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European trade credit use and SME survival[1]

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Abstract

We examine if trade credit helped financially constrained SMEs survive the recent financial crisis. Using data for 202,696 SMEs across 13 European countries over the period 2003-2012, we show that trade credit has a large positive impact on firm survival, especially during the recent financial crisis years, confirming it was an important source of finance for financially constrained SMEs. We also report evidence of a significant *redistribution* effect, with cash rich or unconstrained firms extending significantly *more* net trade credit than their less financially resourced counterparts. The results are robust to several econometric concerns.

Key words: Trade credit, financial crisis, SMEs, panel data, survival, financial distress, country effects.

JEL Classification: G30, G32

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Abstract

We examine if trade credit helped financially constrained SMEs survive the recent financial crisis. Using data for 202,696 SMEs across 13 European countries over the period 2003-2012, we show that trade credit has a large positive impact on firm survival, especially during the recent financial crisis years, confirming it was an important source of finance for financially constrained SMEs. We also report evidence of a significant *redistribution* effect, with cash rich or unconstrained firms extending significantly *more* net trade credit than their less financially resourced counterparts. The results are robust to several econometric concerns.

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1. Introduction

Small and medium sized enterprises (SMEs) are more dependent on bank finance and are more vulnerable to financing constraints (Beck, Demirgüç-Kunt and Maksimovic, 2008; Stiglitz and Weiss, 1981), which increased markedly as a result of the recent banking crisis (Ryan, O'Toole and McCann, 2014). Under these conditions, survival can depend on the actions of financially unconstrained creditors who can extend additional trade credit and/or relax payment terms to their financially constrained counterparts. The financial crisis, and the subsequent economic downturn, led to an increase in firm exits, many of which were involuntary. For example, in 2009, the number of SMEs in the EU fell by 290,000, resulting in the loss of over 650,000 jobs. In the same year, the US population of SMEs[2] fell by over 150,000 resulting in the loss of 2.8 million jobs (European Commission, 2013). This has resulted in a greater policy focus on the role of financing on the survival of SMEs (e.g., Survey on the Access to Finance of Enterprises (SAFE), 2009-2016), and highlighted the need for evidence from large sample empirical research.

Prior studies (e.g., Casey and O'Toole 2014; Carbo-Valverde, Rodriguez-Fernandez, and Udell, 2009 and 2016; Garcia-Appendini and Montoriol Garriga, 2013; Ferrando and Mulier, 2013; Petersen and Rajan, 1997) support the view that trade credit provides a useful buffer for financially constrained firms. We also know that private firms are much more reliant on trade credit than public firms, as the latter have better access to alternative and cheaper sources of funding due to their listing status (Abdulla, Dang and Khurshed, 2017).

In this paper, we extend the analysis by focusing on the usefulness of trade credit in helping EU SMEs survive in general, but also during the more recent banking crisis. We also re-examine the hypothesis that trade credit gives rise to a redistribution effect, whereby cash

[2] The definition of SMEs in the US extends to firms with up to 300 employees, while it extends only to 250 in the EU.

rich or unconstrained firms support their more constrained counterparts, and whether this support increases during and after the financial crisis period. Our study also helps to address the issue of generalizability of prior findings, by extending the analysis to examine the redistribution effects of trade credit for a large cross-country panel EU SME dataset.

Trade credit is an important alternative source to bank finance (OECD, 2014), and is estimated to represent approximately one third of the debt of US SMEs, providing as much external finance as bank loans (Berger and Udell, 2006). Taking all US non-financial firms together, Barrot (2016) reports a trade credit to bank loans ratio of three to one (Flow of Funds Accounts, 2012). For our full sample of over 202,696 SMEs across 13 European countries, accounts payable represent €110 billion on average, or 20% of total assets and account receivables represent €172 billion, or 30% of total assets, indicating that on average, SMEs are net providers of €62 billion in trade credit, equivalent to 14% of total assets.

We show that the likelihood of financial distress is significantly reduced for firms that receive more trade credit. The reduction is statistically and economically significant, and is equivalent to a 21% decrease in the likelihood of distress for firms that receive a one standard deviation increase in trade credit, all else equal. More importantly, we show that trade credit played a more significant role during the post-crisis years, suggesting that it helped many financially constrained firms survive during this period.

We also re-examine the redistribution effect using our large cross-country EU sample. Following the work of Carbo-Valverde et al. (2009 and 2016), we use financial statement data to estimate a set of structural simultaneous equations of credit demand and supply and extend to a cross country setting, to show how trade credit redistribution differs between constrained and unconstrained firms, pre, during, and post financial crisis years. The Carbo-Valverde et al. (2016) study focuses on 40,000 Spanish firms over the period 1994 to 2010, and we extend this analysis to a balanced panel of 107,776 firms from 13 EU countries. Casey and O’Toole (2014) examine whether credit constrained firms substitute trade credit for bank finance over the crisis, using evidence from EU SAFE surveys for over 5,800 managers. Our analysis extends this to examine the redistribution of trade credit amongst credit constrained and unconstrained firms in the EU using balance sheet data.

We find little evidence that trade credit fully substituted for the severe reductions in bank financing experienced during the financial crisis period. However, our results lend some support to previous studies that show trade credit is redistributed to financially constrained firms when bank credit is tightened (Casey and O'Toole 2014; Carbo-Valverde et al., 2009 and 2016; Garcia-Appendini and Montoriol Garriga, 2013; Petersen and Rajan, 1997). Specifically, we find that a significant transfer or redistribution of credit from more liquid (unconstrained) firms to less liquid (constrained) firms occurred during the early crisis years. In volume or economic magnitude terms, the most liquid firms (i.e. those firms in the top quartile of the distribution of cash resources relative to assets) extended approximately 11 times more net credit relative to less liquid firms (bottom quartile). As expected, the redistribution effect is much more pronounced at the onset of the financial crisis especially for those constrained in access to bank finance.

To our knowledge, no previous study has examined the role of trade credit in the context of SME survival or in the aftermath of a financial crisis. Prior work by Altman and Sabato (2007), Gupta, Gregoriou and Healy (2015) use accounting ratios to model bankruptcy and financial distress in SMEs, but do not examine if trade credit substitutes for traditional sources of finance (i.e., bank) to increase survival likelihood during financial shocks. Ferrando and Mulier (2013) examine the impact of trade credit in supporting more financially constrained SMEs to grow over the crisis. We add to this by showing that firms that receive *more* trade credit are significantly more likely to survive in general, and especially for more constrained firms in the aftermath of a financial crisis. We also show that SMEs from countries with more concentrated banking sectors experience greater distress likelihood on average, indicative of potential difficulties in obtaining and rolling over bank finance during the crisis period.

Our findings are robust to concerns about identification and endogeneity. Specifically, for our redistribution analysis, we ensure that firms are observed both pre and post crisis to provide more confidence that our results are driven by the crisis and not non-random changes in sample composition. We use both firm fixed effects models and GMM to address possible endogeneity concerns. Further, we examine the impact of possible omitted time varying institutional (i.e., banking concentration) and country risk factors that might influence differences in the demand and supply of trade credit.

Similar to partial or dynamic regression models employed in the capital structure and cash-holdings literature (e.g., Flannery and Rangan, 2006; Opler, Pinkowitz, Stulz and Williamson, 1999), we also examine the importance of path dependency in the selection of financing method by including lagged values in our trade credit regressions. The results from our Arellano-Bond System-GMM regressions provide some support for the dependency in net trade credit, and confirm more recent work in Abdulla et al. (2017) who focus on trade creditors. However, when we decompose net trade credit into trade creditor and debtor components, we show that trade debtors largely drive this effect, and so our findings highlight the importance of examining net trade credit, and also separately, trade creditors and debtors.

The paper is structured as follows. Section 2 provides a background discussion on the impact of the financial crisis on EU SMEs. Section 3 reviews the literature and develops our testable hypotheses. Section 4 outlines the methodology, data and results, and Section 5 concludes.

2. EU SME financing pre and post crisis

Europe's economic success depends largely on the growth of SMEs achieving their potential (De Wit and De Kok, 2014; European Commission, 2016a). SMEs accounted for over 20.45 million (99.8% of all enterprises), over 86.8 million (66.5% of all jobs), and for over €3.4 trillion, or 57% of total value added by the private, non-financial sectors in EU-27 countries in 2012 (European Commission, 2014). With the exception of the stock of enterprises, these figures were still below levels for 2008, indicating the severity of the financial crisis and highlighting the issue of finance for economic growth as a major focus for both practitioners and policy makers in the EU.

Throughout the financial crisis, SMEs across Europe were adversely affected by dramatic reductions in both aggregate demand and bank lending. According to the European Commission data, over the years 2008-2011, loans of less than €1 million to SMEs declined by an average of 47% against the pre-crisis peaks, with falls in the region of 66% in Spain and 82% in Ireland (European Commission, 2014). GDP per capita growth declined across the EU, with the most severe reductions reported for Greece, Ireland, Latvia, Lithuania and Finland. Average growth and recovery since 2011 in GDP per capita has been strongest in Lithuania, Ireland, Poland, Sweden and Germany, and weakest in Portugal and Italy. Spanish SMEs report the greatest losses in employment, turnover and profitability compared to SMEs in other European countries.

Financial indebtedness increased, with private sector credit to GDP exceeding 200% in Ireland, Spain and Portugal, while remaining at the 100% level for Germany, Sweden and France (European Commission, 2013). The proportion of non-performing loans was highest in Ireland, Portugal, Spain and the United Kingdom. Non-performing loans in Ireland reached 20% in 2012 compared to 2% for Sweden. In Ireland, SMEs were more reliant on bank overdrafts with over 60% of Irish SMEs using this source of finance compared to 7% of

Swedish SMEs (Mazars, 2010). German and Swedish SMEs had greater financial reserves and less financial indebtedness at the onset of the crisis.

In the aftermath of the economic downturn of 2008-2009, many SMEs closed. Some closures were voluntarily, whilst many others were involuntary and the result of liquidation or bankruptcy. The European Commission estimates that during the financial crisis and its aftermath, approximately 200,000 firms went bankrupt each year, resulting in direct job losses of about 5.1 million, with SMEs accounting for 99% of bankrupt firms (European Commission, 2016b).

3. Background literature and hypotheses development

Trade credit is the finance provided by suppliers to facilitate the transaction of goods and services. Firms act as financial intermediaries by providing finance to other firms comprising both the time differential between the delivery of goods and services and payment, as well as the proportional discounts allowed for payment in bulk or before the payment due date.

Among the many documented advantages of trade credit as a source of finance is the degree of financial flexibility it offers (Danielson and Scott, 2007), including the ability to overcome financial constraints when finance from financial institutions is unavailable (Petersen and Rajan, 1997; Schwartz, 1977).[3] However, there are a number of downsides to this source of financing. Trade credit can often be a very expensive form of finance, especially if firms do not avail of the early discount facility (Nilsen, 2002; Petersen and Rajan 1997). Furthermore, as shown by Jacobson and von Schedvin (2015) and Boissay and Gropp (2007), a trade debtor in bankruptcy will almost certainly default on their obligations to their trade

[3] Research also points to the usefulness of trade credit for reducing transaction costs (Ferris, 1981); verification of product quality before paying (Smith, 1987; Deloof and Jegers, 1996) and for the reasons of sales, profitability and market share (Petersen and Rajan, 1997; Banos-Cabellero, Garcia-Tereul and Martinez-sola, 2012).

creditors, thereby invoking sudden liquidity shortages, and a potential series of liquidity shocks along a given supply chain. Boissay and Gropp (2007) show that firms hit with liquidity shortages try and overcome a quarter of these shocks by involuntarily extracting greater trade credit from their creditors. The real effects of these shocks economy-wide is ultimately determined by the prevalence of unconstrained firms, and those with 'deep pockets' (Kiyotaki and Moore, 1997).

3.1. The impact of trade credit on survival

There are several reasons why more liquid firms extend trade credit to help other constrained firms avoid financial distress. First, more liquid firms may be motivated to sustain sales. Long lasting relationships appear to be an important determinant for trade credit extension (Cunat, 2007). Large suppliers can provide insurance to vulnerable buyers against liquidity shocks that could endanger their survival, and are more likely to offer additional credit if they anticipate additional future sales, especially from long lasting relationships (Cunat, 2007). While suppliers of goods have the ability to control and cut off future supplies, receivables can be used as collateral for bank credit (Burkart and Ellingson, 2004).[4] Second, suppliers often have cheaper access to finance, and a comparative advantage in passing it on via trade credit (Ng, Smith and Smith, 1999; Calomoris et al., 1995). Third, the use of trade credit allows for product verification and warranty (Lee and Stowe, 1993 and Long et al., 1993), and the provision of trade credit can also be used as a screening mechanism to gauge buyer default risk (Mian and Smith, 1992). Suppliers can reduce default risk with their customers through early payment incentives (Klapper, Laeven and Rajan, 2012; Ng, Kilholm Smith and Smith, 1999). Lastly, suppliers often have an implicit equity stake in the

[4] Note this prediction has been challenged in the case of US studies where the legal period in which suppliers can seize goods after delivery is 10 days (Garcia–Appendini and Montoriol-Garriga, 2015).

performance of their debtor firms (Petersen and Rajan, 1997), so a greater incentive to support them during difficult periods.

There is a long tradition of bankruptcy and financial distress prediction studies using samples of large publically listed firms (e.g., see Altman, 1968; Ohlson, 1980; Zmijewski, 1984). The Altman's Z-Score model (1968) based on financial accounting ratios is well established in the literature. While the original model is based on a publicly traded firm model that requires stock price data, it was successfully adapted to depict default levels for private firms in the US by Altman and Sabato (2007).

The literature supports the important role of trade credit as an alternative to bank finance, especially for firms in financial distress (Molina and Preve, 2012; Love, Preve and Sarria-Allende, 2007). Love et al., (2007) show that trade credit increased immediately for a short period of time after the 1990s financial crisis in emerging markets (i.e., Mexico and Southeast Asia), supporting the view that more vulnerable firms benefited when bank credit was constrained. However, they do not show if trade credit helped firms survive the crisis. Further, Cunat (2007) notes that suppliers can support their customers through trade credit financing when they experience temporary liquidity shocks.

We extend the work of Gupta et al (2015) and Pindado, Rodrigues and de la Torre (2008), to examine the link between access to trade credit and SME firm survival, especially over the financial crisis period. While prior research has highlighted the role of trade credit in easing financial distress for SMEs, it has not directly examined the impact of trade credit on survival. This gives rise to our first hypothesis:

H1: Trade credit reduces the likelihood of SME financial distress and failure, especially in the aftermath of the 2008 financial crisis.

3.2. The redistribution effect

Meltzer (1960) first reported that in periods of monetary tightening, larger firms increase their supply of trade credit. Calomiris et al. (1995) reports that liquid firms often provide a cushion of support to financially constrained firms during periods of credit tightening (e.g., Guarglia and Mateut, 2006; Berger and Udell, 1998; Biais and Gollier, 1997). Further, Garcia-Appendini and Montoriol-Garriga (2013), and Love et al. (2007) provide empirical support for the redistribution effect among large firms in general, and large listed firms in emerging market economies in the short term only.

Casey and O'Toole (2014) find that EU SMEs denied access to bank credit for working capital purposes during the crisis were more likely to apply for and use trade credit from other firms. This begs the question – how did other firms increase the supply of trade credit, if they themselves were also subject to a severe credit crunch? In order to get a fuller picture of the impact of the crisis, information on both the provision and receipt of trade credit to firms is needed. This requires examining the supply and demand for trade credit before and after the crisis, taking account of financial constraints. We predict that while overall net credit declined during the crisis period, financially liquid (unconstrained) firms redistributed more trade credit to more financially illiquid (constrained) firms. Specifically:

> H2: A tightening in bank lending to SMEs, such as that experienced during the 2008 financial crisis, led to a significant redistribution effect amongst SMEs. Specifically, liquid (unconstrained) firms extended more trade credit, and illiquid (constrained) firms received more.

4. Data and empirical analysis

4.1. Data

The biggest challenge to research on SMEs financing is the lack of financial statement data to make cross-country comparisons, which is compounded by the lack of conformity in defining SMEs across countries (OECD 2013). In this study, the EU Commission (2005) SME definition is applied to provide uniformity in terms of the reporting unit.[5] All financial and insurance-based firms, in line with prior empirical studies, are excluded. The analysis in this paper is based on Amadeus from Bureau Van Dijk, which claims to provide 'comparable' financial information for public and private firms across Europe derived from national government company offices, and other independent sources.

As a derived database, Amadeus has a number of shortcomings relative to data derived from National Statistical Offices. First, the definition of variables is less harmonised than from National Statistical Offices, but this is less of a problem with Amadeus because of the standard international format of balance sheets according to an OECD review (Pinto Ribeiro, Menghinello and De Backer, 2010). Second, problems arise due to incomplete and/or missing observations that reflect cross-country differences in legal and accounting reporting requirements for SMEs. Amadeus data for German SMEs, for example, is limited as there is no legal obligation on this size class to disclose financial data (Desai et al., 2003). This creates problems when constructing a well-represented balanced cross-country panel, which we address later in the robustness section using a weighting scheme.

Our initial sample includes 284,101 non-financial, unlisted SMEs and over 2.85 million observations across 15 countries. We eliminate two countries, Sweden and Lithuania, due to insufficient data to calculate Z-scores for our survival model, with the loss of over 50,000 firms and half a million observations. About 202,696 SMEs (1,395,135 firm-year observations) meet our data requirements. We use this 'unbalanced' sample to implement our distress model, as a 'balanced' sample, which we use in our redistribution analysis would, by construction, suffer

[5] The European Commission (2005) definition includes firms that employ less than 250 employees in a given year and have either an annual turnover of less than €50m or a balance sheet total of less than €43m.

from a survivorship bias, thereby excluding many firms that exit due to distress or takeover, or new entries.

[Insert Table 1 about here]

Table 1 (Panel A) shows the distribution of observations on SMEs from each country for the unbalanced panel of 202,696 SMEs. Five countries, Spain (27%), France (23%), Portugal (14%), UK (7%), and Italy (7%) account for the majority of observations in the sample. Latvia (0.02%), Ireland (0.3%), Greece (0.4%), and Germany (1%) contribute the smallest number of SMEs observations to the total sample. The number of observations varies over the years from 126,914 in 2003 to 168,228 in 2009. There are only 10,136 observations for the last year of the panel, which reflects the low number of SMEs that had filed their accounts at the time of data collection in March 2013.

A separate 'balanced' panel is constructed for the re-distribution analysis, as it is crucial that firms exist both pre and post crisis for identification purposes. Otherwise, our re-distribution findings could arise due to non-random changes (e.g., bankrupts, merger targets) in the sample of firms overtime. To address this, we construct a second sample that has a balanced component that includes only 107,776 firms (out of 202,696) that provide full coverage of all variables for each of the years immediately prior, during, and post crisis (i.e., 2007-2011). In total, the balanced sample contains 836,063 firm-year observations from 13 EU countries, over the period 2004-2012.[6]

Table 1 (Panel B) provides additional information on the distribution of observations for each of the three firm size divisions included in the SME firm classification criterion; micro

[6] To examine the impact of sample constraints on our empirical analysis, the on-line appendix tabulates results for the redistribution analysis using the full unbalanced panel (Table OA10 and OA12), and for the survival analysis using the more restrictive balanced panel (Table OA7 and Table OA8). For the redistribution analysis, our findings are consistent with those tabulated in the paper. The results based on the more restrictive balanced panel for our survival analysis are also mostly consistent, albeit statistical significance is reduced, largely as a result of the much smaller sample.

(less than 10 employees), small (10 to 49 employees) and medium (50 to 249 employees). Micro firms represent 31% of all 1,395,135 observations over the 10 years, with small firms representing 49%, and medium-sized firms representing 20% of observations.

Table 2 shows the breakdown of industries in the sample. Using the North America Industry Classification Scheme (NAICS) index codes, a total of 17 separate industry sectors are included. Four sectors, manufacturing (24%), wholesale trade (19%), construction (14%), and retail trade (8%) account for the largest proportion of SME observations, representing 65% of the total sample. Overall, the sample contains a broad and representative mix of sectors within the EU as reported by Eurostat (European Commission, 2013).

[Insert Table 2 here]

Before looking at differences in trade credit across countries, we first provide an overview of growth rates for countries included in our sample, measured as GDP per capita. Over the period 2004-2012, growth was highest in the less developed regions of Latvia and Poland, while averages were lowest in Portugal, Italy and Greece. These average growth figures are highly influenced by the severe recession experienced from the period 2008 onwards, with, e.g., Latvia reporting the highest levels of growth, while also experiencing the most severe falls over the financial crisis. More significantly, this can be seen in terms of demand and investment across Europe, but also in terms of the levels of bank credit extended economy wide. Several European countries experienced a rapid expansion in the levels of private sector credit extended by the banking in the years preceding the crisis followed by a dramatic decline subsequently. Over the 10 year period 2003 to 2012, net private credit extended was above 150% of GDP in the UK, Ireland, Portugal, and Spain[7].

[Insert Figure 1 here]

[7] Table OA3 shows the average for key macroeconomic and institutional indicators by country and legal origin.

4.2. Trade credit summary statistics

Table 3 (Panel A) reports sample means for trade credit use across our sample of EU countries, and Panel B presents summary statistics for the main variables.[8] The results in Panel A give a baseline indication of the importance of trade credit to SMEs across our sample. The amount owed to suppliers by SMEs (*Trade credit_a*) represents, on average, 20% of total assets[9] and the amount owed to SMEs by customers (*Trade debtors*_a) represents 30% of total assets, on average, indicating that SMEs are net providers of credit (*Net TC_a) of approximately* 14% of total assets. Noteworthy is Ireland, where SMEs were net recipients of trade credit (-16%).

Timing is also critical in trade credit management, especially if firms are paying suppliers faster (*creditor days*) than they are receiving payments due to them (*debtor days*), which will give rise to a funding gap. On average SMEs in our sample pay their creditors within 34 days, but have to wait on average 77 days to receive payment, giving rise to a net funding gap of 44 days. Panel A also shows large differences across countries. SMEs from Mediterranean countries have the longest debtor collection days, including Greece (135 days), Portugal (111 days), Spain (96 days) and Italy (95 days), whereas Finland (29 days), Latvia (29 days) and Germany (32 days), have the shortest. Largest net credit extension, debtor and creditor days, and trade credit use in general is observed in Spain, Greece, Portugal and Italy.

This evidence provides little support for Petersen and Rajan (1997) 'helping hand theory', which suggests that larger firms, with easier and cheaper access to finance, are net providers of trade credit to SMEs. Our analysis allows us to examine this theory more closely, controlling for demand and supply factors.

[8] All continuous financial variables are winsorized at the 1 percent and 99 percent level to help mitigate the effect of extreme outliers in the data.

[9] Atanasova (2012) report a value of 20% for a sample of UK firms, while Petersen and Rajan (1995) report an average value of accounts payable to assets of 15% for US firms, and Molina and Preve (2012) report a value of 10% for US listed firms.

The summary statistics in Table 3 Panel B present the mean and median values for the key variables (see Appendix A for variable definitions) employed in our empirical analysis. On average trade payables as a proportion to assets are 0.20 and trade receivables scaled by assets are larger at 0.30. A mean level of cash to assets are 0.16. Of all the variables, the variables with the largest variability include TC/Bank finance, default risk and firm age.

[Insert Table 3 and 4 here]

Table 4 reports the observed relationship between SME financial characteristics and the level of trade credit finance firms received both before and after the financial crisis. The distribution of firms is split into 4 quartiles, and trade credit received is measured by the level of accounts payable scaled by assets. *Pre-crisis* represents the years of 2003-2007, while the *crisis* period is measured as the years 2008 to 2012. The figures illustrate a number of noteworthy findings. In general, older, larger (as measured by assets and employment up to the fourth quartile), and firms with greater levels of operating revenue and bank debt, on average receive more trade credit. Firms with the largest cash reserves receive less trade credit up to the final quartile and are net extenders of credit over the crisis. The level of trade credit received from pre-crisis to the crisis period does not appear to be effected by levels of bank debt.

4.3. Trade credit and financial distress

This section examines the relationship between trade credit and firm financial distress. We measure distress using the Altman Z-Score for private firms, as described in Appendix B. The dependent variable is modelled as a binary choice equal to 1 if a firm is classified as distressed using the Z-score cut-off (<1.23), and 0 otherwise. Formally,

$$Y_{it}^{*} = \mathrm{X}_{it}\beta + \beta_1 trade\ credit_{it-1} + \beta_2\ time + \beta_3\ time * trade\ credit_{it-1} + \varepsilon_{\mathrm{it}} \quad i = 1,2,\dots,n; t = 1,2\dots n,$$
$$Y_{it} = 1 \text{ if } Y_{it}^{*} < 1.23;\ Y_{it} = 0\ otherwise \tag{1}$$

where Y_{it} is likelihood of firm *i* experiencing financial distress in time period t, measured using the Altman Z-Score, $trade\ credit$ is a measure is a measure of trade credit (either Net credit extended (received)) calculated as the difference between accounts receivable and payables scaled by sales or accounts receivable and payable separately scaled by assets; '*time*' refers to crisis time year dummy variable (year 2008), or the post crisis years (2009-2011); *time*trade credit* is an interaction term to determine the impact of trade credit received on the likelihood of distress in the crisis and post crisis years; X_{it} is a vector of explanatory variables influencing distress, and includes firm age, size (ln(assets)), sales growth, banking concentration (Lerner), and ε_{it} is an error term. All independent variables are lagged to avoid simultaneity.

The binary choice regression model assumes the presence of time invariant unobserved heterogeneity in the form of c_i where,

$$Y_{it}^{*} = x_{it}\beta + \beta_1 trade\ credit_{it-1} + \beta_2\ time + \beta_3\ time * trade\ credit_{it-1} + \beta_4 ln(assets)_{it-1} + \beta_5 salesgrowth_{it-1} + \beta_6 cash\_a_{it-1} + \beta_7 age_{it-1} + \beta_8 age_{it-1}^2 + \beta_8 Lerner_{it-1} + c_i + u_{it} \quad (2)$$

The model is similar to a cross sectional model in that the probability function of $x_{it} + \beta + c_i$ is bound to the interval [0,1], i.e., a cumulative distribution function $0 \leq F(x_i\beta) \leq 1$. In the nonlinear panel (a fixed effects logit), we factor out the time invariant unobservable component c_i, which allows for the control of the unobserved time invariant heterogeneity without making assumptions about the relationship between $x_{it} + c_i$.[10] A disadvantage of the fixed effects logit is that (a) fixed effects is less efficient as you can only use when there is a change for each firm; and (b) due to our lack of knowledge regarding c_i, partial effects cannot be estimated, so odds ratios are reported instead and (c) affects the number of observations in

[10] With the fixed effect probit model it is not possible to factor out c_i. Instead, c_i is treated as parameters to be estimated. As is the case in this sample, with fixed T and large N, as $N \rightarrow \infty$ the number of parameters to be estimated gets very large and all estimates become inconsistent. This is also known as the *incidental parameters problem*, in which the fixed effects panel probit gives inconsistent estimates.

regression. The model also requires that the conditional independence assumption holds (i.e., no serial correlation in *y* conditional on *x* and *c*). Following both Pindado et al. (2008) and Arrelano and Honoré (2001), the choice of using probit and logit models depend on assumptions regarding the distribution of the error term, therefore estimating both is advised. While the disadvantage of random effects probit is that it may not control for all time invariant heterogeneity. We also estimate a random effects probit for interpretation of average partial effects, which we show are similar to the fixed effects logit.

[Insert Table 5 and Insert Figure 2 here]

Tables 5 reports the number and proportion of firms experiencing financial distress by SME size class and year in Panel A, and by country of origin in Panel B. Firms reporting a Z-score of <1.23 are deemed likely to be experiencing financial distress with a greater likelihood of bankruptcy. Panel A reports a higher likelihood of financial distress of about 15% in the post crisis years (2009 to 2011) relative to the pre-years (2003-2007) of about 11%. The average Z-score rose from 3.17 in the pre-crisis years to 3.42 in the post crisis period, which is statistically significant at the 1% level. Further, all SME size classifications (micro, small, medium) experience an increase in distress likelihood. Panel B shows that across all countries, Portugal has the highest proportion of SMEs experiencing financial distress at 25%, followed by Italy (15%) and Latvia (15%). Figure 2 shows that on average over the years 2008-2011, SMEs in likelihood of distress, across all sizes (small, medium and large) received greater trade credit (as measured by payables –receivables over sales) over their non-distressed counterparts.

[Insert Table 6 and 7 about here]

Table 6 and 7 report the results from logit fixed effects regressions, and random effects probit regressions, respectively.[11] The results are similar for both models, so we focus on Table

[11] Analysis of transition matrices from year to year of the two main binary indicators of financial distress based on the Z-score indicate significant persistence in the dependent variables. For example, 96% of those that did not go bankrupt in one year did not do so in the next year either, while 70% of those that are in danger of bankruptcy in one year are also at risk in the next year.

7 as the partial effects are more convenient to interpret relative to odds ratios reported for the logit models in Table 6. The regression models in Table 7 report both the average effect of trade credit extended (net received in model 1), relative to bank finance (model 4), received via accounts payable (models 3,5,6 and 9) and the amount net received (models 2,7 and 8) on SME financial distress, as well as the specific impact of credit received at the onset of the crisis on subsequent distress/ survival over the crisis years. The results show that firms that receive higher levels of trade credit are significantly *less* likely to experience financial distress.[12] In terms of economic magnitude, Table 7 (probit) model 2 shows a partial effect of (-0.215) in terms of net trade credit received (payables minus receivables/sales) suggesting that a one standard deviation (0.22) increase in trade credit results in a 5% (0.22*-0.215) decrease in the likelihood of distress. For accounts payable alone over total assets (model 9) shows an even larger effect, with a partial effect (-0.559), suggesting a 21% (0.37*-0.559) decrease in the likelihood of distress.

The results also show that firms, on average, were more likely to fail in the post crisis years (post_crisis_dummy). More importantly, the interaction term 'post_crisis_dummy*trade credit_a$_{t-1}$' and 'post_crisis_dummy*NetTC reeived$_{t-1}$' are negative and significant, supporting our hypothesis that trade credit was particularly valuable in helping to mitigate distress in the post-crisis years. Model 6 and 8 in Table 7 show this interaction with both net trade credit received, and trade credit received (proxied by accounts payable). The partial effects for both these equations are (-0.025) and (-0.059), respectively, indicating reductions in the likelihood of bankruptcy by 0.6% (0.22*-0.025) and 2.2% (0.37*-0.059) in addition to the reductions outlined above.

[12] While the results presented are based on the Z-score calculations for a large sample of European firms, an analysis was also conducted on the whole sample using a direct failure measure of bankruptcy of which included approximately 3,500 insolvent firms out of the total sample, which confirm the findings obtained here (available on request).

The results for some of the control variables are worth highlighting. Firms from countries with more concentrated banking sectors (Lerner) are significantly more likely to experience distress, consistent with the view that banking concentration gives rise to constraints in lending (Ryan et al., 2014). Further, larger (Ln_assets) and older firms (age), and firms with greater cash reserves (Cash_a) were less likely to experience financial distress over the sample period.

Our findings provide strong support for hypothesis 1 in that trade credit helped SMEs, on average, to reduce likelihood of distress, and this was also more evident in the post crisis years. By drawing on models of bankruptcy and financial distress in SMEs (Altman and Sabato, 2007 and Gupta et al., 2015) we complement and extend existing analysis of trade credit during periods of financial constraint. Prior work by Casey and O'Toole (2014), Carbo-Valverde et al. (2009; 2016), Garcia-Appendini and Montoriol Garriga (2013), Ferrando and Mulier (2013), and Petersen and Rajan (1997) shows that trade credit provides a buffer for financially constrained firms. We add to this by showing that trade credit significantly *reduces* the likelihood of financial distress and bankruptcy, especially during periods when credit is constrained. The next section examines the extent to which financially liquid firms redistributed more trade credit to more financially illiquid firms.

4.4. Trade credit use and redistribution

The section tests for the existence of a redistribution effect by examining the relationship between the financial position of SMEs entering the crisis, and their subsequent financial position and use of trade credit financing during, and post crisis years. The baseline regression model takes the following form:

$$TC_{it} = \beta_1 + \beta_2 crisis + \beta_3 \text{postcrisis} + \beta_4 FS_i \ * \text{crisis}_i + \beta_5 FS_i \ * \text{postcrisis}_i + \beta_6 ln(assets)_{it-1} + \beta_7 salesgrowth_{it-1} + \beta_8 cash\_a_{it-1} + \beta_9 age_{it-1} + \beta_{10} age_{it-1}^2 + \varepsilon_{it}$$

(3)

Where $\varepsilon_{it} = \cap_i + V_{it}$. TC_{it} is the measure of trade credit, calculated as total trade credit or net trade credit[13], FS is the financial strength of the firm measured in the pre-crisis year[14], α is the firm fixed effect, and ε_{it} denotes the error term. Financial strength (FS) of the firm is measured using cash-holdings scaled by book assets. To ensure our findings are not sensitive to our measure of financial strength, we also follow the approach in Carbo Valverde et al., (2009; 2016), who define financial strength or constraints using a structural simultaneous equations model that accounts for both demand and supply-side constraints (see Section 4.2.1 for details of this approach). We include several control variables in our regressions that are predicted to influence the level of trade credit. These include firm age, growth in sales (sales growth), level of short-term bank debt scaled by firm assets (loans_a), size (ln(assets)), and the level of economic activity captured by GDP per capita (Gdppcg).

The fixed effects regression models capture unobserved factors, which are time invariant in short time panels. Factors likely to influence trade credit use can be time invariant firm specific factors. A Hausman test conducted also supports a fixed effects regression over random effects, while the models also include country dummies where appropriate to control for time invariant country fixed effects. Our model assumes that firms do not have a target level of trade credit, and that firm's current level of trade credit is their optimal level. An alternative approach would be to assume that firms move towards an optimal level of trade credit, and that variations in the level of trade credit overtime are the result of trade-off costs. To investigate this possibility, similar to Flannery and Rangan (2006), we explore the use of a dynamic or

[13] Ferrando and Mulier (2013) calculate trade credit as the sum of accounts receivables and payables scaled by sales, and Petersen and Rajan (1997) scale payables by firm assets. We include a net value for trade credit extended and received as the difference between receivables and payables over firm sales to account for net levels of credit extended and the difference between payables and receivables as a measure of trade credit received as a proportion of firm assets, and as a proportion of firm sales, to control for *changes* in economic activity.

[14] We note that the financial crisis initially impacted European countries over the period mid-2007 to late 2008, therefore we use 2008 as the benchmark year.

partial adjustment type specification, which involves including the lagged dependent variable on the right-hand side.[15] Naturally, including lagged values of the dependent variable induces an endogeneity problem, so for this regression specification we employ a GMM specification (see Section 4.4.1 and *Generalised Methods of Moments (GMM)* below for further details).

To examine the responses of SMEs to the crisis, we use the interactions of the financial position of the firm (FS) in the pre-crisis year (2007) with the crisis year (2008), and the post-crisis years (2009 to 2011). To provide direct evidence of a redistribution effect, we examine the change in trade credit use relative to bank credit over the crisis period by replacing the dependent variable with the ratio of net credit extended scaled by the level of bank credit received and outstanding.

4.2.1. Redistribution effects and the financial crisis

SMEs are categorized as fully constrained in accessing bank finance using yearly predicted values from bank finance (debt) demand and supply equations (equation 4 and 5 below). We create a set of dummy variables (=1, 0 otherwise) to capture firm-years that firms are fully constrained, partially constrained, or unconstrained. A firm is classified as fully constrained if predicted demand is more than 1.5 times predicted supply, and partially constrained if demand is greater than supply, and unconstrained if demand is less than supply (Carbo-Valverde et al., 2009).

Demand equation

$$\begin{aligned} bank\ loans_{it}^{D} = \beta_o^d + \beta_1^d cashflow\_a_{it-1} + \beta_2^d loans\_spread_{t-1} \\ + \beta_3^d GDPpcg_{t-1} + \beta_4^d country_i + \beta_5^d industry_{it} + \varepsilon_t \end{aligned} \tag{4}$$

Supply equation

[15] We would like to thank the reviewer for suggesting this specification.

$$bank\ loans_{it}^{s} = \beta_{o}^{s} + \beta_{1}^{s} tangibility_{it-1} + \beta_{2}^{s} Lerner_{it-1} + \beta_{3}^{s} default_{it-1} + \beta_{4}^{s} GDPpcg_{t-1} + \beta_{5}^{d} country_{i} + \beta_{6}^{d} industry_{it} + \varepsilon_{t} \tag{5}$$

where $bank\ loans_{it}^{s}$ and $bank\ loans_{it}^{s}$ are the sum of short-term bank loans plus long-term financial debt to credit institutions scaled by total firm assets (a), operating cash flow scaled by firm assets (cashflow_a), total financial expenses/total bank loans outstanding (loans_spread), average per capita income growth (GDPpcg), fixed assets scaled by total firm assets (tangibility), a measure of firm level banking concentration (Lerner), firm default risk (default), calculated as operating profits scaled by financial expenses, country and industry sector dummy control variables and an error term (ε_t). The yearly regression models are estimated using OLS, and include both industry and country dummies to control for industry and country fixed effects.

[Insert Table 8 here]

Table 8 reports the summary statistics for SMEs that are categorized as constrained, partially constrained, and fully constrained in our sample. In the balanced sample, approximately 30% of firms are categorized as unconstrained, 41% partially constrained, and about 29% fully constrained. Not surprisingly, the percentage of firms fully constrained increases markedly in post crisis years, rising from 12% in 2008 to 49% in 2009 and 84% in 2010.

Generalised method of moments (GMM)

To address the potential of a habitual nature or targeting behaviour in trade credit use, and potential omitted variable bias, we re-estimate equation (3) using a GMM specification. The GMM regressions are estimated using a first differenced system GMM (Blundell and Bond, 1998).

$$TC_{it} = \alpha\, TCi_{t-1} + \beta_1 crisis + \beta_2 \text{postcrisis} + \beta_3 FS_i \;\; * \text{crisis}_i + \beta_4 FS_i \;\; * \text{postcrisis}_i$$
$$\beta_5 ln(assets)_{it-1} + \beta_6 salesgrowth_{it-1} + \beta_7 cash\_a_{it-1} \quad + \beta_8 age_{it-1}$$
$$+\beta_9 age^2_{it-1} \; + f_i + \; e_{it} \tag{6}$$

where $f_i + \; e_{it}$ denote the firm specific effect and error term, respectively. The results from the two-step System GMM are presented in Table 9 (Panel A). The standard errors presented in parentheses are robust and corrected according to Windmeijer (2005). The Hansen test is used to test for over identifying restrictions.

Equation (6) is similar to equation (3), but uses first differences for variables and contains a lagged dependent variable (for trade credit) to specifically test if prior changes in trade credit help predict next period changes (partial adjustment). It is well documented that OLS will give a biased and inconsistent estimate for the coefficient on the lagged dependent variable, and the coefficient estimates obtained from fixed effects are likely to be biased downwards (Arrelano and Bond, 1991). The estimate for the first differences Arrelano-Bond estimator uses all available lagged levels as instruments, which removes the unobserved individual effects, thereby eliminating the source of omitted variable bias. The system estimator (Blundell and Bond, 1998) assumes that when explanatory variables are persistent over time, lagged levels provide weak instruments for the differenced equations, and can produce biased coefficients.

The system GMM estimator improves on the Arrelano-Bond difference estimator by utilising all available moment conditions by combining a set of moment conditions obtained from the difference equations with lagged levels used as instruments, with an additional set of moment conditions obtained from the equation in levels. The additional set of instruments is argued to improve the efficiency of the estimator. The estimator has a number of benefits, including the ability to deal with potential endogeneity as a result of the inclusion of the lagged dependent variable, and the ability to control for time invariant effects. The consistency of the system GMM estimates depend on the validity of the instruments and the set of specification tests. These include namely the Sargan/Hansen test of over-identifying restrictions, which tests the overall validity of the instruments, and the first and second order autoregressive tests (See Roodman, 2006). We report these specification tests in the regression tables. We report all specification for AR(1) and AR(2) and Hansen. The Hansen J test is based on the null hypothesis that the instruments are orthogonal to the error process. A rejection of the null hypothesis would indicate invalid instruments and inconsistent estimates.

Table 9 reports OLS (models 1 to 4) and system GMM regressions (models 5 to 7) that directly examine the relationship between firms' financial position at the time of the crisis and their subsequent use of trade credit finance during the crisis/post-crisis years. Table 9 Panel A (models 1-6) show the interaction between trade credit received, extended, and net extended using interaction terms (i.e., cash-holdings scaled by assets (cash_a) multiplied by crisis and post crisis year dummy variables). The balance panel of 107,776 firms ensures that the same firms are captured over the pre and post crisis period, and that the results are not driven by non-random changes in the underlying sample distribution.

[Insert Table 9 about here]

The results show that firms in a stronger financial position when entering the crisis, in particular, those with the largest cash reserves were net providers of credit in the subsequent years. Furthermore, they consistently extended *more* credit and received *less* than prior to the onset of the financial crisis, so providing strong support for hypothesis 2. This result holds when controlling for firm characteristics, firm fixed effects, and country fixed effects. The results also hold for the levels of credit received (trade credit_a), the levels of credit extended (trade debtors_a), and the net level of credit extended (NetTC_a).

In terms of the degree of redistribution, in volume (economic) terms, the most liquid SMEs (i.e., those in the top quartile of the distribution of cash resources relative to assets) at the onset of the crisis (2008) were net providers of credit, and extended approximately 11 times more credit relative to less liquid SMEs (bottom quartile).[16] Net trade credit is worth highlighting, and shows that firms with the largest levels of cash reserves entering the financial crisis period were net providers of credit throughout the crisis period. The adjusted R^2 for each of the regressions reported in Table 9 is in excess of 70%, indicating that the models are well specified.

The system GMM regressions (models 5-7) provide some support for a dynamic or partial adjustment model with prior net trade credit (model 7) significantly impacting on the current level of net trade credit. Decomposing net trade credit into creditors and debtors (models 5 and 6, respectively) indicates that debtors drive this relationship. The significant coefficient on the lagged value of net trade credit (0.418) indicates that firms, on average, reach target levels of net trade credit fairly rapidly, consistent with larger costs of being in disequilibrium.[17]

Panel B of Table 9 reports the relation between trade credit use using dummy variables that capture the demand and supply (i.e., equations 4 and 5) of bank finance (Carbo-Valverde et al., 2009; 2016). The results indicate that firms unconstrained in their access to bank finance received statistically *less* trade credit than prior to the onset of the crisis, and extended significantly *more* trade credit in the form of net trade credit. Further, SMEs fully constrained in access to bank finance at the onset of the crisis extended *less* in the form of net credit in the subsequent years, and received *more* in the latter years of the crisis period. We also estimate

[16] Using Table 9 (model 4), the net effect for the year 2011 is the coefficient on the interaction term 'year 2011*$cash\_a_{2007}$' less the coefficient on the 'year 2011' dummy (0.023-0.010=0.013) times the cash position at the 75th percentile in 2007 (0.22) scaled by 0.013 times the cash position at the 25th percentile (i.e., 0.00286/0.00026 =11).

[17] The speed of adjustment is calculated as 0.582 (1-0.418: model 7), suggesting that firms, on average, reach target levels of net trade credit in approximately 2 years.

Panel B regressions using system GMM, and report the results, which are consistent with Panel A[18].

[Insert Table 10 about here]

Table 10 examines the relation between trade credit and bank credit. Results are shown for both firm fixed effects and GMM regressions, which show that the level of trade credit extended relative to bank finance received rises for firms with the highest levels of cash reserves over the years of the crisis, 2008 to 2011, providing further support for hypothesis 2. This result reinforces the finding that irrespective of changes in the banking sector, firms' role as financial intermediaries increased over the crisis period, and this role is particularly noticeable for firms in the strongest financial position when entering the crisis.

In summary, the results confirm a strong redistribution effect for our sample of EU SMEs consistent with the findings for larger firms (Garcia-Appendini and Montoriol-Garriga 2013 and Love et al. 2007), and for Spanish SMEs (Carbo-Valverde et al. 2009 and 2016) and EU SMEs (Ferrando and Mulier 2013). Extending the work of Carbo-Valverde et al. (2009 and 2016) for Spanish SMEs, we estimate credit demand and supply, to show how trade credit redistribution differs between constrained and unconstrained firms, pre, during, and post the financial crisis years across Europe. Our findings are consistent with those of Casey and O'Toole (2014) that indicate that many European SMEs constrained in access to finance from financial institutions over the crisis period increased their reliance on trade credit.

4.4. Robustness tests

This section reports the results to several additional robustness tests that deal with endogeneity concerns arising from potential omitted variables, and sample composition concerns,

[18] See Table OA10 in online appendix.

specifically, differences in the number of observations across countries. The results from this analysis are tabulated in the online appendix, and if not, are available from the authors on request.

4.4.1. Omitted variables

Omitted variables concerns are a significant concern in empirical corporate finance, and this is especially the case when cross-country samples are used. To mitigate against this concern, we employ a firm fixed effects specification to deal with potential omitted time-invariant firm-level variables, and we also use a system GMM specification. Nevertheless, the models could still suffer from an omitted variable problem with respect to time varying variables. We address this by examining several additional variables that prior literature shows impact on trade credit.

Banking concentration and country time-varying variables

The degree of banking concentration and interest rates charged has a significant negative influence on the financing outcomes for SMEs (Ryan et al., 2014). Since the onset of the financial crisis in 2008, there has been a renewed interest in the relationship between banking market competition and the level of private sector credit extended by banks. Drakos (2013) finds that European SMEs, particularly in the sovereign debt crisis countries (i.e., Greece, Ireland, Spain and Portugal) experienced considerable tightening in bank lending conditions.

Given the dependence of SMEs on short-term bank loans, differences in banking systems are likely to impact on the role of trade credit in SME finance over the crisis period, so is a potential omitted variable. We measure banking concentration using the Lerner index, calculated for each firm as one minus the yearly average (medium) of earnings before interest and tax minus financial expenses over firm sales.

We also explore the relationship between the use of trade credit financing and the role of time varying country differences, including institutional factors, GDP per capita growth, and credit extended by the banking sector, interest rates, and the International Country Risk Guide (ICRG) composite time varying index. The composite index is a weighted average of indices that reflect political, economic and financial risk. A higher value of the index indicates lower overall country risk. Table OA3 in the on-line appendix includes summary statistic information on cross country differences in macroeconomic variables over the sample period that were likely to influence both the performance of SMEs and access to external finance of all sources. As illustrated by the skewness, there were wide variations in the average values of macroeconomic variables over the sample period. Similar to Figure 1 (GDPpcg), the average growth rates of European economics deteriorated significantly from the year 2008.

All regressions reported in Table OA11 control for firm level characteristics, including the level of short-term bank debt, firm cash and an interaction term for firm cash and size (to capture the impact of scale/size on cash holdings). In model 1 and 4, we include the ICRG composite index in determining the level of net credit, while in models 2, 6 and 7 we assess the role of individual country specific factors. Regression models (1) and (4) shows a negative coefficient for the ICRG index, suggesting that less trade credit is extended in countries with lower levels of country risk. The results are consistent with prior research that do not specifically refer to country 'risk' but do refer to trade credit levels being higher in regions where financial markets are less well developed (e.g., Fishman and Love, 2003) and that trade credit usage appears to be higher in regions where lower creditor protection rights exist (e.g., Burkart and Ellingson, 2004; Demirguc-cunt and Maksimovic, 2004).

In model 2, banking concentration, GDP growth, and the level of private sector credit issued by the banking sector are all positively associated with the level of net credit extended. While an inverse relationship between regulatory quality and net trade credit is observed higher regulatory quality is associated with lower levels of trade credit use. These variables, however, lose statistical significance in models 6 and 7 using GMM. Importantly, while a number of the explanatory variables lose statistical significance, the results across three different categories of trade credit show that in the case of both trade debtors and net credit extended, past levels of trade credit have a significant impact on current trade credit use. The consistency of the estimates is supported by the Hansen test of over-identifying restrictions. Hansen p-values are higher than 10% supporting the validity of the instruments, and uncorrelated with the error term. For regressions AR(1) and AR(2) support the validity of the GMM instruments. The associated AR(2) p-values fails to reject the null hypothesis of no evidence of second order serial correlation in the first differenced residuals.

4.4.2 Cross-country weights

Since data size and quality vary significantly across countries, it is important to test that the results are not driven by any one country. In Amadeus data on manufacturing and services across countries is quite good, and industry coverage is stable and representative across countries and over time (Gomez-Salvador et al., 2004), however data availability for Germany is noticeably sparse. While the regressions include country fixed effects as a robustness measure, we also employ a weighted least squares specification to control for any biases that may arise from countries whose SMEs are over represented in the total sample. The weighting scheme uses the inverse of the proportion of country observations, therefore increasing the importance of countries with lower firm year observations as a proportion of the total sample.

The weighting least squares procedure is as follows: The weighted measure is simply the number of observations for country *i* scaled by the total number of observations for the total sample. To get the inverse of the weight, we use the measure of 1 over the individual country weight as illustrated below.

$$\text{weighting Wi} = \frac{1}{\frac{Ci}{\sum_{i=1}^{n} Ci}} \tag{7}$$

where $C_i =$ The number of observations for country i and n= number of observations for the total sample. The regression results from using weighted least squares regressions are similar to those already tabulated, and due to brevity concerns, are not tabulated, but available from the authors on request.

Within country weights

In addition to ensuring that the results are not primarily driven by cross-country differences in sample size, we also apply a weighting scheme to ensure within country representatives. To do this, we used a number of weighting approaches including, applying weights according to the total number of SMEs in the final year (Table 1 Panel A) and comparing to the total number of SMEs in each European country sourced from the European Commission Eurostat statistics on SMEs in 2013.[19] We also applied weights according to the number of people employed by SMEs in each country according to Eurostat figures. See table OA12 in the on-line appendix. The results are consistent with those presented in Table 10.

[19] We also applied weights according to industry sector. The number of enterprises across industry sector classifications was weighted against the number of enterprises by industry sector according to the Eurostat figures. Matching here was challenging for a couple reasons, including: (a) Eurostat defines industry sector according to NACE Rev.2 classification, whereas our panel is based on American (NAICS) industry sector classifications. Therefore, we manually matched the industry sector number of SMEs as closely as possible.

5 Conclusion

We use a large sample of European SMEs to examine the role of trade credit in financing SMEs over the financial crisis period. The analysis extends the existing literature and empirical evidence on the redistribution theory of Petersen and Rajan (1997), to examine the impact of trade credit on the likelihood of distress and bankruptcy by drawing on models of bankruptcy and financial distress in SMEs (Altman and Sabato, 2007 and Gupta et al., 2015). Prior work (see, e.g., Casey and O'Toole 2014; Carbo-Valverde, et al., 2009 and 2016; Garcia-Appendini and Montoriol Garriga, 2013; Ferrando and Mulier, 2013; and Petersen and Rajan, 1997) shows that trade credit provides a buffer for financially constrained firms, and we extend this to show that trade credit significantly reduced the likelihood of financial distress, especially in the aftermath of the 2008 financial crisis.

The increased levels of financing extended by cash rich or unconstrained SMEs over the crisis years played a significant role in funding less liquid and financially constrained SMEs for a period of time, and ultimately, had a positive impact on their survival. In statistical terms, a one standard deviation increase in trade credit leads to a 21% decrease in the likelihood of distress, all else equal. More importantly, we show that trade credit played a more significant role during the post-crisis years, suggesting that it helped many financially constrained firms survive during this period.

The findings also show that SMEs are more likely to rely on trade credit financing if they are (a) experiencing difficulty in accessing bank financing, and (b) the level of banking concentration is high.

Our findings have important implications for SME financing policy. In aftermath of the economic crisis, there is increasing acknowledgment of the role of young micro SMEs in terms of stimulating economic growth and employment, accompanied by an increased awareness of the high failure rates amongst these firms (European Commission, 2015). Across the EU member states, one third of newly created firms die before their second birthday, primarily due to bankruptcies and other forms of involuntary business cessations (European Commission, 2016a). It is also clear from several series of SAFE data that these micro SMEs make little use of external finance apart from bank overdrafts and lines of credit. Therefore, greater focus on trade credit as a source of financing is required.

In regard to policy, our findings support emerging evidence in the literature that suggests a shift in focus away from solely bank finance towards encouraging inter-firm finance and facilitating new forms of finance provision in the SME sector. These include forms of invoicing, discounting, and measures that allow larger suppliers and financial intermediaries with vast industry sectorial knowledge to play a greater role in finance provision to SMEs. These initiatives also reduce transaction costs and information asymmetry that historically have been important in limiting the supply of finance in the SME sector.

Our results support a more proactive policy to facilitate greater trade credit extension by suppliers in times of financial crisis, especially given the anticyclical nature of trade credit. Finally, whilst trade credit is an important source of finance for SMEs, an examination of net trade credit gives a fuller picture of its role as an adjustment mechanism in the economy. To this end, our key finding that trade credit played a significant role in SME survival in periods of severe credit tightening is an important contribution to SME research.

Appendix A: Variable names

Variable names	Description
Dependent variables	
Net TC_s	Capturing net trade credit extended (calculated as trade receivables minus payables scaled by sales)
Net TC_a	Trade receivables minus payables scaled by assets
Net TC/Bank Finance	Receivables minus payables scaled by bank debt outstanding
Tradecredit_a	Accounts Payable scaled by assets
Tradedebtors_a	Accounts receivables scaled by assets
Net TC received	Accounts payable minus receivables over sales
Loan demand variables	
Total_debt_a	Loans (short-term bank loans) plus long-term financial debt to credit institutions scaled by total firm assets*
Loan_spread	Total financial expenses/total bank loans outstanding
Cashflow_a	EBIT – financial expenses + depreciation over total assets
Loan supply variables	
Tangibility	Fixed assets/ total assets.
Default risk	Default risk calculated as (Operating profits/ Financial Expenses.*
Lerner_index	A measure of banking concentration. Calculated as 1 minus the yearly average (median) of EBIT minus financial expenses)/firm sales within each of the 18 separate industry sectors.
GDP per capita growth	Real GDP growth per capita
Independent variables	
Size (Ln_assets)	Firm size, measured as the natural log of total assets
Sales growth	Firm $sales_t$ - $sales_{t-1}$ /$sales_{t-1}$
Age	Firm age, number of years since incorporation
Loans_a	Short-term financial debts and part of long-term financial debts payable within one year scaled by firm assets
Cash_a	Amount of cash in hands of firm and deposited in bank scaled by firm assets
Employees	Number of employees
Cash_s	Total cash and deposits of firm scaled by sales
Financial distress variables	
WCTA	Working capital scaled by total assets
Ebitda_a	Earnings before interest and tax over firm assets (EBIT/total assets)
SFTL	Total shareholders' funds over total liabilities
Sales_a	Total sales over total assets
Z-score	Sum((.7.17(wcta) +.847(cashta) +3.107(ebitta) +.42(sftl)+ .998(salesta))

*Loans = (current liabilities - trade creditors). We have also calculated from variable direct from Amadeus on short-term bank loans and yielded similar results. * Financial expenses include all financial expenses such as interest charges on loans and the write off of financial assets.

Appendix B

Financial distress classification model

The first step in the analysis involves creating variables that predict firm failure and financial distress. These estimations are also supported by data on actual firm failure.[20] We use the Altman and Sabato (2007) Z-score for private firms. This measure relies on the complete coverage of a number of variables, including working capital, cash-holdings, sales, earnings before interest and tax, and total liabilities. Firms reporting a Z-score of <1.23 are deemed more likely to experience financial distress and bankruptcy. The Altman Z- Score for private firms is given by:

$$Z_{it} = \sum 0.717 * wcta_{it} + .847 * cashta_{it} + 3.107 * ebitta_{it} + 0.42 * sftl_{it} + 0.998 * salesta_{it} \quad \text{(A1)}$$

where $wcta_{it}$ is working capital (current assets less current liabilities) scaled by total assets, $cashta_{it}$ is the retained earnings scaled by total assets, $ebitta_{it}$ is earnings before interest and tax scaled by total assets, $sftl_{it}$ is the total book value of firm debt as a proportion of total firm liabilities, and $salesta_{it}$ measures total firm sales scaled by total assets. All variables are measured at time t.

[20] Tests were conducted based on observations of approximately 3,500 failed firms as a robustness check to the results obtained from the financial distress analysis.

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Figure 1 GDP per capita growth across Europe 2003-2012

Figure 2 Trade credit received over period 2003-2011

The figure illustrates trade credit received (calculated as trade payables minus receivables/ firm sales) over the period 2003-2012 for both distressed (_D) and non-distressed (_ND) cases. An independent t-test was run on the balanced sample to determine if there were differences in the average net trade credit received based on whether SMEs where classified as distressed or non-distressed based on their calculated Z scores. Both groups consisted of approximately 56,719(172,355 observations) distressed and 194,002 firms and 1,222,780 observations. The mean for distressed is 0.17 and for non-distressed 0.12. The mean difference between the groups is -0.048. The t-test finds that the means are statistically significant and different from each other based on a two-tailed significance level. $t(-52) = 170309$, $p = 0.00$.

Table 1 (Panel A) Sample size across country and years

The table shows the sample composition across country and years 2003 to 2012. The sample includes only firms with sufficient data to calculate an Altman Z score in each year. All enterprises are within the criteria for SMEs as defined by the European Commission (2005) and outlined in Section 4. The total number of observations per year are presented, as well as the total number over the sample period (column 11). The proportion of all enterprises (large and small) across the 13 countries as sourced from Eurostat "Statistics on small and medium-sized enterprises" 2012 is presented in column 13, and the proportionate breakdown of the 13 countries are illustrated in column 14, while the proportion of observations in our sample as a proportion of all European enterprises is presented in column 15.

Columns	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Country	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	Total	%	Total enterprises	% of total	% of total
Belgium	5,082	5,174	5,167	5,200	5,341	5,486	5,749	5,957	6,159	582	49,897	4%	566,006	3%	9%
Finland	6,856	8,909	8,100	7,793	7,618	7,391	7,345	7,249	7,167	1,869	70,297	5%	226,373	1%	31%
France	33,556	35,887	36,063	36,168	35,902	35,924	35,951	35,955	35,894	3,945	325,245	23%	2,882,419	16%	11%
Germany	1,595	2,358	2,343	2,117	1,980	2,286	2,600	2,533	2,083	41	19,936	1%	2,189,737	12%	1%
Greece	636	635	636	630	621	618	615	607	608	618	6,224	1%	726,581	4%	1%
Hungary	2,138	5,626	5,889	5,997	6,084	6,023	6,018	5,612	5,324	2	48,713	3%	528,519	3%	9%
Ireland	433	458	506	502	559	643	580	572	500	28	4,781	0.3%	146,741	1%	3%
Italy	9,917	11,443	11,393	11,319	11,244	11,114	11,157	11,074	10,967	253	99,881	7%	3,825,458	22%	3%
Latvia	21	25	27	28	28	30	33	33	34	10	269	0.02%	91,939	1%	0%
Poland	3,139	6,619	9,131	10,005	12,069	14,888	16,251	15,937	13,936	0	101,975	7%	1,519,904	9%	7%
Portugal	9,805	10,503	24,728	25,015	25,165	25,138	24,752	24,834	24,495	6	194,441	14%	793,235	5%	25%
Spain	45,650	47,493	47,924	48,084	15,598	43,940	44,591	44,598	44,046	222	382,146	27%	2,385,077	14%	16%
UK	8,086	8,298	8,265	8,294	8,409	8,958	12,586	13,077	12,797	2,560	91,330	7%	1,703,562	10%	5%
Total	126,914	143,428	160,172	161,152	130,618	162,439	168,228	168,038	164,010	10,136	1,395,135	100%	17,585,551	100%	8%

Table 1 (Panel B) Distribution of sample across firm size

Columns	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Year	Micro	Small	Medium	Total	Micro	Small	Medium	Total
2003	49,107	56,101	21,706	126,914	39%	44%	17%	100%
2004	55,696	63,610	24,122	143,428	39%	44%	17%	100%
2005	65,746	68,075	26,351	160,172	41%	43%	16%	100%
2006	51,558	79,637	29,957	161,152	32%	49%	19%	100%
2007	39,046	61,787	29,785	130,618	30%	47%	23%	100%
2008	46,312	83,161	32,966	162,439	29%	51%	20%	100%
2009	40,754	91,105	36,369	168,228	24%	54%	22%	100%
2010	45,905	86,071	36,062	168,038	27%	51%	21%	100%
2011	38,276	89,623	36,111	164,010	23%	55%	22%	100%
2012	2,772	4,568	2,796	10,136	27%	45%	28%	100%
Total	435,172	683,738	276,225	1,395,135	31%	49%	20%	100%

Table 2 Industry sector sample composition

The table show the sample composition by industry sector across years. NAICS (North American Industry Classification Scheme) represents NAICS 2007 industry sector classification codes. Industry sectors with codes 22, 52, 91, 92 are excluded as they represent public utilities, finance and insurance related activities and public administration. Note NAICS 11 (1110-1159), 21 ((2111-2139), 23(- 2389).

Industry sector	NAICS	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	Total	%
Agriculture, forestry, fish	11	2,575	3,046	3,418	3,703	2,779	3,735	3,876	3,822	3,727	255	30,936	2%
Mining, Quarrying and Oil and Gas Extraction	21	634	697	770	778	574	775	809	815	775	29	6,656	0.5%
Construction	23	18,520	20,908	23,524	23,708	18,312	23,516	24,026	23,676	23,023	1,581	200,794	14%
Manufacturing	31-33	31,244	34,667	39,219	39,419	32,505	39,966	41,186	40,900	39,989	2,028	341,123	24%
Wholesale trade	41, 42	25,899	28,973	30,980	30,573	24,420	31,180	32,232	32,023	31,349	1,646	269,275	19%
Retail trade	44-45	9,773	11,259	12,720	12,714	9,939	12,965	13,286	13,229	12,905	669	109,459	8%
Transportation and warehousing	48-49	7,036	7,909	8,505	8,695	6,810	8,423	8,681	8,695	8,502	610	73,866	5%
Information and Cultural industries	51	1,671	1,952	2,142	2,143	1,815	2,173	2,266	2,278	2,184	126	18,750	1%
Real estate and rental and leasing	53	3,307	3,674	3,942	4,154	3,266	4,338	4,629	4,565	4,310	190	36,375	3%
Professional, Scientific and Technical services	54	7,370	8,816	9,768	9,804	8,250	9,705	9,943	9,948	9,629	766	83,999	6%
Management of company and enterprises	55	786	836	876	882	782	819	874	865	869	95	7,684	1%
Administrative and support, Waste management	56	4,351	5,053	5,632	5,656	5,122	5,828	6,055	6,025	5,922	498	50,142	4%
Educational services	61	930	1,078	1,446	1,430	1,261	1,368	1,552	2,084	2,050	412	13,611	1%
Health care and social assistance	62	2,325	2,716	3,169	3,299	3,033	3,402	3,857	4,071	3,990	267	30,129	2%
Arts, Entertainment and Recreation	71	1,218	1,360	1,455	1,483	1,140	1,404	1,634	1,704	1,686	159	13,243	1%
Accommodation and Food services	72	5,842	6,615	8,261	8,357	6,928	8,432	8,665	8,633	8,537	460	70,730	5%
Other services except public administration (beauty salons, repair shops etc)	81	3,269	3,684	4,159	4,161	3,483	4,197	4,453	4,540	4,439	329	36,714	3%
Other		164	185	186	193	199	213	204	165	124	16	1,649	0.1%
		126,914	143,428	160,172	161,152	130,618	162,439	168,228	168,038	164,010	10,136	1,395,135	100

Table 3 Panel A: Average trade credit across countries and summary statistics

The table reports the average (mean) levels of trade credit across countries over the sample period (Panel A) and summary statistics for variables used in our empirical analysis (Panel B). Tradecredit_a is calculated as accounts payable scaled by total assets (a), Tradedebtors_a refers to accounts receivable scaled by total assets. Net TC_a is trade receivables less payables, scaled by total assets, *Net TC_s* is trade receivables minus payables, scaled by sales, Cash_a is cash and deposits, scaled by book assets, debtor and creditor is reported in days, and sales growth is calculated as the percentage change in sales measure from the previous financial year.

Country	Tradecredit_a	Tradedebtors_a	Net TC_a	Net TC_s	Cash_a	Creditor days	Debtor days	Sales growth	Obs
Belgium	0.26	0.34	0.08	0.06	0.40	52	72	0.08	49,897
Finland	0.12	0.16	0.04	0.03	0.14	20	29	0.13	70,297
France	0.20	0.29	0.09	0.06	0.21	37	58	0.09	325,245
Germany	0.13	0.20	0.08	0.04	0.14	19	32	0.10	19,936
Greece	0.44	0.49	0.05	0.17	0.20	84	135	0.05	6,224
Hungary	0.03	0.19	0.05	0.04	0.09	8	49	0.11	48,713
Ireland	0.44	0.28	-0.16	0.03	0.29	35	44	0.06	4,781
Italy	0.30	0.37	0.07	0.07	0.08	72	95	0.13	99,881
Latvia	0.14	0.13	0.00	0.00	0.08	29	29	0.18	269
Poland	0.24	0.27	0.03	0.04	0.11	49	60	0.12	101,975
Portugal	0.18	0.36	0.17	0.18	0.13	57	111	0.09	194,441
Spain	0.21	0.30	0.26	0.25	0.12	10	96	0.08	382,146
UK	0.15	0.22	0.08	0.05	0.44	29	46	0.09	91,330
Total	0.20	0.30	0.14	0.13	0.17	34	77	0.09	1,395,135

Table 3 Panel B: Summary statistics for unbalanced sample

Firm level variables	Observations	Mean	Median	S.D.
Dependent variables				
Net TC_s	1,242,448	0.13	0.08	0.22
Net TC_a	1,243,808	0.14	-0.49	0.24
TC/Bank Finance	1,243,567	0.82	0.32	2.33
Tradecredit_a	1,246,951	0.20	0.15	0.17
Tradedebtors_a	1,246,475	0.3	0.27	0.23
Net TC_received	1,242,448	-0.13	-0.08	0.22
Loan demand variables				
Total_debt_a	1,012,989	0.61	0.61	0.29
Loan_spread	1,216,310	0.07	0.03	0.12
Cashflow_a	1,119,060	0.09	0.08	0.18
Loan supply variables				
Tangibility	1,395,135	0.33	0.28	0.25
Default risk	1,188,819	63.35	3.56	323
Lerner_index	1,268,221	0.93	0.98	0.01
GDP per capita growth	1,395,135	0.62	1.21	2.4
Independent variables				
Ln(assets)	1,395,135	14.36	14.31	1.4
Sales growth	1,208,156	0.09	0.04	0.41
Firm age	1,394,399	21.5	16	42.31
Loans_a	1,381,991	0.27	0.23	0.23
Cash_a	1,280,051	0.16	0.06	0.33
Employment	1,222,177	30	16	39
Cash_s	1,280,051	0.16	0.06	0.33
Cash_a07	1,217,469	0.14	0.07	0.16

Financial distress variables				
WCTA	1,395,135	0.24	0.24	0.32
Cash_a	1,395,135	0.17	0.09	0.2
Ebitda_a	1,393,270	0.11	0.09	0.21
SFTL	1,395,135	1.62	0.69	3.29
Sales_a	1,395,135	1.78	1.51	1.29
Z-score	1,395,135	2.98	2.66	1.86

Table 4 Firm characteristics by the levels of trade credit received.

The table below represents the relation between SME characteristics and the levels of trade credit received before and during (after) the crisis period. The distribution of firms is split into quartiles and trade credit is measured as the proportion of accounts payable scaled by firm assets. 'Pre-crisis' represents the years preceding the financial crisis (2003-2007) and '(Post) crisis' crisis represents the onset of the financial crisis and beyond (2008-2012). All figures are represented by mean values. All variables are defined according as in Table 3.

	1st Quartile		**2nd Quartile**		**3rd Quartile**		**4th Quartile**	
Variables	Pre- crisis	(Post) Crisis	Pre- crisis	(Post) Crisis	Pre- crisis	(Post) Crisis	Pre - crisis	(Post) Crisis
Ln(assets)	13.6	13.9	13.6	13.8	13.8	13.9	14	14
Age	13.7	18	16	21	20	23	16.5	22
Loans_a	0.07	0.07	0.09	0.09	0.13	0.12	0.11	0.12
Cash_a	0.19	0.15	0.2	0.19	0.17	0.17	0.13	0.134
Employees	18	18	20	22	29	30.6	30	30.1
Sales growth	0.2	0.01	0.18	0.03	0.14	0.05	0.18	0.07
Total_debt_a	3.45	1.54	1.37	0.68	0.61	0.6	2.1	1.05

Table 5 Number and Origin of SMEs experiencing financial distress

The table reports the number of financially distressed SMEs based on their calculated Z-score, by size class and year (Panel A) and by country of origin (Panel B). Firms reporting a Z-score of <1.23 are deemed likely to be experiencing financial distress and a greater likelihood of bankruptcy. Specifications for the calculation of Z-score are detailed in Appendix B. The figures reported are based on the unbalanced sample presented in Table 1 to mitigate against survivorship bias.

Panel A: Year								
	Firm Size				Percentage			
Year	Micro	Small	Medium	Total	Micro	Small	Medium	Total
2003	5,214	4,575	3,200	12,989	11%	8%	15%	10%
2004	5,719	5,266	3,441	14,426	10%	8%	14%	10%
2005	8,274	6,219	3,886	18,379	13%	9%	15%	11%
2006	5,212	8,892	4,446	18,550	10%	11%	15%	12%
2007	3,493	6,731	3,989	14,213	9%	11%	13%	11%
2008	4,368	9,991	5,152	19,511	9%	12%	16%	12%
2009	4,963	13,048	6,566	24,577	12%	14%	18%	15%
2010	5,936	12,001	6,100	24,037	13%	14%	17%	14%
2011	6,436	12,503	5,986	24,925	17%	14%	17%	15%
2012	195	267	286	748	7%	6%	10%	7%
Total	49,810	79,493	43,052	172,355	11%	12%	16%	12%
Panel B: Origin								
Country	Micro	Small	Medium	Total	Micro	Small	Medium	Total
Belgium	556	1,930	2,430	4,916	12%	8%	12%	10%
Finland	3,668	1,793	411	5,872	8%	8%	9%	8%
France	8,849	9,031	3,108	20,988	6%	6%	11%	6%
Germany	169	428	1,446	2,043	5%	7%	15%	10%
Greece	90	146	87	323	5%	5%	6%	5%
Hungary	2284	2,672	399	5,355	9%	13%	13%	11%
Ireland	52	31	27	110	3%	2%	2%	2%
Italy	277	2,916	11,997	15,190	8%	7%	22%	15%
Latvia	5	19	16	40	19%	23%	10%	15%
Poland	3566	5,690	3,579	12,835	11%	13%	14%	13%
Portugal	17,003	27,138	4,403	48,544	24%	25%	26%	25%
Spain	12,129	24,354	8,188	44,671	13%	10%	15%	12%
UK	1,162	3,345	6,961	11,468	16%	12%	13%	13%
Total	49,810	79,493	43,052	172,355	11%	12%	16%	12%

Table 6 Bankruptcy and trade credit use

The dependent variable 'Bankruptcy' is a binary variable capturing the likelihood of firm bankruptcy based on the Atlman Z-score of less than 1.23. Independent variables are measured as lags (t-1) and include Net TC_s, which represents the net credit extended by firms calculated as the difference between trade receivables minus payables scaled by firm sales, and Net TC received, capturing the net credit received by firms calculated as trade payables minus receivables scaled by sales. Tradecredit_a refers to accounts payable scaled by assets as a proxy for trade credit received. Net TC/Bank Finance is calculated difference trade receivables minus payables, scaled by the total outstanding bank debt. Additional explanatory include a measure of firms size (Ln_assets), cash holdings scaled by assets (Cash_a), sales growth (Sales growth) ,the age of the firm (Age), age squared (Age^2), and banking concentration (Lerner_index). Post-crisis dummy refers to all years post the onset of the financial crisis (including 2009-2012). Crisis_dummy*$Tradecredit\_a_{t-1}$ refers to the interaction of accounts payable with the post crisis years. Post_crisis dummy*Net TC $received_{t-1}$ refers to the interaction between post crisis years and the net credit received by firms. All regressions are estimated using Panel logit with and without fixed effects. Standard errors are represented in parentheses, while the ***, **, *, represent coefficients significant at the 1%, 5% and 10% level.

	Bankruptcy (1)	Bankruptcy (2)	Bankruptcy (3)	Bankruptcy (4)	Bankruptcy (5)	Bankruptcy (6)	Bankruptcy (7)	Bankruptcy (8)	Bankruptcy (9)
Net TC_s_{t-1}	0.105***	0.175***							
	(0.015)	(0.033)							
Net TC $received_{t-1}$			-0.094***	-0.157***					
			(0.015)	(0.033)					
$Tradecredit\_a_{t-1}$					-0.555***		-0.538***	-0.454***	-0.559***
					(0.054)		(0.054)	(0.059)	(0.054)
Net TC/Bank $Finance_{t-1}$						-0.000			
						(0.000)			
Year 2008 dummy							-0.205***		-0.217***
							(0.020)		(0.018)
Year 2008_dummy*$Tradecredit\_a_{t-1}$							-0.059		0.022
							(0.061)		(0.043)
Post_crisis dummy								0.453***	
								(0.022)	
Post_crisis dummy*$Tradecredit\_a_{t-1}$								-0.109**	
								(0.051)	
Post_crisis dummy* $Lerner\_index_{t-1}$									-0.288***
									(0.022)
$Ln(assets)_{t-1}$	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Sales $growth_{t-1}$	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$Cash\_a_{t-1}$	-5.000***	-1.938***	-5.002***	-1.955***	-1.975***	-2.066***	-1.987***	-1.952***	-1.957***
	(0.035)	(0.066)	(0.035)	(0.066)	(0.065)	(0.068)	(0.065)	(0.065)	(0.065)

Age_{t-1}	-0.007***	0.163***		0.111***	0.145***	0.146***	0.158***	0.061***	0.195***
	(0.000)	(0.003)		(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.007)
Age^2_{t-1}	0.000***	0.000*		0.000**	0.000	0.000*	0.000	0.000*	0.000*
	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$Lerner\_index_{t-1}$				24.330***	10.673***	7.076***	0.468	2.680**	11.252***
				(1.307)	(1.061)	(1.156)	(1.346)	(1.126)	(1.591)
Industry dummies	Y	N	Y	N	N	N	N	N	N
Country dummies	Y	N	Y	N	N	N	N	N	N
Fixed Effects	N	Y	N	Y	Y	Y	Y	Y	Y
Year dummies	Y	N	Y	N	N	N	N	N	N
Constant	-1.000***		-0.999***						
	(0.271)		(0.271)						
Observations	919,363	195,080	919,363	195,080	201,898	183,443	201,898	201,898	201,709
Number of groups		33,398		33,398	34,572	32,360	34,572	34,572	34,546
Pseudo R-squared	0.15		0.15						

Table 7 Probit Random Effects: Bankruptcy and trade credit use

The dependent variable ‘Bankruptcy’ is a binary variable capturing the likelihood of firm bankruptcy based on the Atlman Z-score of less than 1.23. Independent variables are ‘Net TC_s’ which represents the net credit extended by firms calculated as the difference between trade receivables minus payables scaled by firm sales. ‘Net TC received’ capturing the net credit received by firms and Tradecredit_a refers to accounts payable scaled by assets as a proxy for trade credit received. 'Net TC/Bank finance' capturing the ratio of trade credit to bank finance. Additional explanatory include variables of ‘Size (Ln_assets)’ represented by firm assets, 'Cash_a' which captures the ratio of cash stocks of the firm scaled by assets, 'Sales growth' and the age of the firm ‘Age’. ‘Lerner_index’ captures the lagged value of banking concentration. ‘Age^2’ represents the square of the Age variable. All explanatory variables are lagged. All regressions are estimated using Panel Probit regression and marginal effects are presented. Crisis_dummy*Tradecredit_a_{t-1} refers to the interaction of accounts payable with the post crisis years. Post_crisis dummy*Net TC $received_{t-1}$ refers to the interaction between post crisis years and the net credit received by firms. Standard errors are represented in parentheses, while the ***, **, *, represent coefficients significant at the 1%, 5% and 10% level.

	Bankruptcy (1)	Bankruptcy (2)	Bankruptcy (3)	Bankruptcy (4)	Bankruptcy (5)	Bankruptcy (6)	Bankruptcy (7)	Bankruptcy (8)	Bankruptcy (9)
Net TC_s_{t-1}	0.180***								
	(0.016)								
Net TC $received_{t-1}$		-0.215***					-0.023***	0.002	
		(0.008)					(0.002)	(0.002)	
Trade credit_a_{t-1}			-0.048***		-0.046***	-0.040***			-0.559***
			(0.002)		(0.002)	(0.002)			(0.054)
Net TC/Bank $Finance_{t-1}$				-0.200***					
				(0.003)					
Year 2008 dummy					0.013***		0.006***		-0.217***
					(0.001)		(0.001)		(0.018)
Year 2008_dummy*Trade credit_a_{t-1}					-0.039***				0.022
					(0.004)				(0.043)
Year 2008_dummy*Net TC $received_{t-1}$							-0.002		
							(0.004)		
Post_crisis dummy						0.034***		0.023***	
						(0.001)		(0.001)	
Post_crisis dummy*Trade credit_a_{t-1}						-0.025***			
						(0.003)			
Post_crisis dummy*Net TC $received_{t-1}$								-0.059***	
								(0.003)	
Post_crisis dummy*Lerner_$index_{t-1}$									-0.288***
									(0.02)
$Ln(assets)_{t-1}$	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Sales $growth_{t-1}$	-0.000	-0.001	-0.000	-0.001	-0.000	-0.000	-0.000	-0.000	-0.000

	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$Cash\_a_{t-1}$	-2.469***	-2.244***	-0.309***	-2.845***	-0.311***	-0.310***	-0.304***	-0.302***	-1.963***
	(0.031)	(0.015)	(0.002)	(0.032)	(0.002)	(0.002)	(0.002)	(0.002)	(0.065)
Age_{t-1}	-0.003***	-0.004***	-0.001***	-0.007***	-0.000***	-0.001***	-0.000***	-0.000***	0.195***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.005)
Age^2_{t-1}	0.000***	0.000***	0.000***		0.000***	0.000***	0.000***	0.000***	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$Lerner\_index_{t-1}$	-2.732***	1.489**	1.095***	5.554***	2.650***	0.554***	2.644***	0.504***	11.252***
	(0.396)	(0.595)	(0.118)	(0.912)	(0.074)	(0.080)	(0.075)	(0.081)	(1.591)
Industry dummies	Y	Y	Y	Y	Y	Y	Y	Y	Y
Country dummies	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year dummies	Y	Y	Y	Y	N	N	N	N	N
Observations	919,363	919,363	919,363	947,987	947,987	947,987	919,363	917,633	947,284

Table 8 Proportion of firms constrained in accessing bank finance
This table reports the number and percentage of bank finance constrained firms in our balanced sample of firms over the 2007-2011 period. Firms are categorised as fully constrained if the yearly estimated OLS predicted values for demand for bank finance is more than 1.5 times greater than their estimated predicted values for supply of bank finance. Partially constrained firms are those whose yearly demand is greater than supply, and unconstrained are those whose yearly demand is less than estimated supply (see equations 2 and 3 for more details).

Year	Unconstrained	%	Partially Constrained	%	Fully Constrained	%	Total
2005	47,785	48%	49,157	49%	3,441	3%	100,383
2006	20,486	20%	46,159	45%	36,836	36%	103,481
2007	23,989	22%	73,951	69%	9,836	9%	107,776
2008	19,920	18%	74,809	69%	13,047	12%	107,776
2009	16,060	15%	38,973	36%	52,743	49%	107,776
2010	16,567	15%	3,057	3%	88,152	82%	107,776
2011	19,085	18%	52,065	48%	36,626	34%	107,776
2012	1,407	19%	2,299	32%	3,581	49%	7,287
Total	251,331	30%	340,470	41%	244,262	29%	836,063

Table 9 Trade credit regressions

The table reports trade credit regressions and measures of financial constraints pre and post crisis. Panel A regressions measure financial constraints using lagged cash holdings scaled by assets, and Panel B estimates financial constraints that account for firm demand and supply-side constraints using equations (2) and (3). The regressions are estimated using a balanced panel of 107,776 firms for the years 2007-2011, which captures the same firms' pre and post the crisis period. The dependent variables are trade credit_a, calculated as accounts payable scaled by book assets, trade debtors, calculated as accounts receivable scaled by book assets, and net trade credit (TC), representing the net credit extended by firms, and calculated as the difference between trade receivables minus payables scaled by book assets. Independent variables include 'crisis', representing a year dummy variable for the year of the financial crisis (2008), and time dummy variables for the years 2009, 2010 and 2011, respectively. Cash_a_{2007}*Crisis is an interaction term capturing the SME level of cash to assets ratio one year prior to the crisis year. The interactions with 'Cash_a07' show the effects of 'Cash_a_{2007}' during the crisis, and the three years following the onset of the crisis. Firm level controls include firm size, measured as the natural log of book assets, % sales growth, firm age, and firm age squared, to capture any non-linearity. All firm level controls are measured as lagged values. Models 1 to 4 are estimated using OLS firm fixed effects. Models 5 to 7 use the System (Blundell and Bond, 1998) GMM estimates with the inclusion of lagged values for the dependent variables. Panel B regression models replace lagged cash holdings with the predicted values from demand and supply regression models. Firms are categorised (using dummy variables) as fully constrained if the yearly estimated demand for bank finance is more than 1.5 times greater than their estimated supply of bank finance. Partially constrained firms are those whose yearly demand is greater than supply, and unconstrained are those whose demand is less than supply. The interactions with 'unconstrained, full constrained and partially constrained' show the effects of access to bank financing constraints during the crisis, and the three years following the onset of the crisis. Robust standard errors are reported in parentheses. ***, **, *, indicate significance at the 1%, 5% and 10% levels, respectively. Models estimated with GMM with lagged values of variables t-3 and t-4 and beyond as instruments.

Panel A: Trade credit and cash

Variables	Tradecredit_a (1)	Tradedebtors_a (2)	Net TC_a (3)	Net TC_a (4)	Tradecredit_a Sys-GMM (5)	Tradedebtor_a Sys-GMM (6)	Net TC_a Sys-GMM (7)
Year 2008	-0.015***	-0.012***	0.005***	0.006***	0.027	-0.019***	-0.044***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.194)	(0.003)	(0.007)
Year 2009	-0.026***	-0.019***	0.007***	0.009***	-0.017	-0.024***	-0.059***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.197)	(0.004)	(0.009)
Year 2010	-0.020***	-0.012***	0.007***	0.011***	-0.006	-0.035***	-0.105***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.196)	(0.011)	(0.011)
Year 2011	-0.017***	-0.013***	0.004***	0.010***	0.014	-0.002	-0.050***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.230)	(0.005)	(0.017)
Year 2008*Cash_a_{2007}	0.011***	0.018***	-0.010**	-0.003	-0.209	0.050***	0.293***
	(0.003)	(0.002)	(0.002)	(0.002)	(1.151)	(0.015)	(0.043)
Year 2009*Cash_a_{2007}	0.024***	0.029***	-0.005**	0.002*	-0.002	0.002	0.324***
	(0.003)	(0.002)	(0.002)	(0.002)	(1.139)	(0.012)	(0.054)
Year 2010*Cash_a_{2007}	0.015***	0.036***	0.004*	0.011***	-0.059	0.044*	0.541***
	(0.003)	(0.002)	(0.002)	(0.002)	(1.070)	(0.024)	(0.058)

Year 2011*Cash_a$_{2007}$	0.014***	0.053***	0.016***	0.023***	-0.105	-0.030**	0.412***
	(0.003)	(0.002)	(0.002)	(0.002)	(1.189)	(0.014)	(0.079)
Tradecredit_a$_{t-1}$					0.256		
					(0.189)		
Net TC_a$_{t-1}$							0.418***
							(0.028)
Tradedebtors_a$_{t-1}$						0.697***	
						(0.027)	
Ln(assets)$_{t-1}$	-0.000***	-0.000***		0.000	-0.000	-0.000***	0.000
	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)
Sales growth$_{t-1}$	0.009***	0.006***		-0.001***	-0.048	-0.181***	-0.234***
	(0.001)	(0.000)		(0.000)	(0.112)	(0.031)	(0.032)
Age$_{t-1}$	-0.001***	-0.002***		-0.002***	-0.000	-0.002***	-0.011***
	(0.000)	(0.000)		(0.000)	(0.016)	(0.001)	(0.003)
Age$^2_{t-1}$	-0.000***	-0.000***		-0.000***	-0.000	-0.000	-0.000***
	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)
Constant	0.253***	0.401***	0.114***	0.159***			
Lagged firm controls	Y	Y	N	Y	Y	Y	Y
Firm fixed effects	Y	Y	Y	Y	N	N	N
Country dummies	N	N	N	N	Y	Y	Y
Observations	697,601	681,500	813,687	680,816	697,162	680,865	679,768
Number of firms	107,736	105,187	105,286	105,185	107,725	105,112	105,099
Observations (group average)	6.5	6.5	8.4	6.5			
Adjusted R-squared	0.70	0.84	0.76	0.79			
Number of instruments					44	55	52
AR(1) p-value					0.03	0.000	0.000
AR(2) p-value					0.873	0.019	0.797
Hansen test					0.083	0.00	0.201

** Note ‘Cash_a$_{2007}$’ drops out of the model due to collinearity with the year dummy interaction terms. The models were also estimated using the lag level of ‘Cash_a’, which yielded similar results. These are available on request.

Table 9 (Continued)

Panel B: Demand and supply models

Variables	Trade Credit_a (1)	Trade Credit_a (2)	Trade Credit_a (3)	Trade debtor_a (4)	Net TC_a (5)	Net TC_a (6)	Net TC_a (7)
Year 2008	-0.012***	-0.013***	-0.013***	-0.008***	0.005***	0.005***	0.005***
	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)
Year 2009	-0.021***	-0.024***	-0.016***	-0.014***	0.009***	0.011***	0.009***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Year 2010	-0.016***	-0.018***	-0.011***	-0.007***	0.013***	0.015***	0.012***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Year 2011	-0.014***	-0.016***	-0.008***	-0.005***	0.013***	0.016***	0.009***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Unconstrained dummy$_{t-1}$	-0.020***			-0.009***	0.011***		
	(0.001)			(0.001)	(0.001)		
Fully Constrained dummy $_{t-1}$		-0.002***				-0.002***	-0.002***
		(0.001)				(0.001)	(0.000)
Partially Constrained dummy $_{t-1}$			0.010***				
			(0.001)				
Year 2008*Unconstrained $_{t-1}$	-0.000			0.002*	0.000		
	(0.001)			(0.001)	(0.001)		
Year 2009*Unconstrained $_{t-1}$	0.001			0.004***	0.003***		
	(0.001)			(0.001)	(0.001)		
Year 2010*Unconstrained $_{t-1}$	0.004***			0.007***	0.001		
	(0.001)			(0.001)	(0.001)		
Year 2011*Unconstrained $_{t-1}$	0.008***			0.011***	-0.000		
	(0.001)			(0.001)	(0.001)		
Year 2008*Fully constrained $_{t-1}$		0.000				-0.001	
		(0.002)				(0.001)	
Year 2009*Fully constrained $_{t-1}$		0.005***				-0.000	
		(0.001)				(0.001)	
Year 2010*Fully constrained $_{t-1}$		0.003**				-0.001	
		(0.001)				(0.001)	
Year 2011*Fully constrained $_{t-1}$		0.005***				-0.008***	
		(0.001)				(0.001)	
Year 2008*Partially constrained $_{t-1}$			-0.001				0.001
			(0.001)				(0.001)

Year 2009*Partially constrained $_{t-1}$			-0.009***				0.001
			(0.001)				(0.001)
Year 2010*Partially constrained $_{t-1}$			-0.006*				-0.001
			(0.003)				(0.002)
Year 2011*Partially constrained $_{t-1}$			-0.012***				0.009***
			(0.001)				(0.001)
Ln(assets)$_{t-1}$	-0.000***	-0.000***	-0.000***	-0.000***	-0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Sales growth$_{t-1}$	0.009***	0.009***	0.009***	0.007***	-0.001***	-0.001***	-0.001**
	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Age$_{t-1}$	-0.001***	-0.001***	-0.001***	-0.002***	-0.001***	-0.001***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Age$^2_{t-1}$	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Firm fixed effects	Y	Y	Y	Y	Y	Y	Y
Constant	0.271***	0.252***	0.247***	0.409***	0.150***	0.159***	0.161***
	(0.005)	(0.005)	(0.005)	(0.003)	(0.004)	(0.004)	(0.004)
Observations	697,601	697,601	697,602	681,500	680,816	680,816	680,816
Number of groups	107,736	107,736	107,736	105,185	105,185	105,186	105,187
Adjusted R-squared	0.62	0.62	0.62	0.84	0.79	0.79	0.79

Table 10 Trade credit and bank credit

The table reports trade credit as a proportion of bank credit on measures of financial constraints pre and post crisis based on a balanced panel in years 2007-2011. The dependent variables are Net TC scaled by bank finance, where net TC is calculated as the difference in trade receivables and payables, and bank finance is total outstanding bank debt. Independent variables include 'crisis', representing a year dummy variable for the year of the financial crisis (2008), and time dummy variables for the years 2009, 2010 and 2011, respectively. $Cash\_a_{t-1}$ therefore represents the firm level of cash to assets ratio in the year 2007 one-year prior to the onset of the financial crisis in 2008. The interactions with '$Cash\_a_{2007}$' show the effects of '$Cash\_a_{2007}$' during the crisis, and the three years following the onset of the crisis. Firm level controls include firm size, measured as the natural log of book assets, sales growth, firm age, and firm age squared, to capture any non-linearity. All firm level controls are measured as lagged values. Models 1 and 2 are estimated using OLS firm fixed effects, and model 3 System (Blundell and Bond, 1998) GMM estimates with the inclusion of lagged values for the dependent variable. Standard errors are reported in parentheses. ***, **, *, indicate significance at the 1%, 5% and 10% levels, respectively.

Variables	Net TC/ Bank finance (1)	Net TC/ Bank finance (2)	Net TC/ Bank finance Sys - GMM (3)
Year 2008	-0.003	-0.026***	0.486
	(0.005)	(0.006)	(1.539)
Year 2009	-0.043***	-0.067***	-0.307
	(0.005)	(0.007)	(0.354)
Year 2010	-0.029***	-0.052***	0.186
	(0.005)	(0.009)	(0.524)
Year 2011	-0.026***	-0.046***	-0.160
	(0.005)	(0.010)	(0.420)
Year 2008*$Cash\_a_{2007}$	0.075***	0.128***	-8.057
	(0.020)	(0.021)	(13.131)
Year 2009*$Cash\_a_{2007}$	0.230***	0.282***	-0.289
	(0.020)	(0.021)	(2.169)
Year 2010*$Cash\_a_{2007}$	0.270***	0.322***	1.236
	(0.020)	(0.021)	(2.069)
Year 2011*$Cash\_a_{2007}$	0.332***	0.387***	0.617
	(0.020)	(0.021)	(2.000)
$Ln(assets)_{t-1}$		-0.000**	0.001**
		(0.00)	(0.00)
TC/Bank $Finance_{t-1}$			0.640***
			(0.093)
Sales $growth_{t-1}$		-0.010**	0.320
		(0.004)	(2.23)
Age_{t-1}		-0.001	-0.167
		(0.002)	(0.11)
Age^2_{t-1}		-0.000	-0.001
		(0.000)	(0.00)
Country dummies	N	Y	Y
Fixed effects	Y	Y	Y
Constant	0.560***	0.651***	-1.872
	(0.002)	(0.040)	(0.005)
Observations	813,615	680,768	616,745
Number of groups	105,285	105,184	95,374
Adjusted R-squared	0.62	0.65	
Number of instruments			31
AR(1) p-value			0.01
AR(2) p-value			0.342
Hansen test			0.865

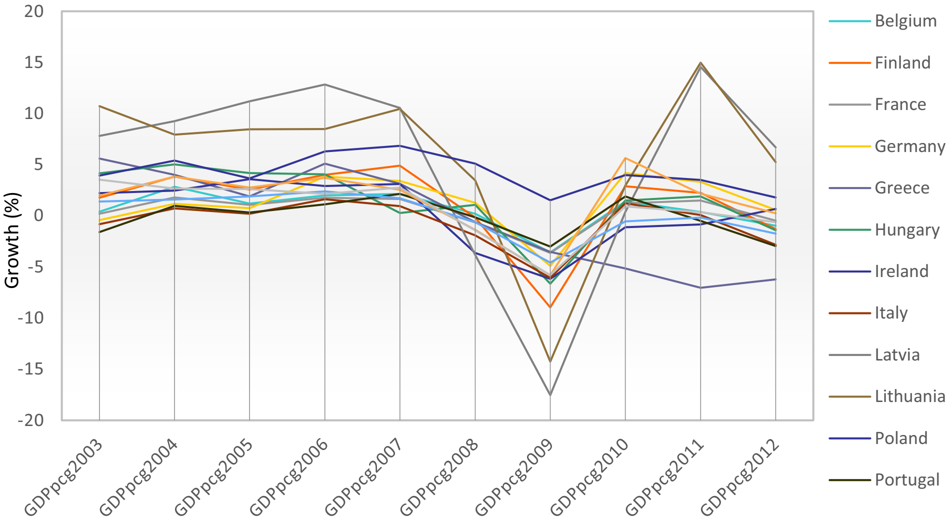
Highlights

1 Trade credit significantly *reduces* the likelihood of financial distress, especially during periods when credit is constrained.

2 A one standard deviation increase in net trade credit results in a 21% decrease in the likelihood of distress.

3 Financial unconstrained SMEs, on entering the financial crisis, consistently extended *more* credit and received *less* than prior to the onset of the financial crisis

4 EU SMEs are net providers of trade credit, equivalent to 14% of total assets.



20
15
10
5
0
-5
-10
-15
-20
Growth (%)
GDPpcg2003
GDPpcg2004
GDPpcg2005
GDPpcg2006
GDPpcg2007
GDPpcg2008
GDPpcg2009
GDPpcg2010
GDPpcg2011
GDPpcg2012
Belgium
Finland
France
Germany
Greece
Hungary
Ireland
Italy
Latvia
Lithuania
Poland
Portugal

Figure 1

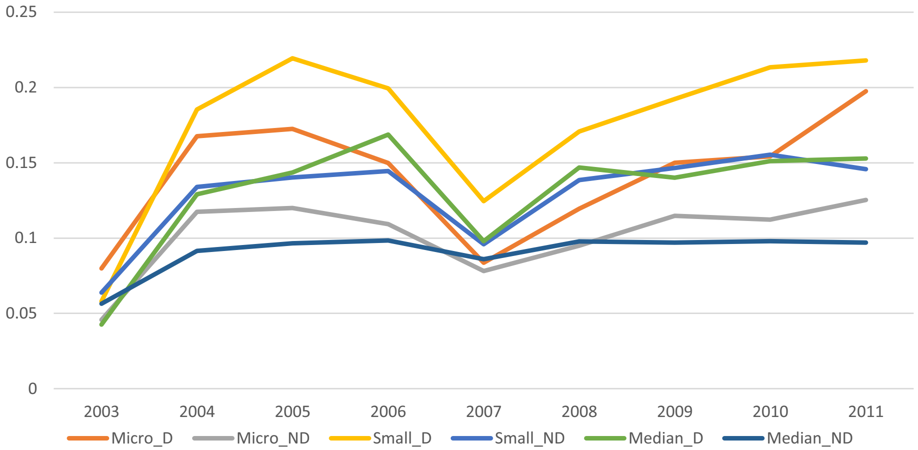

0.25
0.2
0.15
0.1
0.05
0
2003
2004
2005
2006
2007
2008
2009
2010
2011
Micro_D
Micro_ND
Small_D
Small_ND
Median_D
Median_ND

Figure 2