda, \boldsymbol{\gamma}, \boldsymbol{\rho})\bar{\mathbf{X}}\boldsymbol{\beta}$$

where $\mathbf{B}(\lambda, \boldsymbol{\gamma}, \boldsymbol{\rho}) = ((1 - \sum_{l=1}^{L_e} \gamma_l)\mathbf{I} - (\lambda + \sum_{l=1}^{L_e} \rho_l)\mathbf{W})^{-1}$.

The ATI in the steady state of a regressor k is therefore given by:[20]

$$\begin{aligned}
\frac{\beta_k}{n}\boldsymbol{\iota}'\mathbf{B}(\lambda, \boldsymbol{\gamma}, \boldsymbol{\rho})\boldsymbol{\iota} =& \frac{\beta_k}{(1 - \sum_{l=1}^{L_e} \gamma_l)} \left(n^{-1}\boldsymbol{\iota}' \left(\mathbf{I} - \frac{\lambda + \sum_{l=1}^{L_e} \rho_l}{1 - \sum_{l=1}^{L_e} \gamma_l}\mathbf{W} \right)^{-1} \boldsymbol{\iota} \right) \\
=& \frac{\beta_k}{(1 - \sum_{l=1}^{L_e} \gamma_l)} \left(1 - \frac{\lambda + \sum_{l=1}^{L_e} \rho_l}{1 - \sum_{l=1}^{L_e} \gamma_l} \right)^{-1} = \frac{\beta_k}{1 - \lambda - \sum_{l=1}^{L_e}(\gamma_l + \rho_l)}
\end{aligned}$$

where $\boldsymbol{\iota}$ is a column vector of ones and n the number of cross-sectional units.

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[20] The derivation is similar to the ATI for the SAR model (see LeSage and Pace, 2009, Ch.2, for details).

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