Trade debts and bank lending in years of crisis

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Abstract

This paper provides an empirical investigation of the substitution hypothesis between trade indebtedness and bank loans, using a large sample of about 245.000 Italian firms for the period 2010-2015, which encompasses the sovereign debts crisis when episodes of bank credit contraction occurred. The econometric approach is based on a shift-and-share IV strategy aimed at isolating the causal effect of bank credit supply shocks on trade indebtedness, tackling endogeneity issues like unobserved demand factors and the reverse causality from trade credit to bank credit due to a signaling effect. A negative and significant elasticity of trade debt to bank loans is found, thus providing evidence for substitutability. These findings are consistent with the implications of the pecking order theory according to which firms rank external finance preferring bank debt to (more costly) trade debt: an exogenous reduction in the former spurs the use of the latter. This substitution allows firms to rebalance their financial structure, thus increasing their resilience to external credit shocks. Heterogeneity is detected as the substitutability is much lower or even absent for smaller, riskier, highly leveraged firms and for firms in Southern Italy. This suggests that weaker firms or operating in a less favorable economic environment may not to able to substitute bank credit with trade credit when needed.

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1 Introduction

Many commercial transactions among firms involve trade finance: when customers postpone payments for goods or services received by suppliers, they finance the transaction via trade debt. Account payables, that is the balance-sheet counterparty of trade indebtness, plays a central role among financing sources commonly used by firms, alongside bank loans. Firms can choose to be financed by their suppliers rather than financial institutions for a variety of reasons, including availability and cost; in their seminal paper, Petersen and Rajan (1997) review the possible motivations for the use of trade credit and test them empirically. Their results are consistent with a pecking-order theory framework, which states that firms prefer to resort to bank credit, when available, since it appears to be less costly than trade credit.

After the global financial crisis, the role of trade credit as a financing source gained renewed interest: with firms facing bank credit supply restrictions, alternative sources of finance could potentially provide a buffer for constrained firms. In recent years a number of papers investigated the relationship between trade indebtedness and bank loans during a crisis (Casey and O'Toole, 2014; Carbó-Valverde *et al.*, 2016; Coricelli and Frigerio, 2019; Amberg *et al.*, 2021). More recently, Adelino *et al.* (2022) showed how trade credit has been important also for the transmission of unconventional monetary policies, while Tingbani *et al.* (2022) found that trade credit use leads to greater operational, financial and commercial benefits for firms during periods of financial downturn and financial constraints.

In the analysis of the relationship between the use of bank finance and trade finance by firms it remains difficult to empirically disentangle the causal effect from one to the other. On the one hand it is problematic to net out confounding factors, such as those related to the demand side; on the other hand, endogeneity issues could also arise through reverse causality as the effects can go in both directions.[1]

In this paper we focus on the effect of changes in bank finance due to bank credit supply shock on firms' trade debt in Italy in the period 2010-2015, investigating in particular whether trade finance counterbalanced the contraction in bank lending. We leverage a unique matched bank-firm dataset, comprehending about 245.000 firms for which balance-sheet data are matched with Credit Registry information on bank loans.

The use of Italian data is very suitable to study the effect of bank finance on trade indebtedness for at least four main reasons: (i) In Italy, where the reliance of firms on capital markets is still limited, the role of both bank loans and trade debt as sources of finance is particularly relevant by international comparison.[2] Moreover, there is a high degree of heterogeneity in the incidence of trade debt across firm features and country areas,[3] thus providing a natural ground for the

[1]Trade creditors may have informational advantages over bank creditors as they know better the firm production process, have detailed screening over transactions and can redeploy collateral more easily (Schwartz, 1974; Smith, 1987; Burkart and Ellingsen, 2004). In presence of these asymmetries, receiving trade credit by commercial partners could work as a positive signal to banks (Biais and Gollier, 1997).

[2]De Socio (2010) examines the main differences in the firms' financial structures at European level, finding that, for the period 2004-07, the incidence of debt trade on total assets is much higher for Italian firms (24%, against a value of about 16% for the pool of European countries included in the analysis).

[3]The reliance on trade debt is structurally higher in the Southern part of the country, an area which suffers from a long-lasting economic divide with respect to the Center-North (Accetturo *et al.*, 2022) and with less favorable conditions

analysis of the possibile heterogeneity of the effects; (ii) in the period under analysis (2010-2015) Italy experienced significant variations in bank credit supply: in particular, in connection with the effect of the sovereign debt crisis on Italian banks, Italian firms faced a significant credit crunch (Bofondi *et al.*, 2018). As the timing and the intensity of credit supply changes was not the same across banks, there is the necessary heterogeneity to assess their effect according to firms' exposure; (iii) the availability of information on bank-firm relationship over years allows to exploit a high degree of heterogeneity at the micro level, while being able to control for possible confounding factors; furthermore, it allows to apply micro-econometric techniques for identification; (iv) The large number of firms in the sample, many of which are SMEs, allows to improve on representativeness and external validity with respect to evidence based on particular settings or surveys.

In order to isolate the causal effect of bank credit contraction on trade indebtedness, we use an identification strategy based on an instrumental variable approach with a shift-and-share instrument à la Bartik: this approach exploits, on one hand, bank-specific shifters on credit supply and, on the other hand, persistence in bank-firm relationship through predetermined shares of each bank for the initial bank credit of any firm. By combining the heterogeneity in banks credit supply shocks and the heterogeneity in initial linkages among banks and firms, this methodology exploits the different exposure of firms to credit supply shocks. This kind of identification strategy has been applied to study the impact of bank shocks on a number of economic outcomes, including employment (Berton *et al.*, 2018), firm financial structure and performance (Degryse *et al.*, 2019) and house prices (Barone *et al.*, 2020). However, to the best of our knowledge, it has not been applied to trade debt yet.

Our estimates suggest that there is a significant elasticity of substitution of trade credit to bank credit, as we find a negative coefficient with magnitude close to unity. When bank credit supply decreases, firms increases their trade debt, while when credit supply increases, firms reduces their trade debt. Our findings are consistent with an interpretation based on pecking order theory (Petersen and Rajan, 1997; Bougheas *et al.*, 2009) according to which bank credit, when available, is preferred by firms to trade credit as it is less costly. So when bank credit supply shortens, firms are willing to increase their trade debt, possibly to reduce it again as bank credit returns to be available. In this sense, trade debt is an important buffer against credit supply shocks.

Moreover, our analysis detects a significant heterogeneity behind the overall results. Not all firms manage to use trade finance as a substitute for bank credit: for some subgroups of firms we find that the substitutability is much lower or even absent. We find that this is the case for more risky firms (compared to safer ones), for very small firms (compared to all others), for highly leveraged firms (compared to low-medium leveraged ones) and for firms in Southern Italy (where the use of trade debt is structurally higher than for Center-Northern firms). All these groups of firms seem to have smaller room for substitution between financing sources, thus making their financial structure more vulnerable to external credit shocks as they have a lower likelihood to absorb them by rebalancing their financial sources (by increasing trade debt obtained from their suppliers); hence, for these firms financial shocks are more likely to produce real effects. We do not find evidence of net complementarity (positive and significant elasticity of trade debt to a credit

relative to bank credit (Albareto *et al.*, 2022).

supply shock) for any group of firms defined with the above criteria.[4]

While remaining consistent with a pecking order theory framework, these findings suggest that firms with *weaker* characteristics (highly leveraged, riskier, very small or operating in a less favorable economic environment) may not to able to substitute bank credit with trade credit when needed, hence showing less resilience.

Our analysis contributes to the extant literature on the relationship between trade credit and bank credit in three main respects. First, only a few studies have explicitly assessed the causal direction from credit supply shocks to trade funding. A remarkable instance is Restrepo *et al.* (2019) who, in a quasi-natural experimental setting due to a tax-regime change in Colombia, provide evidence that trade debt can substitute for bank-provided liquidity following an exogenous supply shock, absorbing potential distortions in real decisions. Our results – obtained in another institutional context, applied to a broader definition of bank credit and based on a different methodology – are in line with theirs, thus reinforcing and broadening the available evidence. Moreover, while Restrepo *et al.* (2019) had to focus on large firms, our analysis includes also many small and medium firms, allowing to shed light on this group of firms too and explore heterogeneity with respect to firm size.

Our study is also more generally connected to other contributions that deal with the correlation between trade and bank credit studying the channels through which these variables are mutually related: see e.g. Biais and Gollier (1997); Severin *et al.* (2004); Lin and Chou (2015); Carbó-Valverde *et al.* (2016). In particular, our finding that firms faced with higher bank credit reduction increase more their trade debt is consistent with previous papers using different methodologies, such as Casey and O'Toole (2014) and McGuinness and Hogan (2016), which study whether and to what extent trade credit acted as a substitute for bank finance for European SMEs in the aftermath of the global financial crises. Our results are also consistent with Garcia-Appendini and Montoriol-Garriga (2013), where the authors use a sample of US public firms and find that trade credit taken by constrained firms increased after the onset of the financial crisis. With respect to these studies, we put a greater emphasis on identification issues in order to assess a causal effect from bank debt to trade debt following a bank credit supply shock, dampening the threats to identification of potential confounding factors that might affect other approaches. Similarly to Restrepo *et al.* (2019), we view our results as complementary to those obtained under other methodologies.

A second relevant contribution to extant literature comes from the richness of our dataset. We base our analysis on a unique dataset with a very large number of firms, for which we match balance-sheet data with confidential information on firm-bank relationships drawn from the Credit Registry. Our dataset includes a wide range of firms with heterogeneous characteristics; this allows to improve the representativeness of the results with respect to papers based on surveys (e.g. Casey and O'Toole (2014); Bertrand and Murro (2018)) or focusing only on large corporations (e.g. Love *et al.* (2007); Garcia-Appendini and Montoriol-Garriga (2013)). In particular, our dataset is highly heterogeneous with respect to firm size. Previous papers looking specifically at SMEs, which suffered particularly tight credit supply restrictions in times of crises, often find

[4]We refer to *net* complementarity as we can only identify a reduced form effect, which theoretically could derive from offsetting opposite effects.

peculiar developments in trade credit. For instance, Love and Zaidi (2010) focus on a sample of small and medium enterprises in four East Asian countries around the 1998 financial crisis and do not find evidence in support of the substitutability hypothesis between trade and bank credit in times of crisis, in contrast with a previous result of Love *et al.* (2007), where the analysis focuses on large publicly traded firms in six emerging economies facing a shock during the 1990s. Coricelli and Frigerio (2019) use a large dataset of European enterprises (nearly 2 million firms from 2004 to 2013) and show that trade credit amplified the liquidity squeeze on SMEs, affecting their real activity; their results show that SMEs basically transferred financial resources to larger firms, possibly due to a limited bargaining power in their credit relationship with larger corporations. Among the papers dealing specifically with SMEs, Carbó-Valverde *et al.* (2016) use a sample of about 38,000 Spanish firms and study whether trade credit provided an alternative source of external finance for smaller firms particularly exposed to credit crunch during the global financial crisis; they find that credit constrained SMEs depend on trade credit, but not bank loans, and that the intensity of this dependence increased during the crisis.

Third, our analysis covers the period of the sovereign debt crisis and the subsequent credit crunch, whereas the extant literature on substitutability between bank and trade credit mostly deals with earlier periods (among papers focusing on Italy, see e.g. Bertrand and Murro (2018) and Deloof and La Rocca (2015)). In this respect, the fact that our paper concerns Italian firms is particularly relevant, not only because most available studies on trade finance for this country are based on previous periods,[5] but also in view of the severity of the sovereign debt crises for the Italian economy. Among the few studies looking at the use of trade finance by Italian firms in a period that includes the sovereign debt crisis there is a recent contribution by Cosci *et al.* (2020), who mainly focus on redistribution efficiency via trade credit, finding no supportive evidence in this respect.[6] With respect to their paper, based on balance-sheet and survey data for a sample of Italian manufacturing firms, we have a different focus and can base the analysis on a much wider dataset, including also many firms in other sectors, and use information on specific bank-firm relationships.

Our paper also relates to the vast stream of literature studying real and financial effects of credit supply shocks (dealing in particular with identification issues in disentangling supply and demand factors),[7] to which it provides further evidence concerning trade credit dynamics.

The paper is organized as follows. Section 2 describes the data we use and provides a descriptive analysis of the sample. In Section 3 we discuss our econometric strategy. Estimated results are

[5] The relevance of trade finance for Italian companies spurred research interest on various topics, including motivations for inter-firm credit and its implications for monetary policy (Cannari *et al.* (2005)), financial motivations (Russo and Leva (2004)), enforcement and judicial efficiency (Carmignani (2004)), signalling and role in economic transactions (Omiccioli (2004, 2005); Cannari *et al.* (2004)). Substitutability between bank and trade credit was studied in de Blasio (2005), in addition to more recent papers by Deloof and La Rocca (2015), Bertrand and Murro (2018) and Cosci *et al.* (2020).

[6] On a more general note, they highlight the potential threats posed by the extensive use of trade credit in case of excessively delayed payments, especially for small firms.

[7] Among the main references, we mention Khwaja and Mian (2008); Chodorow-Reich (2014); Jiménez *et al.* (2020). Moving from the seminal paper by Khwaja and Mian (2008), who developed a a simple approach to identify the effect of a bank liquidity shock on credit supply while accounting for observed and unobserved determinants of credit demand, Cingano *et al.* (2016) quantify the real effects of the bank-lending channel after the global financial crisis using a large sample of matched firm-bank data from Italy.

presented in Section 4 for the baseline specifications; Section 5 provides some robustness checks; Section 6 focuses on heterogeneity issues, taking into account location, riskiness, size and leverage of firms; Section 7 concludes.

2 Data and descriptive evidence

2.1 Data

Our dataset is built using three different sources, containing information on company accounts (Cerved), loans at bank-firm level (Central Credit Register: CR), and other bank characteristics (Bank of Italy Supervisory Reports: SR). Thus, we obtained an unbalanced panel of 245.000 firms for the 2010-2015 period. The choice of the analysis period is due to two reasons: i) it encompasses the sovereign debts crisis when episodes of bank credit contraction occurred, thus allowing to evaluate the response of trade indebtedness to bank credit supply shocks; ii) due to an accounting reform came into effect in 2016, information on trade debt and credit is no longer available from that year onwards for a large number of firms (generally small and medium-sized enterprises).

First, we use a dataset from Cerved Group containing information on company accounts. Cerved draws information from official data recorded at the Italian Registry of Companies and from financial statements filed annually at the Italian Chambers of Commerce on a compulsory basis. The dataset provides information on the universe of Italian joint stock companies as well as public and private limited liability companies. The provided information includes company profiles and summary financial statements (balance sheets, income statements and financial ratios). We restrict the analysis to non-financial private firms; following Coricelli and Frigerio (2019) we also exclude the primary sector, utilities, mining and quarrying. We winsorize the dependent variables and covariates (to limit the measurement error due to few unreliable outliers) at 1 and 99 per cent.

In particular, the dataset contains information about both trade credit and debt credit, according to the following definitions:

- *Trade credit*: the trade credit definition refers to postponing payment for goods or services received, i.e. extending credit to customers: not only firms, but also final consumers (persons) and government or local government.

- *Trade debt*: accounting counterpart of trade credit. Trade debt is defined as the money payable by a company to its supplier for goods or services received by it. Thus, it refers to business to business relationships.

- *Net trade credit*: difference between trade credit and trade debt.

Given our interest on the substitution hypothesis between trade indebtedness and bank finance, it is natural to choose trade debt as our main variable of interest. We also run some robustness checks using net trade credit, i.e. the difference between receivables and payables. Indeed, given that firms are generally both suppliers and customers in the supply chain and thus both lenders and borrowers in the credit chain, the liquidity effect acts through net trade credit; anyway this measure is not restricted to business to business relations, given that trade credit is granted to families and government as well.

In order to build a time-varying, firm specific measure of credit availability we use information from the Central Credit Register (CR), managed by the Bank of Italy, which contains data on all outstanding loans extended by reporting intermediaries and exceeding the threshold of 30,000 euros.[8] Namely, for each firm in our dataset, we consider the total amount of outstanding loans (granted by all banks operating in Italy) at the end of each year; moreover, we compute bank market shares for each borrower by looking at the amount of outstanding loans from each lending bank at the end of the baseline year (2009). In addition, the estimate of time-varying bank lending policies relies on information drawn from Bank of Italy Supervisory reports (SR): for each bank, we consider the amount of outstanding loans extended to the firms of each province at the end of each year.

After matching firm and bank datasets for the sample period 2009-2015, we have approx. 600 banks, which on average account for more than 90 per cent of outstanding loans of the firms in the final dataset at the end of the baseline year (total coverage is attained for 62 per cent of the firms).

2.2 Descriptive evidence

In Italy trade debts are an important funding source for firms (De Socio, 2010). In 2015 trade debt represented in aggregate terms more than one fifth of total funding (liabilities and net worth) of firms. Though this share decreased with respect to the period before the financial crisis (it was almost 4 percentage points higher in 2007), it remains substantial (Fig. 1). If we compare trade debts to financial debt, we see that the former is as high as two thirds of the latter and it was even higher in the early 2000s.

The overall trends for Italy hide remarkable differences across territories. By disentangling the two macro-regions of Center-North (C-N) and South and Islands (Mezzogiorno, MZ), we can observe that the national indicator mainly mirrors the Central-Northern area of the country, where more firms (especially the largest ones) are present (Fig. 2). Moreover, we can see that the relevance of trade debt in fact is even higher in Mezzogiorno: in this area the weight of trade debt over total funding sources (defined as the sum of liabilities and net wealth) is about 4 percent points higher than in the Center-North at the end of the period, a statistically significant and – considering the denominator – economically sizable difference. A structurally higher level of trade debt could be related to a weaker financial system, associated to a relatively lower role for financial debt and a higher relative importance of implicit contractual relations with trade partners (see Ge and Qiu, 2007).[9] This is confirmed by looking at the ratio between trade debt and financial debt, which is steadily higher in Mezzogiorno.

Figure 3 shows the 12-month percentage variation of bank loans to Italian non-financial corporations during the period of our analysis (2009-2015), while keeping on the background the ratio

[8] For each borrower, intermediaries have to report monthly to the Register the amount of each loan (granted and used) above a threshold, which was 75,000 until December 2008 and 30,000 euros afterwards; non-performing loans are reported regardless of their amount.

[9] Concerning weaknesses of the financial system in Mezzogiorno, see e.g. Albareto *et al.* (2022), Bonaccorsi di Patti (2009).

of trade debt to total funding. The plot shows how bank credit started to decelerate in late 2011, after a year of sustained growth, and shrank in the following years. While the turmoils on the sovereign debts markets started to generate negative feedbacks on banks, credit supply conditions tightened, thus contributing to the sharp decrease in bank loans.

Table 1 shows the distribution of firms in the estimation sample among three size classes and the three main broad sectors. A bit more than half of the total of 246 thousands firms belong to the service sectors while manufacturing firms make up about 28 per cent of total. Small firms represents more than 90 per cent of the total sample. Medium and big firms are relatively more represented in manufacturing, while they are rarer in the building sector.

While our main focus is on the substitutability between bank debt and trade debt following a shock in the former, a brief descriptive analysis of trade debt *levels* and their main covariates can be helpful to put the issue into context. Table 2 shows the incidence of trade debt on the sum of total liabilities and net worth (which we denote as trade ratio) across several firm groups. The trade ratio is higher for larger, riskier, more leveraged and less profitable (measured by return on assets, ROA) firms (see Table 2). Among sectors, it is higher in the wholesale and retail sector, while it is lower in real estate and accommodation and food services.

3 Empirical strategy

The relationship between bank credit availability and trade debt is firstly investigated by estimating the model

$$\Delta \text{td}_{it} = \beta\, \Delta L_{it} + \gamma_i + \delta_t + \varepsilon_{it}\,, \tag{1}$$

where td_{it} is the amount of outstanding trade debt for firm i at time t, L_{it} is the amount of outstanding bank loans, γ_i is a fixed-effect which captures firm specific time invariant determinants of credit demand and the time-fixed-effect δ_t accounts for common shocks. Following Berton *et al.* (2018) and Moscarini and Postel-Vinay (2012), variations in td and L are computed as follows:

$$\Delta \text{td}_{it} = \frac{\text{td}_{i,t} - \text{td}_{i,t-1}}{0.5 \times \text{td}_{i,t} + 0.5 \times \text{td}_{i,t-1}}\,,$$
$$\Delta L_{it} \equiv \frac{L_{i,t} - L_{i,t-1}}{0.5 \times L_{i,t} + 0.5 \times L_{i,t-1}}\,;$$

Weighted variations computed in this way are symmetric and bounded between -2 and 2. Computing the percentage variations in the standard way would be more affected by the presence of values equal to zero in the data, thus either preventing the computation or yielding very high and not economically meaningful variations.

The model is then augmented by adding one by one a set of firm covariates $\mathbf{C}$, lagged by one year to reduce endogeneity concerns due to simultaneity issues or reverse causality: total assets (in log) as a measure of firm size, ratio between tangible fixed assets and total assets (as a proxy for the degree of rigidity of firm's assets), cash and other liquid assets over total assets (as a proxy of liquid resources available to the the firm), gross operative profits ("margine operativo lordo", MOL) over total assets (as a measure of internal gross profitability). These variables or similar ones were used in previous literature on trade debt: as they may concur to explain the *level* of trade debt, we follow an agnostic approach and include them to allow for the possibility that they could also have an influence on the *change* of trade debts. As the regression include a firm fixed effect (γ_i), all time invariant unobserved heterogeneity is controlled for; this also implies that all the regressors have effect through their within-firm variation. We do not include categorical variables for risk classes or leverage classes because they are often time invariant and hence would be dropped for a lot of observations; we do not include a continuous variable for leverage since variations in this variable within the firm would be correlated in a mechanistic way to other variables in the regressions (trade debt, bank debt, total assets).[10] However, in Section 6 we analyse how results might change according to firm riskiness and leverage.

We then estimate the model with all covariates:

$$\Delta \text{td}_{it} = \beta\, \Delta L_{it} + \boldsymbol{\mu}\mathbf{C}_{i,t-1} + \gamma_i + \delta_t + \varepsilon_{it} \tag{2}$$

We finally control for heterogeneous trends by progressively including time fixed-effects by Ateco 2-digit industry ($\tau_t \times \nu_{\text{sect}(i)}$), year fixed-effect interacted with firm size classes (small, medium, large; $\tau_t \times \xi_{\text{size}(i)}$) and year fixed-effects by area (Center-North vs South; $\tau_t \times \psi_{\text{area}(i)}$). The saturated model reads as follows:

$$\Delta \text{td}_{it} = \beta\, \Delta L_{it} + \gamma_i + \boldsymbol{\mu}\mathbf{C}_{i,t-1} + \tau_t \times \nu_{\text{sect}(i)} + \tau_t \times \xi_{\text{size}(i)} + \tau_t \times \psi_{\text{area}(i)} + \varepsilon_{it}. \tag{3}$$

In our estimation we must take into account possible endogeneity issues in the relationship between observed bank loans and firms' economic conditions and use of trade finance: on one hand, unobserved demand factors could bias OLS estimates; on the other hand, a signalling effect could determine reverse causality from trade credit to bank credit. Firms which are deemed worthy of large amounts of trade credit, in fact, may bear a larger credit worthiness also in front of lending banks (Biais and Gollier, 1997). Both channels (unobserved demand factors and signalling effect) tend to introduce a positive correlation between estimation errors and the dependent variable: the OLS coefficient β in Equation (2) could be upward biased.

In order to isolate a credit supply shock from demand factors, we adopt an IV approach and build a firm-specific time-varying instrument, following the approach of Greenstone *et al.* (2020), used among others by Berton *et al.* (2018).

We first estimate:

$$\Delta L_{pbst} = \alpha + \delta_{bt} + \gamma_{pst} + \varepsilon_{bpst}\,, \tag{4}$$

where ΔL_{pbst} is the change in outstanding business loans by bank b, in province p, in sector s, in year t; γ_{pst} is a province-sector-year fixed effect, which acts as a proxy for local demand; δ_{bt} is a bank-time fixed effect, which represents nationwide lending policy for bank b at time t.

Identification of γ and δ is guaranteed by the presence of multiple banks in each province-sector market (exposed to the same demand) and the presence of each bank in multiple province-sector

[10] Similarly, we do not include a proxy for credit rationing either: besides being often highly persistent, such variable could not be a proper control in our context as it could capture part of the genuine effect of credit supply shock that we aim to estimate.

markets (subject to the same bank supply conditions).

For each firm i and year t, we construct an index of credit supply CSI_{it} as the weighted average of bank-specific credit supply $\hat{\delta}_{bt}$ from Equation (4), where the weights ω_{bit_0} are bank shares for each firm at the beginning of the sample period ($t_0 = 2009$):

$$\text{CSI}_{it} = \sum_b \omega_{bit_0} \times \hat{\delta}_{bt}. \tag{5}$$

By construction, credit supply index CSI_{it} reflects both time-varying lending policies applied by different banks and pre-determined heterogeneity in bank market shares across firms. CSI_{it} is then used to instrument variable the variation in bank loans ΔL_{it} in a two-stage least square estimate.

In order for CSI_{it} to be a valid instrument, it has to be sufficiently correlated with the observed dynamics of bank loans[11] and it has to be exogenous with respect to the *change* (not levels) of firm's trade debt. With respect to the former requirement, in every version of the model that we estimate, we report and discuss the value of the first-stage F-stat for weak instruments. The commonly followed rule of thumb considers a threshold level of 10 above which instruments are rated powerful for identification (Staiger and Stock, 1997).Our baseline estimates based on the whole sample are associated to F-stats always above 10. When we move to the analysis of heterogeneity, where estimations are more demanding, F-stats are lower : accordingly, we have to interpret these results with more caution, refraining from emphasizing them from a quantitative point of view; nevertheless insightful qualitative results still emerge.

As a further support to the instrument, we provide some suggestive evidence that our estimates of bank credit supply shifters ($\hat{\delta}_{bt}$) are substantially correlated with an aggregate measure that also concern banks' stance with respect to credit supply: the diffusion index from the ECB Bank Lending Survey on Italian banks (henceforth, BLS index). The BLS index measures how widespread is a tightening/easing of credit supply conditions among the banks participating in the survey; technically, it is computed as the (weighted) difference between the share of banks reporting that credit standards have been tightened and the share of banks reporting that they have been eased. By construction, higher values of the BLS index indicate widespread tightening.[12] As our measure of credit supply shifters is at the bank level, we construct a synthetic measure by taking the median value across firms year by year and compute its inverse value in order to have a variable increasing with restrictions in credit supply as it is for the BLS index. As shown in Fig. 4, for almost all the period under analysis there is a clear correlation between the two measures, in particular when the most relevant tightening occurred, in 2011, in correspondence with the sovereign debt crisis. Only

[11] Berton *et al.* (2018) show how a similarly computed instrumental variable result highly correlated with the evolution of bank lending policies and bank credit supply orientation at the national level and with the bank credit pattern at the micro level.

[12] The BLS diffusion index is calculated from answers provided by Italian banks to the following question of the ECB Bank Lending Survey: *Over the past three months, how have your bank credit standards as applied to the approval of loans or credit lines to enterprises changed?* The possible answers are (1) tighten considerably, (2) tighten somewhat, (3) remain basically unchanged, (4) ease somewhat, and (5) ease considerably. The diffusion index varies between -1 and 1; it is computed as the weighted mean of answers (1)-(5), where the values attributed to each answer are 1, 0.5, 0, -0.5, and -1, and the weights are the observed frequencies. See www.ecb.int/stats/money/surveys/lend/html/index.en.html for details. In order to compare developments in our annual credit supply shifters to quarterly BLS index, we take annual averages of the latter.

almost at the end of the time interval under analysis, in 2014, the correlation weakens as the the bank shifter indicator remains basically flat, while the BLS index signals an easing.

Concerning the exogeneity requirement, it cannot be directly tested but concerns about the presence of spurious correlation are limited by the fact that, by construction, the shift component $\hat{\delta}_{bt}$ has been computed net of province-sector-time varying factors,[13] while the share component ω_{bit_0} is computed in 2009, before the estimation years. Moreover, we address the possible correlation of the shares with firm specific trends by controlling for firm-fixed effects γ_i, in a model where the dependent variable is expressed in change and not in level. The saturated version of the model in Eq. 3 provides a further reassurance against the possibility of spurious correlation due, for instance, to heterogeneous trends or responsiveness to the business cycle in presence of banks specializing in specific sectors or firm types (Berton *et al.*, 2018).

4 Baseline Results

We begin by estimating the baseline model with no covariate, but with firm fixed effects and year fixed effects (Eq. 1). Then we progressively and cumulatively add time varying firm covariates lagged by one period. We clusterize standard errors at the intersection between main creditor bank (there are 578 of them in total), macro-sectors (they are 20) and macro-areas (Center-North vs South and Islands); in this way errors are robust to serial correlation within the same broad group.

Results are shown in Table 3. Our coefficient of interest is β (the responsiveness to a credit supply shock) estimated by two stage least squares. In each column we report a different model starting from the baseline with no firm covariate, to end up with the model with full covariates, after having added each of them progressively. In the second-last row of the table, we report the first-stage F-statistic for weak instruments based on the first-stage regression. In all models this statistic is above the rule of thumb value of 10 (Staiger and Stock, 1997). In the last row we report the p-value for the null hypothesis $H_0 = \beta = -1$, which states at which confidence level we can reject the hypothesis of full substitutability between bank debt and trade debt.

In all models the estimated β is statistically different from zero. In absolute values, the magnitude of the point estimate is higher in the model with no firm covariate, at -0.95; in the model with full covariates it scores at -0.84. This suggests that substitutability between bank credit and trade credit could be not perfect, but still it is present to a substantial degree (and indeed the p-value for the full substitutability hypothesis remains rather high). This is consistent with a pecking order theory interpretation, according to which firms have ordering preferences concerning their funding sources. If bank debt is preferred to trade debt (for example because it is less costly, Petersen and Rajan, 1997; Bougheas *et al.*, 2009), firms increase trade debt when bank credit is reduced because of a supply shock, and they decrease it when the supply of bank credit is restored. This hints that during the years of crisis, when the credit supply decreased, firms on average increased their trade debt by a comparable proportion.

In order to evaluate to what extent the two stage least square is able to correct from some

[13] This implies, for example, that it is possible to control for possible sectoral specific demand shock that may affect banks unevenly if the specialize, within the same provinces, in lending to different sectors.

sources of spurious correlation, it is interesting to compare results in Table 3 with those obtained with the OLS estimators (reported in Table 4). As mentioned in Section 3, based on economic reasons, the β coefficient estimated by OLS can be suspected to be upward biased: a channel of positive spurious correlation operates through demand effects (when a firm reduces its demand for credit, it could decrease both bank and trade debts); another channel may operate through reverse causality due to signalling (as trade creditors may have more information on the firm's soundness, banks' credit supply may be affected by what they observe about the trade credit that a firm receives from its partners). Since the bias of the OLS estimates occurs in the expected direction, the evidence seems to support the ability of the identification strategy to remove (at least some) of the expected bias.

5 Some robustness checks

In Section 4, we have seen that our main finding about a statistically significant negative relationship between bank debt and trade debt is robust to the inclusion of firm covariates (either together or progressively cumulated, Table 3). In this section we provide further robustness checks.

Heterogeneous trends. In this robustness check we allow for possible heterogeneity in time trends according to sector, firm size, or area. In particular, we interact the time fixed effects with dummy variables related to industries, size, or area. This is done as it is possible that, while we control for firm-specific fixed effect and time fixed effect common to all firms, some particular trend are specific only to a subset of firms. This trends could induce a bias if they are simultaneously correlated with the dynamics of trade debt and with the dynamics of credit supply. For example, if there is a particular trend in credit supply toward an expanding sector, by omitting this specific time trend there could be a spurious correlation (arguably positive) with trade debt. In this respect, however, two remarks are in order: first, in our estimation of $\hat{\delta_{bt}}$ we have already taken into account province and sector specific fixed effects; second, the baseline model is estimated in first differences, not in levels, and two-set fixed effects (firm and time): linear trend specific to the firm (and its sector, for example) are already controlled for. In the augmented models we nonetheless allow for the possibility of more complex time dynamics.

Table 5 reports the 2SLS estimates for the baseline model augmented with time fixed effects interacted by industry (ateco 2 digit), then also by firm size (3 classes), and then again also by macroareas (Center North vs South and Islands). Columns from 1 to 4 refer to the baseline model with no firm covariate, while columns from 5 to 8 refer the full covariate model. In each group, the first column reports the baseline model and the following ones add the specific trends in the order described above. The first-stage F-stat is below 10 in the most saturated and demanding versions of the model, but it remains always above 5, maintaining a reasonable power (Goldsmith-Pinkham *et al.*, 2020). When F-stat is lower, standard errors get larger and estimates becomes less precise. However, in the most saturated versions (columns 4 and 8), the point estimates for β are quite in line with their respective baseline version (columns 1 and 5): in the no covariate model β scores at -0.91, while in the full covariate version it scores at -0.86. Although the statistical significance decreases due to the higher standard errors, they remain significant at 10%. Therefore, we can conclude that results in Table 5 support the robustness of our main results in Table 3; at the same time, it seems preferable to keep results in Table 3 as the baseline, since in in Table 5 we obtain similar point estimations paying the price of more imprecise and weaker identification.

Alternative outcomes We have clarified in Section 2.1 the reasons why we focused on commercial debt among a firm balance sheet items to assess the effect of a shock on bank credit supply. However, it could be possible that the effect that we have detected actually holds for other variables too, such as trade credits or net trade credit (i.e., trade credit net of debt credit). Should this be the case, one could doubt that the negative effect found for trade debt is really related to a substitution between funding sources and could perhaps be related to some spurious uncontrolled factors.

In order to address this issue, in Table 6 we replicate our baseline model considering as alternative dependent variable the percentage variation in trade credit or the difference in net trade credit to total assets ratio. Both in the no-covariate and in the full-covariate versions of the model, it turns out that there is a negative and statistically significant β coefficient only when we consider the original dependent variables (i.e. trade debt), whereas the effect is not significantly different from zero either for trade credit or net trade credit, while it is significantly different from -1 (complete substitution). Looking at the estimated sign, it is negative for trade credit and positive for net trade credit: this is consistent as the more negative effect on trade debt overwhelm the one on credit. Concerning the estimates with trade credit as dependent variable, the fact that the estimated effect is lower in magnitude and it is not significant suggests that on average firms affected by bank credit shocks could extend their trade credit but an important part of the trade credit received by affected firms (that we observe as trade debt) comes from less affected firms. Another possible interpretation of the absence of significance when we look at trade credit is that in this case the effect is attenuated by a concurrent positive correlation with firm willingness to extend credit to its customers when its availability of bank credit increase: when bank credit conditions ease, firms might have easier access to liquidity and could be more willing to extend credit to final customers, thus inducing a positive correlation with bank credit supply shock.

This evidence reinforces the idea that the baseline model actually captures the effect through a recomposition of firm funding sources due to a bank credit supply shock on firm trade debt: for firms experiencing a reduction in bank credit supply, trade debt increases on average. In light of all these considerations, we see as confirmed the choice to focus on the liability side (trade debt) for the purpose of our analysis.

Alternative clustering Another potential issue regards the level at which standard errors are clustered. In setting the level of clustering we have to cope with a trade-off between efficiency and robustness (Cameron and Miller, 2015; Hansen, 2007). The lower the number of clusters (and hence the more populated is each cluster) the more estimates are robust to correlation within clusters; however, with a low number of clusters inference becomes problematic as standard errors broadens and coefficients are more imprecisely estimated (Donald and Lang, 2007). In our baseline specification we have considered clusters defined by the intersection of main creditor bank,[14]

[14]This means that for each firm we tag its main bank creditor as the bank with the higher share of total bank credit received by the firm, similarly to Berton *et al.* (2018).

sectoral broad groups (20 classes) and two macroareas. Following Cameron and Miller (2015), in doing so we have included as controls more granular variables, such as firm fixed effects and heterogeneous trends with respect to sector, area and firm dimension (Table 5).

Now we assess if and how much our main results are affected if we consider alternative cluster-structures, for example by reducing the number of clusters and using broader groups. Table 7 compares the results obtained under the baseline specification (column 1) to results obtained considering alternative cluster definitions.[15] As mentioned, by broadening the definition (thus reducing the number of clusters) the bias risk is reduced but also efficiency is (standard errors get larger), thus making estimates less precise. In column 2, standard errors are clustered at groups defined by the intersection of main bank, area and macrosector (only 3 categories rather than 20);[16] in column 3 we consider the broadest classification by clustering just at the main bank level, while in column 4 we add a greater granularity by considering the intersection of main and second-main bank. When clusters are defined as in column 3, they are robust to any correlation within firms that have the same bank in common thus being arguably exposed to similar bank credit supply shock. The main result from Table 7 is that the estimate for β keeps its statistical significance at 5% in every cluster specification, even in column 3 with the largest standard errors.

As the coefficient of interest remains significant under more robust specifications, the statistically significant negative effect detected under our baseline model is less suspected to be biased due to a wrong or too restrictive cluster specification.[17]

6 Heterogeneity

In this section we investigate whether the trade debt response to credit shocks varies according to firm characteristics and the context in which they operate. In particular, we distinguish firms according to their size, riskiness, leverage and macro-area.

For each dimension, we consider two groups of firms and create a dummy variable that we interact not only with the endogenous variables (and with the instrument) but also with all time dummies and firm covariates. This approach is more flexible than the simple interaction on the variable of interest as it does allow each group to have its own responsiveness to controls, similarly to what would occur under a sample splitting.[18] With respect to a sample-splitting strategy, this approach allows to directly compare coefficients by means of statistical tests.

More in detail, we estimate the following model by 2SLS:

$$\Delta \text{td}_{it} = \beta\, \Delta L_{it} + \lambda \Delta L_{it} \times D_{it} + \gamma_i + \boldsymbol{\mu} \mathbf{C}_{i,t-1} + \boldsymbol{\nu} \mathbf{C}_{i,t-1} \times D_{it} + \delta_t + \delta_t \times D_{it} + \varepsilon_{it}. \tag{6}$$

Since this model has two endogenous variables, we have to introduce a second instrument, which

[15]Table 7 consider the full covariate version of the model. Results are qualitatively similar for the no-covariate version: they are not reported but they are available from the authors upon requests.

[16]The three categories are: manufacturing industries, construction, services.

[17]At the same time, taking one of this alternative cluster specification as baseline would imply lower first-stage F-stat, thus undermining the possibility of exploring heterogeneity as done in Section 6; therefore, we confirm the baseline specification.

[18]We do not interact the dummy with firms fixed effects both for tractability reasons and because in most cases firms do not switch across groups and so these effects could not be identified.

is given by the dummy variable interacted with the original instrumental variable: $CSI_{it} \times D_{it}$. This second instrument has however a limited additive explanatory power; because of that, the F-stats are lower and standard errors are larger than in the baseline, making coefficients less precisely estimated. Therefore, estimates are to be interpreted carefully, refraining from emphasizing them from a quantitative viewpoint.

The results of this analysis, though with the necessary caution in their interpretation due to the lower statical power, are suggestive of the presence of significant elements of heterogeneity. We report them in Table 8, where in each column we can see the considered dimension and which category represents the group for which $D = 1$. In each column, the coefficient of the reference category (i.e. $D = 0$) is given by β, while the coefficient on the interaction is λ. Therefore, the effect for the category $D = 1$ is given by $\beta + \lambda$, that we report together with a test for the Null hypothesis that it is zero.

Firstly, we directly explore heterogeneity according to firm size, in order to assess whether very small firms (defined as those with assets below €2 million) are different from the others.[19] As shown in column (1) of Table 8, the estimated elasticity for the group of firms above this size level ($D = 0$) is negative, though it does not achieve the conventional stastical levels (the p-values scores at 0.15). For the group of smallest firms ($D = 1$), the coefficient is lower in magnitude and more clearly insignificant. Albeit with the necessary caution due to the weak identification power, this suggests that bank and trade debt are less substitutable for smallest firms. This might be connected to the (usually) lower market power of small firms, that limits the possibility to switch between funding sources (Coricelli and Frigerio, 2019).

In Section 2.2 we have seen that risky firms tend to rely on trade debt more. So it seems worth assessing whether they have the same sensitivity of trade debt to bank debt shocks as safer firms have. Hence, we split firms between safer ($D = 0$) and riskier ($D = 1$), considering in the latter group all firms whose Cerved rating is greater or equal to 7.[20] Results are reported in column (2) of Table 8. It can be seen that for safer firms some statistical evidence of substitutability between bank debt and trade debt is found, whereas the elasticity is in absolute terms much lower for riskier firms and it is clearly not significant. Safer firms seem to have a higher possibility to obtain trade credit when their bank credit supply shrinks and then restore it to a lower level when bank credit increases again. For risky firms instead, following a reduction in credit supply, the availability of trade-credit might be lower given the higher risk that the trade creditor would bear, thus resulting in a lower substitutability.

A similar finding is obtained if we group firms distinguishing highly leveraged firms (defined as those with a leverage above the third quartile) from the others (column 3).[21] For highly leveraged firms, which can be perceived as riskier from their creditors, there is no evidence of sub-

[19] This threshold roughly corresponds to two thirds of the firms in the baseline sample, but less than 7% of total assets. Note that we are referring to a narrower number of small firms compared to the classification used in Section 2.2, as the latter is based on a threshold of €10 million that would have covered more than 90% of firms, almost the whole sample.

[20] With respect to the classification in three classes used in Section 2.2 we have basically grouped together the medium and the high risk class, while labeling as "safe" the firms in the low risk class.

[21] Leverage is defined as the ratio of financial debt over the sum of financial debts and net worth. The third quartile of the distribution corresponds to about 80%.

stitutability, with a substantial orthogonality. Hence the overall negative elasticity found in the baseline model seems to be driven by the other firms, with a lower leverage. Indeed for these firms we find a negative coefficient, stastistically significant at 5%.

An additional dimension of heterogeneity we are interested in is the geographic one, dividing firms between those in Center-North (C-N) and those in Mezzogiorno (MZ). Since in Section 2.2 we have seen that MZ firms structurally operates with higher level of trade debt, it is interesting to analyse whether they have similar or different sensitivity to bank credit shocks compared to C-N firms.

As shown in column (4) of Table 8, while the elasticity for C-N is negative and significant (albeit only at 10% due to more imprecise estimation), the elasticity for Mezzogiorno is low (-0.09) and by far not statistically different from zero. Hence, this suggests that the negative elasticity of substitution found in Section 4 for the baseline model mainly regards the C-N firms, while MZ firms might not manage to similarly adjust trade debt in response to a credit shock.

A possible concern with this result is that it could be driven by the concentration of large firms in C-N, which might have peculiar features. Therefore, in column (5) we exclude large firms (defined as those with assets above €50 million) from the sample and repeat the analysis for geographical heterogeneity. The coefficient on C-N (-1.18) remains negative and significant at 10%, whereas the elasticity for Southern firms is confirmed to be much lower (-0.07) and it is still clearly not statistically different from 0.

Recalling that firms in Mezzogiorno structurally operate with higher levels of trade debt, it is possible that the room for manoeuvre to increase it further when other credit sources go down may be limited. In this case, we should observe less differences between C-N and MZ for firms with a lower trade debt. Suggestive evidence in this respect is provided in column (6), where the model is estimated on a sample made only of firms for which the incidence of trade debts over total assets is relatively low (not higher than the second quintile): the estimated point elasticity for Southern firms almost coincides in the sample of firms with trade debt ratio below the second quintile.

All in all, the results from the heterogeneity analysis show that the substitutability between trade and bank debt following a bank supply shock mainly concerns firms that are larger, safer and financially sound (characterized by a low level of leverage) and firms located in the Center-North. These firms cope with a reduction in bank credit supply by increasing their trade debt, which they then reduce again when credit supply improves. This adjustment channel, which is consistent with the implications of the pecking order theory, may curb the likelihood or attenuate the intensity with which a shock in the banking system propagates to the real economy.

Conversely, our results suggest that trade and bank debt are somewhat orthogonal for firms that are smaller, riskier and highly leveraged and located in the Mezzogiorno. This suggests that firms with weaker characteristics or operating in a less favorable economic environment[22] have a more rigid financial structure and so may not to able to substitute bank credit with trade credit when needed. It could be possible that these firms would have operated the same adjustments of

[22] It is possible that the geographical dummy captures a mix of other unmeasured "favorable" characteristics, which may encompass infrastructure, availability of services, social capital, and so on. See Guiso *et al.* (2004) about the relationship between social capital and financial systems; for recent analysis concerning the financial effects of heterogeneity in social capital in Italy see e.g. Mistrulli and Vacca (2015), Galardo *et al.* (2019).

the other groups of firms, but their higher demand for trade-debt in times of bank-credit reduction is not met by a high enough increase in supply. Because of the lower likelihood of absorbing the shock by rebalancing their financial sources (i.e., by increasing trade debt obtained from their trade creditors), these firms are more vulnerable to external credit shocks, that could more likely produce real effects, for example in terms of lower investment (as in Restrepo *et al.*, 2019), employment, etc.

While providing evidence in support of a higher substitutability in presence of a greater financial soundness, our findings also suggest a possible role for market power, which is arguably higher for the firm groups for which a higher substitutability is found (that is safer, financially sound, larger firms, mainly located in the Center-North).

7 Concluding remarks

This paper analyses the substitution hypothesis between trade indebtedness and bank loans for the Italian case in the period 2010-2015. Both the country and the period under examination represent very interesting case studies, given that in Italy bank loans and trade debts are relevant sources of finance for firms and that, during the analysed period, which encompasses the sovereign debts crisis, episodes of bank credit contraction occurred thus highlighting the importance of sources substitution to stabilize firms finance. We use a large sample of about 245.000 Italian firms and adopt an econometric approach based on a shift-and-share IV strategy aimed at isolating the causal effect of bank credit supply shocks on trade indebtedness.

In the econometric analysis a negative and significant elasticity of trade debt to bank loans is estimated, thus providing evidence for substitutability. The hypothesis of substitutability is consistent with the pecking order theory, according to which firms rank external finance preferring bank debt to (more costly) trade debt: an exogenous reduction in the former spurs the use of the latter. In the analysed period the substitutability between trade indebtedness and bank loans represented a factor of resilience to external credit shocks for firms, allowing them to rebalance and stabilize their financial structure; real effects from shocks on bank credit are thus less likely to occur.

Moreover, our analysis detects a significant heterogeneity behind the overall results, not all firms being able to substitute bank loans with trade indebteness: for some categories of firms the substitutability is much lower or even absent. This is the case for firms with weaker characteristics (highly leveraged, riskier, very small or operating in a less favorable economic environment). In particular, in Southern Italy, where the incidence of trade debt on total financial sources is significantly higher compared to the Centre-North, firms lacked the possibility to substitute financial sources during the analysed period, thus highlighting a financial structure more vulnerable to external credit shocks.

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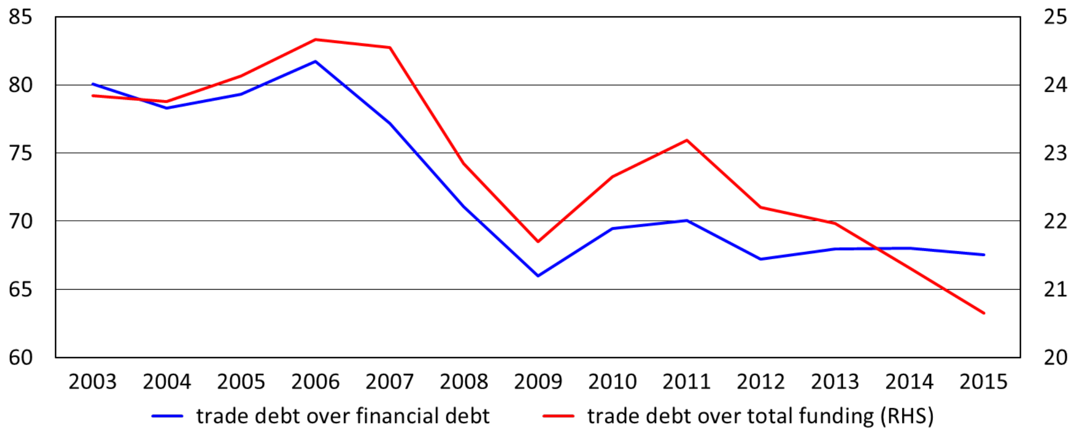
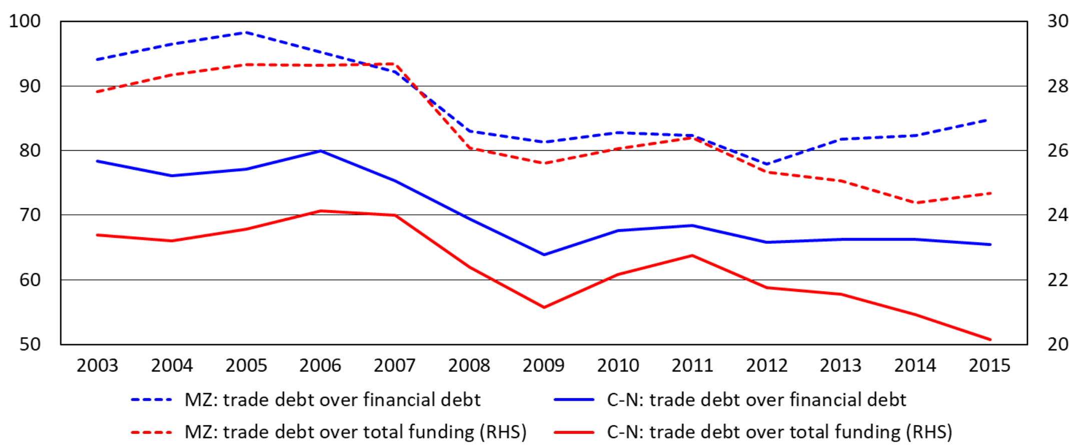
Figures

Figure 1: Trade debt in Italy
(percentage points)



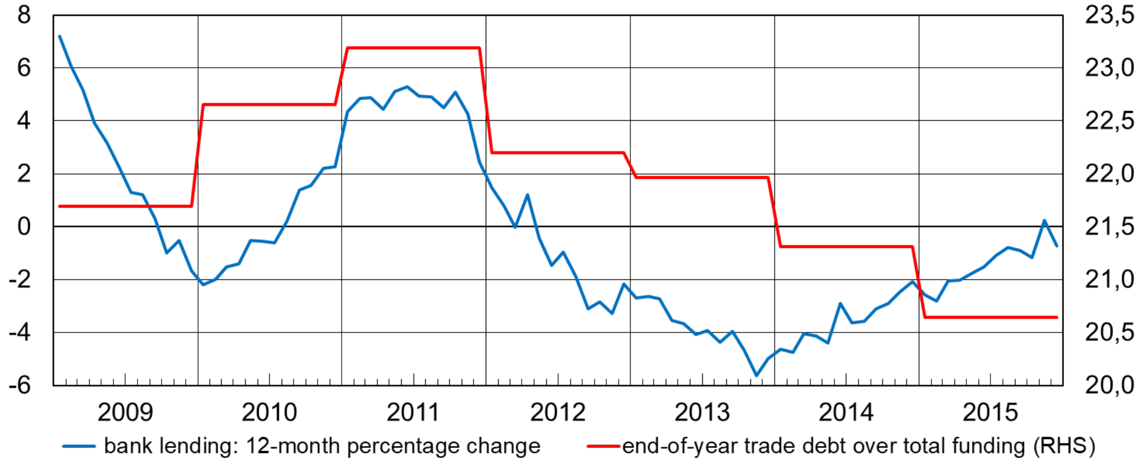
Source: authors' calculations on Cerved data.
The blue line shows the ratio between trade debt and financial debt for Italian firms; the red line (right-hand side values) shows the share of total funding (sum of liabilities and net worth) represented by trade debt.

Figure 2: Trade debt in Center-North vs Mezzogiorno
(percentage points)



Source: authors' calculations on Cerved data.
The blue lines show the ratio between trade debt and financial debt for firms located in the two macroareas; the red lines (right-hand side values) show the share of total funding (sum of liabilities and net worth) represented by trade debt.

Figure 3: Bank lending and trade debt
(percentage points)



Source: for the blue line, Supervisory reports; for the red line, authors' calculations on Cerved data.
The blue line shows the monthly time series of 12-month percentage change in bank loans to Italian non-financial corporations, net of reclassifications, value adjustments and other variations not due to transactions. The red line (right-hand side values) shows the ratio between trade debt and total funding (liabilities and net worth).

Figure 4: Bank shifter (inverse) and BLS diffusion index
(standardized variables)

Source: for the blue line, authors' calculations on Cerved, Supervisory reports and Credit Register data; for the red line, authors' calculations on ECB Bank Lending Survey data. The figure shows the inverse of the median of the estimated bank shifters $\hat{\delta}_{bt}$ and the annual mean of Bank Lending Survey diffusion index relative to non-financial corporations. An increase (decrease) in Bank Lending Survey diffusion index is associated to easing (tightening) credit supply conditions. Both variables are standardized over the period under analysis.

Tables

Table 1: Firms in the estimation sample

	Small	Medium	Big	Total
Manufacturing	60,228	7,347	1,786	69,361
	86.8	*10.6*	*2.6*	*100.0*
	26.7	*45.3*	*48.9*	*28.2*
Building	46,774	1,250	188	48,212
	97.0	*2.6*	*0.4*	*100.0*
	20.7	*7.7*	*5.2*	*19.6*
Services	118,863	7,610	1,680	128,153
	92.8	*5.9*	*1.3*	*100.0*
	52.6	*47.0*	*46.0*	*52.2*
Total	225,865	16,207	3,654	245,726
	91.9	*6.6*	*1.5*	*100.0*
	100.0	*100.0*	*100.0*	*100.0*

Firm size classes are based on the amount of sales per year: firms are classified as small if sales are not higher €10 million, medium if sales are between €10 million and €50 million, big if sales are higher than €50 million. Below the absolute number of observations, relative frequencies are reported out of the total for each sector and each size class, respectively.

Table 2: Trade debt ratio

	Mean	Std Dev	1st quartile	Median	3rd Quartile
Size					
Small	26,8	21,1	10,6	22,6	38,2
Medium	31,1	18,0	18,0	28,0	41,2
Large	30,8	18,3	17,7	27,5	40,1
Riskiness					
Low	24,3	17,5	10,5	21,5	34,9
Medium	26,9	20,1	10,8	23,2	39,0
High	31,1	24,6	12,7	25,6	43,0
Sector					
Food and beverages (10-12)	26,6	18,0	13,9	23,3	35,2
Textiles (13-15)	28,2	20,3	13,6	24,3	38,2
Wood and furnishing (16, 31)	26,8	18,3	14,0	23,4	35,8
Paper and printing (17-18)	27,2	17,4	15,0	24,2	35,6
Chemical and pharmaceutical prod. (19-21)	25,9	15,8	15,2	23,3	33,5
Rubber and plastic (22)	27,4	16,8	15,8	24,8	35,6
Metal (23-25)	25,4	17,0	13,5	22,4	33,5
Electronic prod. and electrical equipm. (26-27)	26,6	17,5	14,5	23,6	35,2
Machinery and equipment (28)	30,1	18,3	17,1	27,1	39,6
Motor vehicles and transport equipm. (29-30)	25,9	18,8	13,0	22,1	34,5
Other manufacturing (32-33)	24,7	18,1	11,5	21,0	33,4
Construction (41-43)	25,6	21,5	8,2	21,2	37,5
Wholesale and retail trade (45-47)	33,4	21,7	17,2	30,5	46,0
Transportation and storage (49-53)	29,3	22,7	11,3	24,3	42,7
Accomodation and food service (55-56)	17,7	19,1	3,8	11,4	25,3
Information and communication (58-63)	20,5	19,0	6,3	15,0	28,9
Real estate activities (68)	14,5	20,0	1,6	6,6	19,2
Profess., scient. and techn. activities (69-75)	23,1	21,6	6,7	16,7	33,4
Admin. and support service activities (77-82)	22,9	21,2	6,8	16,3	33,3
Other services (84-98)	25,1	16,9	12,3	22,9	34,5
Leverage					
Low	26,5	20,8	10,4	22,0	38,1
Medium	26,6	18,2	12,5	23,7	37,6
High	28,4	23,2	10,9	23,7	39,7
Profitability					
Low	27,5	24,8	8,5	21,0	39,2
Medium	27,6	19,4	12,5	24,5	39,4
High	26,5	17,9	12,8	23,8	37,1

This table reports summary statistics for the trade debt ratio, defined as the ratio between trade debt and total assets (which, by accounting identity, are equal to the sum of net worth and liabilities). Classes of firm size are defined according to sales values (small: equal or lower than 10 million euro; medium: higher than 10 million and lower than 50 million; big: higher than 50 million). Classes of risk are defined according to Cerved rating scores (safe: equal or lower than 4; medium: 5 or 6; risky: from 7 to 10. Sectors are grouped according to Ateco classification (Ateco 2 digit codes are in parenthesis). Leverage and profitability classes are defined according to terciles of the yearly distribution of firms with respect to leverage and return on assets, respectively.

Table 3: Baseline IV-FE estimates

	(1)	(2)	(3)	(4)	(5)
β	-0.951**	-0.776**	-0.750**	-0.760**	-0.839**
	(0.412)	(0.344)	(0.343)	(0.355)	(0.383)
Observations	997,683	997,683	997,683	997,683	997,683
Number of firms	214,698	214,698	214,698	214,698	214,698
Firm covar. (lagged)		+assets	+tangib./ assets	+liquid./ assets	+mol/ assets
Firm FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
First-stage F-stat.	11.94	14.02	13.82	13.15	12.24
$H_0 : \beta = -1$ (pv.)	0.905	0.515	0.466	0.499	0.674

***, **, * denote significance at the 1%, 5% and 10% level, respectively. In all columns the dependent variable is the yearly per cent change in trade debts. 2SLS estimates where β is the coefficient associated to the per cent change in bank credits to the firm, instrumented as described above. Standard errors are clustered by main banks (#578)/sectoral branch (#20)/macroarea (#2) and reported in parentheses. All firm covariates are 1-year lagged; they are: total assets, tangible fixed assets over total assets, liquid assets (cash and other liquid assets) over total assets, gross operative profits over total assets. The time span ranges from 2010 to 2015.

Table 4: OLS Panel FE estimates

	(1)	(2)	(3)	(4)	(5)
β	0.0363***	0.00468**	0.00525**	0.00615***	0.00183
	(0.00223)	(0.00169)	(0.00168)	(0.00169)	(0.00172)
Observations	1,028,711	1,028,711	1,028,711	1,028,711	1,028,711
Number of firms	245,726	245,726	245,726	245,726	245,726
Firm covar. (lagged)	NO	+assets	+tangib./ assets	+liquid./ assets	+mol/ assets
Firm FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓

***, **, * denote significance at the 1%, 5% and 10% level, respectively. In all columns the dependent variable is the yearly per cent change in trade debts. OLS estimates where β is the coefficient associated to the per cent change in bank credits to the firm. Standard errors are clustered by main banks/sectoral branch (#20)/macroarea (#2) and reported in parentheses. All firm covariates are 1-year lagged; they are: total assets, tangible fixed assets over total assets, liquid assets (cash and other liquid assets) over total assets, gross operative profits over total assets. The time span ranges from 2010 to 2015.

Table 5: Two stages least squares estimates with heterogeneous trends

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	no covariates				full covariates			
β	-0.951**	-0.702*	-0.730*	-0.914*	-0.839**	-0.672*	-0.715*	-0.858*
	(0.412)	(0.398)	(0.420)	(0.518)	(0.384)	(0.390)	(0.416)	(0.492)
Observations	997,683	997,683	997,683	997,683	997,683	997,683	997,683	997,683
Number of firms	214,698	214,698	214,698	214,698	214,698	214,698	214,698	214,698
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓
Firm covariates (lagged)					✓	✓	✓	✓
Year FE	✓				✓			
Industry $\times$ Year FE		✓	✓	✓		✓	✓	✓
Size $\times$ Year FE			✓	✓			✓	✓
Area $\times$ Year FE				✓				✓
First-stage F-stat.	11.94	10.43	9.637	7.538	12.24	10.29	9.380	7.580
$H_0 : \beta = -1$ (pv.)	0.905	0.455	0.520	0.868	0.674	0.401	0.493	0.773

***, **, * denote significance at the 1%, 5% and 10% level, respectively. In all columns the dependent variable is the yearly per cent change in trade debts. 2SLS estimates where β is the coefficient associated to the per cent change in bank credits to the firm, instrumented as described above. Standard errors are clustered by main banks/sectoral branch (#20)/macroarea (#2) and reported in parentheses. Firm covariates are 1-year lagged and include: total assets, tangible fixed assets over total assets, liquid assets (cash and other liquid assets) over total assets, gross operative profits over total assets. The time span ranges from 2010 to 2015. Industry FE are defined at Ateco 2-digit; firm sizes FE have 3 classes; area FE have 2 classes.

Table 6: Two stages least squares estimates for different dependent variables

	(1)	(2)	(3)	(4)	(5)	(6)
	no covariates			full covariates		
	Trade debt (var. %)	Trade credit (var. %)	$\Delta \frac{\text{net trade cred.}}{\text{assets}}$	Trade debt (var. %)	Trade credit (var. %)	$\Delta \frac{\text{net trade cred.}}{\text{assets}}$
β	-0.951**	-0.270	0.485	-0.839**	-0.184	0.427
	(0.412)	(0.375)	(0.314)	(0.383)	(0.371)	(0.313)
Observations	997,683	956,243	1,002,163	997,683	956,243	1,002,163
Number of firms	214,698	206,873	215,499	214,698	206,873	215,499
Firm covariates (lagged)				✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
First-stage F-stat.	11.94	10.79	12.22	12.23	11.30	12.49
$H_0 : \beta = -1$ (pv.)	0.905	0.051	0.000	0.674	0.028	0.000

***, **, * denote significance at the 1%, 5% and 10% level, respectively. In col. (1) and (4) the dependent variable is the yearly per cent change in trade debts; in col. (2) and (5) it is the yearly per cent change in trade credits; in col. (3) and (6) it is the level of the ratio between net trade credits and total assets. 2SLS estimates where β is the coefficient associated to the per cent change in bank credits to the firm, instrumented as described above. Standard errors are clustered by main banks/sectoral branch (#20)/macroarea (#2) and reported in parentheses. Firm covariates are 1-year lagged and as described in previous tables. The time span ranges from 2010 to 2015.

Table 7: Different clusterizations of standard errors

	(1)	(2)	(3)	(4)
β	-0.839**	-0.839**	-0.839**	-0.839**
	(0.383)	(0.425)	(0.428)	(0.407)
Observations	997,683	997,683	997,686	997,686
Number of firms	214,698	214,698	214,699	214,699
Firm covariates (lagged)	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Cluster	main bank/ sect. branch/ area	main bank/ macro-sect./ area	main bank	main bank/ second bank
First-stage F-stat.	12.23	10.25	9.009	7.257
$H_0 : \beta = -1$ (pv.)	0.674	0.705	0.707	0.692

***, **, * denote significance at the 1%, 5% and 10% level, respectively. In all columns the dependent variable is the yearly per cent change in trade debts. In col. (1), standard errors are clustered by main banks/sectoral branch (#20)/macroarea (#2); in col. (2) by main bank/macro sector (#3)/area(#2); in col. (3) by main banks; in col. (4) by main bank/second main bank. Firms with just one lender have been assigned second bank equal to zero. Firm covariates are 1-year lagged and as described in previous tables. The time span ranges from 2010 to 2015.

Table 8: Hetergeneity analysis

	(1)	(2)	(3)	(4)	(5)	(6)
	Size	Risk	Leverage	Area	No large firms	$\frac{\text{tr. debt}}{\text{assets}}$ low
	D=Smallest	D=Risky	D=High	D=MZ	D=MZ	D=MZ
β	-1.579	-1.303*	-1.442**	-1.294*	-1.182*	-0.783
	(1.116)	(0.679)	(0.702)	(0.772)	(0.676)	(0.670)
λ	0.899	0.945	1.543	1.200	1.109	-0.0198
	(1.301)	(0.899)	(0.959)	(1.028)	(0.933)	(1.194)
$\beta + \lambda$	-0.680	-0.359	0.101	-0.0931	-0.0728	-0.803
$H_0 : \beta + \lambda = 0$ (pv.)	0.190	0.532	0.876	0.870	0.898	0.405
Observations	997,683	997,669	997,536	997,683	976,872	370,716
Number of firms	214,698	214,693	214,680	214,698	211,497	95,445
Firm covariates (lagged)	✓	✓	✓	✓	✓	✓
Firm covariates (lagged)$\times$ D	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Year FE $\times$ D	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓
Fist-stage F-stat.	3.435	3.082	2.987	2.444	2.922	3.576
$H_0 : \beta = -1$ (pv.)	0.604	0.655	0.529	0.704	0.788	0.746
$H_0 : \beta + \lambda = -1$ (pv.)	0.537	0.265	0.087	0.111	0.104	0.838

***, **, * denote significance at the 1%, 5% and 10% level, respectively. For each dimension reported in columns, the group dummy D takes value 1 for the specified category. In all columns the dependent variable is the yearly per cent change in trade debts. Estimates are by 2SLS, where β is the coefficient associated to the per cent change in bank credits to the firm and λ is the coefficient for the same variable interacted with D. Instrumental variables are as described in the main text. Hence, $\beta + \lambda$ is the effect for group $D = 1$; it is reported below coefficients together with the significance level for the null hypotheis that it is equal to zero. In column (1) the dummy for very small firms is equal to one for firms with assets below €2 million. In column (2) risky firms are defined according to (lagged) Cerved rating as those with lagged score ≥ 7. In column (3) leverage is defined as the ratio between financial debt and the sum of financial debt and net worth; highly leveraged firms are defined as those with lagged leverage above the third quartile of the sample distribution (about 87%). In column (5) very large firms (defined as those with assets above €50 million) are excluded from the sample. In column (6) the sample is restricted to firms with a relatively low level of trade debt ratio (i.e., trade debts over total assets); more specifically, firms with a trade debt ratio below the second quintile (roguhly corresponding to 19%) are considered. Standard errors are clustered by main banks/sectoral branch (#20)/macroarea (#2) and reported in parentheses. Firm covariates are 1-year lagged and include: total assets, tangible fixed assets over total assets, liquid assets (cash and other liquid assets) over total assets, gross operative profits over total assets. All models include the interaction of covariates and time fixed effects with the group dummy D. The time span ranges from 2010 to 2015.