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

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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 originating 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 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. Moreover, trade credit chains are considered together with data on the bank-firm relationship in the second step of the model, in order to assess determinants of firm distress in 2009-13. Results show that outstanding trade debt is affected by the liquidity status of a firm and spatial effects. Chain reactions are found to exert, in turn, a positive impact on Italian distress likelihoods during the crisis. The latter effect is comparable in magnitude to the one exerted by individual financial rigidity and stresses the need for the inclusion of complex interactions between firms in the analysis of the solvency behavior, at both the individual and systemic levels.

JEL Classification numbers: C21, D22, G01, G32, G33, G39, L14
Keywords: trade credit, spatial models, firm behavior, manufacturing, financial crises, financing policy, insolvency, contagion, network

Introduction

The crisis that affected financial markets in 2007-08 resulted into harsh and prolonged effects on the real side of the economy, at an international level. Real impacts concentrated mainly in 2009[1]. Nevertheless, the weak 2010 recovery was suddenly dampened by the outbreak of the sovereign debt crisis, that marked the starting point of 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 paper focuses attention on trade credit channel as a source of distress and contagion effects between firms during the last crisis. Firm interdependencies are suitable to generate chain reactions when liquidity tensions arise: i.e. trade credit accumulation or default of payments to suppliers. We contribute to the existing literature modeling a direct spatial lag dependence in trade credit data pertaining to interconnected manufacturing firms. More in detail, we propose a two-step spatial econometric design (SAR) that moves the first steps towards a proper modeling of trade credit and financial rigidity of firms as simultaneous core determinants of distress likelihoods.

Italy represents a preferred environment to analyze the selected topics because of its fragmented and clustered production base, and because of the pronounced exposure of Italian firms to bank debt. A representative sample of around 12,000 manufacturing entities is analyzed in the period 2008-13. A pronounced lengthening of payment terms emerges from Italian aggregate data since 2009. Data are drawn from *Intesa Sanpaolo Integrated Database* (ISID) on corporate customers. Moreover, spillover effects from trade credit accumulation are modeled resorting to a unique dataset of firm-to-firm transactions executed before the outbreak of the crisis (delayed cash payments and invoice discounting facilities). The proposed spatial weights matrix can be considered a proxy of the Italian manufacturing supply chain. Transactions are extracted from Intesa Sanpaolo systems.

Results show that the level of outstanding trade debt is affected by the liquidity status of a firm and by spatial neighborhood effects: i.e. accumulation of trade credit at the level of neighboring firms. A positive spatial autoregressive coefficient in the first step of the model can be interpreted in favor of a chain reaction at work during crisis. 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. The estimated impact is comparable in magnitude to the one exerted by financial rigidity characterizing firms at the onset of the crisis. In light of the above, we stress the need for trade credit incorporation into models explaining the solvency behavior, at both the individual and aggregate levels.

The rest of the paper is organized in three more sections. Literature review is considered in the first Section. Section 2 is instead devoted to data description and empirical strategy. Results are presented in Section 3. Conclusions follow.

[1]. 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 the above, the remainder of the paper will focus attention on 2009 as the main recessionary shock.

1. Trade credit channel and financial distress in literature

The paper 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, together with financial fragility 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 did characterize for a high level of financial debt at the onset of the recession. Leverage is suitable to act as a powerful amplifier of macroeconomic shocks. Despite Italian firms being traditionally heavily exposed to bank debt, it is worth stressing that trade credit received from suppliers (i.e. trade debt) represents another important financing channel in the manufacturing industry. The latter can be defined as the credit offered by suppliers in exchange for an anticipated delivery of inputs[2] (outstanding trade debt).

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; Cuñat, 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 (2007) exploit a unique dataset on trade credit defaults among French firms to show that entities that face idiosyncratic liquidity shocks are more likely to default on trade credit payments, especially when shocks are unexpected: shocks transmit along trade credit chains. 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, especially 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 payment terms occurs. It is sometimes 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 more likely to rely on supplier credit during contractionary phases (Nilsen, 2002) and credit-constrained firms, in general, are suitable 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,

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

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 suitable to generate, in turn, contagion effects (Battiston et al., 2007).

The present paper 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 concentrating on distress from the debtors' side. More in detail, our analysis goes beyond existing work in treating multiple aspects of the trade credit phenomenon. *In primis* we model directly trade credit chains, together with determinants of trade credit accumulation at the firm level (outstanding trade debt), resorting to spatial econometric techniques. In light of the above, we move a step ahead with respect to the paper by Jacobson and von Schedvin, where propagation effects are only indirectly proxied. Intuitively, outstanding trade debt can be the result of internal disequilibria and imported disequilibria from neighboring firms, or interconnected firms. Moreover, we investigate the impact of both 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 period 2009-13. Attention is paid to disentangle individual (traditional) determinants or factors of firm distress (e.g. financial indebtness or rigidity) from imported factors in explaining corporate solvency during the last recessionary phase. The focus is especially on trade credit received from suppliers (in exchange for an anticipated delivery of inputs) during the crisis, as a reaction to the paralysis induced by the severe 2009 macroeconomic shock.

Accumulated trade credit, or outstanding trade debt, is here defined as the mean value of the ratio between accounts payable and purchases in the period 2009-13. Unfortunately data do not allow distinguishing between the fraction of trade debt accumulated to comply with standard financing needs and the fraction that is correlated with the rising of additional disequilibria within the firm. Nevertheless, a suspicious sharpening of trade debt dynamics clearly emerges from sampled data in 2009-13, as a result of a global liquidity crisis. It is in fact worth observing that accounts payable days (corresponding to trade credit offered by suppliers multiplied by 360) increased sharply in 2009, towards a mean value of 127 (it was 111 in 2008[3]) and stabilized around a mean threshold of 123 in 2013 (the last year of observation).

Outstanding trade debt can be interpreted as a signal of potential liquidity imbalances within a firm, because of temporary factors or, more drastically, of a wrong working capital management. Disequilibria can trace back to factors or strategies pursued internally to the firm or, by contrast, can be the result of imported imbalances from interconnected firms. Trade credit interconnections can result into the propagation of shocks within a network of manufacturing firms: firms might be forced to default on trade credit payments to suppliers because of imported shocks. We refer to the phenomenon as trade credit chain.

Is there any role for chain reactions in conditioning distress probabilities of Italian firms? What happened during the last recessionary phase? To evaluate the relative importance of the

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

phenomenon, together with the effect exerted by financial rigidity, a large representative sample of 11,920 Italian firms is analyzed in the period 2008-13: 62% of the entities are small firms, 30% medium-sized firms and the residual 8% large firms[4]. The sample composition mirrors the fragmented structure of the Italian manufacturing industry. The dataset excludes a priori micro-firms, i.e. those firms presenting a value for sales (at current prices) below the threshold of two million Euros in the first year of observation (2008)[5]. However, sales are allowed fluctuating downward in subsequent years to avoid an overestimation of results during recessionary peaks (i.e. to incorporate distressed firms)[6]. In addition, sampled data prove to be representative of the Italian production base from a sectorial point of view (refer to Appendix A for a detailed breakdown of the branches of economic activity considered in the analysis and for 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[7] with information on credit events, bank overdrafs and qualitative variables. Moreover, we employ a definition of distressed firms that is based on information from *Central Credit Register* of the Bank of Italy[8].

2.1 Modeling 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 and its impact on distress probabilities of Italian firms.

Attention is paid to disentangle recessionary effects from effects due to pre-crisis firm characteristics. For this purpose the original panel structure of the dataset is reduced into a cross-section structure, where variables are specifically designed to account for historical firm behavior, as detailed in the next coming sections. The two-step econometric framework introduced in the paper encompasses a complete restyling of the concept of trade credit chains mentioned before, with respect to the one considered in literature, and can be summarized as follows:

$$Tradecredit\_rec\ (09\text{-}13) = \lambda Wtradecredit\_rec(09\text{-}13) + X\beta + \varepsilon \qquad [Step\ 1]$$

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

2.1.1 First Step: a Spatial Autoregressive approach (SAR)

Spatial econometric tools are employed to estimate spillover effects from trade credit accumulation during the crisis. The former techniques allow chain reactions to be directly incorporated within an econometric framework. We propose a spatial autoregressive model of

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

[5]. Financial statements pertaining to micro-firms are suitable 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.

[6]. The balanced structure is nevertheless needed to estimate a model where most of the variables are in cumulative terms or designed to account for historical firm behavior.

[7]. Reference is made to financial statements reclassified by 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.

[8]. *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.

order one (SAR)[9] that encompasses direct spatial lag dependence in trade credit data: the amount of trade credit received (by a generic firm *i*) during the recessionary phase 2009-13 (the mean value or outstanding stock of trade debt) comes to represent the dependent variable of the model. Again, the focus is on trade credit received from suppliers (i.e. defaulted or delayed payments to suppliers), as a result of disequilibria that are internal to the firm or imported from the neighbours. The spatial lag variable *Wtradecredit_rec(09-13)* is in fact defined as the weighted average of trade credit received (accumulated) during the crisis at the level of neighboring firms, or customer firms. If the λ coefficient is significantly different from zero we are able to identify spatial effects in trade credit usage by Italian manufacturing firms.

In light of the above, the proposed SAR model allows incorporating (at least indirectly) another parallel direction in trade credit data, the one of credit granted by firms to their customers during the crisis. This represents a major advantage compared to traditional frameworks, that are suitable to model single directions in trade credit data. A battery of LM (Lagrange Multiplier) tests is exploited to provide a formal justification for the model setup or, in other words, to justify the exclusion from the analysis of more complex spatial models[10].

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 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. Spatial weights are binary: they are assigned a value of one if a transaction of the above type occurred between firms in the dataset and zero otherwise[11]. More precisely, binary weights contribute to partially mitigate the problem of potential missing links into the mapped matrix of interactions. By contrast, such a criticality

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[9]. 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. When correlation is of the direct type, 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).

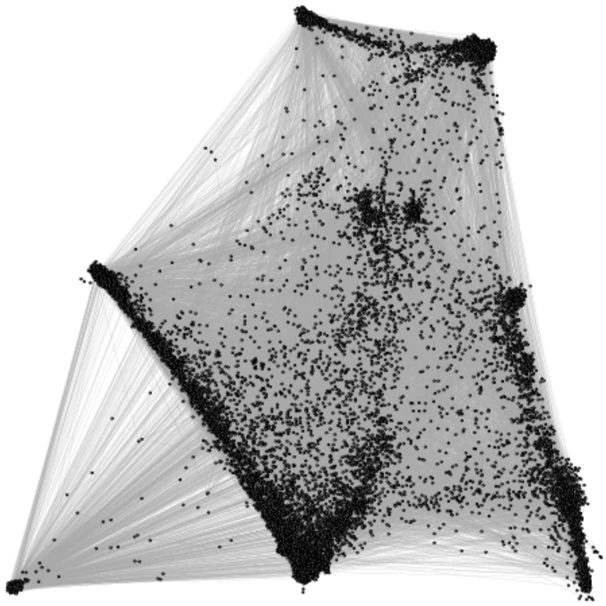
[10]. The robust version of LM tests is selected to evaluate the fit of the model: reference is made to RLMlag and RLMerr tests, testing respectively for spatial lag dependence (λ autoregressive coefficient different from zero) and for spatial error dependence (ρ autoregressive coefficient different 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 assumed (ρ different from zero). In light of the above, results corroborate our choice to select a simple spatial model of the SAR type, focusing attention on direct spatial dependence in trade credit data (spatial lag variable).

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

would be exacerbated by the choice of a matrix structure that is based on the levels of performed transactions. Transactions are in fact extracted from Intesa Sanpaolo systems (actually the first Italian commercial bank) but are suitable to return a partially incomplete picture of the real links that are in place between firms in our manufacturing sample[12].

In order to explore in detail the structure of the links that are included in the model we resort to basic network analysis instruments.

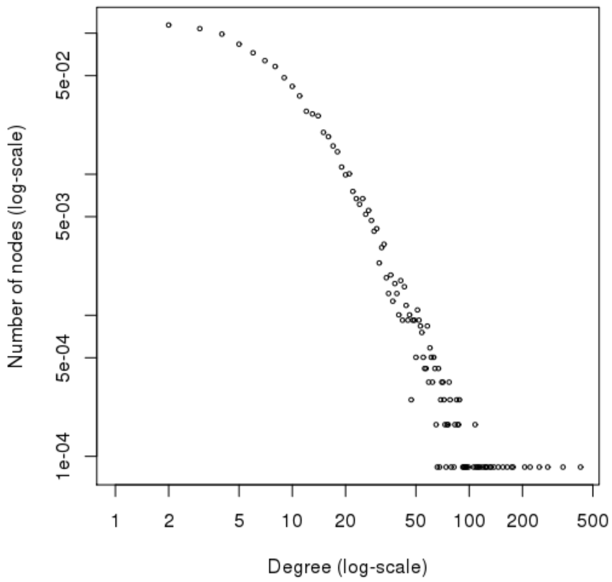
Fig.1 – Network representation of firm-to-firm links: the biggest community



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

Source: Intesa Sanpaolo Research Department

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



Source: Intesa Sanpaolo Research Department

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

Statistics	Values
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

Source: Intesa Sanpaolo Research Department

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. To comply with the structure of the W spatial weights matrix described before, the network is represented as undirected (e.g. it focuses 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

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

network). The 11,920 manufacturing firms that are part of our database are connected through 55,759 links.

The degree distribution[13] *P(k)* of the network, that represents a synthetic snapshot of its complexity, is reproduced graphically in Figure 2. The vertex degree *k*, measuring 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.

The log-log plot of the degree distribution does not show a clear scale-free structure of the network[14] when the full domain is accounted for[15]. In the context of firm networks, the scale-free topology is characterized by both the presence of powerful and influential subjects (hubs) within the system, and a considerable share of entities lying on the system's periphery (i.e. with limited influential power). Scale-free networks are resistant to random defaults but particularly vulnerable to the default of hubs. Nevertheless, such a result could be partially driven by sample composition: i.e. by the presence of missing links into the extracted 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[16]. Such an evidence does represent a precise warning on contagion effects coming directly from the networked structure of our data.

Furthermore, a warning emerges as well clearly when assortativity is analyzed. The latter measures the tendency for vertices (firms) to be correlated with similar vertices in the network. More precisely, 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 vertex attribute[17]. Intuitively, firms that received high levels of trade credit during recessionary phase 2009-13 show a greater probability to be connected with firms displaying similar levels of outstanding trade debt[18].

What a direction for contagion effects from trade credit? We shift again our attention to the spatial parameter λ in step [1], the one capturing the strength of spillover effects in trade credit usage by Italian firms. Under the assumption that the eruption of the crisis generated a global and prolonged lengthening of payment terms, we expect a positive value associated to λ. The positiveness of the parameter can be preliminarily inferred resorting to a Global Moran's I

[13]. 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.

[14]. 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).

[15]. 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.

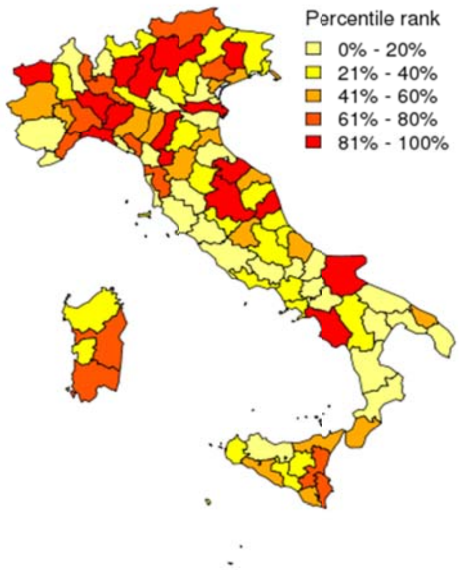
[16]. If we fit a power-law distribution introducing a threshold, i.e. considering $k \geq 25$ (the most interconnected firms), we obtain a higher exponent $\gamma = 3.328$ and a better fit of the distribution (the log-likelihood is -3372). The value of the Kolmogorov-Smirnov test (0.030) suggests an acceptance of the null hypothesis of power law distribution. In literature, scale-free networks are suitable to 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. By contrast, when $\gamma < 3$ the standard deviation of degrees diverges. Nevertheless, 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.

[17]. 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, resorting to the algorithm "assortativity for continuous attributes" defined by Newman (2003).

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

index[19] of spatial autocorrelation, applied to residuals[20] from an OLS (Ordinary Least Squares) estimation of step [1][21]. 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)[22].

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



Source: Intesa Sanpaolo Research Department

We herewith present a detailed explanation of the exogenous covariates pertaining to step [1]. The latter equation can be expanded as follows:

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

Variables are intended to capture the relationship between the liquidity status of a firm and the usage of trade credit during the crisis. As stated earlier, the proposed model displays a cross-section structure where covariates are specifically designed to analyze the behavior of firms in subsequent years within the observation period. More precisely, attention is paid to isolate recessionary impacts from effects due to pre-crisis firm characteristics.

19. 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).

20. Reference is made to studentized residuals.

21. More precisely, we estimate a model of the type $Tradecredit\_rec\ (09\text{-}13) = X\beta + \varepsilon$. A detailed description of the exogenous covariates that are included in X will follow.

22. The index can take values between -1 (perfect dispersion) and +1 (perfect spatial correlation). When dealing with micro-data it is reasonable to accept values that fall in an interval around zero: positive spatial dependence is detected when the value is greater than zero.

Reference is made *in primis* to the *acid_test* variable, representing the mean value of the acid test ratio during the recessionary period 2009-13. The former, being the ratio of current assets (net of inventories) to current liabilities, is suitable to detect liquidity tensions (at least temporary) that may arise at the firm level[23]. A firm is considered illiquid when the ratio is less than unity. According to preliminary statistics the median value of the ratio is 0.82 in 2008, at the onset of the crisis (the value ranges indeed from 0.81 for small firms to 0.83 for large firms). In light of the above, 50% of firms in the sample (and within each dimensional cluster) are found to suffer 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 turned to illiquidity status during the entire 2009-13 recessionary phase. Moreover, an additional 2.2% switched to illiquidity status during the period 2010-13, an additional 1.8% in 2011-13 and an additional 1.3% in 2012-13. We expect a negative relationship linking internal liquidity and trade credit usage during the crisis. According to literature, more liquid firms should, by contrast, absorb part of the shocks to the liquidity of interconnected firms.

Furthermore, the model is inclusive of categorical variables whose purpose is to identify the belonging of firms to some critical areas during the crisis. The latter are respectively the area of financial debt unsustainability and the area of massive usage of revocable credit lines (lines are in place with the Italian banking system). Again, we focus attention on the need to simultaneously analyze the behavior of firms in multiple years in order to define the perimeter of the before mentioned areas of criticality. Dummy variables comply with this need. In fact, the values assumed by some ratios in single years are not *per se* indicative of the presence of structural disequilibria within a firm.

We consider *in primis* the binary variable *debt_burden*: the latter takes on a value of one if firms fall in the area of financial debt unsustainability for at least two consecutive years during recessionary phase 2009-13, while settling outside the area in 2008[24]. The purpose is to identify a broadly irreversible status of monetary disequilibrium at the firm level. More in detail, unsustainability is present when the coverage ratio (the ratio of interests paid on debt to Ebitda[25]) is greater than one. 4.6% of firms in the sample are part of this cluster. In general, percentages of firms experiencing binding debt interests (compared to the Ebitda generated in the same year) increased substantially in correspondence to 2009 and 2012 recessionary peaks: from 9.5% in 2008 to 16.4% in 2009 and 13.7% in 2012.

The dummy variable *rationed_revocablelines* is instead suitable to identify firms in a critical position from the point of view of massive usage of revocable credit lines during the recessionary period (i.e. firms in a weak rationing status). Data on credit lines are drawn from *Central Credit Register* of the Bank of Italy and merged to the information contained in ISID[26]. 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

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[23]. A firm is considered risky when the ratio is less than unity: i.e. current assets net of inventories are lower than current liabilities (Sangalli, 2013).

[24]. More precisely, firms have to place inside the unsustainability area of debt during one of the following periods: 2009-13 entire recessionary phase, 2010-13 period, 2011-13 period or 2012-13 biennium. Moreover, we require firms to locate outside the same area in 2008 (i.e. at the onset of the crisis). The purpose of the analysis is to identify a broadly irreversible status of monetary disequilibrium after the eruption of the crisis. In light of the above, situations of potential temporary difficulties are discarded (e.g. firms whose debt is classified as unsustainable for multiple years within the observation period and settling outside the unsustainability area in 2013, or firms displaying a single evidence of debt unsustainability).

[25]. 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.

[26]. Data on revocable credit lines are available to all firms included in the sample.

the recessionary phase[27] and below 80% at the onset of the crisis (2008). Again, we focus attention on a potential irreversible status of massive usage of credit lines after the eruption of the crisis. The behavior of firms in terms of revocable credit lines has been analyzed in several works based on Italian data in order to identify constrained entities[28]. On the one hand, credit usage acts as a signal of current demand of financial resources at the firm level. On the other, credit granted is a synthetic indicator of the credit market status, from the supply side. In particular, the 80% threshold is suitable to identify a weak rationing status, being in principle indicative of structural disequilibria within the firm. We expect indeed a positive relationship linking the variable *rationed_revocablelines* and trade credit usage during the crisis. 7.7% of firms 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 underlying ratio) and a decline in the supply of credit by lenders (credit granted by the Italian banking system, the denominator) - because of an increased perceived risk of the borrower. In both the cases firms are granted a reduced flexibility in terms of external liquidity and should have relied on trade credit accumulation on a greater extent while experiencing internal disequilibria.

Last but not least, step [1] incorporates a proxy for vertical integration (*vertical_int,* the ratio of value added to sales) in 2008 (before the outbreak of the crisis) and control variables: i.e. dimensional controls (small, medium and large dummy variables, constructed based on the European Commission's thresholds for sales), sectorial controls (branches of economic activity, as described in the Appendix) and geographical controls (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. In median terms, value added accounts for 25% of firm sales in the sample (in 2008). The percentage is higher (27%) in correspondence to small firms.

From the point of view of an econometric estimation of the model, it is worth stressing inconsistency and inefficiency of standard estimators (e.g. OLS estimator). The latter do not account appropriately for the correlation in place between errors and the spatially lagged dependent variable (endogeneity issue). We resort to a Maximum Likelihood estimator (Ord, 1975)[29] to estimate the parameters of the spatial framework. More precisely, we select a Monte Carlo approach (Barry and Pace, 1999) to approximate the log determinant of the Jacobian term in the log-likelihood function[30]. The method is suited for big datasets.

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[27]. More precisely, the ratio has to place consecutively above 80% during one of the following periods: 2009-13 entire recessionary phase, 2010-13 period, 2011-13 period or 2012-13 biennium. We consider the mean value of both the items credit used and credit granted, in each year within the observation period. Situations of potential temporary difficulties are discarded (e.g. firms presenting evidence of massive usage of credit lines in multiple years within the observation period and settling outside the critical area in 2013, or firms displaying a single evidence of massive usage of credit lines).

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

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

[30]. 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 is suitable to introduce 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. More in detail, the log-determinant of the Jacobian term constrains the autoregressive parameter values to remain within their feasible range (in between the inverse of the smallest and the largest eigenvalues of W). The feasible range corresponds indeed to [-1,1] when the matrix is row-

2.1.2 Second Step: assessing determinants of firm distress

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

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

The dependent variable is binary and the regression employs a probit link function. The former 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*[31] - while proving to be considered *in bonis* at the onset 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). While the *bad loans* (sofferenze) status has to be treated as a broadly irreversible status of firm insolvency, the other blocks might refer to a temporary situation of distress at the firm level. In light of the above we refer to selected firms as distressed: 15.4% of firms in the sample experienced distress during the observed recessionary phase. By contrast, 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 are concerned, the second step of the model is inclusive of fitted values from spatial model [1] or *fitted_tradecredit.* The variable represents trade credit augmented by spillover effects and determinants of trade credit accumulation during the crisis[32].

Moreover variables on individual financial strategies, especially bank debt, are included 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 components. The two phenomena are instead included separately within the model. 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 (at the onset of the crisis), is specifically designed to capture potential tightening in financial elasticity at the firm level: an high ratio is suitable to reflect criticalities in the repayment of short-term obligations. Those firms entering a recessionary period (i.e. a period of prolonged drop in sales, the denominator of the ratio) while showing already binding intensity rates of bank financing, are more prone to suffer from a situation of distress. The variable displays a median value of 18.5% in 2008, while remaining above 20% during the subsequent recessionary phase.

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standardized. Nevertheless, 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.

31. Substandards (incagli) are loans associated to 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). By contrast, bad loans (sofferenze) represent 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.

32. By contrast, the baseline version of step [2] is inclusive of the variable *tradecredit_received (2009-13),* that is calculated directly from financial statements. It represents indeed the dependent variable in step [1]. The former variable is incorporated in the model in place of fitted trade credit (from step [1]).

As far as capitalization is concerned, we have to acknowledge the implementation of two important decree-laws during the observation period, 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[33]. In light of the above, it is interesting to explore if - and in what direction - those measures did condition aggregate data on firm capitalization and, by reflection, the distress likelihood[34]. The variable *capitalization*, being the degree of firm capitalization (the ratio of equity to financial debt)[35] is included in the model in level, as mirroring the capitalization status at the onset of the crisis (2008) and in delta-terms, reflecting cumulative variation in the ratio between 2008 and 2013. The capitalization degree is 67.6% in 2008, in median terms, because of the prevalence of small firms in the sample (firms showing a median capitalization value of 59.9% in the same year, compared to a value of 78.7% for medium-sized firms and a value of 88% for large firms). As expected, data encompass a predominant upward trend in the degree of firm capitalization during the period affected by the legislative changes: a 3% up, in median terms[36].

Moreover, the *debt_burden* binary variable is again considered as part of the second step of the model. In fact, if the intensity of bank financing ratio is suitable to mirror financial rigidity at the firm level, the latter variable addresses the point of debt sustainability from a monetary perspective: firms are not profitable enough to repay their interest related expenses. Both the variables are expected to exert relevant and complementary impacts on distress likelihoods during the crisis.

Step [2] includes as well a set of control variables. The content of the control set is similar to the one described in step [1]: dimensional dummies, sectorial dummies, geographical dummies. 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 likely to experience distress. On the other, the variable cumulative growth 2008-13 proxies for an individual recessionary shock.

The equation outlined is estimated resorting to a 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.

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[33]. Reference is made in primis to the decree-law number 185/2008. The former introduced an explicit opportunity for asset revaluation (except for 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).

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

[35]. More precisely, the variable *degree_capitalization (2008)* 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. By contrast, the variable *delta_degree_capitalization (2009-13)* is the log-difference between the degree of capitalization in 2013 and the degree 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.

[36]. The revaluation option (introduced by the Decree-law 185/2008) has been extensively selected by Italian SMEs. This is what emerges from the analysis of manufacturing financial statements performed by Intesa Sanpaolo and Prometeia: reference is made to the 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 Analisi dei Settori Industriali (Industry Analysis). The former is a proprietary forecasting model on Italian manufacturing performance. The related ASI report is issued by Intesa Sanpaolo and Prometeia on a semester basis.

3. Commenting on empirical estimates

Results from estimation of the spatial model in step [1] are suitable to identify neighborhood effects in trade credit usage by Italian firms during the observed 2009-13 recessionary phase. In other words, levels of trade credit received by interconnected firms (outstanding trade debt) prove to be closely related. The evidence does confirm the existence of a trade credit chain at work during the crisis: the trade credit accumulation process is driven by imported unbalances from customer firms. An explanation for this phenomenon can be identified in the paralysis of the manufacturing system that followed the burst of the severe 2009 shock. The former generated in turn a prolonged and pervasive lengthening of payment terms in the Italian manufacturing industry.

The value of the λ coefficient, which identifies the strength of the neighborhood effect in trade credit, 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 unconnected firms within the sample. We reasonably assume that the bias is downward because of the prevalence of small and medium-sized firms in the sample, that should have suffered from a lengthening of payment terms to a greater extent. However, the direction of the bias could be even reversed.

Outstanding trade debt proves to be negatively influenced by the internal liquidity status of a firm, proxied by the *acid_test* variable. The recursive structure that is typical of spatial models allows computing both direct and indirect effects of a change in the covariate pertaining to a generic firm *i*. The change of a variable at the level of a single firm *i* is suitable 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). Average impacts are reported in Table 2b. A simulation of the impacts' distribution is performed in order to retrieve information on their significance[37]. An estimated direct impact of -0.068 is identified in correspondence to the variable *acid_test*. As expected, more liquid firms did rely on accumulation of trade credit on a lesser extent in 2009-13. The indirect impact of the variable is negative as well but reduced in magnitude. By contrast, firms that are identified in a critical position from the point of view of bank credit lines' usage during the recessionary period (variable *rationed_revocablelines*) reacted in terms of a positive trade credit accumulation, as expected: we document a direct impact of 0.021 and a positive indirect impact of 0.002.

No direct connection is established within trade credit usage during the crisis and the belonging of firms to the unsustainability area of debt (variable *debt_burden*). Moreover, the effect of the proxy for vertical integration (reflecting the pre-crisis structure of sampled firms) is ambiguous in our model: in fact, we identify a positive and significant direct impact of the variable *vertical_integration* on trade credit accumulation (0.128). Such a result could nevertheless find justification into sample composition: according to preliminary statistics, in fact, small firms are the most vertically integrated ones and the predominant cluster within the sample. They represent as well the cluster that suffered to a greater extent than others from a lengthening of payment terms, because of the limited contractual power. Accordingly, dummies proxying for dimensional clusters highlight the presence of a more pronounced sensitivity of small firms (the baseline cluster) to outstanding trade debt during the crisis, with respect to medium and large firms.

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

Results from probit estimation of step [2] return a highly significant positive impact of fitted values from spatial model [1] (variable *fittedvalues_tradecredit*) on distress likelihoods in 2009-13 (Table 3): an estimated bootstrapped marginal effect of 0.931 is detected (column 8). Trade credit chain reactions did play an active role in conditioning solvency dynamics 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 onset of the crisis) in conditioning the insolvency trend. More precisely, we considered the effect of short-term financial rigidity, 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).

Standardized coefficients[38] (column 5) are suitable to return an impact of fitted trade credit that is comparable in magnitude to the one exerted by financial rigidity. Outstanding trade debt did represent a key determinant of distress likelihoods during the crisis, together with financial rigidity of firms. This corroborates previous findings about the need to jointly model the two potential channels of distress in order to analyze the solvency behavior.

Furthermore, estimates highlight the need to account for trade credit in a complex way, because of the relevance of chain interactions. To our knowledge, the phenomenon is here quantified for the first time resorting to spatial econometric techniques. In fact, when a baseline version of step [2] is estimated (Table 4) and a variable measuring outstanding trade debt is incorporated directly from financial statements - in place of the fitted trade credit variable from the spatial model - we have to acknowledge a reduction in the standardized effect of trade credit on distress likelihoods. We document a coefficient of 0.125, to be compared to a standardized effect of 0.256 corresponding to the intensity of bank financing ratio.

Last but not least, a positive effect is established between the *debt_burden* binary variable and the probability to become a distressed firm during the last recessionary phase. Firms that generated a level of Ebitda lower than the value of 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 so far considered prove to be robust to the inclusion of a proxy for individual recessionary shock into the regression framework: a negative and highly significant effect is established within cumulative growth in sales in the period 2009-13, at the firm level, and the distress likelihood. By contrast, only a slightly significant impact is documented in correspondence to the cumulative growth in sales in the pre-crisis period (2004-08) - i.e. firm dynamicity before the crisis.

[38]. Standardized coefficients allow comparability to emerge between variables that display different metrics.

Table 2a – Coefficient estimates, Step [1]

	OLS Baseline model	ML Spatial model
λ (spatial lag autor. parameter)		0.105 ***
		(0.014)
Acid_test (09-13)	-0.068 ***	-0.068 ***
	(0.002)	(0.002)
Debt_burden (09-13)	0.001	0.001
	(0.005)	(0.001)
Rationed_revocablelines (09-13)	0.021 ***	0.021 ***
	(0.004)	(0.004)
Vertical_integration (08)	0.131 ***	0.127 ***
	(0.009)	(0.009)
Medium	-0.010 ***	-0.010 ***
	(0.002)	(0.002)
Large	-0.026 ***	-0.026 ***
	(0.004)	(0.004)
(Intercept)	0.308 ***	0.281 ***
	(0.005)	(0.006)
Sectorial 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	

Notes: Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1. Standard errors are in parentheses. For the tests, p-values are reported. Dimensional dummies are constructed based on the value for sales in 2013 (European Commission thresholds).

Source: Intesa Sanpaolo Research Department

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

	Direct impacts		Indirect impacts	
	Coefficient	Simulated z-value	Coefficient	Simulated z-value
Acid_test (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)	0.127 ***	13.894	0.015 ***	6.175

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

Source: Intesa Sanpaolo Research Department

Tab 3 – Probit estimates and marginal effects

	Baseline model			Step [2] Original statistics			Step [2] Bootstrap statistics	
Parameter	Coefficient estimates	Standardized Beta Coefficients	Marginal effects	Coefficient estimates	Standardized Beta Coefficients	Marginal effects	Coefficient estimates	Marginal effects
Tradecredit_received (09-13)	1.035 *** (0.122)	0.125 ***	0.226 *** (0.027)					
Fitted_tradecredit				4.247 *** (0.568)	0.213 ***	0.925 *** (0.130)	4.215 *** (0.575)	0.931 *** (0.127)
Intensity_bankfinancing (08)	1.735 *** (0.107)	0.256 ***	0.379 *** (0.023)	1.565 *** (0.110)	0.231 ***	0.366 *** (0.027)	1.560 *** (0.110)	0.343 *** (0.024)
Capitalization (08)	-0.077 *** (0.015)	-0.094 ***	-0.017 *** (0.003)	-0.057 *** (0.015)	-0.070 ***	-0.012 *** (0.003)	-0.057 *** (0.016)	-0.013 *** (0.003)
Delta_capitalization (09-13)	-0.096 *** (0.016)	-0.103 ***	-0.021 *** (0.004)	-0.069 *** (0.016)	-0.074 ***	-0.015 *** (0.004)	-0.068 *** (0.018)	-0.015 *** (0.004)
Debt_burden (09-13)	0.144 *** (0.066)	0.030 ***	0.034 *** (0.016)	0.135 *** (0.066)	0.028 ***	0.031 * (0.016)	0.134 *** (0.064)	0.030 *** (0.014)
Cum_growth (04-08)	0.066 (0.043)	0.023	0.014 (0.010)	0.097 * (0.043)	0.034 *	0.021 * (0.010)	0.098 * (0.047)	0.021 * (0.010)
Cum_growth (08-13)	-0.305 *** (0.039)	-0.305 ***	-0.067 *** (0.009)	-0.312 *** (0.039)	-0.127 ***	-0.068 *** (0.009)	-0.311*** (0.042)	-0.068 *** (0.009)
(Intercept)	-1.848 *** (0.077)	-0.124 ***		-2.695 *** (0.167)			-2.683 *** (0.170)	
Dimensional dummies	added			added			added	
Sectorial dummies (m_{ℓ})	added			added			added	
Macro-geogr. dummies (m_v)	added			added			added	
Number of observations	11,920			11,920			11,920	
Log-likelihood	-4720.57			-4726.902			-4726.902	

Notes: Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1. Standard errors are in parentheses. For the tests, p-values are reported. Dimensional dummies are constructed based on the value for sales in 2013 (European Commission thresholds).

Source: Intesa Sanpaolo Research Department

4. Conclusions and future directions

The relationship between trade credit accumulation and firm solvency was here analyzed, focusing attention on contagion effects originating from the supply chain.

Trade credit interconnections between Italian manufacturing firms during the recessionary phase 2009-13 were preliminarily explored resorting to basic network analysis tools. Evidence was found of firms receiving high levels of trade credit from suppliers showing an higher probability to connect with firms displaying a similar level of trade credit. This accumulation process, jointly with the presence of densely connected clusters of firms, can lead to chain-reactions in case of liquidity shocks.

In order to model the potential impact of the trade credit channel on firm-level probabilities of distress (i.e. negative spillover effects from trade credit accumulation), a two-step framework was proposed. The first step is a SAR spatial model accounting for direct spatial lag dependence in trade credit data pertaining to interconnected firms. In the second step, the trade credit channel is considered together with data on the bank-firm relationship to assess distress likelihoods 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 payment terms that simultaneously affected interconnected firms within our proxied supply chain. The phenomenon was found to exert, in turn, a positive and considerable impact on the probability to become a distressed subject during the analyzed recessionary period. The latter effect is comparable in magnitude to the one exerted by individual financial rigidity, stressing the importance for considering complex interactions between firms to analyze the solvency behavior, at both the individual and systemic levels.

Future research directions move towards the construction of an agent based simulation framework where firms' interactions are based on the aforementioned results. The networked structure of the economy can lead to complex interactions between firms and emergent phenomena, that are sometimes difficult to be captured within an econometric model. In particular, the goal is set to assess direct and indirect effects of shocks to the Italian industrial system, that can be observed at the micro-level (e.g. financial difficulties of a single firm), 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).

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Appendix

Branches of economic activity

Branch	Name	Ateco 2007 (Nace Rev.2) corresponding codes	Sample composition by branches of economic activity	
			Number of firms	Percentage
1	Food and beverage	C.10, C.11	1,184	9.9
2	Textiles and textile products; Leather and footwear	C.13, C.14, C.15	1,460	12.2
3	Wood-made products; Furniture sector	C.16, C.31	873	7.3
4	Paper, print and publishing sector	C.17, C.18	636	5.3
5	Chemical and pharmaceutical sector; Rubber and plastic products	C.20, C.21, C.22	1,504	12.6
6	Other non-metallic mineral products	C.23	621	5.2
7	Metallurgical sector; Fabricated metal products	C.24, C.25	2,687	22.5
8	Mechanic sector, electronic equipment, medical equipment, transport equipment	C.26, C.27, C.28, C.29, C.30	2,955	24.8

Source: Intesa Sanpaolo Research Department

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