Substitution effects in SME finance*

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Abstract

We investigate whether SMEs with demand for credit increase their trade credit usage after they experience a negative shock to bank credit. We base our analysis on a large sample of SMEs from the five biggest European countries. First, SMEs' ability to substitute largely depends on their credit quality. Second, substitution decreases during the financial crisis of 2007-09. Third, high credit quality firms with moderate financial constraints are the most likely to substitute. We confirm these results on a subsample with matched bank-firm data. The evidence highlights the limits of substitution in SME finance.

JEL classification: G20, G30, G32

Keywords: Bank loans, trade credit, asymmetric information, financial constraints, external finance dependence

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1. Introduction

Financing small- and medium-sized enterprises (SMEs) is challenging because these firms are more informationally opaque, risky, financially constrained, and bank-dependent than large firms. SMEs cannot raise finance in capital markets. Instead, they mainly rely on credit from banks and trade credit from suppliers as sources of external finance (e.g., Petersen and Rajan, 1994; Petersen and Rajan, 1997; Berger and Udell, 2006). Bank credit tends to be more important than trade credit, but little is known about substitution effects in SME finance at the firm level and over time. Substitution between both types of credit is important because it can smoothen the business cycle, while a complementary relation can amplify the business cycle (King and Levine, 1993; Beck et al., 2000; Huang et al., 2011). Moreover, substitution of bank credit by trade credit can cause negative real effects through propagation in trade credit chains (Jacobson and von Schedvin, 2015; Boissay and Gropp, 2013; Jorion and Zhang, 2009). In this paper, we focus on substitution effects in SME finance. We investigate whether SMEs that have demand for credit increase trade credit (accounts payable) after a negative supply-side driven shock to their bank credit and which factors influence their response. We base the analysis on a large sample of SMEs from France, Germany, Italy, Spain and the U.K. and a subsample with matched bank-firm data.

The earlier literature suggests a substitution relation between bank credit and trade credit (e.g., Biais and Gollier, 1997; Petersen and Rajan, 1997). Substitution may occur because trade credit represents a source of external finance for firms that are unable to attract sufficient bank credit due to severe informational asymmetries. Cuñat (2007) shows for a large sample of U.K. firms that trade credit insures firms against liquidity shocks and that it is mainly used when other forms of finance have been exhausted. These results are more pronounced when the links between supplier and customer are tight and the production process very specific. The substitution hypothesis coincides with the redistribution view on trade credit (e.g., Meltzer,

1960; Calomiris et al., 1995; Petersen and Rajan, 1997; Ng et al., 1999; Nilsen, 2002; Love et al., 2007). Financially unconstrained suppliers redistribute part of their bank credit to financially constrained customers by providing trade credit.

Recent studies that are based on data from the 2007-09 financial crisis provide some evidence in favor of the substitution hypothesis. Garcia-Appendini and Montoriol-Garriga (2013) investigate trade credit provision and usage by large US firms, using a comprehensive sample of matched supplier-customer data. They find that firms with a pre-crisis liquidity surplus increased trade credit provision during the first stage of the financial crisis. Moreover, external finance dependent firms increased their trade credit usage when they had cash-rich suppliers. Importantly, this inter-firm liquidity provision is consistent with the substitution hypothesis and the redistribution view, but it was temporary during the first stage of the crisis and turned into the opposite after the failure of Lehman Brothers in fall 2008. Casey and O'Toole (2014) provide cross-sectional evidence for substitution, using firm survey data from 2009-2011: Firms that experienced volume-based rationing of bank credit in the past six months increased their usage of trade credit by 9% and their applications for trade credit by 7.5% relative to other firms. Carbo-Valverde et al. (2016) investigate the importance of bank credit and trade credit for financing investments of Spanish SMEs, using a Granger causality model. They find that bank credit significantly predicts the investments of unconstrained firms, but trade credit significantly predicts the investments of bank credit-constrained firms. These Granger causal-effects become stronger during the 2007-09 financial crisis. The study does not examine substitution effects between bank credit and trade credit, but it shows that the sensitivity of investments to different sources of credit varies with the level of firms' credit constraints.

There is also evidence against the substitution hypothesis. First, the general view is that trade credit is more expensive than bank credit. This view has been challenged by a number of

studies. For instance, Fabbri and Menichini (2010) find that trade credit is less expensive than bank credit if the liquidation value of the purchased goods is relatively high. There is also evidence that challenges the redistribution view of trade credit. Large customers use their bargaining power vis-a-vis smaller suppliers to obtain trade credit at low cost (e.g., Giannetti et al., 2011; Murfin and Njoroge, 2015). Furthermore, the most and the least profitable firms make use of trade credit, but young firms do not (Petersen and Rajan, 1997; Fisman and Love, 2003). Second, substitution only works if the customers have demand for credit and the suppliers are able to provide additional credit. The latter condition is met if the suppliers are less affected, or not affected, by the negative credit supply shock that hit their customers. Garcia-Appendini and Montoriol-Garriga (2013) document that this happened among large US firms, but only during the first stage of the financial crisis. Third, there are clear economic limits of substitution because trade credit, unlike bank credit, does not create a cash inflow for the borrowing firm. Trade credit corresponds to a delayed cash outflow for a specific purpose (Breza and Liberman, 2017). The latter limits its suitability to serve as substitute for bank credit.

We base our analysis on data from ORBIS, covering a large sample of SMEs from the five biggest European countries and the period before, during and after the global financial crisis. We focus on SMEs because they are by definition smaller, more informationally opaque, more financially constrained and riskier than large firms. The median leverage (total debt/total assets) in our European SME sample is 70.0%, while Garcia-Appendini and Montoriol-Garriga (2013) report a median leverage 19.7% for large US firms in their matched supplier-customer Compustat sample. Unlike large firms, SMEs mainly rely on two forms of external finance: bank credit and trade credit. We employ data from Europe because there is no data on SMEs from the United States available for the global financial crisis of 2007-2009 or more recent

times as the Federal Reserve discontinued the Survey of Small Business Finances ((N)SSBF) after its last wave in 2003.

We establish three main results. First, we find that substitution becomes significantly more likely the higher the firms' credit quality is. This result remains robust when we control for industry, country, year fixed effects, potential selections effects, time-varying cross-country heterogeneity, and for the credit quality of the firms' suppliers. We obtain similar results when we analyze continuous changes of bank credit and trade credit. Second, substitution decreased during the financial crisis of 2007-09 and further declined as the crisis deepened. This result indicates that SMEs could not fill their funding gap with trade credit during times of crisis when it was most needed. Third, credit quality and financial constraints display an inversely U-shaped impact on the probability of substitution. The relation is not significant for the firms that exhibit low financial constraints because they are more likely to attract alternative forms of external finance. It is also not significant for the firms that exhibit high financial constraints because they are likely to be credit-rationed and therefore cannot borrow anyway. However, credit quality has a significantly positive impact for firms with moderate financial constraints.

The evidence highlights the limits of substitution in SME finance after a negative shock to bank credit and complements the study of large US firms by Garcia-Appendini and Montoriol-Garriga (2013). On the one hand, our results are different because we show that the probability of substitution decreased during the crisis. This is plausible if we consider that SMEs are riskier than large firms and that their suppliers might have been affected by the crisis as well. But, we also show that high credit quality SMEs managed to counter the shock to bank credit with trade credit to some extent. On the other hand, the results are consistent for the second stage of the crisis when the liquidity provision of trade credit suppliers in the U.S. came to an end. The financial crisis affected the European countries in our sample mainly in 2008 and 2009 when the probability of substitution in SME finance decreased as well.

To ensure that we identify causal effects, we proceed as follows. First, we define a firm-specific time-varying Substitution Indicator (SI) that measures the probability of substitution (i.e., firms increase in trade credit after a negative supply-side driven shock to their bank credit) relative to a negative complementary relation (firms decrease of trade credit and a decrease of bank credit). Second, we consider SMEs that have demand for external finance. We focus on firms' need and ability to substitute because we rule out that firms do not want to substitute because they have sufficient alternative funding sources available. In our setting, a negative complementary relation between bank credit and trade credit indicates firms' inability to substitute because we consider external finance-dependent firms that have demand for credit (Rajan and Zingales, 1998; Garcia-Appendini and Montoriol-Garriga, 2013; Becker and Ivashina, 2014). Third, we conduct an additional analysis with detailed matched bank-firm data from Spain where we differentiate between SMEs that are borrowers of distressed banks and those that are not. This analysis makes it possible to identify the negative shock to bank credit supply during the financial crisis and study whether SMEs can fill the funding gap with trade credit. This analysis confirms the results of the five-country analysis.

The remainder of the paper is organized as follows. In Section 2, we present the theoretical framework, develop a set of hypotheses and present our empirical strategy. In Section 3, we describe the data and provide summary statistics. In Section 4, we report the main results. In Section 5, we report additional analyses based on matched-bank firm data. We conclude in Section 6.

2. Theoretical framework, hypotheses and empirical strategy

2.1. Theoretical framework and hypotheses

The literature has proposed theories and evidence about the provision and usage of trade credit. Theories refer to financing advantages of firms due to better information, control and

liquidation rights, price discrimination, and transaction costs (see, for an overview of theories and evidence, Petersen and Rajan, 1997). Some theories predict that suppliers have incentives to provide trade credit to those customers that experience temporary liquidity shocks (e.g., Wilner, 2000; Cuñat, 2007). For example, Cuñat (2007) shows that suppliers provide liquidity to their customers when the latter have temporary liquidity needs. Other theories predict that firms increase their demand for trade credit when they become credit-rationed by banks (e.g., Bias and Gollier, 1997; Burkard and Ellingsen, 2004). Theories generally consider trade credit as more expensive than bank credit.

Evidence from the study of Petersen and Rajan (1997) suggests that the customer's credit quality, using size and profitability as proxies, is important in determining whether trade credit is offered. They note that the price of trade credit does not vary with the customer's credit quality because firms get standard industry terms. Instead, suppliers of trade credit use quantity restrictions. However, they also show that suppliers tend to support growing, cash-constrained firms with trade credit. Giannetti et al. (2011) provide evidence for the influence of customers on suppliers. First, customers that produce more differentiated goods receive more, less expensive and more long-term trade credit than others. Second, customers that use trade credit obtain credit from relatively uninformed banks (larger number of banks, more distant banks, and shorter relationships with their banks). Third, most firms in their sample receive trade credit at low cost because they do not receive early payment discounts that they would forego if they used trade credit. Theories and evidence suggest that firms prefer bank credit over trade credit because the latter tends to be more expensive than the former (Petersen and Rajan, 1997; Cuñat, 2007; Klapper et al., 2012). However, the findings of Giannetti et al. (2011) and Murfin and Njoroge (2015) show, contrary to the standard view, that firms can obtain trade credit at low cost.

Following this framework, we study substitution effects in SMEs. We investigate whether

SMEs increase trade credit usage (accounts payable) after a negative shock to their bank credit. This setting is well-suited to study substitution effects because SMEs, unlike large public corporations, predominantly rely on two sources of external finance: bank credit and trade credit. If firms are external finance-dependent and there is a negative shock to one source, firms are facing a financing gap. We investigate whether they can close this gap or not. The answer informs us about the general discussion on the dynamic relation between firms' bank credit and trade credit, especially whether there is a substitution or complementary relation over time.

In the first step, we consider firms' ability to obtain trade credit from their suppliers after they experienced a negative shock to bank credit. Theoretically, all firms that are external finance dependent have positive demand for credit. Firms that experience a negative shock to their bank credit face two options. The first option is to accept the decrease in credit, become constrained and shrink. The second option is to try to fill the financing gap with additional trade credit, resulting in substitution of bank credit with trade credit. In this situation, the trade-off is between lower credit availability (option 1) versus potentially higher cost of credit (option 2). Note that trade credit does not have to be more expensive, as found by Giannetti et al. (2011) and other recent studies. Importantly, there is no guarantee that the additional demand for trade credit under option 2 will be satisfied by the firm's suppliers. Suppliers care about key characteristics of their customers when they extend trade credit. Earlier studies document that financially healthier firms exhibit a higher level of trade credit usage than others (Petersen and Rajan, 1997). Garcia-Appendini and Montoriol-Garriga (2013) examine large U.S. firms and show that liquidity-rich suppliers extend trade credit to external finance dependent customers firms during the crisis. In our setting, we expect that suppliers are more willing to grant additional trade credit to financially healthy SMEs after the latter experienced a negative shock to their bank credit. This expectation is not trivial because of two reasons. First, trade credit is fully secured debt, implying that suppliers might be indifferent about the credit quality of their

customer. Second, we consider the potential response of firms in trade credit after they experienced a negative shock to their bank credit. This setup implies that, if there is substitution, the lending behavior of the suppliers is the opposite of that of banks. This situation can occur if suppliers are not, or not as strongly, hit by the same shock as banks. We propose the following hypothesis:

Hypothesis 1 (credit quality and supply of trade credit): The higher the credit quality of the firm the more likely that it obtains additional trade credit from its suppliers.

In the second step, we consider the impact of the negative shock to bank credit during the financial crisis. We argue that the decrease in bank credit is due to a negative shock to credit supply during the financial crisis (e.g., Ivashina and Scharfstein, 2010). Banks realized unprecedented losses that reduced their capital, resulting in a contraction of bank credit supply. Firms that depend on external finance, especially on bank credit, should be the ones that are most affected. If firms are affected, they have the option to either deleverage and shrink or to accept potentially higher costs of credit by resorting to trade credit. Considering that we focus on firms that are dependent on external finance, it is likely that their demand for trade credit, which is the second most important source of external finance, increases. However, during the financial crisis, this effect of additional demand for trade credit by customer firms might not be met by their suppliers because the latter also face liquidity constraints. We therefore propose the following hypothesis:

Hypothesis 2 (supply and demand of trade credit versus supply of bank credit): Firms with additional demand for trade credit – due to a decrease in bank credit supply - have more difficulties to obtain trade credit during the crisis years compared to other years.

In the third step, we consider the interplay of trade credit supply and demand. On the one hand, external finance-dependent firms have demand for trade credit to fill the financing gap after the negative shock to credit supply. On the other hand, in addition to their credit quality,

the level of financial constraints might influence SMEs' ability to obtain additional trade credit. We note that financial constraints and credit quality are related to each other, but not the same (e.g., Fazzari et al., 1988; Kaplan and Zingales, 1997). Financially constrained firms have difficulties in acquiring external finance because there is a mismatch of investment and financing opportunities or because there are severe informational asymmetries. Because of these informational asymmetries, they have difficulties in signaling their true credit quality, which results in higher costs of debt. Consequently, credit quality should matter less for the access to trade credit for unconstrained firms and for highly constrained firms. The first group is unlikely to use additional trade credit because they have access to alternative forms of external finance, while the second group is credit-rationed (Stiglitz and Weiss, 1981). The latter firms do not get any credit as bank lenders and suppliers ignore differences in credit quality of these firms. However, suppliers might be willing to provide additional trade credit to firms that exhibit moderate financial constraints and a sufficiently high credit quality. This group comprises firms with relatively high and relatively low credit quality because financial distress and financial constraints are related but not exactly the same. Hence, for the high-quality firms, trade credit supply and demand are likely to be matched. We therefore propose the following hypothesis:

> *Hypothesis 3 (credit quality, financial constraints and trade credit usage): Credit quality and financial constraints together have a non-monotonic effect on the access to trade credit.*

2.2. Empirical strategy

To test our hypotheses, we define a substitution indicator (SI_{it}). This indicator is firm-specific and time-varying, and it measures the probability of substitution in SME finance. The substitution indicator equals zero for a negative complementary relation between changes in

bank credit (ΔB_{it-1}) and changes in trade credit (ΔT_{it}), measured by changes in accounts payable, and one for a substitution relation between changes in bank credit and changes in trade credit, both conditional on a negative shock to short-term bank credit in the previous year. It is defined in Equation (1).[1]

$$SI_{it} = \begin{cases} 0 \text{ if } \Delta B_{it-1}<0 \cap \Delta T_{it}<0 \\ \\ 1 \text{ if } \Delta B_{it-1}<0 \cap \Delta T_{it}>0 \end{cases} \tag{1}$$

A major challenge in studying the relation between bank credit and trade credit at the firm level is that both variables can change simultaneously. This potential endogeneity makes it difficult to draw conclusions about the complementary or substitution relation between both types of credit (e.g., Kestens et al., 2012; Nilsen, 2002). To ensure that we identify causal effects, we proceed as follows.

We focus on firms that have demand for external finance to ensure that they want to substitute bank credit for trade credit. To identify firms with demand for credit, we use the concept of external finance dependence, as proposed by Rajan and Zingales (1998). Firms that have no demand for external finance do not need to substitute bank credit because they have sufficient internal finance to fund their operations (e.g., Becker and Ivashina, 2014; Garcia-Appendini and Montoriol-Garriga, 2013; Duchin et al., 2010). Moreover, demand side rationales can be excluded because interest rates decreased significantly during the financial crisis, as pointed out by Ivashina and Scharfstein (2010). This strategy makes it possible for us to exclude firms that redeem maturing debt or that reduce their debt voluntarily. External

[1] In further analyses, we consider a modified substitution indicator that takes also contemporaneous shocks to bank credit into account (Section 4.5). The main results are similar.

finance dependence is calculated as shown in Equation (2):

$$\mathrm{EFD_{it}} = \frac{\Delta \mathrm{TA_{it}} - \mathrm{CF_{it}}}{\Delta \mathrm{TA_{it}}} \tag{2}$$

ΔTA_{it} is a proxy for a firm's level of investments and CF_{it} represents the firm's cash flows in year t. Only observations with a positive outcome are included in the analyses conditional on EFD because these are the firms that theoretically need credit.[2] We calculate EFD_{it} at the firm level and, alternatively, at the industry-country level. For the latter, we use the median values of ΔTA_{it} and CF_{it} at the industry-country level. On the one hand, EFD_{it} at the firm level is more informative about a firm's specific needs for external finance than EFD_{it} at the country-industry level. On the other hand, the level of investments depends on a firm's access to finance, making EFD_{it} potentially endogenous at the firm level, but not at the country-industry level. Because of these reasons, we decided to consider both measures of $EFD_{it.}$[3]

Our sample period contains the global financial crisis of 2007-2009 when many banks had to reduce their lending significantly because of subprime mortgage-finance related losses, illiquidity, and insolvency concerns (Ivashina and Scharfstein, 2010; Duchin et al., 2010; Puri et al., 2011). Therefore, we study the response of trade credit after a negative shock to SMEs' bank credit, which is for the vast majority of SMEs an exogenous and credit supply-side driven shock. We also address potential endogeneity due to sample selection effects or omitted variables by estimating a two-stage Heckman selection model with firm fixed effects (Heckman, 1979).

Furthermore, we conduct an additional analysis with matched bank-firm on Spain that

[2] Alternatively, we computed *EFD* only for observations with $\Delta TA>0$ because *EFD* becomes positive for $\Delta TA<0$ and $CF>0$. The (unreported) results are similar.

[3] We perform every analysis twice, i.e., for the full sample and for our EFD sample, and the results are similar. The specific definition of external finance dependence does not affect our results.

allows a direct identification of firms that were facing a negative shock to bank credit during our sample period. We distinguish between SMEs that have a relationship with an unhealthy bank and firms that do not have a relationship with an unhealthy bank. SMEs that borrow from unhealthy banks were facing a stronger reduction in credit supply and therefore had a higher need for substitution during the recent financial crisis. We examine whether trade credit helped these firms to replace the funding gap.

3. Data

3.1. Data source

We collect firm data from the Orbis and SABI databases, both provided by Bureau van Dijk. These databases contain firm-year observations from the five biggest European countries (Germany, France, Italy, Spain, and the United Kingdom), covering the years before, during and after the global financial crisis of 2007-2009. Data for Spain come from the SABI database, while the data from the other four countries are gathered from Orbis. We restrict our analysis to non-financial firms that are not publicly listed and that exhibit total assets not larger than €43 million in the last available year, consistent with the definition of SMEs from the European Commission (European Commission, 2005). Moreover, in Orbis there are many data points that report values of zero, potentially having an ambiguous meaning; they can either mean zero, "missing," or "unknown." To prevent this ambiguity in our dataset, we only include firms where the value of accounts payable, accounts receivable, and short-term bank credit equals at least €1,000 in any of the years in our sample period. Applying these selection criteria results in a final sample with yearly data from 2006 to 2011 (2006 to 2010 for Spain). Since we use financial statement information we do not know the identity and number of firms' suppliers and banks. Nevertheless, we use data from the input-output matrix from Eurostat and a matched bank-firm dataset for Spain in additional analyses.

The number of firms included in the ORBIS database differs for each country, which results in certain countries being heavily over- or underrepresented in the raw dataset. Therefore, we construct a representative dataset in a way that gives each country a weight that is proportional to its average GDP over the sample period. The final dataset is comprised of 1,186 SMEs from Germany (28%), 922 from France (22%), 920 from the U.K. (21%), 751 from Italy (17%), and 501 from Spain (12%). In that sample, we include the largest SMEs from each country. We further conduct separate analyses using the larger raw samples for each country. To rule out that our results are driven by a selection bias, we also stratify the raw samples in size quintiles and randomly draw a number of firms (equal to the number of firms for each country in the main dataset divided by five) within each country-quintile and repeat this procedure 100 times.

3.2. Variables and summary statistics

Our dependent variable is the substitution indicator SI_{it}. Figure 1 shows the relative frequency of substitution (SI_{it}=1) by country and over time. There is a sharp decrease in the fractions of substitution relations throughout the financial crisis until 2009, as well as an increase during the recovery in 2010. All five countries show a similar pattern but the effects vary in terms of their magnitude. The mean of SI in the entire sample equals to 0.49, indicating that substitution and complementary relationships are on average almost equally likely to occur. However, the overall mean value clouds that there is substantial variation over time (e.g., the yearly mean of SI in the U.K. changes from 0.28 in 2008 to 0.65 in 2010) that indicates that the probability of substitution depends on the state of the economy.

(Insert Figure 1 here)

The main explanatory variable is the credit quality of the firm, which we measure with the

Altman Z-score (Z) for private firms (Altman, 1968). The Z-score is a widely used composite measure of credit quality (firm default risk) and is based on several factors, such as liquidity, retained earnings, profitability, leverage, sales, and size. Agarwal and Taffler (2007) show that the Z-score predicts the default risk of firms in different time periods and different countries. Altman's Z-score[4] for private companies is computed as shown in Equation (3). All components are winsorized at the 1st and 99th percentile to ensure that the Z-score is not driven by extreme observations.

$$Z_{it} = 0.7\frac{\text{WorkingCapital}_{it}}{\text{TotalAssets}_{it}} + 0.85\frac{\text{RetainedEarnings}_{it}}{\text{TotalAssets}_{it}} + 3.1\frac{\text{EBIT}_{it}}{\text{TotalAssets}_{it}} + 0.4\frac{\text{TotalAssets}_{it}}{\text{TotalLiabilities}_{it}} + \frac{\text{Sales}_{it}}{\text{TotalAssets}_{it}}. \quad (3)$$

As stated in Hypothesis 3, the influence of Altman's Z-score on the probability of substitution might interact with the level of financial constraints of the firm. We measure financial constraints with the KZ index, a widely-used measure in the corporate finance literature (Kaplan and Zingales, 1997; Lamont, Polk, Saá-Requejo, 2001). It is defined in Equation (4).[5] All components are winsorized at the 1st and 99th percentile. In order to measure the non-monotonicity between the Z-score and the KZ index, we create quintile dummies for the latter (KZ_Q).

$$KZ_{it} = -1.002\frac{CF_{it}}{TA_{it-1}} + 3.139\frac{TL_{it}}{TA_{it-1}} + 39.368\frac{Div_{it}}{TA_{it-1}} - 1.315\frac{Cash_{it}}{TA_{it-1}}. \quad (4)$$

Because there has been debate about how to measure financial constraints (e.g., Farre-Mensa and Ljungqvist, 2016), we consider the WW index (Whited and Wu, 2006) and the SA

[4] Sales are not available for firms from the U.K. We therefore use operating revenues in all countries. For EBIT, we take ROA before taxes instead. Retained earnings are not directly available in Orbis. We have estimated them as equity minus capital (firm wealth minus the value of the shares).

[5] Dividends are not available in Orbis. We estimate dividends as net income minus the change in equity (i.e., the proportion of income that is not retained by the company).

index (Hadlock and Pierce, 2010) as alternative measures in robustness tests.

We add year dummies to capture macro-economic effects. We consider the year 2008 as the first year of the crisis because the subprime mortgage crisis started to affect several European economies in that year. We consider 2009 as the second crisis year because this is the year after the collapse of Lehman Brothers in September 2008, which triggered a global recession.

We add several control variables that might influence the substitution indicator. The first variable is a proxy for the supplier credit quality (*SupplierZ*).[6] The second variable is firm size (*Size*), measured by the natural logarithm of total assets. The third variable is the sum of cash and cash equivalents divided by total assets (*Cash*). Fourth, we consider two proxies for collateral (e.g., Cuñat, 2007). Long-term collateral is measured with fixed tangible assets (*TangFA*) and short-term collateral with inventories (*Inv*) (e.g., Campello and Giambona, 2013; Norden and van Kampen, 2013), both scaled by total assets. The fifth variable is profitability measured by *ROA*. Z and ROA are sensitive to outliers and are winsorized at the 1st and 99th percentile at the country level. In all regressions, we control for industry and country fixed effects, where industry is based on the two-digit SIC code. Industry fixed effects are important because suppliers are more willing two extend trade credit to customers in industries with high product specificity (Cuñat, 2007). Country fixed effects are important because heterogeneity in financial and legal systems creates heterogeneity in financial markets (e.g., La Porta et al., 1997). Table 1 reports summary statistics separately for the firms that exhibit a complementary relation (column (0)) and those that exhibit a substitution relation (column (1)). Panel A reports

[6] A firm's ability to substitute bank credit for trade credit depends on whether suppliers are able to provide additional trade credit, which is related to their credit quality. We cannot measure the suppliers' credit quality directly because our sample does not contain supplier-customer matched data. Instead, we collected industry-level information from the input-output matrix of European countries from Eurostat. We use the pre-crisis input-output matrix from 2006 to derive the weights of the supplier industries for each customer industry. We then calculate the median Z-score for each supplier industry, country and year, using the Orbis data. In the last step, we calculate for each firm-country-year observation the weighted average of its supplier industries' median Z-scores.

the descriptive statistics for all firms experiencing a negative shock in bank credit, while Panel B reports the statistics for the firms that have demand for external finance (EFD firms).

(Insert Table 1 here)

The mean and median values of the Z-score are higher for the substitution firms, indicating that firms of higher credit quality substitute credit more often. The mean and median of the Z-score differ substantially across countries (not reported); German firms have the highest credit quality with a mean (median) Z-score of 3.36 (3.13), while Italian firms have the lowest credit quality with a mean (median) Z-score of 1.78 (1.68). Firms from the other three countries have Z-scores that range between values of 2.0 and 3.0. In addition, the value for Z (KZ) drops (rises) when we exclude firms that have no demand for external finance. This is intuitive because firms that do not need external finance display usually a higher credit quality and lower financial constraints.

4. Empirical analysis

4.1. Baseline analysis

We investigate which factors influence whether SMEs increase trade credit after they have experienced a negative shock to their bank credit by regressing the SI_{it} on the firm's lagged Z-score, year dummies, the lagged supplier Z-score, lags of the firm control variables, industry dummies, and country dummies. Table 2 reports the results of the logit regressions. We report odds ratios (i.e., values above one indicate positive effects and values below one negative effects) and corresponding p-values in parentheses.

(Insert Table 2 here)

We find that the credit quality of firms, measured by Z_{it-1}, has a significantly positive impact on the probability of substitution. The odds ratios for Z_{it-1} in all specifications of Table 2 are above one and statistically significant. A one-unit increase in Z_{it-1} is associated with an increase in the probability of substitution between 7.9% (column 1) and 10.5% (column 6). This result implies that credit substitution for low credit quality firms is difficult because suppliers are not willing to increase trade credit to these firms, although trade credit is fully secured debt. The result supports our Hypothesis 1. However, the odds ratios we obtain for the year dummies are below one and indicate that the probability of substitution significantly decreased during the stages of the global financial crisis: it is 44.7% lower in 2008 and 43.9% lower in 2009 compared to 2007. The findings on the financial crisis are consistent with our Hypothesis 2, suggesting that firms could not counter the negative shock to bank credit with an increase of trade credit usage. This finding shows the limits of substitution in SME finance.

In column (2), we obtain similar results when we add lagged firm characteristics as controls. The results are even stronger in column (3) where we consider only firms that have demand for external finance (EFD firms). In column (3), a one-unit increase in Z_{it-1} is associated with a 10.4% increase in the probability of substitution. The sample size decreases only slightly when we exclude firms that do not depend on external finance (from 8,825 to 7,040). This is not surprising because SMEs are in general strongly dependent on external finance. We conclude that, all else being equal, the relation between credit quality and substitution is positive and monotonic. In column (4), we report the estimation results of a regression in which the variables are demeaned at the country level and we obtain similar results. In column (5), we report the results for firms from external finance-dependent industries. A one unit increase in Altman's Z-score increases the probability of substitution with 6.9%, the result becomes weakly significant though (p=0.060). The impact of the year dummies remains similar in terms

of economic and statistical significance. In column (6), we re-estimate the specification of column (3) but we replace the countries dummies by time-varying country characteristics such as credit protection rights, the median Z-score of the banks, the C5-concentration ratio and the median bank size. The coefficients of the Z-score and the year dummies are highly significant and similar to those reported in column (3).

Moreover, to shed light on the magnitude of substitution, we regress the continuous change in trade credit (accounts payable, in euros) on the lagged Z-score, the lagged absolute value of the change in short-term bank credit (in euros), and the interaction term of these two variables. We further add firm controls, year fixed effects, industry fixed effects and country controls. We estimate this model for firms that experience a negative shock to bank credit in the previous period using (i) the full sample, (ii) the full sample with time-varying firm controls, (iii) the sub-sample of external finance dependent firms (EFD>0) with time-varying firm controls, and (iv) the sub-sample of external finance dependent firms (EFD>0) with time-varying firm controls and time-varying country controls. Table 3 reports the results (coefficients and p-values in parentheses):

(Insert Table 3 here)

Again, we find that the coefficient of the Z-score is significantly positive. Moreover, the coefficient for $\Delta B(t-1)$ is also positive and significant. This result indicates that the size of the negative shock to bank credit directly influences the magnitude of substitution with trade credit. A one euro decrease in bank credit translates, ceteris paribus, into a 0.05 euro increase in trade credit in the subsequent period. Importantly, we also find a significantly positive coefficient for the interaction term $Z(t-)*\Delta B(t-1)$ in all four columns. To illustrate the economic magnitude of this continuous interaction effect (column 2; EFD firms), let us consider two firms that

dependent on external finance. Firm A has a Z-score of 1.8 (distressed) and firm B one of 3.0 (healthy). Both firms experience a one-standard deviation decrease in bank credit (6.088 million euros). This shock to bank credit results in an increase of trade credit by 579 K euros for firm A (=22.725*1.8 + 0.056*6,088 + 0.018*6,088*1.8) and by 737 K euros for firm B (=22.725*3.0 + 0.056*6,088 + 0.018*6,088*3.0). In sum, we find that the credit quality of firms has a strong and positive effect on the magnitude of substitution, which confirms our earlier findings and is consistent with Hypothesis 1.

We also find negative coefficients of the year dummy 2008 (ranging between -325 and -407) and the year dummy 2009 (ranging between -288 and -365). These findings are in line with our earlier results and Hypothesis 2. The evidence suggests that firms could not increase trade credit to counter the negative shock to their bank credit. These additional findings based on continuous changes of bank credit and trade credit confirm the results for the probability of substitution shown in Table 2. Therefore, we continue the remainder of the analysis using the substitution indicator *SI*.

4.2. Sample selection and cross-country heterogeneity

In the previous analysis, we did not consider two potential issues. The first issue is related to potential selection effects that might influence our estimation results, the second one is related to cross-country heterogeneity.

First, it is possible that the analysis above is subject to selection effects because we condition the analysis on firm-year observations after a negative shock to the firm's bank credit. The probability of such shock might not be random and could influence the probability of substitution. Moreover, we could not add firm fixed effects to the regression because our sample contains mainly cross-sectional firm data from different years.

To address this issue, we estimate a two-stage Heckman selection model (Heckman, 1979).

In the first stage regression, we consider the full sample before applying the selection condition. We regress an indicator variable that equals one if a firm experienced a negative shock to its bank credit, and zero otherwise, on all the explanatory variables and firm-fixed effects. Importantly, the latter control for any remaining time-invariant firm-specific heterogeneity. In the second stage regression, we add the *Inverse Mills Ratio* from the first stage regression to control for possible selection effects. Table 4 reports the results.

(Insert Table 4 here)

In the first stage regression, we find that all the explanatory variables from Table 2 have a significant effect on the likelihood of experiencing a negative shock to bank credit. Most importantly, when we add the *Inverse Mills Ratio* to the second stage regression, we still find that the effect of the Z-score on the probability of substitution remains positive and significant. In addition, the probability of substitution during the years 2008 and 2009 is significantly lower than in the pre-crisis period, as found in Table 2.

Second, we examine the cross-country heterogeneity of the substitution in SME finance. We expect a significantly positive effect of the Z-score on the probability of substitution in all five countries, as stated in Hypothesis 1. Moreover, according to Hypothesis 2, we expect negative effects for the years 2008 and 2009. For the U.K. and Spain, we expect the strongest effects for the year 2008 because the crisis started earlier in these two countries. For France, Germany and Italy, we expect the strongest effects for the year 2009. In this analysis, we employ the larger raw samples from each country to make full use of the data instead of using the smaller GDP-weighted aggregate sample. Table 5 reports the results.

(Insert Table 5 here)

Overall, the reported odds ratios in Table 5 confirm the earlier findings from the baseline analysis and are consistent with our predictions.[7] First, the Z-score is significantly positive at the 1%-level in four out of five countries. The only exception is Germany, where the firms' Z-score is borderline insignificant (p-value of 0.14). Possible reasons are that German SMEs display a higher Z-score level than the SMEs from other countries,[8] the German banking system was less strongly hit by the global financial crisis, there is more long-term bank credit, and, unlike in other countries, the *SupplierZ* is significant, pointing at spillover effects in trade credit chains. Second, we find strong and significantly negative effects for Spain (-69%) and the U.K. (-65%) in the probability of substitution for the year 2008. For the other three countries, the substitution declined in 2008, too, but the effects are less pronounced (France: -18%; Germany: -15%; Italy: -27%). For the latter countries, the decline of the substitution indicator peaks in 2009 (France: -41%; Germany: -51%; Italy: -37%). We find the biggest cumulative effect of the crisis for Spain where approximately half of the banking system imploded (see, e.g., Illueca, Norden and Udell, 2014) and the GDP had not grown for five years. This evidence supports our earlier findings and is consistent with Hypothesis 2.

In unreported analyses[9], we find that the results are similar for the Altman's Z-score and D_2009 when we investigate firms from external finance-dependent industries: D_2009 is significant in all five countries and the Altman's Z-score in four countries (Germany is the only exception). Furthermore, we estimated the baseline model with interaction effects between the explanatory variables and country dummies using the country-specific raw samples. The results

[7] We obtain similar results when we repeat the analysis with the model for continuous changes in trade credit and bank credit as in Table 3.

[8] The median Z-scores per country in our sample are: Germany: 3.13; France: 2.87; UK: 2.74; Spain: 2.17; Italy: 1.67. This relatively high general level for German SMEs might lower the sensitivity of the probability of substitution to credit quality.

[9] Results are available from the authors on request.

are similar to the ones we report in Table 2.

The evidence suggests that the effects of credit quality and the crisis on the probability of substitution in SME finance are consistent, but the magnitude and timing of the effects vary across countries.

4.3. Credit quality and financial constraints

It is possible that the effect of credit quality on the probability of substitution is related to firms' financial constraints. In particular, we test whether there is a non-monotonic impact of credit quality and financial constraints on trade credit usage, as stated in Hypothesis 3. The concept of financial constraints is related to, but not identical to financial distress (e.g., Fazzari, Hubbard and Petersen, 1988; Kaplan and Zingales, 1997). When we inspected the raw data we notice that the variation of the Z-score across firms and over time is higher for moderately financially constrained firms compared to not financially constrained and fully constrained firms. This fact is plausible and suggests that suppliers are likely to differentiate when they provide trade credit to customers from this middle group.

To test our Hypothesis 3 in a multivariate model, we interact the Altman Z-score (Z_{it-1}) with KZ index quintile dummies (KZ_Q_{it}), using the first quintile as reference category. Using quintile dummies makes it possible to uncover possible non-monotonic interaction effects. Table 6 reports the results.

(Insert Table 6 here)

The regression results indicate an inversely U-shaped relation between the probability of credit substitution and the interaction term for the full sample (column 1) and the sample of the external finance dependent firms (column 2). The finding indicates that credit quality is most

important for the firms with moderate financial constraints. For firms in quintile 3 (4), a one-unit increase in the Z-score of EFD firms increases the probability of substitution by 15.1% (23.8%) relative to quintile 1. The effect is statistically significant but less pronounced for the firms with no financial constraints because these firms have access to alternative forms of finance. In contrast, the Z-score matters less for the firms with the highest financial constraints because these firms are likely subject to credit rationing.

In addition, we repeated the regression with the quintile dummies for the WW index.[10] The results for the interaction effects with the WW index are similar to those for the KZ index, indicating that the probability of substitution exhibits the highest sensitivity to credit quality for the firms in the fourth quintile. We also considered the SA index (Hadlock and Pierce, 2010), but we do not find any significant interaction effects of this index with credit quality. One explanation is that the SA index does not sufficiently discriminate between the SMEs in our sample because they are all relatively small.

Finally, we conduct the baseline regression from Table 2 for external finance-dependent firms separately for each KZ quintile by country. The odds ratios of the Z-score in each KZ quintile group in the raw sample are plotted in Figure 2.

(Insert Figure 2 here)

Four of five countries display an inversely U-shaped pattern. The results for Germany are not monotonic, but the maximum effect is found for the fourth KZ quintile. The results are consistent with our Hypothesis 3, confirming that firms with a high credit quality and intermediate financial constraints exhibit a higher probability of credit substitution than others.

[10] Results are available on request.

4.4. Total bank credit and trade credit

In the previous analyses, we investigated SMEs' reaction with trade credit in year t after a negative shock to their short-term bank credit in year t-1. On the one hand, it is possible that SMEs were also facing a negative shock to their long-term bank credit, especially those firms that had long-term bank credit expiring during the recent financial crisis (Campello et al., 2012). On the other hand, it is likely that firms mainly substitute short-term bank credit (and not long-term bank credit) with trade credit (and vice versa). In other words, it is unlikely that firms substitute a permanent decrease in long-term bank credit with a permanent increase in trade credit because the purpose and the cash flow effects of these two types of debt finance are very different.

To provide further evidence on the substitution effects between bank credit and trade credit, we examine the response of trade credit in year t after a negative shock to total bank credit (short-term and long-term bank credit) in year t-1 (SI_{it}^{total}). Table 7 reports the results.

(Insert Table 7 here)

When comparing the results for the shock to total bank credit reported in Table 7 with the baseline results from Table 2, we find that the Z-score and the years of the financial crisis have a similar impact on the probability of credit substitution. For external finance-dependent firms, a one-unit increase in the Z-score increases the probability of substituting total (short-term) bank credit for trade credit by 6.5% (10.4%). In addition, the probability of substituting total (short-term) bank credit decreases 40.3% (48.5%) during 2008 and 44.8% (48.9%) during 2009. The fact that the results do not change when we use total bank credit as input for the substitution indicator increases the reliability of the evidence. It is can also be explained with

the fact that short-term bank credit accounts for a large fraction of total bank debt in some of the countries in our sample (e.g., Spain and Italy).

4.5. Definition of substitution

We consider three modified definitions of the substitution indicator to examine the robustness of our earlier findings.

First, we investigate how much SMEs could substitute, using the three-outcome $SI3_{it}$.[11] This modified version has three possible outcomes: (1) negative complementary relation; (2) partial substitution; and (3) perfect substitution. Partial substitution refers to the situation where trade credit increases in year t to a lower extent than bank credit decreased in year t-1, while perfect substitution refers to the situation where trade credit increases in year t at least as much as bank credit decreased in year t-1. In other words, we investigate two different forms of substitution; the situation where firms do not fully fill the funding gap resulting from the decrease in bank credit and the situation where they do fully fill this gap. Table 8 presents the results. We estimate the probability of partial or perfect credit substitution relative to the probability of a negative complementary relation.

(Insert Table 8 here)

We find that perfect credit substitution is more likely the higher the credit quality of the firm. For firms with external finance dependence at the firm (industry) level a one-unit increase in the Altman Z-Score increases the probability of substitution with 18% (15.6%). Furthermore, substitution decreased in both years of the financial crisis. The likelihood of perfect substitution

[11] We also considered the elasticity of trade credit to bank credit as an alternative version of the substitution indicator. However, it turned out that the elasticity measured at the firm level is too volatile. The discrete SI3 indicator is more robust and implicitly depends on the elasticity as input.

decreases with 40-50% in 2008 and 50-60% in 2009. By and large, these results are consistent with those from the former tables.

Second, to provide further evidence that our results are not driven by a selection bias, we repeat the baseline analysis with a substitution indicator that is unconditional on the nature of the shock to bank credit in year t-1 ($SI4_{it}$) as shown below. We now consider positive and negative shocks to SMEs' bank credit in year t-1 to study their response in trade credit.

$$SI4_{it} = \begin{cases} 1 & \text{if } \Delta B_{it-1}<0 \cap \Delta T_{it}<0 \text{ (complementary)} \\ 2 & \text{if } \Delta B_{it-1}<0 \cap \Delta T_{it}\geq 0 \text{ (substitution)} \\ 3 & \text{if } \Delta B_{it-1}\geq 0 \cap \Delta T_{it}<0 \text{ (substitution)} \\ 4 & \text{if } \Delta B_{it-1}\geq 0 \cap \Delta T_{it}\geq 0 \text{ (complementary)} \end{cases} \quad (6)$$

Table 9 presents the results of the multinomial regression. All probabilities are relative to having a negative complementary relation ($SI4_{it}$=1). In the least restrictive sample, we find that a one-unit increase in Altman's Z increases (decreases) the probability of substituting bank credit (trade credit) for trade credit (bank credit) with 8.5% (10.2%). This means that firms with higher credit quality are more likely to use trade credit when bank credit is unavailable and that these firms are less dependent on trade credit when bank credit is available. Furthermore, we show that the occurrence of a crisis decreases the probability of being in group 2, 3 or 4 because the Odds-Ratios for D_2008 and D_2009 are significantly negative. In other words, a negative complementary relation is most likely to occur during a crisis.

(Insert Table 9 here)

Third, the substitution indicator in Equation (1) does not take into account a potential change in bank credit in year t. The latter could influence the probability of substitution because if a decrease in bank credit in the previous year is fully offset by an increase in bank credit in the current year, then substitution is not necessary, and hence, a complementary relation becomes more likely. For this reason, we additionally condition the substitution indicator on either $\Delta B_{it} < 0$ or $|\Delta B_{it}| < |\Delta B_{it-1}| \cap \Delta B_{it} > 0$. In other words, we only include cases where the negative shock to bank credit in year t-1 is not fully offset by a positive shock in year t. The results, which are available on request, qualitatively confirm our previous findings.

4.6. Stratified random sampling

Our baseline analysis is based on a sample comprised of the largest SMEs from the five biggest European countries. To rule out that there is a selection effect due to firm size, we stratified the raw samples using firm size quintiles. For each country, we select a fixed number of firms by random sampling from each size quintile. The fixed number equals the number of firms per country in the raw sample divided by five. We repeat this procedure 100 times. We then re-estimate our main regressions for firms that are externally financially dependent for each of the 100 subsamples and report the mean estimation results in Table 10.

(Insert Table 10 here)

Repeating the baseline analysis, we find that the Z-score has a significantly positive impact on the probability of credit substitution, where the mean odds ratio is 1.114 (p=.000). In addition, in all 100 reiterations, the years 2008 and 2009 have a significantly negative impact on the probability of credit substitution. The mean odds ratios are 0.573 (p=0.000) and 0.580

(p=0.000), respectively. Hence, our previous results remain robust when we repeat the analysis on the stratified random sample.

5. Evidence from matched bank-firm data

We carry out one more analysis to complement the previous evidence. The following analysis allows us to directly identify a causal relation between an exogenous decrease of bank credit supply in year t-1 and the potential response in trade credit in year t at the individual firm level. We do so by using detailed matched bank-firm data on SMEs from Spain.[12]

For each firm and year, we observe the number and names of banks from which the SMEs obtain credit, resulting in a dataset comprised of 59,534 bank-firm-year observations for the period 2005-2010. The changes in credit we observe in this dataset are effective changes in credit used by firms. This approach is consistent with the earlier analysis based on the substitution indicator that captures firms' response to an exogenous negative shock to bank credit supply.[13]

To ensure that firms did not decrease their borrowings voluntarily (credit demand-side effect), but that banks cut lending to the firms (credit supply-side effect), we collect information on bank bailouts in the Spanish banking sector. The indicator variable *Bailout* equals one if the bank was eventually bailed out during the recent financial crisis, and zero otherwise. We follow the Bank of Spain and consider all types of government intervention: full bailout, capital infusion, debt guarantees, and other instruments.[14] The Spanish banks that were eventually bailed out, which are almost all the savings banks and some commercial banks, started to

[12] For the other European countries, we cannot use matched bank-firm data because the information on the firms' bank relationships is either not available in ORBIS or it is time-invariant and therefore not reliable.

[13] It would be interesting to distinguish binding and non-binding shocks to bank credit supply. However, information on unused lines of credit is not available in our database. We focus on binding shocks to bank credit supply, as the substitution indicator is based on changes in bank credit and trade credit.

[14] Details on the total amount of public money injected into troubled banks are available at the Bank of Spain's website: http://www.bde.es/f/webbde/GAP/Secciones/SalaPrensa/NotasInformativas/Briefing_notes/es/notabe040515.pdf.

experience dramatic losses in 2007-2008. This situation arose due to the collapse of the Spanish housing bubble and the resulting losses from domestic mortgage lending and banks' credit exposure to securitized U.S. subprime mortgages, which forced these banks to significantly reduce their lending activities (Illueca et al., 2014). This decrease in lending of bailed out banks was significantly stronger than that of banks that were not bailed out. Firms borrowing from bailed out banks faced an exogenous supply-side driven shock to their bank credit. Our identification strategy follows Puri et al. (2011), who study the change in rejection rates of German savings banks that are connected with Landesbanks that were (or were not) affected by the U.S. subprime mortgage crisis. We consider only firms having demand for credit, i.e., those that are considered as external finance dependent (Garcia-Appendini and Montoriol-Garriga, 2013; Rajan and Zingales, 1998).

The variable *Bailout* is an ex-post indicator for banks that were forced to cut lending due to financial distress. However, being bailed out by the government is a result of fundamental financial problems. Therefore, it is reasonable to assume that the bailout banks had to cut lending during this time period. Alternatively, we consider the indicator variable for savings banks that serves as an ex ante indicator of unhealthy banks. Savings banks in Spain were taking substantial risks before the 2008 financial crisis through aggressive loan growth. Their loan growth came to an abrupt end in 2007-2008. As consequence of substantial losses, the savings banks were forced to cut their domestic lending, resulting in a significant credit crunch for SMEs in Spain (Carbo-Valverde et al., 2016).

We estimate the probability of substitution with the indicator variables for the financial crisis (D_2008 and D_2009**)**, for either bailed out banks (*Bailout*) or savings banks (*Savingsbank*), the interaction term between them, firm controls, bank controls, and industry

fixed effects. We cluster the standard errors at the bank-firm level. Table 11 reports the odds ratios and p-values from three specifications of the logit regression model.[15]

(Insert Table 11 here)

This analysis yields a clear result. The odds ratios of the interaction terms *Bailout*D_2008* and *Bailout*D_2009* are significantly below one in all specifications in Table 11.[16] This finding indicates that firms borrowing from bailed out banks during the recent financial crisis had a lower probability of credit substitution than other firms. The effect is significant at the 1% level for the baseline model reported in column (1); it remains significant at the 1% level when we add a comprehensive set of time-varying firm and bank controls in columns (2) and (3) and when we replace the *Bailout* dummy by the *Savingsbank* dummy in column (4). The odds ratio for the firms' Z-score is persistently above one and significant, confirming our earlier result that higher credit quality increases the probability of substitution. These results are consistent with the ones for the five biggest European countries and the aggregate sample, as shown in Table 2, 4 and 5.

We consider the analysis with matched bank-firm data as additional evidence for a causal effect: SMEs with demand for credit found it difficult during the recent financial crisis to (sufficiently) replace the decrease in bank credit with trade credit. In other words, trade credit did not help to fill SMEs' funding gap caused by the negative shock to bank credit supply.

[15] An alternative model specification, in which the bailout indicator is defined as the ratio of total amount of funds injected by the government to total banks' equity at the beginning of the financial crisis, leads to similar results. This alternative analysis is available from the authors upon request.

[16] D_2008 is omitted from most specifications because it perfectly predicts that SI equals zero (indicating no substitution). This result is not surprising because the Odds-ratio for D_2008 in Table 5 is very low for Spain.

6. Conclusion

We investigate whether SMEs that have demand for credit increase trade credit usage after they experience a negative shock to their bank credit and which factors influence their response over time and across countries. We base our analysis on a large sample of SMEs from France, Germany, Italy, Spain and the U.K. that covers the period before, during and after the global financial crisis.

We find that substitution and complementary relationships between bank credit and trade credit are on average equally likely during 2006-2011, but their importance varies substantially over time and across countries. Firms with higher credit quality are significantly more likely to substitute credit. Substitution became less likely during the financial crisis and it further declined as the crisis deepened. High credit quality firms with moderate financial constraints are the ones that are most likely to substitute. We carry out an additional analysis with matched bank-firm data and find that the SMEs that are hit more by the shock to bank credit supply are less likely to substitute.

We show that the probability of credit substitution depends on firms' credit quality, financial constraints, and macroeconomic conditions. Our findings highlight the limits of substitution in SME finance. Increasing trade credit usage is not a sufficient response to fill the funding gap that emerges after banks cut lending to SMEs. Policymakers should focus on enhancing financial stability, and thereby stabilize bank credit supply and the bank lending environment in the first place, rather than considering trade credit as alternative mode of external finance to mitigate the adverse effects on the real economy. SMEs can stabilize their access to bank credit by combining forward lending and spot lending and by diversifying across loan types and financial institutions.

References

Agarwal, V., Taffler, R., 2007. Twenty-five years of the Taffler Z-score model: Does it really have predictive ability? Account. Bus. Res. 37, 285-300.

Altman, E., 1968. Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy. J. Financ. 103, 589-609.

Beck, T., Levine, R., Loayza, N., 2000. Finance and the Sources of Growth. J. Financ. Econ. 58, 261-300.

Becker, B., Ivashina, V., 2014. Cyclicality of Credit Supply: Firm Level Evidence. J. Monet. Econ. 62, 76-93.

Berger, A., Udell, G., 2006. A more complete conceptual framework for SME finance. J. Bank. Finance 30, 2945-2966.

Biais, B., Gollier, C., 1997. Trade Credit and Credit Rationing. Rev. Financ. Stud. 10, 903-937.

Boissay, F., Gropp, R., 2013. Payment Defaults and Interfirm Liquidity Provision. Rev. Finance 17, 1853-1894.

Breza, E., Liberman, A., 2017. Financial Contracting and Organizational Form: Evidence from the Regulation of Trade Credit. J. Finance 72, 291-324.

Burkart, M., Ellingsen, T., 2004. In-kind finance: a theory of trade credit. Am. Econ. Rev. 94, 569-590.

Calomiris, C., Himmelberg, C., Wachtel, P., 1995. Commercial paper, corporate finance, and the business cycle: a microeconomic perspective. Carnegie Rochester Conf. Ser. Public Policy 42, 203-250.

Campello, M., Giambona, E., 2013. Real Assets and Capital Structure. J. Financ. Quant. Anal. 48, 1333-1370.

Campello, M., Giambona, E., Graham, J., Harvey, C., 2012. Access to Liquidity and Corporate Investment in Europe during the Financial Crisis. Rev. Finance 16, 323-346.

Carbo-Valverde, S., Rodriguez-Fernandez, F., Udell, G., 2016. Trade Credit, the Financial Crisis, and SME Access to Finance. J. Money, Cred. Bank. 48, 113-143.

Casey, E., O'Toole, C., 2014. Bank lending constraints, trade credit and alternative financing during the financial crisis: Evidence from European SMEs. J. Corp. Finance 18, 151-172.

Cuñat, V., 2007. Trade Credit: Suppliers as Debt Collectors and Insurance Providers. Rev. Financ. Stud. 20, 491-527.

Dietsch, M., Petey, J., 2002. The credit risk in SME loans portfolios: Modeling issues, pricing, and capital requirements. J. Bank. Finance 26, 303-322.

Duchin, R., Ozbas, O., Sensoy, B., 2010. Costly external finance, corporate investment, and the subprime mortgage credit crisis. J. Financ. Econ. 97, 418-435.

European Commission, 2005. The new SME definition. User guide and model declaration.

Fabbri, D., Menichini, A., 2010. Trade Credit, Collateral Liquidation, and Borrowing Constraints. J. Financ. Econ. 96, 413-432.

Farre-Mensa, J., Ljungqvist, A., 2016. Do Measures of Financial Constraints Measure Financial Constraints? Rev. Financ. Stud. 29, 271-308.

Fazzari, S., Hubbard, G., Petersen, B., 1988. Financing Constraints and Corporate Investment. Brookings Papers Econ. Activity, 141-195.

Fisman, R., Love, I., 2003. Trade Credit, Financial Intermediary Development and Industry Growth. J. Finance 58, 353-73.

Garcia-Appendini, E. Montoriol-Garriga, J., 2013. Firms as liquidity providers: Evidence from the 2007-2008 financial crisis. J. Financ. Econ. 109, 272-291.

Giannetti, M., Burkart, M., Ellingsen, T., 2011. What You Sell Is What You Lend? Explaining Trade Credit Contracts. Rev. Financ. Stud. 24, 1261-1296.

Hadlock, C., Pierce, J., 2010. New Evidence on Measuring Financial Constraints: Moving Beyond the KZ Index. Rev. Financ. Stud. 23, 1909-1940.

Heckman, J., 1979. Sample Selection Bias as a Specification Error. Econometrica 47, 153-161.

Huang, H., Shi, X., Zhang, S., 2011. Counter-cyclical substitution between trade credit and bank credit. J. Bank. Finance 35, 1859-1878.

Illueca, M., Norden, L., Udell, G., 2014. Liberalization and Risk Taking: Evidence from Government-controlled Banks. Rev. Finance 18, 1217-1257.

Ivashina, V., Scharfstein, D., 2010. Bank lending during the financial crisis of 2008. J. Financ. Econ. 97, 319-338

Jacobson, T., von Schedvin, E., 2015. Trade Credit and the Propagation of Corporate Failure: An Empirical Analysis. Econometrica 83, 1315-1371.

Jorion, P., Zhang, G., 2009. Credit contagion from counterparty risk. J. Finance 64, 2053-2087.

Kaplan, S. Zingales, L., 1997. Do Investment-Cash Flow Sensitivities Provide Useful Measures of Financing Constraints? Q. J. Econ. 112, 169-215.

Kestens, K., Van Cauwenberge, P., Van Der Bauwhede, H., 2012. Trade credit and company performance during the 2008 financial crisis. Account. Finance 52, 1125-1151.

King, G., Levine, R., 1993. Finance and Growth: Schumpeter Might Be Right. Q. J. Econ. 108, 717-737.

Klapper, L., Laeven, L., Rajan, R., 2012. Trade Credit Contracts. Rev. Financ. Stud. 25, 838-867.

La Porta, R., Lopez-de-Silanes, F., Shleifer, A., Vishny, R., 1997. Legal Determinants of External Finance. J. Finance 52, 1131-1150.

Lamont, O., Polk, C., Saá-Requejo, J., 2001. Financial Constraints and Stock Returns. Rev. Financ. Stud. 14, 529-554.

Love, I., Preve, L., Sarria-Allende, V., 2007. Trade credit and bank credit: Evidence from recent financial crises. J. Financ. Econ. 83, 453-469.

Meltzer, A., 1960. Mercantile credit, monetary policy, and size of firms. Rev. Econ. Stat. 42, 429–437.

Murfin, J., Njoroge, K., 2015. The Implicit Costs of Trade Credit Borrowing by Large Firms. Rev. Financ. Stud. 28, 112-145.

Ng, C., Smith, J., Smith, R., 1999. Evidence on the determinants of credit terms used in interfirm trade. J. Finance 54, 1109-1129.

Nilsen, J., 2002. Trade Credit and the Bank Lending Channel. J. Money, Cred. Bank. 34, 226-253.

Norden, L., van Kampen, S., 2013. Corporate Leverage and the Collateral Channel, J. Bank. Finance 37, 5062-5072.

Petersen, M., Rajan, R., 1994. The Benefits of Lending Relationships: Evidence from Small Business Data. J. Finance 49, 3-37.

Petersen, M., Rajan, R., 1997. Trade Credit: Theories and Evidence. Rev. Financ. Stud. 10, 661-691.

Puri, M., Rocholl, J., Steffen, S., 2011. Global Retail Lending in the Aftermath of the US Financial Crisis: Distinguishing between Supply and Demand Effects. J. Financ. Econ. 100, 556-578.

Rajan, R, Zingales, L., 1998. Financial Dependence and Growth. Am. Econ. Rev. 88, 559-586.

Stiglitz, J., Weiss, A., 1981. Credit Rationing in Markets with Imperfect Information. Am. Econ. Rev. 71, 393-410.

Whited, T., Wu, G., 2006. Financial Constraints Risk. Rev. Financ. Stud. 19, 531-559.

Wilner, B., 2000. The exploitation of relationships in financial distress: the case of trade credit. J. Finance 55, 153-178.

Table 1: Summary statistics

This table reports descriptive statistics for all non-indicator variables. We present the number of firm-years for each variable and the mean, median, and standard deviation for both outcomes of SI_{it}. (0, 1). Panel A presents the descriptive statistics for all firms that were facing a negative shock to bank credit in year t-1. Panel B presents the descriptive statistics only for the firms that are externally finance-dependent (hereinafter: EFD firms; the increase in total assets exceeds the value of operating cash flows, as is proposed by Rajan and Zingales 1998).

Panel A: All firms

	Firm-Years	Mean		Median		St. Dev.	
		(0)	(1)	(0)	(1)	(0)	(1)
Z	9,222	2.72	2.89	2.58	2.71	1.36	1.47
KZ	8,808	-0.24	-0.12	0.01	0.29	3.45	3.33
KZ_Q	8,808	2.85	3.03	3.00	3.00	1.40	1.42
SupplierZ	9,668	2.61	2.60	2.62	2.52	0.80	0.82
Size	9,672	9.63	9.44	10.14	9.98	1.22	1.25
Cash	9,434	0.08	0.08	0.03	0.03	0.12	0.11
Inventories	9,570	0.20	0.20	0.14	0.14	0.22	0.21
Tangibles	9,618	0.27	0.28	0.20	0.20	0.26	0.26
ROA	9,392	0.03	0.03	0.02	0.02	0.08	0.08

Panel B: External finance-dependent firms (EFD firms)

	Firm-Years	Mean		Median		St. Dev.	
		(0)	(1)	(0)	(1)	(0)	(1)
Z	7,365	2.65	2.86	2.49	2.66	1.35	1.50
KZ	7,011	-0.22	0.09	0.06	0.45	3.49	3.33
KZ_Q	7,011	2.88	3.13	3.00	3.00	1.41	1.42
SupplierZ	7,742	2.58	2.58	2.62	2.50	0.80	0.82
Size	7,746	9.68	9.42	10.19	9.98	1.24	1.29
Cash	7,561	0.07	0.07	0.03	0.03	0.11	0.11
Inventories	7,663	0.21	0.22	0.15	0.15	0.22	0.22
Tangibles	7,693	0.27	0.26	0.19	0.18	0.26	0.26
ROA	7,479	0.02	0.03	0.02	0.02	0.07	0.07

Table 2: The probability of substitution

This table reports results of the logit regressions where SI_{it} is regressed on the Z-score, year dummies, firm controls, industry dummies and country controls. These regression analyses inform how the explanatory variables increase or decrease the probability of substitution between short term bank credit and accounts payable. We report the odds ratios with the p-values in parentheses for each explanatory variable. ***, **, * indicate coefficients that are statistically significant at the 1%, 5%, and 10% levels, respectively, using robust standard errors clustered at the firm level.

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.: SI_{it}	Full Sample	Full Sample	EFD Firms	EFD Firms, demeaned	EFD Ind.	EFD Firms
Z(t-1)	1.079	1.089	1.104	1.097	1.069	1.105
	(0.000) ***	(0.000) ***	(0.000) ***	(0.000) ***	(0.059) *	(0.000) ***
D_2008	0.553	0.564	0.513	0.505	0.533	0.499
	(0.000) ***	(0.000) ***	(0.000) ***	(0.000) ***	(0.000) ***	(0.000) ***
D_2009	0.561	0.560	0.508	0.505	0.581	0.501
	(0.000) ***	(0.000) ***	(0.000) ***	(0.000) ***	(0.000) ***	(0.000) ***
D_2010	1.289	1.272	1.199	1.196	1.274	1.264
	(0.000) ***	(0.001) ***	(0.026) **	(0.020) **	(0.024) **	(0.006) ***
D_2011	0.923	0.929	0.855	0.863	1.086	0.883
	(0.291)	(0.342)	(0.074) *	(0.078) *	(0.511)	(0.178)
Supplier Z(t-1)		0.965	0.936	0.964	1.051	1.245 *
		(0.791)	(0.669)	(0.265)	(0.850)	(0.091)
Size(t-1)		0.894	0.872	0.883	0.598	0.866
		(0.000) ***	(0.000) ***	(0.000) ***	(0.000) ***	(0.000) ***
Cash(t-1)		1.109	1.308	1.258	0.848	1.221
		(0.607)	(0.286)	(0.374)	(0.649)	(0.425)
Inv(t-1)		0.975	1.051	1.048	1.158	1.050
		(0.846)	(0.722)	(0.734)	(0.424)	(0.727)
TangFA(t-1)		1.223	1.186	1.147	1.156	1.208
		(0.064) *	(0.166)	(0.251)	(0.415)	(0.123)
ROA(t-1)		0.692	0.522	0.564	1.135	0.532
		(0.260)	(0.094) *	(0.140)	(0.806)	(0.103)
Industry dummies	Yes	Yes	Yes	Yes	Yes	Yes
Country dummies	Yes	Yes	Yes	Yes	Yes	No
Country characteristics	No	No	No	No	No	Yes
Pseudo R^2	0.029	0.030	0.037	0.035	0.047	0.037
Number of obs.	9,215	8,825	7,040	7,040	3,651	7,040

Table 3: The magnitude of substitution

This table reports results of OLS models where we regress the change in trade credit usage *ΔT* of firms that experience a negative shock to bank credit in t-1 on the lagged *Z-score*, the absolute value of the lagged change in bank credit *ΔB*, their interaction *Z*(t-1)**ΔB*(t-1), year dummies, firm controls, industry dummies and country controls. We report coefficients with the p-values in parentheses for each explanatory variable. ***, **, * indicate coefficients that are statistically significant at the 1%, 5%, and 10% levels, respectively, using robust standard errors clustered at the firm level.

Dep. Var.: *ΔT*	(1) Full Sample		(2) EFD Firms		(3) Full Sample		(4) EFD Firms	
Z(t-1)	22.457		22.725		23.165		26.562	
	(0.023)	**	(0.052)	*	(0.094)	*	(0.054)	*
ΔB(t-1)	0.058		0.056		0.051		0.048	
	(0.003)	***	(0.006)	***	(0.023)	**	(0.033)	**
*Z(t-1)*ΔB(t-1)*	0.011		0.018		0.018		0.016	
	(0.085)	***	(0.005)	***	(0.013)	**	(0.028)	**
D_2008	-346.417		-325.894		-381.871		-407.504	
	(0.000)	***	(0.000)	***	(0.000)	***	(0.000)	***
D_2009	-288.746		-289.784		-352.530		-365.670	
	(0.000)	***	(0.000)	***	(0.000)	***	(0.000)	***
D_2010	161.980		1625.475		152.639		195.836	
	(0.000)	***	(0.000)	***	(0.002)	***	(0.000)	***
D_2011	-9.304		9.312		-18.517		7.781	
	(0.806)		(0.824)		(0.708)		(0.879)	
Supplier Z(t-1)			83.125		69.898		232.602	
			(0.210)		(0.371)		(0.000)	***
Size(t-1)			-121.496		-146.325		-139.866	
			(0.000)	***	(0.000)	***	(0.000)	***
Cash(t-1)			-23.144		27.742		-33.452	
			(0.812)		(0.816)		(0.777)	
Inv(t-1)			-0.834		-17.742		-14.508	
			(0.991)		(0.827)		(0.856)	
TangFA(t-1)			175.993		178.839		198.853	
			(0.001)	***	(0.004)	***	(0.001)	***
ROA(t-1)			-191.951		-261.267		-228.128	
			(0.292)		(0.239)		(0.280)	
Industry dummies	Yes		Yes		Yes		Yes	
Country dummies	Yes		Yes		Yes		No	
Country Characteristics	No		No		No		Yes	
R^2	0.0414		0.0480		0.0562		0.0581	
Number of obs.	9,216		8,827		7,045		7,045	

Table 4: Two-stage selection model

This table reports the results of a two-stage Heckman selection model. In column (1), we report the first stage logit regression. D_Shock (equal to one if bank debt decreased, and zero otherwise) is regressed on the Altman's Z-score, the year dummies, firm controls, firm fixed effects and country controls. In column (2), we report the results of the second stage logit regression. SI_{it} is regressed on the Z-score, the year dummies, firm controls, industry dummies and country dummies. All regressions are based on external finance-dependent firms (EFD firms). ***, **, * indicate coefficients that are statistically significant at the 1%, 5%, and 10% levels, respectively, using robust standard errors clustered at the firm level.

	(1)		(2)	
	First stage:		Second stage:	
Dep. Variable:	*D_Shock*		*SI*	
Z(t-1)	1.976		1.084	
	(0.000)	***	(0.001)	***
D_2008	4.212		0.463	
	(0.000)	***	(0.000)	***
D_2009	5.457		0.451	
	(0.000)	***	(0.000)	***
D_2010	7.752		1.029	
	(0.000)	***	(0.781)	
D_2011	4.709		0.743	
	(0.000)	***	(0.003)	***
SupplierZ(t-1)	0.771		0.952	
	(0.176)		(0.762)	
Size(t-1)	0.521		0.874	
	(0.000)	***	(0.000)	***
Cash(t-1)	2.822		1.257	
	(0.010)	***	(0.377)	
Inv(t-1)	0.871		1.016	
	(0.704)		(0.921)	
TangFA(t-1)	3.080		1.094	
	(0.000)	***	(0.506)	
ROA(t-1)	0.379		0.549	
	(0.048)	**	(0.140)	
Inverse Mills Ratio			0.882	
			(0.013)	**
Firm fixed effects	Yes		No	
Industry fixed effects	No		Yes	
Country fixed effects	Yes		Yes	
Pseudo R^2	0.182		0.037	
Number of obs.	16,544		6,808	

Table 5: The probability of substitution by country

This table reports results of logit regressions where SI_{it} is regressed on the Z-score, the year dummies, firm controls and industry dummies. We report the odds ratios with the p-values in parentheses. All regressions are based on external finance-dependent firms (EFD firms). ***, **, * indicate coefficients that are statistically significant at the 1%, 5%, and 10% levels, respectively, using robust standard errors clustered at the firm level.

	(1)		(2)		(3)		(4)		(5)	
Dep. Var.: *SI_{it}*	France		Germany		Italy		Spain		U.K.	
Z(t-1)	1.190		1.064		1.151		1.083		1.095	
	(0.000)	***	(0.148)		(0.000)	***	(0.000)	***	(0.000)	***
D_2008	0.814		0.850		0.731		0.306		0.351	
	(0.000)	***	(0.377)		(0.000)	***	(0.000)	***	(0.000)	***
D_2009	0.590		0.493		0.625		0.486		0.836	
	(0.000)	***	(0.000)	***	(0.000)	***	(0.000)	***	(0.000)	***
D_2010	1.008		1.865		1.202		1.008		2.025	
	(0.929)		(0.004)	***	(0.000)	***	(0.870)		(0.000)	***
D_2011	0.974		1.131		1.075				1.351	
	(0.543)		(0.577)		(0.027)	**			(0.004)	***
Supplier Z(t-1)	1.381		1.581		1.435		0.995		1.011	
	(0.278)		(0.091)	*	(0.238)		(0.982)		(0.964)	
Size(t-1)	0.975		0.959		0.956		0.916		0.986	
	(0.036)	**	(0.332)		(0.000)	***	(0.004)	***	(0.218)	
Cash(t-1)	0.713		1.361		0.654		0.650		1.047	
	(0.000)	***	(0.610)		(0.000)	***	(0.145)		(0.638)	
Inv(t-1)	0.928		0.725		1.011		0.665		1.070	
	(0.299)		(0.377)		(0.771)		(0.003)	***	(0.479)	
TangFA(t-1)	1.267		1.524		1.203		0.991		1.300	
	(0.004)	***	(0.190)		(0.000)	***	(0.937)		(0.000)	***
ROA(t-1)	0.673		1.247		0.378		0.791		0.819	
	(0.007)	***	(0.796)		(0.000)	***	(0.480)		(0.173)	
Industry dummies	Yes		Yes		Yes		Yes		Yes	
Pseudo R^2	0.016		0.046		0.014		0.050		0.064	
Number of obs.	31,741		1,587		81,358		12,182		20,237	

Table 6: The interaction of credit quality and financial constraints

This table reports results of logit regressions where SI_{it} is regressed on the interaction terms between the Z-score and the quintile dummies for the KZ index, the quintile dummies for the KZ index, year dummies, firm controls, industry dummies and country dummies. These regression analyses indicate how the explanatory variables increase or decrease the probability of substitution between short term bank credit and trade credit. We report the odds ratios with the p-values in parentheses for each explanatory variable. ***, **, * indicate coefficients that are statistically significant at the 1%, 5%, and 10% levels respectively, using robust standard errors clustered within firms.

	(1)		(2)	
Dep. Var.: SI_{it}	Full Sample		EFD Firms	
Z(t-1)	1.164		1.180	
	(0.000)	***	(0.000)	***
*KZ_Q2*Z(t-1)*	1.028		1.069	
	(0.635)		(0.320)	
*KZ_Q3*Z(t-1)*	1.109		1.166	
	(0.148)		(0.053)	*
*KZ_Q4*Z(t-1)*	1.187		1.262	
	(0.020)	**	(0.005)	***
*KZ_Q5*Z(t-1)*	0.959		0.983	
	(0.4998		(0.794)	
Firm controls	Yes		Yes	
KZ_Q Dummies	Yes		Yes	
Industry dummies	Yes		Yes	
Country dummies	Yes		Yes	
Year dummies	Yes		Yes	
Pseudo R^2	0.035		0.045	
Number of obs.	8,561		6,822	

Table 7: The probability of substitution for total bank credit

This table reports results of logit regressions in which we regress SI_{it}^{total} on the Z-score, the year dummies, industry dummies and country dummies. These regression analyses inform how the explanatory variables increase or decrease the probability of substitution between total bank credit and accounts payable. We report the odds ratios with the p-values in parentheses for each explanatory variable. ***, **, * indicate coefficients that are statistically significant at the 1%, 5%, and 10% levels, respectively, using robust standard errors clustered within firms.

	(1)		(2)		(3)	
Dep. Var.: SI_{it}	Full Sample		Full Sample		EFD Firms	
Z(t-1)	1.061		1.064		1.079	
	(0.000)	***	(0.001)	***	(0.000)	***
D_2008	0.596		0.599		0.559	
	(0.000)	***	(0.000)	***	(0.000)	***
D_2009	0.562		0.555		0.503	
	(0.000)	***	(0.000)	***	(0.000)	***
D_2010	1.244		1.207		1.122	
	(0.002)	***	(0.008)	***	(0.149)	
D_2011	0.928		0.919		0.887	
	(0.313)		(0.262)		(0.158)	
Supplier Z(t-1)	1.044		1.057		0.971	
	(0.725)		(0.663)		(0.845)	
Size(t-1)			0.905		0.870	
			(0.000)	***	(0.000)	***
Cash(t-1)			1.074		1.184	
			(0.713)		(0.474)	
Inv(t-1)			0.830		0.891	
			(0.144)		(0.414)	
TangFA(t-1)			1.153		1.128	
			(0.157)		(0.300)	
ROA(t-1)			0.865		0.698	
			(0.651)		(0.349)	
Industry dummies	Yes		Yes		Yes	
Country dummies	Yes		Yes		Yes	
Pseudo R^2	0.026		0.027		0.033	
Number of obs.	10,060		9,668		7,637	

Table 8: The probability of partial or perfect substitution

This table reports results of multinomial logit regressions where we regress the three-outcome variable $SI3_{it}$ on the Z-score, the year dummies, firm controls, industry dummies and country dummies. We report the odds ratios with the p-values in parentheses for each explanatory variable. ***, **, * indicate coefficients that are statistically significant at the 1%, 5%, and 10% levels, respectively, using robust standard errors clustered within firms.

	(1) Full Sample				(2) Full Sample				(3) EFD Firms				(4) EFD Ind.			
Dep. Var:	partial		perfect		Partial		perfect		partial		perfect		partial		perfect	
Z(t-1)	1.003		1.163		1.010		1.170		1.029		1.180		0.992		1.156	
	(0.904)		(0.000)	***	(0.714)		(0.000)	***	(0.334)		(0.000)	***	(0.858)		(0.001)	***
D_2008	0.526		0.579		0.536		0.591		0.516		0.511		0.538		0.527	
	(0.000)	***	(0.000)	***	(0.000)	***	(0.000)	***	(0.000)	***	(0.000)	***	(0.000)	***	(0.000)	***
D_2009	0.671		0.459		0.666		0.465		0.642		0.398		0.732		0.465	
	(0.000)	***	(0.000)	***	(0.000)	***	(0.000)	***	(0.000)	***	(0.000)	***	(0.027)	**	(0.000)	***
D_2010	1.491		1.103		1.493		1.074		1.470		0.982		1.693		0.953	
	(0.000)	***	(0.256)		(0.000)	***	(0.420)		(0.000)	***	(0.861)		(0.000)	***	(0.720)	
D_2011	0.903		0.942		0.920		0.937		0.902		0.820		1.277		0.946	
	(0.292)		(0.507)		(0.399)		(0.481)		(0.361)		(0.054)	*	(0.110)		(0.714)	
Supplier Z(t-1)	0.904		0.941		0.953		0.959		0.939		0.930		1.183		1.002	
	(0.575)		(0.704)		(0.794)		(0.798)		(0.771)		(0.694)		(0.624)		(0.994)	
Size(t-1)					0.932		0.865		0.918		0.837		0.682		0.543	
					(0.070)	*	(0.000)	***	(0.056)	*	(0.000)	***	(0.002)	***	(0.000)	***
Cash(t-1)					0.619		1.719		0.716		2.060		0.589		1.270	
					(0.100)	*	(0.023)	**	(0.333)		(0.015)	**	(0.266)		(0.613)	
Inv(t-1)					1.303		0.729		1.375		0.800		1.525		0.852	
					(0.105)		(0.059)	*	(0.079)	*	(0.225)		(0.065)	*	(0.514)	
TangFA(t-1)					1.200		1.222		1.147		1.243		1.294		1.030	
					(0.193)		(0.158)		(0.392)		(0.245)		(0.255)		(0.899)	
ROA(t-1)					1.087		0.476		0.691		0.443		2.349		0.491	
					(0.841)		(0.061)	*	(0.450)		(0.088)	*	(0.163)		(0.291)	
Industry dummies	Yes				Yes				Yes				Yes			
Country dummies	Yes				Yes				Yes				Yes			
Pseudo R^2	0.043				0.044				0.053				0.06			
Number of obs.	9,216				8,827				7,045				3,654			

Table 9: The probability of substitution based on SI4

This table reports results of multinomial regressions in which we regress the four-outcome variable $SI4_{it}$ on the Z-score, the year dummies, firm controls, industry dummies and country dummies. These regression analyses inform how the explanatory variables increase or decrease the probability of having a substitution relation (SI=2 or SI=3) or a positive complementary relation (SI=4) relative to having a negative complementary relation (SI=1). We report the odds ratios with the p-values in parentheses for each explanatory variable. ***, **, * indicate coefficients that are statistically significant at the 1%, 5%, and 10% levels, respectively, using robust standard errors clustered within firms.

	(1) Full Sample						(2) EFD Firms					
Dep. Var:	*SI*=2		*SI*=3		*SI*=4		*SI*=2		*SI*=3		*SI*=4	
Z(t-1)	1.085		0.898		0.965		1.099		0.890		0.968	
	(0.000)	***	(0.000)	***	(0.062)	*	(0.000)	***	(0.000)	***	(0.146)	
D_2008	0.564		0.831		0.508		0.513		0.802		0.461	
	(0.000)	***	(0.005)	***	(0.000)	***	(0.000)	***	(0.001)	***	(0.000)	***
D_2009	0.560		0.699		0.372		0.505		0.703		0.333	
	(0.000)	***	(0.000)	***	(0.000)	***	(0.000)	***	(0.000)	***	(0.000)	***
D_2010	1.254		0.585		0.618		1.181		0.585		0.555	
	(0.002)	***	(0.000)	***	(0.000)	***	(0.042)	**	(0.000)	***	(0.000)	***
D_2011	0.940		0.765		0.736		0.881		0.736		0.677	
	(0.401)		(0.000)	***	(0.000)	***	(0.118)		(0.000)	***	(0.000)	***
Firm controls	Yes						Yes					
Industry dummies	Yes						Yes					
Country Dummies	Yes						Yes					
Pseudo R^2	0.023						0.027					
Number of obs.	18,802						15,070					

Table 10: Stratified random sampling

This table reports the average estimation results from the logit regressions in which we regress SI_{it} on the Z-score, the year dummies, the interaction terms between the previous two, firm controls, industry dummies and country dummies for 100 randomly drawn stratified samples. For each country, the firms are divided in size quintiles and within each quintile we have drawn a fixed number of firms. The sample includes firms that are external finance-dependent (EFD firms), as proposed by Rajan and Zingales (1998). The table reports the mean odds ratios, the mean p-values, and the mean pseudo R-squares for the 100 regression analyses. ***, **, * indicate coefficients that are statistically significant at the 1%, 5%, and 10% levels, respectively, using robust standard errors clustered at the firm level.

	(1)		(2)	
	Replication Table 2		Replication Table 6	
Dep. Var.:	*SI*			
	EFD Firms		EFD Firms	
Z(t-1)	1.114		1.111	
	(0.000)	***	(0.022)	**
D_2008	0.575		0.669	
	(0.000)	***	(0.050)	**
D_2009	0.581		0.550	
	(0.000)	***	(0.003)	***
D_2010	1.275		1.145	
	(0.002)	***	(0.469)	
D_2011	0.992		0.998	
	(0.923)		(0.992)	
*D_2008*Z(t-1)*			0.953	
			(0.425)	
*D_2009*Z(t-1)*			1.018	
			(0.764)	
*D_2010*Z(t-1)*			1.037	
			(0.516)	
*D_2011*Z(t-1)*			0.998	
			(0.977)	
Firm controls	Yes		Yes	
Industry dummies	Yes		Yes	
Country dummies	Yes		Yes	
Pseudo R^2	0.031		0.043	

Table 11: Analysis with matched bank-firm data

This table reports the logit regression with matched bank-firm data from Spain. We regress the SI_{it} on year dummies, a dummy for banks that were bailed out (*Bailout*), and the interaction term of the previous two, time-varying firm controls, time-varying bank controls, and industry dummies. The variable *NumberRel* indicates the number of bank relationships per firm and year. In column (4), we replace the *Bailout* dummy with the *SavingsBank* dummy. We report odds ratios and p-values in parentheses. All firms are dependent on external finance following Rajan and Zingales (1998). ***, **, * indicate coefficients that are statistically significant at the 1%, 5%, and 10% levels, respectively, using robust standard errors clustered at the bank-firm level.

Dep. Var.: SI_{it}	(1)		(2)		(3)		(4)	
D_2006	1.095		1.096		1.119		1.128	
	(0.022)	**	(0.024)	**	(0.009)	***	(0.007)	***
D_2007	0.785		0.783		0.796		0.793	
	(0.000)	***	(0.000)	***	(0.000)	***	(0.000)	***
D_2008	0.336							
	(0.000)	***						
D_2009	0.852		0.821		0.830		0.854	
	(0.000)	***	(0.000)	***	(0.000)	***	(0.003)	***
D_2010	0.761		0.820		0.828		0.835	
	(0.000)	***	(0.000)	***	(0.000)	***	(0.000)	***
Bailout	1.097		1.143		1.123		1.138	
	(0.127)		(0.032)	**	(0.079)	*	(0.032)	**
*Bailout*D_2006*	1.013		1.011		1.021		0.993	
	(0.888)		(0.908)		(0.821)		(0.935)	
*Bailout*D_2007*	0.945		0.930		0.944		0.974	
	(0.497)		(0.391)		(0.517)		(0.735)	
*Bailout*D_2008*	0.849							
	(0.066)	*						
*Bailout*D_2009*	0.863		0.850		0.853		0.801	
	(0.047)	**	(0.033)	**	(0.045)	**	(0.002)	***
*Bailout*D_2010*	0.804		0.790		0.786		0.849	
	(0.004)	***	(0.003)	***	(0.004)	***	(0.022)	**
Z(t-1)			1.329		1.338		1.338	
			(0.000)	***	(0.000)	***	(0.000)	***

Table 11 (continued):

	(1)	(2)		(3)		(4)	
SupplierZ(t-1)		1.392		1.311		1.320	
		(0.399)		(0.498)		(0.487)	
Size(t-1)		1.466		1.471		1.471	
		(0.000)	***	(0.000)	***	(0.000)	***
Cash(t-1)		0.360		0.345		0.345	
		(0.000)	***	(0.000)	***	(0.000)	***
TangFA(t-1)		1.084		1.076		1.078	
		(0.126)		(0.175)		(0.163)	
Inv(t-1)		0.548		0.543		0.543	
		(0.000)	***	(0.000)	***	(0.000)	***
ROA(t-1)		0.292		0.290		0.291	
		(0.000)	***	(0.000)	***	(0.000)	***
NumberRel				1.029		1.029	
				(0.000)	***	(0.000)	***
Bank_ROA				0.058		0.019	
				(0.417)		(0.258)	
Bank_eqta				1.231		1.691	
				(0.723)		(0.375)	
Bank_depta				1.119		0.953	
				(0.405)		(0.720)	
Industry Dummies	Yes	Yes		Yes		Yes	
Pseudo R^2	0.026	0.030		0.031		0.031	
Number of obs.	59,534	51,290		50,216		50,216	

Fig. 1: The substitution indicator during the period 2007-2011

This figure displays the substitution indicator SI_{it} over time by country. The years are shown on the x-axis; the fractions of substitution relationships ($SI_{it} = 1$) are shown on the y-axis.

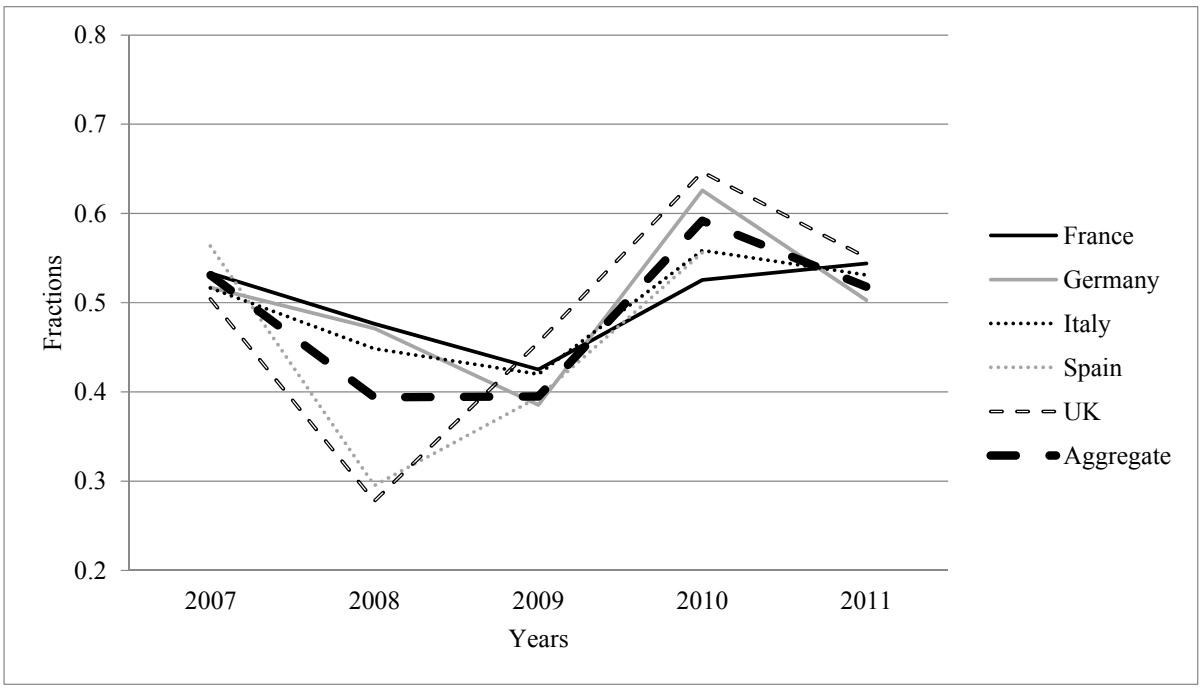
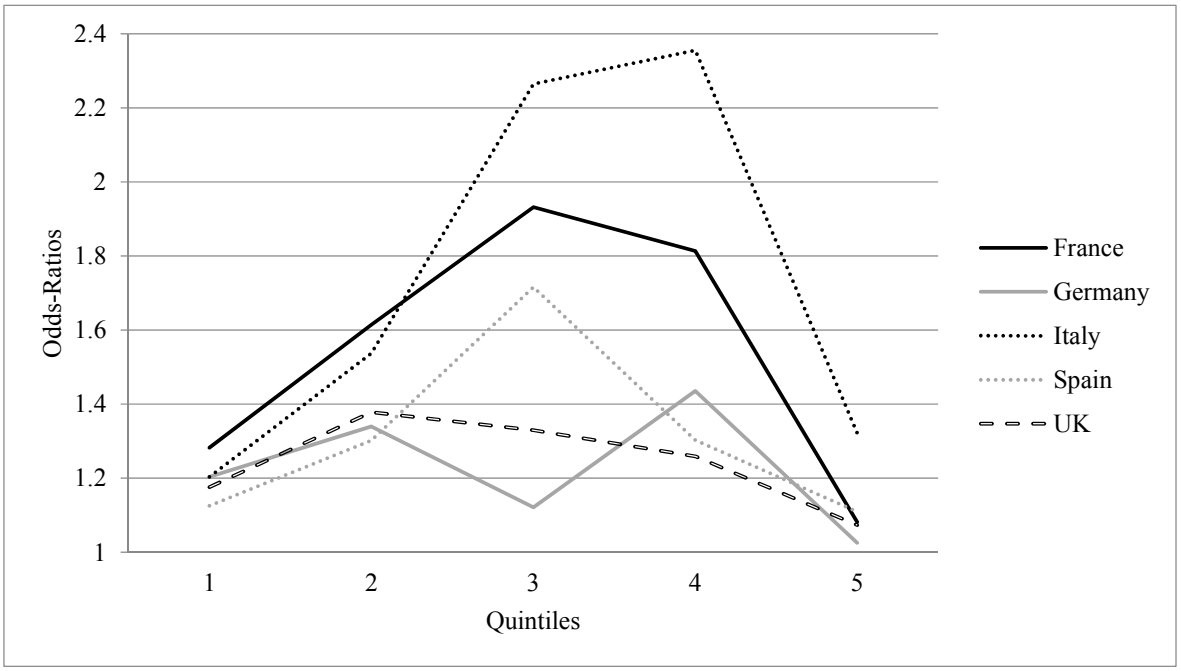


Fig. 2: Odds ratios of the interaction terms between the Z-score and the KZ-index quintiles

This figure presents the odds ratios for the interacted Z-Score (t-1) and KZ quintile dummies by country on the y-axis and the KZ index quintile dummies on the x-axis. The KZ quintiles are computed separately for each country.