DIPLOMARBEIT

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"Trade credit theories and panel data analysis of the effect of financial distress on trade credit"

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List of Abbreviations

CPI	Consumer Price Index
EBITDA	Earnings before Interest, Taxes, Depreciation and Amortization
EBITD	Earnings before Interest, Taxes and Depreciation
EMU	European Economic and Monetary Union
EWU	Europäische Wirtschafts- und Währungsunion
FD	Financial Distress
k_e	Cost of Equity
LN	Natural Logarithm
OLS	Ordinary Least Squares
MM	Modigliani Miller
TC	Trade Credit
UK	United Kingdom
US	United States
USA	United States of America
WACC	Weighted Average Cost of Capital

1. Introduction

According to Ng, Smith and Smith (1999, p.1109) trade credit "is created whenever a supplier offers terms that allow the buyer to delay payment." Trade credit, although it is costly, is a very common used form of financing in interfirm trade. Lee and Stowe (1993) argue that trade credit outstanding exceeds the volume of corporate bonds, state and local securities and by far exceeds the business lending of the entire banking system (Federal Reserve Bulletin, 1986). Surveys by Rajan and Zingales (1995) and Petersen and Rajan (1997) provide evidence that trade credit is the single most important source of short-term business credit despite its high costs from unfavorable credit terms for debtors. Elliehausen and Wolken (1993) show that 87 % of US firms participating in the National Survey of Small Business Finances offer trade credit and that 91 to 100 % of these firms' sales are on credit. For the UK, Wilson and Summers (2002) report that more than 80 % of commercial transactions are on credit terms.

However, financing via trade credit through suppliers is an area that is not been studied in depth in corporate finance literature despite its importance. Financial distress and bankruptcy have recently gained much attention in academic and public policy debates but investigations in the effect of financial distress on trade credit are still in its infancy. Since the first comprehensive examination by Petersen and Rajan (1997) several hypotheses of trade credit have been developed. The theories try to answer why supplier firms act as financial intermediaries, a business that usually is done by banks.

The objective of this work is to give an overview of trade credit theories and policies and consequently to test the hypothesis that the use of trade credit in the extreme situation of financial distress at firm level is significantly different from its use in more "normal" situations. One task of this work is to compare the results of European firms with the results of Preve (2004) whose work examines US firms. Following the line of Preve (2004) in this paper a big panel of European Monetary Union firms is used

to answer the following research question: "What is the effect of financial distress at firm level on trade credit using a big panel of European Monetary Union firms?" Related to this issue further questions like the substitution effect and the effect of firm size are to be examined and tested. The empirical findings of this work are compared with findings in the literature respectively with trade credit theories. Finally, possible reasons for different findings between US and European firms are to be discussed in brief.

The work of Preve (2004) is motivated by the fact that the costs from the different use of trade credit during distressed periods induces an increase of the costs of financial distress and these costs are an important determinant of a firm's capital structure. Similar to Preve (2004) it is assumed in the empirical part that the firms' alternative sources of finance are restricted or even non-existent. This diploma thesis is motivated to show if there are differences in the findings, where are the differences, where do they come from and what does this mean for the relevancy of trade credit especially for European firms in financial distress.

This work will be presented in six parts. Next, in section 2 aspects and theories of trade credit, i.e. trade credit policies and explanations why firms use and grant trade credit, are covered. Particular theories and benefits as well as costs of trade credit are discussed. Further the context of trade credit and capital structure are addressed and a literature review of trade credit and financial distress at firm level are given.

After having covered aspects and theories of trade credit in section 2, section 3 presents arguments for the choice of the data in the empirical part of section 4 and 5. Additionally, descriptive statistics are presented and first conclusions and comparisons are drawn. The data is an 11 year panel from 1997 to 2007 of the "Datastream Europe EM Index". The index contains 1360 firms of the European Monetary Union and after excluding firms by criterias explained in section 3 remain 905 firms in the sample.

Section 4 gives some insights about the methodology used and includes the empirical analysis of the basic model examining the effect of financial distress on trade credit and the substitution effect. The latter tests if

other sources of financing as trade credit like financial debt and equity provide financing when European firms are in financial distress. Hereby, following the lines of Preve (2004) a standard panel data analysis of company accounts data is used. The results of the European panel data are to be compared and discussed with those of the US of Preve (2004). Further, the sample is tested for consistency with trade credit theories. Additionally the trade credit behavior of French firms from the sample is tested.

Section 5 is an extension of the basic model and in particular investigates the importance of firm size to the effect of financial distress on trade credit and to the substitution effect.

Finally, in section 6, some comprehensive remarks, a short summary of the main results, a conclusion as well as an outlook are covered.

2. Aspects of trade credit

In this section aspects of trade credit, a review of trade credit theories as well as at some insights into the financial distress literature are given. It includes trade credit policies and theories as explanations why firms use and grant trade credit. Furthermore costs of trade credit and financial distress as well as capital structure aspects are covered.

2.1 Trade credit policies

The asset trade credit or receivables is tied directly to the lifeblood of any firm, namely cash. Trade credit can be interpreted as a form of credit that is granted by a seller firm to finance another firm's purchase of the seller's goods. Sales on credit imply the application of credit terms according to a firm's credit policy. The trade credit policy of a firm is a trade-off between stimulating demand by permissive terms and limiting sales by restrictive terms. In case of too restrictive firm's policy sales will decrease and in case of too permissive conditions it will face increasing uncollectible accounts. According to Mateut (2005) trade credit terms or policies refer to the timing of payments, the discount for early settlement, the method of payment, the ownership prior to payment, and the interest rate or penalty for late payment. Ng, Smith and Smith (1999) showed that in the market there is a rich variation in credit terms across firms and credit policies across industries. Figure 1 gives a nice overview over possible credit arrangements.
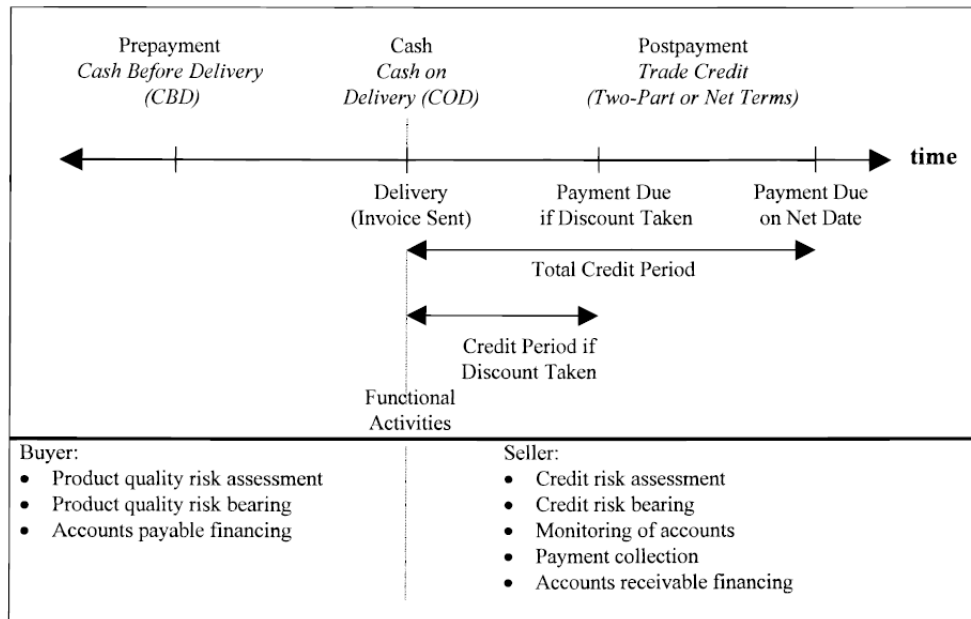
Figure 1: Time profile of payments and functional activities implied by payment policy[1]

The seller can impose payment before delivery or on delivery where the buyer assumes the product quality risk and must arrange for financing, for example by a bank. For payment after delivery, terms can be net, for example "net 30" or two-part, for example "2/10 net 30". In arrangements with payment after delivery the supplier gives financing to a customer and the seller bears the credit risk and receivables financing responsibilities. Net terms imply that full payment has to be done within a certain period, for example "net 30" means full payment due 30 days after the invoice date. Invoicing is normally around the date of delivery or at the end of a billing cycle. After this period the buyer is in default and will normally receive a reminder and/or can be charged interests of delay, a judicial dunning procedure may follow. Two-part terms, the second form of trade credit with payment after delivery provides a discount if payment is made promptly. It has three elements: (1) the discount percentage; (2) the discount period; and (3) the net period. According to Ng, Smith and Smith (1999) "2/10 net 30" is the most common two-part term. This means 2 % discount for payment

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[1] Ng, Smith and Smith (1999).

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within 10 days and a net period of 30 days. The customer gets effectively an interest-free loan until the tenth day. After the net period the buyer is in default. Not paying within the discount period, i.e. the 10 days, but paying on day 30 is effectively a borrowing of 20 days that implies an implicit interest rate of 43.9 % which is the opportunity cost for a buyer that forgoes the discount in exchange for 20 additional days of financing. The implicit interest rate can be calculated this way:

$$\text{implicit rate} = \left\{ \left(\frac{100}{100 - \text{discount \%}} \right)^{360/(\text{\# days net} - \text{\# days discount})} - 1 \right\}_2$$

Applying this formula on frequently used two-part payment terms, the implicit interest rates are:

1/10 net 30 → 19.8%	2/10 net 30 → 43.9%	2/20 net 30 → 106.9%
4/10 net 30 → 108.5%	8/30 net 50 → 349%	

Figure 2: Two-part terms and implicit interest rate of foregone discount[3]

The above calculations show that trade credit respectively the disuse of a discount is very expensive. Therefore creditworthy customers will pay early or net because they try to avoid unfavorable credit terms. On the other side low-quality borrowers will find it worthwhile to borrow because trade credit may still be cheaper than other sources of financing. The following Figure 3 shows a broad range of credit periods between European Union countries.

	Credit period	Days of delay	% payment within 15 days after agreed date(days)
Belgium	45–90	17	53
France	60–90	16	57.9
Germany	30–60	11	79
Italy	60–120	17	62.1
Netherlands	25–40	17	49.8
Portugal	60–90	n.a.	n.a.
Spain	60–90	n.a.	n.a.
United Kingdom	30–60	15	60.3

Figure 3: Trade credit in European Union countries[4]

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[2] Ng, Smith and Smith (1999).
[3] The calculation uses 360 days as the basis.

It points out that the Netherlands and Germany have quite short trade credit periods from 25 to 60 days whereas Italy has extensive large credit periods up to 120 days. This implies that firms from Italy are expected to pay late and, in turn late payment induces costs on the supplier side and may reduce its liquidity. Furthermore firms frequently pay beyond the net-period with average delays from 11 to 17 days. However, Ng, Smith and Smith (1999) found that terms tend to be uniform across an industry and stable over time but have a wide variation across industries.[5] Schwartz (1974) states that the formulation of credit terms can be an integral part of the seller's pricing policy. Varying prices by applying different credit policies may reduce a suppliers risk and furthermore allows price discrimination of dependent buyers or less wealthy customers.[6]

2.2 Costs of trade credit and financial distress

According to the pecking order theory should firms prefer internal financing over bank financing and equity is seen as last resort if external finance is needed. However, Petersen and Rajan (1994, 1995, 1997) show that firms take trade credit when cheaper sources of financing have been exhausted. Even so, for example Elliehausen and Wolken (1993), Demirgüc-Kunt and Maksimovic (2001), Willson and Summers (2002) and Burkart, Ellingsen and Gianetti (2004) show that lenders use the expensive trade credit very often as short-term and medium-term financing. Frequently firms do this even if they face no financial problems and although they have access to alternative sources of finance that are higher according to the pecking order. Note that small firms, start-up firms, fast growing firms and firms with less and exhausted access to bank financing tend to use relatively more trade credit. In this work it is focused on firm characteristics like a firm's financial health, market power, size and age to determine the use of

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[4] Mateut (2005) quoted from Marotta (2001) and Marotta quoted from Dan & Bradstreet (2000). (I have no access to D&B (2000).)
[5] See also Petersen and Rajan (1994) and Smith (1987).
[6] See Brennan, Maksimovic and Zechner (1988) and Pike et. al (2005).

trade credit rather than on determinants like the development of a country's banking system, a country's legal system and a country's financial policy among the most important ones.

Whenever a trade debtor suffers severe financial problems the supplier firm bears the risk of default and the risk of a total loss whenever the trade debtor goes bankrupt. Hence, suppliers need a pre-emptive credit risk management with permanent monitoring of borrowers including their credit ratings. This is necessary due to the fact that firms facing defaults of other firms are themselves more likely to default. In other words suppliers bear costs of financial distress as an indirect cost, i.e. from the bankruptcy of a buyer or late payment. According to a survey by Weiß et al. (2006), German firms generate on average 37 % of their sales volume with their 10 biggest customers. This highlights the risks firms face from a possible single default of payment and the importance of precautionary actions to prevent cash losses. According to Peter Davies, commercial director of the credit insurer Atradius, in 2003 over 15,000 UK businesses failed whereas the majority have been small companies with cash flow problems caused by late and non-payment. Especially for smaller businesses, the impact of a bad debt loss can be devastating. Hence, credit insurance helps to safeguard a company's future.[7] Additionally, factoring may protect from defaults of debtors, or if market power permits it, a supplier can instruct payment in advance. However, generally whenever suppliers begin to demand cash on delivery, there is a lot of speculation whether the buying firm is close to bankruptcy. In short terms it is an important signal of creditworthiness that firms are allowed to delay its payments.

Frank and Maksimovic (2005) argue that firms whose prospects start to deteriorate often respond by increasing the extent to which they offer trade credit to buyers. By doing so suppliers try to hide its financial problems. Commercial credit agencies and firm's internal credit and receivables management are therefore important instruments that can

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[7] http://aon.mediaroom.com/index.php?s=43&item=438 [23.12.2008]

provide information about the creditworthiness of trading partners.[8], [9] In order to reduce a supplier's risk and costs, credit agencies, credit insurances and adequate payment terms reduce information asymmetries and may improve a supplier's liquidity. To show the devastating impact of a bad debt loss a simple calculation is presented.

For example, taking a fictitious bad debt loss of Euro 10,000 and a fictitious profit margin of 5 %: 5 % of 10,000 equals a profit of Euro 500. In this case a business must generate 200,000 Euro in additional sales to regain a loss of 10,000 Euro. It implies 20 times the lost sales volume. This example still excludes the time value of money, namely the opportunity costs of the not gained money as well as the interests for a bank loan or account overdraft in case of low liquidity of the supplier company. An account that must be written off due to failure involves not only the inventory and profit lost, but also additional costs such as legal fees and credit professional time. The importance of cash flow is known by the dictum "Cash is king". Companies have to care about credit management and payment terms because even huge accounts receivables can bring companies short on cash and into bankruptcy if too many customers are in default. To prevent cash or bad debt losses a rigorous credit management may be useful. This is achieved by either monitoring and screening and, if necessary, by adjusting customer's credit terms individually. But, as already mentioned, it implies a trade-off between stimulating and limiting sales. Hence, to regain the loss of a bad debt a firm needs a huge additional sales volume and the prevention of it should have high priority.

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[8] Commercial agencies that pool and sell credit information are for example Dun and Bradstreet, KSV, Creditreform and CEG Creditreform.
[9] Networks for Credit Managers are for example the "Verein für Credit Management" (VfCM) and the "Federation of European Credit Management Associations" (FECMA). They have the vision to establish „best practices" for the credit management. The VfCM supports the "Mindestanforderungen an das Creditmanagement" (MaCM), a kind of codex or guideline to protect suppliers from default of payment. MaCM for corporations is an effort to establish standards like the "Mindestanforderungen an das Kreditgeschäft" for banks (MaK).

2.3 Trade credit and capital structure

According to Preve (2004) the costs of trade credit during financial distress increase, hence these costs are an important factor of a firm's capital structure. Further he argues that trade credit is very expensive implying that the cost of financial distress may be higher.[10] Previously Rajan and Zingales (1995) have shown the importance of trade credit in a firm's capital structure. They present evidence that 15 % of the total liabilities of US firms in 1991 consists of accounts payable. German balance sheets show 11.5 %, French 17 %, Italian 14.7 % and those of the UK 13.7 %. Whereas the ratio of accounts receivables to total assets amounts 17.8 % in the US, 26.9 % in Germany, 28.9 % in France, 29 % in Italy and 22.1 % in the UK. In order to understand firm's capital structure choice in relation to trade credit the Modigliani Miller Theorem and the pecking order theory will be explained briefly. In the literature there was a debate on whether firms target a certain capital structure (e.g. Rajan and Zingales, 1995) or follow a pecking order (see Myers, 1984 and Shyam-Sunder & Myers, 1999) when raising funds.

Next, the capital structure choice. According to the trade-off theory of capital structure firms should choose a debt ratio that maximizes the firm value. Furthermore, firms that target a certain capital structure face a trade-off between tax benefits and the costs of financial distress from bad debt. The choice between bank debt and trade credit implies that entrepreneur's trade-off the cheaper bank debt against the cost induced by a strict bank liquidation policy. According to Brealey, Myers and Allen (2006), firms with safe, tangible assets and plenty of taxable income ought to have high debt targets but unprofitable companies with risky and intangible assets tend to rely primarily on equity financing. The capital structure theory explains many industry differences in capital structure, but it does not explain why most profitable firms within an industry generally are likely having the most conservative capital structures.

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[10] See also Altman (1984), Opler and Titman (1994) and Andrade and Kaplan (1998).

This can be better explained by the pecking-order theory that grounds on the theory of asymmetric information between managers and outside investors because managers know more about the prospects and risks of their company. Therefore managers avoid issuing stock when they believe the share price is too low but try to issue in fairly and overpriced times (equity financing). Further, optimistic managers will prefer debt to undervalued equity and pessimistic managers will be forced to do the same. As a consequence investors often interpret the issue of new share as bad news resulting in falling stock prices after the announcement. This shows that in an imperfect world firms have preferences in the order of the source of finance. More precisely, if internal sources based on retained earnings or cash flow are available they are ranked above external sources like trade credit, bank borrowing and non-bank finance. Further, the fact that less profitable firms in an industry on overall borrow more can be explained by the pecking order theory. Firms where internal funds are exhausted and where financial distress threatens their business activity will choose consequently debt and equity as last resort in the pecking order. Hence, financially distressed firms are expected to use more trade credit.

Next, the theorems of Modigliani and Miller. Modigliani and Miller (henceforth MM) (1958) state that in perfect capital markets without tax capital structure (the ratio of debt to equity) has no impact on either the firm value or the cost of capital.[11] The MM proposition holds as long as the total cash flow generated by the firms' assets is unchanged by its capital structure respectively as long as the capital structure choice does not affect a firm's investment, borrowing and operating policies. MM's Proposition 1 says also that the choice between long-term and short-term debt has no effect on firm value. Thus, the distinction between bank financing and financing by suppliers via trade credit should be irrelevant.[12]

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[11] Further assumptions are: no transaction costs and no dependence between the net operating earnings and the capital structure of the firm.
[12] See Mizen and Yalcin (2006) and Brealey, Myers and Allen (2006).
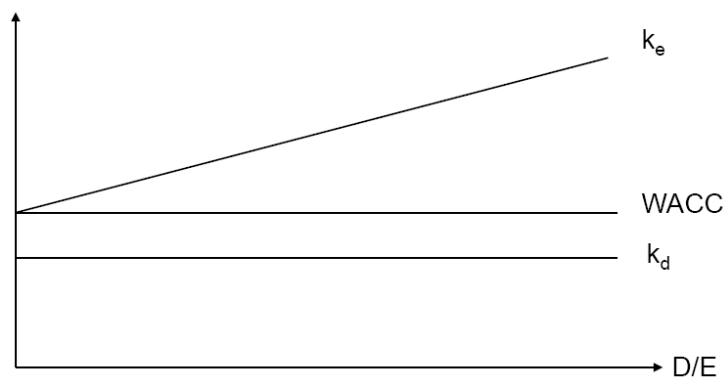
Figure 4: MM world[13]

As depicted in Figure 4, in a MM world (Proposition 2) the substitution of the more expensive equity by the less expensive debt results in an increase in the cost of equity (k_e), leaving the weighted average cost of capital (WACC) constant. Note that the WACC is the expected rate of return on the market value of all of the firm's securities. The WACC is also called overall cost of capital or a company's cost of capital. Note also that the debt value not the debt ratio stays constant with rising leverage. The costs of equity increase linearly as long as debt is risk free (see Figure 4). However, rising leverage increases the risk and according to MM's proposition 2 debtholders will demand a higher return on debt. Thus, costs of debt will rise and the increase in the cost of equity will slow down.[14]
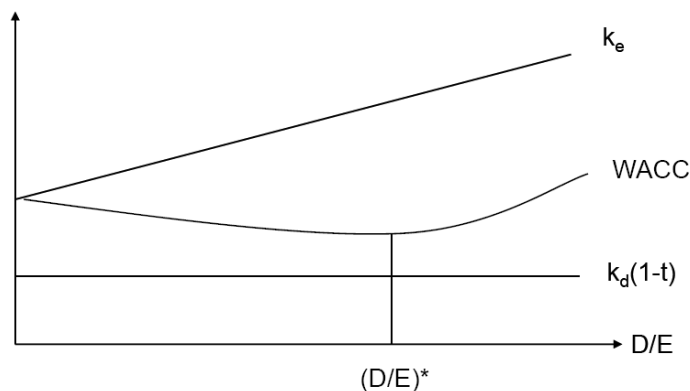
Figure 5: MM world with corporate tax[15]

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[13] Wu (2007).
[14] Brealey, Myers and Allen (2006).
[15] Wu (2007).

Figure 5 shows the real world situation with both, tax and market imperfections. According to Brealey, Myers and Allen (2006), debt provides a corporate interest tax shield and may spur managers to work harder. However, the use of debt has also its drawbacks because it may lead to costly financial distress. In practice there also exist potential conflicts of interest between security holders and information problems that favor debt over equity. Thus capital structure and trade credit affect a firms cost of capital and the value of a firm. Hence, even though trade credit may improve a firm's capital structure it may also increase its costs.

Miller (1977) concludes that the use of liabilities reduces the cost of capital to the corporation. But in fact in the real world firms cannot obtain as much financing from debt as they want. Additionally, with higher leverage the interest rate on debt will rise because of the rising possibility of bankruptcy. Rising interest rates on the other side reduce a firm's profitability. For example 100 % debt financing would definitely force a firm into bankruptcy and its interest rate on debt would rise to infinite. This means that trade credit can contribute to reduce a firm's cost of capital until a certain amount. This proposal holds only if the marginal corporate tax rate is lower than the implicit interest rate of trade credit which is frequently not the case because implicit interest rates range from about 20 % to 350 % and marginal corporate tax rates are normally not higher than 50 %. The discussion of MM and the pecking-order theory has shown that trade credit is an important determinant of capital structure.

2.4 Benefits and theories of trade credit

Why firms rely on trade credit, what are the benefits for both, sellers and buyers? Why act supplier firms as financial intermediaries although they are not specialized in it? And, last but not least, why do they act like banks and provide working capital or short-term finance to its buyers? The next section sheds light on some of these questions by highlighting the main benefits. With respect to the main theories of trade credit the main aspects, similarities and opposing positions will be discussed and reviewed.

Trade credit financing has several advantages. Meltzer (1960) discusses the incidence of changing monetary policy on individual business' mercantile credit. He shows when money tightens firms with large cash balances increase the average length of time they grant credit. Note that during tight monetary policy money or loans are more difficult to obtain in a given country. The early literature argues that trade credit is extended by unsophisticated market participants to secure sales. Bierman and Hausman (1970) present credit granting models to find a trade-off between restrictive and permissive credit granting. These models quantify the expected value of future credit extension opportunities. Schwartz (1974) found that firms with better access to capital have an incentive to offer financing to clients without alternative sources of finance. Lee and Stowe (1993) present a model where there is a separating equilibrium in which the size of the cash discount (the trade credit policy) conveys information about product quality. The driving forces of their equilibrium are risk-sharing motives of the supplier and buyer as well as asymmetric information about product quality.

Petersen and Rajan (1997) are the first presenting evidence why firms extend trade credit and which firms are the largest providers and users of trade credit. They found that the decision to take advantage of early payment discount is driven not by the implicit cost of trade credit but by whether the firm has an alternative source of finance like bank credit. The latter and former literature suggest that firms use more trade credit when they are unable to obtain funds from the financial sector. One theory is about the provision of finance to firms with less credit availability by more profitable firms via interest rate arbitrage. For theories with different credit availability see Biais and Gollier (1997), Smith (1987) and Emery (1984). Due to the leverage effect bank credit is frequently taken by profitable firms. These firms then provide financing to firms without alternative sources of financing via trade credit. However, Frank and Maksimovic (2005) note that this form of financing is not efficient.

Petersen and Rajan (1997) argue that it appears that suppliers have an advantage in financing growing firms, especially when their credit

quality is opaque. They conjecture three potential reasons: (1) Firms may be a source of future business; (2) Firms may obtain information from product market transactions at fewer costs from market transactions and (3) Suppliers appear to rely on their ability to repossess goods and to sell them again. They further argue that suppliers may be better than specialized financial institutions in evaluating and controlling the credit risk of their customers, that suppliers may have an advantage over financial institutions in monitoring and that they may get hard and soft facts at lower costs and also faster from product market transactions and other suppliers.

Theories with superior information of suppliers over financial institutions are provided by Smith (1987), Brennan, Maksimovic and Zechner (1988) amongst others. Fact is that banks are normally more specialized in the provision of credit. However, a comparative advantage of firms over banks is that they know the industry better and that they have advantages in obtaining information about a buyer's creditworthiness. Preve (2004) presents a literature review of trade credit theories where suppliers have an advantage over financial institutions in obtaining information about a buyers' creditworthiness and ensuring repayment.[16]

According to Ng, Smith and Smith (1999) trade credit terms offer firms contractual solutions to reduce informational asymmetries between buyers and sellers. Therefore trade credit terms are important in firms were informational asymmetries are high, for these firms the pecking order theory applies better than the trade-off theory of capital structure. Because of the better information acquisition by suppliers, trade credit users and suppliers have advantages when there are adverse selection problems as in Meyers and Majluf (1984).

Burkart and Ellingsen (2004) report that moral hazard and cash diversion problems may be less important for interfirm relationships than for bank-firm relationships. This means that firm to firm relationships may have an advantage over bank-firm relationships because of less information

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[16] E.g.: Smith (1987), Mian and Smith (1992), Lee and Stowe (1993), Long, Malitz and Ravid (1993), Deloof and Jeggers (1996), Biais and Gollier (1997), Emery and Nayar (1998), Burkart and Ellingsen (2004) and Frank and Maksimovic (2005).

asymmetry or easier monitoring capabilities due to continuous business contacts and knowing the industry better. Huyghebaert (2006) argues that repeating orders allows suppliers to collect more timely information on customer's creditworthiness. Suppliers may visit the buyer's premises more often and the time and size of the buyer's orders give them an idea of the creditworthiness. If a buyer does not take advantage of early payment discounts, it can be an indicator for the deterioration of a buyer's creditworthiness. By monitoring repayment, suppliers get a quick read on a firm's financial and economic health (Smith, 1987).

Other researchers concentrated on the aspect of transaction costs, for example Ferris (1981) and Petersen and Rajan (1997). Ferris (1981) argues that trade credit may reduce the transaction costs of paying bills. Instead of paying bills with every delivered good, bills are frequently paid cumulatively, i.e. monthly or quarterly. Another example is when sales vary seasonally but production stays constant over the year and hence warehouse costs and costs for financing arise. Further, Petersen and Rajan (1997) argue that by offering trade credit selectively across customers and over time, the firm may be able to manage its inventory position better. Bougheas, Mateut and Mizen (2009) present a model concerning the trade-off between the costs of holding inventories and obtaining future cash by granting trade credit. Their theoretical model provides predictions to the response of accounts payable and accounts receivable to changes in inventories, profitability, risk and liquidity. Furthermore, they check their predictions by testing them on a panel of UK firms. They find that accounts payable and accounts receivable respond less to inventories in large firms than they do in small firms.[17] An interpretation of this is that large firms are less influenced by the trade-off of current credit sales and future cash sales because their holding costs are lower.

Another important theory of trade credit is the theory of price discrimination as analyzed by Brennan, Maksimovic and Zechner (1998). A common argument for price discrimination is the suppliers' possibility to set

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[17] Firms are considered to be large when its total assets are in the top 25 percentile of all the firms in that particular industry and year. The remainder are small firms.

unfavorable trade credit payment terms to risky customers. By law it is forbidden to offer goods at different prices but firms can price discriminate by offering different credit terms. According to Brennan, Maksimovic and Zechner (1988) permits it a firm to lower its price to firms whose goods are sensitive to changes in price.[18] Petersen and Rajan (1997) assume that credit terms are usually invariant or independent set to the credit quality of the buyer. Since trade credit exposes a supplier to default risk, the effective price of the credit is lower for low-quality borrowers and allows risky borrowers to extend its demand. If a risky buyer's demand is more elastic in the short run, the supplier can stimulate sales. Petersen and Rajan (1997) found that the higher the profit margin the more likely the supplier offers credit because of higher levels of accounts receivable of them. They also argue that low quality borrowers are the most price elastic in the short run. A negative result is presented by Burkart and Ellingsen (2004). They state that the price discrimination theory has a shortcoming because the theory cannot account for trade credit in competitive markets. Their theory of monitoring advantage of suppliers applies only on input transactions. They argue that bank credit and trade credit can be either complements or substitutes. They are complements for firms whose aggregate debt capacity constrains investment and they are substitutes for firms with sufficient aggregate debt capacity.

Next, note that a buyer may obtain his goods only from a very limited number of suppliers. If so, this gives the supplier the potential to cut off future supplies when the borrower takes actions that reduce the chances of repayment, especially when the buyer accounts only for a small portion of the suppliers sales. This argument of Petersen and Rajan (1997) is only valid, if a supplier has numerous buyers and if she is not dependent from sales with one or a few buyers. In this case she cannot threat to cut future supplies that easily. Actually a supplier may has to grant permissive credit terms to generate enough cash to survive or actually has to accept late payment with taking discount anyway.

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[18] Other discussions of price discrimination are presented by Meltzer (1960), Mian and Smith (1992), Petersen and Rajan (1997) and Pike et al. (2005).

A sub-theory of price discrimination and informational advantage is the theory of "implicit equity financing" in a repeated relationship. Implicit equity financing in customers is a non-salvageable investment that has the potential of adverse selection and the character of an option. It offers the supplier a high potential for future business from firms with high sales growth but with suspect credit quality (current losses). A possible consequence could be that it may destroy firm value in the short run but expected future cash flow and long term firm value will be high. Petersen and Rajan (1997) state that "... the supplier has an implicit equity stake in the firm equal to the present value of the margins he makes on current and future sales of the product to the firm." Bierman and Hausman (1970) state that if credit is not granted then a firm may not only lose today's sales but may also lose future sales. Hence, providing short-term financing and therefore supporting the survival and growing, especially of new and relatively more elastic customers is in the long-term interest of a supplier because of potential future business with it.

Other arguments for implicit equity financing are for example that the provision of finance to suppliers may be more profitable especially in an economic boom when they need more liquidity to expand and when one firm is highly dependent on the other. Wilner (2000) states that firms with high profit margins have a strong incentive in equity financing because by this they will make additional sales. They can cut prices for new possible customers as long as their profit on the next unit is higher than the cost to sell an additional unit at a lower price. However, they are recommended to do this no longer as it does not affect previous sales.

Ng, Smith and Smith (1999) state that a supplier's stake in a relationship may far exceed the implicit equity stake of a financial institution because of the potential for a continuous repeated business relationship. Despite the risk of default of payment or even of a total loss suppliers have advantages in liquidating collateral or certain types of inventories as perceived by Longhofer and Santos (2003). Wilner (2000) and Cuñat (2007) among the most important ones explain that suppliers and

their customers may have a common interest in mutual survival, that they have an interest in maintaining long-term relationships with their customers and that they have an implicit equity stake in the buyer due to shared rents from ongoing business relationships. Furthermore they argue that trade creditors that depend on their customer's business grant more credit to financially distressed firms than banks in order to maintain their relationship.

Other benefits of trade credit are that the credit period permits the buyer to check the product quality before payment and to reduce a sellers' uncertainty concerning a buyers' payment intentions. Signaling aspects are on further aspect that comes to mind when covering trade credit theories. Wilson and Summers (2002) argue that trade credit is a signaling of reputation and financial health. Lee and Stowe (1993) interpret trade credit as an implicit warranty guaranteeing product quality.[19] Note that the buyer normally has a net period over which to test the product to determine whether the product or the delivered goods are of satisfactory quality before making payment. A seller can signal good product quality by offering two-part terms in order to give the buyer more time to check the product. So if a good does not fulfill a buyer's expectations, she can refuse payment and return the good. However, once the buyer pays, normally she can only get refund or seek legal relief for unsatisfactory merchandise. Hence, redemption may be costly and difficult. This means that a buyer that pays early and takes the discount bears the product risk. Further, Lee and Stowe (1993) interpret the difference between the credit and cash price as the price of warranty attached to the product. In order to guarantee product quality sellers may choose either trade credit or legal product warranty. At this point may appear the question why sellers use trade credit rather than product warranty to signal product quality? By giving trade credit in addition to the (legal) warranty the supplier reduces the buyer's product risk. For some products like drugs it is difficult for the buyer to prove if the delivered products quality is lower than the promised. When the buyer has

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[19] For signaling aspects in the context of product quality see also Smith (1987), Long et al. (1993) and Pike et al. (2005).

the option to refuse payment and when the delivered product does not fulfill the buyer's expectations than trade credit may be seen as the strongest form of product warranty. Furthermore, sellers with no reputation or history have frequently no established relationships. These normally small or young firms may have difficulties in selling products with a regular warranty because they are less honored due to of the risk of bankruptcy. For example Long et al. (1993) found that firms extend more credit when the company size is smaller and produce goods that require a relatively long time to assess quality. Buyer and seller reputation are therefore determinants of a firm's choice to extend trade credit. Consequently, the better known the product quality is, especially when asymmetric information is low, and the more confidence in the buyer, the more two-part terms will be used. Furthermore, trade credit permits suppliers to reduce the doubt of a prospective buyer whether the supplier goes bankrupt and consequently losing the regular warranty claim.

If a buyer defaults, the supplier can seize the supplied goods. This argument may be limited by bankruptcy laws. Mian and Smith (1992) and Petersen and Rajan (1997) argue that the more durable goods are and the less they are transformed the better collaterals they are. Better collaterals positively correlate with the amount of credit the supplier is able to grant. Financial institutions may also reclaim assets to pay off the loan but suppliers costs of repossessing and reselling will be lower if the supplier has a network for selling its goods. Biais and Gollier (1997), Burkart and Ellingsen (2004) and Frank and Maksimovic (2005) argue that suppliers have a comparative advantage in liquidating inventories and better enforcement capabilities. Note that Fisman and Love (2003) found that accounts payable and inventory holdings are positively related. An interpretation of this is that firms that hold large amounts of raw material inventories are better able to obtain trade credit financing when necessary.

The efficiency enhancing aspect of trade credit and trade credit as a part of an optimal selling policy are discussed by Burkart and Ellingsen (2004) and Arya et al. (2006). Former develop another theory of trade

credit. While earlier theories concentrate on monitoring advantages of suppliers, the new aspect in their theory is that it exclusively applies to input transactions. They argue that inputs are less easily diverted than cash and that inputs are more easily observed by suppliers and therefore are less subject to moral hazard. Since monitoring costs are therefore lower for suppliers, trade credit can enhance efficiency. A further interesting aspect provided by them is that firms offer trade credit despite the necessity to take bank credit and/or trade credit to finance their operations. They claim that firms simultaneously provide and use trade credit because receivables can be collateralized. When an invoice is pledged as collateral, it becomes illiquid from the firm's perspective and the firm can obtain additional finance from banks against the receivables. Hence, an additional Euro offered in trade credit does not really force a firm to reduce its real investment by the same amount. Burkart and Ellingsen aim to proof their predictions empirically in the future.

Arya (2006) shows that offering trade credit is able to enhance the efficiency of incentive contracts with sales personnel. A credit sale gives the client a second possibility to generate enough cash and this, in turn, gives the sales agent another opportunity to demonstrate his past diligence to the firm.

Preve (2004) sheds light on the relationship between corporate financial distress and trade credit. He finds that financially distressed firms receive more trade credit from their suppliers. This is consistent with the predictions of Frank and Maksimovic (2005). It seems that trade credit usage increases during periods of financial distress and that financially distressed firms extend less trade credit to their buyers. The last finding contradicts the argument of Frank and Maksimovic (2005) who argue that firms whose prospects start to deteriorate try to boost their sales by increasing the grant of trade credit. The distinction may be in the timeline respectively the period short before entering into financial distress and the period of entering and staying in it. When firms note that they will enter into financial distress soon, they try a rebound by stimulating sales by granting

more trade credit. When they are in financial distress they may try to sell relatively less on credit to generate enough liquidity to survive. A counter-argument is that financially distressed firms with low market power may be forced to sell on credit in order to attract more customers. Huyghebaert (2006) argues that compared to banks, suppliers are relatively lenient towards firms in financial distress which is treasured especially by entrepreneurs who highly value control rights. Molina and Preve (2009) study the receivables policy of distressed firms as a trade-off between a firm's willingness to gain sales and the firm's need for cash and estimate costs of financial distress.

Another important advantage of trade credit is that suppliers provide to its buyers liquidity and allows them to increase their leverage which in turn may reduce its tax payment. Note that its use implies a trade-off between tax advantages and costs of financial distress resulting from possible bad debts.[20]

In summary in this section we have seen that trade credit policy might reduce information asymmetry and conveys information about product quality. Furthermore trade credit allows to price discriminate and improves a buyer's working capital, which is one important advantage of trade credit.

2.5 Financial crisis at firm level

After having covered the main advantages of trade credit this section concentrates on literature that focuses on the case where firms are distressed or have financial problems. This stream of literature is related to the fact that financial distress may influence the use and grant of trade credit and this in turn may influence its liquidity and creditworthiness and hence may move a firm into financial distress.

Financial distress at firm level means that firms face problems to generate enough money to pay off their liabilities. According to Brealey, Myers and Allen (2006) financial distress occurs when promises to creditors

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[20] See chapter 2.3.

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are broken or honored with difficulty. This can force a firm into bankruptcy or close to bankruptcy. According to Huyghebaert (2006) financial distress or financial constraints are a major reason for using trade credit. For example Petersen and Rajan (1997) show that bank credit constrained firms tend to rely more on trade credit. In addition they note that managers in distressed firms tend to keep up sales with respect to low credit quality customers in order to maintain business with them. Another explanation provided by them is that financial distressed firms try to signal financial strength like strong firms. Strong firms offer credit and weak firms try to imitate them. This means that suppliers are forced to extend relatively more trade credit which causes potential costs of financial distress.

Gianmarino (1989) and Gertner and Scharfstein (1991) showed the importance of the costs of financial distress. These costs were measured by Altman (1984), Andrade and Kaplan (1998) and Opler and Titman (1994).[21] The pioneer work by Altman (1984) measures the costs of financial distress, the indirect costs of bankruptcy. He measures the loss of market share and unexpected losses of profits for firms that later went bankrupt. Later Opler and Titman (1994) analyze the costs of financial distress. They classify the costs of financial distress in three categories: (1) customer driven costs, (2) competition driven costs, and (3) managerial driven costs. The first includes the loss of sales due to the aversion of customers to buy products of distressed firms. The second includes the costs caused by competitors attacking the distressed firm's position. The last costs are a benefit caused by the higher effort from a manager due to the distressed situation of the firm. They found that the costs of financial distress driven by lower operating profit and loss in market share are positive and significant.

Andrade and Kaplan (1998) address direct and indirect costs of financial distress and note that Altman (1984), who found large indirect cost of financial distress, does not distinguish them from negative operating shocks. They state that the difficulty to measure the costs of financial distress lies in the inability to distinguish whether the poor performance by a

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[21] Other relevant contributions to financial distress are provided by DeAngelo and DeAngelo (1990), Brown, James and Mooradian (1993, 1994) among others.

firm in financial distress comes from the financial distress itself or by factors that brought the firm into financial distress in the first place. Andrade and Kaplan (1998) state also that the firms examined by Asquith, Gertner and Scharfstein (1994) are not only financial distressed, but also economically distressed.[22] This makes it difficult to identify whether they measure costs coming from financial distress, economic distress, or an interaction of them.

The sample of Andrade and Kaplan (1998) consists of highly leveraged transactions that become financially, not economically distressed. They state that their sample is mainly financially distressed because their firms have positive operating margins during distressed periods and operating margins that typically exceed the industry median.[23] This means that these firms would appear healthy relative to other firms in the industry without their high leverage. They found that the primary cause of distress is high leverage, whereas poor firm performance and poor industry performance are less important. Andrade and Kaplan (1998) conclude for their sample of financially distressed firms that costs of financial distress are between 10 and 20 % of total firm value. Interestingly they found no evidence that distressed firms engage in any asset substitution.

Preve (2004) found for a US sample that firms tend to use a significantly larger amount of trade credit from suppliers when they are in financial distress. Additionally he showed that trade credit acts as a substitute for other sources of financing like financial credit and shareholder's equity. Furthermore, from a cross sectional analysis across firms and industries he observes variations in the effect of financial distress on trade credit. Notice the following variations. The increase of trade credit is mostly in small firms. Retail industries do not increase their level of trade credit in financial distress and do not substitute between trade credit and financial credit during financial distress. Manufacturing industries use less

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[22] Economic distress means distress from macro-economic factors respectively economic crisis.
[23] Operating margins are calculated by dividing Earnings before interest, taxes, depreciation and amortization by sales (EBITDA/sales).

trade credit than non-manufacturing firms. Finally, financially distressed firms whose creditworthiness is more difficult to observe by financial institutions tend to substitute financial credit with trade credit. Frank and Maksimovic (2005) show that firm's whose prospects start to deteriorate, frequently respond by increasing the size they offer trade credit. Their theory is supported by the empirical findings of Preve (2004). They interpret financially distressed firms as low type buyers which are allowed to "stretch the payables" whereas high type buyers pay on time. They note that many practitioners recommend stretching payments and collecting receivables to increase profitability. Jostarndt (2006) investigates corporate responses to financial distress. He analyses the impact of distress on corporate governance, a firms choices between private workouts and formal insolvency procedures as well as the role of claimholder conflicts in distressed equity offerings. He argues that the major costs of financial distress result from the fact that managers in fear of existence are detained from doing business as usual.

Molina and Preve (2009) study the trade receivables policy of distressed firms as the trade off between the firm's willingness to gain sales and the firm's need for cash. They divide financial distress in two stages: The pre-financial distress stage, usually with profitability problems, and the financial distress stage, usually with cash flow problems. An additional outcome is that firms increase trade receivables when they have profitability problems but reduce trade receivables when they have cash flow problems. They further found that the performance decline of a firm during financial distress is significantly higher if the firm cuts receivables than if it does not.

To conclude, there are various theories of trade credit and we have seen that a firm's decision to take advantage of early payment discount depends frequently on whether it has alternative sources of finance or not. The aspects and theories of trade credit show that despite its costs it has several advantages as well. Furthermore the literature shows that firms use more trade credit when funds from the financial sector are not available. Hence, financially distressed firms tend to use more trade credit.

The next chapters (Section 3, 4 and 5) provide the empirical part of the work and investigate the use of trade credit by distressed European firms. Notice that a very similar approach as Preve (2004) is used since he studies the effect of the extreme condition of financial distress on trade credit for the US. Section 3 covers a data description, explains the variables and the estimation strategy. Section 4 includes the methodology, hypotheses, the panel data analysis and interpretation of the basic model. The sample is tested for whether firms use more trade credit during financial distress and for the substitution effect. The last tests if other sources of financing as trade credit like long term debt and equity provide financing when European firms are in financial distress. Additionally distressed French firms of the sample are tested on the use of trade credit and the substitution effect. In section 5, the firm size is used as a characteristic to measure the effect of financial distress on trade credit as well as the substitution effect between trade credit and other sources of financing. In Section 4 and 5 comparisons with findings from the literature, especially with those of Preve (2004) will be done. The last section (Section 6) concludes and empirical implications and suggestions are given by the author.

3. Sample description, main variables and summary statistics

This section motivates the sample, defines the variables and consequently summary statistics give a better understanding of a firm's choice of finance in interaction with financial distress and its variation over time. Afterwards chapter 4 and 5 investigate the effect of financial distress on trade credit empirically. In general a very similar methodology as the one in Preve (2004) is used. Therefore, annual panel data from Datastream from 1997 to 2007 are selected. The data consists of firms from the "Datastream Europe EM Index", an index containing 1360 companies of the European Economic and Monetary Union (EMU).[24] Companies with the following characteristics are eliminated: Those that reported net sales of less than Euro 1 million, those that do not report positive costs of goods sold, those with relevant missing data from the Datastream data retrieval as well as firms whose data were retrieved twice.[25, 26] To classify the firms by industry the Datastream "Level 3 Sector Name" is used and as is customary in this type of research, all companies in the banking, insurance, real estate and financial service industry are eliminated.[27] After this selection process 905 companies remain in the sample with a total number of 9,955 observations.

The selected sample henceforth is called "sample". The main variables used in the diploma thesis are summarized and defined in Table 1. Table 2 presents the industry classification identifying each of the industries and including some selected summary statistics from the data. Table 3 presents the firms' countries.

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[24] Preve (2004) uses US Compustat data of the years 1978 to 2000. In 1978 his sample contains 4,000 firms growing to 6,600 firms in the late 1990s. Originally for the study was planned to do an analysis for the period 1985 to 2007 but in the first decade there is too many missing data.

[25] Preve (2004) eliminates companies with net sales of less than $ 1 million.

[26] The Datastream retrieve contains some companies twice and three times with total identical figures and identical company names, only the retrieve "Type" is different, a number that identifies the company. Duplicates like "Bayrische Motoren Werke Aktiengesellschaft", "Buzzi Unicem SPA, Fiat SPA etc. are eliminated.

[27] The classification comprises 19 sectors.

Table 1: Summary of the Main Variables

This table summarizes the main variables used in models.

Measures of trade credit		
TCCGS360	trade payables over cost of goods sold	Measures the trade credit (in days) scaled by the transaction that generated it (Purchases proxied by cost of goods sold).
TRCA	trade payables over total assets	Measures what portion of the assets is financed by suppliers.
TCFD	trade payables over financial debt	Measures the relation between trade credit and financial debt.
TRCE	trade payables over equity	Measures the relation between trade credit and equity.

Measures of Distress		
FINDIST FINDIST_LAG	Dummy Var. = 1 if the firm is in financial distress – (1 Lag). Alternative measure – 0 lags.	A firm is in financial distress (FD) if: EBITD < Interest Payments for two years in a row, **Or**, EBITD < (80% * Interest Payments) in any year
FDYS	Number of years that a company has been in financial distress.	Sum of years in which FINDIST = 1 for a given company.
TIMELINE	Identifies at what stage of the financial distress process the company is.	Zero indicates that the firm entered in financial distress in the same year. Positive numbers indicate the years spent in financial distress, and negative numbers indicate the distance to entering in financial distress.
TROUBLE	Dummy variable = 1 if the firm has FINDIST=1 at any moment in the sample life.	This variable indicates if the firm enters into financial distress at any time during the sample time.

Variables for Firm and Industry Characteristics		
LARGE_S	Auxiliary variable = 1 if a single observation shows sales higher than the median industry sales on a yearly basis.	This variable is a time variant auxiliary variable.
MAX_LARGE_S	Dummy variable = 1 if a single observation of large_s = 1 during sample life time.	Indicates large firms that were large at least once. Hence, this is a time invariant variable.
PRE_LARGE_S	Dummy variable = 1 if a firms sales were above the yearly median of its industry in the pre-financial distress period (during TIMELINE = -1). Note that timeline automatically covers financially distressed firms.	Indicates large firms that were large in the pre-financial distress period in a given year. Note that PRE_LARGE_S is time invariant.
FINDIST_LAG_PRE_LARGE_S	Dummy variable = 1 if pre_large_s = 1 and if findist_lag = 1 on a yearly basis.	Is an interaction term of pre_large_s and findist_lag that identifies firms that were big in the pre-financial distress period (at TIMELINE = -1) and already in financial distress the year before Timeline = -1. Note that this variable is time variant.

Table 2: Industry Division and Summary Statistics

This table presents the Datastream "Level 3 Sector Name" industry division along with selected summary statistics for the industries. **Nobs** is the number of observation and **Nfirms** is the number of firms in each industry whereas **Freq** is the Frequency. **FD** is the number of observations in financial distress and **FD %** is the percentage of observations in financial distress in each industry. **TR.** is the number of TROUBLE firms and **TR. %** is the percentage of firms in financial distress in each industry. **TRCA** is the average value of Trade Payables on Assets and **TCCGS** is the average value of Trade Payables on Cost of Goods Sold in each industry.

Ind	Industry Name	Nobs	Nfirms	Freq.	FD	FD %	TR.	TR. %	TRCA	TCCGS
1	Automobiles & Parts	352	32	3.5%	11	3.1%	6	18.8%	0.144	0.212
2	Basic Resources	418	38	4.2%	20	4.8%	8	21.1%	0.100	0.184
3	Chemicals	396	36	4.0%	22	5.6%	11	30.6%	0.120	0.169
4	Construct. & Material	869	79	8.7%	20	2.3%	10	12.7%	0.160	0.185
5	Food & Beverage	759	69	7.6%	16	2.1%	11	15.9%	0.129	0.215
6	Healthcare	704	64	7.1%	95	13.5%	22	34.4%	0.090	0.354
7	Ind. Goods & Services	2,244	204	22.5%	78	3.5%	38	18.6%	0.121	0.224
8	Media	572	52	5.7%	33	5.8%	17	32.7%	0.132	0.413
9	Oil & Gas	506	46	5.1%	44	8.7%	12	26.1%	0.122	0.407
10	Pers & Househld Goods	616	56	6.2%	20	3.2%	11	19.6%	0.136	0.237
11	Retail	550	50	5.5%	7	1.3%	4	8.0%	0.208	0.162
12	Technology	748	68	7.5%	99	13.2%	34	50.0%	0.125	0.464
13	Telecommunications	165	15	1.7%	20	12.1%	8	53.3%	0.090	0.688
14	Travel & Leisure	451	41	4.5%	32	7.1%	17	41.5%	0.083	0.228
15	Utilities	605	55	6.1%	13	2.1%	6	10.9%	0.086	1.003
∑		9,955	905	100%	530	5.3%	215	23.8%		
ø						5.9%		26.3%	0.123	0.343

The firms have a median in sales of Euro 639.80 million and a mean of Euro 3,685.24 million.[28] The median book value of assets is Euro 698.15 million and the mean Euro 4,841.77 million. Table 2 shows that the Industrial Goods and Service Industry represent the biggest industries in the sample with 22.5 % whereas for example the retail industry only makes up for 5.52 %. 53.3 % of the firms in the Telecommunication sector are at least once in financial distress during the sample period.

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[28] The level of sales and assets are deflated using the Consumer Price Index of the EU15 countries (CPI-EU15 index). The yearly growth rates of sales and assets are calculated in constant values of year 2005.

Table 3: Countries

This table presents the **Countries** according to the International Security Identification Number (ISIN) of the firms respectively the securities of the sample. In other words, for the classification the Datastream retrieve "ISIN Issuer Country" is used. **Nobs** is the number of observations per country and **Freq** is the frequency of the observation per country scaled on the whole sample.

Country	ISSUER COUNTRY	Nobs	Freq.
1	Netherlands Antilles	11	0.11%
2	Austria	341	3.43%
3	Belgium	605	6.08%
4	Switzerland	12	0.12%
5	Germany	1,881	18.90%
6	Spain	979	9.83%
7	Finland	440	4.42%
8	France	1,980	19.89%
9	Gabon	11	0.11%
10	United Kingdom	22	0.22%
11	Greece	363	3.65%
12	Ireland	373	3.75%
13	Italy	1,100	11.05%
14	Luxembourg	187	1.88%
15	Monaco	11	0.11%
16	Netherlands	1,056	10.61%
17	Portugal	451	4.53%
18	Slovenia	121	1.22%
19	Senegal	11	0.11%
	Total	9,955	100.00%

It can be seen that the "Datastream Europe EM Index" is an index mainly with firms located in the European Monetary Union. However, it seems that there are some exceptions; see countries 1, 4, 9, 10, 15 and 19. For example the Netherlands Antilles and Gabon do not have the EURO as their official currency. The company "Hunter Douglas NV" is a company from the Netherlands and Switzerland but has its registered office in Netherlands Antilles. Hence, Datastream classificates it as an European Monetary Union firm although the shares are issued outside the Union. The shares of the companies may be issued abroad because of tax advantages. Note that running the regressions from Table 5 without the 6 countries commented above results in nearly no differences, hence they are left in the sample. Note that France is the country with the biggest fraction in the sample.

3.1 On the measurement of financial distress

Preve (2004) uses a standard definition of financial distress (FINDIST) based on the coverage ratio defined in Asquith, Gertner, and Scharfstein (1994). To calculate FINDIST, EBITD is used instead of EBITDA because of lack of data for "A" respectively amortization causing that less firms will tend to correspond to financial distress.

Defining the dummy variable **FINDIST**, a firm is in financial distress if: [29]

- $(EBITD_{t-1} < Interest\ Payments_{t-1})$ and $(EBITD_t < Interest\ Payments_t)$

Or

- $(EBITD_t < Interest\ Payments_t * 80\ \%)$

In words a firm is considered to be in financial distress if it fails to generate enough EBITD to meet the interest payments for year t and t-1 or if it fails to generate enough EBITD to cover at least 80 % of the interest payments in a given year. In the regression analysis this variable is used with a one-year lag **(FINDIST_LAG)** to observe firms going into distress and then measure the effects on the firm's trade credit one year later when the effects of financial distress appear. Since yearly data is used, financial distress cannot be defined on an accurate date. Therefore it is not possible to control how far from the end of the fiscal year the firm started having problems that moved it into financial distress. Averaging across years and industries, 6.2 % of the observations in the sample correspond to firms in financial distress. Notice that the sample of Preve (2004) shows much more firms in financial distress.[30] An explanation of the differing amount of firms corresponding to financial distress may be a result of different accounting

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[29] FINDIST is equal to 1 if the firm is in financial distress and 0 otherwise.

[30] In the sample of Preve (2004) correspond 17.52 % of the observations to financial distress. To increase the number of observations corresponding to financial distress I tried to change the second criteria in the definition of FINDIST. A change of the above criteria to "Interest Payments * 120 %" results in 6.4 % and an increase to 380 % results in 17.56 % observations in financial distress. Anyway I keep up the standard definition with the 80 % criteria.

standards, the different time horizon respectively different macroeconomic factors as well as that Preve (2004) uses a much broader sample containing more small firms which in general tend to be more often in financial distress (see also below).
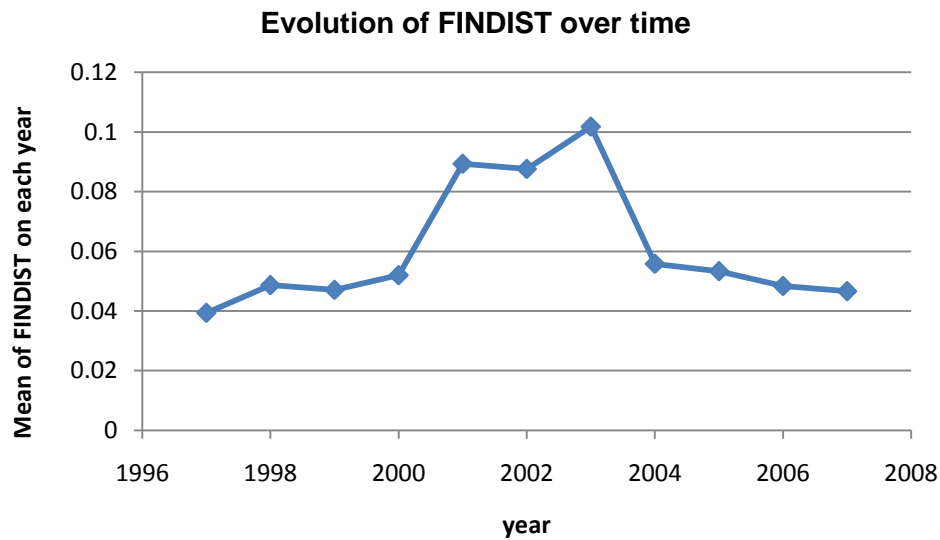
Figure 5: Evolution of FINDIST over Time
The graph shows the evolution of FINDIST over time. FINDIST is a dummy variable that identifies firms in financial distress.

The graph shows the evolution of the number of firms in financial distress during the sample period. Notice the sharp increase of firms in financial distress from 2000 to 2003. This could probably be explained by the "dotcom crisis" 2000 and the recession in the Western countries during 2000 and 2001.[31]

To get the information if the firm enters into financial distress at any time during the 11 year sample period a dummy variable **TROUBLE** is introduced. If a firm is in financial distress at some moment then TROUBLE is equal to 1, and 0 otherwise. Splitting the sample by TROUBLE, 215 firms (23.8 % of the sample) correspond to firms in the group of TROUBLE = 1 and the remaining 690 firms (76.2 % of the sample) are in the group of TROUBLE = 0. Notice that the size of the firms

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[31] The pair wise correlation between the yearly mean of FINDIST and the real GDP growth of the EU 15 between 1998 and 2007 is -0.76.

with TROUBLE = 1 is significantly smaller than the size of those with TROUBLE = 0. This means that the sample contains much more healthy firms than distressed ones. The average level of CPI-adjusted sales is Euro 2,512.86 million for firms with TROUBLE = 1 and Euro 4,052.01 million for TROUBLE = 0. A difference can also be observed when measuring size by CPI-adjusted assets; the average level of CPI-adjusted assets is Euro 4,092.24 million for firms with TROUBLE = 1 and Euro 5,075.98 million for TROUBLE = 0. Notice that the firms of Preve (2004) are on the average smaller in terms of sales and assets.[32] In detail, average sales and assets are much lower for the TROUBLE = 1 and TROUBLE = 0 group and hence for the whole sample because he uses a much bigger index and the bigger the sample the more observations and small firms it contains. Hence, since small firms tend to have financial problems more often, more firms correspond to financial distress.

To identify firms that enter financial distress more than once in the sample a variable called **LOTTROUBLE** is created. It counts the number of times a firm enters financial distress. 158 firms enter financial distress only once in their sample life, 51 firms enter twice, 5 enter three times, and 1 firm enters four times during the sample time (firms that correspond twice or more often in a row to financial distress are counted to enter into financial distress only once).

For the purpose of this research it is interesting to identify the firms that enter into distress in the sample time and follow them throughout their distress process. To get information about the number of years a firm has spent in financial distress (while it is in distress) a counter variable called **FDYS** is defined. FDYS is the sum of years where FINDIST equals 1 in a row. Every time a firm is no longer classified as distressed, the variable FDYS is reset to zero. The implicit assumption in this specification is that a firm that goes out of financial distress is a firm that has undergone a successful restructuring process. FDYS allows to control for the time that

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[32] The average numbers of Preve (2004): CPI-sales $550MM for TROUBLE=1 and $2,388MM for TROUBLE=0; CPI-assets $567MM for TROUBLE=1 and $2,609MM for TROUBLE=0.

the firms spent in financial distress which can be relevant in the level of trade credit.

The variable **TIMELINE** is introduced with the aim to follow through time those firms that enter into financial distress at some moment in the sample period (similar to Preve (2004)). When a firm enters into financial distress TIMELINE takes the value 0. From there on, and using the variables FINDIST (that identifies the firms in financial distress in the present year) and FDYS (that counts the years in financial distress in a row), TIMELINE increases by one unit each year the firm stays in financial distress. This variable gives information about how many financially distressed years a firm has already gone through until a given moment in time (positive values of TIMELINE) as well as how far a healthy firm is from becoming financially distressed (negative values of TIMELINE). Table 4 shows the distribution of the firms in the TIMELINE along with some summary statistics.

Table 4: Distribution of firms along the Timeline

This table shows the distribution of firms along the Timeline and some selected summary statistics. The variables are defined in Table 1. **Nobs** is the number of observation in each group and Freq is the Frequency. **TRCA** is the average value of Trade Payables on Assets and **TCCGS** is the average value of Trade Payables on Cost of Goods Sold in each group. **SALES(cpi)** and **ASSETS(cpi)** in million Euro are the average value of Net Sales and Total Assets in each group. Both variables are presented in constant values of Year 2005. Notice that Timeline represents firms that are at least once in financial distress during their sample life time. The last line represents statistics of the group of TROUBLE = 0, the firms that never enter into financial distress (whereas Timeline automatically represents the TROUBLE = 1 group). A table with winsorized variables can be found in the appendix.

Timeline	Nobs	Freq	TRCA	TCCGS	SALES(cpi)	ASSETS(cpi)
-10	6	0.26%	0.0527	0.1228	478.51	625.13
-9	16	0.71%	0.1156	0.1350	2,552.77	1,928.02
-8	29	1.28%	0.1603	-3.4425	1,742.27	1,857.07
-7	40	1.77%	0.1517	-0.3802	2,018.60	1,847.22
-6	80	3.53%	0.1505	0.3080	1,631.73	1,856.24
-5	111	4.90%	0.1434	0.3564	2,391.94	3,424.71
-4	145	6.40%	0.1418	0.2809	2,814.30	4,124.77
-3	159	7.02%	0.1396	0.3646	2,743.63	4,221.60
-2	172	7.59%	0.1298	0.2833	2,723.59	4,634.03
-1	190	8.38%	0.1236	0.2538	2,656.05	5,542.33
0	695	30.67%	0.1370	0.2596	3,234.30	5,101.32
1	260	11.47%	0.1189	0.4199	2,958.64	4,964.37
2	152	6.71%	0.1288	0.4751	990.69	1,625.29
3	97	4.28%	0.1225	0.6623	344.46	761.36
4	56	2.47%	0.1415	1.4229	270.80	628.12
5	27	1.19%	0.1227	0.6443	134.05	727.65
6	21	0.93%	0.1596	1.7858	237.72	362.75
7	4	0.18%	0.0411	0.2826	15.48	67.94
8	3	0.13%	0.0675	0.6853	20.31	68.75
9	2	0.09%	0.0482	0.0000	2.11	42.52
10	1	0.04%	0.0367	0.0000	2.17	133.92
Total	2,266	100%				
TROUBLE = 0	7,689		0.1243	0.3024	4,039.67	5,081.52

3.2 On the measurement of trade credit

Like Preve (2004) trade credit is measured in this work by scaling it on cost of goods sold (CGS) defining the following variable:

$$TCCGS360 = \frac{TradePayables}{CostofGoodsSold} \times 360$$

The median value of **TCCGS360** in the sample is 59.5 days.[33] This variable relates trade credit to the transaction that has generated it and shows the amount of purchases financed by trade credit.[34] Using purchases in the denominator would be more exact but because the lack of data it is relied on cost of goods sold excluding depreciation as a proxy.[35] Preve (2004) states that the use of this proxy brings in a negative bias in the measurement of TCCGS that is proportional to the value that the companies add to the product they sell. Companies with more value added (firms with a larger difference between CGS and purchases) will use an inaccurately high value in the denominator, causing TCCGS to be downward biased.

In order to test the substitution provided by trade credit in the firm's capital structure, like in Preve (2004) three variables that capture different measures of trade credit as a portion of the capital structure are used. The first, **TRCA** is defined as the ratio of trade payables to the book value of assets, the second, **TRCE** as trade payables to the book value of equity (common shareholders' equity), and lastly, **TCFD** as trade payables to the book value of long term debt.[36]

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[33] The sample of Preve shows 39.3 days.

[34] This variable is widely used by practitioners to assess the payables ratio. Preve notes that the real trade credit on cost of goods sold is actually larger than the one measured by this variable. The bias goes against the results and is therefore not worrying when interpreting them.

[35] See Preve (2004).

[36] Preve (2004) uses in the denominator of TCFD total financial debt whereas this study uses long term debt.

$$TRCA = \frac{TradePayables}{TotalAssets}$$

$$TRCE = \frac{TradePayables}{Equity} \qquad TCFD = \frac{TradePayables}{LongTermDebt}$$

TRCA shows the amount of financing that the firm obtains from suppliers as a percentage of the total capital. This means that it shows which portion of the firm's assets is financed by suppliers. TRCA is used as a scaling variable in several papers measuring trade payables.

TCFD measures the substitution of trade credit and long term debt when firms are in financial distress. It is expected that trade credit substitutes financial credit when the latter is unavailable. Using TCFD as the dependent variable should provide evidence on it showing a positive sign in the coefficient for the financial distress variable.

TRCE, a variable similar to TCFD measures the substitution effect between trade credit and equity.

Evolution of TCCGS and TRCA over time
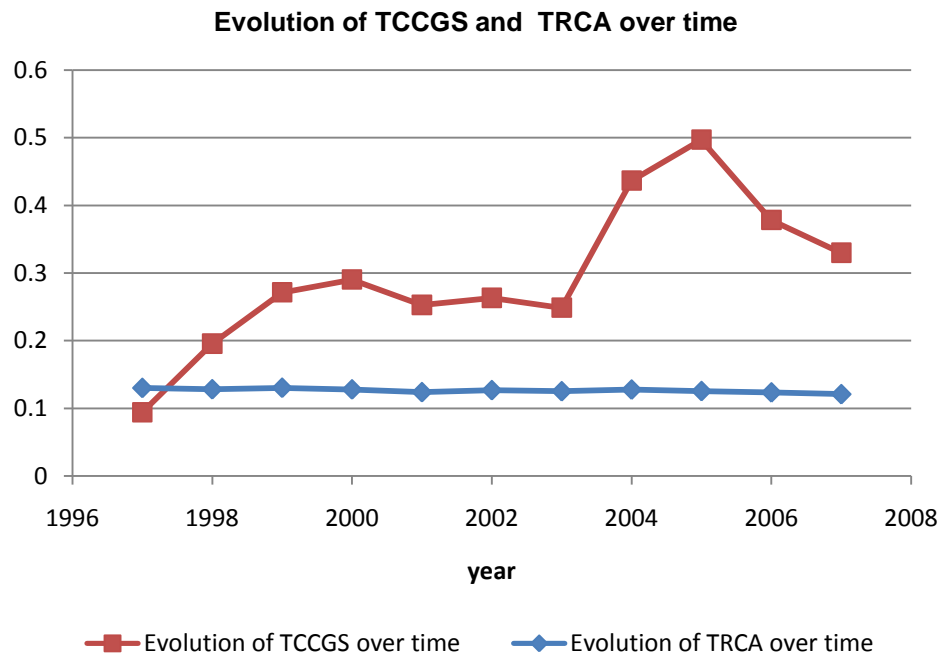
Figure 6: Evolution of TCCGS and TRCA over time

The panel shows the evolution of TCCGS and TRCA (Trade Credit on Cost of Goods Sold and Trade Credit on Assets) over time.

Evolution of Sales and Assets over time
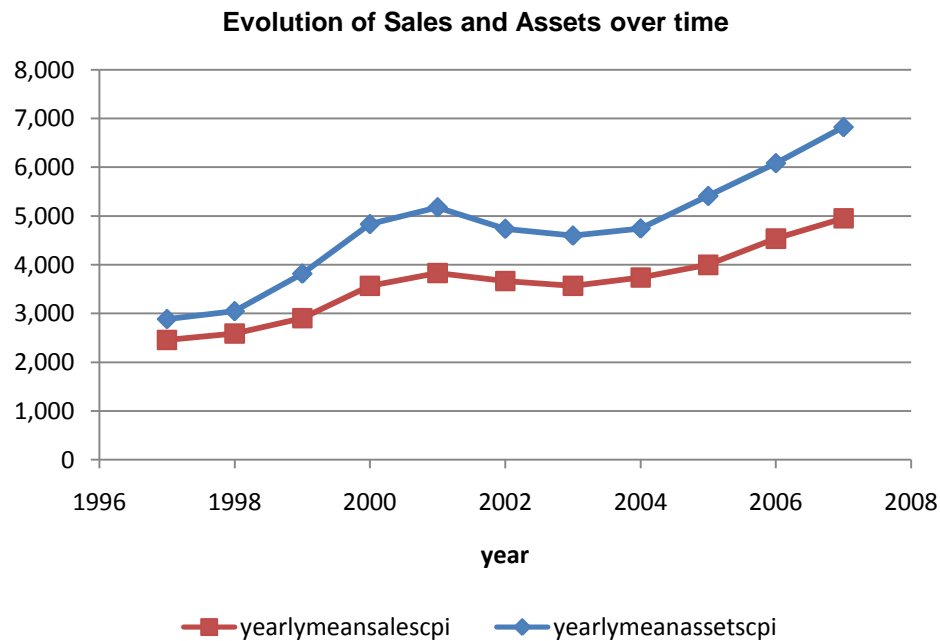
Figure 7: Evolution of Sales and Assets over time

The panel shows the evolution of the level of net sales and total assets (in million Euro) of the firms over time.

Figure 6 shows that during the 11 years, TCCGS displays a positive trend while TRCA a slightly negative one. Since trade credit is generated by

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and closely related to sales, a slight decrease in TRCA can be observed despite an increase in TCCGS.[37] Hence, the amount of purchases financed by trade credit increases over time especially in periods of an economic boom whereas the portion of assets financed by suppliers decreases slightly over the whole sample period.[38] Note that the correlation coefficient of TRCA and TCCGS is 0.0752 and the trend over time tends to differ significantly.[39] This trend may be caused by cost of goods sold that grew less than assets over the sample period. An interpretation of this is that in an economic boom respectively periods of high growth, firms use relatively more trade credit to finance purchases. A further interpretation is that firms may grant more trade credit in periods of an economic boom and consequently firms use more trade credit to finance their purchases. Note that firms may use more trade credit additionally to other sources of finance in order to finance their high growth.

The panel in Figure 7 shows that assets increase slightly more than sales. Additionally, it is very important to study the assets and sales of distressed firms over time. This is due to the tendency that firms in financial distress undergo asset sales and that they experience a decrease in their sales.[40]

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[37] Both measures of trade credit use trade payables in the numerator, but TRCA has a denominator (assets) that grows faster than that of TCCGS. TCCGS is scaled by cost of goods sold and is highly correlated with sales (pair wise correlation between sales and cost of goods sold is 0.98).

[38] Simplified, 1997 to 2000 and 2003 to 2006 are classified as economic boom the periods whereas the years 2000 to 2003 as economic bust period.

[39] The pair wise correlation between GDP growth and the yearly mean of TCCGS is -0.12 while the correlation between GDP growth and the yearly mean of TRCA is 0.30. Notice that these correlations are lower than those in Preve (2004). A reason for the low correlation may be the "dotcom crisis" 2000 reflecting the credit shortage in the market crash.

[40] For asset sales see Asquith, Gertner and Scharfstein (1994), Brown, James and Mooradian (1994) and Pulvino (1998); for decreases in sales see Altman (1984) and Opler and Titman (1994).

Growth Rate of Assets
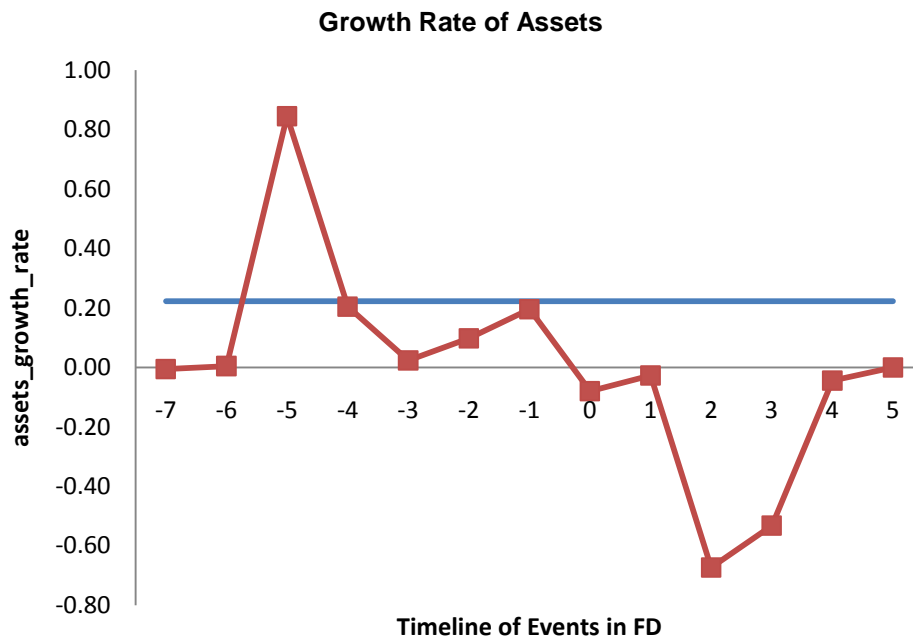
Figure 8: Evolution of the growth rate of Assets

The graph shows the evolution of the growth rate of assets and the TIMELINE. The growth rate of assets is calculated using CPI-adjusted levels of assets. The plotted variable represents the firms in financial distress (TROUBLE = 1 group) whereas the horizontal line in the graph represents the non time varying mean of the plotted variable in a sub-sample of firms that have TROUBLE = 0. Notice that for the graph the non time varying mean and the growth rates are winsorized with p(0.01). Timeline = 0 represents the moment in which the firm enters in financial distress.

Growth Rate of Sales
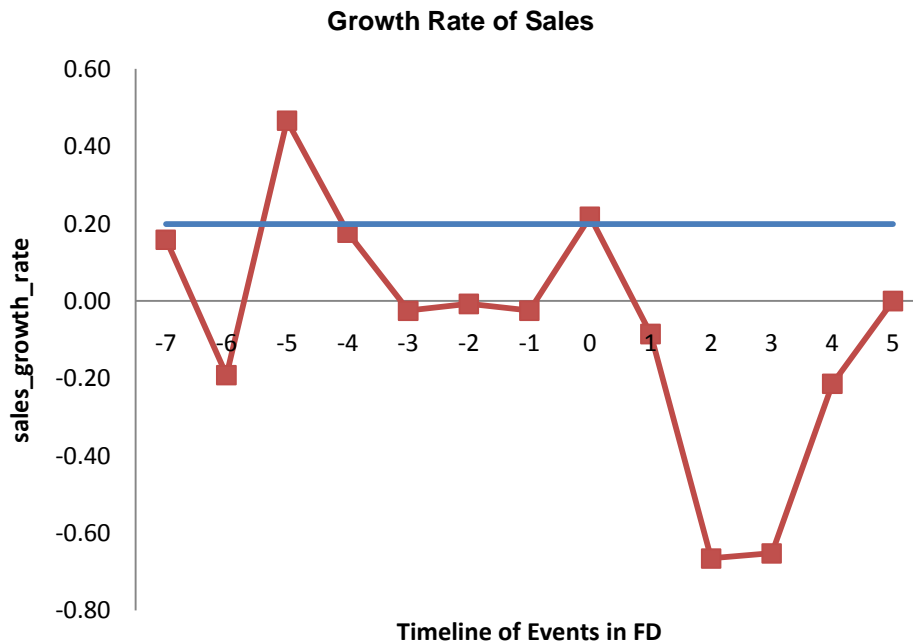
Figure 9: Evolution of the growth rate of Sales

The graph shows the evolution of the growth rate of sales and the TIMELINE. The growth rate of sales is calculated using CPI-adjusted levels of assets. The plotted variable represents the firms in financial distress (TROUBLE = 1 group) whereas the horizontal line in the graph represents the non time varying mean of the plotted variable in a sub-sample of firms that have TROUBLE = 0. Notice that for the graph the non time varying mean and the growth rates are winsorized with p(0.01). Timeline = 0 represents the moment in which the firm enters in financial distress.

The graphs in Figure 8 and 9 help to understand the asset sales effect and the decrease in sales during financial distress. They show an analysis of the behavior of net sales growth and total assets growth during the period of time covered by the TIMELINE. The plotted variable with quadratic points shows the behavior of a sub-sample of firms that enter financial distress at a given point in the sample (TROUBLE = 1 group). To obtain a reference point in the graphs, a horizontal line representing the non-time-varying mean of the plotted variable for the rest of the sample is drawn (TROUBLE = 0 group). Note that TROUBLE = 0 represents firms that do not enter financial distress during the sample time whereas firms with TROUBLE = 1 represents firms that enter into financial distress at least once during the sample period. Notice that TIMELINE = 0 represents the moment in which the firm enters into financial distress.

The graphs further show that the growth rate of assets and sales is affected in a similar way by the firms entering into financial distress.[41] The assets growth drops significantly and is well below the horizontal line of the non-troubled firms, reflecting the need for cash of the firms in financial distress. Furthermore the figures show that a firm's assets growth is reduced by 67 % during TIMELINE = 2 whereas sales also drop by 67 %. The decrease in sales may be interpreted by a company's internal problems and loss in confidence in a firm's products and the survival of a firm in general. When a firm is in financial distress then customers are at risk to lose for example the product warranty in case of the bankruptcy of the supplier. Notice that Petersen and Rajan (1997) found that firms have a greater extension of trade credit when they have negative income and negative sales

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[41] The sample shows few firms with the maximum values of TIMELINE = 10 and -10, hence the graph is cut at TIMELINE = -7 and 5.

growth. Consequently, firms with negative sales growth should tend to have higher receivables because they frequently try to boost their sales by granting trade credit to low quality customers.
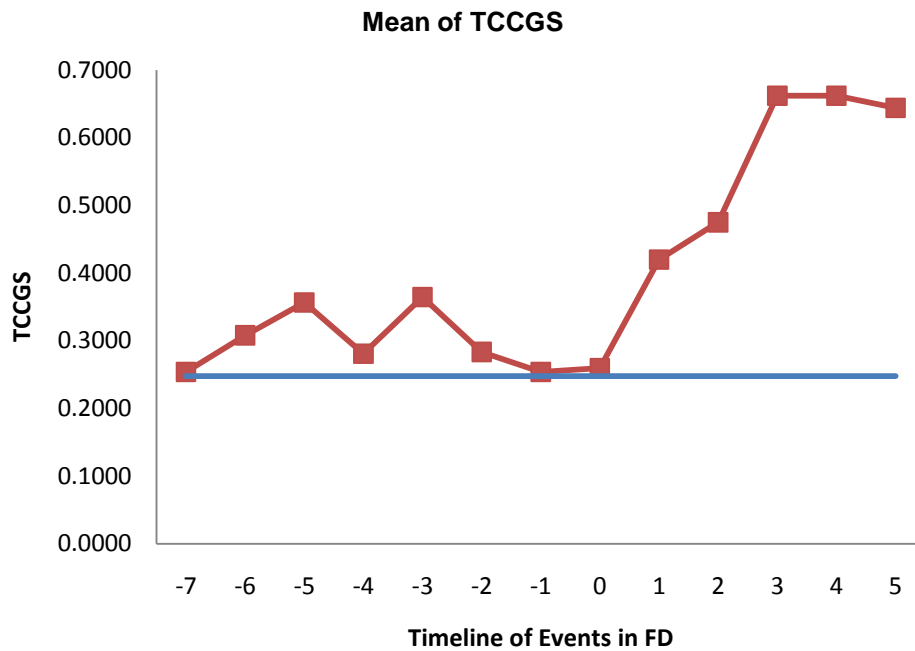
Mean of TCCGS

Figure 10: Evolution of the mean of TCCGS

The graph shows the evolution of the mean of TCCGS (trade payables on cost of goods sold) and the TIMELINE. The plotted variable represents the firms in financial distress (TROUBLE = 1 group) whereas the horizontal line in the graph represents the non time varying mean of the plotted variable in a sub-sample of firms that have TROUBLE = 0. Notice that for the graph the non time varying mean and the mean of TCCGS are winsorized with p(0.01). Timeline = 0 represents the moment in which the firm enters in financial distress.
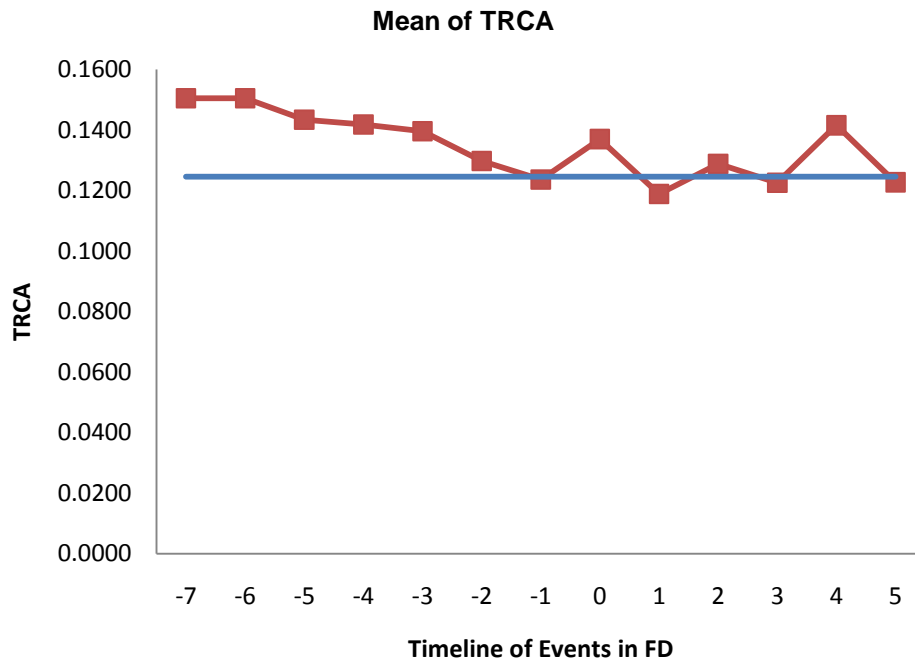
Mean of TRCA

Figure 11: Evolution of the mean of TRCA

The graph shows the evolution of the mean of TRCA (trade payables on total assets) and the TIMELINE. The plotted variable represents the firms in financial distress (TROUBLE = 1 group) whereas the horizontal line in the graph represents the non time varying mean of the plotted variable in a sub-sample of firms that have TROUBLE = 0. Notice that for the graph the non time varying mean and the mean of TRCA are winsorized with p(0.01). Timeline = 0 represents the moment in which the firm enters in financial distress.

Figure 10 and 11 show the behavior of TCCGS and TRCA along the TIMELINE when firms enter into financial distress. The graph in Figure 10 shows that firms in financial distress use more trade credit because the TCCGS line rises well above the horizontal non-time-varying mean of not distressed firms. There is a clear peak in TCCGS after firms enter financial distress. Notice that until TIMELINE = 5 there is a trend towards the use of trade credit to finance purchases. Furthermore it is interesting that firms in the TROUBLE = 1 sample use trade credit more frequently during the whole TIMELINE.

In contrast to Preve (2004) a departure from the horizontal line in the last years before entering into financial distress cannot be observed , rather the opposite respectively not until TIMELINE = 0. He suggests that firms that start sliding down in profitability start using more expensive and "forgiving" trade credit and replace the cheaper but "stricter" financial credit. An interpretation could be that European firms react to profitability problems slower than US firms. Hence, they start increasing the use of trade credit not before entering into trade credit. Molina and Preve (2009) report for firms in the pre-financial distress stage profitability problems and an increase in trade receivables whereas for firms in the financial distress stage they suggest cash flow problems and a decrease in trade receivables.[42] Consequently it is expected that financially distressed European firms reduce the amount of trade credit they offer whereas Figure 10 suggests that they increase the use of trade credit.[43]

The graph in Figure 11 shows for TRCA no clear tendency after firms enter into financial distress. However, firms in the TROUBLE = 1

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[42] Notice that Preve (2004) examines trade payables whereas Molina and Preve (2009) trade receivables.

[43] Notice that in the empirical part of this study only trade payables are examined.

group as represented by the graph by the line with the quadratic points show mostly higher levels of TRCA (higher TRCA and hence higher trade payables or higher portion of assets financed by suppliers) than the rest of the sample (the horizontal line).

3.3 On the other control variables

Like Preve (2004) in this model some other control variables are used, specifically for size and sales growth. Larger firms are expected to use their market power in trade relations, especially when they can choose among a large number of clients. Wilner (2000) found that if one party generates a large percentage of its partners profits, it is more willing to enter into a seemingly unfavorable contract. Hence, dependent companies grant more trade credit. In order to control for this asymmetry of power measures like **LNSALES** and **LNASSETS** are defined.[44]

Likewise it is controlled for sales growth in the model as firms with sharpe increases or decreases in sales may experience it from exogenous factors. Hence, it is likely that these firms show similar changes in trade payables. Consequently, by suppliers such firms may are seen as fast growing firms which may positively affect the amount of trade credit their offer, or the opposite when sales decrease steeply. To control for variations in sales growth the variable **WDIFSALES_SLES** is used as the difference of $SALES_t$ and $SALES_{t-1}$ scaled on $SALES_{t-1}$. Notice that this growth rate is winsorized with p(0.01) to reduce the impact of outliers and potential erroneous data points.

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[44] Preve (2004) uses in some models additionally a firm's market share and the Herfindahl index of the industry to measure market power respectively to control for the asymmetry of power.

4. Empirical Analysis of the Base Case Model

The observation consists of a panel of European Monetary Union firms over an 11 year period. The firms show, both, variations in time series and cross sectional patterns that are captured in the model. Likewise Preve (2004) a variable for firm-level unobserved factors that might affect the amount of trade credit the firms receive from suppliers is used. Chapter 4 analyses the response of trade credit to financial distress and the substitution effect.

4.1 The Methodology

To analyze the trade credit that distressed firms receive from their suppliers, the following equation is used:

$$TC_{it} = \gamma_i + \beta_1 * FINDIST\_LAG_{it} + \psi * X_{it} + \varepsilon_{it} \qquad (1)$$

The dependent variable, TC_{it} is a measure of trade credit. **FINDIST_LAG** is the first lag of the financial distress at firm level and X_{it} is a matrix of controls. γ_i is a vector of dummy variables for firms and countries in the fixed effects estimation, and dummy variable for industries and countries in the pooled OLS model. The matrix of control includes a measure of size, typically LNASSETS and the sales growth, WDIFSALES_SLES. In certain specifications $FDYS_{it}$ (and $FDYS^2_{it}$) controls for the time that the firms spent in financial distress. The estimations with pooled OLS include clustering procedures, for example for firms (company cluster) in the computation of the standard errors for the purpose to tolerate an unspecified correlation between different observations of the same firm in the sample.

As a first approach equation (1) is estimated on the sample to get the amount of trade credit firms use in financial distress. Positive coefficients for FINDIST_LAG would imply that financially distressed firms use more

trade credit from suppliers than healthy ones. The results are presented in Table 5 and 6.

4.2 The response of trade credit to financial distress

If suppliers support firms in financial distress, β_1, the coefficient of the dummy variable identifying financially distressed firms, FINDIST_LAG, should be positive and significant. More specifically, in the model without FDYS the coefficient, β_1, tells how many more days of trade credit are taken by firms in financial distress (with respect to non-distressed firms). One of the specifications of the model controls for the time that the firm has spent in financial distress, which may be an important factor in trade credit. The coefficient on FDYS controls for this and provides some indication on the shape of the effect of financial distress as a function of time. This information however, comes at a certain cost in terms of multicollinearity, since the correlation coefficient between FINDIST_LAG and FDYS is, fairly high.[45] Note that the correlation of FDYS and $FDYS^2$ is very high as well. Furthermore, the joint use of them in a model results in insignificant coefficients for both. Hence, in contrast to Preve (2004) only models with FDYS but without $FDYS^2$ are reported since this improves the coefficients on FDYS due to the multicollinearity of FDYS and $FDYS^2$.[46]

Likewise Preve (2004) it is assumed that suppliers can force a firm into bankruptcy but it is not possible for them to send it into financial distress. In detail, one supplier's reduction of trade credit cannot bring healthy firms into financial distress. However, suppliers can force financially distressed firms to file for bankruptcy if they are not repaid on time.

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[45] The correlation of FINDIST_LAG and FDYS is 0.62.
[46] The correlation of FDYS and $FDYS^2$ is 0.88 and the correlation of FINDIST_LAG and $FDYS^2$ is 0.46. The results with $FDYS^2$ are not reported but can be provided on request.

Table 5: Trade Credit and Financial Distress

This table shows the results of the estimation of Equation (1) for trade payables. The Dependent Variable is **TCCGS**, Trade Payables on Cost of Goods Sold. **FINDIST_LAG** is a dummy variable that is 1 if a firm is in financial distress as defined in the diploma thesis and 0 otherwise. **FDYS** is a variable that counts how many years the firm has spent in Financial Distress. **WDIFSALES_SLES** is the first difference in sales scaled by sales, notice that this variable is winsorized at $p(0.01)$. **LNASSETS** is the natural log of total assets. The sample is a selected sample as described in chapter 4 of the Datastream "Europe EM" index from 1997 to 2007. The value of t-stats is shown in brackets. T-stats that are clustered imply robust standard errors. Coefficients with *** are significant at 1% level, ** at 5%, and * at 10% in a two-tails test. Model 1 and 2 are company fixed effects models. Model 3 is a random effects model. Model 4 to 9 are the main regressions with country and industry fixed effects. Model 10 to 15 are pooled OLS models.

VARIABLES	(1) TCCGS360	(2) TCCGS360	(3) TCCGS360	(4) TCCGS360	(5) TCCGS360	(6) TCCGS360	(7) TCCGS360	(8) TCCGS360	(9) TCCGS360	(10) TCCGS360	(11) TCCGS360	(12) TCCGS360	(13) TCCGS360	(14) TCCGS360	(15) TCCGS360
findist_lag	-31.09	-40.87*	-23.51	70.99***	67.89***	70.99	-18.94	-18.79	-18.94	77.80**	77.80*	77.80*	-13.46	-13.46	-13.46
	(-1.568)	(-1.901)	(-1.202)	(2.817)	(2.661)	(1.626)	(-0.607)	(-0.598)	(-1.175)	(2.302)	(1.773)	(1.792)	(-0.828)	(-0.679)	(-0.751)
wdifsales_sles	-9.764	-10.58	-6.895	28.08*	28.67**	28.08	27.02*	29.17**	27.02	36.50*	36.50	36.50	36.70	36.70	36.70
	(-0.911)	(-0.970)	(-0.651)	(1.943)	(1.968)	(1.367)	(1.833)	(1.963)	(1.315)	(1.652)	(1.608)	(1.486)	(1.624)	(1.571)	(1.515)
fdys		9.552					65.41***	64.51***	65.41**				67.72**	67.72**	67.72**
		(0.965)					(5.076)	(4.973)	(2.728)				(2.497)	(2.213)	(2.771)
lnassets										7.176	7.176	7.176	8.639**	8.639	8.639*
										(1.611)	(1.299)	(1.387)	(1.984)	(1.593)	(1.785)
Constant	107.6***	107.2***	129.2***	95.83***	95.90***	95.83***	94.15***	93.89***	94.15***	-54.19	-54.19	-54.19	-86.53	-86.53	-86.53
	(26.03)	(25.41)	(5.943)	(15.29)	(15.22)	(10.63)	(14.92)	(14.79)	(10.48)	(-0.613)	(-0.545)	(-0.530)	(-1.006)	(-0.896)	(-0.916)
Observations	7271	7226	7271	7271	7271	7271	7226	7226	7226	7270	7270	7270	7225	7225	7225
R-squared	0.001	0.001	.	0.019	0.013	0.019	0.023	0.017	0.023	0.003	0.003	0.003	0.006	0.006	0.006
Adjusted R-squared	-0.137	-0.138								0.00222	0.00222	0.00222	0.00590	0.00590	0.00590
F test	1.630	1.553		6.447	5.942	5.726	12.95	12.42	6.432	4.033	6.679	4.576	3.469	6.695	5.908
Number of company	880	880	880												
Prob >F	0	0		0.00159	0.00264	0.0152	1.96e-08	4.26e-08	0.00580	0.00730	0.00351	0.0196	0.00802	0.00200	0.00532
Model	Fixed Effects	Fixed Effects	Random Effects	Fixed Effects	Fixed Effects	Fixed Effects	Fixed Effects	Fixed Effects	Fixed Effects	Pooled OLS	Pooled OLS	Pooled OLS	Pooled OLS	Pooled OLS	Pooled OLS
absorb	company	company		country	industry	country	country	industry	country						
cluster						industry			industry	company	country	industry	company	country	industry

Table 6: Trade credit and Financial Distress with 380 % criteria

This table shows the results of the estimation of Equation (1) for trade payables. The Dependent Variable is **TCCGS**, Trade Payables on Cost of Goods Sold. **FINDIST_LAG** is a dummy variable that is 1 if a firm is in financial distress and 0 otherwise, notice that for this table a 380 % criteria instead of the 80 % standard definition from chapter 3.1 is used in order to get a similar percentage of firms in financial distress as Preve (2004). **FDYS** is a variable that counts how many years the firm has spent in Financial Distress. **WDIFSALES_SLES** is the first difference in sales scaled by sales, notice that this variable is winsorized at p(0.01). **LNASSETS** is the natural log of total assets. The sample is a selected sample as described in chapter 4 of the Datastream "Europe EM" index from 1997 to 2007. The value of t-stats is shown in brackets. T-stats that are clustered imply robust standard errors. Coefficients with *** are significant at 1% level, ** at 5%, and * at 10% in a two-tails test.

VARIABLES	(1) TCCGS360	(2) TCCGS360	(3) TCCGS360	(4) TCCGS360	(5) TCCGS360	(6) TCCGS360	(7) TCCGS360	(8) TCCGS360	(9) TCCGS360	(10) TCCGS360	(11) TCCGS360	(12) TCCGS360	(13) TCCGS360	(14) TCCGS360	(15) TCCGS360
findist_lag	-0.380	3.390	4.457	48.81***	58.10***	48.81**	34.14*	36.92*	34.14	59.61**	59.61**	59.61**	39.81	39.81	39.81
	(-0.0293)	(0.239)	(0.349)	(3.161)	(3.765)	(2.240)	(1.712)	(1.844)	(0.886)	(2.323)	(2.668)	(2.542)	(0.945)	(1.031)	(1.017)
wdifsales_sles	-9.607	-11.64	-6.659	30.53**	30.19**	30.53	32.04**	32.82**	32.04	38.58*	38.58*	38.58	41.06*	41.06*	41.06*
	(-0.895)	(-1.060)	(-0.628)	(2.122)	(2.080)	(1.611)	(2.176)	(2.210)	(1.698)	(1.819)	(1.818)	(1.665)	(1.925)	(1.964)	(1.798)
fdys		-4.057					7.131	10.22*	7.131				9.564	9.564	9.564
		(-0.829)					(1.222)	(1.749)	(0.602)				(0.922)	(0.748)	(0.868)
lnassets										6.589	6.589	6.589	6.775	6.775	6.775
										(1.328)	(1.113)	(1.173)	(1.421)	(1.191)	(1.254)
Constant	105.9***	107.3***	126.8***	91.21***	89.72***	91.21***	90.38***	88.44***	90.38***	-48.05	-48.05	-48.05	-53.14	-53.14	-53.14
	(23.12)	(22.22)	(5.805)	(13.72)	(13.45)	(13.70)	(13.45)	(13.13)	(12.54)	(-0.470)	(-0.431)	(-0.423)	(-0.544)	(-0.502)	(-0.489)
Observations	7271	7226	7271	7271	7271	7271	7226	7226	7226	7270	7270	7270	7225	7225	7225
R-squared	0.000	0.000	.	0.020	0.014	0.020	0.020	0.015	0.020	0.003	0.003	0.003	0.004	0.004	0.004
Prob >F	1.000	1.000		0.000571	7.63e-05	0.0880	0.000900	5.12e-05	0.0298	0.0989	0.0214	0.105	0.000926	0.00935	0.0107
Number of company	880	880	880												
F test	0.401	0.548		7.476	9.493	2.906	5.502	7.513	4.008	2.098	4.203	2.472	4.704	4.747	4.950
Adjusted R-squared	-0.138	-0.139								0.00299	0.00299	0.00299	0.00328	0.00328	0.00328
Model	Fixed Effects	Fixed Effects	Random Effects	Fixed Effects	Fixed Effects	Fixed Effects	Fixed Effects	Fixed Effects	Fixed Effects	Pooled OLS	Pooled OLS	Pooled OLS	Pooled OLS	Pooled OLS	Pooled OLS
absorb	company	company		country	industry	country	country	industry	country						
cluster						industry			industry	company	country	industry	company	country	industry

4.2.1 Results and Interpretation

Tables 5 and 6 show the results of the base case models. Notice that only winsorized difsales_sles (wdifsales_sles) are used in order to reduce the impact of outliers and potential erroneous data points. Winsorizing improves the significance of the coefficients of difsales_sles slightly and the most coefficients become positive.[47]

The coefficients of determination R^2, showing the amount of variance of TCCGS360 explained by the dependent variables, are very low in all of the models. R^2's are between 0.1 % and 1.9 % implying that the models may not be appropriate for the sample. The sample of Preve shows much higher R^2's, they are around 0.7 (70 %) for the fixed effects models and around 0.15 for the pooled OLS models. This makes an interpretation of the results difficult, hence, the results have a limited explanatory power. Because of the considerable deviation to Preve (2004) it seems that there are big differences between the US market and firms of the European Monetary Union. Hence, the models of Preve for the US do not apply well for the sample. Because of this and in order to find a suitable description of trade credit behavior a large variation of regressions and clusters were calculated.

Fdys shows mostly significant coefficients implying that the duration of financial distress has an impact on the trade credit use. Lnassets shows few significant coefficients for the pooled OLS models, implying that it may not improve the model significantly. **Model (1)** with company fixed effects does not show significant coefficients compared to the result of Preve (2004, 123 (1)). Notice that this study includes relatively few observations per firm, hence, the many degrees of freedom may make a robust and significant estimation difficult. Thus, by using country fixed effects the coefficients may be better estimated. **Model (2)** with (company) fixed effects and the use of fdys shows surprisingly that distressed firms take 40.87 days less trade credit relatively to healthy ones, significant at the 10 %

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[47] The tables with "normal" difsales_sles are not reported in this diploma thesis but can be provided on request.

level. Hence the time firms have spent in financial distress improves the significance of the model compared to the model (1). The coefficient might be negative because of the low percentage of firms in financial distress. **Model (3)** with random effects does not show significant coefficients. Explaining one model more in detail, **model (4)** with country fixed effects shows a ratio of F (2, 7251) of 6.45 and a Prob > F of 0.0016. Since the Prob > F is less than 0.05, the null hypothesis that the coefficients on all variables in the model equal zero (for both findist_lag and wdifsales_sles) can be rejected with a 95 % level of confidence. Hence, the joint variables are statistically significant at the 95 % level of confidence. Absorbing the country in the model shows an F (17, 7251) of 7.541 (with P=0). Further, the coefficient on findist_lag shows that firms in financial distress take nearly 71 days more trade credit relatively to those not being in financial distress significant at the 1 % level. Furthermore, the t-value of findist_lag with 2.82 (> 1.96) shows the importance of the variable for the model. Concluding, the variable wdifsales_sles is significant at the 10 % level and hence improves the model. **Model (5)** shows a quite similar result as model (4). **Model (6)** with country fixed effects and industry cluster deteriorates the significance of the coefficient for findist_lag. **Models (7 to 9):** In order to refine the previous model more variables are used but it weakens the coefficients on TCCGS360, making them statistically insignificant and negative.[48] **Models (10 to 12)** are pooled OLS models with the additional variable lnassets and either company, country or industry clusters. The additional variable results in a positive and significant coefficient compared to model (1). The coefficient shows that firms in financial distress take about 78 days more trade credit relatively to those not being in financial distress. Notice that the additional use of lnassets in the model limits the last statement. **Models (13 to 15):** The two additional variables compared to

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[48] Notice that the clustering option adjusts standard errors for intragroup correlations. It specifies that the observations are independent across groups (clusters), but not necessarily within groups. Clustering helps in the treatment of residuals when observations repeat in time. Notice also that the company cluster implies the country and industry cluster because one firm has only one country and one industry. Finally, note that "absorb" generates dummies.

model (1) do not improve it, making the coefficients on findist_lag negative and statistically insignificant.

Table 6 can be interpreted as follows: By softening the inancial distress criteria resulting in a similar percentage of firms in financial distress like Preve (2004), the significance levels improve compared to Table 5. The time that distressed firms take more trade credit declines for example for model (4) from about 71 days to 49 days. Note that the time may get reduced because the firms that are heavily financially distressed become diluted.

Since the coefficients on findist_lag are positive and significant, insignificant but also negative and significant the model can only partly support that firms in financial distress take significantly longer terms to repay their suppliers than healthier firms. In the case of the fixed effects model (4) it can be observed that firms in financial distress take 71 more days to repay their suppliers than firms with good financial standing. Fdys shows significant coefficients which indicates the importance of the duration of financial distress on the trade credit use. However, the models with significant coefficients on fdys show no significant coefficients on findist_lag. This suggests that the duration of years firms stay in financial distress does not improve the model because of the high multicollinearity. Another interpretation is that due to the already mentioned high multicollinearity it seems that a separate identification of the time of distress is not possible. Notice that despite various models and regressions the dependent variables do not describe the variance of trade credit well as highlighted by the low R^2.

Notice that the median value of TCCGS360 (that shows the amount of purchases financed by trade credit) is higher in Europe compared to the US as well as the coefficients on findist_lag are higher in Europe. A possible interpretation of this is that American suppliers are more restrictive and do not satisfy trade credit even if buyers demand more.[49] Furthermore, the use of credit insurers may have the effect of less trade credit supply or

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[49] For typical credit periods see Figure 3.

use as they tend to cut the limits earlier. Note that in the use of credit insurers there are large variations between European countries and industries. A further reason for the different results may be different accounting systems in the US and Europe. In order not to get an averaged inclination coefficient the regressions are applied only on the country with the most observations in Chapter 4.4.[50]

Finally, notice that the results do not imply that suppliers voluntarily offer to extend longer trade credit terms to financially distressed firms or that clients postpone repayment. Anyway, the evidence indicates that the number of days it takes to repay the suppliers is higher for financially distressed debtors.

4.3   The substitution effect

It is expected that firms in financial distress increase their use of trade credit to substitute other sources of capital that become unavailable when they face financial distress. To address this point like Preve (2004) did, equation (1) is applied on different sets of dependent variables, on TRCA, TRCE and TCFD. The results are presented in Table 7 and 8. Notice, to estimate the equation, a random effects model, a pooled OLS model and fixed effect models are used for each of the alternative dependent variables.

Notice that the substitution of trade credit with TRCA shows the participation of trade payables in the capital structure. Finding a positive coefficient for the dummy identifying firms in financial distress would indicate that the relative importance of trade payables in the capital structure increases when the firm is in financial distress. From the literature it is known that firms in financial distress undergo asset sales and experience a decrease in sales. However, although asset sales result in a new level of assets, the coefficient still captures the relative importance of trade payables in the capital structure. Since TRCA does not show the relative change with respect to financial debt and equity, the two main sources of capital, TCFD

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[50] According to Table 3 is it France.

and TRCE are considered separately using them as the dependent variables of the model. As commented above, the coefficient of the dummy variable identifying firms in financial distress tells us the relative change in trade payables with respect to financial debt and equity.[51]

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[51] Notice that this work uses long term debt to calculate TCFD whereas Preve (2004) uses financial debt.

Table 7: Substitution Effect between Trade Credit and Financial Distress

This table shows the result of the estimation of Equation (1). The Dependent Variables are **TRCA**, Trade Payables on Total Assets, **TRCE**, Trade Payables on Shareholder's Equity, and **TCFD**, Trade Payables on Financial Debt. **FINDIST_LAG** is a dummy variable that is 1 if a firm is in financial distress as defined in the diploma thesis and 0 otherwise. **WDIFSALES_SLES** is the first difference in sales scaled by sales, notice that this variable is winsorized at p(0.01). **LNASSETS** is the natural log of total assets. The sample is a selected sample as described in chapter 4 of the Datastream "Europe EM" index from 1997 to 2007. The value of t-stats is shown in brackets. T-stats that are clustered imply robust standard errors. Coefficients with *** are significant at 1% level, ** at 5%, and * at 10% in a two-tails test. Model 1, 6 and 11 are company fixed effects models. Model 2, 7 and 12 are random effects models. Model 3, 4, 8, 9, 13 and 14 are the main regressions with country and industry fixed effects. Model 5, 10 and 15 are pooled OLS models.

VARIABLES	(1) TRCA	(2) TRCA	(3) TRCA	(4) TRCA	(5) TRCA	(6) TRCE	(7) TRCE	(8) TRCE	(9) TRCE	(10) TRCE	(11) TCFD	(12) TCFD	(13) TCFD	(14) TCFD	(15) TCFD
findist_lag	0.00950***	0.00856***	0.000920	0.0112**	0.0139*	1.910***	2.114***	2.194***	2.266***	2.224	-34.56**	-31.35*	-6.041	-10.90	-13.97
	(3.590)	(3.279)	(0.208)	(2.561)	(1.781)	(3.313)	(4.451)	(4.767)	(4.869)	(1.425)	(-2.004)	(-1.899)	(-0.359)	(-0.641)	(-1.155)
wdifsales_sles	0.00389***	0.00386***	0.00414	0.00777***	0.00702**	0.0258	0.194	0.219	0.167	0.228	11.02	13.04	19.38**	18.20*	19.49
	(2.740)	(2.744)	(1.608)	(3.067)	(2.177)	(0.0833)	(0.716)	(0.815)	(0.620)	(0.814)	(1.202)	(1.470)	(2.000)	(1.871)	(1.026)
lnsales					0.00622***					0.0139					-3.514*
					(4.563)					(0.256)					(-1.703)
Constant	0.125***	0.124***	0.125***	0.124***	-0.00368	0.465***	0.434***	0.417***	0.421***	0.130	24.30***	36.63***	21.45***	21.90***	94.39**
	(224.0)	(44.57)	(110.8)	(112.0)	(-0.133)	(3.836)	(3.108)	(3.548)	(3.577)	(0.123)	(6.993)	(3.468)	(5.233)	(5.339)	(2.177)
Observations	7306	7306	7306	7306	7300	7307	7307	7307	7307	7301	6775	6775	6775	6775	6772
R-squared	0.003	.	0.061	0.102	0.016	0.002	.	0.004	0.006	0.003	0.001	.	0.004	0.008	0.001
Adjusted R-squared	-0.134				0.0159	-0.136				0.00296	-0.144				0.000709
Number of company	883	883				883	883				858	858			
Prob >F	0		0.256	0.000169	1.99e-05	0		5.10e-06	4.28e-06	0.434	0		0.134	0.155	0.249
F test	10.08		1.362	8.694	8.265	5.489		12.21	12.38	0.913	2.751		2.012	1.868	1.374
Model	Fixed Eff.	Random Eff.	Fixed Effects	Fixed Effects	Pooled OLS	Fixed Eff.	Random Eff.	Fixed Effects	Fixed Effects	Pooled OLS	Fixed Eff.	Random Eff.	Fixed Effects	Fixed Effects	Pooled OLS
absorb	company		country	industry		company		country	industry		company		country	industry	
cluster					company					company					company

Table 8: Substitution Effect between TC and FD with 380 % criteria

This table shows the result of the estimation of Equation (1). The Dependent Variables are **TRCA**, Trade Payables on Total Assets, **TRCE**, Trade Payables on Shareholder's Equity, and **TCFD**, Trade Payables on Financial Debt. **FINDIST_LAG** is a dummy variable that is 1 if a firm is in financial distress as defined in the diploma thesis and 0 otherwise, notice that for this table a 380 % criteria instead of the 80 % standard definition from chapter 3.1 is used in order to get a similar percentage of firms in financial distress as Preve (2004). **WDIFSALES_SLES** is the first difference in sales scaled by sales, notice that this variable is winsorized at p(0.01). **LNASSETS** is the natural log of total assets. The sample is a selected sample as described in chapter 4 of the Datastream "Europe EM" index from 1997 to 2007. The value of t-stats is shown in brackets. T-stats that are clustered imply robust standard errors. Coefficients with *** are significant at 1% level, ** at 5%, and * at 10% in a two-tails test. Model 1, 6 and 11 are company fixed effects models. Model 2, 7 and 12 are random effects models. Model 3, 4, 8, 9, 13 and 14 are the main regressions with country and industry fixed effects. Model 5, 10 and 15 are pooled OLS models.

VARIABLES	(1) TRCA	(2) TRCA	(3) TRCA	(4) TRCA	(5) TRCA	(6) TRCE	(7) TRCE	(8) TRCE	(9) TRCE	(10) TRCE	(11) TCFD	(12) TCFD	(13) TCFD	(14) TCFD	(15) TCFD
findist_lag	0.00278	0.00253	0.000978	0.00773***	0.00844	1.062***	1.076***	1.075***	1.109***	1.053**	-13.76	-16.21	-19.11*	-16.95*	-21.72***
	(1.593)	(1.472)	(0.354)	(2.869)	(1.560)	(2.799)	(3.568)	(3.738)	(3.867)	(2.042)	(-1.265)	(-1.561)	(-1.913)	(-1.703)	(-3.123)
wdifsales_sles	0.00396***	0.00394***	0.00416	0.00808***	0.00746**	0.0639	0.270	0.311	0.243	0.303	10.39	12.16	19.54**	18.09*	19.09
	(2.782)	(2.800)	(1.623)	(3.200)	(2.320)	(0.206)	(0.998)	(1.164)	(0.906)	(0.922)	(1.131)	(1.369)	(2.026)	(1.866)	(1.005)
lnsales					0.00608***					-0.0184					-3.877*
					(4.493)					(-0.262)					(-1.890)
Constant	0.125***	0.124***	0.125***	0.123***	-0.00155	0.390***	0.364**	0.348***	0.353***	0.730	24.92***	37.79***	24.37***	24.24***	104.9**
	(202.0)	(44.33)	(104.4)	(105.1)	(-0.0561)	(2.904)	(2.476)	(2.790)	(2.833)	(0.530)	(6.423)	(3.536)	(5.588)	(5.562)	(2.415)
Observations	7306	7306	7306	7306	7300	7307	7307	7307	7307	7301	6775	6775	6775	6775	6772
Number of company	883	883				883	883				858	858			
F test	4.893		1.403	9.532	8.040	3.917		7.833	8.005	2.748	1.542		3.779	3.112	3.801
R-squared	0.002	.	0.061	0.102	0.016	0.001	.	0.003	0.005	0.002	0.001	.	0.005	0.008	0.002
Adjusted R-squared	-0.136				0.0159	-0.136				0.00176	-0.145				0.00130
Prob >F	0		0.246	7.34e-05	2.74e-05	0		0.000400	0.000337	0.0419	0		0.0229	0.0446	0.0100
Model	Fixed Eff.	Random Eff.	Fixed Effects	Fixed Effects	Pooled OLS	Fixed Eff.	Random Eff.	Fixed Effects	Fixed Effects	Pooled OLS	Fixed Eff.	Random Eff.	Fixed Effects	Fixed Effects	Pooled OLS
absorb	company		country	industry		company		country	industry		company		country	industry	
cluster					company					company					company

4.3.1 Results and Interpretation

The R^2's of the models are between 0.1 % and 10.2 % which is much better compared to the models for the response of trade credit to financial distress. Notice that Preve (2004) reports for the models of the substitution effect R^2's between 6 % and 71 %. Hence, the models are not as appropriate for firms of the European Monetary Union. The positive coefficients for findist_lag in Table 7 for model (1) and (5) indicate that firms in financial distress increase trade credit in their capital structure by almost 1 % in the fixed effects model and 1.4 % considering the results of the pooled OLS. Notice that this is a relative increase, since it is measured relative to the other sources of financing, and is therefore meaningful even taking into account that firms in financial distress undergo asset sales as noted above. In columns (6) to (10) TRCE is used as the dependent variable to measure the substitution effect of trade credit with respect to equity. With the exception of the pooled OLS model the coefficients on FINDIST_LAG are positive and significant suggesting that the level of trade payables decreases less than the book value of equity in financially distressed firms. A possible explanation for this result is that firms in financial distress incur in losses that diminish the book value of equity and thus the ratio tends to go up. However, the result suggests that the level of trade credit does not decrease at the same speed.

The columns (11) to (15) of Table 7 consider the substitution effect between trade payables and long term debt. The results for TCFD differ from those of TRCA and TRCE and those of Preve (2004). The difference may come from the fact that he uses financial debt whereas in this study long term debt is used in the denominator of TCFD. For example, the fixed effects model and the random effects model of TCFD show negative significant coefficients. This suggests that long term debt is not replaced by trade payables in the financially distressed firm's capital structure, rather the opposite is true. Table 8 with the alternative definition of financial distress (the 380 % criteria) shows also negative coefficients for the models of

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TCFD. This result is really surprising since it is against fundamental findings in the literature, the pecking order theory and contrary to that of Preve (2004). A possible explanation for this result is that TCFD is determined by unknown factors since the R^2's are very low (partly nearly 0) except for the industry fixed effects model. Note that the correlation of an unknown factor with findist_lag may produce such a surprising result. However, the result implies that banks grant relatively more credit than suppliers of trade credit to financially distressed firms.

To sum up, the results from Table 7 and 8 tend to support the hypothesis that trade payables provide a substitution for other sources of financing like total assets and equity for firms in financial distress. Notice that this study cannot support the hypothesis that distressed firms substitute long term debt with trade payables when the former is unavailable. Rather, the negative coefficient suggests that distressed firms increase their financial debt relative to trade payables. An interpretation of this result is that financially distressed European Monetary Union firms may obtain financial debt easier than trade credit and equity as they are more bank-oriented whereas US firms are more market-oriented.[52]

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[52] Rajan and Zingales (1995) classify for example France, Germany and Italy as bank-oriented countries and the US and UK as market-oriented countries.

4.4 Financial distress and trade credit for France

Preve (2004) mentioned that it would be interesting to study the reaction of suppliers to financial distress in France because Biais and Malecot (1996) report a heavy use of trade credit in France where the suppliers do not get anything in the case of bankruptcy of the debtor. Hence, this section investigates this country. Furthermore, since France shows the biggest fraction in the sample, its investigation should be illuminative as the examination of a single country does not have the drawbacks of an averaged inclination coefficient from different countries when doing regression analysis.

Notice that according to Table 3 19.89 % of the 1.980 observations represent French firms which adds up to 180 firms. From these 180 firms belong 31 firms to the TROUBLE = 1 group. To get an idea of the response of trade credit to financial distress and the substitution effect equation (1) is applied.

Table 9: Trade Credit and Financial Distress in France

This table shows the results of the estimation of Equation (1) for trade payables. The Dependent Variable is **TCCGS**, Trade Payables on Cost of Goods Sold. **FINDIST_LAG** is a dummy variable that is 1 if a firm is in financial distress as defined in the diploma thesis and 0 otherwise. **FDYS** is a variable that counts how many years the firm has spent in Financial Distress. **WDIFSALES_SLES** is the first difference in sales scaled by sales, notice that this variable is winsorized at p(0.01). **LNASSETS** is the natural log of total assets. The sample is a selected sample as described in chapter 4 of the Datastream "Europe EM" index from 1997 to 2007. The value of t-stats is shown in brackets. T-stats that are clustered imply robust standard errors. Coefficients with *** are significant at 1% level, ** at 5%, and * at 10% in a two-tails test. Model 1 and 2 are company fixed effects models. Model 3 is a random effects model. Model 4 to 9 are the main regressions with country and industry fixed effects. Model 10 to 13 are pooled OLS models.

VARIABLES	(1) TCCGS360	(2) TCCGS360	(3) TCCGS360	(4) TCCGS360	(5) TCCGS360	(6) TCCGS360	(7) TCCGS360	(8) TCCGS360	(9) TCCGS360	(10) TCCGS360	(11) TCCGS360	(12) TCCGS360	(13) TCCGS360
findist_lag	23.85	22.46	28.31	45.69**	46.60**	45.69***	39.13*	38.54*	39.13***	47.13**	47.13***	39.42*	39.42***
	(1.236)	(1.076)	(1.539)	(2.405)	(2.475)	(3.286)	(1.718)	(1.713)	(3.670)	(1.995)	(3.408)	(1.907)	(3.665)
wdifsales_sles	10.54	11.86	10.26	8.332	10.39	8.332	9.971	11.41	9.971	9.923	9.923	11.36	11.36
	(1.022)	(1.116)	(1.040)	(0.796)	(0.999)	(0.532)	(0.924)	(1.063)	(0.605)	(0.759)	(0.716)	(0.833)	(0.766)
fdys		4.023					7.470	8.234	7.470			8.293	8.293
		(0.407)					(0.734)	(0.822)	(0.970)			(1.244)	(1.178)
lnassets										2.345	2.345	2.284	2.284
										(0.870)	(0.846)	(0.843)	(0.817)
Constant	91.75***	91.14***	95.96***	91.29***	90.98***	91.29***	90.62***	90.40***	90.62***	41.28	41.28	41.91	41.91
	(27.76)	(27.04)	(11.86)	(24.08)	(24.46)	(9.516)	(23.69)	(24.06)	(9.522)	(0.707)	(0.743)	(0.713)	(0.745)
Observations	1528	1517	1528	1528	1528	1528	1517	1517	1517	1528	1528	1517	1517
F test	1.205	0.926		3.368	3.733	8.149	2.657	2.831	10.59	2.810	12.93	2.356	33.02
R-squared	0.002	0.002	.	0.004	0.057	0.004	0.005	0.056	0.005	0.005	0.005	0.006	0.006
Prob >F	0.0425	0.741		0.0347	0.0241	0.00450	0.0470	0.0372	0.000673	0.0410	0.000254	0.0556	5.45e-07
Number of company	177	177	177										
Adjusted R-squared	-0.130	-0.132								0.00350	0.00350	0.00361	0.00361
Model	Fixed Effects	Fixed Effects	Random Effects	Fixed Effects	Fixed Effects	Fixed Effects	Fixed Effects	Fixed Effects	Fixed Effects	Pooled OLS	Pooled OLS	Pooled OLS	Pooled OLS
Sub-sample	French firms	French firms	French firms	French firms	French firms	French firms	French firms	French firms	French firms	French firms	French firms	French firms	French firms
absorb	company	company		country	industry	country	country	industry	country				
cluster						industry			industry	company	industry	company	industry

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Table 10: Substitution Effect between TC and FD in France

This table shows the result of the estimation of Equation (1). The Dependent Variables are **TRCA**, Trade Payables on Total Assets, **TRCE**, Trade Payables on Shareholder's Equity, and **TCFD**, Trade Payables on Financial Debt. **FINDIST_LAG** is a dummy variable that is 1 if a firm is in financial distress as defined in the diploma thesis and 0 otherwise. **WDIFSALES_SLES** is the first difference in sales scaled by sales, notice that this variable is winsorized at p(0.01). **LNASSETS** is the natural log of total assets. The sample is a selected sample as described in chapter 4 of the Datastream "Europe EM" index from 1997 to 2007. The value of t-stats is shown in brackets. T-stats that are clustered imply robust standard errors. Coefficients with *** are significant at 1% level, ** at 5%, and * at 10% in a two-tails test. Model 1, 6 and 11 are company fixed effects models. Model 2, 7 and 12 are random effects models. Model 3, 4, 8, 9, 13 and 14 are the main regressions with country and industry fixed effects. Model 5, 10 and 15 are pooled OLS models.

VARIABLES	(1) TRCA	(2) TRCA	(3) TRCA	(4) TRCA	(5) TRCA	(6) TRCE	(7) TRCE	(8) TRCE	(9) TRCE	(10) TRCE	(11) TCFD	(12) TCFD	(13) TCFD	(14) TCFD	(15) TCFD
findist_lag	0.00245	0.000516	-0.0268**	-0.00650	-0.0137	2.418	1.799	1.799	1.731	1.910	-4.287	-4.139	0.683	3.801	5.321
	(0.342)	(0.0731)	(-2.257)	(-0.579)	(-0.753)	(1.556)	(1.554)	(1.554)	(1.464)	(0.996)	(-0.247)	(-0.241)	(0.0238)	(0.132)	(0.356)
wdifsales_sles	0.00259	0.00254	0.00580	0.0160**	0.00998	0.972	0.0855	0.0855	0.171	0.105	0.906	0.789	-3.219	-9.206	-1.272
	(0.699)	(0.692)	(0.835)	(2.434)	(1.088)	(1.210)	(0.126)	(0.126)	(0.247)	(0.266)	(0.0999)	(0.0875)	(-0.187)	(-0.536)	(-0.169)
lnsales					0.00626**					0.0405					2.604
					(2.162)					(0.224)					(0.473)
Constant	0.146***	0.145***	0.147***	0.145***	0.0145	0.238	0.388	0.388	0.379	-0.469	18.89***	35.40	19.25***	19.94***	-36.01
	(117.7)	(22.61)	(56.77)	(59.98)	(0.239)	(0.883)	(1.533)	(1.533)	(1.488)	(-0.131)	(6.275)	(1.415)	(3.052)	(3.210)	(-0.332)
Observations	1543	1543	1543	1543	1542	1543	1543	1543	1543	1542	1503	1503	1503	1503	1502
Adjusted R-squared	-0.132				0.0170	-0.129				-0.000228	-0.136				-0.00150
Number of company	179	179				179	179				179	179			
F test	0.289		2.735	3.032	2.171	1.830		1.247	1.141	1.750	0.0382		0.0175	0.150	0.214
Prob >F	1.000		0.0652	0.0485	0.0931	2.59e-09		0.288	0.320	0.159	1.000		0.983	0.861	0.887
R-squared	0.000	.	0.004	0.149	0.019	0.003	.	0.002	0.007	0.002	0.000	.	0.000	0.047	0.000
Model	Fixed Eff.	Random Eff.	Fixed Effects	Fixed Effects	Pooled OLS	Fixed Eff.	Random Eff.	Fixed Effects	Fixed Effects	Pooled OLS	Fixed Eff.	Random Eff.	Fixed Effects	Fixed Effects	Pooled OLS
Sub-sample	French firms	French firms	French firms	French firms	French firms	French firms	French firms	French firms	French firms	French firms	French firms	French firms	French firms	French firms	French firms
absorb	company		country	industry		company		country	industry		company		country	industry	
cluster					company					company					company

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4.4.1 Results and Interpretation

The median value of TCCGS360 for French firms is 71.3 days and shows that the amount of purchases financed by trade credit is higher in France than in Europe and the US.[53] This result is in line with the literature. Table 9 shows R^2's between 0.2 % and 5.6 % and are higher than the received values in previous estimations (see Table 5). This indicates that the models of the US apply better for France than for the whole sample of the European Monetary Union. However, the results are still not very meaningful. Moreover, differently to Table 5, Table 9 shows only positive and mainly significant coefficients. For example in the models (4) (5) and (6) the coefficient on findist_lag shows that French firms in financial distress take about 46 days more trade credit relatively to healthy firms. Note that for the EMU (Table 5) this study reports 71 days and Preve (2004) reports for the US 5.2 days.

The result suggests that French firms in financial distress use much more trade credit than US firms but less than the average of the European Monetary Union. However, the median value of TCCGS360 showing the amount of purchases financed by trade credit for the whole sample (healthy and distressed firms jointly) implies that France uses more trade credit than the EMU and the US. In other words, French firms use more trade credit compared to the US and EMU in general. However, in the case of financial distress French firms use less trade credit than the EMU but still more than in the US.

Next the substitution effect in France is covered. Table 10 shows nearly no significant coefficients on findist_lag and R^2's are close to zero. This indicates that the model of Preve (2004) for the US does not apply for French firms to measure the substitution effect.

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[53] Preve (2004) reports for the US 39.3 days and section 3.2 of this study reports 59.5 days for the EMU.

5. Empirical Analysis of the Extension model

In this chapter the firm size is used as a characteristic to measure the effect of financial distress on trade credit as well as the substitution effect between trade credit and other sources of financing. Comparisons will be made with Preve (2004) and other implications of the literature.

Unfortunately from balance sheet data the price respectively the terms of trade credit that would better allow estimating its demand cannot be observed. Hence, only a reduced form for the quantity of trade credit outstanding at firm level can be estimated. Because of this limitation Preve (2004) uses additionally firm characteristics that according to trade credit theories should explain the cross sectional variations in the data to get information about the response of trade credit to financial distress.

Like Preve (2004), the first equation (1) is estimated on different sub-groups of data (large and small firms) and then specific characteristics under study with the dummy identifying firms in financial distress are used. Hence this section studies the importance of size (relatively large firms and relatively small firms) to the use of trade credit during financial distress.

Additionally, Preve (2004) studies retailers (theory of deployable assets as collateral for supplier), manufacturing firms (theory of ability to repossess and resell the goods) and the asymmetry in the cost of assessing the creditworthiness of the buyer (for this he uses smaller firms and alternatively R&D and selling and general expenses as a proxy for the asymmetry in the cost of evaluating firms). Although further improvements of the model by the use of additional variables may be fruitful this study concentrates on the estimation of equation (1) and its extension with an alternative specification of size in equation (2). Anyway the use of size variables already can shed some light on the reasons that drive the reduced forms found when estimating equation (1).

5.1 Using the firm size to measure the effect of FD on TC

This model uses firm characteristics to explain firm's trade credit response to financial distress. First equation (1) is estimated on different sub-groups of data, i.e. relatively large and small firms and the whole TROUBLE sample (large and small firms combined). Secondly, specific characteristics and dummies (pre_large_s and findist_lag_pre_large_s) are used to identify firms in financial distress. This specification brings out the slope of the linear relation between financial distress and trade credit. The estimating equation for this is:

$$TC_{it} = \gamma_i + \beta_1 * FINDIST\_LAG_{it} + \beta_2 * C_{it} +$$
$$\beta_3 * (FINDIST\_LAG * C)_{it} + \beta_4 * X_{it} + \varepsilon_{it} \qquad (2)$$

C is a variable that captures firm or industry characteristics like firm size. It enters the model alone and in an interaction term with FINDIST_LAG. As a first step a firm is considered to be large if its sales are bigger than the median of its industry. Note that the median and the size are determined for each year individually. Note that the dummy C is calculated as the value of the last year before entering into financial distress (i.e. TIMELINE -1).

5.2 The importance of the size and market power

In this section first the trade credit of large and small firms in financial distress are compared. Larger firms are assumed to have better management and corporate governance. This enables to generate more reliable information and to get better access to bank financing. According to existing literature on trade credit it is predicted that larger firms use less trade credit from their suppliers.[54] Since trade credit is more expensive than for example bank credit it is expected that firms use the latter if it is

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[54] See Petersen and Rajan (1995, 1997), Preve (2004), Frank and Maksimovic (2005) and Cunat (2007) among others.

available. Extending this intuition it can be expected that larger firms use less trade credit from suppliers when they are in financial distress.

The dataset is divided into large and small firms. Firms are considered as large if their sales are larger or equal to the median of their industry in any year. The auxiliary variable **LARGE_S** is used to separate the sample and consequently equation (1) is estimated on both sub-samples.

The fact that financial distress may affect the size and, hence, the market power of the firm, there may be some concern in the interpretation of the results. To circumvent this potential criticism (like Preve (2004)), the size of the firm is computed alternatively at the last pre-financial distress period (at Timeline = -1) which generates the dummy variables pre_large_s and findist_lag_pre_large_s.[55] Pre_large_s is 1 if the firm was large at the pre-financial distress time, and 0 otherwise. The dummy is used alone and interacted with findist_lag in the estimation of equation (2). Notice that by construction this model only considers any company that will enter into financial distress during the sample period, so the sample becomes mechanically restricted to firms with TROUBLE = 1. This specification allows to see the effect of financial distress on trade credit on firms that were large before entering in financial distress.

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[55] For a definition see Table 1.

Table 11: Trade Credit, Financial Distress and Firm Size

This table shows the result of the estimation of Equations (1) and (2) for trade payables dividing the sample in **LARGE** and **SMALL** firms. The Dependent Variable is **TCCGS**, Trade Payables on Cost of Goods Sold. **FINDIST_LAG** is a dummy variable that is 1 if a firm is in financial distress and 0 otherwise. **WDIFSALES_SLES** is the first difference in sales scaled by sales, notice that this variable is winsorized at $p(0.01)$. **PRE_LARGE_S** is a time invariant dummy variable that identifies firms whose sales were above the yearly median of its industry during Timeline=-1. **FINDIST_LAG_PRE_LARGE_S** is a time variant interaction term that identifies financially distressed firms that were large in the pre-financial distress period. The sample is a selected sample as described in chapter 4 of the Datastream "Europe EM" index from 1997 to 2007. The value of t-stats is shown in brackets. T-stats that are clustered imply robust standard errors. Coefficients with *** are significant at 1% level, ** at 5%, and * at 10% in a two-tails test.

VARIABLES	(1) TCCGS360	(2) TCCGS360	(3) TCCGS360	(4) TCCGS360	(5) TCCGS360	(6) TCCGS360	(7) TCCGS360	(8) TCCGS360	(9) TCCGS360	(10) TCCGS360	(11) TCCGS360	(12) TCCGS360	(13) TCCGS360
findist_lag	-7.634	100.7***	90.66***	91.43*	-75.51***	22.38	-0.0339	22.56*	-63.52*	-5.108	-15.24	60.72*	-7.978
	(-0.299)	(2.931)	(2.611)	(1.734)	(-2.595)	(0.884)	(-0.00129)	(1.723)	(-1.961)	(-0.165)	(-0.489)	(1.735)	(-0.381)
wdifsales_sles	3.607	38.03**	38.31**	45.26	-37.03**	-2.621	-13.04	2.983	-1.540	22.75	11.51	22.75	20.53
	(0.264)	(2.010)	(2.012)	(1.579)	(-2.299)	(-0.166)	(-0.803)	(0.248)	(-0.0987)	(1.485)	(0.739)	(0.975)	(0.864)
findist_lag_pre_large_s									54.60	100.4***	99.45***		113.4*
									(1.303)	(2.656)	(2.624)		(1.942)
pre_large_s												13.41	-15.32
												(0.544)	(-0.634)
Constant	107.0***	96.02***	96.48***	95.31***	107.4***	94.84***	98.11***	93.94***	133.9***	107.1***	112.2***	97.42***	115.9***
	(21.17)	(11.88)	(11.90)	(11.18)	(15.59)	(13.29)	(13.50)	(9.424)	(13.36)	(9.868)	(10.22)	(4.822)	(5.206)
Observations	5385	5385	5385	5385	1886	1886	1886	1886	1620	1620	1620	1620	1620
Number of company	667				213				205				
R-squared	0.000	0.020	0.018	0.003	0.007	0.042	0.019	0.000	0.003	0.046	0.036	0.007	0.011
Prob >F	1.000	0.000899	0.00265	0.00519	0	0.673	0.724	0.227	0.00290	0.000594	0.00695	0.0163	0.0270
F test	0.0808	7.023	5.939	5.303	6.006	0.396	0.323	1.493	1.321	5.819	4.058	3.508	2.800
Adjusted R-squared	-0.142			0.00227	-0.120			-0.000612	-0.143			0.00529	0.00882
Model	Fixed Effects	Fixed Effects	Fixed Effects	Pooled OLS	Fixed Effects	Fixed Effects	Fixed Effects	Pooled OLS	Fixed Effects	Fixed Effects	Fixed Effects	Pooled OLS	Pooled OLS
Sub-sample	Large Firms	Large Firms	Large Firms	Large Firms	Small Firms	Small Firms	Small Firms	Small Firms	Trouble Firms	Trouble Firms	Trouble Firms	Trouble Firms	Trouble Firms
absorb	company	country	industry		company	country	industry		company	country	industry		
cluster				company				company				company	company

Table 12: TC, FD and Firm Size with 380 % criteria

This table shows the result of the estimation of Equations (1) and (2) for trade payables dividing the sample in **LARGE** and **SMALL** firms. The Dependent Variable is **TCCGS**, Trade Payables on Cost of Goods Sold. **FINDIST_LAG** is a dummy variable that is 1 if a firm is in financial distress and 0 otherwise, notice that for this table a 380 % criteria instead of the 80 % standard definition from chapter 3.1 is used in order to get a similar percentage of firms in financial distress as Preve (2004). **WDIFSALES_SLES** is the first difference in sales scaled by sales, notice that this variable is winsorized at $p(0.01)$. **PRE_LARGE_S** is a time invariant dummy variable that identifies firms whose sales were above the yearly median of its industry during Timeline=-1. **FINDIST_LAG_PRE_LARGE_S** is a time variant interaction term that identifies financially distressed firms that were large in the pre-financial distress period. The sample is a selected sample as described in chapter 4 of the Datastream "Europe EM" index from 1997 to 2007. The value of t-stats is shown in brackets. T-stats that are clustered imply robust standard errors. Coefficients with *** are significant at 1% level, ** at 5%, and * at 10% in a two-tails test.

VARIABLES	(1) TCCGS360	(2) TCCGS360	(3) TCCGS360	(4) TCCGS360	(5) TCCGS360	(6) TCCGS360	(7) TCCGS360	(8) TCCGS360	(9) TCCGS360	(10) TCCGS360	(11) TCCGS360	(12) TCCGS360	(13) TCCGS360
findist_lag	20.25	61.93***	64.97***	67.47**	-62.21***	16.36	15.04	26.67**	-41.94	-23.05	13.60	43.58*	3.593
	(1.293)	(3.111)	(3.277)	(2.077)	(-2.783)	(0.909)	(0.823)	(2.238)	(-1.464)	(-0.712)	(0.421)	(1.955)	(0.230)
wdifsales_sles	4.701	42.39**	41.20**	48.70*	-39.46**	-2.359	-13.47	2.846	-6.535	35.70	31.79	42.71*	41.33*
	(0.344)	(2.252)	(2.172)	(1.819)	(-2.448)	(-0.149)	(-0.830)	(0.238)	(-0.405)	(1.599)	(1.411)	(1.768)	(1.739)
findist_lag_pre_large_s									66.67*	95.65**	46.37		66.96*
									(1.845)	(2.440)	(1.182)		(1.748)
pre_large_s												21.59	-1.846
												(0.743)	(-0.0801)
Constant	103.0***	89.97***	89.66***	88.03***	112.7***	93.67***	95.65***	91.12***	126.9***	107.6***	105.4***	88.59***	104.3***
	(18.40)	(10.47)	(10.42)	(16.55)	(14.79)	(12.46)	(12.50)	(8.515)	(13.30)	(7.681)	(7.515)	(5.218)	(6.333)
Observations	5385	5385	5385	5385	1886	1886	1886	1886	3680	3680	3680	3680	3680
Prob >F	0.989	0.000522	0.000374	0.0932	0	0.659	0.516	0.0770	0.00948	0.0137	0.0918	0.00779	0.0158
Number of company	667				213				450				
F test	0.873	7.569	7.902	2.381	6.511	0.418	0.662	2.595	1.176	3.558	2.150	4.010	3.088
R-squared	0.000	0.020	0.018	0.003	0.008	0.042	0.019	0.001	0.001	0.018	0.016	0.002	0.003
Adjusted R-squared	-0.141			0.00309	-0.119			0.000182	-0.139			0.00130	0.00155
Model	Fixed Effects	Fixed Effects	Fixed Effects	Pooled OLS	Fixed Effects	Fixed Effects	Fixed Effects	Pooled OLS	Fixed Effects	Fixed Effects	Fixed Effects	Pooled OLS	Pooled OLS
Sub-sample	Large Firms	Large Firms	Large Firms	Large Firms	Small Firms	Small Firms	Small Firms	Small Firms	Trouble Firms	Trouble Firms	Trouble Firms	Trouble Firms	Trouble Firms
absorb	company	country	industry		company	country	industry		company	country	industry		
cluster				company				company				company	company

5.2.1 Results and Interpretation

Tables 11 and 12 show the results whereas below, results and interpretations are provided. R^2's are very low (between 0 % and 4.6 %) hence, the extension models may be not better than those of presented in Chapter 4. However, the country and industry fixed effects models and the pooled OLS model suggest that large firms use significantly more trade credit from suppliers during financial distress. In comparison, Preve (2004) found a contradicting result. Note that the sub-sample of small firms shows few significant coefficients for findist_lag. Further, the coefficient for the company fixed effects model (5) is negative and significant (-75.5) while the coefficient for the pooled OLS model (8) with company cluster is positive and significant (22.6). Hence, the results show no clear tendency. Notice that the size and the statistically significance of the coefficients are higher in the case of large firms.

However, the pooled OLS models of Table 9 suggest that large firms delay their payment to suppliers by 91.4 days while smaller ones by 22.6 days during financial distress. Hence, the company fixed effects model suggests that small firms use significantly less trade credit during financial distress than large firms. In detail, the difference suggests that large firms delay their payment 58.8 days more than small firms in financial distress. This result is not in line with existing trade credit theories. As already mentioned in Chapter 4 this may be due to unknown factors that correlate with findist_lag.

The results in Table 11 and 12 are an indication that the size of the firm plays an important role in the use of trade credit in financial distress. It could be argued, however, that size can be affected by financial distress because, as shown in the literature, firms entering into financial distress tend to reduce their size as a consequence of a decrease in sales, market share or assets. In other words, the fact that financial distress may affect the size of the firm could cause some concern in the interpretation of the results. In

order to prevent this potential criticism, similar to Preve (2004) a different specification to study the effect of size is used.

The results as presented in columns 9 to 13 of Table 11, are models with "troubled" firms (large and small ones). The pooled OLS model (12) shows a positive significant coefficient on findist_lag whereas the company fixed effects model shows a negative significant coefficient. In contrast to Preve (2004) the coefficients of the interaction term pre_large_s and findist_lag_pre_large_s are positive and mainly statistically significant in both the fixed effects and the pooled OLS, suggesting that larger firms in financial distress use more trade credit than smaller firms. More specifically, the country fixed effects model (10) indicates that large firms in financial distress take 100.4 days longer than smaller ones to repay their suppliers. The case of the pooled OLS model (13) shows this difference to be around 113.4 days. The coefficients on pre_large_s are not significant, hence the variable cannot give information about how many more days distressed large firms need to repay suppliers compared to smaller ones. Note that a positive significant coefficient on pre_large_s in the model (12) would suggest how many more days large firms need to repay suppliers than smaller ones during normal non-financial distress times.

Therefore, the results are not in line with the literature. Suggesting that smaller firms prefer to choose financing from financial creditor (if available) rather than trying to obtain longer payment terms from suppliers.

5.3 The substitution effect

Additionally, the effect of size by the use of the pre-financial distress variables on the substitution effect between trade credit and other sources of capital is tested. Consequently, equation (2) is applied on the sample. As in Chapter 4, TRCA is examined first showing the participation of trade payables in the capital structure. Note again that the coefficients of findist_lag on TCFD and TRCE show the relative change of trade payables with respect to long term debt and equity respectively. Furthermore, the use of the dummies pre_large_s and findist_lag_pre_large_s allows to see the

effect of financial distress on firms that were large before entering into financial distress.

Table 13: Substitution Effect and Firm Size

This table shows the result of the estimation of Equation (2) for trade payables. The Dependent Variables are **TRCA** Trade Payables on Total Assets, **TRCE**, Trade Payables on Shareholder's Equity, and **TCFD**, Trade Payables on Financial Debt. **FINDIST_LAG** is a dummy variable that is 1 if a firm is in financial distress and 0 otherwise. **WDIFSALES_SLES** is the first difference in sales scaled by sales. **PRE_LARGE_S** is a time invariant dummy variable that identifies firms whose sales were above the yearly median of its industry during Timeline=-1. **FINDIST_LAG_PRE_LARGE_S** is a time variant interaction term that identifies financially distressed firms that were large in the pre-financial distress period. The sample is a selected sample as described in chapter 4 of the Datastream "Europe EM" index from 1997 to 2007. The value of t-stats is shown in brackets. T-stats that are clustered imply robust standard errors. Coefficients with *** are significant at 1% level, ** at 5%, and * at 10% in a two-tails test.

VARIABLES	(1) TRCA	(2) TRCA	(3) TRCA	(4) TRCA	(5) TRCA	(6) TRCE	(7) TRCE	(8) TRCE	(9) TRCE	(10) TRCE	(11) TCFD	(12) TCFD	(13) TCFD	(14) TCFD	(15) TCFD
findist_lag	0.00953**	0.00826**	-0.0101	0.00589	-0.00395	3.668***	4.379***	4.489***	4.540***	4.463	-25.18	-24.05	-14.89	-11.92	-9.479
	(2.288)	(2.012)	(-1.522)	(0.900)	(-0.275)	(4.044)	(6.041)	(6.480)	(6.526)	(1.181)	(-0.887)	(-0.892)	(-0.569)	(-0.454)	(-1.124)
pre_large_s					0.0162*					0.130					31.86
					(1.821)					(1.622)					(1.388)
findist_lag_pre_large_s	-4.74e-05	0.000497	0.0191**	0.00919	-0.00547	-2.948**	-3.860***	-3.975***	-3.938***	-4.067	-14.86	-11.65	14.67	1.689	-22.63
	(-0.00878)	(0.0936)	(2.218)	(1.089)	(-0.327)	(-2.510)	(-4.123)	(-4.429)	(-4.393)	(-1.053)	(-0.416)	(-0.343)	(0.441)	(0.0509)	(-0.755)
wdifsales_sles	0.00389***	0.00385***	0.00391	0.00766***	0.00376	0.0369	0.238	0.266	0.211	0.272	11.11	13.12	19.22**	18.18*	20.62
	(2.739)	(2.742)	(1.518)	(3.024)	(1.162)	(0.119)	(0.878)	(0.993)	(0.782)	(0.807)	(1.212)	(1.479)	(1.981)	(1.868)	(1.106)
Constant	0.125***	0.124***	0.125***	0.124***	0.123***	0.460***	0.427***	0.410***	0.415***	0.395***	24.27***	36.61***	21.48***	21.90***	17.76***
	(224.0)	(44.56)	(110.8)	(112.0)	(39.69)	(3.799)	(3.082)	(3.492)	(3.528)	(4.861)	(6.980)	(3.463)	(5.238)	(5.339)	(2.939)
Observations	7306	7306	7306	7306	7306	7307	7307	7307	7307	7307	6775	6775	6775	6775	6775
Number of company	883	883				883	883				858	858			
R-squared	0.003	.	0.061	0.102	0.004	0.003	.	0.006	0.009	0.006	0.001	.	0.004	0.008	0.002
F test	6.716		2.549	6.192	1.414	5.762		14.70	14.71	1.356	1.891		1.406	1.246	0.780
Adjusted R-squared	-0.134				0.00299	-0.135				0.00545	-0.144				0.00117
Prob >F	0		0.0540	0.000338	0.227	0		1.54e-09	1.51e-09	0.248	0		0.239	0.291	0.538
Model	Fixed Eff.	Random Effects	Fixed Eff.	Fixed Eff.	Pooled OLS	Fixed Eff.	Random Effects	Fixed Eff.	Fixed Eff.	Pooled OLS	Fixed Eff.	Random Effects	Fixed Eff.	Fixed Eff.	Pooled OLS
absorb	company	country	country	industry		company	country	country	industry		company	country	country	industry	
cluster					company						company				company

Table 14: Substitution Effect and Firm Size with 380 % criteria

This table shows the result of the estimation of Equation (2) for trade payables. The Dependent Variables are **TRCA** Trade Payables on Total Assets, **TRCE**, Trade Payables on Shareholder's Equity, and **TCFD**, Trade Payables on Financial Debt. **FINDIST_LAG** is a dummy variable that is 1 if a firm is in financial distress and 0 otherwise, notice that for this table a 380 % criteria instead of the 80 % standard definition from chapter 3.1 is used in order to get a similar percentage of firms in financial distress as Preve (2004). **WDIFSALES_SLES** is the first difference in sales scaled by sales, , notice that this variable is winorized at p(0.01). **PRE_LARGE_S** is a time invariant dummy variable that identifies firms whose sales were above the yearly median of its industry during Timeline=-1. **FINDIST_LAG_PRE_LARGE_S** is a time variant interaction term that identifies financially distressed firms that were large in the pre-financial distress period. The sample is a selected sample as described in chapter 4 of the Datastream "Europe EM" index from 1997 to 2007. The value of t-stats is shown in brackets. T-stats that are clustered imply robust standard errors. Coefficients with *** are significant at 1% level, ** at 5%, and * at 10% in a two-tails test.

VARIABLES	(1) TRCA	(2) TRCA	(3) TRCA	(4) TRCA	(5) TRCA	(6) TRCE	(7) TRCE	(8) TRCE	(9) TRCE	(10) TRCE	(11) TCFD	(12) TCFD	(13) TCFD	(14) TCFD	(15) TCFD
findist_lag	0.00210	0.00230	0.00235	0.0138***	0.0102	1.887***	1.903***	1.874***	1.882***	1.826	-14.82	-17.03	-22.35	-13.17	-19.50***
	(0.738)	(0.826)	(0.595)	(3.570)	(1.019)	(3.042)	(4.278)	(4.548)	(4.585)	(1.447)	(-0.812)	(-0.999)	(-1.542)	(-0.913)	(-2.597)
pre_large_s					0.00822					-0.0434					-3.310
					(1.269)					(-0.214)					(-0.266)
findist_lag_pre_large_s	0.00107	0.000358	-0.00246	-0.0108**	-0.0173	-1.316*	-1.429**	-1.426***	-1.384***	-1.343	1.646	1.291	5.666	-6.635	3.315
	(0.298)	(0.102)	(-0.485)	(-2.187)	(-1.533)	(-1.681)	(-2.527)	(-2.705)	(-2.632)	(-1.027)	(0.0726)	(0.0609)	(0.308)	(-0.362)	(0.232)
wdifsales_sles	0.00395***	0.00394***	0.00420	0.00821***	0.00419	0.0777	0.291	0.334	0.260	0.339	10.37	12.13	19.44**	18.18*	21.60
	(2.772)	(2.796)	(1.638)	(3.250)	(1.298)	(0.251)	(1.078)	(1.250)	(0.967)	(0.892)	(1.127)	(1.366)	(2.014)	(1.875)	(1.132)
Constant	0.125***	0.124***	0.125***	0.123***	0.122***	0.372***	0.358**	0.344***	0.350***	0.357***	24.94***	37.80***	24.39***	24.22***	24.88***
	(201.4)	(44.33)	(104.3)	(105.1)	(34.31)	(2.765)	(2.440)	(2.758)	(2.811)	(5.963)	(6.402)	(3.535)	(5.591)	(5.558)	(3.131)
Observations	7306	7306	7306	7306	7306	7307	7307	7307	7307	7307	6775	6775	6775	6775	6775
Adjusted R-squared	-0.136				0.00173	-0.136				0.00257	-0.145				0.000650
R-squared	0.002	.	0.061	0.103	0.002	0.002	.	0.004	0.006	0.003	0.001	.	0.005	0.008	0.001
Prob >F	0		0.385	2.72e-05	0.280	0		4.11e-05	4.21e-05	0.0694	0.281		0.0539	0.0957	0.0371
F test	3.292		1.014	7.953	1.269	3.554		7.666	7.650	2.181	1.030		2.551	2.118	2.563
Number of company	883	883				883	883				858	858			
Model	Fixed Eff.	Random Effects	Fixed Eff.	Fixed Eff.	Pooled OLS	Fixed Eff.	Random Effects	Fixed Eff.	Fixed Eff.	Pooled OLS	Fixed Eff.	Random Effects	Fixed Eff.	Fixed Eff.	Pooled OLS
absorb	company	country	country	industry		company	country	country	industry		company	country	country	industry	
cluster					company					company					company

5.3.1 Results and Interpretation

The pooled OLS models have very low explanatory power as shown by R^2's (0.1 % to 10.2 %).[56] Furthermore, the results are ambiguous because findist_lag_pre_large_s shows few significant coefficients, depending on which model and cluster option is applied. The negative and significant coefficient for the interaction term in the model using TRCE as the dependent variable suggests that larger firms in financial distress use less trade credit than smaller firms confirming the results of Preve (2004). This implies that smaller firms substitute more equity with trade credit than larger firms during financial distress. Note that only models 6, 7, 8 and 9 present significant coefficients on findist_lag and the interaction term. However, the positive and significant coefficients on findist_lag suggest that the level of trade payables increases faster than the denominator (book value of equity) in the case of large distressed firms. A more likely interpretation is that during financial distress the level of trade payables decreases less than the book value of equity since the book value of equity gets reduced when firms lose money.

Examining the substitution of long term debt (TCFD) and the participation of trade payables on the capital structure (TRCA) provides no significant coefficients. Hence, the models do not give information on whether there is some substitution between trade credit and long term debt as well as about the relation of trade credit and assets when firms are in financial distress. This shows that the models do not apply well.

In sum, the result using size as a firm characteristic suggests that firms that are able to get some financing from issuing stock tend to use it before relying on trade credit. A possible reason for preferring equity is because it is cheaper or the fact that it does not involve any obligation for repayment. Concluding, the result only partly confirms that firms consider trade credit to be lower in the pecking order of financing.

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[56] The models of Preve (2004) show R^2's between 6 % and 14 %.

6. Conclusion, Implication, Remarks and Summary

The first part of this diploma thesis gave some insights on trade credit theories, benefits and aspects. It has been shown that the supply and the use of trade credit is likely to improve liquidity, reduce information asymmetry and facilitate monitoring, it allows to price discriminate and it implies insurance and signaling as well as product quality aspects among the most important ones. However, trade credit has also drawbacks and costs caused by financial distress and the possibility of default.

In the second half some theories have been tested. A main task was to apply the models of Preve (2004), who used US firms, on a sample of European Monetary Union firms. To reach this goal standard panel data analysis are applied on a sample of eleven years of European Monetary Union corporate data. In order to find an adequate model for the sample of European firms various model specifications regarding clusters and absorbing variables have been tested. However, all test-results show quite low R^2's as well as partly ambiguous coefficients. Hence, for the analyzed data no variant of his model could be empirically confirmed outright. An outcome is that the models of Preve (2004) for the US do not apply well for European Monetary Union firms. An interpretation is that the payment-behavior between suppliers and buyers during financial distress is significantly different from that in Europe. The low explanatory power of the models and partly differing results to Preve (2004) may be caused by the accounting systems, the use of credit insurers and a different creditor protection between the US and the European Monetary Union as well as between European countries. A further reason may be the financial structure since European firms tend to be more bank-oriented whereas US firms tend to be more market-oriented. Last but not least, the statutory law that US banks are prohibited from holding equity in firms suggests better relations between European banks and firms.[57], [58] Hence, due to the European house

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[57] See Petersen and Rajan (1994).
[58] Table 13 suggests that financially distressed EMU firms substitute equity with trade credit.

banking system there may be less information asymmetry but also more dependency between them. As a consequence, European banks may support EMU firms by providing financial credit even if they are in financial distress.[59] This might explain the finding that financially distressed EMU firms increase the use of long term debt compared to trade credit. Hence, there are a lot of factors that may drive the results.

The Results

Examining only those models with significant coefficients on the main explanatory variable (findist_lag), supports the theory that firms use more trade credit from suppliers when they are in financial distress. Furthermore, Figure 10 shows that firms that are financially distressed once over the sample period have significantly higher levels of trade payables. This is in line with the trade credit literature. For example Petersen and Rajan (1997) showed that firms with less access to bank credit use more trade credit. The result confirms also that of Preve (2004) who demonstrated that financially distressed firms use more trade credit.

Neglecting the low R^2's, this work supports the substitution effect in 2 out of 3 regression specifications in Table 7. It shows that firms in financial distress significantly increase trade credit in their capital structure respectively that trade payables decrease less than assets and equity. An explanation for the finding that financially distressed EMU firms use more trade credit compared to equity may be the tendency that the book value of equity gets reduced when firms lose money. However, it cannot be supported that firms substitute long term debt with trade payables when they are in financial distress. Actually, the company fixed effects models and the random effects model indicate the opposite. A reason may be that firms prefer long term debt because it is cheaper than trade credit or that for example EMU banks grant relatively more credit to financially distressed EMU firms than suppliers of trade credit do. Furthermore, the result suggests that when a firm is in financial distress the costs of goods sold

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[59] However, notice that Table 5 and the median value of TCCGS360 suggest more trade credit use in Europe compared to the US, even when firms are in financial distress.

decrease faster than trade payables. They may decrease faster due to rising inventory costs caused by a decrease in sales as shown in Figure 9. Finally, the result that financially distressed firms undergo asset sales is in line with the literature.[60]

It seems that the models apply slightly better for French firms than for European Monetary Union firms in general. The result suggests that during financial distress French firms use more trade credit than US firms but less than the average of the EMU.[61] Another interpretation of this is that French firms may receive less trade credit than other European firms because of a higher risk of a total loss in the case of bankruptcy of the debtor. For example Davydenko and Franks (2008) commented that French banks require more collateral than lenders elsewhere because of a creditor-unfriendly code. In France trade creditors may substitute for bank credit but still grant less credit than other European firms. This may be due to the risk of a total loss when the trade debtor goes bankrupt. The argument holds especially if the delivery cannot be claimed back as an unprocessed product or good. Finally, the substitution effect for France cannot be explained with the models.

Table 11 shows that larger European Monetary Union firms increase their use of supplier's trade credit when they are in financial distress. For smaller or less dominant firms the results are mixed or ambiguous. The company fixed effects model predicts that they use less trade credit during financial distress while the pooled OLS model shows the opposite. The latter shows a coefficient that is less pronounced than those of large firms which indicates that in financial distress large firms use more trade credit than small firms. However, note that the results of Preve (2004) and trade credit theories suggest that small firms use more trade credit than larger ones, especially when they are in financial distress.

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[60] See for example Asquith, Gertner and Scharfstein (1994).
[61] Notice that the median value of TCCGS360 showing the amount of purchases financed by trade credit during "normal" times is 71.3 days for France, 59.5 days for the EMU and 39.3 days for the US. The time that distressed firms take longer trade credit than healthy firms are: 71 days in the EMU, 46 days for France and 5.2 days for the US.

The result that there is no tendency whether smaller or larger firms use more trade credit during financial distress may be due to the fact that the sample was selected from an index of Datastream and that its database solely contains companies listed on stock exchanges.[62] Consequently, as EMU companies are not as often listed on stock exchanges as US firms, listed EMU firms might be larger on the average. Hence, the sample tends to contain mostly large firms which would explain the results showing no clear tendency for larger and smaller firms. Accordingly, when the firm size has no linear effect, differing results to the US sample may arise. However, Table 16 indicates that smaller EMU firms tend to be more frequently in financial distress than larger ones.

Abstaining the low explanatory power like in all of the interpretations, Table 13 shows evidence that in financial distress larger firms use less trade credit than smaller firms confirming the results of Preve (2004). Furthermore, it is demonstrated that in financial distress smaller firms substitute more equity with trade credit than larger firms. A reason may be that the book value of equity decreases faster than trade payables since the size of the book value of equity tends to decrease during financial distress. Finally, the models investigating the substitution of long term debt (TCFD) and the participation of trade payables on the capital structure (TRCA) provides no significant coefficients. Hence, the substitution effect is not explained well with the models. However, the result suggests that firms that are able to get alternative sources of finance like equity from issuing stock tend to use it before relying on trade credit.

In sum, this paper has shown evidence that financially distressed firms use more trade credit than healthy ones. Furthermore, it is shown that trade credit substitutes other sources of financing like equity and demonstrates its importance in the financially distressed firm's capital structure. An interesting outcome is that firms reduce trade credit compared

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[62] Notice that even the whole sample (financially distressed and healthy firms) shows little difference in the trade credit use as the median value of TCCGS360 is 60.2 days for larger firms and 57.7 days for smaller firms (see Table 16).

to long term debt in the case of financial distress. Additionally, the result suggests that large and small firms use more trade credit during financial distress. However, there is no clear tendency whether smaller firms use more than larger ones. Last but not least the result tends to imply that compared to trade credit, long term debt comes higher and equity lower in the pecking order of financing.

This thesis helps to better understand trade credit and especially the effect of financial distress on trade credit. It highlights the aspects but also the risks and costs of trade credit. Furthermore it provides insights to a firm's financing decision and the creditor to debtor behavior. Taken together, it is shown evidence that the models cannot be applied uncritically to different countries.

To conclude, some of the main aspects of Preve (2004) could be confirmed. The low explanatory power of the regressions shows that in the European Monetary Union the amount of trade credit use is either considerably more random than in the US or that in the EMU other not considered factors may be more important.

Outlook

In order to explain cross sectional variations, the models of Chapter 5 use firm and industry characteristics like relative firm size. Making the results more robust it would be interesting to test alternative definitions of financial distress. For example it is possible to classify for high and low book to market securities. When market values of debt and equity are lower than their book values, firms may be in financial distress. Alternatively, they may be categorized as in financial distress when the book to market value rises significantly between years.

Preve (2004) uses additionally further definitions of financial distress, for example the dummy variable DISTIND for exogenous shocks respectively for firms whose industry is in distress. Using "default" as an alternative dummy variable would also be interesting. For example Preve (2004) defines the variable "default" for firms whose credit rating is

categorized as in Default by Standard & Poor's. A firm's leverage as a determinant of financial distress would be very illuminative as well, for example using it as a dummy variable (high or low leverage) to determine the trade credit use respectively the effect of an industry shock on highly levered firms. The leverage of a firm should have a significant influence on financial distress as Andrade and Kaplan (1988) found that high leverage is the primary cause. Petersen and Rajan (1997) found that firms with less access to financial credit use more trade credit. This would be the case for highly leveraged firms as they have to pay higher risk premiums and have in general less access to bank credit.

Future research may show a heavier use of trade credit for the years 2008 and 2009 due to the global financial crisis respectively the global recession and financial distress of banks and firms. Notice that the rising use of trade credit is relative to the use of bank credit because trade-creditors reduce their receivables during a macroeconomic crisis or exogenous shock as well.[63] This prediction would be in line with Petersen and Rajan (1997) and the pecking order theory because firms whose internal funds are exhausted and whose business activity is threatened by financial distress will choose debt and equity as last resort. This issue of equity can easily be observed by investors and analysts. They further found that firms use more trade credit when credit from financial institutions is unavailable. This should apply especially here because there is a situation where financial debt is more difficult to obtain due to the mistrust in the interbank lending and low liquidity levels on the credit market. In other words, firms receive less bank credit and will try to substitute it with trade credit.

Furthermore firms should tend to substitute equity and debt by using relatively more trade credit. The portion of assets financed by trade credit will rise as well. Note that macroeconomic factors may have much more influence on a firm's financial distress situation than financial distress through "culpa" of the firm itself or a crisis of its industry. The costs of financial distress will also rise for the predicted period as reported by

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[63] See Love, Preve and Sarria-Allende (2007).

Shleifer and Vishny (1992). They show that financial distress is more costly when a firm's whole industry performs poorly because potential asset-buyers who value most the distressed firm's assets itself have problems to finance the deal respectively a buyout. Hence, there is still a lot of interesting research outstanding, especially with respect to the current global financial and economic crisis.

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Appendix

Table 15: Distribution of firms along the Timeline with winsorized means

This table shows the distribution of firms along the Timeline and some selected summary statistics. The variables are defined in Table 1. **Nobs** is the number of observation in each group and Freq is the Frequency. **TRCA** is the average value of Trade Payables on Assets and **TCCGS** is the average value of Trade Payables on Cost of Goods Sold in each group. **SALES(cpi)** and **ASSETS(cpi)** in million Euro are the average value of Net Sales and Total Assets in each group. Both variables are presented in constant values of Year 2005. Notice that this table is similar to Table 4 with the difference of winsorized variables.

Timeline	Nobs	Freq	TRCA	TCCGS	SALES(cpi)	ASSETS(cpi)
-10	6	0.26%	0.1189	0.2538	478.51	727.65
-9	16	0.71%	0.1189	0.2538	2,552.77	1,928.02
-8	29	1.28%	0.1505	0.2538	1,742.27	1,857.07
-7	40	1.77%	0.1505	0.2538	2,018.60	1,847.22
-6	80	3.53%	0.1505	0.3080	1,631.73	1,856.24
-5	111	4.90%	0.1434	0.3564	2,391.94	3,424.71
-4	145	6.40%	0.1418	0.2809	2,814.30	4,124.77
-3	159	7.02%	0.1396	0.3646	2,743.63	4,221.60
-2	172	7.59%	0.1298	0.2833	2,723.59	4,634.03
-1	190	8.38%	0.1236	0.2538	2,656.05	5,542.33
0	695	30.67%	0.1370	0.2596	3,234.30	5,101.32
1	260	11.47%	0.1189	0.4199	2,958.64	4,964.37
2	152	6.71%	0.1288	0.4751	990.69	1,625.29
3	97	4.28%	0.1225	0.6623	344.46	761.36
4	56	2.47%	0.1415	0.6623	270.80	727.65
5	27	1.19%	0.1227	0.6443	270.80	727.65
6	21	0.93%	0.1505	0.6623	270.80	727.65
7	4	0.18%	0.1189	0.2826	270.80	727.65
8	3	0.13%	0.1189	0.6623	270.80	727.65
9	2	0.09%	0.1189	0.0000	270.80	727.65
10	1	0.04%	0.1189	0.0000	270.80	727.65
Total	2,266	100%				
TROUBLE = 0	7,689		0.1243	0.3024	4,039.67	5,081.52

Table 16: Levels of sales, assets and trade credit

This table shows the levels of CPI-adjusted sales and assets in million Euro and the level of TCCGS360 in days for the whole sample, larger firms and smaller firms. Firms are considered to be large when max_large_s=1 (see Table 1).

Median CPI-sales	Larger & Smaller firms	Larger firms	Smaller firms
TROUBLE = 1	204.912	724.792	50.587
TROUBLE = 0	766.280	1,363.452	208.039
TROUBLE = 1 & 0	639.797	1,213.578	146.501

Median CPI-assets	Larger & Smaller firms	Larger firms	Smaller firms
TROUBLE = 1	309.968	803.053	86.164
TROUBLE = 0	827.082	1,402.438	233.807
TROUBLE = 1 & 0	698.154	1,270.013	180.145

Median TCCGS360	Larger & Smaller firms	Larger firms	Smaller firms
TROUBLE = 1	69.8	69.1	70.8
TROUBLE = 0	57.1	58.3	52.6
TROUBLE = 1 & 0	59.5	60.2	57.7

Table 17: Company Name list of the sample (the selected index)

Nr.	Type	COMPANY NAME
1	307298	A-B VASSILOPOULOS S.A.
2	41436T	A-TEC INDUSTRIES AG
3	685120	A2A SPA
4	749352	AALBERTS INDUSTRIES NV
5	885354	AARDVARK INVESTMENTS S.A.
6	917065	ABBEY PLC
7	885095	ABENGOA SOCIEDAD ANONIMA
8	772273	ABERTIS INFRAESTRUCTURAS
9	688324	ACCELL GROUP NV
10	741112	ACCIONA SA
11	929363	ACCOR
12	672736	ACEA SPA
13	258572	ACEGAS-APS SPA
14	741901	ACERINOX, S.A.
15	755087	ACKERMANS & VAN HAAREN NV
16	299517	ACOTEL GROUP S.P.A.
17	539621	ACS ACTIVIDADES DE CONSTRUCCION Y SERVICIOS
18	15222W	ACTELIOS SPA
19	866013	ADIDAS AG
20	291599	ADLINK INTERNET MEDIA AG
21	885560	ADOLFO DOMINGUEZ S.A.
22	412214	AER LINGUS
23	31133K	AEROPORTO DI VENEZIA MARCO POLO - SAVE SPA
24	36066K	AEROPORTS DE PARIS
25	682852	AES CHEMUNEX SA
26	679622	AFC AJAX NV
27	672548	AGFA-GEVAERT N.V.
28	307059	AGRANA BETEILIGUNGS AG
29	32956M	AHLSTROM OYJ
30	929286	AIR FRANCE - KLM
31	923295	AIR LIQUIDE
32	35785W	AIR-BERLIN
33	896674	AIXTRON AG
34	912643	AKZO NOBEL N.V.
35	998418	ALANHERI NV
36	692629	ALAPIS S.A.
37	755022	ALCATEL-LUCENT SA
38	881832	ALES GROUPE
39	998250	ALITALIA-LINEE AEREE ITALIANE SPA
40	30901L	ALMA MEDIA OYJ
41	682858	ALSTOM SA
42	951477	ALTANA AG

43	692445	ALTEN
44	756882	ALTRAN TECHNOLOGIES
45	30416C	ALTRI SGPS S.A.
46	946457	AMER SPORTS OYJ
47	50788M	AMG ADVANCED METALLURGICAL GROUP N.V.
48	701691	AMPER, S.A.
49	259288	AMPLIFON SPA
50	932754	AMSTERDAM COMMODITIES NV
51	888804	AND INTERNATIONAL PUBLISHERS N.V.
52	929049	ANDREAE-NORIS ZAHN AG
53	255055	ANDRITZ AG
54	35619C	ANSALDO STS SPA
55	27685F	ANTENA 3 DE TELEVISION, S.A.
56	36095R	ANTICHI PELLETTIERI SPA
57	301773	ARCADIS NV
58	922888	ARCANDOR AG
59	756190	ARCELOR RODANGE S.A.
60	899069	ARCELORMITTAL
61	307655	AREVA
62	35720C	ARKEMA GROUP
63	741783	ARNOLDO MONDADORI EDITORE SPA
64	51129T	ARSEUS NV
65	41474T	ASCOPIAVE SPA
66	888051	ASM INTERNATIONAL NV
67	152001	ASML HOLDING NV
68	25590M	ASTALDI
69	688826	AT&S AUSTRIA TECHNOLOGIE & SYSTEMTECHNIK AG
70	276727	ATHENS WATER SUPPLY & SEWERAGE SA
71	685756	ATLANTIA SPA
72	740622	ATOS ORIGIN SA
73	308895	ATTICA HOLDINGS S.A.
74	922819	AUDI AG
75	673926	AUDIKA
76	772803	AUSTRIAN AIRLINES AG
77	892360	AUTOGRILL SOCIETA PER AZIONI
78	29786H	AUTOROUTES PARIS RHIN RHONE
79	933327	AUTOSTRADA TORINO-MILANO SPA
80	504846	AVANZIT SA
81	702300	AXEL SPRINGER VERLAG AG
82	772790	AZKOYEN, S.A.
83	142433	BALLAST NEDAM N.V.
84	729569	BARCO NV
85	892258	BARON DE LEY S.A.
86	904881	BASF SE

87	932777	BATENBURG BEHEER N.V.
88	36197U	BAUER AG
89	905243	BAYER AG
90	504700	BAYERISCHE MOTOREN WERKE AKTIENGESELLSCHAFT
91	775017	BAYWA AG
92	866096	BE SEMICONDUCTOR INDUSTRIES N.V.
93	290298	BECHTLE AG
94	681791	BEFESA MEDIO AMBIENTE SA
95	929048	BEIERSDORF AG
96	932532	BEKAERT S.A.
97	27597M	BELGACOM SA
98	749880	BENETEAU
99	729164	BENETTON GROUP SPA
100	882292	BERTRANDT AG
101	896382	BERU AG
102	882832	BETER BED HOLDING NV
103	259266	BIESSE SPA
104	772756	BIJOU BRIGITTE MODISCHE ACCESSOIRES AKTIENGESELLSCHAFT
105	929080	BILFINGER BERGER AG
106	29169X	BIOMERIEUX SA
107	756551	BIOTEST AG
108	698258	BLUE FOX ENTERPRISES N.V.
109	143668	BOEHLER-UDDEHOLM AG
110	755323	BOIRON SA
111	885058	BOIZEL, CHANOINE, CHAMPAGNE
112	997966	BOLLORE
113	682921	BONDUELLE
114	992701	BONGRAIN SOCIETE ANONYME
115	685788	BOURBON
116	923500	BOUYGUES SA
117	143980	BREMBO SPA
118	866704	BRICORAMA SA
119	890858	BRISA-AUTO ESTRADAS DE PORTUGAL, S.A.
120	897486	BRUNEL INTERNATIONAL N.V.
121	135487	BULGARI SOCIETA PER AZIONI
122	51185D	BUREAU VERITAS SA
123	779067	BUZZI UNICEM SPA
124	288910	BWIN INTERACTIVE ENTERTAINMENT AG
125	307555	BWT AKTIENGESELLSCHAFT
126	35785U	C A T OIL AG
127	28961U	C&C GROUP
128	289329	CALTAGIRONE EDITORE SPA
129	505249	CALTAGIRONE SPA
130	289277	CAMAIEU

131	505951	CAMFIN SPA
132	772879	CAMPOFRIO ALIMENTACION SA
133	756920	CANAL+
134	702043	CAPGEMINI S.A.
135	936590	CARBONE-LORRAINE
136	31116C	CARGOTEC CORPORATION
137	287936	CARL ZEISS MEDITEC AG
138	922029	CARREFOUR S.A.
139	729105	CASINO, GUICHARD-PERRACHON ET CIE
140	997826	CEGEDEL-COMPAGNIE GRAND-DUCALE D'ELECTRICITE DU LUXEMBOURG
141	143693	CEGEDIM
142	951741	CELESIO AG
143	929377	CEMENTIR HOLDING S.P.A.
144	307702	CEMENTOS PORTLAND VALDERRIVAS SA
145	51163N	CENTROTHERM PHOTOVOLTAICS AG
146	929549	CEPSA - COMPANIA ESPANOLA DE PETROLEOS, S.A.
147	539616	CHRISTIAN DIOR
148	143260	CIA LEVANTINA DE EDIFICACION Y OBRAS PUB
149	929412	CICCOLELLA SPA
150	892349	CIE AUTOMOTIVE SA
151	929173	CIMENTS FRANCAIS
152	142802	CIMPOR - CIMENTOS DE PORTUGAL SGPS SA
153	29716D	CINTRA CONCESIONEX DE INFRAESTRUCTURAS DE TRANSPORTE SA
154	307631	CIPAN-CIA IND. PRODUTORA DE ANTIBIOTICOS
155	905397	CLARINS
156	50375D	CLINICA BAVIERA SA
157	923814	CLUB MEDITERRANEE SA
158	307612	COCA-COLA HELLENIC BOTTLING COMPANY S.A.
159	51205X	CODERE, S. A.
160	719620	COFIDE - COMPAGNIA FINANZIARIA DE BENEDETTI S.P.A.
161	673252	COFINA SGPS, SA
162	929247	COLAS S.A.
163	950997	COLRUYT
164	929336	COMPAGNIE D'ENTREPRISES CFE S.A.
165	143369	COMPAGNIE DES ALPES
166	998054	COMPAGNIE GENERALE DE GEOPHYSIQUE- VERITAS
167	912397	COMPAGNIE GENERALE DES ETABLISSEMENTS MICHELIN
168	933357	COMPAGNIE INDUSTRIALI RIUNITE SPA
169	756159	COMPAGNIE INTERNATIONALE DE CULTURES SA
170	929356	COMPAGNIE MARITIME BELGE
171	923891	COMPAGNIE PLASTIC OMNIUM
172	755165	COMPANHIA INDUSTRIAL DE RESINAS SINTETICAS, CIRES, S.A.
173	892300	COMPANIA VINICOLA DEL NORTE DE ESPANA SA
174	26496V	COMPLETEL EUROPE NV

175	876246	COMPUGROUP HOLDING AG
176	702134	CONAFEX HOLDINGS SA
177	13760R	CONERGY AG
178	143726	CONSTANTIA PACKAGING AG
179	273296	CONSTANTIN FILM AG
180	749789	CONSTRUCCIONES Y AUXILIAR DE FERROCARRILES, S.A.
181	929030	CONTINENTAL AG
182	50781W	CONTITECH AG
183	685205	CORINTH PIPEWORKS SA
184	31334W	CORPORACION DERMOESTETICA
185	772710	CORTICEIRA AMORIM, SOCIEDADE GESTORA DE PARTICIPACOES SOCIAIS, S.A.
186	670595	CPL RESOURCES PLC
187	142831	CRAMO OYJ
188	911840	CRH PLC
189	41221D	CROPENERGIES AG
190	701548	CROWN VAN GELDER NV
191	269490	CRUCELL NV
192	933025	CSM NV
193	676629	CTAC NV
194	284265	CTS EVENTIM AG
195	932706	D'IETEREN S.A
196	295059	D+S EUROPE AG
197	688700	DAIMLER AG
198	730973	DANIELI & C. OFFICINE MECCANICHE S.P.A.
199	912833	DANONE
200	936564	DASSAULT AVIATION
201	866708	DASSAULT SYSTEMES SA
202	268403	DATALEX PLC
203	258614	DATALOGIC SPA
204	259385	DAVIDE CAMPARI MILANO SPA
205	135586	DCC PLC
206	259437	DE LONGHI SPA
207	702511	DECEUNINCK SA
208	772311	DELACHAUX
209	36133R	DEMAG CRANES AG
210	143409	DERICHEBOURG.
211	929114	DEUTSCHE LUFTHANSA AG
212	280598	DEUTSCHE POST AG
213	882362	DEUTSCHE TELEKOM
214	916181	DEUTZ AKTIENGESELLSCHAFT
215	31174F	DEVGEN NV
216	25603E	DIAGNOSTIC & THERAPEUTIC CENTER OF ATHENS
217	50831K	DIASORIN S.P.A.
218	929028	DIDIER-WERKE AKTIENGESELLSCHAFT

219	756886	DISTRIBORG GROUPE
220	14910P	DISTRIGAZ
221	932876	DNC DE NEDERLANDEN COMPAGNIE NV
222	892007	DOCDATA NV
223	676805	DONEGAL CREAMERIES PLC
224	930095	DOUGLAS HOLDING AKTIENGESELLSCHAFT
225	697057	DPA FLEX GROUP N.V.
226	998222	DRAEGERWERK AG
227	974980	DRAGON OIL PLC
228	307364	DRAKA HOLDING NV
229	692689	DUCATI MOTOR HOLDINGS SPA
230	775672	DUERR AG
231	672624	DUVEL MOORTGAT NV
232	929014	DYCKERHOFF AG
233	916235	E.ON AG
234	539731	EBRO PULEVA SA
235	729463	ECONOCOM GROUP SA
236	41383K	EDF ENERGIES NOUVELLES SA
237	772670	EDISON SPA
238	885986	EDP - ENERGIAS DE PORTUGAL S.A.
239	936469	EIFFAGE
240	951664	EISEN UND HUTTENWERKE
241	974839	ELAN CORPORATION PLC
242	779471	ELECNOR, S.A.
243	32269V	ELECTRICITE DE FRANCE
244	929290	ELECTRICITE DE STRASBOURG SA
245	31250R	ELIA SYSTEM OPERATOR
246	698783	ELISA OYJ
247	142358	ELLAKTOR S.A.
248	775188	ELRINGKLINGER AG
249	25714E	ENAGAS SA
250	933063	ENBW ENERGIE BADEN-WUERTTEMBERG AG
251	701720	ENDESA SA
252	275791	ENEL SPA
253	505918	ENERTAD
254	255794	ENGINEERING INGEGNERIA INFORMATICA SPA
255	866154	ENI - ENTE NAZIONALE IDROCARBURI
256	50803P	ENIA S.P.A.
257	31281X	ENTREPOSE CONTRACTING
258	50788W	ENVITEC BIOGAS AG
259	275562	EPCOS AG
260	143191	ERAMET
261	929475	ERCROS, S.A.
262	879965	ERG SPA

263	923871	ERIKS GROUP NV
264	31915W	ERSOL SOLAR ENERGY AG
265	775055	ESCADA AG
266	259444	ESPRINET SPA
267	936514	ESSILOR INTERNATIONAL SOCIETE ANONYME
268	929189	ESSO SOCIETE ANONYME FRANCAISE
269	741782	ESTORIL - SOL, S.A.
270	929349	ETABLISSEMENT DELHAIZE FRERES CIE LE LION SA
271	505969	ETABLISSEMENTS MAUREL ET PROM
272	885924	ETAM DEVELOPPEMENT
273	892981	EUROFINS SCIENTIFIC
274	41026Q	EUROKAI KOMMANDITGESELLSCHAFT AUF AKTIEN
275	29848W	EURONAV NV
276	289361	EUROPEAN AERONAUTIC DEFENCE AND SPACE COMPANY EADS NV
277	32057D	EUTELSAT COMMUNICATIONS
278	505096	EVN AKTIENGESELLSCHAFT
279	685755	EVS BROADCAST EQUIPMENT SA
280	698444	EXACT HOLDING NV
281	885915	EXEL INDUSTRIES
282	741258	EXIDE TECHNOLOGIES, S.A.
283	27189U	EXMAR NV
284	142523	EXXON MOBIL CHEMICAL
285	275955	F-SECURE OYJ
286	307660	F. REICHELT AG
287	505632	FAES FARMA SA
288	143061	FAIVELEY SA
289	288944	FASTWEB SPA
290	937211	FAURECIA
291	50506D	FERSA ENERGIAS RENOVABLES, S.A.
292	729813	FIAT SPA
293	143170	FIELMANN AG
294	936644	FINANCIERE DE L'ODET SA
295	936720	FINANCIERE MARC DE LACHARRIERE SOCIETE ANONYME
296	772639	FINATIS
297	936428	FINMECCANICA SPA
298	505966	FINNAIR OYJ
299	533130	FINNLINES OY
300	50647K	FIRST DERIVATIVES PLC
301	759829	FISIPE-FIBRAS SINTETICAS DE PORTUGAL SA
302	772948	FISKARS OYJ
303	775058	FLEISCHEREI BEDARF AG
304	307594	FLUGHAFEN WIEN AG
305	51245F	FLUIDRA SA
306	866714	FLUXYS

307	307039	FNM S.P.A.
308	890305	FOLLI-FOLLIE S.A.
309	539877	FOMENTO DE CONSTRUCCIONES Y CONTRATAS SA
310	682849	FONCIERE EUROPE LOGISTIQUE
311	308444	FORNIX BIOSCIENCES
312	690351	FORTUM OYJ
313	772774	FOURLIS HOLDING SA
314	885569	FRANCE TELECOM
315	13922L	FRAPORT AG
316	278659	FREENET AG
317	882294	FRESENIUS MEDICAL CARE AG & CO. KGAA
318	307694	FRESENIUS SE
319	276536	FRIGOGLASS S.A.
320	929228	FROMAGERIES BEL
321	504299	FUCHS PETROLUB AG
322	307521	FUGRO NV
323	673963	FUTEBOL CLUB DO PORTO FUTEBOL SAD
324	901432	FYFFES PLC
325	30939T	GALAPAGOS GENOMICS
326	41289P	GALP ENERGIA SGPS, S.A.
327	269298	GAMESA CORPORACION TECNOLOGICA SA
328	929306	GAMMA HOLDING NV
329	929544	GAS NATURAL SDG, S.A.
330	41456P	GAS PLUS SPA
331	936669	GAUMONT
332	31270N	GDF SUEZ
333	929057	GEA GROUP AG
334	308872	GEK GROUP OF COMPANIES S.A.
335	929118	GELSENWASSER AG
336	28985C	GEMALTO N.V.
337	912163	GEMINA - GENERALE MOBILIARE INTERESSENZE AZIONARIE S.P.A.
338	36120C	GENERAL DE ALQUILER DE MAQUINARIA S.A.
339	259250	GENERALE DE SANTE SA
340	29858J	GEOX SPA
341	50634F	GERRESHEIMER AG
342	881098	GERRY WEBER INTERNATIONAL AG
343	29104U	GESTEVISION TELECINCO SA
344	505044	GEWISS SPA
345	275497	GFK AG
346	289005	GIFI
347	929021	GILDEMEISTER AKTIENGESELLSCHAFT
348	692009	GL EVENTS
349	692528	GL TRADE
350	943979	GLANBIA PLC

351	672669	GLOBAL INTELLIGENT TECHNOLOGIES, SGPS, S.A
352	685242	GORENJE GOSPODINJSKI APARATI DD
353	745099	GOUDA VUURVAST HOLDING
354	142602	GR. SARANTIS S.A.
355	911868	GRAFTON GROUP PLC
356	951473	GRAND MARNIER
357	259218	GRANITIFIANDRE SPA
358	928730	GREENCORE GROUP PLC
359	290300	GRENKELEASING AG
360	29238T	GRIFOLS SA
361	998414	GRONTMIJ NV
362	50767F	GROUPE EUROTUNNEL S.A.
363	143656	GROUPE PARTOUCHE SA
364	672558	GROUPE STERIA
365	950640	GRUPO DURO-FELGUERA, S.A.
366	772509	GRUPO EMPRESARIAL ENCE SA
367	692810	GRUPO FERROVIAL, S.A.
368	28769N	GRUPO MEDIA CAPITAL SGPS S.A
369	672670	GRUPPO COIN SPA
370	779427	GRUPPO EDITORIALE L'ESPRESSO SPA
371	50629T	GRUPPO ZIGNAGO VETRO S.P.A
372	32357R	GUALA CLOSURES GROUP
373	741849	GUERBET
374	916750	GUYENNE ET GASCOGNE SA
375	951778	H&R WASAG AG
376	885357	HALOGEN HOLDINGS SA
377	51234R	HAMBURGER HAFEN UND LOGISTIK AG
378	892030	HAMON & CIE (INTERNATIONAL) SA
379	692039	HAULOTTE GROUP
380	936677	HAVAS SA
381	929015	HEIDELBERGCEMENT AG
382	671294	HEIDELBERGER DRUCKMASCHINEN AG
383	309341	HEIJMANS NV
384	929708	HEINEKEN HOLDING
385	905001	HEINEKEN NV
386	673454	HELLENIC DUTY FREE SHOPS SA
387	681817	HELLENIC PETROLEUM S.A.
388	866513	HELLENIC TELECOMMUNICATIONS ORGANISATION S.A.
389	702812	HENKEL KGAA
390	27202M	HERA SPA
391	777331	HERACLES GENERAL CEMENT COMPANY S.A.
392	309037	HERMES INTERNATIONAL SCA
393	929956	HES BEHEER NV
394	698014	HIGHLIGHT COMMUNICATIONS AG

395	681292	HITT N.V.
396	929018	HOCHTIEF AG VORM. GEBR. HELFMANN
397	951190	HOLCIM (DEUTSCHLAND) AG
398	504918	HOLLAND COLOURS NV
399	14048T	HOMAG GROUP AG
400	755415	HORNBACH HOLDING AG
401	309869	HORNBACH-BAUMARKT-AKTIENGESELLSCHAFT
402	504458	HUGO BOSS AG
403	772286	HUHTAMAKI OYJ
404	933240	HUNTER DOUGLAS NV
405	775787	HYMER AG
406	289086	IASO SA
407	953204	IAWS GROUP PLC
408	51390L	IBERDROLA RENOVABLES S.A
409	998213	IBERDROLA S.A.
410	258615	IBERIA, LINEAS AEREAS DE ESPANA, S.A.
411	892901	IBERPAPEL GESTION SA
412	890859	IBERSOL SGPS SA
413	698243	ICON PLC
414	897830	ICT AUTOMATISERING N.V.
415	698008	IDS SCHEER AG
416	28400H	ILIAD SA
417	912049	IMERYS SA
418	285540	IMMSI SPA
419	777307	IMOBILIARIA CONSTRUTORA GRAO - PARA, SA
420	951104	IMPREGILO SPA
421	289223	IMPRESA SGPS SA
422	755190	IMS - INTERNATIONAL METAL SERVICE SA
423	916108	IMTECH NV
424	289504	INBEV SA
425	911819	INDEPENDENT NEWS & MEDIA PLC
426	755149	INDESIT COMPANY SPA
427	13863H	INDITEX
428	749799	INDRA SISTEMAS
429	301573	INDUS HOLDING AG
430	143729	INDUSTRIA MACCHINE AUTOMATICHE SPA
431	287489	INFINEON TECHNOLOGIES AG
432	921366	INGENICO - COMPAGNIE INDUSTRIELLE ET FINANCIERE D'INGENIERIE
433	679334	INNOCONCEPTS N.V.
434	26624K	INNOGENETICS NV
435	142572	INTER PARFUMS
436	30402X	INTERCELL AG
437	682020	INTEREUROPA INC
438	885153	INTERPUMP GROUP SPA

439	681309	INTERSEROH AG
440	276388	INTRALOT S.A. - INTEGRATED LOTTERY SYSTEMS & SERVICES
441	756625	INVESTIMENTOS, PARTICIPACOES E GESTAO, S.A.
442	685499	INYPSA INFORMES Y PROYECTOS S.A.
443	682862	ION BEAM APPLICATIONS SA
444	892609	IONA TECHNOLOGIES PLC
445	32376D	IPSEN
446	672675	IPSOS SA
447	255231	IRIDE SPA
448	136519	IRISH CONTINENTAL GROUP PLC
449	682022	ISTRABENZ DD
450	702055	ITALCEMENTI SPA
451	779032	ITALMOBILIARE SPA
452	885474	ITI - INTERNATIONAL TRADING & INVESTMENTS
453	772809	ITINERE INFRAESTRUCTURAS SA
454	756167	JABELMALUX SA
455	259244	JC DECAUX SA
456	681441	JENOPTIK AG
457	504692	JERONIMO MARTINS SGPS SA
458	278304	JETIX EUROPE NV
459	775099	JOHN DEERE-LANZ VERWALTUNGS-AKTIENGESELLSCHAFT
460	885996	JUMBO SA
461	505973	JUNGHEINRICH AG
462	929035	K+S AKTIENGESELLSCHAFT
463	741618	KAP-BETEILIGUNG AG
464	50696N	KAPSCH TRAFFICCOM AG
465	276765	KAUFMAN & BROAD SA
466	143267	KEMIRA OYJ
467	932895	KENDRION NV
468	991530	KENMARE RESOURCES PLC
469	921260	KERAMAG-KERAMISCHE WERKE AG
470	901049	KERRY GROUP PLC
471	698494	KESKO OYJ
472	673493	KINEPOLIS GROUP
473	953547	KINGSPAN GROUP PLC
474	284267	KIZOO AG
475	36133K	KLOECKNER & CO. AG
476	929098	KLOECKNER-WERKE AKTIENGESELLSCHAFT
477	992562	KOENIG & BAUER AG
478	772959	KONE OYJ
479	866457	KONECRANES OYJ
480	916642	KONINKLIJKE AHOLD NV
481	932775	KONINKLIJKE BAM GROEP NV
482	899432	KONINKLIJKE BRILL N.V

483	779426	KONINKLIJKE DSM N.V.
484	142440	KONINKLIJKE KPN NV
485	933031	KONINKLIJKE PHILIPS ELECTRONICS N.V.
486	930119	KONINKLIJKE TEN CATE NV
487	278066	KONINKLIJKE VOPAK NV
488	308977	KONINKLIJKE WESSANEN NV
489	290657	KONTRON AG
490	41383J	KORIAN
491	682027	KRKA DD NOVO MESTO
492	686872	KRONES AKTIENGESELLSCHAFT HERMANN KRONSEDER MASCHINENFABRIK
493	929060	KSB AKTIENGESELLSCHAFT
494	28221H	KTM POWER SPORTS AG
495	929024	KUKA AG
496	921289	KWS SAAT AG
497	923386	L'OREAL
498	866097	L.D.C. SOCIETE ANONYME
499	929622	LA SEDA DE BARCELONA, S.A.
500	50804V	LABORATORIOS ALMIRALL SA
501	51375N	LABORATORIOS FARMACEUTICOS ROVI S.A.
502	916745	LAFARGE S.A.
503	998500	LAGARDERE S.C.A.
504	777334	LAMPSAS GREEK HOTEL CO. SA
505	50703P	LANDI RENZO S.P.A.
506	30169F	LANXESS AG
507	772961	LASSILA & TIKANOJA OY
508	672582	LAURENT PERRIER
509	929125	LECHWERKE AG
510	35612E	LEGRAND S.A.
511	533160	LEMMINKAINEN OY
512	702589	LENZING AG
513	944429	LEONI AG
514	412647	LHS AG
515	923551	LINDE AKTIENGESELLSCHAFT
516	143524	LISGRAFICA - IMPRESSAO DE ARTES GRAFICAS
517	504524	LISI
518	13871C	LOTTOMATICA S.P.A.
519	505325	LOTUS BAKERIES NV
520	682032	LUKA KOPER, D.D.
521	997842	LUNDIN INTERNATIONAL
522	255249	LUXOTTICA GROUP
523	916658	LVMH MOET HENNESSY LOUIS VUITTON
524	772967	M-REAL OYJ
525	143198	M6 - METROPOLE TELEVISION SA
526	932850	MACINTOSH RETAIL GROUP

527	51337W	MAIRE TECNIMONT SPA
528	929560	MAN AG
529	772644	MANITOU BF S.A.
530	702598	MANUTAN INTERNATIONAL SA
531	41221V	MANZ AUTOMATION AG
532	298539	MARIELLA BURANI SPA
533	31250P	MARR SPA
534	50760V	MARTIFER SGPS, S.A.
535	142344	MAYR-MELNHOF KARTON AG
536	926349	MCINERNEY HOLDINGS PLC
537	692849	MECALUX SA
538	866990	MEDIASET
539	695480	MEDION AKTIENGESELLSCHAFT
540	143049	MEDITERRANEA DELLE ACQUE SPA
541	31988K	MEETIC
542	50478N	MEINL AIRPORTS INTERNATIONAL LIMITED
543	25544L	MELEXIS NV
544	41412F	MEMBER COMPANY (THE) (TMC) N.V.
545	13759Q	MERCATOR POSLOVNI SISTEM
546	301774	MERCK KGAA
547	13759U	MERKUR KRANJ
548	982585	METKA S.A.
549	882059	METRO AG
550	505967	METSO OYJ
551	885055	MIQUEL Y COSTAS & MIQUEL SA
552	672614	MITISKA
553	685686	MOBISTAR SA
554	695615	MORPHOSYS AG
555	866032	MOTA-ENGIL SGPS SA
556	259467	MOTOR OIL SA
557	31131W	MTU AERO ENGINES HOLDING AG
558	695482	MVV ENERGIE AG
559	362541	MYTILINEOS HOLDINGS S.A.
560	932859	N.V. NEDERLANDSCHE APPARATENFABRIEK 'NEDAP'
561	531874	NATRA SA
562	26577L	NATRACEUTICAL SA
563	933085	NAVIGAZIONE MONTANARI SPA
564	916698	NEDFIELD
565	27028Q	NEOCHIMIKI LV LAVRENTIADIS SA
566	692552	NEOPOST S.A.
567	30754M	NESTE OIL OYJ
568	741467	NEWAYS ELECTRONICS INTERNATIONAL
569	32302C	NEWCOURT GROUP PLC
570	259181	NEXANS SA

571	31976M	NEXTRADIOTV
572	997952	NH HOTELES SA
573	35968L	NICE SPA
574	504444	NICOLAS CORREA S.A.
575	276432	NICOX SA
576	729882	NOKIA CORPORATION
577	143730	NOKIAN RENKAAT OY
578	142650	NORBERT DENTRESSANGLE
579	681983	NORDDEUTSCHE AFFINERIE AG
580	13703L	NORDEX AKTIENGESELLSCHAFT
581	36183C	NORKOM GROUP PLC
582	289402	NOVABASE SGPS SA
583	289270	NRJ GROUPE
584	897320	NUTRECO HOLDING NV
585	896676	NYLOPLAST NV
586	51218T	NYRSTAR NV
587	289380	OBERTHUR TECHNOLOGIES
588	505540	OBRASCON HUARTE LAIN SA
589	922887	OCE NV
590	41249J	OCTOPLUS
591	779332	OESTERREICHISCHE ELEKTRIZITATSWIRTSCHAFTS AG (VERBUNDGESELLSCHAFT)
592	681806	OMEGA PHARMA NV
593	756879	OMV AKTIENGESELLSCHAFT
594	259035	OPAP S.A.
595	308273	OPG GROEP NV
596	27399U	OPTION NV
597	923433	ORANJEWOUD NV
598	741609	ORDINA NV
599	308504	ORION CORPORATION
600	15406Q	ORPEA SA
601	36062H	OSTERREICHISCHE POST AG
602	505135	OUTOKUMPU OYJ
603	41266N	OUTOTEC OYJ
604	255282	PADDY POWER PLC
605	29170F	PAGESJAUNES
606	672520	PALFINGER AKTIENGESELLSCHAFT
607	779368	PAPELARIA FERNANDES-INDUS. E COMERCIO,SA
608	685054	PAPELES Y CARTONES DE EUROPA SA
609	31974N	PARMALAT SPA
610	952284	PAUL HARTMANN AG
611	672735	PERMASTEELISA GROUP SPA
612	923539	PERNOD RICARD
613	308649	PESCANOVA, S.A.
614	41026D	PETROCELTIC INTERNATIONAL PLC

615	682040	PETROL LJUBLJANA
616	912709	PEUGEOT S.A.
617	679205	PFEIFFER VACUUM TECHNOLOGY AG
618	951678	PFLEIDERER AG
619	698852	PHARMING GROUP NV
620	29955U	PHOENIX SOLAR AG
621	36232W	PIAGGIO NC SPA
622	672583	PIERRE ET VACANCES
623	929016	PILKINGTON DEUTSCHLAND AG
624	672653	PINGUIN NV
625	27348D	PIRAEUS PORT AUTH
626	933333	PIRELLI & C SPA
627	13760V	PIVOVARNA LASKO DD
628	866421	PLACOPLATRE LAMBERT
629	35744M	POLYTEC HOLDING AG
630	876263	PONSSE OYJ
631	946281	PORSCHE AUTOMOBIL HOLDING SE
632	152477	PORTUCEL - EMPRESA PRODUTORA DE PASTA E PAPEL SA
633	152311	PORTUGAL TELECOM SGPS SA
634	28541U	POWEO SA
635	898791	POYRY OYJ
636	923657	PPR SA
637	32320H	PRAKTIKER BAU- UND HEIMWERKERMARKTE HOLDING AG
638	30409V	PREMIERE AG
639	504675	PRIM, S.A.
640	289300	PROMOTORA DE INFORMACIONES S.A. (PRISA)
641	772773	PROSEGUR, COMPANIA DE SEGURIDAD, S.A.
642	897801	PROSIEBENSAT.1 MEDIA AG
643	892788	PROVIDENCE RESOURCES PLC
644	259364	PROVIMI SA
645	50483U	PRYSMIAN SPA
646	14861Q	PUBLIC POWER CORPORATION SA
647	936775	PUBLICIS GROUPE SA
648	14453H	PULEVA BIOTECH SA
649	729717	PUMA AKTIENGESELLSCHAFT RUDOLF DASSLER SPORT
650	897915	PUNCH GRAPHIX NV
651	692657	PUNCH INTERNATIONAL
652	31915V	Q-CELLS AG
653	882416	QIAGEN N.V.
654	290665	QSC AG
655	320334	QUILMES INDUSTRIAL SA
656	690103	QURIUS N.V.
657	729209	RALLYE
658	679421	RAMIRENT OYJ

659	505482	RANDSTAD HOLDING NV
660	287943	RATIONAL AG
661	504843	RAUTARUUKKI OYJ
662	926522	READYMIX PLC
663	885888	REAL SOFTWARE GROUP NV
664	923325	RECORDATI SPA
665	923969	RECTICEL
666	672716	RED ELECTRICA DE ESPANA, S.A.
667	308471	REDITUS-GESTORA PARTICIPACOES SOCIAIS SA
668	307428	REMY COINTREAU
669	50776X	REN - REDES ENERGETICAS NACIONAIS, SGPS, S.A.
670	143366	RENAULT (REGIE NATIONALE DES USINES) SA
671	952299	RENK AG
672	15314M	REPOWER SYSTEMS AG
673	504421	REPSOL-YPF SA
674	50367K	REXEL S.A.
675	929129	RHEINMETALL AG
676	756422	RHI AKTIENGESELLSCHAFT
677	682867	RHODIA
678	307055	RHOEN-KLINIKUM AG
679	885552	RIZZOLI CORRIERE DELLA SERA MEDIAGROUP SPA
680	741499	ROOD TESTHOUSE INTERNATIONAL NV
681	540017	ROSIER SA
682	35923C	ROTH & RAU AG
683	692036	ROULARTA MEDIA GROUP NV
684	922358	ROYAL BOSKALIS WESTMINSTER NV
685	923857	ROYALREESINK N.V.
686	932783	RSDB N.V.
687	143381	RTL GROUP
688	929242	RUBIS
689	902191	RWE AG
690	897365	RYANAIR HOLDINGS PLC
691	912622	SACYR VALLEHERMOSO
692	142963	SAES GETTERS SPA
693	32506N	SAFILO GROUP
694	929273	SAFRAN
695	31281W	SAFT GROUPE S.A.
696	685082	SAG GEST - SOLUCOES AUTOMOVEL GLOBAIS, SGPS, SA
697	929298	SAGA
698	741689	SAINT GOBAIN
699	729304	SAINT-GOBAIN OBERLAND AG
700	906090	SAIPEM SPA
701	929099	SALZGITTER AG
702	997702	SAMAS-GROEP NV

703	992594	SANOFI-AVENTIS
704	775543	SAP AG - SYSTEME ANWENDUNGEN PRODUKTE IN DER DATENVERARBEITUNG
705	932565	SAPEC SOCIETE ANONYME
706	35918T	SARAS RAFFINERIE SARDE SPA
707	682050	SAVA DD
708	916775	SBM OFFSHORE NV
709	929541	SCA HYGIENE PRODUCTS AG
710	998075	SCHNEIDER ELECTRIC SA
711	885985	SCHOELLER-BLECKMANN OILFIELD EQUIP. AG
712	923065	SCHUITEMA N.V.
713	143787	SCHWARZ PHARMA AG
714	27337K	SEAT PAGINE GIALLE SPA
715	936411	SEB S.A.
716	890413	SECHE ENVIRONNEMENT
717	540162	SECHILIENNE-SIDEC
718	41405J	SELOGER.COM
719	152499	SEMAPA - SOCIEDADE DE INVESTIMENTO E GESTAO SGPS, S.A.
720	929039	SEMPERIT AKTIENGESELLSCHAFT HOLDING
721	885336	SEO-STE ELECTRIQUE DE L'OUR SA
722	673898	SEQUANA
723	749819	SERVICE POINT SOLUTIONS SA
724	685030	SES S.A.
725	143641	SGL CARBON AG
726	15188U	SIAS
727	143463	SIDENOR SA
728	902192	SIEMENS AG
729	729499	SIMAC TECHNIEK NV
730	898719	SINGULUS TECHNOLOGIES AG
731	881905	SIOEN INDUSTRIES
732	932404	SIPEF SOCIETE ANONYME
733	413547	SITESERV PLC
734	775697	SIXT AG
735	504959	SLIGRO FOOD GROUP NV
736	53614P	SMA SOLAR TECHNOLOGY AG
737	362709	SMARTRAC NV
738	950807	SMIT INTERNATIONALE NV
739	50259L	SMURFIT KAPPA GROUP PLC
740	936417	SNAI SPA
741	14822X	SNAM RETE GAS SPA
742	881457	SNCF PARTICIPATIONS
743	929482	SNIACE SA
744	755787	SOARES DA COSTA SGPS SA
745	998392	SOCFINAL - STE FINANCIERE LUXEMBOURGEOISE SA
746	997606	SOCFINASIA SA

747	929535	SOCIEDAD GENERAL DE AGUAS DE BARCELONA, S.A.
748	759833	SOCIEDADE COMERCIAL OREY ANTUNES SA
749	930885	SOCIETE BIC
750	932654	SOCIETE COMMERCIALE DE BRASSERIE 'CO. BR. HA.'
751	776488	SOCIETE DES BAINS DE MER ET DU CERCLE DES ETRANGERS A MONACO
752	539941	SOCIETE FERMIERE DU CASINO MUNICIPAL DE CANNES
753	936699	SOCIETE INTERNATIONALE DE PLANTATIONS D'HEVEAS
754	776576	SOCIETE SUCRIERE DE PITHIVIERS LE VIEIL
755	993597	SODEXO
756	697269	SOFTWARE AG
757	779062	SOGEFI SPA
758	692515	SOITEC
759	866797	SOL MELIA S.A.
760	685000	SOL SPA
761	31446E	SOLAR MILLENNIUM AG
762	50678L	SOLARIA ENERGIA Y MEDIO AMBIENTE, S.A.
763	278333	SOLARWORLD AG
764	688751	SOLON AG FUER SOLARTECHNIK
765	945992	SOLVAC
766	912543	SOLVAY SOCIETE ANONYME
767	982099	SOMFY SA
768	51504P	SONAE CAPITAL, SGPS, S.A.
769	729744	SONAE INDUSTRIA, SOCIEDADE GESTORA DE PARTICIPACOES SOCIAIS, SA
770	741812	SONAE-SGSP SA
771	289230	SONAECOM SGPS S.A.
772	505319	SOPRA GROUP
773	28283X	SORIN SPA
774	682937	SOS CUETARA SA
775	932652	SPADEL SA
776	741723	SPERIAN PROTECTION
777	504853	SPIR COMMUNICATION
778	673964	SPORTING SOCIEDADE DESPORT DE FUTEBOL SAD
779	29027R	SPYKER CARS N.V.
780	676138	STADA ARZNEIMITTEL AG
781	685132	STALLERGENES
782	866148	STE DES BRASSERIES DE L'OUEST AFRICAIN
783	143238	STEDIM
784	681804	STEF-TFE
785	932773	STERN GROEP NV
786	936326	STINAG STUTTGART INVEST AG.
787	143375	STMICROELECTRONICS NV
788	932700	STOCKMANN OYJ ABP
789	755028	STORA ENSO OYJ
790	929083	STRABAG BETEILIGUNGS AG

791	51200L	STRABAG SE
792	775158	SUDWESTDEUTSCHE SALZWERKE AG
793	936915	SUED-CHEMIE AKTIENGESELLSCHAFT
794	929100	SUEDZUCKER AG
795	53595N	SUEZ ENVIRONNEMENT COMPANY
796	504845	SUMOLIS CIA. IND. DE FRUTAS E BEBIDAS SA
797	745052	SUPER DE BOER
798	275512	SURTECO SE
799	41442V	SYMRISE AG
800	936933	SYNERGIE SA
801	273293	TAKKT AG
802	504527	TAVEX ALGODONERA, S.A.
803	275577	TECHEM AG & CO
804	143241	TECHNIP
805	36159L	TECNICAS REUNIDAS S.A.
806	749111	TECNOCOM TEL Y ENE SA
807	685840	TEIXEIRA DUARTE - ENGENHARIA E CONSTRUCOES SA
808	885184	TELECOM ITALIA MEDIA
809	27337N	TELECOM ITALIA SPA
810	929534	TELEFONICA SA
811	697528	TELEGATE AG
812	921048	TELEGRAAF MEDIA GROEP
813	289469	TELEKOM AUSTRIA AG
814	41251Q	TELEKOM SLOVENIJE DD
815	32011D	TELENET GROUP HOLDING NV
816	936782	TELEPERFORMANCE
817	26613D	TENARIS S.A.
818	51278E	TERNA ENERGY SA
819	29096C	TERNA SPA
820	916015	TESSENDERLO CHEMIE S.A.
821	755793	TF1 - TV FRANCAISE
822	923543	THALES SA
823	26033U	THEOLIA
824	276479	THOMSON
825	36232R	THROMBOGENICS NV
826	929097	THYSSENKRUPP AG
827	719741	TIETOENATOR OYJ
828	275610	TISCALI SPA
829	755486	TITAN CEMENT COMPANY S.A.
830	932903	TKH GROUP N.V.
831	681714	TNT NV
832	269965	TOD'S SPA
833	50698Q	TOGNUM AG
834	31102D	TOMTOM N.V.

835	932482	TOTAL GABON SA
836	41368F	TOTAL PRODUCE
837	912398	TOTAL SA
838	500414	TOYOTA CAETANO PORTUGAL SA
839	673306	TRANSGENE
840	672738	TREVI FINANZIARIA INDUSTRIALE
841	673286	TRIGANO
842	504383	TUBACEX SA
843	26530D	TUBOS REUNIDOS SA
844	929059	TUI AG
845	866709	UBISOFT ENTERTAINMENT SA
846	916676	UCB SA
847	929345	UMICORE SA
848	933282	UNI LAND SPA
849	936591	UNIBEL
850	932414	UNIBRA SA
851	905478	UNILEVER N.V.
852	929540	UNION FENOSA SA
853	779452	UNIPAPEL SA
854	676348	UNIT 4 AGRESSO NV
855	953818	UNITED DRUG PLC
856	676648	UNITED INTERNET AG
857	539717	UPM-KYMMENE OYJ
858	533136	UPONOR OYJ
859	932820	USG PEOPLE N.V.
860	276631	UTOPIA
861	255977	VACON OYJ
862	533192	VAISALA OYJ
863	922053	VALEO SA
864	892877	VAN DE VELDE SA
865	31989M	VELCAN ENERGY
866	289374	VEOLIA ENVIRONNEMENT
867	50420T	VERSATEL AG
868	50940H	VERTICE TRESCIENTOS SESENTA GRADOS S.A.
869	41357X	VETOQUINOL SA
870	741715	VIANINI LAVORI S.P.A.
871	997836	VICAT SA
872	776436	VIDRALA SA
873	876262	VIKING LINE ABP
874	309810	VILMORIN & CIE
875	772568	VINCI
876	500341	VIOHALCO HELLENIC COPPER & ALUM IND. SA
877	772692	VIRBAC
878	749099	VISCOFAN SA

879	539567	VIVARTIA S.A.
880	923139	VIVENDI
881	413931	VOCENTO SA
882	303482	VOEST-ALPINE AG
883	741053	VOLKSWAGEN AG
884	505509	VOSSLOH AG
885	692782	VPK PACKAGING GROUP NV
886	673494	VRANKEN - POMMERY MONOPOLE
887	50704T	VTG AG
888	414438	VUELING AIRLINES, SA
889	35649C	WACKER CHEMIE AG
890	50507P	WACKER CONSTRUCTION EQUIPMENT AG
891	772963	WARTSILA OYJ
892	41271K	WAVIN N.V.
893	998096	WIENERBERGER AG
894	28990K	WINCOR NIXDORF AG
895	268562	WIRECARD AG
896	929056	WMF WURTTEMBERGISCHE METALLWARENFABRIK AKTIENGESELLSCHAFT
897	932826	WOLTERS KLUWER NV
898	142836	YIT OYJ
899	745012	ZARDOYA OTIS SA
900	775185	ZEAG ENERGIE AG
901	890502	ZELTIA SA
902	50760Q	ZHONGDE WASTE TECHNOLOGY AG.
903	993501	ZODIAC SA
904	276529	ZON MULTIMEDIA - SERVICOS DE TELECOMUNICACOES E MULTIMEDIA, SGPS, S.A.,
905	685680	ZUMTOBEL AG

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10/2000 – 03/2009	University of Vienna Master in International Business Administration (Mag. rer. soc. oec.) with specialization in Corporate Finance (Prof. Josef Zechner) and Management Accounting (Prof. Thomas Pfeiffer) and elective courses in Investments (Prof. Engelbert Dockner)
07/2006 – 09/2006	Libertas 7 SA, Asset Management, Valencia, Spain (Internship) Applying fundamental analyses with Excel, working with Bloomberg, seeking for relevant business and market informations in Spanish, English and French and providing of summaries for the financial director
09/2005 – 06/2006	Universitat de València (Erasmus Scholarship) Administración y Dirección de Empresas; DELE-Intermedio (05/2006)
05/2000 – 10/2000	Technisches Büro Obkircher GmbH, Engineering office, Salzburg, Austria (permanent full-time job) Construction engineer, design of hydraulic plans for and in the voestalpine AG with AutoCAD
09/1992 – 06/1999	HTBLA – Linzer Technikum (Secondary College for Mechanical Engineering) Special Training Focus Mechanical Engineering and Plant Technology Final year project: Calculation and construction of a borehole pump and of a manipulator

Abstract in English

Trade credit financing can entail several advantages such as stimulating sales and investments and the possibility to reduce information asymmetries. However, it also involves some risks and costs caused by financial distress and default. The literature shows that trade credit provides relatively more financing when alternative sources like bank credit are exhausted. Previous research by Preve (2004) shows for the US that financially distressed firms use relatively more trade credit than their undistressed counterparts. This paper, which makes use of panel data of European Monetary Union firms over a period of eleven years, partially supports this finding. It shows that financially distressed European Monetary Union firms substitute equity with trade credit but surprisingly reduce trade credit compared to long term debt. Further, the results suggest that large and small firms use more trade credit during financial distress but there is no clear tendency whether smaller firms use more than larger ones. However, due to the low explanatory power and partly ambiguous or conflicting results the models of Preve (2004) for the US do not apply well for the European Monetary Union. An interpretation is that the financing behavior of US and European firms is different and that creditor protection and accounting standards are not the same.

Abstract in German

Die betriebliche Finanzierung mittels Handelskredit bringt mehrere Vorteile mit sich. Zum Beispiel können auf der Verkäuferseite Umsätze stimuliert werden und auf der Käuferseite notwendige Finanzierungen leichter getätigt werden, besonders dann wenn andere Finanzierungsquellen wie Bankkredite erschöpft sind. Die Handelskreditfinanzierung kann weiters Informationsasymmetrien zwischen Handelskreditnehmer und -geber reduzieren, weil Käufer und Verkäufer meist häufiger in Geschäftskontakt treten als Banken mit Kreditnehmern. Handelskreditgeber kennen oft das Gewerbe besser und können somit speziell mittels Soft-Facts die Geschäftslage und Kreditwürdigkeit ihrer Geschäftspartner bzw. Handelskreditnehmer besser als Banken einschätzen.

Die Handelskreditfinanzierung birgt natürlich aber auch Risiken und Kosten für den Handelskreditgeber. Zum Beispiel aus Zahlungsverzögerungen und Totalausfällen bei Konkurs eines Schuldners, speziell wenn das gelieferte Gut bereits weiterverarbeitet wurde oder verderblich ist. Die Literatur zeigt dass Firmen mehr Handelskredit verwenden wenn alternative Finanzierungsquellen versiegt sind. Empirische Untersuchungen von Preve (2004) zeigen weiters dass amerikanische Unternehmen mit finanziellen „Problemen" (financial distress) relativ mehr Handelskredit verwenden. Diese Erkenntnis wird durch die vorliegende Arbeit mittels empirischer Untersuchung eines Panels von 11 Jahren von Firmen der Europäischen Währungsunion belegt.

Weiters werden in dieser Arbeit der Substitutionseffekt und die Bedeutung der Firmengröße auf den Handelskreditgebrauch bei finanziellen Problemen getestet. Die Resultate zeigen, dass europäische Firmen mit finanziellen Problemen dazu tendieren Eigenkapital mit Handelskredit zu substituieren, was die Erkenntnisse von Preve (2004) bestätigt. Die vorliegende Arbeit kann jedoch nicht die Substituierung

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von Finanzschulden untermauern. Dies kann damit begründet werden, dass Modelle von Preve (2004) verwendet werden. Folglich passen diese nicht gut für Firmen der Europäischen Währungsunion, wie gezeigt durch die Regressionen dieser Arbeit, welche sehr niedrige Bestimmtheitsmaße aufweisen. Eine alternative Interpretation des Resultats ist, dass Europäische Banken Europäische Firmen trotz „financial distress" mit mehr Bankkredit versorgen.

Die Ergebnisse zeigen weiters, dass relativ große und kleine Firmen mehr Handelskredit verwenden, wenn sie finanzielle Probleme haben. Im Gegensatz zu Preve (2004) zeigen die Resultate jedoch keine klare Tendenz ob große oder kleine Firmen mehr Handelskredit verwenden. Generell sind die Erkenntnisse dieser Arbeit aber nicht nur aufgrund geringer R^2's, sondern auch durch die teilweise zweideutigen Ergebnisse bzw. einzelne nicht signifikante Koeffizienten je nach dem welche „Cluster-" und „absorbing" Spezifikationen verwendet werden, mit Vorsicht zu genießen. Ein Grund warum die Ergebnisse teilweise widersprüchlich sind, ist die Verwendung von „US-Modellen", die offenbar nicht gut für Firmen der Europäischen Währungsunion geeignet sind. Folglich ist das Resultat, dass in der EWU im Vergleich zu den USA deutlich mehr Handelskredit verwendet wird entweder zufällig passiert oder durch andere hier nicht betrachtete Faktoren verursacht worden. Weitere Deutungen der vorliegenden Ergebnisse sind dass das Finanzierungsverhalten von US und EWU Firmen unterschiedlich ist, dass es Unterschiede im Kreditorenschutz gibt und dass die Ergebnisse auf unterschiedliche Finanzierungsverhalten aber auch eventuell unterschiedliche Bilanzierungsstandards zurückzuführen sind. Als Implikation sind Modelle nicht auf alle Länder bzw. Finanzsysteme anwendbar.