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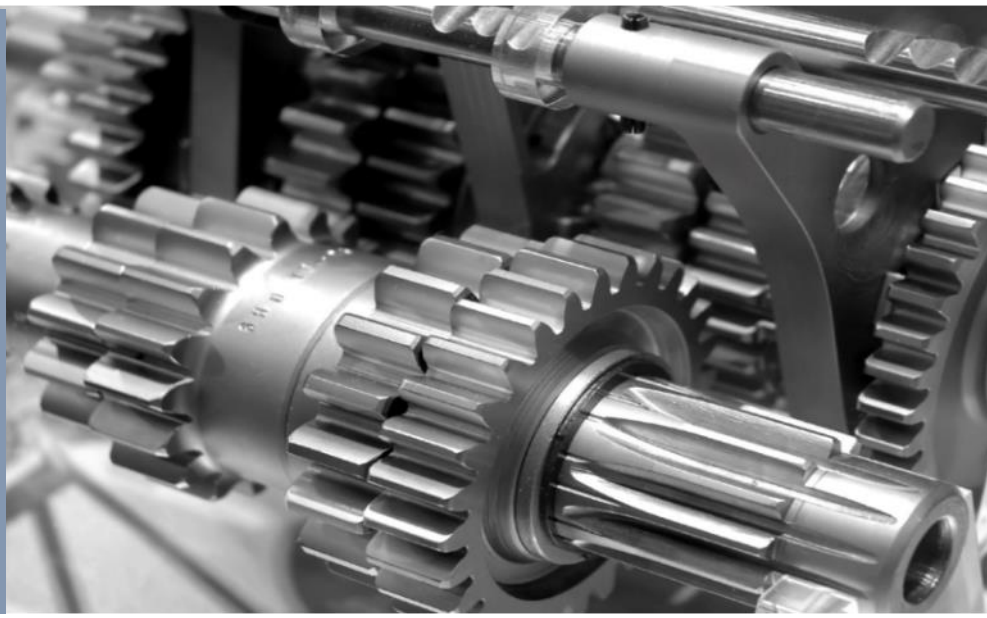

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La Grande Recessione e le imprese manifatturiere

The Impact of the Great Recession on Manufacturing Firms

Proceedings

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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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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 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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[**] Intesa Sanpaolo, Research Department – Industry & Banking Division; ilaria.sangalli@intesasanpaolo.com. The present paper represents a chapter of my PhD Dissertation discussed on March 23rd, 2016 at Catholic University of the Sacred Heart Milan.
We wish to thank Elisa Coletti, Giovanni Foresti, Fabrizio Guelpa, Angelo Palumbo and Stefania Trenti from Intesa Sanpaolo Research Department, as well as Carlo Altomonte (Bocconi University), Giuseppe Arbia (Catholic University of Rome), Luigi Benfratello (Turin Polytechnic), Bernard Fingleton (Cambridge University), Hua Kiefer (Office of the Controller of the Currency, USA), Maria Luisa Mancusi (Catholic University of Milan), Paola Rossi (The Bank of Italy), and the participants to the X World Conference of the Spatial Econometrics Association (SEA 2016) held in Rome, June 13-15, 2016, for the support and the useful comments.

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[1]. 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[2]. 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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[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 this, the remainder of the paper will focus attention on 2009 as the main recessionary shock.

[2]. 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[3] 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 paper 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 paper contributes 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.

[3]. 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[4]. 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[5] (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

[4]. 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.

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

from customers with higher trade receivables in order to avoid large losses. In 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 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 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[6]) 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[7]. 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)[8]. 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[9] with information on credit events, bank overdrafs and qualitative variables. Moreover, we employ a

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

[7]. 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.

[8]. 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.

[9]. 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.

definition of distressed firms that is based on information from *Central Credit Register* of the Bank of Italy[10].

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):

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

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

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.

[10]. *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[11]. 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:

[11]. 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[12]. 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[13]. 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[14]) is greater than unity at least for two consecutive years during the recessionary

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

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

[14]. 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)[15]. 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[16] - 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*)[17]. 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[18]. 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,

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[15]. 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).

[16]. 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).

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

[18]. 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).

they should have fostered a process of trade debt accumulation. Equation *[1b]* incorporates a proxy for vertical integration (*vertical_int*, the ratio of value added to sales in 2008[19]) 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[20]), 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)[21] 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)[22].

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[19]. 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.

[20]. 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.

[21]. 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).

[22]. 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

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[23]. 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[24]. 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)[25]. 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.

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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 of a simple spatial model of the SAR type.

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

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

[25]. 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).

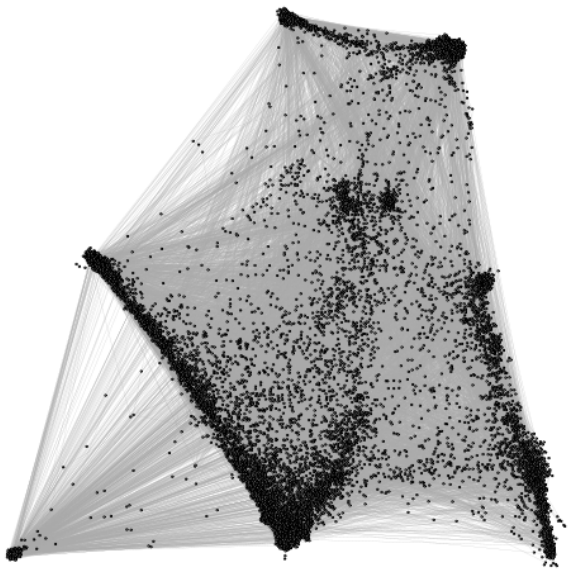
In order to investigate further the structure of the links that are included in the model we resort to basic network analysis instruments. The selected transactions can in fact be better visualized into a network structure, where firms are vertex (nodes) and firm-to-firm interactions (delayed cash payments 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.

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[26]

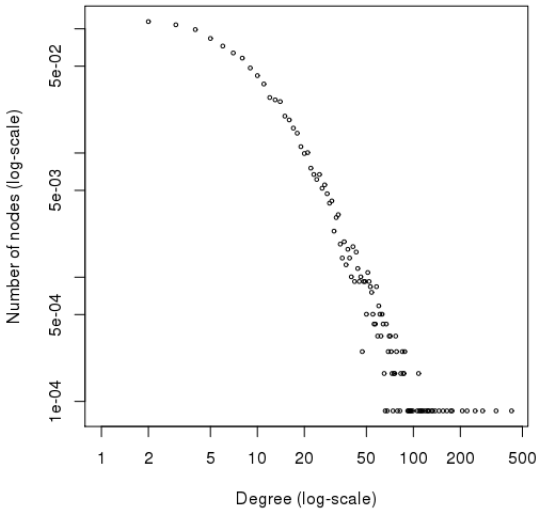


[26]. The subset is the biggest community, as selected by the "walktrap community finding" algorithm (Pons and Latapy, 2005). A network is said to have a community structure if nodes can be easily grouped into sets of nodes, such that each set of nodes is densely connected internally.

The degree distribution[27] *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.

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[28] 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[29]. The evidence is indicative of a precise warning

[27]. 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.

[28]. 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).

[29]. 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 $\gamma=1.405$ (with a log-likelihood of -46192). The value

message of contagion effects that might originate from the structure of the network itself.

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[30]. 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[31].

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[32] of spatial autocorrelation, applied to residuals[33] from an OLS (Ordinary Least Squares) estimation of model *[1b]*[34].

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

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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.

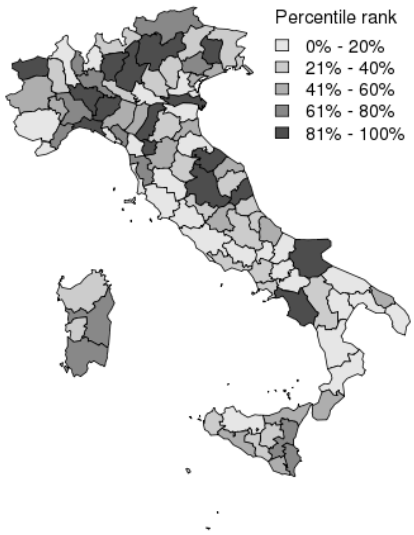
[30]. As a general argument, assortativity is calculated with reference to the vertex degree of a network. The concept of assortativity may, however, be applied to other characteristics of a vertex. We compute assortativity relatively to outstanding trade debt accumulated during the crisis, by resorting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

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

[32]. 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).

[33]. Reference is made to studentized residuals.

[34]. More precisely, we estimate a model of the type $Tradecredit\_rec\ (09\text{-}13) = X\beta + \varepsilon$.



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)[35].

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)[36] 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[37]. The method is suited for big datasets. Results are presented in Table 2a.

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[35]. 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).

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

[37]. 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 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 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”[38] -

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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 - λW) 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.

[38]. 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

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 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[39]. 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

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overdue loans (from more than 90 days). We sometimes observe overlapping between substandards and past-due.

[39]. 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).

likelihoods[40]. The variable *capitalization* is indicative of the level of firm capitalization: namely the ratio of equity to financial debt[41]. 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[42].

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

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

[41]. 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.

[42]. 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 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.

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[43]. 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 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[44].

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

[43]. 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.

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

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 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[45] (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

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

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).

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[46]. 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.

[46]. 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)[47].

***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[48] 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"[49]– while proving to be considered *in bonis* at the eve of the crisis (2008).

***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;

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[47]. 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).

[48]. 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).

[49]. 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.

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).

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