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CREDIT QUALITY AND SUBSTITUTION IN SME FINANCE

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We investigate whether and how SMEs' credit quality influences their substitution of bank credit for trade credit. Using data from the five largest European countries, we find that substitution of bank credit for trade credit decreases during the financial crisis, but it decreases significantly less for *ex ante* low credit quality firms. We control for pre-crisis or lagged firm characteristics including size and external finance dependence, industry effects, sample selection effects and cross-country heterogeneity. We also find that low credit quality firms increase their absolute and relative trade credit usage significantly more than high credit quality firms during the financial crisis. The effects are consistent across countries and stronger for net trade credit borrowers and financially constrained firms. The evidence highlights how credit quality influences demand-side driven substitution in SME finance.

Keywords: Trade credit; bank credit; credit risk; substitution; financial crisis.

JEL Classification: G20, G30, G32

1. Introduction

A key principle in finance is that credit quality should influence the availability and cost of credit, everything else equal. The lower the firms' credit quality the lower the availability of credit and the higher the cost of credit. However, economic frictions arising from asymmetric information, transaction costs or other market imperfections can compromise this principle. For example, SME finance is subject to severe frictions because these firms are more informationally opaque, financially constrained, riskier and more bank-dependent than large firms. SMEs cannot raise finance in capital markets, they rely on credit from banks and suppliers (e.g. Berger & Udell 2006, Biais & Gollier 1997, Petersen & Rajan 1997). Bank credit has been considered more important than trade credit, but there has been debate about the dynamic relation of these two types of credit. Bank credit and trade credit might co-move over time because firms make complementary use of these sources of finance or move in opposite directions because firms substitute (Meltzer 1960). This topic gained increased attention during the global financial crisis when banks reduced their credit supply in an unprecedented way (e.g. Carbó-Valverde *et al.* 2016, Casey & O'Toole 2014).

In this paper, we investigate whether and how credit quality influences the substitution of bank credit for trade credit in SME finance. Understanding the effect of credit quality on the relation between bank credit and trade credit is important for several reasons. First, substitution may reduce the indirect costs of financial distress and increase firms' chance of survival (Sautner & Vladimirov 2018, McGuiness *et al.* 2018). Second, substitution weakens the business cycle and monetary policy transmission, while a complementary relation can amplify them (Huang *et al.* 2011, Mateut *et al.* 2006, Beck *et al.* 2000). Third, access to trade credit helps firms to manage growth (Ferrando & Mulier 2013) and participate in international trade (Minetti *et al.* 2019). Fourth, substitution can have significant adverse effects because of up- and down-stream credit risk propagation in the supply chain (Jacobson & von Schedvin 2015, Boissay & Gropp 2013, Jorion & Zhang 2009).

Importantly, the direction of the effect of credit quality on the relation between bank credit and trade credit is not clear. On one hand, supply-side reasoning suggests that credit quality should uniformly influence firms' access to total credit. High-quality firms have easy access to credit at favorable terms from any lender, while low-quality firms have limited access to credit and face tighter terms of credit from any lender. This reasoning is independent of the composition of firms' total credit. Hence, the dynamic relation between bank credit and trade credit at the firm level would be complementary, implying that banks and suppliers increase (decrease) credit supply in an economic expansion (contraction).

On the other hand, there are arguments why credit quality might influence the substitution of bank credit for trade credit at the firm level. First, the relation might be non-stationary, varying with the state of the economy and/or the financial system. The global financial crisis was characterized by large negative shock to bank credit supply. In such situation, low credit quality (high risk) firms that have less internal finance available than high-quality firms are hit harder (Ivashina & Scharfstein 2010). Hence, low-credit quality firms should have additional demand for non-bank credit to fill the funding gap resulting from the contraction of bank credit supply, everything else equal. Second, trade credit is bundled with the purchase of goods that serve as collateral and results from delayed cash outflows (credit days), while bank credit is a cash inflow that can be used to fund any investment. Because of the bundling of purchases and trade credit, suppliers have a secured claim combined with proprietary and timely information about their customers (Petersen & Rajan 1997, Cunat 2007), explaining why they might extend the duration of trade credit. This reasoning is consistent with the model of Barbosa *et al.* (2017) and evidence that interest rates in trade credit do not or only imperfectly reflect borrower default risk (Klapper *et al.* 2012, Giannetti *et al.* 2011). Third, the risk profiles of bank credit and trade credit differ (Petersen & Rajan 1997). Suppliers have a claim similar to an equity stake in their customers and care about upside potential including future business, while banks have a debt stake and care about downside risk. These differences in risk profiles of suppliers and banks are important and also explain, to some extent, why their lending behavior vis-à-vis low-quality firms might differ.

We base our study on SMEs from the five largest European countries (France, Germany, Italy, Spain and the United Kingdom). We gather detailed financial statement information from Bureau van Dijk's Orbis database for the period before, during and after the global financial crisis. We focus on SMEs because they are riskier, more informationally opaque and more financially constrained than large firms. The median leverage (total debt/total assets) in our European SME sample is 70.0%, while Garcia-Appendini & 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 bank credit and trade credit. We focus on (the largest) European countries to ensure external validity and because there is no SME data from the United States available for the global financial crisis as the Federal Reserve System discontinued the Survey of Small Business Finances ((N)SSBF) after 2003.

We first investigate whether and how firms' credit quality influences their probability to substitute bank credit for trade credit. We measure firms' credit quality using the Altman Z-score (Altman 1968) adapted for private firms and based either on values from pre-crisis times or lagged by one year. We consider both options because there is a trade-off between endogeneity and timeliness of firms' credit quality. Pre-crisis credit quality is reasonably exogenous to changes of bank credit and trade credit during the crisis, while credit quality lagged by one year contains more timely information and still avoids simultaneity. We find that the probability of substitution decreases during the financial crisis, but it decreased significantly less for *ex ante* low credit quality (high risk) firms than for high credit quality firms. The differential effect is large as it corresponds to approximately one-third of the general effect of the financial crisis. This finding is statistically highly significant and remains robust when we control for pre-crisis or lagged firm characteristics including external finance dependence and firm size, industry effects, selections effects and cross-country heterogeneity. The finding is in line with the view that *ex ante* low credit quality (high-risk) firms are hit harder by the global financial crisis than high credit quality firms. We observe in our sample that short-term bank credit to low-quality SMEs decreased by factor 2.5 more than short-term bank credit to high-quality

SMEs. It is also consistent with the fact that *ex ante* low-credit quality firms have less internal finance available and therefore a higher need for substitution than high-credit quality firms.

We then examine whether we can complement the previous result on the probability of substitution by considering more direct measures of trade credit usage such as the absolute or relative change in accounts payable. This analysis informs us about the magnitude of substitution. We find that low-quality firms increase their absolute and relative trade credit usage significantly more than high-quality firms during the financial crisis. The evidence is in line with the reasoning above why suppliers are willing to extend trade credit to low credit quality firms. Importantly, these results are robust when we add firm fixed effects to the regression models to mitigate concerns about unobserved heterogeneity between high and low credit quality firms.

We show that the findings are consistent across the five largest European countries, although the magnitude of the effects varies. The effect is largest in Italy and smallest in Germany. This is plausible because in our sample Italian firms exhibit the highest trade credit usage and German firms the lowest. The finding is also plausible because Lawrenz & Oberndorfer (2018) show that small firms in Germany substitute less than large firms during the crisis. Moreover, the maturity of bank credit is more short-term in Italy than in Germany. The heterogeneity across countries can be explained with differences in the level of trade credit usage, institutional differences in the banking systems and the severity and nature of the financial crisis in these countries.

We conduct several additional empirical checks to ensure that our main results are robust and not the product of particular choices of samples, methods or model specifications. First, we show that our results are stronger for SMEs that are net trade credit borrowers in pre-crisis times than for net trade credit lenders. The positive interaction effect for low credit quality firms is significant in most of the subsamples, but it is twice as large for net trade credit borrowers. Second, we distinguish between firms with high and low financial constraints in pre-crisis times. We find that significant substitution effects exist for firms that exhibit high and low financial constraints, but the effect is stronger for firms that exhibit high financial constraints. Third, our result remains robust when we consider firms' total bank credit rather than short-term bank credit. Fourth, our main result is robust to alternative definitions of substitution. Instead of using a binary indicator we consider three outcomes (no, partial or full substitution) or four outcomes (all pairs of in-/decreases of bank credit and trade credit) or condition on a decrease in bank credit in the same year.

This paper contributes to the literature on banking and finance in three ways. First, we show that low-credit quality SMEs substitute bank credit for trade credit significantly more than high-quality SMEs during the crisis. This finding is novel and can be explained with differences in demand for trade credit between high- and low-quality firms. One one hand, low-quality firms are hit harder by the contraction of bank credit supply and therefore had extra demand for non-bank credit from their suppliers. Suppliers extend additional trade credit because, unlike bankers, they have an equity claim in their customers, proprietary and timely information, and deployable collateral. We argue that suppliers were aware that they provided temporary rather than permanent finance to their risky customers when extending the credit days in the supply chain. This reasoning is consistent with McGuiness *et al.* (2018) showing that trade credit usage has increased SME's chance of survival in the post-crisis times and with Sautner & Vladimirov (2018) showing that riskier firms face lower indirect costs due to reduced access to trade credit and foregone sales when debt enforcement is stronger. On the other hand, high-quality firms demand less trade credit during the crisis than low-quality firms because the former have more internal finance available, easier access to less expensive bank credit in the aftermath of the crisis, and are generally more. Our findings complement evidence on substitution by high risk and low risk firms in China after two regulatory shocks to interest rates that increased bank credit supply (Chen *et al.* 2019).

Second, our findings highlight the non-stationarity of the relation between bank credit and trade credit at the firm level. The related literature provides mixed evidence on this issue. Some studies find evidence for a substitution relation (e.g. Palacín-Sánchez *et al.* 2019, Lawrenz & Oberndorfer 2018, Carbó-Valverde *et al.* 2016, Casey & O'Toole 2014, Garcia-Appendini & Montoriol-Garriga 2013), while others find a complementary relation (e.g. Andrieu *et al.* 2018, Deloof & La Rocca, 2015). We show that the dynamic relation between bank credit and trade credit shifts when moving from pre-crisis to crisis times and that firm credit quality influences the magnitude of this shift.

Third, the evidence is consistent across the five largest European countries, but there is heterogeneity in the magnitude of the effects. We note that the main effect is in none of the countries sufficient to fully offset the negative shock to bank credit during the financial crisis. Hence, there are clear limits on using trade credit as an alternative to bank credit.

The remainder of the paper is organized as follows. In Sec. 2, we briefly summarize the related literature, develop our hypothesis and present the empirical strategy. In Sec. 3, we describe the data. In Sec. 4, we report the empirical results. Section 5 concludes.

2. Literature, Hypothesis and Empirical Strategy

2.1. *Literature and hypothesis*

The literature has proposed theories and evidence about the provision and usage of trade credit. Subsequently, we briefly review the literature on trade credit and the relation between bank credit and trade credit[a] before we develop our hypothesis.

[a] In this paper, we focus on firm credit quality as determinant of substitution. We do not directly investigate the redistribution view but acknowledge that it is inherently related (e.g., Meltzer 1960, Calomiris *et al.* 1995, Petersen & Rajan 1997, Ng *et al.* 1999, Nilsen 2002, Love *et al.* 2007).

Theories of trade credit 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 & Rajan 1997). Some theories predict that suppliers have incentives to provide trade credit to customers that experience temporary liquidity shocks (e.g. Wilner 2000, Cuñat 2007). Other theories predict that firms increase their demand for trade credit when they become credit-rationed by banks (e.g. Biais & Gollier 1997, Burkart & Ellingsen 2004). The traditional view considers trade credit as more expensive than bank credit.

Evidence from the study of Petersen & 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. Importantly, they also show that suppliers support growing, cash-constrained firms with trade credit. Cuñat (2007) shows for a large sample of UK firms that trade credit insures firms against liquidity shocks and that it is mainly used when other forms of finance have been exhausted. 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 & Rajan 1997, Cuñat 2007, Klapper *et al.* 2012). However, there is recent evidence that, contrary to the traditional view, firms can obtain trade credit at low cost because of high liquidation value of the purchased goods or bargaining power (Gonçalves *et al.* 2018, Fabbri & Klapper 2016, Murfin & Njoroge 2015, Giannetti *et al.* 2011, Fabbri & Menichini 2010).

In the aftermath of the global financial crisis and its unprecedented decline in bank credit supply, there has been increased debate about the dynamic relation between bank credit and trade credit. Some studies find evidence for a substitution relation (e.g. Chen *et al.* 2019, Palacín-Sánchez *et al.* 2018, Lawrenz & Oberndorfer 2018, Carbó-Valverde *et al.* 2016, Casey & O'Toole 2014, Garcia-Appendini & Montoriol-Garriga 2013), while others find a complementary relation (e.g. Andrieu *et al.* 2018, Deloof & La Rocca, 2015). Garcia-Appendini & Montoriol-Garriga (2013) investigate trade credit provision and usage by large US firms, using a sample of matched supplier-customer data. They find that firms with a pre-crisis liquidity surplus increased trade credit provision to external finance-dependent firms that were severely hit during the crisis. These findings suggest a substitution relation for external finance-dependent firms. Casey & O'Toole (2014) provide evidence for substitution, using SAFE firm survey data from the period 2009–2011. Firms that experienced credit rationing by banks increased their trade credit usage by 9% and their new applications for trade credit by 7% relative to other firms. Carbó-Valverde *et al.* (2016) investigate the role 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 2007–2009 financial crisis. The study does not directly 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 and over time. Lawrenz & Oberndorfer (2018) examine trade credit provision and usage by German firms and find a firm size effect in substitution: large firms substitute more than small firms. Chen *et al.* (2019) study the response of high and low risk firms to two positive regulatory shocks to bank credit in China. The removal of interest rate ceilings (interest rate floors) increased high risk (low risk) firms' usage of bank credit relative to trade credit.

In light of this literature, we investigate whether and how firms' credit quality influences the probability and magnitude of substitution in SME finance. We focus on firms that experience a negative shock to bank credit. These firms may respond in two ways, depending on their need for external finance. One way is not to substitute bank credit for trade credit (no substitution). In this situation, the firm might use internal finance such as cash flows or cash holdings or deleverage and shrink. Another way is to fund the financing gap by stretching out the payments to suppliers, increasing the usage of trade credit (substitution). Firms face a trade-off between lower credit usage (no substitution) versus potentially higher cost of credit (substitution). Note that trade credit does not have to be more expensive, as found by some recent studies. How does credit quality influence the response of the firm? Low-quality (high risk) firms have less internal finance available than high-quality firms and they are hit harder by the negative bank credit supply shock during the financial crisis. Hence, low-quality firms should have additional demand for non-bank credit to fill the funding gap, everything else equal. This demand-side reasoning predicts that low-credit quality firms prefer option (2).

However, suppliers consider the characteristics of their customers and it is *a priori* unclear whether they would meet their additional demand for trade credit. The following reasoning explains why suppliers might provide additional trade credit to low-credit quality firms. First, because of the bundling of purchases and trade credit, suppliers have a secured claim combined with proprietary (less asymmetric) timely information about their customers (Petersen & Rajan 1997, Cuñat 2006). Moreover, the risk profiles of bank credit and trade credit differ (Petersen & Rajan 1997). Suppliers have *de facto* an equity stake in their customers and care about upside potential including future business, while bankers have a debt stake and care about downside risk. These supply-side arguments explain why suppliers might be willing to extend trade credit to any firm. However, considering that high-credit quality firms have a lower need to substitute, we argue that differential demand for trade credit — after the negative shock to bank credit supply during the financial crisis — is the driving factor. Based on this reasoning, we state the following hypothesis:

Low-credit quality firms substitute bank credit for trade credit relatively more than high credit quality firms during the financial crisis.

2.2. *Empirical strategy*

To test our hypothesis, we consider the regression model shown in Eq. (2.1). Specifically, we estimate how firms' *ex ante* credit quality influences their probability of substituting bank credit for trade credit during the financial crisis.

$$\begin{aligned} P(S_{it}=1) = {} & \beta_1 \text{Credit quality}_{it-1} + \beta_2 \text{Crisis}_t + \beta_3 \text{Credit quality}_{it-1} \times \text{Crisis}_t \\ & + \gamma X_{it-1} + \delta \text{Industry}_i + \mu \text{Country}_i + \varepsilon_{it}. \end{aligned} \tag{2.1}$$

The dependent variable, the substitution indicator (S_{it}), indicates the relation between bank credit and trade credit for firm i at time t. S_{it} equals one for a substitution relation between changes in bank credit in $t-1$ and changes in trade credit in t, and zero for a negative complementary relation between changes in short-term bank credit (ΔB_{it-1}) and changes in trade credit (ΔT_{it}). We measure trade credit T using accounts payable. Formally, S_{it} equals 1 if $\Delta B_{it-1} < 0 \cap \Delta T_{it} > 0$ and 0 if $\Delta B_{it-1} < 0 \cap \Delta T_{it} < 0$.

To measure *Credit quality*, we employ Altman's Z-score adapted for private firms (Altman 1968). The Z-score is a widely used measure of credit quality (default risk). It is based on financial statement information related to liquidity, retained earnings, profitability, leverage, sales and size. To mitigate concerns about potential endogeneity, we employ the firm's Z-score with values either from pre-crisis times or lagged by one year, both denoted by subscript $t-1$ in Eq. (2.1). Agarwal & Taffler (2007) show that the Z-score predicts the default risk of firms remarkably well in different time periods and different countries. Altman's Z-score[b] for private companies is computed as shown in Eq. (2.2). All components are winsorized at the 1st and 99th percentile to ensure that the Z-score is not driven by extreme observations. We expect that low-credit quality reduces the firms' probability of substitution.

$$\begin{aligned} Z-\text{score}_{it} = {} & 0.7\frac{\text{WorkingCapital}_{it}}{\text{TotalAssets}_{it}} + 0.85\frac{\text{RetainedEarnings}_{it}}{\text{TotalAssets}_{it}} + 3.1\frac{\text{EBIT}_{it}}{\text{TotalAssets}_{it}} \\ & + 0.4\frac{\text{TotalAssets}_{it}}{\text{TotalLiabilities}_{it}} + \frac{\text{Sales}_{it}}{\text{TotalAssets}_{it}}. \end{aligned} \tag{2.2}$$

The variable *Crisis* equals one during the global financial crisis (in the years 2008 and 2009), and zero otherwise. In the year 2008, increasing losses from subprime mortgage lending and credit securitization spilled over from the US banks to European

[b] Sales are not available for firms from the UK. 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).

banks and other parts of the world and Lehman Brothers failed. During the year 2009, the global financial crisis unfolded. We expect that the financial crisis reduced the average firm's probability of substitution.

Our main interest is in in the interaction term of $\textit{Credit quality} \times \textit{Crisis}$ that captures a potential effect of the credit quality during the financial crisis. The coefficient of this interaction term — together with the base effect of credit quality — makes it possible to test our hypothesis, that is whether low-credit quality firms substitute bank credit for trade credit significantly more than high-credit quality firms during the financial crisis. Note that this demand-side effect is identified because theory predicts that suppliers should prefer to extend additional trade credit to high-credit quality firms rather than to low-quality firms.[c]

We consider several time-varying firm control variables, all lagged by one year, which are summarized by the vector X_{it-1}. We consider a proxy for the suppliers' credit quality (*SupplierZ*),[d] firm size measured by the natural logarithm of total assets (*Size*), the sum of cash and cash equivalents divided by total assets (*Cash*), two proxies for collateral such as fixed tangible assets (*TangFA*) and inventories (*Inv*) (e.g. Campello & Giambona 2013, Norden & van Kampen 2013), both scaled by total assets, and profitability measured by ROA. The *Z-score* and ROA are sensitive to outliers and are winsorized at the 1st and 99th percentile at the country level.

We control for industry fixed effects and country fixed effects, where industry is based on the two-digit SIC code. Industry fixed effects are important to consider because suppliers are more willing to extend trade credit to customers in industries with high product specificity (Cuñat 2007). Country fixed effects are important because there is cross-country heterogeneity in the economic and legal systems and lending environments (e.g. Palacín-Sánchez *et al.* 2019, Berger & Udell 2006, La Porta *et al.* 1997).

Several explanations are in order. First, our sample period contains the global financial crisis when many banks had to significantly reduce their lending because of subprime mortgage-finance related losses, illiquidity and insolvency concerns (Ivashina & Scharfstein 2010, Duchin *et al.* 2010). Hence, the decrease of bank credit — that we employ as a condition for the substitution indicator — can been seen as an exogeneous negative credit supply shock for the majority of SMEs. Second, because of the definition of the substitution indicator, the sample is conditional on a negative shock to bank credit and therefore not a panel dataset. More specifically,

[c] The effect comes from differential demand for trade credit, even if suppliers are indifferent between extending trade credit to high- or low-credit quality firms.

[d] 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.

there are no repeated observations over time for many firms (the exception are firms that exhibit two or more negative shocks to their bank credit during the sample period). We therefore control for industry fixed effects in the model shown in Eq. (2.1) because we cannot add firm fixed effects. Third, in further analyses, we consider the absolute and relative change of SMEs' trade credit usage (change in accounts payable in euros or percent) as alternative dependent variable. This specification makes it possible for us to replace the industry fixed effects by firm fixed effects, while maintaining the time-varying lagged firm controls. Fourth, we conduct the analysis for all SMEs and for SMEs that are external finance-dependent. We employ the concept of external finance dependence, as proposed by Rajan & Zingales (1998). Firms that are not dependent on external finance might not need to substitute bank credit because they have sufficient internal finance to fund their operations (e.g. Becker & Ivashina 2014, Garcia-Appendini & Montoriol-Garriga 2013, Duchin *et al.* 2010). External finance dependence EFD is computed as shown in Eq. (2.3).

$$\mathrm{EFD}_{it} = \frac{\Delta\mathrm{TA}_{it} - \mathrm{CF}_{it}}{\Delta\mathrm{TA}_{it}}. \tag{2.3}$$

$\Delta\mathrm{TA}_{it}$ is a proxy for a firm's level of net investments and CF_{it} represents the firm's cash flows in year t. In the EFD subsample, we consider observations with positive values for EFD because these are the firms that likely depend on external finance.[e] We calculate EFD_{it} at the firm level and, alternatively, at the industry-country level [denoted by subscript i, respectively, in Eq. (2.2)]. For latter, we consider the median values of $\Delta\mathrm{TA}_{it}$ and CF_{it} at the industry-country level. On 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} less exogenous at the firm level. We therefore employ both measures of EFD_{it}. Note that the way of measuring external finance dependence is not critical because our sample, despite the cross-country heterogeneity, contains only SMEs, which are considered as bank-dependent anyway.

3. Data

We collect detailed financial statement data of SMEs from Bureau van Dijk's Orbis database. Our sample contains firm-year observations from the five largest European countries (Germany, France, Italy, Spain and the United Kingdom), covering the years before, during and after the global financial crisis. 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

[e] 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.

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 €1000 in any of the years in our sample period. Applying these criteria results in a final sample with yearly data from 2006 to 2011. Since we use financial statement information, we do not know the identity of firms' suppliers. To address this issue, we consider yearly data from the industry-level input-output matrix of the five largest European countries from Eurostat. This approach makes it possible to compute the average credit quality of firms' suppliers based on their industry affiliation.

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 share over the sample period. The final dataset is comprised of 1186 SMEs from Germany (28%), 922 from France (22%), 920 from the UK (21%), 751 from Italy (17%) and 501 from Spain (12%). In that sample, we include the largest SMEs from each country. We also conduct further analyses using the larger raw samples from Orbis for each country that confirm the results on the GDP-weighted sample.

The main dependent variable in our study is the substitution indicator S_{it}. Figure 1 shows the relative frequency of substitution ($S_{it} = 1$) by country and over time.

There is a sharp decrease in the fraction of substitution during the financial crisis in 2008 and 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 S_{it} is close to 0.5 during the whole sample period, indicating that substitution and

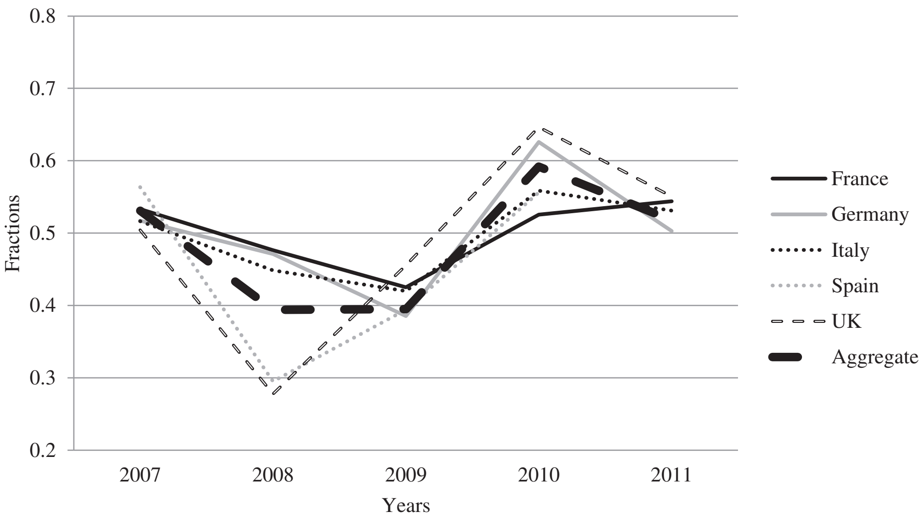

Fig. 1. The substitution indicator during the period 2007–2011.
Notes: This figure displays the substitution indicator S_{it} over time by country. The years are shown on the x-axis; the fractions of substitution relationships ($S_{it} = 1$) are shown on the y-axis.

complementary relationships are approximately equally likely. However, the overall mean value clouds that there is substantial variation over time (e.g. the yearly mean of S_{it} in the UK changes from 0.28 in 2008 to 0.65 in 2010) that indicates that the probability of substitution is non-stationary.

Table 1 reports summary statistics for the full sample and differentiated by crisis and pre-crisis credit quality.

The mean of the substitution indicator S_{it} is 0.487, indicating that a substitution relation ($S = 1$) and complementary relation ($S = 0$) are almost equally likely during the sample period. The mean (median) *Z-score* is 2.7 (2.6). The mean of *Size* measured by the natural logarithm of total assets is 9.5, corresponding to 22.2 million euros. Mean ROA is 2.5%. 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 3.3 (3.1), while Italian firms have the lowest credit quality with a mean (median) Z-score of 1.7 (1.6). Firms from the other three countries have Z-scores that range between values of 2.0 and 3.0.

The right side of Table 1 reports the means of the variables differentiated by crisis and credit quality measured at pre-crisis times. Consistent with the average dynamics shown in Fig. 1, substitution S becomes lower during the global financial crisis, but the decrease is smaller for low-credit quality firms (0.519–0.408) than for high-credit quality firms (0.562–0.408). Moreover, the decrease in absolute and relative trade credit usage (ΔT; $\Delta T/TA$) is less pronounced for low-credit quality firms than for high-credit quality firms. Hence, these observations point at differences in substitution effects between high and low credit quality firms during the financial crisis. Finally, consistent with the split by pre-crisis Z-score, liquidity ($Cash$) and profitability (ROA) are substantially lower for low credit quality firms than for high-credit quality firms.

4. Empirical Analysis

4.1. *Baseline analysis*

We investigate whether and how credit quality influences the substitution of bank credit for trade credit in SME finance. Specifically, we examine whether the probability of substitution for trade credit increases after a firm has experienced a negative shock to its bank credit. We regress the substitution indicator S_{it} (1 indicates that firms increase trade credit; 0 indicates that firms decrease trade credit) on the dummy *Z-score low* measured at pre-crisis times or lagged by one year, the interaction term *Z-score low* $\times$ $Crisis$, the dummy *Crisis*,[f] lagged time-varying firm control variables (size, cash holdings, inventories, tangible fixed assets and ROA), industry fixed effects and country fixed effects. Table 2 reports the results of the probit regressions for the probability of substitution, using robust standard errors clustered

[f] In alternative analyses, we used year fixed effects or the country-specific yearly GDP growth rate. All results are similar to the ones when we use the dummy *Crisis*.

Table 1. Summary statistics.

	Full sample			No crisis		Crisis	
				High credit quality	Low credit quality	High credit quality	Low credit quality
Variable	Mean	Median	St. dev.	Mean	Mean	Mean	Mean
S	0.487	0.000	0.499	0.562	0.519	0.396	0.408
ΔT	−121.616	−4.833	2486.528	191.080	96.786	−451.905	−254.805
ΔT/TA	−0.643	−0.069	9.976	0.856	0.481	−2.381	−1.422
Z-score	2.782	2.636	1.420	3.599	1.896	3.510	1.884
Supplier Z-score	2.646	2.668	0.817	2.167	2.111	2.704	2.620
Size (ln total assets)	9.537	10.065	1.212	9.336	9.661	9.416	9.743
Cash	0.077	0.029	0.117	0.092	0.062	0.088	0.060
Inventories	0.203	0.139	0.213	0.220	0.181	0.222	0.182
Tangibles	0.276	0.198	0.256	0.201	0.353	0.214	0.365
ROA	0.025	0.020	0.075	0.045	0.013	0.037	0.011

Notes: This table reports the mean, median and standard deviation for the full sample and the mean of the variables by crisis and credit quality (median split of pre-crisis Z-score). The full sample comprises firm-year observations from France, Germany, Italy, Spain and the UK for which the substitution indicator S_{it} displays non-missing values (9668 observations).

at the firm level. We consider different model specifications and samples using firms' pre-crisis or lagged Z-score, the continuous lagged inverse Z-score (columns 4 and 8),[g] and samples containing all firms or external-finance dependent firms (EFD; columns 3, 6 and 7). We report marginal effects evaluated at the mean and the corresponding p-values in parentheses.

The estimation results provide a clear picture. We find that low-credit quality firms are less likely to substitute and substitution became less likely during the crisis. However, the interaction term *Z-score low* $\times$ *Crisis* displays a positive and highly significant coefficient in all model specifications. The effect is economically large as it more than offsets the negative base effect of *Z-score low* (in columns 3, 5 and 7 it is almost twice as large). Alternatively, the interaction term reduces the negative effect of *Crisis* by approximately one-third. Hence, low-credit quality firms substitute bank credit for trade credit significantly more than high-quality firms during the financial crisis. This effect is consistent with the fact that the shock to bank credit for low-credit quality firms was more than twice as large than for high-credit quality firms. The finding is due to differential demand for trade credit during the crisis because theoretically suppliers should prefer to extend more trade credit to high-credit quality firms than to low-credit quality firms, everything else equal.

In the next step, we examine whether we can complement the previous result by using more direct measures of trade credit usage that inform us about the magnitude

[g] The continuous inverse Z-score is the raw Z-score multiplied by (-1) to facilitate the comparison with the dummy *Z-score low*. For the ease of interpretation, we employ in all subsequent analyses the dummy variable *Z-score low*. We obtain the same results with the continuous inverse Z-score.

Table 2. Credit quality and debt substitution.

Dep. var.:	(1) S_{it}	(2) S_{it}	(3) S_{it}	(4) S_{it}	(5) S_{it}	(6) S_{it}	(7) S_{it}	(8) S_{it}
Measurement	Z-score low dummy Pre-crisis	Z-score low dummy Pre-crisis	Z-score low dummy, EFD Pre-crisis	Z-score inverse continuous Pre-crisis	Z-score low dummy Lagged	Z-score low dummy, EFD Lagged	Z-score low dummy, EFD ind. Lagged	Z-score inverse continuous Lagged
Z-score low$_{it-1}$	−0.047***	−0.048***	−0.039**	−0.020***	−0.036**	−0.030*	−0.047**	−0.029***
	(0.000)	(0.001)	(0.013)	(0.001)	(0.015)	(0.070)	(0.038)	(0.000)
Z-score low$_{it-1}$ *x Crisis*$_t$	0.054**	0.058***	0.067***	0.024***	0.064***	0.056**	0.085**	0.023***
	(0.012)	(0.009)	(0.008)	(0.005)	(0.004)	(0.023)	(0.014)	(0.000)
Crisis$_t$	−0.169***	−0.184***	−0.188***	−0.092***	−0.186***	−0.189***	−0.203***	−0.092***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Firm controls								
Supplier Z-score$_{i,t-1}$		0.093***	0.094***	0.101***	0.089***	0.078**	−0.035	0.101***
		(0.002)	(0.000)	(0.001)	(0.004)	(0.028)	(0.539)	(0.001)
Size$_{i,t-1}$		−0.028***	−0.032***	−0.029***	−0.029***	−0.037***	−0.112***	−0.027***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Cash$_{i,t-1}$		0.031	0.038	0.025	0.031	0.068	−0.050	0.016
		(0.514)	(0.517)	(0.611)	(0.523)	(0.268)	(0.554)	(0.736)
Inventories$_{i,t-1}$		−0.001	−0.013	−0.009	−0.012	0.001	0.031	−0.005
		(0.977)	(0.696)	(0.774)	(0.700)	(0.960)	(0.490)	(0.868)
Tangibles$_{i,t-1}$		0.034	0.031	0.033	0.026	0.015	0.026	0.050*
		(0.193)	(0.294)	(0.209)	(0.319)	(0.616)	(0.544)	(0.057)
ROA$_{i,t-1}$		0.0328	0.043	0.026	0.033	0.001	0.107	−0.078
		(0.655)	(0.608)	(0.727)	(0.665)	(0.988)	(0.364)	(0.323)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.0218	0.0250	0.0267	0.0257	0.0253	0.0304	0.0437	0.265
Number of obs.	9665	9.020	7046	9020	8831	7044	3653	8831

Notes: This table reports results of probit regressions where the substitution indicator S_{it} is regressed on the dummy *Z-score low*, the dummy *Crisis*, the interaction of the *Z-score low* and *Crisis*, firm controls, and industry and country fixed effects. We report marginal effects evaluated at the mean 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.

of substitution. We take the absolute change in accounts payable (ΔT; in euros) and the relative change in accounts payable ($\Delta T/\mathrm{TA}$; in percent) as alternative dependent variables. Moreover, we consider the conditional sample containing observations from firms that experience a negative shock to bank credit (sample S; columns 1 and 5) and the unconditional sample, where we do not condition on a shock to bank credit (Full sample; columns 2–4 and 6–8). The advantage of using the unconditional sample is that it has a panel structure, making it possible to add firm fixed effects to control for unobserved heterogeneity at the firm level rather than adding industry fixed effects. Table 3 reports the pooled OLS and panel data regression results.

The results are consistent with the findings from Table 2. We find mostly significantly negative effects of *Z-score low* and *Crisis*. Importantly, the interaction term *Z-score low* × *Crisis* exhibits a significantly positive coefficient in all regression models. We now find that low-credit quality firms increase significantly their

Table 3. Credit quality and trade credit usage.

Dep. var.: Sample	(1) ΔT_{it} S	(2) ΔT_{it} Full	(3) ΔT_{it} Full	(4) ΔT_{it} Full	(5) $\Delta T/TA_{it}$ S	(6) $\Delta T/TA_{it}$ Full	(7) $\Delta T/TA_{i}$ Full	(8) $\Delta T/TA_{it}$ Full
Measurement	*Z*-score low dummy Pre-crisis	*Z*-score low dummy Pre-crisis	*Z*-score low dummy, EFD Pre-crisis	*Z*-score low dummy, EFD Lagged	*Z*-score low dummy Pre-crisis	*Z*-score low dummy Pre-crisis	*Z*-score low dummy, EFD Pre-crisis	*Z*-score low dummy, EFD Lagged
Z-score low$_{it-1}$	−126.375**	−86.402**		132.08	−0.739***	−0.471***		−0.413
	(0.043)	(0.022)		(0.232)	(0.006)	(0.001)		(0.314)
Z-score low$_{it-1}$ *x Crisis*$_t$	363.186*** (0.002)	307.888*** (0.000)	304.152*** (0.000)	488.629*** (0.000)	1.429*** (0.001)	1.497*** (0.000)	1.503*** (0.000)	2.312*** (0.000)
Crisis$_t$	−636.548***	−613.684***	−450.945***	−594.526***	−2.990***	−3.077***	−2.325***	−2.898***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
Firm controls								
Supplier Z-score$_{i,t-1}$	120.450*** (0.002)	−54.485*** (0.008)	−6.373 (0.789)	−8.738 (0.778)	1.011* (0.100)	−0.392*** (0.000)	−0.142** (0.036)	−0.204** (0.022)
Size$_{i,t-1}$	−260.305***	−227.10***	−2087.51***	−2413.409***	−0.997***	−1.125***	−10.168***	−11.684***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Cash$_{i,t-1}$	−147.237	−309.822**	401.896	140.592	−0.473	−1.143**	0.286	−1.031
	(0.530)	(0.048)	(0.474)	(0.810)	(0.554)	(0.018)	(0.858)	(0.622)
Inventories$_{i,t-1}$	46.469	−71.919	−574.769	−407.437	−0.007	−0.676*	−4.593**	−3.791
	(0.777)	(0.376)	(0.128)	(0.357)	(0.992)	(0.076)	(0.046)	(0.162)
Tangibles$_{i,t-1}$	447.580***	219.890***	1436.514***	1513.957***	2.169***	1.255***	7.139***	7.650***
	(0.000)	(0.002)	(0.000)	(0.007)	(0.000)	(0.000)	(0.000)	(0.000)
ROA$_{i,t-1}$	777.696**	798.015***	477.926		5.715***	5.530***	6.314***	8.699***
	(0.043)	(0.001)	(0.239)		(0.001)	(0.000)	(0.000)	(0.000)
Industry FE	Yes	Yes	No	No	Yes	Yes	No	No
Firm FE	No	No	Yes	Yes	No	No	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Within R^2	0.0264	0.0196	0.0483	0.0563	0.0290	0.0332	0.0804	0.0937
Number of obs.	9022	23,351	23,351	18,306	9022	23,351	23,351	18,306

Notes: This table reports results of pooled OLS models with industry fixed effects and panel data models with firm fixed effects with the absolute (relative) change in trade credit usage ΔT ($\Delta T/TA$) as dependent variables, respectively. 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.

trade credit usage during the financial crisis. The effect of the interaction term *Z-score low* $\times$ *Crisis* is positive and 3–4 times larger than the negative base effect of *Z-score low*. For example, in column (2), we find that the yearly absolute change of trade credit usage (ΔT; accounts payable in euros) for low-credit quality firms is 86.4 K Euros lower than for high-credit quality firms in pre-crisis times. However, during the crisis, low-credit quality firms use 307.8 K more trade credit than high-quality firms and the combined effect is 221.4 K Euros ($= 307.8 - 86.4$). The negative coefficient of *Crisis* (−613.6 K) shows that trade credit usage decreased during the financial crisis. The results for the regression models with relative change of trade credit usage (ΔT/TA) as dependent variable in columns (4)–(8) are qualitatively similar. These findings complement our first analysis on the probability of substitution, showing that, although trade credit usage (similar to the probability of substitution) decreased during the financial crisis, low-quality firms increased their absolute and relative trade credit usage during this period more than high-quality firms. Furthermore, we document that the results are not sensitive to the conditioning on the negative shock to bank debt (sample S versus full sample), the measurement of credit quality (pre-crisis or lagged values), external finance dependence (all firms or EFD firms) or unobserved heterogeneity at the firm level (fixed effects models). In unreported analyses, we confirm these results using the continuous inverse Z-score instead of the dummy *Z-score low*.[h]

4.2. *Sample selection and cross-country heterogeneity*

We now examine in more detail two potential issues that might influence our results. The first issue one is a potential selection effect due to the definition of the substitution indicator S, the second one is cross-country heterogeneity.

First, it is possible that the findings reported in Table 2 are influenced by 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. We know already from Table 3, where we use the conditional and unconditional sample, that a selection effect — even if present — is not critical for our interpretation.

Nevertheless, to address this issue formally, 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 the indicator variable *Dshock* 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. The latter control for any time-invariant unobserved heterogeneity at the firm level. 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. The results reported in columns (1) and (2) are based on the full sample, columns (3) and (4) are based on data from EFD firms.

In the first-stage regressions in columns (1) and (3), we find that all the explanatory variables from Table 2 have a significant effect on the probability of a negative shock to bank credit. Most importantly, when we add the *Inverse Mills Ratio* to the second-stage regression in columns (2) and (4), we still find a significantly positive coefficient of the interaction term *Z-score low* $\times$ *Crisis*. We also find that the probability of substitution is significantly lower during the financial crisis than in non-crisis times. The results are similar for all firms and EFD firms and confirm the previous findings from Tables 2 and 3.

Second, we examine the cross-country heterogeneity of substitution effects in SME finance, estimating the base regressions with the substitution indicator S and

[h] The results are available from the authors on request.

Table 4. Two-stage selection models.

Dep. var.:	(1) $Dshock_{it}$ (1st stage) Z-score low lagged, full sample	(2) S_{it} (2nd stage) *Z*-score low lagged	(3) $Dshock_{it}$ (1st stage) *Z*-score low lagged, EFD	(4) S_{it} (2nd stage) *Z*-score low lagged, EFD
Z-score low_{it-1}	−0.187***	−0.001	−0.137*	0.003
	(0.003)	(0.940)	(0.060)	(0.879)
Z-score low_{it-1} *x* $Crisis_t$	−0.028	0.069***	−0.002	0.057**
	(0.645)	(0.002)	(0.973)	(0.022)
$Crisis_t$	−0.248***	−0.142***	−0.255***	−0.136***
	(0.000)	(0.000)	(0.000)	(0.000)
Firm controls				
Supplier Z-score$_{i,t-1}$	1.941***	−0.225***	1.971***	−0.311***
	(0.000)	(0.007)	(0.000)	(0.000)
$Size_{i,t-1}$	−1.017***	0.117***	−1.021***	0.140***
	(0.000)	(0.000)	(0.000)	(0.000)
$Cash_{i,t-1}$	0.423	−0.044	0.812**	−0.104
	(0.177)	(0.400)	(0.030)	(0.140)
$Inventories_{i,t-1}$	0.054	−0.025	0.069	−0.016
	(0.855)	(0.424)	(0.833)	(0.642)
$Tangibles_{i,t-1}$	1.562***	−0.025	1.571***	−0.314***
	(0.000)	(0.424)	(0.000)	(0.000)
$ROA_{i,t-1}$	0.970	−0.127	0.789**	−0.148
	(0.003)	(0.146)	(0.039)	(0.121)
Inverse Mills ratio$_{it}$		−0.182***		−0.222***
		(0.000)		(0.000)
Industry FE	No	Yes	No	Yes
Firm FE	Yes	No	Yes	No
Country FE	Yes	Yes	Yes	Yes
Pseudo R^2	0.0803	0.0267	0.0829	0.0325
Number of obs.	21,885	8831	16,560	7.044

Notes: This table reports the results of two-stage Heckman selection models. In column (1) and (3), we report coefficients from the first stage regression with *Dshock* (equal to one if bank debt decreased, and zero otherwise) as dependent variable. In column (2) and (4), we report the marginal effects evaluated at the mean from the second stage probit regression with S_{it} as dependent variable. ***, **, * indicate coefficients that are statistically significant at the 1%, 5% and 10% levels, respectively, using robust standard errors.

relative changes in trade credit usage $\Delta T/\mathrm{TA}$ as dependent variables and separately by country. We expect a significantly positive effect of interaction term *Z-score low* × *Crisis* on the probability and magnitude of substitution in all five countries. In this analysis, we employ the larger raw samples from each country separately to make full use of the data instead of using the smaller GDP-weighted aggregate sample. Table 5 reports the results.

Overall, the findings from Table 5 are consistent with our previous analyses based on the representative aggregate dataset. First, the interaction term *Z-score low* × *Crisis* is positive and highly significant in 13 of 15 regressions. The results for $\Delta T/\mathrm{TA}$ are consistent and highly significant in the regressions with industry fixed effects and firm fixed effects, respectively, for all five countries. The results for the substitution indicator S are consistent and highly significant for France, Italy

Table 5. Credit quality, debt substitution, and trade credit usage by country.

Country	Dep. var.:	*Z-score* low_{it-1}	*Z-score* $low_{it-1} x\ Crisis_t$	Crisis	Firm controls	Industry FE	Firm FE	Pseudo or within R^2	Number of observations
France	S_{it}	−0.076***	0.031***	−0.106***	Yes	Yes	No	0.0119	31,741
		(0.000)	(0.001)	(0.000)					
	$\Delta T/TA$	−2.146***	1.202***	−2.785***	Yes	Yes	No	0.0226	81,705
		(0.000)	(0.000)	(0.000)					
	$\Delta T/TA$	−1.722***	0.959***	−2.301***	Yes	No	Yes	0.1398	81,705
		(0.000)	(0.000)	(0.000)					
Germany	S_{it}	−0.008	−0.021	−0174***	Yes	Yes	No	0.0394	1,589
		(0.824)	(0.686)	(0.000)					
	$\Delta T/TA$	−1.322***	1.583***	−3.455***	Yes	Yes	No	0.0455	4,302
		(0.000)	(0.000)	(0.000)					
	$\Delta T/TA$	0.079	1.382**	−2.899***	Yes	No	Yes	0.1095	4,302
		(0.905)	(0.028)	(0.000)	−1.200				
Italy	S_{it}	−0.049***	0.068***	−0.139***	Yes	Yes	No	0.0123	81,358
		(0.000)	(0.000)	(0.000)					
	$\Delta T/TA$	−1.200***	2.255***	−3.541***	Yes	Yes	No	0.0059	220.428
		(0.000)	(0.000)	(0.000)					
	$\Delta T/TA$	3.188***	1.484***	−1.150***	Yes	No	Yes	0.0861	220,428
		(0.000)	(0.001)	(0.000)					
Spain	S_{it}	−0.012	0.005	−0.226***	Yes	Yes	No	0.0461	12,182
		(0.405)	(0.798)	(0.000)					
	$\Delta T/TA$	−1.228***	1.495***	−5.090***	Yes	Yes	No	0.0676	31,624
		(0.000)	(0.000)	(0.000)					
	$\Delta T/TA$	−0.077	1.403***	−3.822***	Yes	No	Yes	0.1346	31,624
		(0.805)	(0.000)	(0.000)					
UK	S_{it}	−0.004	0.059***	−0.271***	Yes	Yes	No	0.0374	20,610
		(0.693)	(0.000)	(0.000)					
	$\Delta T/TA$	0.0571*	1.517***	−3.663***	Yes	Yes	No	0.0045	47,089
		(0.077)	(0.000)	(0.000)					
	$\Delta T/TA$	2.191***	1.192**	−0.175	Yes	No	Yes	0.0399	47,089
		(0.000)	(0.030)	(0.901)					

Notes: This table reports regression results for S_{it}, ΔT and $\Delta T/TA$, using the raw samples from each country. We report marginal effects and coefficients, respectively, with the p-values in parentheses. All regressions are based on the lagged Z-score low dummy and the EFD samples. ***, **, * indicate coefficients that are statistically significant at the 1%, 5% and 10% levels, respectively, using robust standard errors clustered at the firm level.

and the UK, but not significant for Germany and Spain. Possible reasons are that German SMEs display a higher Z-score level than the SMEs from other countries,[i] the German banks were less strongly hit by the financial crisis, and SMEs rely more on long-term bank credit (instead of short-term bank credit) than in other countries. Moreover, this finding is plausible since Lawrenz & Oberndorfer (2018) show that in contrast to large firms, German SMEs were less able

[i] 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.

substitute bank credit for trade credit. In Spain, where half of the banking system imploded (see, e.g. Illueca *et al.* 2014) and the GDP had not grown for five

years, the financial crisis had the strongest impact. It is possible that substitution in Spain was more difficult than in other countries because suppliers were more adversely affected. Nevertheless, based on the unconditional samples, we do find that Spanish firms increased their trade credit usage during the crisis, consistent with Carbó-Valverde *et al.* (2016). We also repeated the country-by-country analysis with GDP growth instead of the dummy *Crisis* and find similar results.

The evidence suggests that the effects of credit quality on substitution in SME finance during the financial crisis are qualitatively similar, but the magnitude of the effects varies across countries.

4.3. *Further checks and robustness tests*

In the remainder, we conduct further empirical checks to ensure that our main results are robust and not the product of particular choices of samples, methods or model specifications.

First, we estimate regression models with S or $\Delta T/\mathrm{TA}$ as dependent variables, distinguishing between SMEs that are net trade credit borrowers (accounts payable $>$ accounts receivable) and those that are net trade credit lenders (accounts payable $<$ accounts receivable). The impact of credit quality on substitution of bank credit for trade credit during the financial crisis should be especially relevant for firms that are net trade credit borrowers. These firms have already access to supply chain finance and increasing trade credit usage corresponds to stretching out the payment to their suppliers. We measure firms' net trade credit position in pre-crisis times to mitigate potential endogeneity with changes in bank credit and trade credit during the financial crisis. Table 6 reports the results. Columns (1), (3) and (5) show the results for pre-crisis net trade credit borrowers, columns (2), (4) and (6) for net trade credit lenders.

The results are in line with our earlier findings. The coefficient of the interaction term *Z-score low* $\times$ *Crisis* is positive in all models and highly significant in five of the six models. Interestingly, the effects are stronger for SMEs that are net trade credit borrowers in pre-crisis times than for SMEs that are net trade credit lenders. The coefficients of the interaction term in columns (1), (3) and (5) are approximately twice as large as the ones in columns (2), (4) and (6). For example, for the regression of $\Delta T/\mathrm{TA}$ with firm fixed effects in columns (5) and (6), we find a coefficient of 2.879 (p-value < 0.01) for net trade credit borrowers and 1.551 for net trade credit lenders (p-value < 0.01). In unreported analyses, we consider the inverse lagged continuous Z-score and find similar results.

Second, our result that low-credit quality firms substitute bank credit for trade credit more than high-credit quality firms during the crisis might be driven by firms' financial constraints. The concept of financial constraints is related but not identical to financial distress (e.g. Fazzari *et al.* 1988, Kaplan & Zingales 1997). To analyze this issue, we consider the Kaplan–Zingales index (KZ index) and differentiate between firms with high and low financial constraints using a median split of the KZ

Table 6. Credit quality and debt substitution by pre-crisis net trade credit usage.

Dep. var.:	(1) S_{it} *Z*-score low dummy Pre-crisis (Net borrower)	(2) S_{it} *Z*-score low dummy Pre-crisis (Net lender)	(3) S_{it} *Z*-score low dummy Lagged (Net borrower)	(4) S_{it} *Z*-score low dummy Lagged (Net lender)	(5) $\Delta T/TA_{it}$ *Z*-score low dummy Lagged (Net borrower)	(6) $\Delta T/TA_{it}$ *Z*-score low dummy Lagged (Net lender)
Z-score low$_{it-1}$	−0.087***	−0.030*	−0.068**	−0.021	−0.883	−0.226
	(0.001)	(0.081)	(0.010)	(0.249)	(0.232)	(0.498)
Z-score low$_{it-1}x$ *Crisis*$_t$	0.097**	0.040	0.099**	0.049*	2.879***	1.551***
	(0.012)	(0.144)	(0.011)	(0.073)	(0.000)	(0.000)
Crisis$_t$	−0.221***	−0.171***	−0.220***	−0.175***	−3.981***	−1.839***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Firm controls						
Supplier Z-score$_{i,t-1}$	−0.010	0.147***	−0.039	0.154***	−0.345**	−0.122*
	(0.846)	(0.000)	(0.491)	(0.000)	(0.025)	(0.089)
Size$_{i,t-1}$	−0.022*	−0.031***	−0.022	−0.034***	−12.472***	−8.870***
	(0.097)	(0.000)	(0.103)	(0.000)	(0.000)	(0.000)
Cash$_{i,t-1}$	0.059	0.022	0.082	0.015	−2.329	1.284
	(0.492)	(0.706)	(0.360)	(0.793)	(0.599)	(0.432)
Inventories$_{i,t-1}$	0.058	−0.027	0.051	−0.038	−4.641	−4.254
	(0.248)	(0.521)	(0.306)	(0.370)	(0.274)	(0.111)
Tangibles$_{i,t-1}$	0.074*	0.025	0.063	0.021	9.063***	6.115***
	(0.095)	(0.444)	(0.166)	(0.523)	(0.000)	(0.000)
ROA$_{i,t-1}$	0.188	−0.048	0.122	−0.019	11.290***	4.337**
	(0.176)	(0.584)	(0.391)	(0.833)	(0.000)	(0.042)
Industry FE	Yes	Yes	Yes	Yes	No	No
Firm FE	No	No	No	No	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo or within R^2	0.0395	0.0246	0.0389	0.0252	0.0999	0.0712
Number of obs.	2975	6028	2906	5908	7615	15,265

Notes: This table reports results of probit regressions where S_{it} or $\Delta T/TA_{it}$ is regressed on the dummy *Z-score low*, the dummy *Crisis*, the interaction of *Z-score low* and *Crisis*, firm controls, and industry fixed effects (or firm fixed effects) and country fixed effects. We split the sample by pre-crisis net trade credit usage (net trade credit borrowers in column 1, 3 and 5; net trade credit lenders in columns 2, 4 and 6). We report marginal effects evaluated at the mean 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.

index in pre-crisis times. We measure financial constraints with the KZ index, a widely used measure in the corporate finance literature (Kaplan & Zingales 1997, Lamont *et al.* 2001). It is defined in Eq. (3.1).[j] All components are winsorized at the 1st and 99th percentile.

$$\mathrm{KZ}_{it} = -1.002\frac{\mathrm{CF}_{it}}{\mathrm{TA}_{it-1}} + 3.139\frac{\mathrm{TL}_{it}}{\mathrm{TA}_{it-1}} + 39.368\frac{\mathrm{Div}_{it}}{\mathrm{TA}_{it-1}} - 1.315\frac{\mathrm{Cash}_{it}}{\mathrm{TA}_{it-1}}. \qquad (3.1)$$

[j] 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).

Table 7. Credit quality and debt substitution by pre-crisis level of financial constraints.

Dep. var.:	(1) S_{it} Z-score low dummy Pre-crisis (High constraints)	(2) S_{it} Z-score low dummy Pre-crisis (Low constraints)	(3) $\Delta T/TA_{it}$ Z-score low dummy Lagged (High constraints)	(4) $\Delta T/TA_{it}$ Z-score low dummy Lagged (Low constraints)
Z-score low$_{it-1}$	−0.027	−0.684***	−0.247	−0.579
	(0.232)	(0.002)	(0.595)	(0.202)
Z-score low$_{it-1}$ *x Crisis*$_t$	0.076**	0.067*	2.604***	1.212***
	(0.046)	(0.064)	(0.000)	(0.006)
Crisis$_t$	−0.203***	−0.183	−3.117***	−2.258***
	(0.000)	(0.000)	(0.000)	(0.000)
Firm controls				
Supplier Z-score$_{i,t-1}$	0.069	0.102**	−0.380***	0.000
	(0.153)	(0.012)	(0.000)	(0.998)
Size$_{i,t-1}$	−0.037***	−0.023***	−8.835***	−11.745***
	(0.002)	(0.007)	(0.000)	(0.000)
Cash$_{i,t-1}$	0.049	0.024	3.418	−2.156
	(0.641)	(0.664)	(0.255)	(0.273)
Inventories$_{i,t-1}$	−0.029	0.003	3.834	−16.086***
	(0.493)	(0.937)	(0.105)	(0.000)
Tangibles$_{i,t-1}$	0.018	0.060	6.767***	8.628***
	(0.584)	(0.136)	(0.000)	(0.000)
ROA$_{i,t-1}$	0.003	0.041	4.536**	8.289***
	(0.980)	(0.689)	(0.026)	(0.002)
Industry FE	Yes	Yes	No	No
Firm FE	No	No	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Pseudo or within R^2	0.0281	0.0304	0.0735	0.0957
Number of obs.	4375	4629	11,211	11,669

Notes: This table reports results of probit regressions where S_{it} or $\Delta T/TA_{it}$ is regressed on the dummy *Z-score low*, the dummy *Crisis*, the interaction of *Z-score low* and *Crisis*, firm controls, and industry fixed effects (or firm fixed effects) and country fixed effects. We split the sample by high and low financial constraints based on pre-crisis KZ index median split. We report marginal effects evaluated at the mean 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.

Because there has been debate in the literature about how to measure financial constraints (e.g. Farre-Mensa & Ljungqvist 2016), we also consider the WW index (Whited & Wu 2006) and the SA index (Hadlock & Pierce 2010) as alternative measures in robustness tests. Table 7 reports the results for the models with the substitution indicator S or $\Delta T/\mathrm{TA}$ as dependent variable and the KZ index as measure of financial constraints.

We find that our main result holds for firms with high financial constraints (columns 1 and 3) and low financial constraints (columns 2 and 4). Moreover, magnitude of the effect is stronger for firms with high constraints. In addition to the sample split, we add a dummy variable that equals one for firms with relatively high financial constraints in pre-crisis times and zero otherwise to our base regression model. We then interact this dummy with *Z-score low*, *Crisis* and *Z-score low* $\times$ *Crisis*, leading to a model with one triple interaction. We find that the coefficient of the triple interaction term is not statistically significant, confirming the results of the sample splits in Table 7. In unreported analyses, we employ the WW index and the SA index to differentiate by firms' pre-crisis level of financial constraints and obtain qualitatively similar results.[k]

Third, in the previous analyses, we investigated whether SMEs substitute bank credit in t for trade credit in t after a negative shock to their short-term bank credit in year $t-1$. On the one hand, it is possible that SMEs also experienced 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, because of the financing purpose (working capital), it is likely that firms mainly substitute short-term bank credit (and not long-term bank credit) for trade credit (and vice versa). In other words, it is unlikely that firms substitute a permanent decrease in long-term bank credit for a permanent increase in trade credit because the purpose and the cash flow effects of these two types of debt finance are very different. Therefore, we now 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}). The coefficient of the pre-crisis *Z-score low* is -0.032 (p-value $= 0.016$) and pre-crisis *Z-score low* $\times$ *Crisis* 0.039 (p-value $= 0.067$). The coefficient of the lagged *Z-score low* is -0.036 (p-value $= 0.009$) and lagged *Z-score low* $\times$ *Crisis* 0.039 (p-value $= 0.006$). Hence, both model specifications lead to results that are similar to those reported in Table 2. This can also be explained with the fact that short-term bank credit accounts for a large fraction of total bank debt in several the countries in our sample (e.g. France, Spain and Italy).

Fourth, we consider three modified definitions of the substitution indicator. The first modification is the three-outcome substitution indicator $S3_{it}$.[l] It has the following outcomes: 1 if negative complementary relation; 2 if partial substitution; and 3 if 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 $t-1$. We estimate the probability of partial or perfect credit substitution relative to the probability of a negative complementary relation. The results are in line with our previous findings. We find significantly negative coefficients for the *Z-score low* and significantly positive coefficients for the interaction term *Z-score low* $\times$ *Crisis* for partial substitution (-0.053, p-value $= 0.444$; 0.219, p-value $= 0.047$) and for perfect substitution

[k] The results are available from the authors on request.

[l] 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 at the firm level is relatively volatile and exhibits extreme values. The discrete substitution indicator is more robust and implicitly depends on the elasticity as input.

(-0.330, p-value $= 0.000$; 0.268, p-value $= 0.017$). The second modification is the substitution indicator $S4_{it}$ that is unconditional on the nature of the shock to bank credit in year $t-1$. We now take into account positive and negative shocks to bank credit in year $t-1$ to study SMEs' response in trade credit. $S4_{it}$ equals: 1 if $\Delta B_{it-1} < 0 \cap \Delta T_{it} < 0$ (negative complementary); 2 if $\Delta B_{it-1} < 0 \cap \Delta T_{it} \geq 0$ (substitution); 3 if $\Delta B_{it-1} \geq 0 \cap \Delta T_{it} < 0$ (inverse substitution); and 4 if $\Delta B_{it-1} \geq 0 \cap \Delta T_{it} \geq 0$ (positive complementary). All estimated probabilities are relative to the base category $S4_{it} = 1$ (negative complementary relation). When we estimate the corresponding multinomial probit model, we find that the coefficient of *Z-score low* is significantly negative for outcomes 2, 3 and 4 (ranging between -0.168 and -0.192), while the interaction term is positive and highly significant only for outcome 2 (0.240, p-value $= 0.007$). It is twice as large as the negative base effect of *Z-score low*. These findings are plausible because the category $S4 = 2$ (substitution) corresponds to $S3 = 2$ (partial substitution) and $S3 = 3$ (perfect substitution) as well as to $S = 1$. The result also shows that the conditions imposed by the definition of the binary substitution indicator S are not critical for our main results. The third modification relates to the condition about the change in bank credit. It is possible that a negative shock to bank credit in year $t-1$ is fully offset by an increase in bank credit in year t (which is ignored in the definition of *SI*), then there is no need for substitution, and hence, it is more likely to observe a complementary relation in year t. When we take into account the change of bank debt in year t, we find similar results as in the baseline analysis.

5. Conclusion

In this paper, we investigate whether and how credit quality influences SMEs' substitution of bank credit for trade credit. We base our analysis on a large sample of SMEs from France, Germany, Italy, Spain and the UK that covers the period before, during and after the global financial crisis.

We find that the probability of substituting bank credit for trade credit decreases during the crisis, but it decreased significantly less for *ex ante* low-credit quality (high risk) firms that experience a negative shock to bank credit. The effect is large since it offsets approximately one-third of the general effect of the financial crisis. The finding remains robust when we control for pre-crisis or lagged firm characteristics including size and external finance dependence, industry effects, country fixed effects, selections effects and cross-country heterogeneity. We also find, controlling for firm fixed effects, that low-quality firms increase their absolute and relative trade credit usage significantly more than high-quality firms during the financial crisis. The results are consistent across the five largest European countries, although the magnitude of the effects varies. The effect is largest in Italy and smallest in Germany, which can be explained with cross-country differences in the economic and lending environment. We conduct several additional empirical checks that show the robustness of our results. We find stronger effects for firms that are net trade credit borrowers or financially constrained in pre-crisis times. The results remain also robust when we consider firms' total bank credit rather than short-term bank credit and different ways of measuring the probability of substitution.

Our study provides novel evidence that informs researchers and policy makers about the influence of credit quality on substitution effects in SME finance. Our main finding can be explained with differences in demand for trade credit between high and low credit quality firms. We further show that the relation between bank credit and trade credit at the firm level transitions from a state where substitution and complementary relation are almost equally likely (no crisis) to a state where a complementary relation dominates (crisis). The findings are consistent across the five largest European countries, but the higher substitution by low-credit quality firms is in none of the countries sufficient to fully offset the negative shock to bank credit during the financial crisis.

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