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The Italian manufacturing industry through the great recession: financial constraints, productivity and spatial neighborhood effects

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Alla mia famiglia,
a tutte le persone vicine e lontane,
che mi hanno sostenuta in questo percorso,
passo dopo passo...
...ed in particolare ai miei cari amici
Aldo, Barbara, Matteo e Vittoria,
un grazie di cuore.

Inoltre,
un ringraziamento speciale va
ai miei supervisor
e al mio collega Marco,
per il loro impegno
e il loro prezioso supporto.

To my family,
to all the people, near and far away,
who sustained me throughout this path,
step by step…
…and especially to my dear friends
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and continuous support.

Abstract

The financial crisis that erupted in 2008 translated into harsh recessionary effects at an international level, that were passed on to the real economy. A solid recovery is still lagging behind. The dissertation contributes to the econometric literature on the great recession by focusing attention on two debated topics: financing constraints and total factor productivity (TFP). The fragmented and strongly bank-dependent Italian production base is a preferred environment to conduct the analysis. The role played by financing constraints as amplifiers of manufacturing dynamics is firstly investigated. As a second step, financial rigidity of firms and contagion effects that occurred via trade credit interconnections are considered, and jointly modelled as core determinants of distress likelihoods by resorting to spatial econometric techniques. In the last section, geographical and sectoral clustering phenomena are spatially analyzed in order to investigate knowledge spillovers at the micro level. Results highlight the pervasive nature of the last crisis. The harshness of the recessionary effects fostered a change in manufacturing equilibria and caused the proliferation of distress episodes. Nevertheless, a clustered production base still represents a driver for the formation of positive externalities.

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Introduction

The global crisis that erupted in 2008, as a result of disequilibria in financial markets, translated into harsh and long lasting effects on the real side of the economy, at an international level. The aforementioned shock is frequently referred to as the double-dip crisis or the great recession. In fact, if 2009 represented the most critical year as far as the pervasiveness of real impacts is concerned, the weak recovery that followed in 2010 was suddenly dampened by the outbreak of the sovereign debt crisis, that marked the point of departure for a new recessionary phase. The European manufacturing base was seriously affected by the recessionary effects; a solid recovery is still lagging behind.

The present dissertation contributes to the econometric literature on the great recession by focusing attention on two debated topics: financing constraints and total factor productivity. The Italian manufacturing industry, being the second biggest production base in Europe, is a preferred environment to analyze the topics, because of its fragmented production structure. Moreover, Italian firms are strongly bank dependent and characterize for a high propensity to cluster.

Italy entered the last recessionary phase after a period of prolonged growth in output and manufacturing production. In light of this, the crisis of 2008-09 can be considered an unexpected shock, as comparison to the past shocks that affected the country. Nevertheless, the recessionary effects were quickly passed on to the real economy. Since the early stage of the crisis, core health status indicators of the economic cycle started being affected by major downward shifts, including export, that traditionally plays a key role in sustaining the manufacturing-centered Italian economy. The impact of the crisis was so intense, that manufacturing equilibria were deeply and permanently shaken.

Financing constraints are frequently advocated as amplifiers of shocks that occur to the real side of the economy. The phenomenon is tackled here from a twofold perspective. On the one hand, we focus attention on financial rigidity of firms as a driver of manufacturing dynamics. On the other hand, the global liquidity crisis that followed the entrance of the country into recession, represents the right framework to investigate the contagion effects that potentially occurred between manufacturing firms, as a result of the propagation of individual shocks, or imbalances, along the supply chain. Specifically, contagion effects are here modeled via trade credit interconnections, that do characterize the clustered structure of the Italian manufacturing base. Moreover, the clustered nature of the Italian firms is considered from a different perspective in the last part of the dissertation. In particular, emphasis is placed on investigating whether a clustered production base can still foster positive externalities (knowledge transfer) that enhance, in turn, total factor productivity. The remainder of the introductory section presents a broad outline of the dissertation content.

Chapter 1 is intended to shed light on the role played by financial rigidity of firms as an amplifier of inventory movements. Inventories represent priority health status indicators, at both the macro and micro levels, and are subject to low adjustment costs. Firms that characterize for financial rigidity at the eve of a crisis are expected to absorb potential liquidity shocks via downward correction to inventories. A plethora of models have been formalized and tested with the purpose of investigating what factors determine short-run variability in inventories with respect to sales, their long-run path. Target adjustment models (Lovell, 1961; Blanchard, 1983), production smoothing models (Blinder and Maccini, 1991) and production-cost smoothing models (Blinder, 1986; Eichenbaum, 1989; West, 1990) were developed in earlier studies on the subject. According to the latter studies, inventories tend to respond negatively to cost shocks affecting the firms' operating ground. Conversely, a second strand of the literature focuses attention on the sensitivity of inventories to frictions, in order to provide an alternative explanation for their short-run dynamics. As state earlier, firms that characterize for financial rigidity and face increased liquidity pressures are likely to refer to inventory decumulation as a buffer strategy. Evidence of binding financial constraints is found in several studies based on US data: reference is made to the papers by Kashyap et al. (1993, 1994), Carpenter et al. (1994, 1998), Gertler and Gilchrist (1994), Choi and Kim (2001). As far as studies that rely on European data are specifically concerned, it is worth quoting the papers by Guariglia (1999, 2000) and Bagliano and Sembenelli (2004), that are closely related to our analysis. Chapter 1 contributes to the existing literature on inventory response to frictions by exploring the effects of the great recession of 2008-09 in Italy. The Italian manufacturing is a preferred environment to analyze the selected topic because of the pronounced exposure of firms to bank debt. Three large unbalanced panels are exploited to estimate a dynamic target adjustment model. Individual frictions are proxied by different measures of financial rigidity, combined with additional risk separation criteria. The length of the observation period (that spans from 1991 to 2009) is suitable for extending the analysis backward. Specifically, the peculiar nature of the great crisis is investigated, as comparison to the crises that affected the country in the recent past: namely the early 1990s recession and the soft slowdown of 2002-03.

In the second Chapter we shift our attention to solvency dynamics of Italian firms. During the recessionary phase of 2009-13 the number of distressed firms experienced a sharp increase. Several papers have examined the effect of financial rigidity on default probabilities during economic downturns, pointing in the direction of an active role played by firm indebtness in conditioning default events. Reference is made to the recent studies by Molina (2005), Carling et al. (2007), Bonfim (2009), Loffler and Maurer (2011), Bonaccorsi di Patti et al. (2015). Nevertheless, the role played by contagion effects that originate from the supply chain is often neglected. Chapter 2 focuses attention on the trade credit channel as a source of contagion effects between manufacturing firms, and core determinant of distress likelihoods during the great recession as well. Trade credit comes to represent the largest exposure to bankruptcy of an industrial firm (Jorion and Zhang, 2009; Evans and Koch, 2007), in the sense of being potential vehicle of losses' propagation in the case of a default event. This holds particularly true during a recessionary phase, when a global lengthening of the payment terms occurs. In a network of firms that borrow from each other, a temporary shock to the liquidity of some firms may cause a chain reaction in which other firms also suffer from financial difficulties, resulting into a large and persistent decline in aggregate activity (Love et al., 2007; Love and Zaidi, 2010): firms respond to late payment from customers by delaying payments to their suppliers (Raddatz, 2010). This is likely to generate, in turn, contagion effects or trade credit chains

(Battiston et al., 2007). Specifically, Chapter 2 is related to the paper by Jacobson and von Schedvin (2015) that quantifies the importance of trade credit chains for the propagation of corporate bankruptcy. We contribute to the existing literature by modelling trade credit chains in a direct way. Supply chains are proxied by a matrix of links or transactions executed between pairs of firms in the sample before the outbreak of the crisis (delayed cash payments and invoice discounting facilities that follow directly from the presence of a prior trade credit position between firms). The way in which supply chains are proxied and embodied within a spatial econometric model represents a step forward towards a more realistic formulation of inter-agent interaction. More precisely, the focus is on trade credit received from suppliers (in exchange for an anticipated delivery of inputs) in the Italian manufacturing industry during the period 2009-13, or outstanding trade debt. We argue that the accumulation of trade debt at the firm level during the crisis (namely default of payments to suppliers, or at least a temporary extension of the payment terms) is driven by traditional financing needs (especially the liquidity position of a firm and/or the presence of internal imbalances), and by shocks imported from interconnected firms, or customer firms, that are mapped via the matrix of links. It is worth stressing again that firms respond to late payments from customers by delaying payments to suppliers. A pronounced lengthening of accounts payable days is in fact observable in the Italian aggregate data since 2009. Italy is a preferred environment to test these predictions because of the relevance of supply-chain interconnections. A representative sample of around 12,000 firms is considered to model a two-step econometric design, where trade credit chain reactions during the big crisis are firstly analyzed, by resorting to a Spatial Autoregressive (SAR) approach. The second step is instead a standard binary outcome model, where trade credit and financial rigidity of Italian firms are modelled as determinants of distress likelihoods in 2009-13.

The last Chapter of the dissertation is intended to shed light on another important and debated topic: total factor productivity (TFP). Italy is frequently regarded as disadvantaged in the international context, where comparative analysis of productivity growth matters across competing manufacturing countries, because of its fragmented production base. A fragmented production does act as a friction to investment in core inputs and strategical factors (e.g. innovation), that are likely to enhance individual total factor productivity. Specifically, the Chapter assesses knowledge spillovers in the Italian manufacturing industry accounting for spatial distances in place between firms. We draw upon the theoretical theory of externalities from geographical proximity, that deals with the knowledge transfer among neighboring firms. The seminal work by Marshall (1890) started investigating the advantages that stem from spatial concentration of firms within an industry. Sharing, learning and matching are the key mechanisms that explain the tendency to cluster in space, with particular reference to input sharing - even in the form of specialized workers. Nevertheless, these static externalities or localization externalities were mainly intended to explain regional specialization and city formation, instead of knowledge spillovers and growth. During the 1990s the attention shifted towards dynamic externalities as a way to explain simultaneously how cities form and why they grow. Knowledge spillovers represent the bridge between regional specialization and growth. Both the Marshall-Arrow-Romer (MAR) and the

Porter's theories concern knowledge spillovers between firms in an industry, and treat them as a powerful growth engine. The primary difference between MAR's[1] and Porter's (1990) models is the effect of local competition. In MAR models of externalities firms' property rights have to be sufficiently protected to facilitate a fast pace of innovation and growth. On the contrary, Porter argues that local competition within an industry increases the pressure to innovate (i.e. geographical concentration and local competition facilitate the flow of ideas and imitation). The competitive theory of externalities by Jacobs (1969) favors, as Porter's theory does, local competition as a stimulus to innovation. Nevertheless, Jacob's theory predicts that variety of geographically proximate industries promotes growth, as knowledge spills over industries. Empirical tests conducted from time to time have produced controversial results in terms of the prevailing effect. The debate is still open. In Chapter 3 of the present dissertation industrial clustering phenomena, and the related knowledge transfer issue, are tackled through the lens of spatial econometrics. As stressed earlier, spatial models move a step forward towards a more realistic formulation of inter-firm interaction. An indirect spatial production function framework of the SARAR type (spatial autoregressive model with spatial autoregressive disturbances) is selected and estimated on a large representative dataset of around 9,000 Italian manufacturing firms, observed between 2004 and 2011. As a first step, geographical space is considered to model inter-firm interaction. More precisely, interaction matrices are structured according to the theoretical literature on externalities. We elect interactions between sectorally homogeneous neighboring firms in the sample as the ideal framework to analyze externalities of the Marshall-Arrow-Romer or the Porter's types, and interactions between sectorally heterogeneous neighboring firms in the sample as the ideal point of departure to investigate externalities of the Jacobian type. As a second step, we extend the notion of interaction distance to the input-output configuration of the Italian manufacturing base, in order to investigate further the role played by sectoral heterogeneity as a driver for the knowledge transfer within the neighborhood. A unique dataset of patent applications filed with the *European Patent Office* is considered to construct an indicator of technological space, or innovative environment where firms can interact.

Results from empirical estimation of the models presented in the three Chapters shed light on the pervasive nature of the last recession. The harshness of the recessionary effects fostered a deep change in manufacturing dynamics, starting from an inventory investment perspective. The 2008-09 shock was so pervasive and global, with domestic and international demand for manufacturers severely affected, that the shock effects could not be totally absorbed via downward correction to inventories, as in the past. Rather the impact was largely absorbed by disinvestments in financial assets, at least during the early stage of the crisis. In other words, the turmoil that affected international financial markets fostered a reaction of firms in terms of financial assets decumulation, that fits nicely with the lack of an alternative escape route, due to the paralysis that occurred to the manufacturing framework. Moreover, evidence emerges of a chain

[1]. Refer to the contributions by Marshall (1890), Arrow (1962) and Romer (1986). In 1992, Edward Glaeser, Hedi Kallal, José Scheinkman, and Andrei Shleifer pulled together the Marshall-Arrow-Romer views on knowledge spillovers and accordingly named the view MAR spillover.

reaction at work during the crisis: the trade credit accumulated by Italian firms during the recessionary phase 2009-13 (outstanding trade debt) is positively affected by spatial effects, namely the accumulation of trade credit at the level of the neighboring firms, or customer firms. Trade credit interconnections did act as amplifiers of individual liquidity imbalances along the supply chain - modelled via spatial econometrics techniques. Furthermore, trade credit chain reactions are found to exert a positive impact on distress likelihoods of Italian manufacturing firms in 2009-13. The estimated effect is comparable in magnitude to the one exerted by financial rigidity of firms (evaluated at the eve of the crisis). In light of this, complex interactions between firms need to be accounted for to consistently analyze the solvency behavior, at both the individual and systemic levels. This result prepares the ground to re-think existing credit rating practices. International banks are indeed pointing in the direction of incorporating the trade credit channel into early warning models and rating models.

Finally, results show that total factor productivity benefits from positive spatial effects. Innovation emerges as the key TFP-enhancing mechanism, that fosters the convergence of levels of total factor productivity of neighboring firms. This mechanism does not appear to work differently across sectorally heterogeneous proximate firms, as comparison to sectorally homogeneous neighboring firms in the sample. Such a result is likely to prompt a revaluation of the role played by traditional industrial clusters in the Italian manufacturing base (i.e. industrial districts), frequently overlooked in the recent years. Moreover, results show that a patent intensive operating area can be regarded as a stimulus to total factor productivity, irrespective of the individual propensity to innovate.

From a policy perspective, results stress the need for preserving a clustered production base in order to foster positive externalities. Interventions that point in the direction of sustaining liquidity needs of manufacturing firms are nevertheless envisaged, in order to prevent the propagation of shocks along the supply chain. This holds particularly true for recessionary phases, when a global lengthening of the payment terms occurs. The diffusion of supply chain finance facilities could in principle represent a valid instrument to mitigate liquidity needs. Moreover, the introduction of European rules, which are precisely aimed at regulating payment terms, might contribute to rebalance disequilibria that are structural to the Italian industry. Conversely, the problem of financial rigidity of Italian firms is more difficult to be addressed, because of the presence of a considerable share of small and medium-sized enterprises that rely on bank debt as the priority financing channel.

Chapter 1

Inventory investment and financial constraints in the Italian manufacturing industry: a panel data GMM approach[°]

Abstract

We estimate a target adjustment framework at the firm level, that is designed to investigate the response of inventories to individual financial frictions. The focus is especially on Italian manufacturing dynamics during the pervasive 2008-09 shock, as comparison to the past shocks that affected the country. Inventories are priority health status indicators, at both the micro and macro levels, and are subject to low adjustment costs. Firms that characterize for financial rigidity at the eve of a crisis are expected to absorb potential liquidity shocks via downward correction to inventories. Italy is a preferred environment to test these predictions because of the exposure of firms to bank debt. Results show that a pronounced inventory decumulation was present during the 1990s recession. Conversely, a similar excessive inventory decumulation is not detected in the recent years, neither in 2002-03 nor during the great recession of 2008-09. Alternative hypotheses are considered to investigate further this apparently puzzling result. The shock of 2008-09 was so pervasive and global, with domestic demand and international demand of manufacturing goods severely affected, that the shock effects could not be absorbed via inventory decumulation, as in the past. The empirical evidence suggests that recessionary effects were largely absorbed via disinvestments in financial assets, at least during the early stage of the crisis.

JEL Classification numbers: D92, E52, F14.

Keywords: Financial constraints, Panel data, Inventory investment.

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Introduction

Financing constraints are frequently advocated as drivers of the transmission process of shocks to the real side of the economy.

A flourishing literature has documented the negative response of inventory movements to financial frictions. In other words, deviations of inventories from their long-run path have to be acknowledged in the short-run, due to the presence of individual frictions. Inventories represent *per se* priority health status indicators at the micro level. Constrained firms, or firms that characterize for financial rigidity, are likely to exploit the inventory channel to generate internal liquidity as fast as possible while facing increasing liquidity pressures. Moreover, an additional downward correction to inventories (i.e. excessive decumulation) is expected during recessionary peaks, when global liquidity crises arise.

The present Chapter focuses attention on financial rigidity of manufacturing firms as a key amplifier of inventory movements during the great recession[2]. Italy is a preferred environment to conduct the analysis because of the pronounced exposure of firms to bank debt. Data cover the first peak of the crisis: i.e. the 2008-09 shock[3]. To the best of my knowledge, the latter is here investigated for the first time in the literature on inventory response to frictions in the Italian manufacturing. Moreover, the length of the observation period (that spans from 1991 to 2009) allows the analysis to be extended backward, in order to compare the shock of 2008-09 with the early 1990s recession and the soft slowdown of 2002-03.

We exploit three large unbalanced panels of Italian manufacturing firms; each panel covers a distinct recessionary episode for the Italian economic cycle. Data are extracted from *Intesa Sanpaolo Integrated Database* (ISID).

A dynamic target adjustment model is considered and estimated by GMM First Difference approach. Financial frictions are proxied at the firm level, based on alternative definitions of financial rigidity. Moreover, constrained firms are further isolated by resorting to risk separation criteria.

A negative response of inventory investment to individual financial frictions is detected at the micro level over the entire 1991-2009 period. Inventories are subject to low adjustment costs compared to other investment-type variables. In light of this, firms that characterize for financial rigidity are likely to rely on inventory decumulation as a powerful leverage to generate liquidity (buffer stock role of inventories). Moreover, significant recessionary effects are found during the early 1990s: financially constrained firms experienced an excessive correction to inventories, compared to what is predicted by sales fluctuation. Conversely, the

[2]. The global crisis that erupted in 2008, as a result of disequilibria in financial markets, resulted into harsh and long lasting effects on the real side of the economy, at an international level. The former is frequently referred to as the double-dip crisis or the great recession. 2009 represented the most critical year as far as the pervasiveness of real impacts is concerned. Nevertheless, the weak recovery that followed in 2010 was suddenly dampened by the outbreak of the sovereign debt crisis, that marked the starting point of a new recessionary phase. The Italian manufacturing base was severely affected by recessionary effects (at least till 2013) and a solid recovery is still lagging behind.

[3]. The proposed econometric design will be inclusive of variables proxying for financial markets' dynamics. Disequilibria did characterize the international financial markets in 2007 (last quarter) and 2008. In light of this, 2008 will be considered as part of the recessionary shock to the Italian economy. Conversely, in the remainder of the dissertation the focus of attention will be on 2009 as the main recessionary peak for the Italian output.

empirical evidence suggests that a similar pattern in firm inventories was not present in the most recent years, neither in 2002-03 nor during the great recession of 2008-09. Alternative hypotheses were considered in order to investigate further this apparently puzzling result, and to identify the drivers of the different response of firms to the shock. The recessionary shock of 2008-09 was so pervasive and global that the shock effects could not be completely absorbed via internal liquidity buffers or inventory decumulation. In other words, the harshness of the recessionary effects, with reduced domestic demand and international demand severely affected, gave no scope for inventory decumulation as in the past. Results show that the impact was extensively absorbed by disinvestments in financial assets, at least during the early stage of the crisis, when a big turmoil was characterizing international financial markets.

The remainder of the Chapter is organized as follows. Next Section discusses the theoretical background on inventory behavior. Section 2 is devoted to data description while the model setup is addressed in Section 3. Section 4 displays summary statistics. Empirical results and further tests are included in Section 5. Conclusions follow.

1. Theoretical background on inventory behavior

A plethora of models have been formalized and tested on both macro and micro-data, with the purpose of investigating what factors determine short-run variability in inventories with respect to sales (the long-run path). Target adjustment models (Lovell, 1961; Blanchard, 1983), production smoothing models (Blinder and Maccini, 1991) and production-cost smoothing models (Blinder, 1986; Eichenbaum, 1989; West, 1990) were developed in earlier studies on the subject. Specifically, target adjustment models are set to explain a reverting behavior of firm inventories towards a target level, because of the rising of adjustment costs when (for some reasons) the fixed proportion “inventories to sales” is overcome. Conversely, production smoothing models posit that inventories react negatively to demand shocks, in the context of profit-maximizing firms that smooth production relative to fluctuations at the demand side. More generally, inventories respond negatively to cost shocks affecting the firms’ operating ground.

A second strand of the literature analyzes inventories’ sensitivity to liquidity shocks and constraints, in order to provide an alternative explanation for their short-run dynamics. At this stage of the analysis, the econometric set-up consists of fixed investment regressions augmented by financial variables. Inventories are subject to low adjustment costs compared to fixed assets. This allows firms to strongly react in terms of inventory decumulation as soon as external shocks require the adoption of smoothing strategies, and fosters inventories to be more volatile than sales - especially during recessionary periods. Financially constrained firms (rigid firms, in our case)[4] or firms that are likely to suffer from informational asymmetry, exploit the inventory channel to generate internal liquidity as fast as possible while facing contingencies.

Evidence of binding financial constraints that affect the inventory investment is found in several studies based on US data. Kashyap et al. (1993) and Gertler and

[4]. In the sense of experiencing difficulty in catching more credit from the market.

Gilchrist (1994) exploit time series data on credit to sustain the view that financial frictions are likely to explain the inventory excessive decumulation at the macro level, during periods of slowdown of the American economy. The same view is supported by Carpenter et al. (1994, 1998) and by Kashyap et al. (1994) at the micro level. Emphasis is placed on small firms and firms without bond ratings.

A panel data approach is employed in selected works based on European microdata. Reference is made *in primis* to the papers by Guariglia (1999, 2000) - that focus attention on the UK industry, and to the paper by Bagliano and Sembenelli (2004), that are closely related to our analysis. Bagliano and Sembenelli analyze the effects of the early 1990s recession on inventory investment in Italy, France and the United Kingdom. A major sensitivity of inventories to proxies for individual financial rigidity is detected in correspondence to small and young manufacturing firms in their sample. As far as Italian firms are specifically concerned, an excessive downward correction to inventories (compared to what is predicted by sales fluctuation) is found during the early 1990s.

A different strand of the literature employ dynamic approaches to investigate the inventory response to frictions. Specifically, error-correction inventory investment equations augmented by a financial variable are designed to capture both the influence of a long-run relationship between inventories and sales (the target level) and the response of inventory-investment to financial pressure in the short-run.

Choi and Kim (2001) apply this approach on quarterly panel data of US firms to argue that inventory investment has been liquidity constrained in most periods of the American economic history, but not necessarily during recessionary episodes. An explanation was found in the deep accumulation of liquidity monitored at the firm level in the period preceding the fall into recession. Guariglia and Mateut (2010) explore for the first time the link between firms' global engagement and financial health, at the micro level, in the context of inventory investment regressions. The focus is on UK manufacturing firms. They argue that smaller, younger and riskier firms, on the one hand, and firms that do not export and are not foreign owned, on the other, are likely to exhibit higher sensitivity in inventory decumulation. Global engagement can mitigate the response of inventories to individual frictions.

A dynamic model is adopted in the present Chapter in order to analyze the impact of financial rigidity on inventory investment in the Italian manufacturing industry. The focus is on manufacturing dynamics during the pervasive 2008-09 shock, as comparison to the past shocks that affected the country. We concentrate especially on firms that, at the eve of the crisis, were characterized by individual financial rigidity.

2. Data description

We consider three large unbalanced panels of Italian manufacturing firms observed between 1991 and 2009. The length of the observation period (19 years) is suitable for extending the analysis backward, in order to compare results from the great recession with the dynamics that pertain to the early 1990s recession and to the slowdown of 2002-03. Firm-level data are extracted from *Intesa Sanpaolo Integrated Database* (ISID)[5].

Choice was made to split the original database into three distinct datasets, according to the following temporal breakdown:

- First panel: 1991-97;
- Second panel: 1998-2003;
- Third panel: 2004-09.

Each dataset covers a key recessionary episode for the Italian economy.

Recursive screening procedures have been performed in order to achieve data comparability across the datasets. A firm enters the sample if inventories, sales and the main variables of interest in the analysis (that will be detailed in the next coming sections) are reported for at least 4 consecutive years. Once the screening step is completed (refer to Appendix A for details), we are left with unbalanced panels containing respectively: 10,564 firms in the period 1991-97, 11,443 firms in 1998-2003 and 11,226 firms in 2004-09 (Tables 1 and 2).

Each dataset is comprised of manufacturing firms categorized into 22 industries, according to the NACE Rev.1.1 classification of industrial activities defined by the European Union (2-digit sectorial breakdown).

In addition, firms are assigned a dimensional cluster (small, medium and large firms[6]), a Pavitt industrial cluster[7] and a dummy that identifies whether firms belong to an industrial district. Industrial districts represent agglomerations of firms that are specialized into typical "Made in Italy" productions (i.e. mechanic, textiles, food and beverage, leather and footwear etc.). The specifications that are selected to identify industrial districts are designed to closely mirror the analytical criteria adopted by the Intesa Sanpaolo Research Department (144 Italian industrial districts are monitored periodically).

It is worth stressing that the use of unbalanced datasets allow us to preserve variability in the cluster of small firms, that characterize indeed for frequent entrances of new firms and exits of bad-performer firms from the market. Additional information is reported in Appendix A.

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[5]. ISID (*Intesa Sanpaolo Integrated Database*) is a proprietary dataset managed by the Research Department of Intesa Sanpaolo: it matches information on corporate financial statements with qualitative variables (e.g. certifications, patent applications filed with the European Patent Office, brands, foreign directs investments, exporting activity) and information on corporate ratings (i.e. CEBI ratings, CERVED Group; the latter is the leading information provider in Italy and one of the major rating agencies in Europe).

[6]. Additional details follow in Section 3.2.

[7]. According to the Pavitt taxonomy the sectors of specialization are classified as traditional, scale intensive, high-tech and specialised suppliers. See Pavitt (1984).

Table 1 – Sample composition, by firm size

	Whole sample	***Small***	***Medium***	***Large***
		1991-1997		
Number of firms	10,564	4,484	5,036	1,044
Number of observations	59,270	23,742	29,226	6,302
		1998-2003		
Number of firms	11,443	4,937	5,396	1,110
Number of observations	63,775	28,324	29,420	6,031
		2004-2009		
Number of firms	11,226	4,860	5,191	1,175
Number of observations	61,972	28,153	27,594	6,235

Notes: refer to the Appendix for a definition of dimensional thresholds.

Table 2 - The structure of the unbalanced datasets

Number of continuous observations per firm:	***1991-1997***		***1998-2003***		***2004-2009***	
	Frequency	***%***	***Frequency***	***%***	***Frequency***	***%***
7	4,009	37.95	-	-	-	-
6	1,115	10.55	7,974	69.68	7,413	66.03
5	3,125	29.58	2,055	17.96	2,252	20.06
4	2,315	21.91	1,414	12.36	1,561	13.91
Total	10,564	100.00	11,443	100.00	11,226	100.00

3. Empirical model specification and estimation methodology

3.1 *Baseline specification of the model*

The model considered in the Chapter is a variant of the Lovell's target adjustment model (1961), that is inclusive of a proxy for the strength of financial constraints faced by firms (i.e. financial rigidity). The dynamic inventory adjustment model, applied at the micro level, is set to account for both a long-term relation between inventories and sales (the target level) and specific factors that might boost short-run deviations of inventories from their long-run path.

Denoting with *Inv* the logarithm of firm inventories[8] and with *Sales* the logarithm of sales, both in real terms[9] and defined at the end of the period, the basic equation for inventory investment takes the form:

$$\Delta Inv_{it} = \alpha + \beta_0 \Delta Inv_{i,t-1} + \beta_1 \Delta Sales_{it} + \beta_2 \Delta Sales_{i,t-1} + \beta_3 (Inv_{i,t-1} - Sales_{i,t-1}) + \beta_4 Fin_{i,t-1} + \mu_i + \mu_t + \mu_j + \mu_d + u_{it,} \qquad [1]$$

[8]. Inventories are the sum of raw materials, intermediate inputs and finished products. It is worth noting that raw materials account for a minimum fraction in the variable setting.

[9]. Variables are deflated according to 3-digit production price indexes extracted from the ASI forecasting model on Italian manufacturing trends, developed by Intesa Sanpaolo and Prometeia. ASI is the acronym for Analisi dei Settori Industriali (Industry Analysis).

where the subscript i stands for the panel variable (firms), the subscript t indexes the time variable and the subscript j refers to firm sectors of affiliation (NACE Rev.1.1 classification of industrial activities, 2-digit sectorial breakdown).

According to the theoretical model, firms tend to keep inventories stable relative to sales in the long-run (target level of inventories) and to adjust inventories relative to a desired stock in the short-run. The dependent variable ΔInv_{it} represents, in fact, the fraction of investment that is necessary to adjust the firm stock of inventories to the equilibrium level. The only partial adjustment towards the target level, which takes place in the short-run, is driven by the presence of adjustment costs. We assume that individual financial frictions, proxied by *Fin,* account to amplify this phenomenon. Emphasis is placed on financial rigidity that characterizes Italian firms. The slow adjustment path of firm inventories is modeled by considering an AR(1) specification for both the inventory investment and the growth in sales variables[10].

The term ($Inv_{i,\ t-1} - Sales_{i,\ t-1}$) is responsible for the error-correction format of the model: if the stock of inventories in *t-1* ($Inv_{i,\ t-1}$) is lower than the desired one (which in turn is a function of sales), the future inventory investment ΔInv_{it} would be higher - or conversely, a correction to inventories is envisaged if the actual stock overcomes the desired one. To be consistent with these findings, the coefficient of the error-correction term should be negative.

Furthermore, controlling for sales separately from inventories in regression allows us to account for situations where inventories play a crucial role in smoothing the effects of unpredictable demand shocks (i.e. buffer stock role).

As mentioned earlier, the variable *Fin* identifies the (expected negative) reaction of inventory investment to individual financial frictions. To proxy for a situation of financial pressure at the firm level, three different measures of financial rigidity are considered: leverage (the ratio of short and long term debt to total liabilities, including debt and shareholders' funds), short term leverage and debt maturity (the ratio of short term debt to total debt) – refer to Appendix B for further details. The effect of leverage on inventory investment has been long established in literature. However, the definition of leverage adopted in the paper is augmented by trade debt (as part of the short-term component). The choice moves from considering that trade debt represents a widely employed financing channel in the Italian industrial framework[11], especially during periods that are characterized by a slowdown of the economy and scarcity of liquidity.

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[10]. Preliminary versions of the model were estimated in order to assess the long-run relationship between inventories and sales, as well as the persistency of the inventory path.

Long run relationship between inventories and sales: $Inv_{it} = \alpha + \beta_0\, Sales_{it} + u_{it}$

The variant "in levels" of the original model:

$Inv_{it} = \alpha + \beta_0\, Inv_{i,t-1} + \beta_1\, Sales_{it} + \beta_2\, Sales_{i,\ t-1} + \beta_3\, Fin_{i,\ t-1} + \mu_i + \mu_t + \mu_j + \mu_d + u_{it}$

The GMM First Difference estimator developed by Arellano and Bond (1991) is required in this case. We exploit the available set of instruments for the variables inventories and sales. The variable proxying for financial pressure is considered exogenous by construction.

[11]. Trade debt is a form of financing generated automatically by the system when customers delay payments of their bills to suppliers. Extended payment terms characterize the operating ground of Italian firms on a structural basis, both at the supply and the customer sides. Moreover, scarcity of liquidity may boost a further lengthening of the payment terms. Conversely, a lot of studies based on US or UK data have documented that the higher costs associated to trade debt makes it less preferable with respect to bank debt; therefore, firms should refer to the former when facing severe contingencies (see for example Kashyap et al., 1996; Hoshi et al., 1993; Huang, 2003 and Guariglia and Mateut, 2010).

We discarded *a priori* the inclusion of additional variables that proxy for financial constraints at the firm level. Reference is made *in primis* to the cash flow variable, that is recurrent in the literature on inventory investment. Collinearity effects are in fact likely to emerge between the cash flow item and sales in the model. Moreover, small firms are required to deposit simplified financial statements, that do not allow reliable values of the cash flow item to be computed. Collinearity effects arise as well when the model is augmented by the coverage ratio variable (the ratio of interests paid on debt to Ebitda[12]). Furthermore, the latter variable is likely to identify monetary disequilibria in the process of debt repayment, rather than a real situation of financial rigidity.

The *Fin* variable is evaluated at time *t-1* and is therefore assumed exogenous. In fact, firms that characterize for financial rigidity at the eve of a recessionary shock should experience a more pronounced correction to inventories.

The error term in equation *[1]* is inclusive of the following components:

- idiosyncratic error term u_{it};
- firm-specific component μ_i, modelling firm heterogeneity (unobserved time-invariant heterogeneity);
- time-specific component μ_t accounting for business-cycle effects and/or effects due to a general improvement in the way of treating inventories (e.g. the “just-in-time” technique that became popular during the 1990s);
- industry specific component μ_j capturing sectorial peculiarities of the inventory behavior;
- dimensional component μ_d capturing dimensional peculiarities of the inventory behavior.

We control for firm heterogeneity by estimating the model in first-differences, for time-specific effects by including time dummies (year dummies), for sectoral effects by adding industry dummies (NACE Rev.1.1 classification, 2-digit sectorial breakdown[13]), and for dimensional effects by including dimensional dummies[14]. Specifically, the inclusion of industry dummies ensures that econometric estimates are not merely the result of cross-industry variation.

3.2 *Risk separation criteria*

We formulate the hypothesis that distressed firms or risky firms might display a greater sensitivity to inventory decumulation.

As a first step, we account for risk heterogeneity of firms by splitting the original sample into dimensional clusters. Specifically, firms are assigned a dimensional dummy (small, medium or large) based on their level of sales. The thresholds defined by the European Commission are employed to segment the sample from 2000 onwards[15]. Small firms are likely to display major

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[12]. Earnings before interests, taxes, depreciation and amortization.

[13]. See the Appendix for details. Firms are segmented in 22 industrial sectors belonging to the manufacturing industry, according to the NACE Rev.1.1 classification defined by the European Union (codes from 15 to 36).

[14]. Dimensional clusters are constructed, based on the level of sales. Specifically, the thresholds defined by the European Commission are employed to segment the sample from 2000 onwards. Dimensional clusters are detailed extensively in note 15.

[15]. From 1991 to 1999 (data in Euro millions):

Small firms: $1.5 \leq$ sales < 7

vulnerability, and a greater exposure to frictions, as comparison to medium-sized firms and large firms in the sample. To test the sensitivity of inventories to frictions at different levels of firm size, we allow the coefficient associated to our *Fin* proxy in regression equation *[1]* to vary across firms segmented by dimensional dummies.

As a second step, three different measures of risk, or proxies to identify riskier firms, are considered in order to construct a dummy *Risk*. The *Risk* binary variable takes on a value of one if a firm is classified risky and zero otherwise, and enters the model in interaction with the *Fin* financial proxy as well:

$$\Delta Inv_{it} = \alpha + \beta_0\, \Delta Inv_{i,t\text{-}1} + \beta_1\, \Delta Sales_{it} + \beta_2\, \Delta Sales_{i,\,t\text{-}1} + \beta_3\, (Inv_{i,\,t\text{-}1} - Sales_{i,\,t\text{-}1}) + \beta_4\, Fin_{i,\,t\text{-}1} * Risk_{it} + \beta_5\, Fin_{i,\,t\text{-}1} * (1\text{-}Risk_{it}) + \mu_i + \mu_t + \mu_j + \mu_d + u_{it} \qquad [2]$$

Two out of the three selected proxies (coverage ratio and acid test ratio) can be retrieved from financial statements. The third variable represents instead a multivariate proxy for risk. More precisely, we refer to CEBI ratings (CEBI is the acronym for Centrale dei Bilanci, CERVED Group)[16].

The coverage ratio is calculated as the ratio of interests paid on debt to Ebitda and measures the capability of a firm to cover interest-related expenses. If the ratio is greater than one a firm is not profitable enough to face debt burdens. In light of this, the first method that is here adopted to select risky firms encompasses the generation of a binary variable that takes on a value of one when the coverage ratio is greater than unity (and zero otherwise).

The acid test ratio is defined as the ratio of current assets, net of inventories, to current liabilities and determines whether a firm has enough short-term assets to cover immediate liabilities (without selling inventories). Therefore, the variable is suitable for detecting liquidity tensions that may arise at the firm level. A firm is assumed risky for the scope of our analysis (dummy *Risk* equal to one) when the ratio is less than unity (i.e. current assets net of inventories are lower than current liabilities).

CEBI ratings are instead the expression of the likelihood of company failure in the twelve months following the release date of the score. They represent an assessment of credit worthiness of corporations, calculated periodically by the main collector of corporate financial statements in Italy, Centrale dei Bilanci, on the basis of both economic and financial characteristics of the firms under scrutiny. In this sense, they can be considered a multivariate measure of risk (see Bottazzi et al., 2010). A firm is assumed risky (dummy *Risk* equal to one) for the scope of our analysis when the score varies between 5 (vulnerability) and 9 (very high risk) - according to the ranking detailed in Appendix B.

Medium-size firms: $7 \leq$ sales < 40
Large firms: sales ≥ 40

From 2000 onwards (European Commission's thresholds, Euro millions):

Small firms: $2 \leq$ sales < 10
Medium-size firms: $10 \leq$ sales < 50
Large firms: sales ≥ 50

[16]. CEBI ratings are available for the most recent years within the observation period (i.e. since 2004). CERVED Group is the leading information provider in Italy and one of the major rating agencies in Europe.

Interacted variables (both dimensional and risk dummies are interacted with *Fin*) can better discriminate between firms that are actually financially constrained and firms that, although displaying financial vulnerabilities (or rigidity, from a leverage or a debt maturity perspective) are likely to repay interest expenses, and/or are likely to benefit from a good liquidity position. In light of this, we expect a higher negative elasticity of inventory investment to frictions to emerge in correspondence to risky firms in the sample.

Finally, sectoral aspects of the inventories' sensitivity to frictions can be explored by segmenting the sample into Pavitt clusters of industrial activity or, alternatively, by isolating firms that belong to industrial districts.

3.3 *The inclusion of recessionary dummies*

The inclusion of recessionary dummies *Recess* provides additional interest to our investigation. A severe slowdown in output is expected to exacerbate firm-level liquidity needs and to foster an excessive downward correction to inventories – compared to what is predicted by sales fluctuation. The phenomenon should be more pronounced in correspondence to firms that characterize for financial rigidity at the eve of the crisis. In fact, these firms might experience difficulties in getting more credit from the market, in order to address their liquidity problems. Emphasis is placed on testing what happened during the 2008-09 recessionary shock, as comparison to the early 1990s recession and the soft slowdown of 2002-03. A deep occupational crisis followed the burst of the 1993 recession in Italy, entailing changes in the industrial model of "doing business" in the country. Step by step, larger companies were replaced by small and less verticalized companies. Conversely, the shock of 2008-09 finds roots in disequilibria in financial markets[17]. The financial crisis translated into harsh and long-lasting effects on the real side of the economy, with major downward shifts in demand for manufacturers. For the sake of completeness, it is worth noting that a cyclical downturn did characterize the Italian economy in 1996 and in 2002-03[18] as well. The former slowdown was primarily induced by a prolonged period of tightening monetary policy in Italy, when the country was involved in the process of fulfilling EU requirements to join the Monetary Union. The 2002-03 slowdown was instead driven by imported uncertainty from international markets, because of the bubble burst on internet stocks and the attack to the Twin Towers in 2001.

In order to model the impact of recessionary effects on the inventory path, three distinct recessionary dummies are constructed. The first two variables take on a value of one in 1993 and 1996 (first dummy), and in 2002-03 (second dummy), respectively. The third recessionary dummy, that represents our main interest, takes on a value of one in 2008-09. Moreover, an interaction is performed between the *Recess* binary variable and our proxy for financial rigidity (*Fin*):

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[17]. See also Caivano et al. (2010). The authors explore the contribution of different channels of transmission of global shocks to the Italian real economy during the 2009 severe slowdown. They document that a worsening of the international context did represent, as a matter of fact, the main driver of the recessionary effects that were passed on to the Italian real economy. The credit crunch and the confidence crisis that followed the burst of the recessionary phase played indeed only a secondary role.

[18]. See also Baffigi and Bassanetti (2004) for a complete analysis of the main peaks and thoughts that affected the Italian production-growth cycle.

$$\Delta Inv_{it} = \alpha + \beta_0\, \Delta Inv_{i,t-1} + \beta_1\, \Delta Sales_{it} + \beta_2\, \Delta Sales_{i,\, t-1} + \beta_3\, (Inv_{i,\, t-1} - Sales_{i,\, t-1})$$
$$+ \beta_4\, Fin_{i,\, t-1} + \beta_5\, Fin_{i,\, t-1} {*} Recess + \mu_i + \mu_t + \mu_j + \mu_d + u_{it} \qquad [3]$$

Finally, recessionary dummies are additionally interacted with dimensional dummies and/or *Risk* dummies.

$$\Delta Inv_{it} = \alpha + \beta_0\, \Delta Inv_{i,t-1} + \beta_1\, \Delta Sales_{it} + \beta_2\, \Delta Sales_{i,\, t-1} + \beta_3\, (Inv_{i,\, t-1} - Sales_{i,\, t-1})$$
$$+ \beta_4\, Fin_{i,\, t-1} + \beta_5\, Fin_{i,\, t-1} {*} Recess {*} Risk_{it} + \beta_6\, Fin_{i,\, t-1} {*} Recess {*} (1\text{-}Risk_{it})$$
$$+ \mu_i + \mu_t + \mu_j + \mu_d + u_{it} \qquad [4]$$

3.4 *Estimation methodology*

The presence of a lagged dependent variable ($Inv_{i,t-1}$) biases standard estimators for panel data, because of violation of the strict exogeneity assumption. Moreover, it is worth considering the variable *Sales* as predetermined[19].

In light of the above, the adoption of the dynamic GMM estimator developed by Arrellano and Bond (1991) is required in order to obtain consistent estimates. The First Difference GMM exploits a sequential exogeneity assumption for the error term to retrieve a proper set of linear moment conditions. More precisely, lagged values of the dependent variable and of the endogenous/predetermined variables in the original model prove to be valid instruments for the endogenous first differences in the transformed model. A first difference transformation of the original model is in fact performed to remove individual effects.

We exploit the entire set of available instruments (from *t-2* backwards) for the variables inventories, sales, and for the error-correction term, in order to deal with the endogeneity issue. For this purpose, we require that firms are present in each dataset at least for four consecutive years.

Specifically, the two-step version of the dynamic GMM estimator is selected (including Windmeijer correction for standard errors). The use of the Blundell and Bond (1998) System-GMM estimator is not strictly required[20]. In fact, the inventory investment path is a persistent series but is not a process with unit root properties.

Variables that proxy for financial pressure (defined in *t-1*) and additional dummy variables in the model are assumed exogenous.

4. Summary statistics

Tables 3 and 4 display summary statistics as far as the variables real sales, inventories (as a ratio to sales), leverage, short term leverage and debt maturity are concerned. Small and medium-size firms show a higher degree of leverage, compared to large firms in the sample, in each of the selected time period. Small firms and medium-sized firms are in fact assigned a leverage of 0.77 and 0.73, respectively (in median terms, 2004-09 period) and large firms display a leverage of 0.67. The inclusion of trade debt in the leverage setup is likely to have partially

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[19]. Potentially influenced by past shocks.

[20]. The adoption of a more complex System-GMM framework is not supported by data on the inventory behavior.

offset the decreasing trend in financial debt that follows the recent approval of tax policy changes[21].

Conversely, no evidence is found of a discordant behavior of larger firms in the sample, compared to smaller ones, from a debt maturity side. Both the clusters rely on short term debt in a similar fixed proportion: debt maturity is around 0.80, in median terms, in each of the selected time periods.

Table 3 - Statistics on real sales (Euro millions)

	Whole sample	***Small firms***	***Medium-size firms***	***Large firms***
		1991-1997		
Mean	27.99	5.06	17.41	163.47
1st quartile	5.53	3.59	10.14	55.55
Median	9.67	4.90	14.32	78.24
3rd quartile	20.25	6.34	21.97	137.28
		1998-2003		
Mean	27.65	5.37	19.35	172.77
1st quartile	5.58	3.54	11.72	60.30
Median	10.23	5.16	16.15	84.28
3rd quartile	20.61	6.95	24.25	146.03
		2004-2009		
Mean	28.37	4.82	18.65	177.70
1st quartile	4.70	3.05	11.35	56.89
Median	9.74	4.38	15.51	79.18
3rd quartile	19.81	6.26	23.16	135.86

Notes: refer to the Appendix for a definition of dimensional thresholds. Sales were deflated according to 3-digit production price indexes extracted from the ASI forecasting model on Italian manufacturing trends, developed by Intesa Sanpaolo and Prometeia. ASI is the acronym for Analisi dei Settori Industriali (Industry Analysis).

[21]. Reference is made to the introduction of the DIT and the super-DIT taxation policies in the Italian industrial framework. Upon approval of the latter policies, firms should have started accumulating external debt on a lesser extent, compared to the past.

Table 4 - Summary statistics: inventories (as a ratio to sales) and variables proxying for financial pressure at the firm level

	1991-1997				**1998-2003**				**2004-2009**			
	Inventories	***Leverage***	***Short-term leverage***	***Debt maturity***	***Inventories***	***Leverage***	***Short-term leverage***	***Debt maturity***	***Inventories***	***Leverage***	***Short-term leverage***	***Debt maturity***
Whole sample												
Mean	0.18	0.71	0.56	0.78	0.18	0.71	0.56	0.78	0.19	0.71	0.54	0.77
1st quartile	0.09	0.61	0.43	0.70	0.08	0.60	0.42	0.69	0.08	0.59	0.40	0.67
Median	0.15	0.74	0.57	0.82	0.15	0.75	0.57	0.81	0.15	0.74	0.55	0.80
3rd quartile	0.24	0.84	0.70	0.91	0.24	0.86	0.71	0.91	0.25	0.85	0.69	0.90
Small firms												
Mean	0.18	0.71	0.56	0.77	0.17	0.73	0.57	0.77	0.18	0.73	0.56	0.76
1st quartile	0.08	0.61	0.42	0.68	0.07	0.62	0.43	0.67	0.07	0.62	0.42	0.66
Median	0.14	0.75	0.57	0.81	0.14	0.77	0.58	0.80	0.14	0.77	0.57	0.79
3rd quartile	0.25	0.85	0.70	0.90	0.24	0.87	0.72	0.90	0.24	0.87	0.71	0.90
Medium-size firms												
Mean	0.18	0.71	0.57	0.79	0.18	0.71	0.56	0.79	0.20	0.69	0.54	0.78
1st quartile	0.09	0.61	0.44	0.71	0.09	0.60	0.43	0.71	0.10	0.58	0.40	0.69
Median	0.15	0.74	0.59	0.83	0.16	0.75	0.58	0.82	0.17	0.73	0.55	0.81
3rd quartile	0.24	0.84	0.71	0.91	0.25	0.85	0.71	0.91	0.26	0.84	0.68	0.90
Large firms												
Mean	0.16	0.67	0.53	0.79	0.17	0.66	0.51	0.78	0.18	0.64	0.49	0.77
1st quartile	0.09	0.56	0.39	0.70	0.09	0.53	0.38	0.69	0.09	0.52	0.36	0.67
Median	0.14	0.70	0.54	0.82	0.15	0.69	0.52	0.81	0.15	0.67	0.49	0.80
3rd quartile	0.21	0.80	0.66	0.92	0.22	0.80	0.65	0.91	0.23	0.79	0.63	0.91

Notes: refer to the Appendix for a definition of dimensional thresholds and of the main variables of interest in the table.

5. Regression results

5.1 *Estimates from a baseline specification of the model*

We begin by estimating[22] an error correction inventory investment model augmented by a financial variable, like the one presented in equation *[1]*[23]. From now on we will concentrate on leverage as the reference proxy for individual financial rigidity, and on the period 2004-09. Results are reported in Table 5. The variables short term leverage and debt maturity will be employed as robustness checks (see the Appendix[24]).

The presence of a long-run target inventory level is captured by the negative and statistically significant elasticity that is documented in correspondence to the error-correction term ($Inv_{i,t-1}$ $-Sales_{i,t-1}$), across all the selected time periods. More precisely, the coefficient measures the speed of adjustment towards the desired stock of inventories.

Short-run dynamics are instead captured by additional variables. The lagged inventory investment variable $\Delta Inv_{i,t-1}$ is assigned a negative and statistically significant coefficient, across all the datasets, after controlling for business-cycle effects including yearly dummies (a Wald test is performed to test the joint significance of time effects). The magnitude of the $\Delta Inv_{i,t-1}$ coefficient is nevertheless shrinking over time. This highlights the presence of an inventory adjustment path that is decreasing in intensity.

The elasticity of inventory investment to sales' growth at time *t* ($Sales_{it}$) is positive and precisely determined. The magnitude of the coefficient brings clear evidence of the active role played by inventories in accommodating production targeting strategies, and in buffering production shocks as well (production smoothing argument). Nevertheless, the AR(1) specification for sales is preserved in the case of estimation of the model on the dataset 1991-97 only. In fact, once the model is estimated on the most recent datasets, the variable $\Delta Sales_{it-1}$ is assigned a not-significant coefficient.

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22. Estimates are performed through STATA.

23. As a preliminary step, we assessed the persistency of the inventory path. Reference is made to the model described in note 10. A positive relationship is detected between the stock of inventories at time t (the dependent variable) and the stock of inventories at time *t-1*. The coefficient associated to the lagged dependent variable is around 0.50. This result supports our findings as far as the application of the Two-Step version of the GMM First Difference estimator is concerned.

24. Results are reported for the most recent dataset only (2004-09), that represents our main interest.

Table 5 - Standard estimates: inventory investment and financial constraints, model [1]

	1991-1997			***1998-2003***			***2004-2009***		
	Coefficient		***Std. err.***	***Coefficient***		***Std. err.***	***Coefficient***		***Std. err.***
$\Delta Inv_{i,t-1}$	-0.087	***	(0.018)	-0.098	***	(0.026)	-0.063	**	(0.031)
$\Delta Sales_{i,t}$	0.872	***	(0.229)	0.944	**	(0.445)	0.801	**	(0.356)
$\Delta Sales_{i,t-1}$	-0.108	***	(0.027)	-0.011		(0.022)	-0.051		(0.038)
$Inv_{i,t-1}$ - $Sales_{i,t-1}$	-0.454	***	(0.057)	-0.427	***	(0.058)	-0.422	***	(0.072)
$Fin_{i,t-1}$	-0.398	***	(0.034)	-0.280	***	(0.030)	-0.334	***	(0.033)
small	0.238	***	(0.065)	0.365	**	(0.146)	0.268	**	(0.128)
medium	0.072	**	(0.030)	0.164	**	(0.067)	0.095		(0.064)
Time dummies			added			added			added
Sectoral dummies			added			added			added
Observations			27,578			29,446			28,304
Number of firms			10,564			11,443			11,226
m1 (p)			0.000			0.000			0.000
m2 (p)			0.388			0.316			0.266
Hansen (p)			0.703			0.202			0.571
W_t *(p) time effects*			0.000			0.000			0.006

Notes: * p< .1; ** p< .05; *** p< .01 Standard errors are robust to heteroskedasticity (Windmeijer correction). For tests p-values are reported. The *Fin* variable refers to leverage. The impact of dimensional dummies on the inventory investment is extensively presented in this table only. Estimation details are reported in note 25[(25)].

The coefficient of the *Fin* (leverage) variable is also negative and significant. We may interpret this negative relationship as an evidence in favor of inventory investment being strongly influenced by individual financial frictions throughout the entire analyzed period. Results are robust to the adoption of alternative definitions of the financial proxy (short-term leverage, debt maturity; see the Appendix for details).

We also comment on testing procedures that were selected to evaluate the fit of the model. The test *m2,* namely the test for absence of second-order serial correlation in differenced residuals, is always fulfilled. Testing for the absence of second order correlation in differenced residuals[26] is equivalent to test for the

[25]. The estimation strategy is based on a GMM Fist Difference specification, two-step version. See Arellano and Bond (1991). We exploit the entire set of instruments for endogenous and predetermined variables: $\Delta Inv_{i,t-2}$, ...; $\Delta Sales_{i,t-2}$, ...; $Inv_{i,t-2}$ - $Sales_{i,t-2}$, ... Time dummies (year dummies) and industry dummies are included in the equations, both as regressors and instruments.

m1 and m2 are tests for the absence of first order and second order correlation in differenced residuals. Tests are asymptotically distributed as a Normal N(0,1) under the null of no serial correlation.

The Hansen test is a test of overidentifying restrictions that is distributed as a Chi-square under the null of valid instruments.

W_t is a Wald test. The test is applied to time dummies in order to check for their joint significance (null hypothesis: the coefficients associated to time dummies are jointly equal to zero) and to interacted variables in order to check for inequality of coefficients (null hypothesis: no structural difference between coefficients). For all the tests, p-values are reported.

[26]. m2 tests exploit a standardized average residual autocovariance to test for the absence of second-order serial correlation within residuals of the transformed model. The test is distributed asymptotically as a standard Normal N(0,1) under the null of no serial correlation. A first difference transformation of the original model (that is performed by the GMM estimator) implies that differenced residuals are pairwise-joint: in light of this, first order serial correlation is present for sure in the data. The m1 test for the absence of first-order serial correlation is specifically designed to shed light on this phenomenon: we expect a rejection of the null hypothesis. In order to compute the aforementioned m2 test, firms must be present in the dataset at least for 5 consecutive years. See Baltagi (2008).

absence of serial correlation of order one in the original model. In other words, the former test represents the fastest way to assess the validity of the sequential exogeneity assumption[27], that in turn implies consistency of the First Difference GMM developed by Arellano and Bond. Moreover, this implies that lags from *t-2* backwards of the dependent variable are valid instruments to solve for the endogeneity issue discussed in the previous paragraph. Finally, Hansen tests of overidentifying restrictions were performed in order to assess the relevance of additional instrument sets: the ones pertaining to the sales item and the error correction term[28].

5.2 *Estimates from the adoption of risk separation criteria*

As a second research step, we assessed the different sensitivity of risky firms to frictions by interacting the financial proxy *Fin* with a *Risk* dummy (Table 6): risk separation criteria (coverage ratio, acid test ratio, CEBI ratings) were alternatively exploited to segment firms on the basis of their riskiness characteristics. Reference is made to equation *[2]*. Leverage is still employed as the reference financial proxy. Tests of equality between coefficients of the interacted variables are performed accordingly (p-values are reported).

Estimates show that, as a general argument, the negative elasticity of inventory investment to individual frictions is higher for riskier firms. The risk separation approaches that are based on the acid test ratio – that is suitable for identifying liquidity constraints at the firm level – or, alternatively, on ratings (CEBI ratings are available in the 2004-09 dataset) act in the sense of better isolating vulnerable firms. Conversely, when the coverage ratio specification is selected to isolate risky firms (columns 1, 3 and 5 in Table 6), the coefficient associated to the interacted variable *Fin*Risk* is not statistically different from the one associated to the interacted variable *Fin*(1-Risk),* across all the datasets. As far as the shock of 2008-09 is specifically concerned, it worth noting that the fall in interest rates that followed the burst of the crisis was accompanied by a simultaneous fall in gross operating profits (Ebitda), causing the coverage ratio remaining above pre-crisis levels. The same view is supported by the Bank of Italy in the financial stability reports and in the annual reports issued in 2010-11[29].

As an alternative approach to *Risk* dummies, dimensional dummies can be exploited to isolate firms that are likely to face financial constraints in a traditional sense (vulnerable firms or rigid firms). In other words, it is possible to detect a dimensional side of the inventories' sensitivity to frictions. Small firms are in fact assigned a higher *Fin* coefficient with respect to other firm-types, across all the dataset (columns 1, 3 and 5 in Table 7). This is consistent with the findings of Bagliano and Sembenelli.

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[27]. "No serial correlation" is in fact a direct implication of validity of the sequential exogeneity assumption in dynamic models.

[28]. Standard Sargan tests for overidentifying restrictions are biased by the presence of heteroskedasticity . The Hansen test is therefore to be preferred. The former test is asymptotically distributed as a Chi-square under the null hypothesis of validity of the instrument set. See Baltagi (2008).

[29]. Reference is made to the financial stability reports issued in December 2010 and November 2011, respectively, and to the annual reports released during the same years.

Moreover, the dimensional effect is preserved when dimensional dummies are interacted with the *Risk* dummy that proxies for liquidity constraints. In general, bigger liquidity constrained firms characterize for a lower inventory sensitivity to individual frictions, compared to small liquidity constrained firms (columns 2, 4 and 6 in Table 7).

Finally, columns 2, 4 and 6 in Table 8 show again that a stronger negative response of inventories to frictions is present when firms are liquidity constrained, and especially when they belong to the cluster of firms specialized into traditional sectors of industrial activity. Conversely, firms that belong to industrial districts and firms that locate outside industrial districts are likely to exhibit a similar inventory sensitivity to individual frictions (Table 9).

Table 6 - Inventory investment and financial constraints: firms segmented by risk separation criteria

	1991-1997				1998-2003				2004-2009					
	$Risk_{it}$ f (Coverage $ratio_{it}$)		$Risk_{it}$ f (Acid test $ratio_{it}$)		$Risk_{it}$ f (Coverage $ratio_{it}$)		$Risk_{it}$ f (Acid test $ratio_{it}$)		$Risk_{it}$ f (Coverage $ratio_{it}$)		$Risk_{it}$ f (Acid test $ratio_{it}$)		$Risk_{it}$ f (CEBI $rating_{it}$)	
	Coefficient	**Std. err.**	**Coefficient**	**Std. err.**	**Coefficient**	**Std. err.**	**Coefficient**	**Std. err.**	**Coefficient**	**Std. err.**	**Coefficient**	**Std. err.**	**Coefficient**	**Std. err.**
$\Delta Inv_{i,t-1}$	-0.087 ***	(0.018)	-0.090 ***	(0.018)	-0.098 ***	(0.025)	-0.099 ***	(0.026)	-0.062 **	(0.031)	-0.062 **	(0.031)	-0.063 **	(0.031)
$\Delta Sales_{i,t}$	0.869 ***	(0.227)	0.872 ***	(0.227)	0.935 **	(0.441)	0.940 **	(0.443)	0.794 **	(0.353)	0.759 **	(0.354)	0.791 **	(0.356)
$\Delta Sales_{i,t-1}$	-0.107 ***	(0.026)	-0.110 ***	(0.026)	-0.011	(0.022)	-0.016	(0.021)	-0.050	(0.038)	-0.055	(0.038)	-0.049	(0.038)
$Inv_{i,t-1}$ - $Sales_{i,t-1}$	-0.453 ***	(0.057)	-0.457 ***	(0.056)	-0.426 ***	(0.058)	-0.424 ***	(0.058)	-0.422 ***	(0.071)	-0.413 ***	(0.072)	-0.418 ***	(0.072)
$Fin_{i,t-1}*Risk_{it}$	-0.509 ***	(0.062)	-0.623 ***	(0.038)	-0.367 ***	(0.075)	-0.452 ***	(0.033)	-0.322 ***	(0.063)	-0.532 ***	(0.039)	-0.537 ***	(0.039)
$Fin_{i,t-1}*(1-Risk_{it})$	-0.395 ***	(0.035)	-0.260 ***	(0.034)	-0.279 ***	(0.030)	-0.170 ***	(0.031)	-0.335 ***	(0.034)	-0.202 ***	(0.032)	-0.292 ***	(0.034)
Time dummies		added		added		added		added		added		added		added
Sect. dummies		added		added		added		added		added		added		added
Dimensional dummies		added		added		added		added		added		added		added
Observations		27,578		27,578		29,446		29,446		28,304		28,304		28,304
Number of firms		10,564		10,564		11,443		11,443		11,226		11,226		11,226
m1 (p)		0.000		0.000		0.000		0.000		0.000		0.000		0.000
m2 (p)		0.413		0.450		0.320		0.320		0.266		0.241		0.282
Hansen (p)		0.703		0.738		0.200		0.201		0.573		0.509		0.527
W_t *(p) time effects*		0.000		0.000		0.000		0.000		0.006		0.006		0.007
W_t *(p) equality of interacted coeff.*		0.072		0.000		0.203		0.000		0.839		0.000		0.000

Notes: * p< .1; ** p< .05; *** p< .01 Std. errors robust to heteroskedasticity (Windmeijer correction). For all tests p-values are reported. The *Fin* variable refers to leverage. Refer to note 25 for estimation details.

Table 7 - Dimensional aspects of the linkage between inventory investment and financial constraints: variants of models [1] and [2]

	1991-1997				**1998-2003**				**2004-2009**			
	Dimensional dummies		**Dimensional dummies and $Risk_{it}$ f (Acid test $ratio_{it}$)**		**Dimensional dummies**		**Dimensional dummies and $Risk_{it}$ f (Acid test $ratio_{it}$)**		**Dimensional dummies**		**Dimensional dummies and $Risk_{it}$ f (Acid test $ratio_{it}$)**	
	Coefficient	***Std. err.***	***Coefficient***	***Std. err.***	***Coefficient***	***Std. err.***	***Coefficient***	***Std. err.***	***Coefficient***	***Std. err.***	***Coefficient***	***Std. err.***
$\Delta Inv_{i,t-1}$	-0.089 ***	(0.019)	-0.092 ***	(0.018)	-0.097 ***	(0.025)	-0.099 ***	(0.025)	-0.057 **	(0.029)	-0.058 **	(0.029)
$\Delta Sales_{i,t}$	0.876 ***	(0.231)	0.895 ***	(0.230)	0.931 **	(0.436)	0.931 **	(0.433)	0.733 **	(0.319)	0.707 **	(0.319)
$\Delta Sales_{i,t-1}$	-0.111 ***	(0.027)	-0.115 ***	(0.027)	-0.012	(0.021)	-0.016	(0.021)	-0.052	(0.037)	-0.057	(0.037)
$Inv_{i,t-1}$ - $Sales_{i,t-1}$	-0.450 ***	(0.057)	-0.459 ***	(0.056)	-0.433 ***	(0.060)	-0.427 ***	(0.059)	-0.428 ***	(0.071)	-0.415 ***	(0.072)
$Fin_{i,t-1}$	-0.245 ***	(0.062)			-0.051	(0.091)			-0.195 **	(0.095)		
$Fin_{i,t-1\ small}$	-0.304 ***	(0.083)			-0.376 ***	(0.145)			-0.247 **	(0.119)		
$Fin_{i,t-1\ medium}$	-0.095 **	(0.039)			-0.130 **	(0.059)			-0.051	(0.066)		
$Fin_{i,t-1}*Risk_{it\ small}$			-0.861 ***	(0.057)			-0.668 ***	(0.083)			-0.695 ***	(0.057)
$Fin_{i,t-1}*Risk_{it\ medium}$			-0.543 ***	(0.048)			-0.336 ***	(0.055)			-0.432 ***	(0.058)
$Fin_{i,t-1}*Risk_{it\ large}$			-0.352 ***	(0.069)			-0.115	(0.091)			-0.295 ***	(0.106)
$Fin_{i,t-1}*(1-Risk_{it})_{small}$			-0.366 ***	(0.045)			-0.284 ***	(0.063)			-0.281 ***	(0.041)
$Fin_{i,t-1}*(1-Risk_{it})_{medium}$			-0.209 ***	(0.038)			-0.086 *	(0.046)			-0.119 ***	(0.045)
$Fin_{i,t-1}*(1-Risk_{it})_{large}$			-0.148 **	(0.060)			0.007	(0.093)			-0.114	(0.092)
Time dummies		added		added		added		added		added		added
Sectoral dummies		added		added		added		added		added		added
Dimensional dummies		added		added		added		added		added		added
Observations		27,578		27,578		29,446		29,446		28,304		28,304
Number of firms		10,564		10,564		11,443		11,443		11,226		11,226
m1 (p)		0.000		0.000		0.000		0.000		0.000		0.000
m2 (p)		0.464		0.508		0.305		0.329		0.312		0.273
Hansen (p)		0.691		0.741		0.204		0.191		0.666		0.589
W_t *(p) time effects*		0.000		0.000		0.000		0.000		0.004		0.004
W_t *(p) inter. coeff. (Risk)*				0.000				0.001				0.007
W_t *(p) inter. coeff.(1-Risk)*				0.006				0.075				0.003

Notes: * p< .1; ** p< .05; *** p< .01 Standard errors are robust to heteroskedasticity (Windmeijer correction). For all tests p-values are reported. The *Fin* variable refers to leverage. Refer to the Appendix for a definition of the dimensional thresholds and to note 25 for estimation details.

Table 8 - The inclusion of Pavitt clusters' dummies in the linkage between inventory investment and financial constraints: variants of models [1] and [2]

	1991-1997				**1998-2003**				**2004-2009**			
	Pavitt clusters		**Pavitt clusters and $Risk_{it}$ f (Acid test $ratio_{it}$)**		**Pavitt clusters**		**Pavitt clusters and $Risk_{it}$ f (Acid test $ratio_{it}$)**		**Pavitt clusters**		**Pavitt clusters and $Risk_{it}$ f (Acid test $ratio_{it}$)**	
	Coefficient	**Std. err.**	**Coefficient**	**Std. err.**	**Coefficient**	**Std. err.**	**Coefficient**	**Std. err.**	**Coefficient**	**Std. err.**	**Coefficient**	**Std. err.**
$\Delta Inv_{i,t-1}$	-0.087 ***	(0.018)	-0.094 ***	(0.019)	-0.095 ***	(0.025)	-0.105 ***	(0.024)	-0.063 **	(0.030)	-0.060 *	(0.030)
$\Delta Sales_{i,t}$	0.849 ***	(0.223)	0.889 ***	(0.226)	0.909 ***	(0.434)	0.944 ***	(0.440)	0.842 **	(0.357)	0.789 **	(0.355)
$\Delta Sales_{i,t-1}$	-0.109 ***	(0.027)	-0.128 ***	(0.028)	-0.010	(0.022)	-0.019	(0.021)	-0.057	(0.038)	-0.062	(0.039)
$Inv_{i,t-1}$ - $Sales_{i,t-1}$	-0.449 ***	(0.057)	-0.456 ***	(0.056)	-0.430 ***	(0.059)	-0.438 ***	(0.056)	-0.427 ***	(0.072)	-0.424 ***	(0.071)
$Fin_{i,t-1\_high\ technology}$	-0.198 **	(0.087)			-0.231 **	(0.101)			-0.255 ***	(0.069)		
$Fin_{i,t-1\_scale\ intensive}$	-0.358 ***	(0.051)			-0.274 ***	(0.051)			-0.214 ***	(0.046)		
$Fin_{i,t-\_specialised\ suppliers}$	-0.408 ***	(0.083)			-0.399 ***	(0.063)			-0.364 ***	(0.053)		
$Fin_{i,t-1\_traditional}$	-0.495 ***	(0.051)			-0.247 ***	(0.049)			-0.421 ***	(0.053)		
$Fin_{i,t-1}$*$Risk_{it\_high\ technology}$			-0.278 ***	(0.069)			-0.286 ***	(0.064)			-0.273 ***	(0.077)
$Fin_{i,t-1}$*$Risk_{it\_scale\ intensive}$			-0.329 ***	(0.035)			-0.249 ***	(0.041)			-0.227 ***	(0.040)
$Fin_{i,t-1}$*$Risk_{it\_specialised\ suppliers}$			-0.358 ***	(0.042)			-0.297 ***	(0.042)			-0.397 ***	(0.042)
$Fin_{i,t-1}$*$Risk_{it\_traditional}$			-0.448 ***	(0.029)			-0.339 ***	(0.031)			-0.403 ***	(0.035)
$Fin_{i,t-1}$*(1-$Risk_{it}$)			-0.128 ***	(0.035)			-0.108 ***	(0.028)			-0.158 ***	(0.034)
Time dummies		added		added		added		added		added		added
Sectoral dummies		added		added		added		added		added		added
Dimensional dummies		added		added		added		added		added		added
Observations		27,578		27,578		29,446		29,446		28,304		28,304
Number of firms		10,564		10,564		11,443		11,443		11,226		11,226
m1 (p)		0.000		0.000		0.000		0.000		0.000		0.000
m2 (p)		0.442		0.480		0.311		0.330		0.327		0.308
Hansen (p)		0.681		0.738		0.198		0.193		0.661		0.588
W_t *(p) time effects*		0.000		0.000		0.000		0.000		0.005		0.005
W_t *(p) equality of interacted coeff. (Pavitt clusters)*		0.022		0.020		0.221		0.331		0.005		0.004

Notes: * p< .1; ** p< .05; *** p< .01 Standard errors are robust to heteroskedasticity (Windmeijer correction). For all tests p-values are reported. The *Fin* variable refers to leverage. Refer to note 25 for estimation details.

Table 9 - The inclusion of district dummies in the linkage between inventory investment and financial constraints: a variant of model [1]

	1991-1997			***1998-2003***			***2004-2009***		
	Coefficient		***Std. err.***	***Coefficient***		***Std. err.***	***Coefficient***		***Std. err.***
$\Delta Inv_{i,t-1}$	-0.087	***	(0.019)	-0.099	***	(0.026)	-0.065	**	(0.031)
$\Delta Sales_{i,t}$	0.872	***	(0.230)	0.950	**	(0.449)	0.832	**	(0.355)
$\Delta Sales_{i,t-1}$	-0.108	***	(0.027)	-0.011		(0.022)	-0.054		(0.038)
$Inv_{i,t-1}$ - $Sales_{i,t-1}$	-0.454	***	(0.057)	-0.427	***	(0.059)	-0.419	***	(0.072)
$Fin_{i,t-1\_industrial\ districts}$	-0.481	***	(0.099)	-0.317	***	(0.066)	-0.453	***	(0.089)
$Fin_{i,t-1\_rest\ of\ the\ sample}$	-0.382	***	(0.034)	-0.272	***	(0.034)	-0.311	***	(0.032)
Time dummies (μ_t)			added			added			added
Sectorial dummies (μ_j)			added			added			added
Observations			27,578			29,446			28,304
Number of firms			10,564			11,443			11,226
m1 (p)			0.000			0.000			0.000
m2 (p)			0.402			0.323			0.268
Hansen (p)			0.695			0.202			0.547
W_t *(p) time effects*			0.000			0.000			0.005
W_t *(p) equality of interacted coeff. (industrial districts)*			0.323			0.556			0.106

Notes: * p< .1; ** p< .05; *** p< .01 Std. errors are robust to heteroskedasticity (Windmeijer correction). For all the tests p-values are reported. The *Fin* variable refers to leverage. Refer to note 25 for estimation details.

5.3 *Estimates from the inclusion of recessionary dummies and further tests*

To explore in detail how the link between inventory investment and financial constraints behaves during recessionary periods, recessionary dummies are included in the model. As mentioned in Section 3, recessionary dummies take on a value of one in the following years: 1993 and 1996 (first panel), 2002-03 (second panel), 2008-09 (third panel).

To isolate the impact of recessionary effects on the inventory path, an interaction is performed with the *Fin* variable. Reference is made to model *[3]*. Moreover, model *[4]* allows the additional effect of liquidity constraints and riskiness characteristics of firms (incorporated into the dummy *Risk*) to be explored.

It is worth recalling that inventories are subject to low adjustment costs. Firms that characterize for financial rigidity at the eve of a crisis are expected to absorb potential liquidity shocks via downward corrections to inventories. In fact, these firms should experience difficulties in getting more credit from the market in order to rebalance their internal disequilibria. The phenomenon is expected to be more pronounced in correspondence with firms that are additionally liquidity constrained or risky.

An excessive downward correction to inventories (recessionary effect) is found during the early 1990s, as expected and consistent with the findings of Bagliano and Sembenelli. Implications from the other variables in the model remain the same. Specifically, illiquid firms show a greater inventory sensitivity to financial frictions during the recessionary peaks of 1993 and 1996 (column 2, Table 10a). At the same time, it is worth stressing that an excessive downward correction to inventories characterizes the most liquid firms in the dataset as well (identified via the interacted variable *Fin*Recess*(1-Risk)*. Moreover, the inventory decumulation phenomenon of the early 1990s appears to affect firms in all the dimensional classes (column 1, Table 11).

Conversely, when models *[3]* and *[4]* are estimated on the most recent datasets, empirical results identify the presence of recessionary effects that are only weakly significant in the case of the shock of 2008-09 (column 1, Table 10b), and not statistically significant at all in the case of the soft slowdown of 2002-03 (column 3, Table 10a). More precisely, evidence is found of an excessive downward correction to inventories that is limited to the most illiquid firms and the riskiest ones in the sample (column 4, Table 10a and columns 2 and 3, Table 10b).

The 2002-03 period did mark a soft slowdown in the Italian output, compared to the deep crisis that occurred in the early 1990s. The fast recovery that followed may in fact have partly counterbalanced liquidity tensions, at least at the macro level, dampening in turn downward trends in inventories.

Conversely, the recessionary shock of 2008-09, that finds roots in disequilibria in financial markets, translated into harsh and log-lasting recessionary effects that were passed on to the real side of the economy, at an international level. Nevertheless, it can be considered an unexpected shock, compared to other shocks that affected the country in the past. In fact, it occurred after a period of prolonged growth of the Italian output. Moreover, there is ample evidence of abundance of credit to Italian firms during the period 2001-07. These factors are likely to have implied a better positioning of Italian firms at the eve of the crisis, as far as liquidity buffers are concerned (Italy was instead involved in the process of fulfilling EU requirements to join the Monetary Union during the period that precedes the fall into the early 1990s recession, and restrictive monetary policies were in place). Furthermore, several policy interventions did characterize the early stage of the last crisis, that were precisely aimed at smoothing liquidity tensions at the firm level. The lack of a pronounced excessive correction to inventories during the shock of 2008-09 has therefore to be interpreted accordingly.

At the same time, it is worth shedding light on another distinctive feature of the last shock. A pronounced shift occurred to the demand of manufacturing goods, both at the national and international levels, that has no historical precedent. The early stage of the great recession was so all-pervasive and global, with major downward shifts in demand for manufacturers, that the shock effects could not be absorbed via the earlier approach of downward correction to inventories.

Conversely, firms might have selected alternative channels to absorb the recessionary effects and to cope with their increased liquidity needs.

To test these predictions, we investigate the relationship between the liquidity position of firms and different classes of firm capital. In addition to inventories, we consider financial assets and fixed capital. We exploit a dynamic econometric framework that is a variant of the model presented in Fazzari et al. (1993):

$$\begin{aligned} LIQ_{it} = {} & \alpha + \beta_0\, LIQ_{i,t-1} + \beta_1\, financial\_assets_{it} + \beta_2\, financial\_assets_{it}{*}recess \\ & + \beta_3\, fixed\_capital_{it} + \beta_4\, fixed\_capital_{it}{*}recess + \beta_5\, inventories_{it} \\ & + \beta_6\, inventories_{it}{*}recess + \beta_7\, leverage_{i,t-1} + \beta_8\, vertical\_integration_{i,t-1} \\ & + \mu_i + \mu_t + \mu_j + u_{it} \qquad [5] \end{aligned}$$

The dependent variable LIQ_{it} , being the ratio of cash and marketable securities to total assets, is designed to mirror the liquidity position of a firm *i* at time *t*. A time lag of the dependent variable ($LIQ_{i,t-1}$) is included to account for time dependence in liquidity data. In light of this, the First Difference GMM estimator developed by Arellano and Bond is selected to solve for the endogeneity issue. The time lag variable is instrumented with lags from *t-2* backwards.

As stated earlier, we consider three distinct classes of firm capital: financial assets, fixed capital and inventories. The variables *financial_assets* and *fixed_capital* are scaled by total assets, while the variable *inventories* is scaled by sales, in order to account for firms' size. The variables are defined at time *t* and, therefore, are assumed endogenous. In light of this, they are instrumented with lags from *t-1* backwards. Furthermore, the three variables are additionally included in interaction with the recessionary dummy. Interacted variables are suitable for investigating the relationship between liquidity and different classes of firm capital during recessionary peaks.

Finally, we consider a leverage proxy and a proxy for vertical integration as well (the ratio of value added to sales[30]), that are likely to incorporate additional information on the structure of our sampled firms. Both the variables are defined in *t-1* and treated as exogenous covariates.

The equation *[5]* is estimated on the last panel dataset (2004-09) and, as a reasonable comparison, on the first panel (1991-97), that is comprehensive of another important and pervasive recessionary shock for the Italian output.

Regression results (Table 12) document a negative and significant relationship established between liquidity and financial assets, that is stronger in 2004-09. Moreover, we identify an additional negative impact of financial assets during the shock of 2008-09. Conversely, the recessionary effect is not present during the early 1990s. At the same time, a negative relationship is established between liquidity and inventories, across all the selected periods. As expected, the excessive downward correction to inventories is only weakly significant during the recessionary shock of 2008-09.

Furthermore, in the period 1991-97 we identify a negative relationship between liquidity and fixed capital, although not marked by recessionary effects. Finally, leveraged firms and vertically integrated firms characterize for a worse liquidity position in the period 2004-09. The negative impact of vertical integration can nevertheless be justified in light of the lower propensity of larger firms to rely on liquidity as a buffer asset (as a general argument, large firms maintain a solid relationship with banks and benefit from credit lines).

In light of the above, estimates support the view that the pervasive recessionary effects of 2008-09 were only partially absorbed via inventory decumulation, and extensively absorbed via disinvestment in financial assets, at least during the early stage of the crisis. Conversely, the same phenomenon was not present during the early 1990s recession, when an excessive downward correction to inventories is

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[30]. A firm is vertically integrated when different stages of the production process (i.e. of the supply chain) are managed internally to the firm itself. Value added refers to the contribution of the factors of production (capital and labor) to raising the value of a product. It corresponds indeed to the income received by the owner of those factors. More precisely, total value added is equivalent to the revenue less outside purchases of materials and services. Value added is a high portion of revenue for integrated companies. For this reason it is commonly employed as a proxy to identify vertically integrated firms. It enters the model scaled by sales to account for firm dimensions.

documented. On the one hand, the harshness of the recessionary effects, with domestic and international demand of manufacturing goods severely affected, gave no scope for inventory decumulation as in the past. On the other hand, the turmoil that affected international financial markets fostered a reaction of firms in terms of financial assets decumulation, that fits nicely with the lack of an alternative escape route, due to the paralysis that occurred to the manufacturing framework. This econometric evidence is supported by a more qualitative evidence, namely the summary statistics released by the Bank of Italy in 2010. As stated in the 2010 Annual Report, around 21 Euro billions of disinvestments in financial assets were detected in 2008-09, in correspondence to the Italian firms that are active in the non-financial sector.

Table 10a - Inventory investment and financial constraints: the inclusion of recessionary dummies, models [3] and [4], panel (1) and (2)

	1991-1997								**1998-2003**							
	Recessionary dummies				**Recessionary dummies and $Risk_{it}$ f (Acid test $ratio_{it}$)**				**Recessionary dummies**				**Recessionary dummies and $Risk_{it}$ f (Acid test $ratio_{it}$)**			
	Coefficient		**Std. err.**		**Coefficient**		**Std. err.**		**Coefficient**		**Std. err.**		**Coefficient**		**Std. err.**	
$\Delta Inv_{i,t-1}$	-0.087	***	(0.018)		-0.086	***	(0.018)		-0.098	***	(0.025)		-0.105	***	(0.026)	
$\Delta Sales_{i,t}$	0.858	***	(0.229)		0.894	***	(0.228)		0.929	**	(0.440)		0.957	**	(0.449)	
$\Delta Sales_{i,t-1}$	-0.106	***	(0.027)		-0.111	***	(0.027)		-0.011		(0.022)		-0.010		(0.022)	
$Inv_{i,t-1}$ - $Sales_{i,t-1}$	-0.448	***	(0.057)		-0.470	***	(0.056)		-0.427	***	(0.058)		-0.403	***	(0.058)	
$Fin_{i,t-1}$	-0.390	***	(0.034)						-0.276	***	(0.035)					
$Fin_{i,t-1}$* Recess	-0.039	***	(0.012)						-0.004		(0.019)					
$Fin_{i,t-1}$					-0.351	***	(0.034)						-0.273	***	(0.035)	
$Fin_{i,t-1}$*Recess*$Risk_{it}$					-0.189	***	(0.020)						-0.123	***	(0.027)	
$Fin_{i,t-1}$* Recess*(1-$Risk_{it}$)					-0.032	***	(0.011)						0.006		(0.019)	
Time dummies			added				added				added				added	
Sectoral dummies			added				added				added				added	
Dimensional dummies			added				added				added				added	
Observations			27,578				27,578				29,446				29,446	
Number of firms			10,564				10,564				11,443				11,443	
m1 (p)			0.000				0.000				0.000				0.000	
m2 (p)			0.403				0.417				0.312				0.371	
Hansen (p)			0.691				0.776				0.203				0.144	
W_t (p) time effects			0.000				0.000				0.000				0.000	
W_t (p) equality of interacted coeff.							0.000								0.000	

Notes: * p< .1; ** p< .05; *** p< .01 Standard errors are robust to heteroskedasticity (Windmeijer correction). For all the tests p-values are reported. The *Fin* variable refers to leverage. Recessionary dummies correspond to 1993 and 1996 peaks in panel (1) and to 2002-03 in panel (2). Refer to Appendix B for a definition of the main variables of interest in the table. Refer to note 25 for estimation details.

Table 10b - Inventory investment and financial constraints: the inclusion of recessionary dummies, models [3] and [4] – panel (3) 2004-2009

	Recessionary Dummies			***Recessionary dummies and $Risk_{it}$ f (Acid test ratio$_{it}$)***			***Recessionary dummies and $Risk_{it}$ f (CEBI rating$_{it}$)***		
	Coefficient		***Std. err.***	***Coefficient***		***Std. err.***	***Coefficient***		***Std. err.***
$\Delta Inv_{i,t-1}$	-0.061	**	(0.031)	-0.079	**	(0.031)	-0.067	**	(0.031)
$\Delta Sales_{i,t}$	0.779	**	(0.354)	0.815	**	(0.358)	0.753	**	(0.356)
$\Delta Sales_{i,t-1}$	-0.052		(0.038)	-0.060		(0.038)	-0.054		(0.038)
$Inv_{i,t-1}$ - $Sales_{i,t-1}$	-0.425	***	(0.072)	-0.362	***	(0.073)	-0.395	***	(0.071)
$Fin_{i,t-1}$	-0.316	***	(0.037)						
$Fin_{i,t-1}$* Recess	-0.026	*	(0.014)						
$Fin_{i,t-1}$				-0.300	***	(0.037)	-0.304	***	(0.037)
$Fin_{i,t-1}$*Recess*$Risk_{it}$				-0.193	***	(0.024)	-0.208	***	(0.035)
$Fin_{i,t-1}$* Recess*(1-$Risk_{it}$)				-0.004		(0.015)	-0.036		(0.147)
Time dummies			added			added			added
Sectoral dummies			added			added			added
Dimensional dummies			added			added			added
Observations			28,304			28,304			28,304
Number of firms			11,226			11,226			11,226
m1 (p)			0.000			0.000			0.000
m2 (p)			0.266			0.204			0.257
Hansen (p)			0.573			0.670			0.598
W_t (p) time effects			0.003			0.006			0.008
W_t (p) equality of interacted coeff.						0.000			0.000

Notes: * p< .1; ** p< .05; *** p< .01 Standard errors are robust to heteroskedasticity (Windmeijer correction). For all tests p-values are reported. The *Fin* variable refers to leverage. Refer to note 25 for estimation details. The recessionary dummy takes on a value of one in 2008-09. Refer to Appendix B for a definition of the main variables of interest in the table.

Table 11 - Inventory investment and financial constraints: dimensional and recessionary dummies, variants of model [3]

	1991-1997		***1998-2003***		***2004-2009***	
	Coefficient	***Std. err.***	***Coefficient***	***Std. err.***	***Coefficient***	***Std. err.***
$\Delta Inv_{i,t-1}$	-0.086 ***	(0.019)	-0.053	(0.034)	-0.073	(0.064)
$\Delta Sales_{i,t}$	0.821 ***	(0.222)	0.949 **	(0.438)	0.687	(0.430)
$\Delta Sales_{i,t-1}$	-0.135 ***	(0.037)	-0.046	(0.029)	-0.046	(0.043)
$Inv_{i,t-1}$ - $Sales_{i,t-1}$	-0.595 ***	(0.130)	-0.642 ***	(0.170)	-0.356 *	(0.183)
$Fin_{i,t-1}$	-0.356 ***	(0.047)	-0.237 ***	(0.042)	-0.325 ***	(0.052)
$Fin_{i,t-1}$*$Recess_{small}$	-0.044 ***	(0.016)	-0.082 ***	(0.022)	-0.074 ***	(0.026)
$Fin_{i,t-1}$*$Recess_{medium}$	-0.026 **	(0.013)	0.026	(0.020)	0.005	(0.018)
$Fin_{i,t-1}$*$Recess_{large}$	-0.039 **	(0.017)	0.053 *	(0.029)	0.017	(0.027)
Time dummies		added		added		added
Sectoral dummies		added		added		added
Dimensional dummies		added		added		added
Observations		27,578		29,446		28,304
Number of firms		10,564		11,443		11,226
m1 (p)		0.000		0.000		0.000
m2 (p)		0.614		0.108		0.208
Hansen (p)		0.440		0.120		0.747
W_t *(p) time effects*		0.000		0.000		0.004
W_t *(p) equality of interacted coeff.*		0.473		0.000		0.010

Notes: * p< .1; ** p< .05; *** p< .01 Std errors robust to heteroskedasticity (Windmeijer correction). For all the tests p-values are reported. *Fin* refers to leverage. Refer to note 25 for estimation details. Recessionary dummies correspond to 1993 and 1996 peaks in panel (1), to 2002-03 in panel (2) and to 2008-09 in panel (3).

Table 12 - The relationship between liquidity and different classes of firm capital: a comparison between the 2008-2009 recessionary shock and the early 1990s recession

	1991-1997		***2004-2009***	
	Coefficient	***Std. err.***	***Coefficient***	***Std. err.***
$LIQ_{i,t-1}$	0.306 ***	(0.041)	0.312 ***	(0.061)
Financial assets$_{it}$	-0.173 ***	(0.021)	-0.476 ***	(0.138)
Financial assets$_{it}$*Recess	-0.001	(0.006)	-0.076 **	(0.037)
Fixed capital$_{it}$	-0.013 ***	(0.002)	-0.004 *	(0.002)
Fixed capital$_{it}$*Recess	-0.002	(0.002)	0.001	(0.002)
Inventories$_{it}$	-0.150 ***	(0.019)	-0.224 ***	(0.051)
Inventories$_{it}$*Recess	-0.008 **	(0.004)	-0.019 *	(0.011)
Leverage$_{i,t-1}$	-0.008 *	(0.004)	-0.015 ***	(0.004)
Vertical_integration$_{i,t-1}$	-0.011	(0.007)	-0.026 ***	(0.010)
Time dummies		added		added
Sectoral dummies		added		added
Observations		27,578		28,304
Number of firms		10,564		11,226
m1 (p)		0.000		0.000
m2 (p)		0.696		0.744
Hansen (p)		0.142		0.068
W_t *(p) time effects*		0.000		0.004

Notes: * p< .1; ** p< .05; *** p< .01 Standard errors are robust to heteroskedasticity (Windmeijer correction). Recessionary dummies take on a value of one in 1993 and 1996, and 2008-09, respectively. Refer to note 25 for estimation details. All the variables, except leverage and vertical integration, are assumed endogenous. The lagged dependent variable LIQ is instrumented with lags from *t-2* backwards and the other endogenous variables with lags from *t-1* backwards.

Conclusions

We exploited three large unbalanced panels of Italian manufacturing firms, observed between 1991 and 2009, to assess whether individual financial frictions (i.e. financial rigidity of firms) are likely to affect real dynamics. Manufacturing dynamics were here identified by inventory movements, that represent priority health status indicators, at both the macro and micro levels.

A dynamic error-correction model was estimated, based on a First Difference GMM approach.

In line with previous studies on the subject, empirical results suggest that inventories responded negatively to individual frictions throughout the entire observation period. Results are robust to the adoption of different proxies for financial rigidity at the firm-level: leverage, short-term leverage and debt maturity. Moreover, the inventory sensitivity is particularly pronounced in correspondence to liquidity constrained firms and risky firms. The latter clusters of firms were identified via risk separation criteria (acid test ratio, CEBI ratings).

An excessive downward correction to firm inventories is expected during recessionary phases, when additional liquidity pressures arise. In other words, firms that characterize for financial rigidity at the eve of a crisis are expected to absorb potential liquidity shocks via inventory decumulation. Inventories are in fact subject to low adjustment costs compared to other investment-type variables. In this Chapter we did focus attention on the Italian manufacturing dynamics during the pervasive 2008-09 shock, as comparison to the past shocks that affected the country.

A significant recessionary effect is found during the 1990s: a greater sensitivity of inventories to individual financial frictions (compared to what is predicted by sales fluctuation) emerges during the recessionary peaks of 1993 and 1996. Conversely, recessionary effects are absent in 2002-03 and only weakly significant in 2008-09. Alternative hypotheses were considered in order to investigate further this apparently puzzling result. As a matter of fact, the harshness of the recessionary effects of 2008-09, with domestic demand and international demand severely affected, gave no scope for inventory decumulation as in the past. The additional correction to inventories was in fact limited to liquidity constrained firms and riskier firms in the sample. Rather, recessionary impacts were extensively absorbed by disinvestments in financial assets, at least during the early stage of the great recession. In other words, the turmoil that affected the international financial markets in 2008-09 prepared the ground for a massive decumulation in financial assets at the firm level, as a buffer strategy to address the paralysis that occurred to the manufacturing base - especially from a demand side. It is in fact worth stressing that a solid recovery of the Italian manufacturing is still lagging behind, especially in correspondence to the sectors that characterize for a low export propensity.

Appendix A - The construction of the unbalanced panels of firms

As a preliminary step, we constructed a unique unbalanced panel of Italian manufacturing firms observed between 1991 and 2009. Data are extracted from *Intesa Sanpaolo Integrated Database* (ISID) on corporate customers. The database, managed by the Research Department of Intesa Sanpaolo, is inclusive of corporate financial statements reclassified according to CEBI (Centrale dei Bilanci)[31] criteria. Consolidated statements were discarded, and micro-firms[32] as well, in order to render the analysis more stable.

Manufacturing firms were isolated, according to the NACE Rev.1.1 manufacturing codes of industrial activities defined by the European Union (codes from DA.15 to DN.36 were selected).

A continuity of 4 years in the data pertaining to each sampled firm was a strict prerequisite to enter the panel, in order to apply dynamic First Difference GMM techniques. Firms do not satisfying the above condition were removed from the sample.

Moreover, outliers below the 1st percentile and above the 99th percentile of the distribution of the variables of interest in the analysis (inventories - as a ratio to sales, sales in growth terms and the variables that proxy for financial pressure - leverage, short leverage and debt maturity) were discarded[33].

As a second step, the original dataset was split into three distinct datasets, each one covering a distinct recessionary shock (1991-97, 1998-2003 and 2004-09). Moreover, sampled firms were assigned a dimensional cluster, based on the level of sales:

From 1991 to 1999 (data in Euro millions):

- Small firms: $1{,}5 \leq$ sales < 7
- Medium-size firms: $7 \leq$ sales < 40
- Large firms: sales ≥ 40

From 2000 onwards (European Commission's thresholds, in Euro millions):

- Small firms: $2 \leq$ sales < 10
- Medium-size firms: $10 \leq$ sales < 50
- Large firms: sales ≥ 50

Finally, a stratification of firms was performed (random sampling), by firm size and by sector of activity (2-digit, NACE Rev.1.1 classification), in order to make datasets comparable through time.

We were left with three unbalanced datasets of 10,564 manufacturing firms (1991-97 period), 11,443 firms (1998-2003) and 11,226 firms (2004-09), respectively.

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[31]. CEBI (Cerved Group) is the main collector of financial statements in Italy and one of the leading rating agencies in Europe.

[32]. Firms that display a level of sales under the threshold of 1.5 Euro millions during the 1990s, and under the threshold of 2 Euro millions in the most recent years, are referred to as micro firms.

[33]. Firms presenting a negative amount in correspondence to the item "shareholders' funds" were discarded. Moreover, firms displaying a debt maturity exactly equal to 0 (when short-term debt is 0) or to 1 (when long-term debt is 0) were removed from the sample.

Appendix B - Variables and definitions

Acid test ratio: the ratio of current assets (net of inventories: raw materials, intermediate inputs and finished products) to current liabilities;

CEBI (Centrale dei Bilanci) rating: it expresses the likelihood of company failure in the twelve months following the date of release of the score. It is an assessment of the credit worthiness of corporations calculated periodically by the main collector of corporate financial statements in Italy (Centrale dei Bilanci), on the basis of economic and financial characteristics of firms under scrutiny. A firm is considered risky when the score varies between 5 (vulnerability) and 9 (very high risk), according to the following ranking:

1. High credit worthiness;
2. Good credit worthiness;
3. High solvency;
4. Solvency;
5. Vulnerability;
6. High vulnerability;
7. Risky;
8. High risk;
9. Very high risk.

Coverage ratio: the ratio of the interests paid on debt to EBITDA (Earnings before interests, taxes, depreciation and amortization);

Debt maturity: the ratio of short term debt (financial debt and trade debt) to total debt;

Financial assets: investment in fixed financial assets. It enters the regression equation scaled by total assets;

Fixed capital: the sum of tangible and intangible assets. It enters the regression equation scaled by total assets;

Inventories: raw materials, intermediate inputs and finished products;

Liquidity proxy: cash and marketable securities. It enters the regression equation scaled by total assets;

Leverage: the ratio of short and long term debt (trade debt included) to total liabilities (debt and shareholders' funds included);

Sales: sales are deflated according to 3-digit production price indexes. The indexes are extracted from the ASI forecasting model on Italian manufacturing trends, developed by Intesa Sanpaolo and Prometeia. ASI is the acronym for Analisi dei Settori Industriali (Industry Analysis).

Short-term leverage: the ratio of short term debt (trade debt included) to total liabilities (debt and shareholders' funds included).

Appendix C1: *short term leverage* as the reference *Fin* variable, panel 2004-09

Table C1.1 - Standard estimates, model [1]

	Coefficient		Std. err.
$\Delta Inv_{i,t-1}$	-0.063	**	(0.032)
$\Delta Sales_{i,t}$	0.838	**	(0.354)
$\Delta Sales_{i,t-1}$	-0.050		(0.039)
$Inv_{i,t-1}$ - $Sales_{i,t-1}$	-0.423	***	(0.072)
$Fin_{i,t-1}$	-0.197	***	(0.027)
Time dummies			added
Sectoral dummies			added
Dimensional dummies			added
Observations			28,304
Number of firms			11,226
m1 (p)			0.000
m2 (p)			0.271
Hansen (p)			0.534
W_t *(p) time effects*			0.008

Notes: * p< .1; ** p< .05; *** p< .01 Standard errors are robust to heteroskedasticity (Windmeijer correction). Estimation period 2004-09. The *Fin* variable refers to short term leverage. For tests p-values are reported. Refer to note 25 for estimation details.

Table C1.2 – Inventories and financial constraints: firms segmented by risk separation criteria

	$Risk_{it}$ f (Coverage $ratio_{it}$)			$Risk_{it}$ f (Acid test $ratio_{it}$)			$Risk_{it}$ f (CEBI $rating_{it}$)		
	Coefficient		Std. err.	Coefficient		Std. err.	Coefficient		Std. err.
$\Delta Inv_{i,t-1}$	-0.062	*	(0.032)	-0.059	*	(0.032)	-0.062	*	(0.032)
$\Delta Sales_{i,t}$	0.833	**	(0.353)	0.797	**	(0.351)	0.837	**	(0.354)
$\Delta Sales_{i,t-1}$	-0.050		(0.039)	-0.053		(0.039)	-0.048		(0.039)
$Inv_{i,t-1}$ - $Sales_{i,t-1}$	-0.423	***	(0.072)	-0.426	***	(0.071)	-0.425	***	(0.072)
$Fin_{i,t-1}*Risk_{it}$	-0.198	***	(0.023)	-0.284	***	(0.028)	-0.265	***	(0.027)
$Fin_{i,t-1}*(1-Risk_{it})$	-0.197	***	(0.027)	-0.094	***	(0.026)	-0.157	***	(0.028)
Time dummies			added			added			added
Sectoral dummies			added			added			added
Dimensional dummies			added			added			added
Observations			28,304			28,304			28,304
Number of firms			11,226			11,226			11,226
m1 (p)			0.000			0.000			0.000
m2 (p)			0.272			0.297			0.281
Hansen (p)			0.533			0.522			0.520
W_t *(p) time effects*			0.008			0.009			0.016
W_t *(p) equality of interacted coefficients*			0.981			0.000			0.000

Notes: * p< .1; ** p< .05; *** p< .01 Standard errors are robust to heteroskedasticity (Windmeijer correction). Estimation period 2004-09. The *Fin* variable refers to short term leverage. For tests p-values are reported. Refer to note 25 for estimation details.

Table C1.3 - Dimensional aspects of the linkage between inventory investment and financial constraints: variants of models [1] and [2]

	Dimensional dummies			Dimensional dummies and $Risk_{it}$ f (Acid test $ratio_{it}$)		
	Coefficient		Std. err.	Coefficient		Std. err.
$\Delta Inv_{i,t-1}$	-0.059	*	(0.030)	-0.058	*	(0.031)
$\Delta Sales_{i,t}$	0.788	**	(0.324)	0.816	**	(0.352)
$\Delta Sales_{i,t-1}$	-0.051		(0.038)	-0.056		(0.039)
$Inv_{i,t-1}$ - $Sales_{i,t-1}$	-0.425	***	(0.071)	-0.431	***	(0.071)
$Fin_{i,t-1}$	-0.098		(0.076)			
$Fin_{i,t-1\ small}$	-0.173	**	(0.022)			
$Fin_{i,t-1\ medium}$	-0.032		(0.043)			
$Fin_{i,t-1}$*$Risk_{it\ small}$				-0.348	***	(0.024)
$Fin_{i,t-1}$*$Risk_{it\ medium}$				-0.246	***	(0.039)
$Fin_{i,t-1}$*$Risk_{it\ large}$				-0.175	***	(0.048)
$Fin_{i,t-1}$*(1-$Risk_{it}$)				-0.092	***	(0.026)
Time dummies			added			added
Sectoral dummies			added			added
Dimensional dummies			added			added
Observations			28,304			28,304
Number of firms			11,226			11,226
m1 (p)			0.000			0.000
m2 (p)			0.311			0.334
Hansen (p)			0.605			0.560
W_t *(p)*			0.042			0.008
W_t *(p) equality of interacted coefficients*						0.001

Notes: * p< .1; ** p< .05; *** p< .01 Standard errors are robust to heteroskedasticity (Windmeijer correction). Estimation period 2004-09. The *Fin* variable refers to short term leverage. For tests p-values are reported. Refer to note 25 for estimation details.

Table C1.4 - Inventory investment and financial constraints: the inclusion of recessionary dummies, models [3] and [4]

	Recessionary Dummies			***Recessionary dummies and $Risk_{it}$ f (Acid test $ratio_{it}$)***			***Recessionary dummies and $Risk_{it}$ f (CEBI $rating_{it}$)***		
	Coefficient		***Std. err.***	***Coefficient***		***Std. err.***	***Coefficient***		***Std. err.***
$\Delta Inv_{i,t-1}$	-0.060	***	(0.032)	-0.079	**	(0.031)	-0.064	**	(0.032)
$\Delta Sales_{i,t}$	0.788	***	(0.355)	0.835	**	(0.358)	0.782	**	(0.357)
$\Delta Sales_{i,t-1}$	-0.052		(0.039)	-0.059		(0.040)	-0.053		(0.039)
$Inv_{i,t-1}$ - $Sales_{i,t-1}$	-0.424	***	(0.071)	-0.359	***	(0.073)	-0.405	***	(0.071)
$Fin_{i,t-1}$	-0.178	***	(0.027)						
$Fin_{i,t-1}$* Recess	-0.039	***	(0.011)						
$Fin_{i,t-1}$				-0.165	***	(0.027)	-0.173	***	(0.027)
$Fin_{i,t-1}$*Recess*$Risk_{it}$				-0.131	***	(0.017)	-0.092	***	(0.018)
$Fin_{i,t-1}$*Recess*(1-$Risk_{it}$)				-0.019		(0.011)	-0.037		(0.031)
Time dummies			added			added			added
Sectorial dummies			added			added			added
Dimensional dummies			added			added			added
Observations			28,304			28,304			28,304
Number of firms			11,226			11,226			11,226
m1 (p)			0.000			0.000			0.000
m2 (p)			0.272			0.233			0.265
Hansen (p)			0.541			0.686			0.575
W_t *(p)*			0.000			0.020			0.024
W_t *(p) equality of interacted coefficients*						0.000			0.000

Notes: * p< .1; ** p< .05; *** p< .01 Standard errors are robust to heteroskedasticity (Windmeijer correction). Estimation period 2004-09. For tests p-values are reported. The *Fin* variable refers to short term leverage. The recessionary dummy takes on a value of one in 2008-09. Refer to note 25 for estimation details.

Appendix C2: *debt maturity* as the reference *Fin* variable, panel 2004-09

Table C2.1 - Standard estimates, model [1]

	Coefficient		*Std. err.*
$\Delta Inv_{i,t-1}$	-0.068	**	(0.032)
$\Delta Sales_{i,t}$	0.875	**	(0.354)
$\Delta Sales_{i,t-1}$	-0.067	*	(0.038)
$Inv_{i,t-1}$ - $Sales_{i,t-1}$	-0.418	***	(0.072)
$Fin_{i,t-1}$	-0.089	***	(0.029)
Time dummies			added
Sectorial dummies			added
Dimensional dummies			added
Observations			28,304
Number of firms			11,226
m1 (p)			0.000
m2 (p)			0.323
Hansen (p)			0.404
W_t *(p) time effects*			0.006

Notes: * p< .1; ** p< .05; *** p< .01 Standard errors are robust to heteroskedasticity (Windmeijer correction). Estimation period 2004-09. For tests p-values are reported. The *Fin* variable refers to debt maturity. Refer to note 25 for estimation details.

Table C2.2 – Inventories and financial constraints: firms segmented by risk separation criteria

	$Risk_{it}$ f (Coverage ratio$_{it}$)			$Risk_{it}$ f (Acid test ratio$_{it}$)			$Risk_{it}$ f (CEBI rating$_{it}$)		
	Coefficient		*Std. err.*	*Coefficient*		*Std. err.*	*Coefficient*		*Std. err.*
$\Delta Inv_{i,t-1}$	-0.068	**	(0.032)	-0.064	**	(0.032)	-0.067	**	(0.032)
$\Delta Sales_{i,t}$	0.872	**	(0.354)	0.845	**	(0.351)	0.874	**	(0.353)
$\Delta Sales_{i,t-1}$	-0.067	*	(0.038)	-0.066	*	(0.038)	-0.064	*	(0.038)
$Inv_{i,t-1}$ - $Sales_{i,t-1}$	-0.418	***	(0.072)	-0.431	***	(0.072)	-0.424	***	(0.072)
$Fin_{i,t-1}*Risk_{it}$	-0.106	***	(0.031)	-0.208	***	(0.031)	-0.176	***	(0.029)
$Fin_{i,t-1}*(1-Risk_{it})$	-0.089	***	(0.030)	-0.054	*	(0.030)	-0.021		(0.032)
Time dummies			added			added			added
Sectoral dummies			added			added			added
Dimensional dummies			added			added			added
Observations			28,304			28,304			28,304
Number of firms			11,226			11,226			11,226
m1 (p)			0.000			0.000			0.000
m2 (p)			0.324			0.360			0.319
Hansen (p)			0.403			0.449			0.426
W_t *(p)*			0.006			0.001			0.006
W_t *(p) equality of interacted coefficients*			0.692			0.000			0.000

Notes: * p< .1; ** p< .05; *** p< .01 Standard errors are robust to heteroskedasticity (Windmeijer correction). Estimation period 2004-09. For tests p-values are reported. The *Fin* variable refers to debt maturity. Refer to note 25 for estimation details.

Table C2.3 - Dimensional aspects of the linkage between inventory investment and financial constraints: variants of models [1] and [2]

	Dimensional dummies			***Dimensional dummies and Risk$_{it}$ f (Acid test ratio$_{it}$)***		
	Coefficient		***Std. err.***	***Coefficient***		***Std. err.***
$\Delta Inv_{i,t-1}$	-0.068	**	(0.031)	-0.062	**	(0.031)
$\Delta Sales_{i,t}$	0.895	**	(0.352)	0.870	**	(0.355)
$\Delta Sales_{i,t-1}$	-0.071	*	(0.039)	-0.069	*	(0.039)
$Inv_{i,t-1}$ - $Sales_{i,t-1}$	-0.421	***	(0.072)	-0.438	***	(0.072)
$Fin_{i,t-1}$	0.017		(0.081)			
$Fin_{i,t-1\ small}$	-0.202	**	(0.093)			
$Fin_{i,t-1\ medium}$	-0.001		(0.045)			
$Fin_{i,t-1}$*$Risk_{it\ small}$				-0.287	***	(0.030)
$Fin_{i,t-1}$*$Risk_{it\ medium}$				-0.154	***	(0.051)
$Fin_{i,t-1}$*$Risk_{it\ large}$				-0.049		(0.061)
$Fin_{i,t-1}$*(1-$Risk_{it}$)				0.057	*	(0.026)
Time dummies			added			added
Sectoral dummies			added			added
Dimensional dummies			added			added
Observations			28,304			28,304
Number of firms			11,226			11,226
m1 (p)			0.000			0.000
m2 (p)			0.378			0.426
Hansen (p)			0.454			0.482
W_t (p) time effects			0.001			0.000
W_t (p) equality of interacted coefficients						0.001

Notes: * p< .1; ** p< .05; *** p< .01 Standard errors are robust to heteroskedasticity (Windmeijer correction). Estimation period 2004-09. For tests p-values are reported. The *Fin* variable refers to debt maturity. Refer to note 25 for estimation details.

Table C2.4 - Inventory investment and financial constraints: the inclusion of recessionary dummies, models [3] and [4]

	Recessionary Dummies			***Recessionary dummies and $Risk_{it}$ f (Acid test ratio$_{it}$)***			***Recessionary dummies and $Risk_{it}$ f (CEBI rating$_{it}$)***		
	Coefficient		***Std. err.***	***Coefficient***		***Std. err.***	***Coefficient***		***Std. err.***
$\Delta Inv_{i,t-1}$	-0.068	**	(0.032)	-0.099	***	(0.032)	-0.073	**	(0.032)
$\Delta Sales_{i,t}$	0.863	**	(0.356)	0.961	***	(0.364)	0.861	**	(0.356)
$\Delta Sales_{i,t-1}$	-0.068	*	(0.038)	-0.076	*	(0.040)	-0.067	*	(0.039)
$Inv_{i,t-1}$ - $Sales_{i,t-1}$	-0.417	***	(0.072)	-0.308	***	(0.075)	-0.387	***	(0.072)
$Fin_{i,t-1}$	-0.077	***	(0.028)						
$Fin_{i,t-1}$* Recess	-0.030		(0.020)						
$Fin_{i,t-1}$				-0.061	**	(0.029)	-0.079	***	(0.029)
$Fin_{i,t-1}$*Recess*$Risk_{it}$				-0.143	***	(0.017)	-0.071	***	(0.014)
$Fin_{i,t-1}$*Recess*(1-$Risk_{it}$)				-0.008		(0.024)	0.020		(0.024)
Time dummies			added			added			added
Sectorial dummies			added			added			added
Dimensional dummies									
Observations			28,304			28,304			28,304
Number of firms			11,226			11,226			11,226
m1 (p)			0.000			0.000			0.000
m2 (p)			0.325			0.238			0.321
Hansen (p)			0.405			0.609			0.418
W_t *(p)*			0.003			0.006			0.028
W_t *(p) equality of interacted coefficients*						0.000			0.008

Notes: * p< .1; ** p< .05; *** p< .01 Standard errors are robust to heteroskedasticity (Windmeijer correction). Estimation period 2004-09. For tests p-values are reported. The *Fin* variable refers to debt maturity. The recessionary dummy takes on a value of one in 2008-09. Refer to note 25 for estimation details.

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Chapter 2

Financial fragility, trade credit and contagion effects during the crisis: a spatial econometric approach to firm-level data°

Abstract

The number of distressed manufacturing firms increased sharply during recessionary phase 2009-13. Financial indebtness traditionally plays a key role in assessing firm solvency but contagion effects that originate from the supply chain are usually neglected in literature. Firm interconnections, captured via the trade credit channel, represent a primary vehicle of individual shocks' propagation, especially during an economic downturn, when liquidity tensions arise. A representative sample of 11,920 Italian manufacturing firms is considered to model a two-step econometric design, where chain reactions in terms of trade credit accumulation (i.e. default of payments to suppliers) are primarily analyzed by resorting to a spatial autoregressive approach (SAR). Spatial interactions are modeled based on a unique dataset of firm-to-firm transactions registered before the outbreak of the crisis. The second step in instead a binary outcome model where trade credit chains are considered together with data on the bank-firm relationship to assess determinants of distress likelihoods in 2009-13. Results show that outstanding trade debt is affected by the liquidity position of a firm and by positive spatial effects. Trade credit chain reactions are found to exert, in turn, a positive impact on distress likelihoods during the crisis. The latter effect is comparable in magnitude to the one exerted by individual financial rigidity, and stresses the importance to include complex interactions between firms in the analysis of the solvency behavior.

Keywords: trade credit, spatial models, firm behavior, manufacturing, financial crises, financing policy, insolvency, contagion, network

Jel classification: C21, D22, G01, G32, G33, G39, L14

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Introduction

The crisis that affected financial markets in 2007-08 translated into harsh and prolonged recessionary effects, that were passed on to the real economy. Real impacts concentrated mainly in 2009[34]. Nevertheless, the weak 2010 recovery was suddenly dampened by the outbreak of the sovereign debt crisis, that marked the point of departure for a new recessionary phase (double-dip crisis).

The number of distressed manufacturing firms increased sharply during the recessionary period. Financial structure, especially leverage, traditionally plays a key role in assessing firm solvency. Nevertheless, potential contagion effects originating from the supply chain are often neglected in literature.

The present contribution focuses attention on the trade credit channel as a source of contagion effects that occurred between Italian manufacturing firms during the last crisis. Specifically, we argue that the accumulation of trade debt at the firm level (namely default of payments to suppliers, or at least a temporary extension of the payment terms) is driven by traditional financing needs, and by shocks imported from interconnected firms, or customer firms. In other words, firm interdependencies are likely to generate chain reactions in trade debt when liquidity tensions arise. A pronounced lengthening of the payment terms is in fact observable in the Italian aggregate data since 2009[35]. The fraction of debt that is accumulated via shocks imported from customers is assumed in excess, compared to what is predicted by the structure of a firm, and can exacerbate distress episodes.

We contribute to the existing trade credit literature by modelling a two-step econometric design where trade credit chains are spatially analyzed.

In the first step, a Spatial Autoregressive (SAR) framework is considered, that accounts for spatial dependence in the levels of outstanding trade debt accumulated by Italian firms in the period 2009-13. More precisely, exogenous covariates in the SAR model represent the drivers of trade debt usage at the firm level (we consider especially the liquidity position of a firm and/or the presence of internal disequilibria – even in the form of financial debt unsustainability). Shocks to the liquidity of a firm and/or internal imbalances are transmitted to interconnected firms in the model via a matrix of links, or transactions (delayed cash payments and invoice discounting facilities), executed before the outbreak of the crisis itself. This way of modelling supply chains represents a step forward towards a more realistic formulation of inter-agent interaction. The second step of the model is instead a binary outcome model, where trade credit chains and financial rigidity of firms (evaluated at the eve of the crisis) are modelled as determinants of distress likelihoods of Italian firms during the recessionary phase 2009-13.

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[34]. Disequilibria did characterize international financial markets in 2007 (last quarter) and 2008. Nevertheless, impacts of the big crisis concentrated mainly in 2009 as far as the Italian real economy is concerned. In light of this, the remainder of the Chapter will focus attention on 2009 as the main recessionary shock. Conversely, 2008 is incorporated in the econometric setup that is proposed in Chapter 1, because of the inclusion of covariates that proxy directly for financial markets' dynamics.

[35]. Accounts payable days increased to a mean value of 127 in 2009, from 111 in 2008 and remained around a mean threshold of 123 in 2013 (the last year of observation). The former correspond to trade credit received from suppliers (the ratio of accounts payable to purchases) multiplied by 360.

Italy is a preferred environment to conduct the analysis because of its fragmented and clustered production base, and because of the pronounced exposure of Italian firms to trade debt and financial debt. We consider a representative sample of around 12,000 manufacturing firms, observed in the period 2008-13. Data are drawn from *Intesa Sanpaolo Integrated Database* (ISID) on corporate customers The matrix of links is constructed based on a network of transactions extracted from Intesa Sanpaolo[36] systems.

Results show that the level of outstanding trade debt accumulated by Italian firms during the recessionary phase 2009-13 is affected by the liquidity position of firms, and by positive spatial neighborhood effects as well: i.e. accumulation of trade debt at the level of customer firms (that in turn transmit the shock along the supply chain). A positive spatial autoregressive coefficient in the first step of the model can indeed be interpreted in favor of a chain reaction at work during the crisis. The global lengthening of the payment terms that followed the entrance of the country into recession, affected simultaneously the interconnected firms that are mapped in our dataset. The matrix of links represents indeed a proxy of the Italian supply chain.

The phenomenon is found to exert, in turn, a positive and considerable impact on the probability to become a distressed firm during the period 2009-13. Moreover, it is worth stressing that the effect of complex interactions in trade credit is comparable in magnitude to the one exerted by the financial rigidity of firms (evaluated at the eve of the crisis). This highlights the need to incorporate trade credit into the models that are designed to explain the solvency behavior, at both the individual and aggregate levels.

The rest of the Chapter is organized in three more sections. A review of the trade credit literature is considered in the first Section. Section 2 is devoted to data description and empirical strategy. Results are presented in Section 3. Conclusions follow.

1. Trade credit and financial distress in literature

The Chapter is intended to directly contribute to the literature on corporate distress. Emphasis is placed on the trade credit channel as a source of contagion effects, and core determinant of distress likelihoods during the last crisis as well - together with financial rigidity of manufacturing firms.

Several papers have examined the effect of leverage on default probabilities during economic downturns, pointing in the direction of an active role played by firm indebtedness in conditioning default events. Reference is made to the recent studies by Molina (2005), Carling et al. (2007), Bonfim (2009), Loffler and Maurer (2011). The present work is related to the contribution by Bonaccorsi di Patti et al. (2015). The latter authors focus attention on Italian manufacturing firms during the severe 2009 crisis. They document that a higher probability of deterioration in credit quality is associated to firms that were characterized by a high level of financial debt at the eve of the recession. Leverage acts as a powerful amplifier of macroeconomic shocks.

[36]. Actually the first Italian commercial bank as far as capitalization is concerned.

Nevertheless, it is worth stressing that trade credit represents another important source of financing for Italian manufacturing firms, although the relationship between financial debt and trade credit is still controversial[37]. In light of this, we have to account for potential contagion effects that occur via trade credit chains. The focus is on the credit offered by suppliers in exchange for an anticipated delivery of inputs[38] (outstanding trade debt). As state earlier, we argue that the accumulation of trade debt at the firm-level (default of payments to suppliers, or at least a temporary extension of the payment terms) is driven by traditional financing needs (especially the liquidity position of a firm and/or the presence of internal disequilibria), and by shocks imported from interconnected firms as well, or customer firms. We model the presence of different sources of trade debt accumulation by resorting to a spatial econometric design, where firm-to-firm interactions are proxied by a matrix of links, or transactions executed before the outbreak of the last crisis. Details will follow in the next section.

According to trade credit literature, suppliers own an implicit stake in the customers' business: i.e. they own strong incentives to provide credit to clients that are financially distressed, in order to maintain a product-market relationship and to preserve their future earnings (Wilner, 2000; Cunat, 2007). In other words, trade creditors may own more incentive than banks to support firms that experience temporary liquidity shocks (Fisman and Love, 2003). At the same time, trade credit does act as important source of short-term financing for manufacturing firms that experience temporary distress. Boissay and Gropp (2013) exploit a unique dataset on trade credit defaults among French firms to show that entities that face idiosyncratic liquidity shocks are likely to default on trade credit payments, especially when shocks are unexpected: shocks transmit along the supply chain. Nevertheless, liquid firms or firms with access to external financing can successfully absorb the liquidity shock, interrupting in turn the default chain. The importance of trade credit as a source of financing during the recent recessionary phase is stressed as well in Garcìa-Appendini and Montoriol-Garriga (2011), Carbò-Valverde et al. (2012), Molina Pérez (2012).

At the same time, trade credit comes to represent the largest exposure to bankruptcy of an industrial firm (Jorion and Zhang, 2009; Evans and Koch, 2007), in the sense of being potential vehicle of losses' propagation in case of a default event. This holds particularly true during a recessionary phase, when a global lengthening of the payment terms occurs. Trade creditors are unsecured lenders: i.e. they suffer large losses when customers do not repay trade credit. If suppliers are worried about trade credit linkages among firms and the default of customers because of credit contagion, they might withdraw trade credit from customers with higher trade receivables in order to avoid large losses. In

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[37]. This holds particularly true for the Italian case where trade credit usage represents a structural problem, that is likely to be correlated with sectorial habits, market-power issues and the clustered nature of the manufacturing base as well. Supply chain finance instruments, that are specifically designed to offer extended payment terms to small firms, contemplate an extended deadline of 90 days to honour payments. It is worth noting that the average number of accounts payable days in the Italian manufacturing industry was around 110 days in 2008, before the breakdown of the 2009 crisis.

[38]. The importance of trade credit for Italian firms is stated in several papers, starting from the contribution by Omiccioli (2005).

addition, suppliers might refuse to offer trade credit to customers even though the credit risk of the customer is low (Tsuruta, 2013).

It is hard to disentangle causal directions in trade credit usage by manufacturing firms. The extension of trade credit could represent for suppliers a status inflicted by customers' decision: i.e. small firms are likely to rely more on supplier credit during contractionary phases (Nilsen, 2002) and credit-constrained firms, in general, are likely to accumulate more trade credit from their suppliers (Petersen and Rajan, 1997). Moreover, certain sectors may structurally rely on trade credit more than others. This is exactly the case of the Italian manufacturing industry, where trade credit usage is often the result of habits rather than a complement (or a substitute) for bank financing.

What clearly emerges from previous contributions is that liquidity shocks experienced by some firms can be transmitted to other firms through supply credit chains. Trade credit interconnections might act in the sense of propagating and amplifying single shocks (Raddatz, 2010). In a network of firms that borrow from each other, a temporary shock to the liquidity of some firms may cause a chain reaction in which other firms also suffer financial difficulties, resulting into a large and persistent decline in aggregate activity (Love et al., 2007; Love and Zaidi, 2010): firms respond to late payment from customers by delaying payments to their suppliers (Raddatz, 2010). This generates, in turn, contagion effects (Battiston et al., 2007).

The present Chapter is related to the contribution by Jacobson and von Schedvin (2015) that quantifies the importance of trade credit chains for the propagation of corporate bankruptcy. Using a data set on claims held by trade creditors (suppliers) on failed debtors (customers) they show that trade creditors experience significant trade credit losses due to trade debtor failures; creditors' bankruptcy risks increase in the size of incurred losses.

Nevertheless, differently from Jacobson and von Schedvin, we approach the topic by concentrating on distress from the debtors' side. *In primis* we model directly trade credit chains, together with determinants of the trade credit accumulation at the firm level (outstanding trade debt), by resorting to spatial econometric techniques. In light of this, we move a step ahead with respect to the paper by Jacobson and von Schedvin, where the propagation effects are only indirectly proxied. Intuitively, outstanding trade debt can be regarded as the result of internal (structural) disequilibria and disequilibria imported from interconnected firms, or customer firms. Moreover, we investigate the impact of trade credit chains and financial rigidity of firms on distress likelihoods in the second step of the model, and we provide insights on the need to account for spatial effects in outstanding trade debt to analyze the solvency behavior.

2. Empirical strategy and data

As outlined in the introductive Section, the present contribution assesses determinants of distress of Italian manufacturing firms during the great recession. More precisely, attention is paid to disentangle traditional (individual) determinants of firm distress from shocks and/or imbalances imported from customer firms, in the process of explaining the solvency behavior of firms in Italy, in the period 2009-13. As far as traditional determinants of distress are concerned, the focus is especially on financial rigidity that characterizes the Italian firms. As stated before, supply-credit interconnections can translate into the propagation of shocks within a network of manufacturing firms. In other words, firms might be forced to default on payments to suppliers (i.e. to accumulate trade debt) because of imported liquidity shocks from their customers. We refer to the phenomenon as trade credit chain.

What is the role played by trade credit chains in conditioning distress probabilities of Italian firms? What happened during the last recessionary phase?

An upward trend is detectable in trade debt dynamics in 2009-13, as a result of a global liquidity crisis. Accounts payable days (corresponding indeed to trade debt multiplied by 360) increased sharply in 2009 compared to the previous years, reaching an average value of 127 days in our sample (it was 111 in 2008[39]) and remaining around an average threshold of 123 days in 2013 (the last year of observation).

To evaluate the relative importance of the trade credit channel for distress likelihoods, together with the effect exerted by financial rigidity of Italian firms (evaluated at the eve of the crisis), a large representative sample of 11,920 Italian firms is analyzed in the period 2008-13: 62% of the entities belong to the cluster of small firms, 30% to the cluster of medium-sized firms and the residual 8% to the cluster of large firms[40]. The sample composition mirrors the fragmented structure of the Italian manufacturing industry. The dataset excludes a priori micro-firms, i.e. firms that present a value for sales (at current prices) below the threshold of two million Euros in the first year of observation (2008)[41]. However, we do not impose any restriction to sales in the subsequent years (i.e. we allow sales to fluctuate downward without restrictions), in order to maintain distressed firms within the sample – firms that are involved in a liquidation procedure included. Moreover, it is worth stressing that sampled data are representative of the Italian production base from a sectoral perspective (refer to Appendix A for a detailed breakdown of the branches of economic activity considered in the analysis, and for detailed information on their relative importance in the sample).

Firm level data are drawn from *Intesa Sanpaolo Integrated Database* (ISID). The proprietary dataset (managed by the Research Department of Intesa Sanpaolo) combines corporate financial statements[42] with information on credit events, bank overdrafs and qualitative variables. Moreover, we

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[39]. Delayed payments are structural to the Italian manufacturing industry.

[40]. Dimensional clusters are defined based on the European Commission's thresholds (Euro millions): Small firms: $2 \leq$ sales < 10; Medium-size firms: $10 \leq$ sales < 50; Large firms: sales ≥ 50.

[41]. Financial statements pertaining to micro-firms are likely to report unreliable data as far as information on financing channels is concerned. In fact, it is sometimes hard to disentangle financial debt from commercial debt in simplified balance sheets.

[42]. Reference is made to financial statements reclassified by the CEBI (Centrale dei Bilanci), the main collector of balance sheets in Italy. CEBI is part of the CERVED Group. The latter is the leading information provider in Italy and one of the major rating agencies in Europe.

employ a definition of distressed firms that is based on information from *Central Credit Register* of the Bank of Italy[43].

2.1 *Modelling trade credit usage during the crisis*

A structured model is needed to simultaneously analyze the functioning of the trade credit channel during the last recessionary phase (Step 1) and the role played by trade credit and individual financial rigidity in conditioning distress probabilities of Italian firms in 2009-13 (Step 2). Spatial econometric tools can be employed to estimate spillover effects from trade credit accumulation in a more realistic way. The former techniques allow chain reactions to be directly incorporated within an econometric framework. Supply chains can be proxied by a matrix of links or firm-to-firm transactions performed before the outbreak of the crisis (2007). The latter are intended in the form of delayed cash payments and invoice discounting facilities, that follow directly from the presence of a prior trade credit position between pairwise entities in the dataset. It is worth stressing the importance to consider transactions registered before the starting point of the 2009 crisis, since the latter contributed to cancel down important connections in the manufacturing industry. Moreover, transactions executed during recessionary years prove to be endogenous to the shock itself. In other words, the proposed two-step econometric framework encompasses a complete restyling of the concept of trade credit chains. The way in which supply chains are proxied and embodied within the standard econometric methodology represents a step forward towards a more realistic formulation of inter-agent interaction. This improves, in turn, the way in which the solvency behavior is analyzed. International banks are indeed pointing in the direction of incorporating the trade credit channel into early warning models and rating models.

The two-step econometric design can be summarized as follows (in stacked form):

$$\textit{Outstanding\_tradedebt (09-13)} = \lambda W\ \textit{out\_tradedebt (09-13)} + X\beta + \varepsilon \qquad \textit{[Step 1]}$$

$$\textit{Pr [Distressed (09-13)]} = \phi(\gamma\ \textit{fitted\_tradedebt} + X\beta) \qquad \textit{[Step 2]}$$

As stated earlier, Step 1 is set to analyze trade credit dynamics of Italian manufacturing firms during the last recessionary phase. A Spatial Autoregressive framework (SAR) of order one is considered to model the impact of the accumulation of trade debt at the level of interconnected firms, or customer firms. This is done via the inclusion of a spatial lag variable and a matrix of links. At the same time, exogenous covariates in the SAR model represent the internal drivers for trade debt accumulation at the firm-level. Step 2 is instead a binary outcome model, that is devoted to investigate the determinants of distress likelihoods of Italian firms during the great recession.

[43]. *Central Credit Register* reports, for each Italian credit institution (banks and specialized financial companies) loans and guarantees to resident borrowers above a given threshold (75,000 euros before 2009 and 30,000 thereafter). For further details see Bonaccorsi di Patti et al. (2015) or visit www.bancaditalia.it.

The focus is especially on comparing the role played by complex trade credit interactions during the crisis (proxied by the fitted values from estimation of the spatial model in Step 1) and the role played by financial rigidity of firms, evaluated at the eve of the crisis.

Choice was made to collapse the original panel structure of our dataset into a cross-section structure, where variables are specifically designed to reflect the behavior of firms across multiple years within the observation period.

The process of identifying vulnerable firms during the crisis requires an in depth analysis to be performed on data, that goes beyond the scrutiny of single financial statements. In fact, the value assumed by certain indicators in single years are not *per se* indicative of the presence of structural disequilibria within the firm. We need to put together information concerning the behavior of firms across multiple years in order to assign firms to the cluster of vulnerable subjects: i.e. we need to identify a recursive trend in the firm behavior. Reference is made in particular to the firms whose debt is likely to be classified as unsustainable because of the lack of a monetary equilibrium (interests paid on debt are larger than the Ebitda generated by the firm) or firms that experience a massive usage of credit lines[44]. We require firms to exhibit an unsustainable debt or a massive usage of credit lines at least for two consecutive years within the recessionary phase 2009-13 in order to be identified as vulnerable subjects. In other words, we assign priority to an operational-based approach that is suitable for identifying vulnerable firms in a more realistic way. Dummy variables comply with this need to split the sample according to the aforementioned approach. Conversely, a panel structure would imply a reduced level of flexibility in data manipulation.

In order to improve the understanding of the variables that enter each step of our econometric model, we allow them to be described in separate subsections.

2.1.1 *First Step: a Spatial Autoregressive approach (SAR) to trade credit dynamics*

The *[Step 1]* equation is designed to model the functioning of the trade credit channel. As stated earlier, outstanding trade debt can be interpreted as a signal of potential liquidity imbalances within a firm. Specifically, disequilibria can trace back to factors or strategies pursued internally to the firm (e.g. a wrong working capital management) or, conversely, can be the result of imported imbalances from interconnected firms, or customer firms. Reference is made to imported shocks, as a result of supply-chain interconnections. The empirical strategy can be summarized as follows:

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[44]. Debt is considered unsustainable when the value of the coverage ratio (the ratio of interests paid on debt to Ebitda) is greater than 1. The coverage ratio is subject to volatility (because of volatility of the Ebitda margin itself). In light of this, we require firms to display a value of the coverage ratio that is greater than 1 at least for two consecutive years during the crisis (2009-13 period) – and lower than 1 in 2008, at the eve of the crisis – in order to be identified as vulnerable subjects in our model. The same logical approach applies to the assignment of firms to the area of massive usage of revocable credit lines during the crisis. Additional details will follow in section 2.1.2.

$$Outstanding\_tradedebt\ (09\text{-}13)_i = \lambda \sum_{j=1}^{n} w_{ij}\ outstanding\_tradedebt\ (09\text{-}13)_j + \\ + \beta_0 + \beta_1\ acidtest\ (09\text{-}13)_i + \beta_2\ debt\_burden\ (09\text{-}13)_i + \\ + \beta_3\ rationed\_revocablelines\ (09\text{-}13)_i + \beta_4\ vertical\_int\ (08)_i + \\ + \beta_5\ medium_i + \beta_6\ large_i + m_\ell + m_g + \varepsilon_i \qquad [1b]$$

The dependent variable is modeled as the stock of the trade credit accumulated by firms during the recessionary phase, or outstanding trade debt: i.e. the credit offered by suppliers in exchange for an anticipated delivery of inputs. More precisely, outstanding trade debt is here defined as the mean value of the ratio of accounts payable to purchases in the period 2009-13. In order to investigate the relationship between the liquidity status of a firm and the usage of trade debt during the crisis, a set of variables is included in equation *[1b]*. These variables represent, in other words, the determinants of trade debt usage by firms, as a result of internal financing needs.

Reference is made *in primis* to the *acid_test* variable, that is defined as the average value of the acid test ratio during the recessionary period 2009-13. The former is defined as the ratio of current assets (net of inventories) to current liabilities and is likely to detect liquidity tensions (at least temporary) that may arise at the firm level[45]. A firm is considered illiquid when the ratio is less than unity. According to preliminary statistics the median value of the ratio was 0.82 in 2008, at the eve of the crisis: more precisely, the value ranges from 0.81 (small firms) to 0.83 (large firms). This means that 50% of firms in the sample (and within each dimensional cluster) were suffering from binding internal liquidity constraints before the outbreak of the severe 2009 recession. It is worth observing that 2.4% of firms classified as liquid in 2008 switched to illiquidity status in 2009, an additional 2.2% in 2010, an additional 1.8% in 2011 and an additional 1.3% in 2012[46]. We expect a negative relationship linking internal liquidity and trade debt usage during the crisis.

Furthermore, the model is inclusive of categorical variables whose purpose is to identify vulnerable firms during the crisis. More precisely, firms are investigated from a twofold perspective: financial debt sustainability and massive usage of credit lines in 2009-13. Again, the selected operational-based approach is precisely aimed at analyzing the behavior of firms across multiple years (i.e. at mapping a recursive trend in the firm behavior).

We consider *in primis* the binary variable *debt_burden* that is likely to identify firms whose debt is unsustainable from a monetary perspective (i.e. debt interests are larger than Ebitda). In particular, the variable takes on a value of one if the coverage ratio (the ratio of interests paid on debt to Ebitda[47]) is greater than unity at least for two consecutive years during the recessionary

[45]. A firm is considered risky when the ratio is less than unity: i.e. current assets net of inventories are lower than current liabilities.

[46]. Percentages are indicative of firms that never reverted back to liquidity status during the observation period.

[47]. Firms presenting a negative value of Ebitda in 2008 were removed from the sample. Moreover, firms displaying a zero value (or a missing value) in correspondence to the items "interests paid on debt" or Ebitda were discarded.

phase 2009-13 and lower than unity in 2008 (at the eve of the crisis)[48]. In other words, the variable captures a broadly irreversible status of monetary disequilibrium at the firm level and is suitable for investigating the (controversial) relationship between trade debt and the financial structure of a firm. The number of firms that experienced an unsustainable debt increased sharply in correspondence to the recessionary peaks of 2009 and 2012: from 9.5% in 2008 to 16.4% in 2009 and 13.7% in 2012. On average, 4.6% of firms in the sample are assigned to this cluster. We expect a negative relationship linking the *debt_burden* variable and trade debt usage during the crisis.

The dummy variable *rationed_revocablelines* is instead designed to identify firms that are assumed vulnerable because of a massive usage of revocable credit lines during the recessionary phase (i.e. firms in a weak rationing status). More precisely, the variable takes on a value of one if the ratio of credit used to credit granted to the firm by the Italian banking system is above 80% for at least two consecutive years during the recessionary phase[49] - and was below 80% at the eve of the crisis (2008). Data on credit lines are drawn from the *Central Credit Register* of the Bank of Italy and merged to ISID (*Intesa Sanpaolo Integrated Database*)[50]. Again, we focus attention on a recursive firm behavior during the crisis. In particular, it is worth stressing that the behavior of firms from the side of revocable credit lines has been analyzed in several works based on Italian data, in order to identify constrained entities[51]. Credit usage acts as a signal of demand of financial resources at the firm level. Conversely, credit granted represents a synthetic indicator of the credit market status, from the supply side. The 80% threshold identifies a weak rationing status, that is indicative of structural disequilibria within a firm. In light of this, we expect a positive relationship linking the variable *rationed_revocablelines* and trade credit usage during the crisis. 7.7% of firms in our sample experienced a massive usage of bank credit lines during the observation period: the phenomenon can be a combination of an increased demand for credit (credit used by the firm, the numerator of the ratio) and a decline in the supply of credit (credit granted by the Italian banking system, the denominator) - because of the increased perceived risk of the borrower. In both the cases firms are granted a reduced flexibility in terms of external liquidity usage. Therefore, they should have fostered a process of trade debt accumulation. Equation *[1b]*

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48. More precisely, firms must display a coverage ratio greater than unity in one of the following periods: 2009-13 entire recessionary phase, 2010-13 period, 2011-13 period or 2012-13 biennium. At the same time, we require firms to display a value of the coverage ratio lower than unity in 2008 (i.e. at the eve of the crisis). Firms experiencing temporary disequilibria are therefore removed from the group (e.g. firms whose debt is classified as unsustainable across multiple years within the observation period and that settle outside the unsustainability area of debt in 2013, or firms displaying sparse evidence of a coverage ratio greater than unity).

49. More precisely, firms must display a ratio above 80% in one of the following periods: 2009-13 entire recessionary phase, 2010-13 period, 2011-13 period or 2012-13 biennium. Both credit used and credit granted are considered at the mean value (yearly values). Firms experiencing temporary disequilibria are therefore removed from the group (e.g. firms presenting sparse evidence of massive usage of credit lines).

50. Data on revocable credit lines are available to all firms included in the sample.

51. Reference is made to the contributions by Finaldi et al. (2001), Del Colle et al. (2006), Bonaccorsi di Patti-Gobbi (2007), Tirri (2008), Buono and Formai (2013). Data on revocable credit lines were also employed in studies that focus attention on the American market (Kaplan-Zingales, 1997; Houston-James, 1996).

incorporates a proxy for vertical integration (*vertical_int,* the ratio of value added to sales in 2008[52]) and control variables as well: i.e. dimensional controls (small, medium and large dummy variables that mirror the dimensional thresholds defined by the European Commission, based on the value of sales[53]), sectorial controls m_ℓ (branches of economic activity, as described in the Appendix) and geographical controls m_g (broad macro-areas). According to trade credit literature, vertically integrated firms prove to be less exposed to customer payments and should rely on trade credit on a lesser extent, as a consequence of imported liquidity imbalances.

The most innovative part of the model outlined in equation *[1b]* is represented by the inclusion of a spatial lag of the dependent variable *Wtradecredit_rec (09-13),* that proxies for the (weighted) effect of trade debt accumulation at the level of interconnected firms. As stated earlier, we formulate the explicit assumption that the accumulation of trade debt at the firm level during the crisis was driven by imported imbalances from customer firms (in addition to the effect exerted by internal determinants of trade debt usage - so far considered). More precisely, we propose a spatial autoregressive model of order one (SAR)[54] that encompasses spatial lag dependence in the levels of trade debt accumulated during the crisis. The λ coefficient identifies the strength of endogenous interaction effects in trade debt usage by Italian manufacturing firms. A battery of LM (Lagrange Multiplier) tests is provided in order to formally justify the model setup (i.e. to justify the exclusion from the analysis of more complex spatial models)[55].

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[52]. A firm is vertically integrated when different stages of the production process (i.e. of the supply chain) are managed internally to the firm itself. Value added refers to the contribution of the factors of production (capital and labor) to raising the value of a product. It corresponds indeed to the income received by the owner of those factors. More precisely, total value added is equivalent to the revenue less outside purchases of materials and services. Value added is a high portion of revenue for integrated companies. For this reason it is commonly employed as a proxy to identify vertically integrated firms. It enters the model scaled by sales to account for firm dimensions.

[53]. Dimensional clusters are defined based on the European Commission thresholds (Euro millions): Small firms: $2 \leq$ sales < 10; Medium-size firms: $10 \leq$ sales < 50; Large firms: sales ≥ 50.

[54]. Spatial dependence emerges when realizations of a certain variable Y are autocorrelated in space or, in other words, when realizations are ordered according to a spatial scheme. A SAR framework (Spatial Autoregressive of order one) can be considered to model the phenomenon: $y = \lambda Wy + X\beta + \varepsilon$. The term λWy is the spatial lag of the dependent variable: the weighted average of y'*s* realizations pertaining to neighboring subjects. The weighting scheme is incorporated within a spatial weights matrix W. The λ coefficient measures the strength of spatial effects. For additional details refer to Ord (1975), Paelink and Klaasen (1979), Anselin (1988), Bivand et al. (2008), Arbia and Baltagi (2009), Le Sage and Pace (2009), Arbia (2014).

[55]. The robust version of LM tests is selected to evaluate the fit of the model: reference is made to RLMlag and RLMerr tests, testing respectively for spatial lag dependence (λ autoregressive coefficient different from zero) and for spatial error dependence (ρ autoregressive coefficient different from zero). As alternative spatial models we could in principle consider a spatial error model (SEM), encompassing spatial error dependence only (or indirect spatial dependence; the autoregressive part is included in the error term) $y = X\beta + u$, $u = \rho Wu + \varepsilon$ and a complete SARAR model, where spatial dependence is modeled both in a direct way (spatial lag dependence) and in an indirect way (spatial error dependence): $y = \lambda Wy + X\beta + u$, $u = \rho Wu + \varepsilon$. While testing for the presence of a single type of spatial dependence in the data (direct or indirect), the proposed tests prove to be robust to the simultaneous presence of the other effect (the variance is properly adjusted to account for the presence of the other effect, resulting into a more correct inference with respect to the case of unconditional tests LMerr and LMlag). The RLMerr test reports a statistic of 0.6817, suggesting not significant spatial error dependence (p-value<0.409) when spatial lag dependence is assumed (λ different from zero). The RLMlag test reports a statistic of 3.3072, suggesting weakly significant spatial lag dependence (p-value<0.069) when spatial error dependence is

The neighborhood structure (i.e. interactions between firms in our sample) is contained into the W matrix, namely the spatial weights matrix. We abstract from a pure definition of space (geographical space) to encompass a broad definition of spatial dependence in trade credit data. Reference is made to a matrix of links: pairwise interconnections or spatial weights are modeled using data on firm-to-firm transactions (namely delayed cash payments and invoice discount facilities that follow from a prior trade credit position between pairs of firms in the sample) performed before the outbreak of the crisis (2007). Spatial weights are binary: they are assigned a value of one if a transaction of the above type occurred between pairs of firms in the dataset and zero otherwise[56]. We have to acknowledge the presence of potential missing links into the mapped matrix of interactions, although each firm in the sample is assigned at least one link (see the network analysis that follows). Transactions are in fact extracted from Intesa Sanpaolo systems (actually the first Italian commercial bank) and are likely to return a partially incomplete picture of the real links that are in place between firms in our manufacturing sample[57]. In light of this, results have to be interpreted accordingly. The W matrix is row-standardized (i.e. spatial weights sum to 1 in each row of the matrix)[58]. This has the effect that the weighting operation can be regarded as an averaging of neighboring values (Elhorst, 2014).

It is worth stressing again that this way of modeling interactions between firms (i.e. supply chains) represents a step forward towards a more realistic formulation of inter-agent interaction.

In order to investigate further the structure of the links that are included in the model we resort to basic network analysis instruments. The selected transactions can in fact be better visualized into a network structure, where firms are vertex (nodes) and firm-to-firm interactions (delayed cash payments and invoice discounting facilities) are edges of the network. The 11,920 manufacturing firms that are part of our database are connected through 55,759 links.

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assumed (ρ different from zero). In light of the above, results corroborate our choice of a simple spatial model of the SAR type.

[56]. The level of performed transactions is not considered to construct spatial weights.

[57]. Transactions of the same type may have been performed through other banking institutions.

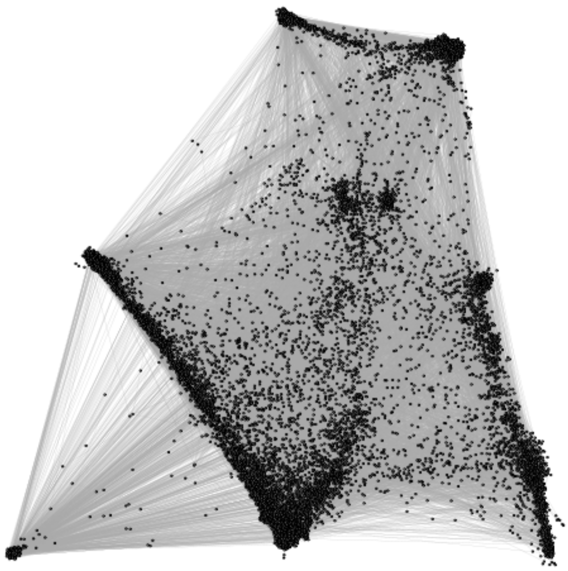
[58]. The spatial autoregressive parameter can assume values in a range delimited by the reciprocals of the minimum (real) and maximum eigenvalues of the W spatial weights matrix. When the W matrix is row-standardized, the upper bound for λ is 1. The lower bound is not necessarily -1 when eigenvalues are complex numbers. It is worth mentioning that row-standardization is not compulsory. A spatial weights matrix W_0, if originally symmetrical, could in principle be scaled by the largest eigenvalue to preserve symmetry (Elhorst, 2001; Kelejian and Prucha, 2010). The operation has the effect that the characteristics roots of the original matrix W_0 (before normalization) are also divided by the largest eigenvalue, as a result of which the largest eigenvalue of the normalized matrix W becomes 1. Alternatively, one may normalize a spatial weights matrix W_0 by $W= D^{-1/2}W_0D^{-1/2}$ where D is a diagonal matrix containing the row sums of the matrix W_0. The operation has been proposed by Ord (1975) and has the effect that the characteristic roots of W are identical to the characteristic roots of a row-normalized W_0. Importantly, the mutual proportions between the elements of W remain unchanged as a result of these two normalizations (Elhorst, 2014). Whatever W spatial weights matrix is used, parameter estimates have to be interpreted in relation to the bounds (the reciprocals of the minimum and maximum eigenvalues) that define a continuous parameter space that avoids problems associated with spatial unit roots, non stationarity and discontinuities (parameters outside the bounds).

Table 1 - Network representation of firm-to-firm links: basic statistics

Statistic	***Value***
Nodes	11,920
Edges	55,759
Average path length	4.129
Clustering coefficient	0.018
Diameter	9.000
Average degree	9.356
Degree range	1-425

To comply with the structure of the W spatial weights matrix described before, the network is represented as undirected (e.g. we focus attention on the existence of a transaction "tout court" between pairwise firms) and unweighted (we neglect both the number and the amount of the transactions that occurred between firms in the network).

Fig.1 - Network representation of firm-to-firm links: the biggest community[59]



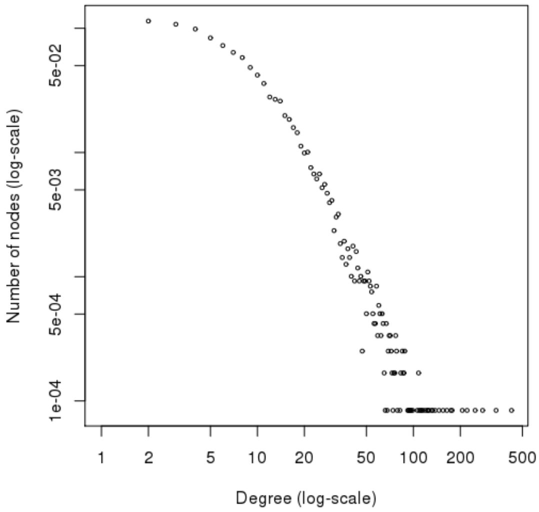
The degree distribution[60] *P(k)* of the network, that represents a synthetic snapshot of its complexity, is reproduced graphically in Figure 2.

The vertex degree *k*, that measures the strength of connection of a specific vertex (firm) to the graph (the number of transactions incident to a firm), ranges from 1 to 425, with an average value of 9.356.

[59]. The subset is the biggest community, as selected by the "walktrap community finding" algorithm (Pons and Latapy, 2005). A network is said to have a community structure if nodes can be easily grouped into sets of nodes, such that each set of nodes is densely connected internally.

[60]. The degree distribution *P(k)* is defined as the fraction of nodes in the network with degree *k*. The vertex degree *k* is the number of edges (firm-to-firm interactions, in our specific case) that are incident to a vertex (firm). It measures the strength of connection of a specific vertex to the graph.

Fig.2 - Network representation of firm-to-firm links: the plot of the degree distribution



The log-log plot of the degree distribution does not show a clear scale-free structure of the network[61] when the full domain is accounted for. In the context of firm networks, the scale-free topology is characterized by the presence of powerful and influential subjects (hubs) within the system, and of a considerable share of entities that lie on the system's periphery (i.e. with limited influential power). Consequently, scale-free networks are resistant to random defaults but are, at the same time, particularly vulnerable to the default of hubs. The scale-free property is apparently not supported by our data. In light of this, we would be induced to think at a low-risk of contagion that is incorporated in the networked structure of the firms under scrutiny. Nevertheless, such a result could be partially driven by sample composition: i.e. by the presence of potential missing links into the mapped dataset of interactions. In fact, when the subgroup of the most interconnected firms is isolated (firms presenting a vertex degree $k \geq 25$), preliminary evidence of a scale-free network emerges[62]. The evidence is indicative of a precise warning message of contagion effects that might originate from the structure of the network itself.

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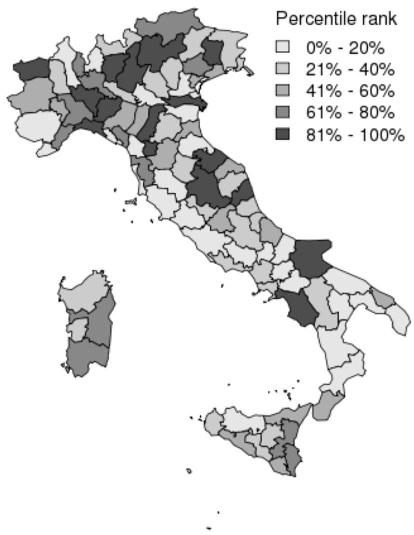
[61]. In scale free networks the distribution of linkages is skewed, heavy tailed and follows a power law. The links' distribution plotted on a double-logarithmic scale results into a straight line. For a comprehensive review of network topologies refer to Strogatz (2001) and Callaway et al. (2000).

[62]. If we fit a power-law distribution $P(k)=k^{-\gamma}$ on the full graph, using a maximum-likelihood approach, we observe a degree exponent γ=1.405 (with a log-likelihood of -46192). The value of the Kolmogorov-Smirnov test (0.334) suggests a rejection of the null hypothesis of power law distribution. If we fit instead a power-law distribution introducing a threshold, i.e. considering $k \geq 25$ (the most interconnected firms), we obtain a higher exponent $\gamma=3.328$ and a better fit of the distribution (the log-likelihood is -3372). The value of the Kolmogorov-Smirnov test (0.030) suggests an acceptance of the null hypothesis of power law distribution. In literature, scale-free networks present exponents between 2 and 3 (Barabási and Bonabeau, 2003). From the power-law distribution we can infer that when $\gamma<2$ the average degree diverges. Conversely, when $\gamma<3$ the standard deviation of degrees diverges. Nevertheless, it is worth stressing that a formal proof of a power-law distribution describing our trade credit transactions, with all the associated implications, would require a much deeper investigation that goes beyond the scope of our analysis. Comments are therefore limited to preliminary evidence.

Furthermore, a similar warning message emerges as well clearly when the assortativity of the network is analyzed. Assortativity measures the tendency for vertices (firms) to be correlated with similar vertices in the network. More precisely, a positive assortativity is detected (0.060) when the level of trade credit received from suppliers during the crisis (outstanding trade debt, the dependent variable in Step *[1]*) is considered as the vertex attribute[63]. Intuitively, firms that received high levels of trade credit during the recessionary phase 2009-13 (i.e. firms that accumulated a high level of trade debt) show a greater probability to be connected with firms that display similar levels of outstanding trade debt[64].

What a direction for contagion effects from trade debt? We shift again our attention to the spatial parameter λ in equation *[1b]*, the one capturing the strength of spillover effects in trade debt usage by Italian firms. Under the assumption that the eruption of the crisis generated a global and prolonged lengthening of the payment terms, we expect a positive value associated to λ. The positiveness of the parameter can be preliminarily inferred by resorting to a Global Moran's I index[65] of spatial autocorrelation, applied to residuals[66] from an OLS (Ordinary Least Squares) estimation of model *[1b]*[67].

Fig.3 - OLS residuals from estimation of step [1]



[63]. As a general argument, assortativity is calculated with reference to the vertex degree of a network. The concept of assortativity may, however, be applied to other characteristics of a vertex. We compute assortativity relatively to outstanding trade debt accumulated during the crisis, by resorting to the algorithm "assortativity for continuous attributes" defined by Newman (2003).

[64]. Similar findings are present in the paper by Golo et al. (2015).

[65]. The index is intended to detect the presence of correlation of the spatial type: the more spatial objects are similar with respect to the values undertaken by a certain variable under scrutiny, the higher the value of the index. For further details refer to Moran (1950) and Bera et al. (1996).

[66]. Reference is made to studentized residuals.

[67]. More precisely, we estimate a model of the type *Tradecredit_rec (09-13)* $= X\beta + \varepsilon$.

Results support a rejection of the null hypothesis of absence of spatial correlation in OLS residuals and encourage a spatial approach to model the functioning of the trade credit channel. More precisely, positive spatial correlation in OLS residuals is documented, with highly robust significance (p-value < 2.2e-16): the empirical value of the Moran's I statistic is 0.0394 (variance V[I]=3.2117e-05)[68].

From the point of view of an econometric estimation of equation *[1b]*, it is worth stressing inconsistency and inefficiency of standard estimators (e.g. OLS estimator). The latter estimators do not account appropriately for the correlation between errors and the spatially lagged dependent variable (endogeneity issue). We resort to a Maximum Likelihood estimator (Ord, 1975)[69] to estimate the parameters of the SAR framework. More precisely, we select a Monte Carlo approach (Barry and Pace, 1999) to approximate the log determinant of the matrix $(I - \lambda W)$ in the log-likelihood function[70]. The method is suited for big datasets. Results are presented in Table 2a.

The process of estimating by Maximum Likelihood assumes that regressors other than the spatial lag variable are exogenous. The variables that proxy for the pre-crisis characteristics of firms are exogenous for sure. Conversely, the variables *acid_test, debt_burden* and *rationed_revocablelines* are measured over the period 2009-13 and might raise concerns. The negative causal effect exerted by firm liquidity on outstanding trade debt is well established in the trade credit literature, and is likely to render a reverse causality hypothesis an unfeasible option. On the contrary, liquid firms should absorb part of the shocks to the liquidity of interconnected firms. This supports an exogeneity assumption for the *acid_test* variable. At the same time, trade debt is likely to

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[68]. Under the null hypothesis of absence of global spatial autocorrelation, the expected value of the Index I is E(I)= -1/(N-1). If the value of the I statistic is larger than its expected value E(I), then the overall distribution of the variable under scrutiny (productivity) can be seen as characterized by positive spatial autocorrelation. The Moran's I statistic is conventionally assumed to take values in the range [-1, 1]. The lower bound should refer to perfect dispersion and the upper bound to perfect spatial correlation. Nevertheless, the contributions by Cliff and Ord (1981) and Upton and Fingleton (1985) offer concrete evidence of the statistic falling outside the selected bounds. When dealing with micro-data it is reasonable to accept values of the Moran's I that fall in an interval around zero. Under the null hypothesis of absence of spatial autocorrelation data are assumed to be distributed according to a normality assumption (alternative is randomization). The variance of the statistic and the Z_i score are computed accordingly. It is worth mentioning that the statistic is not particularly sensitive to departures from normality (Cliff and Ord, 1981).

[69]. The estimator is implemented in the *spdep* library in R.

[70]. The simple SAR model $y= \lambda Wy + X\beta + \varepsilon$ can be rewritten as $(I-\lambda W)y= X\beta + \varepsilon$, with $\varepsilon \sim N(0, I\sigma^2)$. The parameter vector is $\Theta= (\lambda, \beta, \sigma^2)$. For $\lambda \neq 0$ the log likelihood becomes:

$$\ell(\Theta) = -\frac{n}{2}\ln(2\pi) - \frac{n}{2}\ln(\sigma^2) - \frac{(y-\lambda Wy-X\beta)'(y-\lambda Wy-X\beta)}{2\sigma^2} + \ln|I - \lambda W|$$

The inclusion of the $\ln|I - \lambda W|$ term introduces computational problems in the estimation of spatial models with a consistent amount of data. In fact, unlike the case of time series analyses, the logarithm of the determinant of the $(n\ x\ n)$ asymmetric matrix $(I - \lambda W)$ does not tend to zero as the sample size increases. Specifically, the log-determinant constrains the autoregressive parameter values to remain within their feasible range (i.e. in between the reciprocals of the minimum (real) and maximum eigenvalues of the W spatial weights matrix). When the W matrix is row-standardized, the upper bound for λ is 1. Nevertheless, the lower bound is not necessarily -1 when eigenvalues are complex numbers. Approximation methods have been introduced with the purpose of bypassing the problem of a point estimation of the log determinant. In this paper we refer to the MonteCarlo approximation method (Barry and Pace, 1999) that is implemented in the *spdep* library.

represent an additional financing channel for manufacturing firms that experience increased liquidity pressures or internal disequilibria. Consequently, it sounds unfeasible to think at firms suffering from financial debt unsustainability or massive usage of credit lines as a result of the trade debt accumulation. In light of this, we are willing to support an exogeneity assumption for the variables *debt_burden* and *rationed_revocablelines* as well.

2.1.2 *Second step: determinants of firm distress*

In the second step of the model the drivers of firm insolvency are analyzed. The proposed binary outcome framework is similar to the reduced form presented in Bonaccorsi di Patti et al. (2015):

$$\begin{aligned} Pr\,[Distressed(09\text{-}13)_i] = \phi\,(&\beta_0 + \beta_1 fitted\_tradedebt_i + \beta_2\, intensity\_bankfin(08)_i \\ &+ \beta_3\, capitalization(08)_i + \beta_4\, \Delta capitalization(09\text{-}13)_i + \beta_5\, debt\_burden(09\text{-}13)_i \\ &+ \beta_6\, cum\_growth(04\text{-}08)_i + \beta_7\, cum\_growth(08\text{-}13)_i \\ &+ \beta_8\, medium_i + \beta_9\, large_i + m_\ell + m_g\,) \end{aligned} \qquad [2b]$$

The dependent variable takes on a value of one when firms are categorized in one of the following insolvency blocks during the recessionary phase 2009-13 (i.e. the flag is present for at least one year in the observation period): “bad loans” (sofferenze), “substandards” (incagli), “restructured” and “past-due”[71] - while proving to be considered *in bonis* at the eve of the crisis (2008). Data on the solvency status are drawn from *Central Credit Register* of the Bank of Italy (and merged to the information that is contained in ISID, *Intesa Sanpaolo Integrated Database*). While the “bad loans” (sofferenze) status has to be treated as an irreversible status of firm insolvency, the other blocks might refer to a temporary situation of distress of a firm. In light of this, the selected firms are referred to as distressed: 15.4% of the sampled entities experienced distress during the recessionary phase. Conversely, the contribution by Bonaccorsi di Patti et al. exploits the stronger definition of defaulted firms, which is constructed based on the “bad loans” (sofferenze) status only.

As far as covariates in equation *[2b]* are concerned, it is worth stressing the attention on the presence of fitted values from spatial model *[1]* or *fitted_tradedebt.* The variable represents the level of trade debt that is predicted by traditional drivers of trade debt accumulation (especially the liquidity position of a firm), and by spillover effects (imported shocks) that occurred during the crisis.

Moreover, variables on individual financial strategies, especially bank debt, are included in equation *[2b]* as important determinants of firm distress. Choice was made to discard a leverage variable, whose trend can mirror a variation in both the borrowing propensity of a firm and the capitalization

[71]. Substandards (incagli) are loans associated to a high risk of loss for the lender because of (temporary) difficulty of the borrower (i.e. the loss is probable but not sure for the lender). Bad loans (sofferenze) are indicative of a situation where repayments are not being made as originally agreed between the borrower and the lender, and which may never be repaid. Both the categories fall within the definition of problematic repayments. Moreover, the definition is inclusive of two additional non-performing categories: restructured loans and past-due or overdue loans (from more than 90 days). We sometimes observe overlapping between substandards and past-due.

components. The two phenomena are instead analyzed separately. Moreover, the short-term component of debt has to be monitored carefully and preferentially in the process of assessing firm distress. The former can become a primary source of repayment difficulties in case of economic downturns. The variable *intensity_bankfin,* that is defined as the ratio of short-term bank debt to sales in 2008, is specifically designed to identify rigid firms (i.e. firms that lack of financial elasticity) at the eve of the crisis. An high ratio is likely to reflect criticalities in the repayment of short-term obligations. Firms that display a high level of the ratio at the beginning of a recessionary period (i.e. a period of prolonged drop in sales, the denominator of the ratio) are more prone to suffer from a situation of distress. The average value of the ratio was 18.5% in 2008 and remained around an average threshold of 20% during the recessionary phase.

As far as the capitalization issue is concerned, we have to acknowledge the approval of two important decree-laws in the period that is covered by our data, that were precisely aimed at providing fiscal incentives for recapitalization of Italian firms. In particular, the so-called "Allowance for Corporate Equity" (ACE) was introduced at the end of 2011 as part of a package of urgent measures for the Italian industrial recovery[72]. In light of this, it is interesting to explore whether (and in what direction) these measures conditioned aggregate data on firm capitalization and, by reflection, distress likelihoods[73]. The variable *capitalization* is indicative of the level of firm capitalization: namely the ratio of equity to financial debt[74]. More precisely, the variable *capitalization(08)* represents the firms' capitalization status in 2008, at the eve of the crisis and the variable Δ*capitalization(09-13)* is the cumulative variation in the level of capitalization between 2008 and 2013.

The level of capitalization was 67.6% in 2008 (median value). The dataset is in fact primarily comprised of small firms that display a level of capitalization of 59.9% (median value) – compared to the level of 78.7% that identifies large firms. As expected, data encompass a predominant upward trend in the level of capitalization during the period affected by the legislative changes: a 3% up, in median terms[75].

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[72]. Reference is made in primis to the decree-law number 185/2008. The former introduced an explicit opportunity for asset revaluation (with the only exception of assets on sale) at the firm level (namely corporations and commercial entities subject to IRES taxation). Moreover, the decree-law number 201/2011 provided urgent measures for Italian industrial recovery. More precisely, fiscal benefits were made available to firms in the process of strengthening their capital: ACE (Allowance for Corporate Equity).

[73]. The estimation of a causal effect goes beyond the scope of the analysis.

[74]. More precisely, the variable *capitalization(08)* is calculated as the logarithm of the ratio between equity and financial debt and has to be interpreted as the percentage of equity exceeding financial debt. The variable Δ*capitalization(09-13)* is the log-difference between the level of capitalization in 2013 and the level of capitalization in 2008. Firms presenting negative values of the equity component were removed from the sample. Moreover, values below the 1st percentile and above the 99th percentile of the variable's distribution were discarded.

[75]. The revaluation option (introduced by Decree-law 185/2008) has been extensively selected by Italian SMEs. The evidence emerges from the analysis of manufacturing financial statements performed by Intesa Sanpaolo and Prometeia: reference is made to ASI Report 2009(2). Moreover, the introduction of the ACE measure (Allowance for Corporate Equity) in 2011 has fostered a rebalancing of the financial structure at the micro level. A general improvement in leverage has to be acknowledged at the manufacturing level. Additional details are present in the ASI Report 2012(2). ASI is the acronym for

Moreover, the *debt_burden* binary variable is considered as part of the second step of the model as well. In fact, if the intensity of bank financing ratio is likely to mirror financial rigidity at the firm level, the latter variable addresses the point of debt sustainability from a monetary perspective (firms might be not profitable enough to repay their interest related expenses). Both the variables are expected to have exerted an impact on distress likelihoods during the crisis.

Equation *[2b]* includes a set of control variables that is similar to the one described in the previous paragraph: we consider dimensional dummies, sectorial dummies and geographical dummies (broad macro-areas). In addition, we control for dynamicity of firms before the recessionary shock (cumulative growth in sales in the period 2004-08) and after the shock (cumulative growth in sales in the period 2008-13). On the one hand, it is worth analyzing if firms in a stage of expansion before the crisis were more prone to experience distress. On the other, the variable cumulative growth 2008-13 proxies for an individual recessionary shock.

Equation *[2b]* is estimated by standard Maximum Likelihood estimator for probit models. Nevertheless, bootstrapped standard errors are provided (for direct coefficients and marginal effects), because of the inclusion of the fitted values generated variable between covariates. Results are presented in Table 3.

3. Commenting on empirical estimates

Results from estimation of the spatial model *[1b]* identify neighborhood effects in trade debt usage by Italian manufacturing firms during the recessionary phase 2009-13. In other words, the levels of trade debt accumulated by interconnected firms prove to be closely related. The evidence does confirm the existence of a chain reaction at work during the crisis: the process of accumulation of trade debt is driven by imported disequilibria (shocks) from customer firms. In fact, the harshness of the recessionary effects that affected the country from 2009 onwards, generated in turn a prolonged and pervasive lengthening of the payment terms in the manufacturing industry.

The value of the λ coefficient, that identifies the strength of the convergence process of levels of outstanding trade debt in the manufacturing industry, is 0.105 (column 2, Table 2a). Nevertheless, emphasis is placed on the sign (i.e. the direction) of the impact, rather than on the magnitude of the spillover effect. In fact, as outlined earlier, we have to acknowledge the existence of potential missing links into the mapped network of interconnected firms (the one incorporated within the spatial weights matrix). This might cause the spatial coefficient to be biased with respect to the real spillover effect: firms that are interconnected in reality could be treated as directly unconnected firms within the sample[76]. We reasonably assume that the bias is downward because of the prevalence of small and medium-sized firms in the sample, that should

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Analisi dei Settori Industriali (Industry Analysis). The former is a proprietary forecasting model on Italian manufacturing trends. The associated ASI report is issued by Intesa Sanpaolo and Prometeia on a semester basis.

[76]. The recursive structure that is typical of spatial models allows firms to be treated as indirectly connected despite the zero cell in the W matrix.

have suffered from a lengthening of the payment terms to a greater extent. However, the direction of the bias could be even reversed.

Let us comment on the impact of exogenous covariates, that represent, in our specific case, the variables that internally drive the accumulation of trade debt at the firm-level. The recursive structure that is typical of spatial models allows direct and indirect effects of a change in a covariate pertaining to a generic firm *i* to be computed. The change of a variable at the level of a single firm *i* is likely to produce an impact on both the dependent variable of the firm itself (direct impact) and the dependent variable of neighboring firms *j* (indirect impact). Additional details are included in the Appendix. Since direct and indirect effects are different for different units in the sample, summary indicators or average effects are reported in Table 2b. A simulation of the impacts' distribution is performed in order to retrieve information on their significance[77].

Indirect impacts are responsible for a propagation mechanism to emerge within a network of firms. Shocks and imbalances transmit along the supply chain (mapped via the matrix of links). This in turn implies an endogenous convergence of levels of outstanding trade debt within the manufacturing industry.

Outstanding trade debt proves to be negatively influenced by the internal liquidity status of a firm, proxied by the *acid_test* variable. We identify an estimated direct impact of -0.068. As expected, liquid firms did rely on trade debt accumulation on a lesser extent in 2009-13. The indirect impact of the variable *acid_test* is negative as well, although reduced in magnitude. We should recall that the sample is primarily comprised of small firms (that account for 62% of sampled entities). In light of this, changes to the liquidity status of small firms are likely to produce a limited impact on interconnected firms. At the same time, results are again sensitive to the structure of the spatial weights matrix, namely the matrix of links in our case. In other words, the intensity of indirect effects strongly depends upon the degree of connection of firms in the network. In our case, an average vertex degree of 9 (transactions or links) is assigned to firms.

Firms that experienced a massive usage of credit lines during the recessionary period (variable *rationed_revocablelines*) did react in terms of a positive trade debt accumulation, as expected: we document a direct impact of 0.021 and a positive indirect impact on interconnected firms.

Conversely, no direct connection is established within trade debt usage during the crisis and financial debt sustainability at the firm-level (variable *debt_burden*). The evidence is likely to confirm the presence of a controversial relationship between trade debt and the financial structure of a firm, at least in the Italian case.

Moreover, the effect of our proxy for vertical integration (that mirrors the firms' structure at the eve of the crisis) is ambiguous: in fact, we identify a positive and significant direct impact of the variable *vertical_integration* on outstanding trade debt (0.128). Nevertheless, we should recall again that the

[77]. Reference is made to the Markov Chain Monte Carlo approach (MCMC) that is implemented in the *impacts* R command (*spdep* package).

sample is primarily comprised of small firms. They represent, as a matter of fact, the cluster that suffered to a greater extent than others from a lengthening of the payment terms, because of a limited contractual power. Accordingly, dummies that proxy for dimensional clusters highlight the presence of a more pronounced sensitivity of small firms (the baseline cluster) to outstanding trade debt during the crisis, as comparison to medium and large firms.

Results from probit estimation of equation *[2b]* return a highly significant positive impact of fitted values from spatial model *[1b]* (variable *fittedvalues_tradedebt*) on distress likelihoods in 2009-13 (Table 3): an estimated bootstrapped marginal effect of 0.931 is detected (column 8). Chain reactions did play an active role in conditioning the solvency dynamics of manufacturing firms during the recent crisis: a unitary increase in the variable increases the predicted probability of distress by 0.9%.

At the same time, estimates confirm the importance of individual financial rigidity, or firm indebtness (in 2008, at the eve of the crisis), in conditioning the insolvency trend. More precisely, we considered the effect exerted by short-term financial rigidity, by focusing attention on the short-term component of debt. A marginal effect of 0.343 is identified in correspondence to the variable *intensity_bankfin* (column 8, Table 3). This evidence corroborates the findings of Bonaccorsi di Patti et al. (2015).

More importantly, standardized coefficients[78] (column 5) return an impact of fitted trade debt that is comparable in magnitude to the one exerted by financial rigidity in 2008. Outstanding trade debt can be identified as a key determinant of distress likelihoods of Italian manufacturing firms during the crisis, together with financial rigidity of firms. Such a result sheds light over the need to jointly incorporate both of the channels of distress (trade credit and financial debt) into models that are intended to analyze the solvency behavior, at both the individual and systemic levels.

Finally, a positive effect is established between the *debt_burden* binary variable and distress likelihoods in 2009-13. Firms that generated a level of Ebitda lower than the value of the interests paid on debt, for at least two consecutive years during the crisis (unsustainability area for debt), are assigned a higher probability to become insolvent: the estimated bootstrapped marginal effect is 0.030 (Table 3).

The estimated effects prove to be robust to the presence in regression of a proxy for the individual recessionary shock: a negative and highly significant effect is established within firms' cumulative growth (identified by sales) in the period 2009-13 and distress likelihoods. Conversely, only a slightly significant impact is documented in correspondence to the variable cumulative growth 2004-08 (i.e. firm dynamicity before the crisis).

[78]. Standardized coefficients are suitable for comparing variables that display different metrics.

Table 2a - Coefficient estimates, Step [1]

	Baseline model (OLS)			***Spatial model (ML)***		
	Coefficient		***Std. err***	***Coefficient***		***Std. err***
λ (spatial lag autor. parameter)				0.105	***	(0.014)
Acid_test (mean 09-13)	-0.068	***	(0.002)	-0.068	***	(0.002)
Debt_burden (09-13)	0.001		(0.005)	0.001		(0.001)
Rationed_revocablelines (09-13)	0.021	***	(0.004)	0.021	***	(0.004)
Vertical_integration (08)	0.131	***	(0.009)	0.127	***	(0.009)
Medium	-0.010	***	(0.002)	-0.010	***	(0.002)
Large	-0.026	***	(0.004)	-0.026	***	(0.004)
(Intercept)	0.308	***	(0.005)	0.281	***	(0.006)
Sectoral dummies (m_ℓ)			added			added
Macro-geogr. dummies (m_v)			added			added
Number of observations			11,920			11,920
Log-likelihood						9445.203
Moran's I index			0.000			
RLMerr			0.409			

Table 2b - Impact measures from spatial model, Step [1]

	Direct impacts			***Indirect impacts***		
	Coefficient		***Simulated z-value***	***Coefficient***		***Simulated z-value***
Acid_test (mean 09-13)	-0.068	***	-27.283	-0.008	***	-6.677
Debt_burden (09-13)	0.001		0.565	0.001		0.568
Rationed_revocablelines (09-13)	0.021	***	5.569	0.002	***	4.382
Vertical_integration (08)	0.128	***	13.894	0.015	***	6.175

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1. Note: Standard errors are in parentheses. For the tests, p-values are reported.

Table 3 - Probit estimates and marginal effects, Step [2]

	Original statistics								***Bootstrap statistics***					
	Coefficient estimates		***Std. error***	***Standardized Beta Coefficients***		***Marginal effects***		***Std. error***	***Coefficient estimates***		***Std. error***	***Marginal effects***		***Std. error***
Fittedvalues_tradedebt	4.247	***	(0.568)	0.213	***	0.925	***	(0.130)	4.215	***	(0.575)	0.931	***	(0.127)
Intensity_bankfinancing (08)	1.565	***	(0.110)	0.231	***	0.366	***	(0.027)	1.560	***	(0.110)	0.343	***	(0.024)
Capitalization (08)	-0.057	***	(0.015)	-0.070	***	-0.012	***	(0.003)	-0.057	***	(0.016)	-0.013	***	(0.003)
Delta_capitalization (09-13)	-0.069	***	(0.016)	-0.074	***	-0.015	***	(0.004)	-0.068	***	(0.018)	-0.015	***	(0.004)
Debt_burden (09-13)	0.135	***	(0.066)	0.028	***	0.031	*	(0.016)	0.134	***	(0.064)	0.030	***	(0.014)
Cum_growth (04-08)	0.097	*	(0.043)	0.034	*	0.021	*	(0.010)	0.098	*	(0.047)	0.021	*	(0.010)
Cum_growth (08-13)	-0.312	***	(0.039)	-0.127	***	-0.068	***	(0.009)	-0.311	***	(0.042)	-0.068	***	(0.009)
(Intercept)	-2.695	***	(0.167)						-2.683	***	(0.170)			
Dimensional dummies			added								added			
Sectoral dummies (m_ℓ)			added								added			
Macro-geogr. dummies (m_v)			added								added			
Number of observations			11,920											
Log-likelihood			-4726.902											

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1. Note: standard errors are in parentheses.

Conclusions and future directions

The relationship between outstanding trade debt and firm solvency was here analyzed, focusing attention on contagion effects that originate from the supply chain. In other words we modeled the assumption that the accumulation of trade debt monitored at the firm level during the last crisis was driven by imported shocks from customer firms, in addition to traditional financing needs.

Trade credit interconnections between Italian manufacturing firms during the recessionary phase 2009-13 were preliminarily explored through basic network analysis tools. Firms that accumulate high levels of trade debt show an higher probability to connect with firms that display a similar level of outstanding trade debt. This accumulation process, jointly with the presence of densely connected clusters of firms, can lead to chain-reactions in case of a liquidity shock.

A two-step econometric framework was introduced. The first step is a SAR spatial model that accounts for spatial lag dependence in trade debt data pertaining to interconnected firms (i.e. negative spillover effects from trade debt accumulation). In the second step, the trade credit channel is considered together with data on the bank-firm relationship to assess distress likelihoods of Italian firms during the last crisis.

According to estimation results, outstanding trade debt (trade credit received from suppliers) is affected by the liquidity status of a firm and by spatial neighborhood effects. A positive spatial autoregressive coefficient in the first step of the model can be interpreted in favor of a chain reaction at work during the crisis: i.e. a lengthening of the payment terms that simultaneously affected interconnected firms within our proxied supply chain. The phenomenon was found to exert, by reflection, a positive and considerable impact on the probability to become a distressed subject during the recessionary period 2009-13. The latter effect is comparable in magnitude to the effect exerted by individual financial rigidity of firms (well established in literature), and sheds light over the need to incorporate complex interactions between firms in the analysis of the solvency behavior, at both the individual and systemic levels.

Future research directions encompass the construction of an agent based simulation framework that incorporates the aforementioned results. The networked structure of the economy can in fact lead to complex interactions that are sometimes difficult to be properly sketched within an econometric model. In particular, the goal is set to assess direct and indirect effects of shocks to the Italian industrial system, that are likely to be observed at the micro-level, at the industrial-level (e.g. demand contraction) or at the level of the topological structure of the firm network itself (e.g. a market concentration due to merges and acquisitions). This agent-based framework could in principle be employed also for financial policy evaluations (e.g. to evaluate the effects of new banking policies aimed at selecting and financing firms based on their positioning within the network) or to assess new credit rating practices (e.g. incorporating the information on the trade credit channel within rating valuations).

Appendix A – Branches of economic activity

Branch	*Name*	*Ateco 2007/Nace Rev.2 corresponding codes*	*Sample composition by branches of economic activity*
1	Food and beverage	C.10, C.11	9.9
2	Textiles and textile products; Leather and footwear	C.13, C.14, C.15	12.3
3	Wood-made products; Furniture sector	C.16, C.31	7.3
4	Paper, print and publishing sector	C.17, C.18	5.3
5	Chemical and pharmaceutical sector; Rubber and plastic products	C.20, C.21, C.22	12.6
6	Other non-metallic mineral products	C.23	5.2
7	Metallurgical products	C.24, C.25	22.6
8	Mechanic, electronic equipment, medical equipment, transport equipment	C.26, C.27, C.28, C.29, C.30	24.8

Appendix B – Direct and Indirect Effects

In spatial models if a particular explanatory variable in a particular unit changes, not only will the dependent variable in that unit itself change, but also the dependent variables in other units. The first is called the direct effect and the second the indirect effect.

Let us consider a SAR model of the type: $y = \lambda Wy + X\beta + \varepsilon$

The data generating process of the model is: $y = (I-\lambda W)^{-1} X\beta + (I-\lambda W)^{-1} \varepsilon$

Direct impact can be expressed by: $\frac{\partial y_i}{\partial x_{ik}}$ (own derivative)

They identify the effects on y_i resulting of a change in the *k-th* explanatory variable x_k in the *i-th* firm.

Indirect impacts are instead expressed by: $\frac{\partial y_j}{\partial x_{ik}}$, $j \neq i$ (cross-partial derivative)

and identify the effects on y_j resulting of a change in the *k-th* explanatory variable x_k in the *i-th* firm. Dependence expands the information set to include information from neighboring firms.

Following LeSage (2008) the data generating process of the model can be rewritten as:

$$y = \sum_{k=1}^{h} S_k(W)x_k + (I_n - \lambda W)^{-1}\varepsilon$$

where $S_k(W) = (I_n - \lambda W)^{-1}\beta_k$

Whereas the direct effect of the k-th explanatory variable in the OLS model is β_k, the direct effect in the SAR and SARAR models is β_k premultiplied with a number that will eventually be greater than or equal to unity. This can be seen by decomposing the spatial multiplier matrix as follows:

$$(I_n - \lambda W)^{-1} = I + \lambda W + \lambda^2 W^2 + \lambda^3 W^3 \ldots$$

Since the non-diagonal elements of the first term (identity matrix I) are zero, this term represents a direct effect of a change in X only. λW represents instead an indirect effect of a change in X that is limited to first order neighbors because W is taken at the power of 1. All the other terms represent second and higher-order direct and indirect effects. Higher-order direct effects arise as a result of feed-back effects (impacts passing through neighboring units and back to the unit itself). It is these feedback effects that are responsible for the fact that the overall direct effect is eventually greater than unity.

In light of the above, impacts on y_i from changes in the *k-th* explanatory variable x_k in the *i-th* firm can be expressed as: $\frac{\partial y_i}{\partial x_{ik}} = S_k(W)_{ii}$

and impacts on y_j from changes in the *k-th* explanatory variable x_k in the *i-th* firm*:*

$$\frac{\partial y_j}{\partial x_{ik}} = S_k(W)_{ji}, j \neq i$$

To summarize, any change to an explanatory variable in a single firm can affect the dependent variable in all firms. This is a logical consequence of the simultaneous spatial dependence model we are considering.

As stated in Elhorst (2014) direct and indirect effects are different for different units in the sample. Direct effects are different because the diagonal elements of the matrix $(I_n - \lambda W)^{-1}\beta_k$ are different for different units (provided that $\lambda \neq 0$). Indirect effects are different because both the off-diagonal elements of the matrix $(I_n - \lambda W)^{-1}\beta_k$ and of the matrix W are different for different units.

LeSage and Pace (2009) propose to report summary indicators for both the direct and the indirect effects. The average direct impact is obtained by averaging the diagonal elements of $S_k(W)$. A summary indicator for the indirect effect can be obtained by averaging either the row sums or the column sums of the off-diagonal elements of the matrix.

Elhorst (2014) stresses the attention over an important limitation of the spatial lag model: the ratio between the indirect and the direct effect of a particular explanatory variable is independent of β_k[79]. This implies that the ratio between the indirect and direct effects in the spatial lag model is the same for every explanatory variable. Its magnitude depends on the spatial autoregressive parameter λ and the specification of the spatial weights matrix W only.

[79]. β_k in the numerator and β_k in the denominator of the ratio cancel out.

Appendix C - Variables and definitions

STEP [1]

Outstanding_tradedebt (09-13): average value of trade credit received (by a generic firm *i*) from suppliers or outstanding trade debt, during recessionary phase 2009-13;

Acidtest (09-13): average value of the acid test ratio during recessionary phase 2009-13; acid test is calculated as the ratio of current assets (net of inventories) to current liabilities;

Debt_burden (09-13): the variable is likely to identify firms whose debt is unsustainable from a monetary perspective. In particular, it is designed to take on a value of one if the coverage ratio (the ratio of interests paid on debt to Ebitda) is greater than unity for at least two consecutive years during the recessionary phase 2009-13 and lower than unity in 2008 (at the eve of the crisis)[80].

Rationed_revocablelines (09-13)**:** the variable is designed to identify vulnerable firms because of a massive usage of revocable credit lines during the recessionary phase (i.e. firms in a weak rationing status). It takes on a value of one if the ratio of credit used to credit granted to the firm by the Italian banking system was above 80% for at least two consecutive years during the recessionary phase[81] and below 80% in 2008.

Vertical_int (08)**:** the ratio of value added to sales, a proxy for vertical integration of firms at the eve of the crisis (2008);

Medium, large: binary variables identifying the belonging of firms to broad dimensional clusters. Reference is made to the European Commission thresholds (in Euro millions):

- Small firms: $2 \leq$ sales < 10
- Medium-size firms: $10 \leq$ sales < 50
- Large firms: sales ≥ 50;

STEP [2]

Distressed (09-13)**:** binary variable that takes on a value of one when firms are categorized in one of the following insolvency blocks during recessionary phase 2009-13 (i.e. the flag is present for at least one year in the observation period): "bad loans" (sofferenze), "substandards" (incagli), "restructured" and "past-due"[82]– while proving to be considered *in bonis* at the eve of the crisis (2008).

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[80]. More precisely, firms must display a coverage ratio greater than unity in one of the following periods: 2009-13 entire recessionary phase, 2010-13 period, 2011-13 period or 2012-13 biennium. At the same time we require firms to display a value of the coverage ratio lower than unity in 2008 (i.e. at the eve of the crisis).

[81]. More precisely, firms must display a ratio above 80% in one of the following periods: 2009-13 entire recessionary phase, 2010-13 period, 2011-13 period or 2012-13 biennium. Both credit used and credit granted are considered at the mean value (yearly values).

[82]. Substandards (incagli) are loans associated to a high risk of loss for the lender because of (temporary) difficulty of the borrower (i.e. the loss is probable but not sure for the lender). Bad loans (sofferenze) are indicative of a situation where repayments are not being made as originally agreed between the borrower and

***Fitted_tradedebt*:** fitted values from estimation of the spatial model *[1b]*;

Intensity_bankfin (08): intensity rate of bank financing in 2008; it is calculated as the ratio of short-term bank debt to sales;

Capitalization (08): level of firm capitalization in 2008, at the eve of the crisis; it is defined as the logarithm of the ratio between equity and financial debt and has to be interpreted as the percentage of equity exceeding financial debt;

Δ***Capitalization (09-13)***: cumulative growth in the level of capitalization; it is defined as the log-difference between the level of capitalization in 2013 and the level of capitalization in 2008;

***Cum_growth (04-08)*:** cumulative growth (proxied by sales) before the recessionary shock (2004-08 period);

***Cum_growth (09-13)*:** cumulative growth (proxied by sales) during the recessionary shock (2009-13 period).

the lender, and which may never be repaid. Both the categories fall within the definition of problematic repayments. Moreover, the definition is inclusive of two additional non-performing categories: restructured loans and past-due or overdue loans (from more than 90 days). We sometimes observe overlapping between substandards and past-due.

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Chapter 3

A spatial econometric model for productivity and innovation: the role played by geographical and sectoral distances between firms°

Abstract

We model an indirect spatial production function framework of the SARAR type to analyze knowledge spillovers at the micro level. A large representative sample of around 9,000 Italian firms is considered, observed between 2004 and 2011. A rich dataset of patent applications filed with the *European Patent Office* (EPO) is exploited to compute territorial and firm-specific indexes of relative patent intensity. Alternative assumptions regarding the structure of inter-firm interaction are considered. We structure interaction matrices according to the theoretical literature on externalities that stem from geographical proximity of firms (Marshall-Arrow-Romer or Porter's externalities within an industry and Jacobian externalities that occur between heterogeneously specialized firms). Moreover, we extend the notion of interaction distance to encompass the input-output configuration of the Italian manufacturing industry. Results show that total factor productivity benefits from positive spatial effects. A patent intensive operating ground can be regarded as a stimulus to TFP, that fosters the convergence of levels of total factor productivity within the neighborhood. The strength of the convergence path in TFP is similar regardless of the selected definition of neighborhood (sectorally homogeneous versus sectorally heterogeneous proximate firms).

Keywords: panel data, spatial models, TFP, manufacturing, spillover, agglomeration economies, patents

Jel classification: C23, D24, L60, O33, O34, R12

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Introduction

Total factor productivity (TFP) has become a controversial topic in recent years. Italian firms are frequently regarded as disadvantaged in the international context, where comparative analysis of productivity growth matters across competing manufacturing countries, because of its fragmented production base (predominance of small and medium-sized enterprises). A fragmented production does act indeed as a friction to investment in core inputs and strategical factors, that are likely to enhance individual total factor productivity. Nevertheless, there still exists the interest in shedding light on the role played by key factors like clustering of firms and innovation in generating spillover effects.

Specifically, this Chapter assesses knowledge spillovers in the Italian manufacturing industry accounting for spatial distances in place between firms.

We exploit a representative dataset of around 9,000 Italian manufacturing firms observed between 2004 and 2011. Data are extracted from *Intesa Sanpaolo Integrated Database* (ISID). We retrieve TFP estimates at the firm level by using the Levinsohn and Petrin semi-parametric approach. Moreover, a unique dataset of patent applications filed with the European Patent Office (EPO) is considered to construct a comprehensive indicator of technological space or innovative environment where firms can interact.

We propose an indirect spatial production function framework of the SARAR type (spatial autoregressive model with spatial autoregressive disturbances) that is suitable for analyzing knowledge spillovers at the micro level. Spatial econometrics move a step forward towards a more realistic formulation of inter-agent interaction.

We start from a standard geographical space of inter-firm interaction and we structure interaction matrices according to the theoretical literature on externalities that stem from geographical proximity of firms. Marshall-Arrow-Romer externalities or Porter's externalities concern knowledge spillovers between firms in an industry, while Jacobian externalities predict that knowledge spills over heterogeneously specialized firms. All the theories support the view that innovations are quickly disseminated among neighboring firms; geographical proximity facilitates transmission of ideas.

As a second step, inter-sectoral trade coefficients from input-output matrices are considered to extend the notion of interaction distance and to further investigate sectoral heterogeneity as a driver of the knowledge transfer within the neighborhood.

To the best of our knowledge, spatial econometrics has never been applied to investigate dynamic externalities at the micro level. The present Chapter represents one of the first applications of a complete SARAR model on a relevant dataset of microdata. We solve for computational issues by using a 2SLS (Two Stage Least Squares) or GM/IV estimator.

Results show that total factor productivity benefits from positive spatial effects. Innovation emerges as the key TFP-enhancing mechanism, that fosters the convergence of levels of total factor productivity of neighboring firms. This mechanism does not appear to work differently across sectorally heterogeneous proximate firms, as comparison to sectorally homogeneous neighboring firms in the sample. In fact, the strength of the convergence path in TFP, measured by the autoregressive parameter λ in the SARAR model, is similar regardless of the selected definition of the interaction matrix. Such a result is likely to prompt a revaluation of the role played by traditional industrial clusters in the Italian manufacturing base (i.e. industrial districts), frequently overlooked in the recent years. Moreover, results show that a patent intensive operating ground can be regarded as a stimulus to total factor productivity, regardless of the individual propensity to innovate.

The Chapter is organized in six more sections. The first section is devoted to a review of literature. The next section concentrates on productivity estimation at the firm level. Section 3 introduces a spatial econometric approach to productivity data. Results and robustness checks are presented in sections 4 and 5. Conclusions are discussed in the following section.

1. Productivity and Innovation in literature

The present Chapter contributes to the literature on externalities that stem from proximity of firms.

During the 1980s theories on economic growth started considering externalities, and particularly externalities associated with knowledge spillovers, as the engine of growth (Romer, 1986; Lucas, 1988). According to these theories, geographical proximity facilitates the transmission of ideas. In other words, technological externalities occur when innovations and improvements occurring in one firm increase the productivity of neighboring firms (without full compensation). These externalities are in turn a powerful engine of growth.

The existence of a link between productivity and innovation is well established in the literature. The stock of accumulated knowledge (innovative capacity) represents a core determinant of total factor productivity premiums. Since the pioneering papers by Griliches (1979) and Jaffe (1989), concentrating on the real effects of academic research, the literature on the geography of innovation started measuring localized spillovers from R&D spending. This strand of the literature draws upon the knowledge production function approach, that relates innovative outputs (patent data, at the level of states, regions or cities) with measures of innovative inputs (e.g. R&D expenditure)[83]. Anselin et al. (1997) revisited Jaffe's work applying for the first time spatial econometric techniques to innovation models[84], in order to detect cross-border effects of academic research.

Nevertheless, the knowledge production function approach is not free from drawbacks: empirical data do not allow a clear distinction to emerge between pure knowledge spillovers[85] and complex knowledge transfers (mediated by market

[83]. In addition to the paper by Jaffe (1989), it is worth mentioning the contributions by Acs et al. (1994) and Audretsch and Feldman (1996, 1999), that represent milestones in this field. Moreover, the knowledge production function approach inspired a lot of research based on Italian (and European) data: Breschi and Lissoni (2001), Breschi and Malerba (2001), Paci and Usai (2005). Moreover, the papers by Moreno et al. (2005) and Marrocu et al. (2011) employ spatial econometric techniques to model innovation spillovers at the regional level.

[84]. For a recent survey of spatial econometric techniques applied to innovation see Autant-Bernard (2011).

[85]. Pure knowledge spillovers occur when firms benefit from the R&D activity undertaken by neighboring firms without providing direct compensation for it. Innovation becomes a publicly available stock of knowledge. The latter concept establishes a direct link with the process of endogenous knowledge creation (and growth) that is present in Romer (1986, 1990) and Lucas (1988).

exchanges), the latter being identified with pecuniary or rent spillovers[86]. The debate that followed - well summarized in Breschi et al. (2004) - marked a new starting point for innovation research. Some authors started looking for alternative methods to directly measure knowledge flows and to identify transfer mechanisms, retreating towards patent citations - as a sort of paper trail produced by knowledge transfers. At the same time, interest was growing towards formulation of a better understanding of international spillovers. A popular research strand concentrated on detecting spillovers from the presence of multinational corporations (foreign direct investments), by exploiting an indirect production function approach. This means that the presence of horizontal spillovers can be inferred indirectly, through the estimation of their effects on firm-level total factor productivity[87].

If geographical proximity facilitates transmission of ideas, then we should expect knowledge spillovers to be particularly important in cities (Glaeser et al., 1992). The seminal work by Marshall (1890) started investigating the advantages that stem from spatial concentration of firms within an industry. Sharing, learning and matching are the key mechanisms that explain the tendency to cluster in space[88], with particular reference to input sharing - even in the form of specialized workers. Nevertheless, these static externalities or localization externalities were mainly intended to explain regional specialization and city formation, rather than knowledge spillovers and growth.

During the 1990s the attention shifted towards dynamic externalities as a way to explain simultaneously how cities form and why they grow. Knowledge spillovers represent the bridge between regional specialization and growth. Both the Marshall-Arrow-Romer (MAR) and the Porter's theories concern knowledge spillovers between firms in an industry as a powerful growth engine. The primary difference between MAR's[89] and Porter's (1990) models is the effect of local competition. In MAR models of externalities firms' property rights have to be sufficiently protected to facilitate a fast pace of innovation and growth. Lack of property rights to ideas causes innovators to slow down their investment in research and development. In fact, they realize that ideas are imitated by neighboring firms without compensation. On the contrary, Porter argues that local competition within an industry increases the pressure to innovate (i.e.

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[86]. The first theoretical distinction between the two types of spillovers is due to Griliches (1992): pecuniary or rent spillovers are market-mediated knowledge flows. They occur when "new or improved input is sold, but the producer cannot fully appropriate the increased quality of the product. In this case, some of the surplus is appropriated by the downstream producers but the mechanism does not create *per se* further innovation and endogenous growth" (Breschi et al., 2004). It is hard to distinguish between the two types of spillovers in empirical works, especially when the main mechanisms of the transmission of accumulated knowledge are called into question. Reference is made to social networks and labor mobility in the case of local spillovers, and to trade and foreign direct investments from multinational enterprises in the case of international spillovers.

[87]. Refer to the contributions by Aitken and Harrison (1999), Haskel et al. (2002), Javorick (2004).

[88]. Sharing (i.e. the opportunity to share local indivisible public goods that raise productivity), matching (i.e. thick labor markets facilitate the matching between firms and workers), and learning (i.e. the frequent face to face interactions between workers and firms in the agglomerated areas generate localized knowledge spillovers).

[89]. Refer to the contributions by Marshall (1890), Arrow (1962) and Romer (1986). In 1992, Edward Glaeser, Hedi Kallal, José Scheinkman, and Andrei Shleifer pulled together the Marshall-Arrow-Romer views on knowledge spillovers and accordingly named the view MAR spillover.

geographical concentration and local competition facilitate the flow of ideas and imitation).

The competitive theory of externalities by Jacobs (1969) favors, as Porter's theory does, local competition as a stimulus to innovation. Nevertheless, Jacob's theory predicts that variety of geographically proximate industries promotes growth as knowledge spills over industries.

Empirical tests conducted from time to time have produced controversial results in terms of the prevailing effect[90]. The debate is still open.

The present Chapter contributes to the existing empirical literature on externalities from knowledge transfer by modelling spatial relations between firms in a much more flexible and formal way. Spatial techniques introduce a complete restyling of the concept of industrial clustering. Specifically, we employ an indirect spatial production function approach to analyze the impact of innovation on firm-level total factor productivity. A rich dataset of patent applications filed with the *European Patent Office* (EPO) is exploited to compute territorial and firm-specific indexes of relative patent intensity. Alternative assumptions regarding the structure of inter-firm interaction are considered. We start from a geographical space and we structure interaction matrices according to the theoretical literature: we elect interactions between sectorally homogeneous neighboring firms in the sample as the ideal framework to analyze externalities of the Marshall-Arrow-Romer or the Porter's types, and interactions between sectorally heterogeneous neighboring firms in the sample as an ideal point of departure to investigate externalities of the Jacobian type. Moreover, we extend the notion of interaction distance to the input-output configuration of the Italian manufacturing base. When an indirect production function approach is selected, results have to be interpreted in favor of market-based spillovers from innovation[91].

Italy is a preferred environment to test the aforementioned predictions because of its fragmented production base. In fact, during the 1990s a popular strand of the literature started addressing the so called district effect in order to quantify benefits[92] from location within industrial districts. The latter represent agglomerations of sectorally homogeneous firms specialized into typical "Made in Italy" products (e.g. mechanical, textiles, food and beverage, leather and footwear etc.)[93]. Traditionally, the industrial districts' formation is explained by the presence of externalities of the Marshallian type. Marshall (1890) predicts that firms in the same industry locate next to each other to share inputs (localization externalities). Nevertheless, when the concept of knowledge transfer is called into question, attention shifts towards more dynamic externalities. Industrial districts

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[90]. An empirical analysis on US data is presented in Glaeser et al. (1992).

[91]. Nevertheless, it is worth stressing that a precise quantification of a pure innovation spillover goes beyond the scope of our analysis.

[92]. Total factor productivity premiums, growth performance and financial solidity.

[93]. Becattini (1990) is the first one formalizing the concept of industrial district, as a specific socio-territorial entity bounded in space. The latter incorporates firms sharing a common specialization - from leader firms to suppliers - as well as proper institutions (both political and financial) whose mission is to contribute to the functioning of the related environment. Signorini (1994), Fabiani et al. (2000) and Cainelli and De Liso (2005) are seminal papers in the Italian literature on the district effect. For a more complete survey of the contributions based on Italian data, refer to Iuzzolino and Micucci (2011) or Di Giacinto et al (2011).

can be regarded as the expression of MAR or Porter's externalities[94] within industry, depending on the hypotheses that we are willing to make about the structure of the local operating environment (local monopoly of ideas versus local competition as a stimulus to innovation).

More recent contributions in the literature on the Italian manufacturing base concentrate on urban effects[95]: performance premiums emerge in correspondence to firms that locate in urban areas – the latter being associated to externalities of the Jacobian type.

It is worth quoting the papers by Di Giacinto et al. (2011) and Buccellato and Santoni (2012) that are closely related to our analysis. Di Giacinto et al. shed light on the presence of stable productivity advantages of Italian firms as part of urban areas[96], while documenting a weakening of the benefits of firms that locate in industrial districts (the reference period spans from 1995 to 2006). A shrinking district effect is not novel *per se*: a great deal of literature has in fact documented the same phenomenon in recent years[97]. At the first stage, Buccellato and Santoni corroborate the findings of Di Giacinto et al. by conducting a similar analysis based on a representative sample of Italian firms (in the period 2001-10): the level of territorial urbanization emerges as a core determinant of productivity premiums. Moreover, the authors move the first steps towards an in-depth empirical discussion of TFP externalities in the manufacturing industry, both within and between sectors, exploiting gravity variables[98]. The latter variables identify potential premiums that stem from the influence of productivity levels pertaining to neighboring firms. Once gravity variables are included in the model, estimates identify a total absorption of the productivity advantages previously associated to an increased degree of territorial urbanization.

Such a result did represent the incentive to develop the spatial model presented in the Chapter. As stated earlier, we explore knowledge spillovers in the manufacturing industry through the lens of spatial econometrics. Firm productivity is sensitive to changes in the surrounding operating environment. The variable is likely to incorporate indirect effects or feedback loops. It is straightforward to assume that failing to account for spatial dependence in productivity data is likely to result in biased estimates. Specifically, the way in

[94]. Becattini (1990) is the first one formalizing the concept of industrial district, as a specific socio-territorial entity bounded in space. The latter incorporates firms sharing a common specialization - from leader firms to suppliers - as well as proper institutions (both political and financial) whose mission is to contribute to the functioning of the related environment. Signorini (1994), Fabiani et al. (2000) and Cainelli and De Liso (2005) are seminal papers in the Italian literature on the district effect. For a more complete survey of the contributions based on Italian data, refer to Iuzzolino and Micucci (2011) or Di Giacinto et al (2011).

[95]. Urban areas are densely populated areas that are characterized by the presence of interactions between firms belonging to different sectors of specialization.

[96]. The manufacturing space is divided into LLSs according to the criterion provided by ISTAT. The presence of agglomeration economies (industrial districts or urban areas) within local labor systems is accounted for by introducing binary variables in the estimation strategy.

[97]. Reference is made to the contributions by Brandolini and Bugamelli (2009), Corò and Grandinetti (1999), Foresti et al. (2009), Iuzzolino (2008), Iuzzolino and Menon (2010), Iuzzolino and Micucci (2011), Murat and Paba (2005).

[98]. The setup of the variables consists in aggregating productivity levels pertaining to neighboring firms. The latter are assumed to locate within a radius of 20 kilometers. When firms belong to the same sector of industrial activity, within sector externalities are detected. Conversely, when firms belong to different sectors of specialization, between sectors externalities are detected.

which spatial interactions are proxied in the model represents a step forward towards a more realistic formulation of inter-agent interaction. A spatial model is in fact assimilated to an equilibrium model where feed-back effects arise from changes in TFP determinants in one firm that will potentially exert impacts on all other firms within the neighborhood (propagation mechanism). Moreover, these techniques address the problem of endogeneity of the variable that proxies for the influence of neighboring firms (the spatial lag variable). Conversely, gravity models do not allow the propagation mechanism to be directly incorporated within the framework. Furthermore, gravity variables are treated as exogenous regressors.

2. Estimating Total Factor Productivity (TFP) at the firm level

2.1 *The underlying hypotheses*

The estimation process of total factor productivity at the firm level requires several issues to be addressed. Appropriate hypotheses have to be selected in order to econometrically estimate the production function. **A** standard Cobb-Douglas specification is adopted:

$$Y_{it} = \Phi_{it} L_{it}^{\beta l\_sect} K_{it}^{\beta k\_sect} \qquad [1]$$

where Y denotes the output variable, value added and inputs are labor L (the number of workers) and capital K. Subscripts t and i denote time (year) and the firm identifier, respectively. The *beta* coefficients β_l e β_k, that represent labor productivity and capital productivity, are estimated at the sectoral level (subscript *sect*). For this purpose, firms showing similar technologies are grouped into 12 branches of economic activity (Tab.1).

Table 1 - Branches of economic activity

Branch	***Name***	***Ateco 2007/Nace Rev.2 corresponding codes***[99]
1	Food and beverage	C.10, C.11
2	Textiles and textile products	C.13, C.14
3	Leather and footwear	C.15
4	Wood-made products (except furniture)	C.16
5	Paper, print and publishing sector	C.17, C.18
6	Chemical and pharmaceutical sector	C.20, C.21
7	Rubber and plastic products	C.22
8	Other non-metallic mineral products	C.23
9	Metallurgical products	C.24, C.25
10	Mechanic, electronic equipment, medical equipment	C.26, C.27, C.28
11	Transport equipment	C.29, C.30
12	Furniture sector	C.31

The econometric version of equation *[1]*, that implies a logarithmic transformation, is a model of the form (logarithms in small letters):

[99]. Ateco 2007 is the Italian version of the NACE Rev.2 classification of industrial activities, defined by the European Community.

$$y_{it} = \beta_0 + \beta_{l\_sect}\, l_{it} + \beta_{k\_sect}\, k_{it} + \phi_{it}$$
$$\phi_{it} = \omega_{it} + \varepsilon_{it} \qquad [2]$$

where ϕ_{it} denotes a composite error term. The latter is inclusive of the unobserved productivity shock ω_{it} and the idiosyncratic error term ε_{it}, that is uncorrelated with the inputs.

More specifically, the estimation framework relies on the following hypotheses:

- endogenous labor input, because of the correlation with productivity shocks ω_{it};
- a predetermined capital input (i.e. the variable is correlated to past productivity shocks).

In light of this, a simultaneity problem arises in the estimation of equation *[2]*, that is likely to invalidate standard econometric techniques. A Pooled OLS (Ordinary Least Squares) estimator ignores the correlation between regressors and disturbances and results into biased and inconsistent estimates of the *beta* coefficients. A Fixed Effects estimator (Within Estimator) provides a solution to the endogeneity problem while implying, at the same time, a key and quite restrictive assumption of time-invariant unobserved productivity component. It is common knowledge that fixed effects estimates of capital coefficients are often implausibly low and estimated returns to scale are severely decreasing.

The semi-parametric approach developed by Levinsohn and Petrin (2003) allows specific instruments to be employed in order to solve for the simultaneity bias. Reference is made to intermediate inputs m_{it} (raw materials) that enter the production process[100]. Data on net purchases, that represent purchasing costs of raw materials and commodities, are selected as a measure of intermediate inputs.

The demand for intermediate inputs is assumed to depend on capital and unobserved productivity ω_{it} and to be monotonically increasing in ω_{it}: $m_{it} = m_{it}(k_{it}, \omega_{it})$. This allows m_{it} to be inverted, so that ω_{it} can in turn be rewritten as a function of observed inputs: $\omega_{it} = h_{it}(k_{it}, m_{it})$.

Firm-level total factor productivity is computed as the residual of the production function, according to a two-step procedure that is detailed in Appendix B. As stated earlier, a production function with Levinsohn and Petrin correction is estimated for each branch of industrial activity separately (following the breakdown presented in Table 1):

$$Log(tfp)_{it} = y_{it} - \beta_{l\_sect\_LEV}\, l_{it} - \beta_{k\_sect\_LEV}\, k_{it} \qquad [3]$$

l_{it} and k_{it} denote labor and capital of a firm *i* at time *t*, in logs, $\beta_{l\_sect\_LEV}$ and $\beta_{k\_sect\_LEV}$ are labor and capital productivity coefficients estimated at the sectoral level (branches of economic activity) and y_{it} denotes value added.

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[100]. The methodology that is alternatively proposed by Olley and Pakes (1996) relies on the investment item as a proxy to overcome the simultaneity issue. Nevertheless, it is difficult to retrieve reliable data on investment in the Italian manufacturing, especially in correspondence to the cluster of small and medium sized firms.

2.2 *The reference dataset*

A sectorial estimation of labor and capital productivity coefficients requires the consideration of a large representative manufacturing dataset. We exploit a large unbalanced panel of approximately 16,000 Italian manufacturing firms, observed between 2004 and 2011. Data are drawn from *Intesa Sanpaolo Integrated Database* (ISID). This proprietary and confidential dataset, managed by the Research Department of Intesa Sanpaolo[101], combines information on corporate financial statements[102] with additional information on individual strategies (e.g. innovation, foreign direct investments, registration of brands at the international level, subscription of quality and environmental certifications etc.).

Choice is made to exclude a priori micro firms[103]: i.e. to select firms whose sales, at current prices, are higher than the threshold of two million Euros in the first year of observation (2004). However, sales are allowed to fluctuate downward in the following years (2005-11), up to a lower bound of 150 thousands Euros[104], in order to avoid overestimated results. It is in fact worth stressing that 2009 does correspond to a pronounced slowdown in the Italian output[105]. Moreover, a continuity of 4 years is required in the data pertaining to each surveyed firm, in order to render the analysis more robust.

Dealing with missing data on both the accumulated capital stock and the labor force is a mandatory stage to obtain productivity estimates. According to Italian accounting rules small firms may deposit simplified financial statements. These statements are not necessarily inclusive of the items that are needed to estimate the production function, namely the number of workers (labor input) and the total amount of capital accumulated within the firm (gross capital input)[106].

In light of this, it is necessary to proceed systematically to estimate missing data. Following a practice that is common in literature[107], missing data on the labor force (approximately 20% in the dataset) are estimated based on a recursive procedure that exploits information on labor costs (see Appendix A for details). Labor costs are inferred directly from financial statements, at constant prices[108]. Missing data on the accumulated capital stock (36% in the sample), if absent for multiple years for a single firm, are instead retrieved from ISTAT (Italian

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[101]. Intesa Sanpaolo is currently the largest Italian commercial bank by market capitalization.

[102]. This dataset uses financial statements reclassified by the CEBI (Centrale dei Bilanci), the main collector of financial statements in Italy. CEBI is part of the CERVED Group which is the leading information provider in Italy and one of the major rating agencies in Europe.

[103]. Micro firms are likely to bias results.

[104]. The latter threshold is imposed to exclude bankrupt firms from the sample.

[105]. The financial crisis that erupted in 2008 resulted into long lasting effects on manufacturing dynamics. 2009 represented the most critical year as far as the pervasiveness of real impacts is concerned and a solid industrial recovery is still lagging behind.

[106]. The declaration of the amount of tangible fixed assets pertaining to the same fiscal year of the financial statement itself is obligatory.

[107]. A similar approach to the estimation of the number of workers, at the firm level, is described in Di Giacinto et al. (2011).

[108]. Labor costs are deflated according to ISTAT production price indexes (3-digit sectorial breakdown, Nace Rev.2 classification of industrial activities).

National Institute of Statistics) data on gross and net capital (properly deflated)[109], at the maximum detailed sectoral breakdown[110]. On average, the number of workers recruited by sampled firms is 82, while the median value is 33, which suggests the presence of a substantial proportion of small and medium-size firms. Data are in line with the central role played by SMEs in the Italian manufacturing base[111].

As a second step, a screening test is performed, that involves the additional variables entering our estimation framework. As mentioned in the previous paragraph, value added is selected as the reference proxy for the output variable and net purchases are selected as a proxy for intermediate inputs[112]. Firms presenting missing values on designated items are deleted from the sample. After the completion of these steps, total factor productivity is estimated at the firm level, based on an unbalanced panel of 16,181 manufacturing firms observed in the period 2004-11 (115,859 observations)[113]. It is worth recalling that a production function with Levinsohn and Petrin correction is estimated for each branch of industrial activity separately (following the breakdown presented in Table 1). As far as the sectoral composition is concerned, it is worth stressing on the prevalence of observations pertaining to core Italian manufacturing sectors: the "mechanic, electronic equipment, medical equipment" branch accounts for 21.3% of sampled observations, followed by the "metallurgical products" branch (20.3%), "food and beverage" branch (11.7%), "textiles and textile products" branch (7.9%).

Capital and labor productivity coefficients, estimated by branch of activity, identify a prevalent regime of decreasing returns to scale (DRS), that is recurrent in the Italian case (Tab.2)[114]. Table 2 also reports the coefficients estimated by Pooled OLS as a useful benchmark.

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109. Reference is made to ISTAT deflators for gross and net capital, by branch of activity (Ateco 2007/Nace Rev.2).

110. According to Italian accounting rules firms are required to declare the amount of their net capital. By contrast, information on gross capital is optional. In cases information on gross capital is missing, the amount of gross capital is estimated as a proportion of the value of net capital exploiting sectoral weights or proportionality factors between gross and net capital, defined at the level of branches of economic activity (Ateco 2007/Nace Rev.2). Weights are constructed based on the ISTAT tables 'Gross fixed capital formation, stocks of fixed assets, consumption of fixed capital, by branches of economic activity'.

111. Firms are classified as small if they present less than 50 workers, medium-sized if the number of workers ranges from 50 to 249 and large if the number of workers is greater than (or at least equal to) 250.

112. Both the items are deflated according to ISTAT production price indexes, at the 3 digit level (Ateco 2007/Nace Rev.2 classification of industrial activities).

113. Estimates of total factor productivity are obtained by applying the STATA Levpet command.

114. Similar results can be found in the contributions by Di Giacinto et al. (2011) released by the Bank of Italy, Buccellato and Santoni (2012), Benfratello and Razzolini (2008). The former authors exploit a very large representative dataset of 29,000 Italian manufacturing firms (extracted from the Chamber of Commerce-Company Accounts Data Service database, CEBI Centrale dei Bilanci) observed over the period 1995-2006 and estimate total factor productivity according to the strategy proposed by Levinsohn and Petrin. Buccellato and Santoni estimate total factor productivity of Italian manufacturing firms in the period 2001-10 starting from the AIDA dataset (Bureau van Dijk), by resorting to the semi-parametric approach proposed by Levinsohn and Petrin (standard Cobb-Douglas production function) and the non-parametric approach proposed by Caves et al. (1982) as well: i.e. Caves-Christensen-Diewert (CCD) approach. A smaller sample of Italian manufacturing firms is exploited by Benfratello and Razzolini (2008) to investigate total factor productivity dynamics: a similar decreasing returns to scale finding is present in their analysis.

Tab.2 - Labor and capital productivity coefficients by branch of activity

Branch of economic activity	***Numb. Observ.***	***Levinsohn and Petrin***					***Pooled OLS (upward benchmark)***				
		Labor Coeff.	***Std. error***	***Capital Coeff.***	***Std. error***	***Returns to scale***	***Labor Coeff.***	***Std. error***	***Capital Coeff.***	***Std. error***	***Returns to scale***
Food and beverage	13,538	0.570 ***	(0.025)	0.152 ***	(0.014)	0.722	0.688 ***	(0.027)	0.311 ***	(0.016)	0.999
Textiles and textile products	9,160	0.643 ***	(0.019)	0.086 ***	(0.016)	0.729	0.813 ***	(0.019)	0.124 ***	(0.012)	0.937
Leather and footwear	3,838	0.639 ***	(0.019)	0.068 ***	(0.016)	0.707	0.786 ***	(0.023)	0.187 ***	(0.013)	0.973
Wood-made products (except furniture)	3,989	0.647 ***	(0.017)	0.075 ***	(0.020)	0.722	0.759 ***	(0.022)	0.192 ***	(0.015)	0.951
Paper, print and publishing sector	5,966	0.678 ***	(0.025)	0.166 ***	(0.059)	0.844	0.766 ***	(0.036)	0.217 ***	(0.027)	0.983
Chemical and pharmaceutical sector	6,139	0.725 ***	(0.024)	0.094 ***	(0.022)	0.819	0.908 ***	(0.027)	0.160 ***	(0.020)	1.068
Rubber and plastic products	8,338	0.685 ***	(0.015)	0.079 ***	(0.016)	0.764	0.798 ***	(0.160)	0.193 ***	(0.012)	0.991
Other non-metallic mineral products	7,751	0.638 ***	(0.019)	0.106 ***	(0.017)	0.744	0.798 ***	(0.017)	0.207 ***	(0.012)	1.005
Metallurgical products	23,577	0.681 ***	(0.012)	0.107 ***	(0.012)	0.788	0.768 ***	(0.012)	0.206 ***	(0.007)	0.974
Mechanic, electronic equipment, medical equipment	24,677	0.706 ***	(0.013)	0.073 ***	(0.009)	0.779	0.898 ***	(0.010)	0.113 ***	(0.007)	1.011
Transport equipment	3,347	0.636 ***	(0.024)	0.157 ***	(0.028)	0.793	0.788 ***	(0.023)	0.182 ***	(0.017)	0.970
Furniture sector	5,539	0.664 ***	(0.027)	0.104 ***	(0.018)	0.768	0.887 ***	(0.020)	0.113 ***	(0.013)	1.000

Note: *** 5% significance level. Standard errors are in parenthesis. The sample size includes 16,181 manufacturing firms observed over the period 2004-11. At this stage the panel is unbalanced.

3. A SARAR model for productivity and innovation

3.1 *A spatial approach to productivity spillovers*

As a second research step, the estimated TFP (in log-levels) is applied as the reference dependent variable into an indirect spatial production function framework that is suitable for assessing knowledge spillovers in the Italian manufacturing industry.

As outlined earlier, standard econometric techniques are unable to account for important feedback loops that arise from the multi-directional nature of data that are spatially dependent[115] (Anselin and Le Gallo, 2006). Spatial econometrics represents the environment that is selected to properly measure TFP spillovers in the Italian manufacturing industry. Both a geographical space and a pure sectorial space of interaction between firms will be considered accordingly. Specifically, we will concentrate on the role played by sectorial heterogeneity.

The balancing of the original unbalanced dataset (the one described in Section 2) is mandatory for the application of spatial econometric techniques. In fact, the construction of time invariant interaction matrices is required. The balanced sample consists of 8,803 geo-referenced manufacturing firms (70,424 observations out of 115,859 are left), also surveyed over the period 2004-11. A detailed comparison between the reduced sample and the sample of deleted firms (7,378) is provided in Appendix E. The former is primarily comprised of small firms (66.3%) and medium-sized firms (29.5%). Large firms account for the residual 4%[116]. The sectoral composition of the two data-sets proves to be very similar. This can partially mitigate concerns about sectoral representativeness of the balanced one.

In light of this, we could in principle compute firm-level total factor productivity starting directly from the reduced sample. Nevertheless, we consider it preferable to retrieve labor and capital productivity coefficients from the largest possible (unbalanced) manufacturing sample, in order to estimate them more precisely[117] and to move to a balanced dataset when spatial techniques are required.

The geographical distribution of sampled firms is relevant for dealing with spatial techniques at the micro-level. It is worth observing the prevalence of firms that locate in Northern Italy, both in the balanced dataset and in the subsample of deleted firms. This is consistent with the major role played by manufacturing

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115. Spatial dependence (spatial autocorrelation, when the dependence is of the linear type) emerges when realizations of the same variable are ordered according to a spatial scheme. Spatial econometrics comes to represent the branch devoted to formalize and measure spatial relationships in place between objects. The contributions by Paelink and Klaasen (1979) and Anselin (1988) are considered milestones in the spatial econometrics field. Spatial panels are treated also in Kelejian and Prucha (1999), Anselin and Le Gallo (2006), Kapoor et al. (2007), Bivand et al. (2008), Arbia and Baltagi (2009), Le Sage and Pace (2009), Elhorst (2009), Lee and Yu (2010), Baltagi (2013), Arbia (2014).

116. In the subsample of deleted firms small entities account for 67% of the sample, followed by medium-sized firms (29%) and large firms (3%). The slightly higher percentage of large firms in the balanced panel (4%) is due to the higher probability of large firms to remain in the *Intesa Sanpaolo Integrated Database* for longer time periods (i.e. to maintain a longer banking relationship, such that financial statements are present for multiple years in the dataset). At the same time, the percentage of small firms removed from the original dataset (67%) is only slightly higher with respect to the one that characterizes the new balanced panel (around 66%).

117. Total factor productivity was in turn estimated at the firm level, as the residual of the production function.

firms in Northern regions of the country. Nevertheless, firms that locate in the Central and Southern regions are slightly underrepresented in the balanced panel: i.e. they are likely to be deleted from the sample once the original unbalanced panel is forced to become balanced. Therefore, the above considerations have to be properly accounted for when commenting on empirical results from a policy perspective.

To identify spatial relationships in place between testable objects (firms), a basic W matrix of reciprocal influences is constructed (whose structure will be subject to refinement in subsequent steps) based on geographical distances. For this purpose, firms were geo-referenced according to latitude and longitude coordinates (Fig.1).

As a starting point, the location (municipality) of the main operating headquarter pertaining to each sampled firm was identified[118]. Geographical distances in kilometers d_{ij} between pairs of firms (a firms i and a generic neighbor j) were computed accordingly by resorting to the great circle method[119].

Fig.1 - Geo-referenced Italian manufacturing firms, balanced panel 2004-11

Spatial dependence can be preliminary tested using an index of the Moran's I type[120], namely the index of global spatial autocorrelation. Based on the W "raw" matrix introduced before, the Moran's I test highlights the presence of positive spatial correlation in our productivity data[121], with a highly robust significance (p-

[118]. Choice was made to consider pluri-localized firms as uni-localized ones, based on the coordinates of the main operating headquarter of a firm. By proceeding this way it is possible to associate a univocally identified position to each sampled firm and to construct a univocally defined matrix of distances W.

[119]. Distances are measured in kilometers accounting for the Earth's curvature.

[120]. The index detects the presence of correlation of the spatial type: the more spatial objects are similar with respect to the values undertaken by a certain variable under scrutiny, the higher the value of the index. For further details refer to Moran (1950) or Bera et al. (1996).

[121]. Choice was made to test for spatial autocorrelation to time-averaged total factor productivity and to discard a pooled Moran's I test option, that is computationally demanding given the size of the dataset. Indeed, due to the magnitude of the W matrix (8.803 x 8.803) a pooled Moran's I test would involve the

value < 2.2e-16). The empirical value of the Moran's I statistic is 0.0520 (expected value E[I] =-0.0011 and variance V[I]=7.9685e-07)[122].

These results encourage the adoption of a spatial approach to estimate our productivity framework properly. If productivity levels at location *i* depend on the levels observed in location *j* and vice-versa, the data generating process becomes simultaneous. This means that firms that are close in space tend to display similar values of productivity (i.e. clustering phenomenon). Clustering can be present in two different forms. In a true contagion framework leader firms are assumed to locate randomly in space while "followers" or subcontractors display a positive probability to locate closeby. Instead, when exogenous conditions impose the location of firms in certain areas (or certain areas display a higher probability of hosting firms) apparent contagion takes place. We assume that the first type of contagion is predominant in the Italian case, due to the clustered nature of the manufacturing base and the vertically-integrated structure of industrial districts. Moreover, following the literature on static externalities, we argue that only an indirect connection is established between natural resources and/or territorial infrastructural endowment and total factor productivity at the micro level. In fact, the former resources contribute *in primis* to explain firm specialization, but not necessarily growth and productivity (Glaeser et al., 1992). This partially mitigates concerns about endogeneity of the geographical spatial weights matrix.

The presence of endogenous interaction effects can be easily handled by resorting to a SARAR spatial panel model of the type (in stacked form over the N cross-sections of firms for a single period *t*):

$$Log(tfp)_t = \lambda Wlog(tfp)_t + X_t\beta + u_t \qquad [4a]$$

$$u_t = \rho W u_t + \varepsilon_t \qquad [4b]$$

$$\varepsilon_t = \mu + \upsilon_t \qquad [4c]$$

As far as the main equation is concerned, it is worth noting that *Log(tfp)* is an object containing levels of total factor productivity (of a generic firm *i* at time *t*, in logs) estimated in Section 1, *Wlog(tfp)* is the spatial lag variable and X is a matrix of exogenous covariates (that will be detailed in due course). The spatial lag variable accounts for the influence of productivity levels pertaining to neighboring firms *j*. More precisely, the productivity of a firm *i* is affected by the average level of TFP of the neighboring firms (spatial lag dependence). The average strength of this relationship across the sample of firms is captured by the autoregressive coefficient λ. When the parameter is greater than zero the variable

construction of a pooled dense matrix of size $(n*t)^2$ = 7.75e9. Considering a double value storage, this would imply a memory footprint of approximately 58 GB.

122. Under the null hypothesis of absence of global spatial autocorrelation, the expected value of the Index I is E(I)= -1/(N-1). If the value of the I statistic is larger than its expected value E(I), then the overall distribution of the variable under scrutiny (productivity) can be seen as characterized by positive spatial autocorrelation. The Moran's I statistic is conventionally assumed to take values in the range [-1, 1]. The lower bound should refer to perfect dispersion and the upper bound to perfect spatial correlation. Nevertheless, the contributions by Cliff and Ord (1981) and Upton and Fingleton (1985) offer concrete evidence of the statistic falling outside the selected bounds. When dealing with micro-data it is reasonable to accept values of the Moran's I that fall in an interval around zero. Data are assumed to be distributed under the null hypothesis (absence of spatial autocorrelation) according to a normality assumption (alternative is randomization). The variance of the statistic and the Z_i score are computed accordingly. It is worth mentioning that the statistic is found to be not particularly sensitive to departures from normality (Cliff and Ord, 1981).

under scrutiny (productivity) does benefit from positive feedback effects. It is worth stressing again that in a spatial setting feed-back effects arise from changes in TFP determinants in one firm, that will potentially exert impacts on all other firms within the neighborhood (propagation mechanism).

Moreover, the SARAR model accounts for interaction effects among the error terms. The error equation is the sum of an autoregressive structure ρWu and a composite error term ε[123]. By hypothesis, the W matrix in the error equation is assumed identical to the one in the main equation. The innovations ε have a one-way error component structure where υ are independent innovations and μ are random individual effects. Specifically, these types of interaction effects are consistent with a situation where determinants of the dependent variable omitted from the model are spatially autocorrelated, or with a situation where unobserved shocks follow a spatial pattern, as in Kapoor et al. (2007). From now on we will refer to the ρ parameter as the autocorrelation coefficient.

A battery of LM (Lagrange Multiplier) tests is reported to formally support the choice for a SARAR specification. A conditional LM test for λ (the autoregressive parameter) and a Conditional LM test for ρ (the autocorrelation parameter of the error term) were selected to properly evaluate the fit of the model[124]. More precisely, a variant of the tests proposed by Baltagi et al. (2003) is implemented, based on the residuals from a GM/IV estimation of the spatial model (further details on the estimator will follow)[125]. The test for λ (assuming $\rho \geq 0$) reports a statistic of 4.6823, showing a highly significant spatial dependence (p-value = 2.837e-06). The test for ρ (assuming $\lambda \geq 0$) reports instead a statistic of 192.9238, showing strong random spatial dependence (p-value<2.2e-16).

Finally, the Moran's I test can be implemented on residuals from an OLS estimation of model *[4]*[126]. When spatial dependence is present and not modeled properly, OLS residuals tend to cluster in space (i.e. spatially dependent residuals). Such a result corroborates previous findings about the need to switch to a formal spatial framework while dealing with productivity data.

As outlined before, the W matrix is suggestive of the neighborhood structure. Therefore, it is worth discussing in depth the construction of the object. Spatial econometric estimates are in fact particularly sensitive to the choice of W. The latter is a quadratic $n \times n$ matrix (where n is the number of firms in the sample, 8,803) with zero diagonal elements[127]. Different approaches can be accounted for to retrieve w_{ij} coefficients.

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[123]. In particular, once an autoregressive structure is considered, dependence in the error term is potentially allowed to propagate without restrictions. In fact, the AR(1) specification for the error equation can be rewritten as: $\varepsilon = (I + \rho W)^{-1}u = u + \rho Wu + \rho^2 W^2 u + \ldots$ Conversely, when a Moving Average (MA) specification is selected ($u = \rho W\varepsilon + \varepsilon$), dependence is much more restricted (Fingleton, 2008).

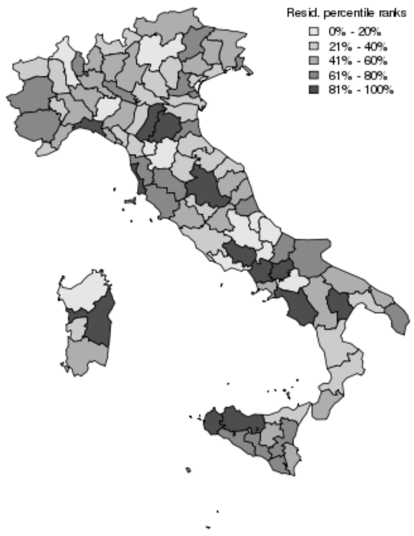
[124]. Conditional LM tests prove to be robust to the simultaneous presence of the other (non-tested) spatial effect.

[125]. The tests presented in Baltagi et al. (2003) and implemented in the *splm* R package are instead based on the residuals from a maximum likelihood estimation of the spatial model. Due to computational issues, the maximum likelihood estimator cannot be applied to the proposed spatial model.

[126]. A simplified version of the model is considered, accounting for exogenous covariates only (matrix X).

[127]. The generic elements w_{ij} are referred to as spatial weights. They measure the strength of the relationship in place between a firm i and a neighbor firm j. Self-neighboring firms are excluded.

Fig.2 - The plot of residuals from non-spatial estimation of model [4]

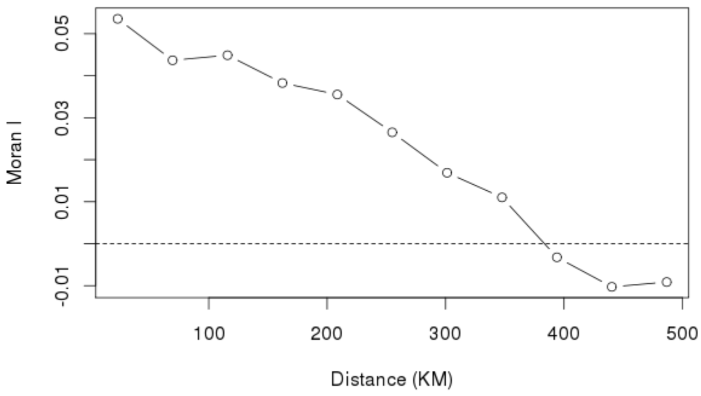


3.1.1 *Modelling geographical interaction effects*

In our analytical framework the reference W matrix relies on geographical influences exerted by first order neighboring firms. Influences are calculated based on d_{ij} distances. More precisely, spatial weights are the reciprocal of d_{ij} pairwise distances in kilometers between firms in the dataset: $w_{ij}=1/d_{ij}$. This way of modelling influences is not free from drawbacks. When distances between firms are small, the elements w_{ij} of the matrix tend to assume large values: $\lim_{d\to 0} w=\infty$. In light of this, it is desirable to introduce some corrections. *In primis* pairwise distances that are lower than 1 kilometer were normalized to a unitary distance (maximal reciprocal influence $w_{ij}= 1$). Moreover, the structure of the W matrix can be further refined. A clear pattern of decay in spatial correlation between TFP levels of Italian firms emerges from a correlogram analysis[128], as the geographical distance increases. Specifically, values of the Moran's I index as a function of pairwise distances between sampled firms are plotted in Figure 3. Correlation vanishes completely when pairwise distances fall within the range [200,400] Km.

[128]. Spatial correlograms are great to examine patterns of spatial autocorrelation that are present in the data. They show how correlated are pairs of spatial observations when the distance (lag) between them increases – they are plots of some index of autocorrelation (Moran's I) against distance. Neighboring values of a correlogram are highly correlated, so its usefulness is restricted to detecting the broad structure of the data.

Fig.3 – Correlogram showing spatial correlation (Moran's I) as a function of firms' pairwise distances (KM)



Combining results from the correlogram analysis with information on the structure of traditional Italian industrial districts (that comes from the periodical observatory on Italian industrial districts managed by the Research Department of Intesa Sanpaolo), a cut-off of 50 Km is selected to cleanse the original W matrix: only valuable reciprocal influences are accounted for to model spatial interactions of the first order type[129]. In other words, the empirical evidence suggests that industrial districts are local networks extending within Italian provincial borders, and being sometimes likely to incorporate neighboring provinces. Moreover, it is worth mentioning that higher cut-offs are likely to result into a misspecification of the geographical inverse distance matrix, that characterizes for high density once a spatial design is applied to microdata[130].

Matrices with shorter cut-offs (20 Km, 30 Km, 40 Km) are considered as a robustness check[131]. In other words, we test for robustness of our results in the worst case scenario of a restricted number of neighboring firms.

In a second stage, the original geographical matrix is split into two distinct matrices in order to disentangle the effects of sectoral homogeneity (or heterogeneity) of neighboring firms in driving potential externalities:

- the W_{ghom} matrix proxies for the clustering of geographical neighboring firms that share a common specialization;
- the W_{ghet} matrix proxies for the clustering of geographical neighboring firms that are active into heterogeneous sectors of specialization.

The first matrix is suitable for capturing the presence of externalities of the Marshall-Arrow-Romer (MAR) type or of the Porter's type, and the second matrix is designed to investigate externalities of the Jacobian type.

[129]. Nevertheless, the recursive structure pertaining to spatial models allows indirect propagation mechanisms to involve higher-order neighbors. Additional details will follow.

[130]. Specifically, once cut-offs from 150 Km onwards are selected to cleanse the matrix, estimates return suspiciously high positive values of the autoregressive parameter λ and suspiciously high negative values of the autocorrelation parameter ρ, that are likely to offset each other.

[131]. Additional details will follow in Section 5. Results are provided in the Appendix.

Moreover, the matrices are row-standardized (i.e. spatial weights sum to 1 in each row of the W matrices). Since W is nonnegative, this ensures that all weights are between 0 and 1 and has the effect that the weighting operation can be interpreted as an averaging of neighboring values (Elhorst, 2014). A spatial model can in fact be assimilated to an equilibrium system that characterizes for simultaneous feedbacks. Sampled firms are assumed to reflect an equilibrium outcome (steady state) of the total factor productivity generation process and the strength of endogenous interactions is measured by λ. The spatial autoregressive parameter can assume values in a range delimited by the reciprocals of the minimum (real) and maximum eigenvalues of the W spatial weights matrix. When the W matrix is row-standardized, the upper bound for λ is 1[132]. Nevertheless, it is worth mentioning that row-standardization is not compulsory[133].

3.1.2 *Modelling sectoral interaction effects and mixed effects*

Spatial dependence in productivity data might follow additional paths. It is possible to model distances between firms from a pure sectorial perspective. Firms that belong to a generic manufacturing sector *r* can potentially benefit from externalities that originate from the proximity to firms specialized into sector *c*. The magnitude of the externality depends on the intensity of trade flows between interconnected firms.

Financial statements do not report information concerning inter-firm trade, but sectoral proxies are available. Input output matrices offer the right framework to disentangle the intensity of trade connections between sectors in the economy (Medda and Piga, 2007).

In order to model endogenous interaction effects (that originate from firms that locate in other industries) a new W_s matrix is constructed. The point of departure is the symmetric input output matrix of the "sector by sector" type[134]. Symmetric tables present the advantage of combining demand and supply flows in the economy. Specifically, we selected the table that mirrors the structure of the Italian inter-sectorial trade at the beginning of the analyzed period (i.e. release

[132]. Nevertheless, the lower bound is not necessarily -1 when eigenvalues are complex numbers.

[133]. A spatial weights matrix W_0, if originally symmetrical, could in principle be scaled by the largest eigenvalue to preserve symmetry (Elhorst, 2001; Kelejian and Prucha, 2010). The operation has the effect that the characteristics roots of the original matrix W_0 (before normalization) are also divided by the largest eigenvalue, as a result of which the largest eigenvalue of the normalized matrix W becomes 1. Alternatively, one may normalize a spatial weights matrix W_0 by $W = D^{-1/2} W_0 D^{-1/2}$ where D is a diagonal matrix containing the row sums of the matrix W_0. The operation has been proposed by Ord (1975) and has the effect that the characteristic roots of W are identical to the characteristic roots of a row-normalized W_0. Importantly, the mutual proportions between the elements of W remain unchanged as a result of these two normalizations (Elhorst, 2014). Whatever W spatial weights matrix is used, parameter estimates have to be interpreted in relation to the bounds (the reciprocals of the minimum and maximum eigenvalues) that define a continuous parameter space that avoids problems associated with spatial unit roots, non stationarity and discontinuities (parameters outside the bounds). Nevertheless, it is worth stressing that only the Maximum Likelihood estimator strictly retains the spatial autoregressive parameter within the stable bounds because of a penalty term in the likelihood function that goes to infinity as the parameter goes to the bounds. Conversely, one disadvantage of the GM/IV estimators is the possibility of ending up with coefficient estimate for λ outside its parameter space (GM/IV estimators ignore the penalty term in the likelihood function).

[134]. Italian input-output matrices are released by ISTAT, the Italian National Institute of Statistics.

2005[135]), in order to render the associated dependence structure exogenous with respect to the explanatory variables included in the model (a block of sectorial dummies will be incorporated accordingly, based on aggregate branches of industrial activity). The new spatial weights ws_{ij} correspond to intermediate purchases of industry *r* (that represents the sectoral specialization of firm i) from industry *c* (that represents the sectoral specialization of firm j). In other words, they represent the demand for intermediate consumption[136]. In light of this, the matrix can be considered an enlarged proxy of the chain connections that are active in the Italian manufacturing industry[137] (supply-chains) and can be exploited to analyze the role played by sectoral heterogeneity from a different perspective. For this purpose, intra-sectoral flows are properly discarded. The sectoral matrix is further row-standardized.

In addition, the matrix can be in principle employed to further refine the structure of the geographical W_{ghet} matrix, the one that is designed to investigate Jacobian externalities in a more traditional sense. By interacting the two matrices[138] W_s and W_{ghet}, geographical neighboring firms that belong to heterogeneous sectors of specialization are assigned new weights, based on the relative importance of both the geographical distance and the intensity of trade between pairwise sectors in the economy. We refer to the interacted matrix as $W_{interacted}$.

3.2 *The role of innovation in generating TFP premiums*

As outlined earlier, the presence of knowledge spillovers can be inferred indirectly, through the estimation of their impact on total factor productivity. In this case, an indirect production function approach is used.

Following the literature on local productivity advantages, and expanding the main equation in *[4]* as far as the exogenous covariates are concerned (matrix X), we consider a model of the following form:

$$\begin{aligned} Log(tfp)_{it} = {} & \lambda \textstyle\sum_{j=1}^{n} w_{ij} log(tfp)_{jt} + \beta_0 + \beta_1 innov\_lls_{\ell t}{*}small_{it} + \beta_2 innov\_lls_{\ell t}{*}medium_{it} \\ & + \beta_3 innov\_lls_{\ell t}{*}large_{it} + \beta_4 innov\_firm_{it} + \beta_5 medium_{it} + \beta_6 large_{it} \\ & + \beta_7 distr_{it} + \beta_8 tec_{it} + \beta_9 infra_r + m_t + m_l + m_g + u_{it} \qquad [5] \end{aligned}$$

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135. Input-output matrices are updated on a five year basis. We considered it preferable to discard the 2000 release of the matrix, because it is likely to describe a manufacturing structure that is far away in time with respect to the starting point of our analysis (2004).

136. More precisely, we start from an input-output symmetric table F of the sector-by-sector type where F_{rc} corresponds to the flow of intermediate purchases of industry *r* from industry c. The F matrix is than row normalized to compute the direct technical coefficients $TC_{rc} = F_{rc}/(\sum_c F_{rc})$. The sector-by-sector matrix of direct technical coefficients TC is than expanded to obtain a bigger firm-by-firm matrix W_S of dimension (8.803 x 8.803), where 8,803 is the number of firms in the database. Each pair of firms i-j in the sample is assigned a unique technical coefficient TC based on sectoral specialization r and c of firms i and j, respectively.

137. The term enlarged is needed to describe a situation where established connections between firms in the sample are forced to resemble the sectorial structure that is present in the input-output snapshot (the manufacturing structure). Real supply chain connections could in principle be different from those proxied in the paper.

138. We performed an interaction between the non-standardized versions of the matrices W_{ghet} and W_s. Both the matrices are of dimension (8,803 x 8,803). As a second step, a row-standardization of the interacted $W_{interacted}$ matrix is performed.

In order to quantify the innovation activity pursued by manufacturing firms, a measure of relative patent intensity is introduced. We exploit a rich dataset of patent applications filed with the *European Patent Office* (EPO), referenced at the level of applicant firms[139] - and matched to the information that is contained in ISID (*Intesa Sanpaolo Integrated Database*). Patents do represent a high-quality proxy for certified innovative output (i.e. the one that is subject to the lowest measurement errors). Specifically, patent data represent a valid alternative to the availability of a comprehensive list of (geo-localized) public and private research centers in Italy[140] (and to the existence of an updated ranking of the research outputs as well). The latter would have symbolizes an ideal information set to be combined with spatial econometric techniques in order to quantify the benefits stemming from firms' proximity to research units[141]. Up to now, the analysis of the technological transfer has been restricted to academic or public research[142]. To the best of our knowledge, a matched dataset of firm-level patent data is rare[143].

We construct a territorial index of relative patent intensity as the reference proxy for innovation. More precisely, patent data are exploited to identify a sort of technological space where sampled firms can interact. The choice moves from the consideration that patenting activity is still restricted to the most structured firms in the Italian manufacturing industry. Nevertheless, even if they are not pursuing a direct innovation activity, firms might benefit from the location within a patent-intensive area.

Specifically, we conduct a summation process of patent applications at the level of broad sectors of industrial activity[144] ℓ and selected territorial units: Local Labor Systems (LLS), defined by ISTAT[145]. The summation process, by "sector ℓ - LLS" pair, is identically computed for each year t covered by our analysis (from 2004 to 2011). At this stage of the process we consider all the innovative manufacturing firms that are mapped in the *Intesa Sanpaolo Integrated Database*

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139. Patent data are extracted from the proprietary database *Thomson Innovation*, managed by Thomson Reuters. A matching process between patent data and the information on corporate financial statements that is present in ISID (*Intesa Sanpaolo Integrated Database*) is performed periodically by the Research Department of Intesa Sanpaolo. Patent data are matched at the level of applicant firms. In the (residual) cases of multiple applicant firms, decision is made to consider a multiple assignment of the same patent application.

140. The matching between patent data and single research centers is sometimes possible but complex, as well as subject to consistent measurement errors, because of the lack of a univocal identifier (fiscal code).

141. The Italian Confederation of Industries (Confindustria) has started mapping the main public and private research centers in Italy (Mappa delle competenze delle imprese in ricerca e innovazione), in order to draw a precise picture of the Italian industrial research and of the produced output. The map is nevertheless still preliminary and incomplete.

142. Among the papers that focus on Italian data it is worth mentioning the contributions by Buganza et al. (2007), Colombo et al. (2009), Fantino et al. (2012), Piergiovanni et al. (1997), Pietrabissa and Conti (2005).

143. A similar dataset has been created and used by the Bank of Italy.

144. Local labor systems are 784 territorial units identified by ISTAT, based on socio-economic relations. More precisely, they come to represent municipalities that are identified by compacting information on daily business trips of the resident population. The data on daily trips are drawn from the population census survey. The scope of the classification is to link municipalities showing consistent interdependence relationships. LLSs are a valid instrument to analyze the socio-economic structure of the country.

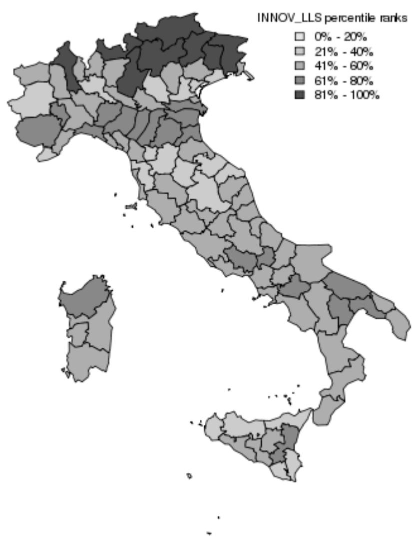
145. Sectors are present at the 3 digit or 2 digit level of the Ateco 2007 classification of industrial activities, depending on the available breakdown in the matching process with patents' IPC codes – International patent classification codes. The correspondence table (between IPC codes and Ateco codes) is based on an updated version of the table that is present in Schmoch et al. (2003).

(around 4,800 firms in ISID are assigned patent innovations)[146]. Moreover, in order to account for a potential time-lag occurring between an application to the *European Patent Office* and the moment of formal assignment of a patent to an applicant firm, we proceed summing applications pertaining to a reference year *t* (pivotal year) in the panel and to the previous four years: the output of the summation process is a sort of rolling composite sum of patent applications. The variable *innov_lls* is the index of *relative patent intensity at the territorial level (LLSs)* and is calculated as the ratio of the rolling composite sum (of patent applications) defined at the level of each "sector ℓ - LLS" pair in the sample to the total number of applications pertaining to the ℓ*-th* sector of industrial activity at the national level (in other words, the summation process is additionally computed by LLSs at the denominator):

$$innov\_lls_{(lls,\ell,t)} = \frac{\sum_{L=0}^{4} patents_{(lls,\ell,t-L)}}{\sum_{L=0}^{4} \sum_{lls} patents_{(lls,\ell,t-L)}}$$

The variable *innov_lls* (that is bounded between 0 and 1) is assigned to firms in the balanced panel according to their sector of specialization ℓ, to the pivotal year *t* and to the LLS where they are located. The mean value of the index is 0.027 and identifies a codified innovative activity that is spread across sectors and local labor systems in Italy. At the sectoral level, patenting attitude can be summarized as follows: patents are predominant in the electronic sector (with an average number of 19 applications, in the period 2004-11), followed by the pharmaceutical sector (average number of 15 applications, in the same period), the chemical sector (average number of 8 applications) and the food sector (average number of 5 applications).

Fig.4 – Index of territorial patent intensity (innov_lls) in the Italian manufacturing industry: mean values 2004-11



[146]. Only 800 innovative firms (out of 4,800) are instead present in our balanced geo-referenced panel.

It can be argued that the index of territorial innovation *innov_lls* is merely the reflection of the investments undertaken by single leading firms. We have to control for this phenomenon in estimation. For this purpose, the model is augmented by three interacted variables: dimensional dummies[147] *small*, *medium* and *large* are interacted with our proxy for territorial patent intensity. Interacted variables are likely to document whether the (expected) positive effect of innovation on TFP survives in correspondence to the clusters of small and medium-sized firms, which represent the most penalized clusters from the point of view of the pursuit of direct innovative activity.

Moreover, we constructed a control variable, namely the *index of relative patent intensity at the firm level*. The variable *innov_firm* is the ratio of patent applications of a firm i that is specialized in sector ℓ (in the pivotal year t and in the previous four years, rolling composite sum) to the sum of applications performed at the level of the ℓ*-th* sector in the local labor system where firm i locates:

$$innov\_firm_{(i,\ell,t)} = \frac{\sum_{L=0}^{4} patents_{(i,\ell,t-L)}}{\sum_{L=0}^{4} patents_{(lls,\ell,t-L)}}$$

The mean value of the index is 0.044 and the median value is 0 because of the limited number of Italian firms that gained a direct access to patenting activity (around 9% in our balanced panel). In particular, 3% of firms are assigned one patent application and 2% of firms two applications[148]. Again, the evidence can be interpreted in favor of an innovative activity that is spread across firms belonging to a specific "sector ℓ - LLS" pair and, in general, across broad dimensional clusters in our dataset[149].

The SARAR model includes an additional set of control variables:

- the binary variables *medium* and *large* identify the belonging of a generic firm i (in the specific year t) to the subsets of medium and large firms[150]. The former variables are suitable for capturing additional TFP premiums that are associated *a priori* to medium and large firms, as comparison to the baseline group (small firms);
- a time-specific component m_t accounting for business cycle effects (yearly dummies);
- an industry-specific component m_ℓ capturing sectorial peculiarities of the TFP behavior (at the level of branches of industrial activity, Table 1). It is

[147]. Dimensional dummies are constructed based on the number of workers according to EU definitions: small firms employ less than 50 workers. Medium-sized firms employ a number of workers that spans from 50 to 249. Large firms employ more than 249 workers.

[148]. The latter value (2 patent applications) corresponds to the median value of the applications that are mapped in the sample. Conversely, the average value corresponds to 6 applications. More specifically, the mean value of patent applications is 2 in the cluster of small firms (that account for 30% of innovative firms), 3 in the cluster of medium firms (that account for 49%) and 15 in the cluster of large firms (that account for the residual 21%).

[149]. The same check has been executed over the subsample of firms that were dropped from the original unbalanced dataset (the one exploited to estimate productivity), in order to uncover the presence of potential differences with respect to the balance dataset described so far. A mean value of 2.5 emerges in correspondence to the variable measuring territorial innovation and a mean value of 4.2 is identified in correspondence to the index of relative patent intensity at the firm level.

[150]. According to the EU definitions medium-sized firms employ fewer than 250 workers but and more than 49 workers.

worth stressing that industrial branches are an aggregate version of the sectorial breakdown that is considered in the input-output matrix mentioned in Section 3.1.2: i.e. the one that is incorporated in the sectoral spatial weights matrix. Moreover, it is worth emphasizing again that sectoral weights are set to closely mirror inter-sectoral trade at the beginning of the observation period in order to preserve the exogeneity of the matrix;

- a territorial specific component m_g accounting for territorial peculiarities of the TFP phenomenon (four categorical variables are exploited to identify broad macro-areas: North-East, North-West, Center, South and Islands).

In addition to macro-geographical dummies, an index proxying for regional infrastructural endowment is included. We use indicators of infrastructural development calculated by the Association of Italian Chambers of Commerce (Unioncamere), in collaboration with Guglielmo Tagliacarne Research Institute[151]. The index *infra* (where the subscript *r* denotes regions) is suitable for absorbing additional spatial heterogeneity that is attributable to common features in the way of exploiting territorial infrastructures and institutional facilities (that might differ considerably from one region to the other)[152].

Furthermore, the binary variables *distr* and *tech* account for whether firms belong to traditional manufacturing clusters. Reference is made to industrial districts and technological clusters. As stated earlier, industrial districts represent agglomerations of firms specialized into typical "Made in Italy" products. Technological clusters are instead inclusive of firms specialized into technological-based activities (aerospace and aeronautical sectors, pharmaceutical sector, Ict). The industrial clusters' specifications are designed to closely mirror the analytical criteria adopted by the Intesa Sanpaolo Research Department (144 Italian industrial districts and 22 technological clusters are monitored periodically)[153] and encompass the strategic proximity to urban areas[154] (industrial districts completely overlap with urban areas, in a few cases). The variables are suitable for capturing additional premiums that are associated *a priori* to firms that locate within industrial districts (22% in the dataset) and technological clusters (2% of firms in the dataset), because of the presence of tangible and intangible factors that are likely to enhance individual TFP, and that cannot be explicitly modeled in our SARAR framework. These clusters are in fact regarded as a networked microcosm where firms benefit from a strategical positioning that is not entirely explained by the knowledge transfer. Reference is made in particular to an higher propensity to export, that triggered performance premiums in the recent recessionary years[155].

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[151]. The indicators were successfully employed in other works based on Italian data. See for example the paper by Minetti and Zhu (2011).

[152]. We assume that a direct link is established between regional infrastructural endowment and firm specialization and only an indirect link is in place with productivity. Nevertheless, the index is suitable for absorbing spatial heterogeneity.

[153]. For further details refer to the periodical reports "Industrial Districts Monitor" (quarterly) and "Economics and Finance of Industrial Districts" (yearly) edited by Intesa Sanpaolo, Research Department.

[154]. There are no reasons to retain *a priori* that industrial districts, being an agglomeration of firms sharing a common specialization, are necessarily located far apart with respect to urban areas.

[155]. For a detailed analysis see the 8th edition (2015) of the report "Economics and Finance of Industrial Districts" issued by Intesa Sanpaolo, Research Department.

Finally, firm level heterogeneity is accounted for by using a random effects estimation framework (RE). The reduced time variability of covariates in the model render an estimation approach based on fixed effects an unfeasible option. Regressors are almost time invariant (with the main exception of the spatial lag variable), especially the ones that mirror the innovation activity. Nevertheless, the degree to which our sample is representative allows selected firms to be reasonably considered as randomly drawn from a bigger population (random specific unobserved heterogeneity).

3.3 *Estimation details*

From the point of view of an econometric estimation of model *[5]*, it is worth stressing again inconsistency and inefficiency of standard panel data estimators (i.e. the RE panel estimator) that do not account for the correlation in place between errors and the spatially lagged dependent variable.

To address the problem of endogeneity we resort to a 2SLS (Two Stage Least Squares) or GM/IV estimator for models with random effects[156].

Specifically, the Generalised Moments (GM) estimator has been introduced by Kelejian and Prucha (1999) to consistently estimate a spatial model with spatially correlated error components. Kapoor et al. (2007) suggest a generalization of the GM estimator to be applied to a spatial model with random effects. The first stage of the estimation by OLS (Ordinary Least Squares) is designed to return consistent residuals, that represent in turn the basis of the error process parameter estimation.

Subsequent works extended the estimation strategy to models with an additional spatial lag variable. The OLS estimation strategy in the first stage is replaced by an IV estimation in order to retain consistency[157].

Specifically, we resort to a customized version of the available GM/IV package in R (*spgm*), tailored to solve computational issues pertaining to dense spatial weights matrices[158]. Dense matrices are a direct consequence of an estimation

[156]. The GM/IV multi-step procedure is likely to bypass the problem of calculating the log-determinant of the (*n x n*) asymmetric matrix $(I - \lambda W)$ in the log-likelihood function, that represents the critical point of the maximum likelihood estimator (when large samples are considered) and to relax as well the normal distributional assumption on disturbances.

[157]. The endogeneity of the spatially lagged dependent variable in a spatial model requires an IV approach to be implemented. The ideal instrument set for the spatial lag, in a generic spatial SAC/SARAR model of the type $y= X\beta +\lambda Wy +u$, with $u= \rho Wu +\varepsilon$, is represented by its expected value (conditional to the exogenous covariates of the model): $E(Wy|X)$. In other words, the set H must contain at least linearly independent columns of (X, WX): $H = [\ X, WX, W^2X, \ldots]$. The proposed 2SLS estimator is based on the crucial assumption $E(H'u)=0$.

[158]. The R package *splm* (Millo and Piras, 2012) was modified in order to deal with dense matrices of distances, by resorting to the class 'dgeMatrix' and to the Lapack routine of the package 'Matrix' (Bates and Maechler, 2014). The routine is suitable for optimizing linear algebra calculations and matrix operations in the presence of dense numeric matrices. Moreover, all the kronecker products that involve the use of big dense spatial matrices W were decomposed accordingly, reducing the allocated memory. In some extreme cases (as the one of a matrix exceeding 80 GB) matrices were stored as memory-mapped files, using the infrastructures 'bigmemory' and 'bigalgebra' (Kane et al., 2013).

strategy that is based on micro-data. A simplified scheme is selected to weight sample moments, in order to account for the size of the dataset[159].

4. Commenting on empirical estimates

Estimation results are presented in Table 3. The focus is on the autoregressive parameter λ, the one capturing the strength of spatial lag dependence in productivity data or, in other words, the strength of endogenous interaction effects and feed-back effects that are incorporated in total factor productivity. The estimated coefficient is positive and statistically significant across all the specifications that are selected to identify the spatial neighborhood. This corroborates previous findings about the existence of spillovers that characterize the formation process of total factor productivity. In other words, the recursive structure that is typical of spatial models identifies productivity as the expression of a steady state equilibrium of a system of endogenous interactions between sampled firms, and of feedback effects that originate from changes to TFP determinants (or shocks to TFP) within the neighborhood. Our indirect spatial production function framework focuses especially on innovation and on the knowledge transfer as total factor productivity-enhancing mechanisms. Specifically, the transfer of knowledge is driven, in our case, by both geographical proximity of firms and sectoral linkages.

The W spatial weights matrices so far considered incorporate by construction first order neighbors, but the recursive spatial structure allows a propagation mechanism to emerge, involving higher order neighbors.

Let us discuss in greater detail the estimated values for λ. When a geographical definition is considered to model spatial interactions between sampled manufacturing firms (with a cut-off at 50 Km), results support the view of a predominance of externalities of the Jacobian type. Interaction effects are stronger in the case of sectorally heterogeneous proximate firms (W_{ghets} spatial weights matrix): the estimated coefficient is 0.665, compared to a coefficient of 0.387 in the case of sectorially homogeneous firms (W_{ghom} spatial weights matrix). The latter interaction matrix was designed to investigate externalities that concern knowledge spillovers between firms in an industry. Reference is made to Marshallian-Arrow-Romer (MAR) externalities or Porter's externalities, depending on the hypotheses that we are willing to formulate on the structure of the operating framework (local monopoly of ideas versus local competition within the industry).

As stated earlier, all these theories of dynamic externalities deal with knowledge spillovers: innovations and improvements occurring in one firm increase the productivity of the other firms (without full compensation) and a pure knowledge spillover occurs. MAR externalities and Porter's externalities concerns knowledge spillovers between firms in an industry (within industry) while Jacobian externalities refer to knowledge spillovers between industries. Estimates confirm the theoretical findings. We identify a positive effect of our index of territorial relative patent intensity on total factor productivity, across all the

[159]. The asymptotic variance covariance matrix of sample moments involves a computational count of up to $O(n^3)$.

selected definitions of neighborhood. Nevertheless, when an indirect production function approach is considered to investigate the knowledge transfer, as in this case, empirical results have to be interpreted in favor of complex knowledge transfers mediated by market exchanges. Specifically, complex spillovers occur when a new input is sold but the producer cannot fully appropriate the increased quality of the product. Some of the surplus is appropriated by the downstream producers[160]. Direct and indirect impacts of the variable *innov_lls* are presented in Table 4.

In a spatial framework the change of a variable at the level of a single firm *i* produces an impact on both the dependent variable of the firm itself and the dependent variable of neighboring firms *j*. The former impact is called the direct effect and the latter impact the indirect effect (additional details are included in the Appendix). Since direct and indirect effects are different for different units in the sample, summary indicators or average effects are reported. We resorted to a simulation strategy in order to compute distributions for the impact measures and to retrieve information on their significance[161].

It is worth stressing that indirect impacts have to be carefully evaluated in this case. In fact, emphasis is placed on a territorial index of relative patent intensity. The variable is not firm-specific. In light of this, indirect impacts generated by the recursive structure of the spatial model are likely to be potentially overestimated. For this reason, we concentrate especially on direct impacts.

As expected, firms that belong to a patent intensive area benefit from total factor productivity premiums. Specifically, we find a positive and strongly significant impact of territorial innovation on TFP in correspondence with the cluster of small firms (interacted variable *innov_lls*small*), across all the selected specifications of the SARAR model. Innovation plays a key role in enhancing total factor productivity, irrespective of firm dimensions.

Moreover, results are robust to the inclusion of a firm-level index of relative patent intensity in the estimation framework (variable *innov_firm*). In light of this, a patent intensive operating area can be regarded as a stimulus to total factor productivity, regardless of the individual propensity to innovate.

The primary role of sectoral heterogeneity in driving the convergence process of total factor productivity within the neighborhood needs to be further investigated. It is possible to abstract from a standard geographical definition of space. In other words, the notion of interaction distance can be modeled via input-output matrices. The W_s matrix represents a proxy of the supply chains that are present in the Italian manufacturing base. When spatial weights are modeled to mirror the demand for intermediate consumption in the manufacturing industry, the strength of the convergence path in TFP (λ coefficient) is 0.290. Nevertheless, this value for λ is not directly comparable to the one estimated in the geographical setting (W_{ghets} matrix). In light of this, we resort to an interacted matrix $W_{\text{interacted}}$ in order to better discriminate between sectorally heterogeneous neighbors in the geographical setting. Specifically, by interacting the matrices W_{ghets} and W_s we

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160. In this case the mechanism does not create *per se* further innovation and endogenous growth. Conversely, pure knowledge spillovers occur when firms benefit from the R&D activity undertaken by neighboring firms without providing direct compensation for it. Innovation becomes a publicly available stock of knowledge.

161. Reference is made to the command *impacts* in the *spdep* package.

allow the pairwise relationships included in the geographical matrix W_{ghets} to be re-defined, based on the relative importance of bilateral inter-sectoral trade in the economy. In this case, the strength of the endogenous interaction effects in total factor productivity takes on an estimated value of 0.378. The value is similar to the one estimated in the case of sectorally homogeneous firms (W_{ghom} matrix). Results are robust to the inclusion of a set of controls in the estimation framework, that are suitable for partially absorbing spatial heterogeneity (i.e. macro-geographical dummies, sectoral dummies, index of infrastructural endowment at the regional level, variables *tech* and *distr*). Moreover, dimensional dummies *medium* and *large* account for the *a priori* capacity of larger firms to accumulate a considerable stock of knowledge (that is incorporated into human capital and within the production process itself), that in turn stimulates innovation and productivity.

In light of the above, innovation emerges as a primary TFP-enhancing mechanism, that is likely to foster the convergence of levels of total factor productivity of neighboring firms. This mechanism does not appear to work differently across sectorally heterogeneous proximate firms, as comparison to sectorally homogeneous proximate firms in the sample. The strength of the convergence path in TFP, measured by λ, is in fact pretty similar, regardless of the selected definition of the interaction matrix. At the same time, such a result is likely to prompt a revaluation of the role played by traditional industrial clusters in the Italian manufacturing base (i.e. industrial districts), frequently overlooked in the recent years - because of the shift of focus on urban effects (sectorial heterogeneity) as a stimulus to growth.

The positive stimulus exerted by territorial patent-attitude on total factor productivity, in addition to the individual propensity to innovate, is likely to support the view of a predominance of a local competition framework between firms - that is consistent with both the Porter's theory of externalities within an industry and the Jacobs's theory of externalities (that stem from heterogeneous sectoral specialization of firms). Porter (1990) has brought concrete empirical evidence of Italian ceramics and gold jewelry industries, in which hundreds of firms are located together and fiercely compete to innovate – since the alternative to innovation is demise. Both the industries are mapped in the *Intesa Sanpaolo Integrated Database* (ISID) and are therefore included in our analysis. The ISID database, managed by the Intesa Sanpaolo Research Department, is indeed exploited to conduct a periodical analysis on Italian manufacturing districts. Moreover, the structure of Italian industrial districts fits nicely with the traditional theory of Marshall (1890), which argues that firms in the same industry locate close to each other in order to share inputs, including specialized labor. Spreading the same employment over neighboring firms increases local competition between firms.

Furthermore, the hypothesis of local competition fits nicely with a negative autocorrelation parameter ρ that is estimated when a geographical setting is selected. The parameter is the expression of the interaction effects among the error terms of our SARAR model. A negative residual spatial dependence is consistent with the view of productivity shocks that spread negatively in a geographical competitive environment, irrespective of the selected interaction matrices (sectorally homogeneous or heterogeneous firms). The only exception in

Table 3 is represented by the SARAR model with a pure sectoral interaction matrix, that displays positive residual spatial dependence. The latter framework is in fact suitable for investigating the behavior of firms that interact along a supply chain; these firms are likely to behave according to a cooperative scheme of spatial interaction.

At the same time, the autocorrelation parameter ρ could potentially pick-up the effect of variables that are omitted from the model (or unobserved) and that display spatial patterns (i.e. reference is made to characteristics that firms have in common). It is worth stressing that the selected specification of our SARAR model follows Kapoor et al. (2007) in the way of treating unobserved heterogeneity. Specifically, we consider a random specific unobserved heterogeneity that is allowed to be spatially lagged. The autocorrelation in errors proves to be stronger in the geographical setting, compared to the pure sectoral setting of inter-firm interaction.

Results bring concrete evidence of the complexity of the interaction effects that occur between proximate firms. The way in which firm interaction is modeled in the proposed spatial framework represents a step forward towards a more realistic econometric formulation of the interactive behavior of manufacturing firms, and of the multidirectional nature of total factor productivity data as well.

5. Robustness checks

In addition to the baseline geographical matrices described in Section 3.1.1, with a cut-off set at 50 Km to identify geographically neighboring firms, the proposed SARAR model was estimated incorporating matrices with different cut-offs. Additional cut-offs were set at 20 Km, 30 Km, and 40 Km respectively. We check for the relevance of endogenous interaction effects and convergence between levels of total factor productivity of Italian firms once the neighboring structure is set to be restricted. Results are provided in the Appendix.

Furthermore, binary matrices were employed as an additional robustness check. In this case spatial weights take on a value of one if firms are neighbors in a geographical radius of 50 Km and zero otherwise. However it is worth stressing that these matrices do not account for the relative importance of neighboring firms within the radius. In fact, neighboring firms are assigned the same spatial weight (that is equal to one) regardless of the relative distance from a target firm. Results are provided in the Appendix.

Table 3 - Coefficient estimates

	SARAR W_{ghom} ***matrix: Geographical setting (common sectoral specialization) cut-off 50Km***			***SARAR*** W_{ghet} ***matrix: Geographical setting (heterogeneous sectoral specialization) cut-off 50Km***			***SARAR*** W_s ***matrix: Pure sectoral setting***			***SARAR*** $W_{interacted}$ ***matrix: Interacted geographical and pure sectoral settings***		
	Coefficient		***Std. err***	***Coefficient***		***Std. err***	***Coefficient***		***Std. err***	***Coefficient***		***Std. err***
λ (spatial lag autor. parameter)	0.387	***	(0.020)	0.665	***	(0.026)	0.245	***	(0.042)	0.378	***	(0.027)
ρ (error term autor. parameter)	-0.194[(a)]			-0.298[(a)]			0.048[(a)]			-0.013[(a)]		
*Innov_lls*small*	0.186	***	(0.044)	0.144	***	(0.045)	0.282	***	(0.046)	0.189	***	(0.046)
*Innov_lls*medium*	0.236	***	(0.052)	0.211	***	(0.053)	0.336	***	(0.053)	0.250	***	(0.053)
*Innov_lls*large*	0.857	***	(0.099)	0.839	***	(0.100)	0.954	***	(0.101)	0.869	***	(0.101)
Innov_firm	0.069	***	(0.008)	0.073	***	(0.009)	0.073	***	(0.009)	0.072	***	(0.009)
Medium	0.134	***	(0.005)	0.143	***	(0.005)	0.144	***	(0.005)	0.144	***	(0.005)
Large	0.306	***	(0.013)	0.327	***	(0.013)	0.330	***	(0.013)	0.329	***	(0.013)
Distr	0.020	**	(0.007)	0.022	**	(0.007)	0.023	**	(0.007)	0.025	**	(0.007)
Tech	0.059	**	(0.020)	0.110	***	(0.021)	0.104	***	(0.021)	0.095	***	(0.021)
Index for infrastructural endowment (regional)	0.001	***	(0.000)	0.001	***	(0.000)	0.001	***	(0.000)	0.001	***	(0.000)
Intercept	2.270	***	(0.080)	1.107	***	(0.106)	2.755	***	(0.182)	2.256	***	(0.115)
Time dummies (m_t)			added			added			added			added
Sectoral dummies (m_ℓ)			added			added			added			added
Macro-geogr. dummies (m_v)			added			added			added			added
Number of observations			70,424			70,424			70,424			70,424
σ^2_ε (var. idiosyncratic error)			0.066			0.067			0.068			0.068
$\sigma^2_1 = \sigma^2_{\varepsilon} + T\sigma^2_\mu$			0.865			0.831			0.858			0.843
$\theta = 1 - \sigma^2_\varepsilon / \sigma^2_1$			0.724			0.715			0.719			0.716

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1. Note: Standard errors are in parentheses. (a) The GM/IV approach does not allow testing for the significance of the autocorrelation coefficient. The inclusion of an additional autoregressive structure in the error equation is justified by Conditional LM tests.

Table 4 – Direct and indirect impacts

	SARAR			SARAR			SARAR			SARAR		
	W_{ghom} matrix: Geographical setting (common sectoral specialization) cut-off 50Km			W_{ghet} matrix: Geographical setting (heterogeneous sectoral specialization) cut-off 50Km			W_s matrix: Pure sectoral setting			$W_{interacted}$ matrix: Interacted geographical and pure sectoral settings		
	Coefficient		Simulated z-value	Coefficient		Simulated z-value	Coefficient		Simulated z-value	Coefficient		Simulated z-value
Direct impacts												
*Innov_lls*small*	0.187	***	4.128	0.144	***	3.212	0.282	***	6.220	0.189	***	4.007
*Innov_lls*medium*	0.236	***	4.819	0.212	***	4.100	0.336	***	6.429	0.250	***	4.918
*Innov_lls*large*	0.859	***	8.596	0.840	***	8.875	0.954	***	9.371	0.869	***	8.563
Innov_firm	0.069	***	8.156	0.073	***	8.330	0.073	***	8.590	0.072	***	8.533
Medium	0.134	***	25.375	0.143	***	26.106	0.144	***	26.926	0.144	***	27.064
Large	0.306	***	23.178	0.327	***	25.450	0.330	***	25.029	0.329	***	24.940
Distr	0.020	**	2.909	0.022	***	3.139	0.023	***	3.366	0.025	***	3.531
Tech	0.060	**	2.953	0.111	***	5.224	0.104	***	4.816	0.095	***	4.429
Indirect impacts												
*Innov_lls*small*	0.117	***	4.128	0.285	***	3.217	0.091	***	3.639	0.115	***	3.837
*Innov_lls*medium*	0.149	***	4.637	0.419	***	4.010	0.109	***	3.686	0.152	***	4.441
*Innov_lls*large*	0.540	***	7.173	1.661	***	6.344	0.309	***	4.085	0.528	***	6.164
Innov_firm	0.043	***	6.832	0.144	***	5.985	0.024	***	3.969	0.044	***	6.077
Medium	0.084	***	11.286	0.283	***	8.301	0.047	***	4.396	0.087	***	8.226
Large	0.193	***	11.151	0.647	***	8.353	0.107	***	4.398	0.200	***	8.206
Distr	0.012	**	2.841	0.044	**	2.968	0.008	**	2.657	0.015	***	3.254
Tech	0.037	**	2.976	0.219	***	4.511	0.034	***	3.257	0.058	***	3.936

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1.

Conclusions and future directions

The goal of the Chapter was to assess knowledge spillovers at the micro level. We resorted to an indirect spatial production function approach of the SARAR type where interaction matrices are structured according to the theoretical literature on externalities that stem from geographical proximity of firms. Reference is made to Marshall-Arrow-Romer (MAR) or Porter's externalities within an industry and to Jacobian externalities that occur between heterogeneously specialized firms. Moreover, we considered sectoral input-output matrices in order to extend the notion of interaction distance.

We brought concrete evidence of the importance to consider a spatial framework of simultaneous endogenous interaction effects in dealing with series of data that characterize for spatial dependence. Total factor productivity benefits from positive spatial effects, regardless of the selected definition of the interaction matrix. Innovation emerges as a key TFP-enhancing mechanism, that fosters the convergence of levels of total factor productivity within the neighborhood. Specifically, a patent intensive and competitive operating ground can be regarded as a stimulus to individual total factor productivity. In light of this, the fragmented Italian production base can still be regarded as a plus in the formation of spillover effects, although the firms' reduced dimensions act *per se* as a friction to investment in strategic factors. These results are likely to gain importance because of the challenging economic and operating environment that emerged after the severe 2009 recession.

The proposed SARAR framework is not intended to be a perfect representation of the real complex interactions between Italian manufacturing firms but moved indeed a step forward towards a more realistic modelling of inter-firm interaction. Future research directions encompass the estimation of a spatial dynamic framework that incorporates both a spatial lag variable and a time lag of the dependent variable. The theoretical literature on spatial models is growing rapidly. Nevertheless, empirical applications and statistical programming facilities are still lagging behind. Statistical packages need to be extended to incorporate dynamic spatial panels, and GMM estimators especially, that represent the only feasible option in micro applications – when the spatial modelling applies to many thousands of firms, as in this case.

Moreover, the recent diffusion of network agreements in the Italian manufacturing context is fostering progressive changes in the traditional clustered nature of Italian firms. The trans-territorial nature of these agreements clearly emerges from preliminary analyses (see Foresti et al., 2015). Very often, therefore, the process of looking for complementarity skills – that represents the primary scope of these agreements - goes beyond pure geographical borders and/or traditional industrial clusters. In order to model these important changes in the way of "doing business" in Italy, spatial econometric techniques need to necessarily point in the direction of a more abstract space of interaction between firms.

Appendix A: Labor force missing values estimation procedure

The recursive procedure adopted to estimate missing data on the labor force (around 20% of observations in the dataset) incorporates multiple steps.

When information on labor costs is available for at least two years within the observation period, the number of workers is estimated by resorting to a simple interpolation (OLS estimator) - controlling for firm size based on the European Commission's thresholds.

In cases where the first stage estimation framework returns a negative value for workers, a second step is performed, based on a Weighted Least Squares (WLS) estimator. Weights are calculated as the reciprocal of the labor costs, including industry and province dummies as controls. The firms that have a negative value for estimated workers at the end of the second step, are removed from the sample.

By contrast, in cases where information on labor costs is not made available for at least two years in the observation period, the WLS procedure uses sectoral weights (maximum detailed sectoral breakdown). Negative estimated values are removed from the sample.

As a final step, estimated positive values for workers are augmented by a stochastic error. This error is distributed according to a normal distribution, with zero mean and variance equal to the variance of the distribution of the labor force item that is observed in financial statements (80% of observations in the sample present point information on the labor force).

Appendix B: The Levinsohn and Petrin two-step estimation strategy of total factor productivity, value added case

Letting y_{it} be value added and l_{it} and k_{it} labor and capital of a firm i at time t, the logarithmic transformation of a Cobb-Douglas production function is:

$$y_{it} = \beta_0 + \beta_l l_{it} + \beta_k k_{it} + \phi_{it}$$
$$\phi_{it} = \omega_{it} + \varepsilon_{it} \qquad [A_1]$$

ϕ_{it} denotes a composite error term. The latter is inclusive of the unobserved productivity shock ω_{it} and the idiosyncratic error term ε_{it} that is uncorrelated with the inputs. The labor input is assumed to be potentially endogenous because of correlation with ω_{it}. The estimation strategy from Levinsohn and Petrin exploits the demand for intermediate inputs m_{it} as a control term to solve for the simultaneity bias. m_{it} is assumed to depend on capital and unobserved productivity ω_{it} and to be monotonically increasing in ω_{it}:

$$m_{it} = m_{it}(k_{it}, \omega_{it}) \qquad [A_2]$$

This property allows m_{it} to be inverted, so that ω_{it} can in turn be rewritten as a function $h(.)$ of observed inputs:

$$\omega_{it} = h_{it}(k_{it}, m_{it}) \qquad [A_3]$$

and equation $[A_1]$ can be rewritten as:

$$y_{it} = \beta_0 + \beta_l l_{it} + \beta_k k_{it} + \omega_{it} + \varepsilon_{it}$$
$$= \beta_l l_{it} + h(k_{it}, m_{it}) + \varepsilon_{it} \qquad [A_4]$$

where $h(k_{it}, m_{it}) = \beta_0 + \beta_k k_{it} + \omega_{it}(k_{it}, m_{it})$

The functional form of $h(.)$ is not known. Therefore the β_k coefficient cannot be estimated at this stage. A partially linear model including a third-order polynomial expansion in capital and intermediate inputs (that is referred to as φ_{it}) to approximate the form of the $h(.)$ is estimated by OLS.

$$\varphi_{it} = \beta_0 + \beta_k k_{it} + h_{it}(k_{it}, m_{it}) \qquad [A_5]$$

Thus,

$$h_{it}(k_{it}, m_{it}) = \varphi_{it} - \beta_k k_{it} \qquad [A_6]$$

This completes the first stage of the estimation routine, from which an estimate of β_l and h_{it} (up to the intercept) are available[162].

The second stage of the routine identifies the coefficient β_k. It considers the expectation of $y_{it+1} - \beta_l l_{it+1}$:

[162]. At this stage β_0 is not separately identified from the intercept of $h_{it}(k_{it}, m_{it})$.

$$E[y_{it+1} - \beta_l l_{it+1} | k_{it+1}] = \beta_0 + \beta_k k_{it+1} + E[\omega_{it+1} | \omega_{it}] \qquad [A_7]$$

Assuming that ω_{it} follows a first-order Markov process[163], one can rewrite ω_{it+1} as a function of ω_{it}, letting ξ_{it+1} be the innovation in ω_{it+1}. Using *[A₃]* and *[A₆]*, equation *[A₇]* becomes a function of m_{it} and k_{it}:

$$y_{it+1} - \beta_l l_{it+1} = \beta_k k_{it+1} + g(\varphi_{it} - \beta_k k_{it}) + \xi_{it+1} + \varepsilon_{it+1} \qquad [A_8]$$

where g is a third-order polynomial of $\varphi_{it} - \beta_k k_{it}$.

This is the equation to be estimated in the second stage of the procedure. Only in this stage it is possible to obtain consistent estimates of β_k. Since the capital in use in a given period is assumed to be known at the beginning of the period (state variable) and ξ_{it+1} is mean independent of all variables known at the beginning of the period, ξ_{it+1} is mean independent of k_{it+1}.

A nonlinear least-squares method is generally used to estimate the above equation. The alternative are non-parametric kernel methods.

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163. Past levels of productivity (with the only exception of the first lag) do not provide information about future productivity.

Appendix C: Direct and Indirect impacts

In spatial models if a particular explanatory variable in a particular unit changes, not only will the dependent variable in that unit itself change, but also the dependent variables in other units. The first is called the direct effect and the second the indirect effect.

Since the disturbances do not come into play when considering the partial derivative of the dependent variable with respect to changes in the explanatory variables, we will provide a point description of direct and indirect impacts in the case of a simple SAR model of the type: $y = \lambda Wy + X\beta + \varepsilon$

The data generating process of the model is: $y = (I-\lambda W)^{-1} X\beta + (I-\lambda W)^{-1} \varepsilon$

Direct impacts can be expressed as: $\frac{\partial y_i}{\partial x_{ik}}$ (own derivative)

They identify the effects on y_i resulting of a change in the *k-th* explanatory variable x_k in the *i-th* firm.

Indirect impacts are instead expressed as: $\frac{\partial y_j}{\partial x_{ik}}$, $j \neq i$ (cross-partial derivative)

and identify the effects on y_j resulting of a change in the *k-th* explanatory variable x_k in the *i-th* firm. Dependence expands the information set to include information from neighboring firms.

Following LeSage (2008) the data generating process of the model can be rewritten as:

$$y = \sum_{k=1}^{h} S_k(W)x_k + (I_n - \lambda W)^{-1}\varepsilon$$

where $S_k(W) = (I_n - \lambda W)^{-1}\beta_k$

Whereas the direct effect of the k-th explanatory variable in the OLS model is β_k, the direct effect in the SAR and SARAR models is β_k premultiplied with a number that will eventually be greater than or equal to unity. This can be seen by decomposing the spatial multiplier matrix as follows:

$$(I_n - \lambda W)^{-1} = I + \lambda W + \lambda^2 W^2 + \lambda^3 W^3 \ldots$$

Since the non-diagonal elements of the first term (identity matrix I) are zero, this term represents a direct effect of a change in X only. λW represents instead an indirect effect of a change in X that is limited to first order neighbors, because W is taken at the power of 1. All the other terms represent second and higher-order direct and indirect effects. Higher-order direct effects arise as a result of feed-back effects (impacts passing through neighboring units and back to the unit itself). It is these feedback effects that are responsible for the fact that the overall direct effect is eventually greater than unity.

In light of the above, impacts on y_i from changes in the *k-th* explanatory variable x_k in the *i-th* firm can be expressed as: $\frac{\partial y_i}{\partial x_{ik}} = S_k(W)_{ii}$

and impacts on y_j from changes in the *k-th* explanatory variable x_k in the *i-th* firm*:*

$\frac{\partial y_j}{\partial x_{ik}} = S_k(W)_{ji}$, $j \neq i$

To summarize, any change to an explanatory variable in a single firm can affect the dependent variable in all firms. This is a logical consequence of the simultaneous spatial dependence model we are considering.

As stated in Elhorst (2014) direct and indirect effects are different for different units in the sample. Direct effects are different because the diagonal elements of the matrix $(I_n - \lambda W)^{-1}\beta_k$ are different for different units (provided that $\lambda \neq 0$). Indirect effects are different because both the off-diagonal elements of the matrix $(I_n - \lambda W)^{-1} \beta_k$ and of the matrix W are different for different units.

LeSage and Pace (2009) propose to report summary indicators for both the direct and the indirect effects. The average direct impact is obtained by averaging the diagonal elements of $S_k(W)$. A summary indicator for the indirect effect can be obtained by averaging either the row sums or the column sums of the off-diagonal elements of the matrix.

Elhorst (2014) stresses the attention over an important limitation of the spatial lag model: the ratio between the indirect and the direct effect of a particular explanatory variable is independent of β_k[164]. This implies that the ratio between the indirect and direct effects in the spatial lag model is the same for every explanatory variable. Its magnitude depends on the spatial autoregressive parameter λ and the specification of the spatial weights matrix W only.

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[164]. β_k in the numerator and β_k in the denominator of the ratio cancel out.

Appendix D1: robustness checks geographical setting, common sectoral specialization

	SARAR			SARAR			SARAR			SARAR		
	Cut-off 20Km			Cut-off 30Km			Cut-off 40Km			Cut-off 50Km, binary matrix		
	Coefficient		*Std. err*	*Coefficient*		*Std. err*	*Coefficient*		*Std. err*	*Coefficient*		*Std. err*
λ (spatial lag autor. parameter)	0.151	***	(0.019)	0.246	***	(0.020)	0.329	***	(0.020)	0.485	***	(0.019)
ρ (error term autor. parameter)	0.004[a]			-0.068[a]			-0.139[a]			-0.361[a]		
*Innov_lls*small*	0.232	***	(0.046)	0.214	***	(0.045)	0.197	***	(0.045)	0.198	***	(0.044)
*Innov_lls*medium*	0.294	***	(0.053)	0.266	***	(0.053)	0.247	***	(0.052)	0.241	***	(0.051)
*Innov_lls*large*	0.904	***	(0.101)	0.890	***	(0.101)	0.872	***	(0.100)	0.867	***	(0.099)
Innov_firm	0.073	***	(0.009)	0.070	***	(0.009)	0.069	***	(0.009)	0.067	***	(0.008)
Medium	0.139	***	(0.005)	0.138	***	(0.005)	0.136	***	(0.005)	0.130	***	(0.005)
Large	0.318	***	(0.013)	0.314	***	(0.013)	0.310	***	(0.013)	0.301	***	(0.013)
Distr	0.021	**	(0.007)	0.020	**	(0.007)	0.020	**	(0.007)	0.020	**	(0.007)
Tech	0.089	***	(0.021)	0.077	***	(0.021)	0.066	**	(0.020)	0.060	**	(0.019)
Index for infrastructural endowment (regional)	0.001	***	(0.000)	0.001	***	(0.000)	0.001	***	(0.000)	0.001	***	(0.000)
Intercept	3.203	***	(0.080)	2.824	***	(0.081)	2.498	***	(0.080)	1.883	***	(0.078)
Time dummies (m_t)			added			added			added			added
Sectoral dummies (m_ℓ)			added			added			added			added
Macro-geogr. dummies (m_v)			added			added			added			added
Number of observations			70,424			70,424			70,424			70,424
σ^2_ε *(var. idiosyncratic error)*			0.067			0.067			0.066			0.065
$\sigma^2_1 = \sigma^2_\varepsilon + T\sigma^2_\mu$			0.862			0.864			0.864			0.873
$\theta = 1 - \sigma^2_\varepsilon / \sigma^2_1$			0.721			0.722			0.723			0.727

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1. Note: Standard errors are in parentheses. (a) The GM/IV approach does not allow testing for the significance of the autocorrelation coefficient. The inclusion of an additional autoregressive structure in the error equation is justified by Conditional LM tests.

Appendix D2: robustness checks geographical setting, heterogeneous sectoral specialization

	SARAR Cut-off 20Km			SARAR Cut-off 30Km			SARAR Cut-off 40Km			SARAR Cut-off 50Km, binary matrix		
	Coefficient		Std. err	Coefficient		Std. err	Coefficient		Std. err	Coefficient		Std. err
λ (spatial lag autor. parameter)	0.391	***	(0.026)	0.530	***	(0.026)	0.595	***	(0.027)	0.754	***	(0.023)
ρ (error term autor. parameter)	-0.130[(a)]			-0.211[(a)]			-0.174[(a)]			-0.628[(a)]		
*Innov_lls*small*	0.197	***	(0.046)	0.167	***	(0.046)	0.151	***	(0.046)	0.188	***	(0.045)
*Innov_lls*medium*	0.258	***	(0.053)	0.233	***	(0.053)	0.218	***	(0.053)	0.263	***	(0.052)
*Innov_lls*large*	0.887	***	(0.101)	0.861	***	(0.101)	0.845	***	(0.101)	0.901	***	(0.100)
Innov_firm	0.073	***	(0.009)	0.073	***	(0.009)	0.073	***	(0.009)	0.073	***	(0.009)
Medium	0.142	***	(0.005)	0.143	***	(0.005)	0.143	***	(0.005)	0.143	***	(0.005)
Large	0.326	***	(0.013)	0.326	***	(0.013)	0.327	***	(0.013)	0.327	***	(0.013)
Distr	0.025	**	(0.007)	0.024	**	(0.007)	0.024	**	(0.007)	0.016	*	(0.007)
Tech	0.112	***	(0.021)	0.111	***	(0.021)	0.111	**	(0.021)	0.116	**	(0.021)
Index for infrastructural endowment (regional)	0.001	***	(0.000)	0.001	***	(0.000)	0.001	***	(0.000)	0.001	**	(0.000)
Intercept	2.215	***	(0.109)	1.655	***	(0.108)	1.389	***	(0.113)	0.747	***	(0.092)
Time dummies (m_t)			added			added			added			added
Sectoral dummies (m_ℓ)			added			added			added			added
Macro-geogr. dummies (m_v)			added			added			added			added
Number of observations			70,424			70,424			70,424			70,424
σ^2_ε *(var. idiosyncratic error)*			0.068			0.068			0.068			0.067
$\sigma^2_1 = \sigma^2_{\varepsilon} + T\sigma^2_\mu$			0.847			0.839			0.834			0.832
$\theta = 1 - \sigma^2_\varepsilon / \sigma^2_1$			0.717			0.716			0.715			0.715

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1. Note: Standard errors are in parentheses. (a) The GM/IV approach does not allow testing for the significance of the autocorrelation coefficient. The inclusion of an additional autoregressive structure in the error equation is justified by Conditional LM tests.

Appendix E: a comparison between the balanced panel and the subsample of deleted firms

Tab. C1- Sample composition by dimensional clusters

Dimensional cluster	*Balanced panel, composition (%)*	*Subsample of deleted firms, composition (%)*
small	66.27	67.19
medium	29.47	29.29
large	4.26	3.53

Tab. C2 - Sample composition by macro-geographical areas

Macro-geographical composition	*Balanced panel, composition (%)*	*Subsample of deleted firms, composition (%)*
North-east	35.19	30.86
North-west	42.53	36.72
Center	12.07	16.70
South and Islands	10.22	15.72

Tab. C3 - Sample composition by branches of economic activity

Branch	*Name*	*Balanced panel, composition (%)*	*Subsample of deleted firms, composition (%)*
1	Food and beverage	11.16	12.71
2	Textiles and textile products	7.61	8.36
3	Leather and footwear	3.16	3.40
4	Wood-made products (except furniture)	3.27	3.68
5	Paper, print and publishing sector	5.24	5.03
6	Chemical and pharmaceutical sector	5.63	4.84
7	Rubber and plastic products	7.26	7.00
8	Other non-metallic mineral products	6.35	7.13
9	Metallurgical products	21.30	18.55
10	Mechanic, electronic equipment, medical equipment	21.33	21.67
11	Transport equipment	2.79	3.18
12	Furniture sector	4.91	4.44

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Conclusive remarks

The present dissertation contributed to the debate that originated in the recent recessionary years.

We concentrated on financial rigidity that was characterizing Italian manufacturing firms at the eve of the last crisis as a key amplifier of shocks that occur to the real side of the economy. Moreover, we focused attention on the role played by liquidity constraints and trade credit interconnections in 2009-13, as a source of potential contagion effects that occurred along manufacturing supply-chains. Furthermore, in the last part of the dissertation emphasis was placed on knowledge spillovers and spatial patterns in total factor productivity (TFP).

The Italian manufacturing industry was selected as the preferred environment to conduct the analysis, because of its fragmented and clustered production structure, and because of the pronounced exposure of firms to bank debt.

Specifically, the first Chapter of the dissertation did focus attention on financial rigidity of firms as an amplifier of manufacturing dynamics during a recessionary phase. We concentrated on inventory investment dynamics during the severe 2008-09 shock, as comparison to the past shocks that affected the country. Inventories are in fact priority health status indicators, at both the macro and micro levels. A dynamic target adjustment model was selected and estimated on three large datasets that are representative of the Italian manufacturing base. Constrained firms (firms that were characterized by financial rigidity at the eve of the crisis) were isolated by resorting to different proxies for financial rigidity, and risk separation criteria as well. Results stress the point of inventories being sensitive to frictions over the entire 1991-2009 observation period: constrained firms are likely to rely on inventory decumulation as a powerful leverage to generate liquidity while facing contingencies. Moreover, an excessive downward correction to inventories (recessionary effect) is found during the early 1990s. Specifically, illiquid firms show a greater inventory sensitivity to financial frictions during the recessionary peaks of 1993 and 1996. At the same time, it is worth stressing that a process of excessive inventory decumulation did characterize during the 1990s the most liquid firms as well. Conversely, empirical results identify the presence of recessionary effects that are only weakly significant in the case of the shock of 2008-09, and not statistically significant at all in the case of the soft slowdown of 2002-03. More precisely, evidence is found of an excessive downward correction to inventories that is limited to the most illiquid firms, and the riskiest firms in the sample. Alternative hypotheses were considered in order to investigate further this apparently puzzling result. Italian firms did enter the great recession after a period of prolonged growth in output and manufacturing production. Moreover, there is ample evidence of abundance of credit to Italian firms during the period 2001-07. This is likely to have implied a better positioning of Italian firms at the onset of the crisis, as far as liquidity buffers are concerned. Conversely, restrictive monetary policies were in place during the early 1990s, when the country was involved in the process of fulfilling EU requirements. Nevertheless, the shock of 2008-09 was so pervasive and global, that the shock effects could not be absorbed via liquidity buffers, or inventory decumulation. In other words, the harshness of the recessionary effects, with domestic and international demand severely affected, gave no scope for inventory decumulation as in the past. Rather, recessionary impacts were extensively absorbed by disinvestments in financial assets, at least during the early stage of the great recession. More precisely, the turmoil that affected the international financial markets in 2008-09 prepared the ground for a massive decumulation in financial assets to address the increased liquidity pressures, that fits nicely with the lack of an alternative escape route at the firm-level, due to the paralysis that occurred to the manufacturing base (especially from a demand side). According to the 2010 Report of the Bank of Italy, 21 Euro billions of disinvestments were identified in correspondence to the Italian firms in the non-financial sector. Estimates do confirm the pervasive nature of the last shock. A solid recovery of the Italian manufacturing is still lagging behind, especially in correspondence to the sectors that characterize for a low export propensity.

In Chapter 2 emphasis was placed on solvency dynamics of Italian firms during the great recession. Both traditional determinants of firm distress (e.g. financial rigidity of firms at the eve of the crisis) and contagion effects that originate from the supply chain were considered to analyze distress likelihoods in 2009-13. Contagion effects were modeled via trade credit interconnections (i.e. trade credit received from suppliers during the crisis, or outstanding trade debt), by resorting to spatial econometric techniques. More precisely, a two-step econometric framework was estimated, that is designed to directly model trade credit chain reactions at work during the crisis (SAR model), and to investigate their impact on distress likelihoods as well. Results show that outstanding trade debt was affected by the liquidity status of firms during the recessionary phase 2009-13 and by positive spatial effects. The process of accumulation of trade debt at the firm-level is driven by imported imbalances from interconnected firms, or customer firms. In other words, a positive spatial autoregressive coefficient in the first step of the model can be interpreted in favor of a chain reaction at work during the crisis. This phenomenon is found to exert, in turn, a positive effect on distress likelihoods of Italian firms in 2009-13. The effect is comparable in magnitude to the one exerted by the financial rigidity of firms (evaluated at the eve of the crisis), and stresses the importance to consider complex interactions between firms to analyze the solvency behavior.

Finally, in the last chapter of the dissertation emphasis was placed on an indirect spatial production function framework of the SARAR type, that is suitable for analyzing knowledge spillovers at the micro level. A rich dataset of patent applications filed with the *European Patent Office* was considered to compute territorial and firm-specific indexes of relative patent intensity. We structured interaction matrices according to the theoretical literature on externalities that stem from geographical proximity of firms (namely Marshall-Arrow-Romer or Porter's externalities within an industry and Jacobian externalities that occur between heterogeneously specialized firms). Moreover, we extended the notion of interaction distance to encompass the sectoral input-output configuration of the Italian manufacturing industry. Innovation emerges as a key TFP-enhancing mechanism, that fosters the convergence of levels of total factor productivity of neighboring firms. A spatial model can in fact be assimilated to an equilibrium model. In our specific case, total factor productivity incorporates feed-back effects that arise from changes in TFP determinants in one firm that potentially exert an impact on neighboring firms (propagation mechanism). This mechanism does not appear to work differently across sectorally heterogeneous proximate firms, as comparison to sectorally homogeneous proximate firms in the sample. Specifically, a patent-intensive operating environment can be regarded as a stimulus to individual productivity, regardless of the pursuit of a direct patenting activity – which is still a restricted and costly activity in the Italian manufacturing base.

To summarize, a clustered production structure emerges as a prerequisite for the occurrence of positive externalities. At the same time, the clustered nature of Italian firms is likely to increase the proliferation of trade credit interconnections. The latter act as a potential vehicle of individual shocks propagation. In light of this, policy instruments need to move in the direction of sustaining liquidity needs of Italian firms, especially during a recessionary phase, when liquidity constrains become binding. On the one hand, the introduction of new European rules aimed at regulating payment terms can result into beneficial effects for the Italian manufacturing, where structural disequilibria are present, and payment terms are primarily affected by cultural and sectoral habits. In fact, extended payment terms increase the risk of contagion effects in case of a global liquidity shock. On the other hand, the diffusion of supply chain finance facilities could represent a valid instrument to partially mitigate liquidity needs, in addition to the support that is traditionally provided by the banking channel.

Furthermore, the issue of pronounced exposure of Italian firms to bank debt needs to be properly addressed. The vast majority of small and medium-sized enterprises rely on bank debt as the priority financing channel. Up till recently, policy interventions have been conceived with the purpose of sustaining the recapitalization of Italian firms (e.g. fiscal incentives). In particular, the so-called "Allowance for Corporate Equity" (ACE) was introduced at the end of 2011 as a part of a package of urgent measures for the Italian industrial recovery.

The diffusion of network agreements could represent a fair opportunity to let SMEs benefiting from strategic factors and skills pertaining to networked firms, without the need for a new leverage investment. Specifically, SMEs could potentially benefit from economies of scale, and from the direct presence of large firms in the network as well, which are in turn more prone to fund innovation and internationalization projects[165].

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[165]. For a detailed description of the phenomenon refer to Foresti G., Guelpa F. and Sangalli I. (2015). Network agreements and the Italian Banking System: preliminary evidence from firm performance. *20th Report on the Italian Financial System*, Fondazione Rosselli.