The Impact of Inter-Firm Finance and Knowledge Spillovers on Exporting and Product Sophistication: A Firm-Level Analysis

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Introduction

Participating in international trade is one important channel through which economic prosperity can be fostered. Trade creates gains from specialization, it raises the average productivity level of a country through increased competition and it enables the diffusion of knowledge. A second channel is the manufacturing of increasingly sophisticated products which has proven to be a successful growth strategy for developing countries. Prominent examples are fast growing countries like China, India, and Taiwan that shifted their production from food and textiles to more sophisticated goods like consumer electronics and pharmaceuticals (Mathews, 2006). However, despite the incontestable gains from trade, the volume of international trade flows is substantially lower than standard trade theory predicts (Trefler, 1995) and bilateral trade flows are actually equal to zero for half of all potential country pairs (Helpman, Melitz, and Rubinstein, 2008). Moreover, only few countries have managed to catch up by upgrading their product basket (Hausmann and Rodrik, 2003).

To understand the origin of these aggregate outcomes, it is necessary to take one step back and look at the micro level since it is not countries that trade and produce, but firms (Mayer and Ottaviano, 2007). Contrary to the prevailing assumption of one representative firm in macroeconomic analyses, firms differ in various respects from each other. With the increasing availability of detailed firm-level data, studies have uncovered several dimensions of firm heterogeneity. For example, one key insight is that the bulk of international trade is conducted by very few firms only, which tend to be the largest and most productive firms (Mayer and Ottaviano, 2007 or Bernard and Jensen, 1999). This selection process hints at considerable impediments that deter a large part of firms from engaging in growth fostering activities. Consequently, in order to design growth

enhancing policies, it is essential to take potential obstacles and their interaction with firm heterogeneity into account.

This dissertation addresses impediments that hinder exporting and the manufacturing of highly sophisticated products by firms. It then analyzes through which channels these obstacles can be alleviated. The first three chapters investigate both theoretically and empirically the effect of inter-firm financing on the export activities of firms. The fourth chapter empirically explores whether foreign direct investment leads to an increase in firms' manufacturing of highly sophisticated products. Each chapter is self-contained and can be read independently.

According to the IMF (2009), about 60% of international transactions are financed via trade credits. Trade credits are extended bilaterally between firms and exist in the form of supplier credits and cash-in-advance. A supplier credit allows the buyer of a good delaying the payment to the seller for a certain period of time. In contrast, cash-in-advance denotes a prepayment from the buyer to the seller of a good. The intensive use of trade credits in international trade is surprising given that inter-firm credits are usually more expensive than bank credits (Petersen and Rajan, 1997). This gives rise to the question as to why internationally active firms rely intensively on trade credit financing.

Compared to domestic trade, exporting not only is associated with higher financing needs but it is also prone to higher uncertainty since firms have limited knowledge about foreign markets and trading partners. Higher uncertainty about the success of the export transaction raises the costs of bank credit financing, even prohibitively so. In the first three chapters of this dissertation, we show that exporters resort to trade credit financing since trade credits convey a signal that reduces asymmetric information in international trade and thus alleviate financial constraints.

The first chapter analyzes the relationship between bank and supplier credits in international trade.[1] We develop a theoretical model showing that a supplier credit provides a signal of the quality of an unknown input supplier. If an exporting firm is granted an

[1]This chapter is based on the article "Trade Credits and Bank Credits in International Trade: Substitutes or Complements?", which is joint work with Martina Engemann and Monika Schnitzer from the University of Munich.

extended payment period by his input supplier, the exporter can observe the quality of the input beforehand and condition the payment of the input based on its quality. The reduction in uncertainty compensates for the higher costs of supplier credit financing. Moreover, it leads to the provision of a complementary bank credit since financing the export transaction has become less of a risk for the bank. Hence, we derive that supplier credits alleviate financial constraints in international trade since they facilitate the provision of additional bank credit to exporters.

We test the signaling hypothesis by analyzing the effect of supplier credit on bank credit financing for a sample of German firms. To mitigate reverse causality between both forms of financing, we apply the generalized method of moments estimation and instrument the use of supplier credits by firms with its lagged value. Our results reveal that an increase in supplier credit financing leads to an increase in bank credit financing for financially constrained firms. The complementary effect is even stronger for financially constrained exporters. These findings confirm our prediction that supplier credits convey a signal and lead to additional bank credit for financially constrained exporters. In contrast, for financially unconstrained firms bank credits and supplier credits are substitutes. This is plausible since unconstrained firms do not depend on the quality signal and either use supplier credits or bank credits.

This chapter provides a rationale for the prominent use of supplier credits by exporters. Moreover, we are the first to deliver empirical evidence on the complementary relationship between bank credits and supplier credits in international trade. Our results imply that supplier credits are an important financing tool for financially constrained firms despite their high costs.

In the second chapter, we study the effect of cash-in-advance financing on the export participation of firms.[2] With the help of a theoretical model, we argue that cash-in-advance paid by a foreign customer sends a signal regarding the customer's ability to pay for the exporter's good. Customers that pay part of the purchasing price in advance are more trustworthy and have a higher incentive to also pay the balance of the purchasing price.

[2]This chapter is based on the article "How Trade Credits Foster Exporting", which is joint work with Martina Engemann and Monika Schnitzer from the University of Munich.

The reduction in uncertainty through prepayments increases the profits from exporting and hence makes exporting more attractive to firms. This effect is particularly relevant for financially constrained firms that are not profitable enough to export if only bank credit financing is available. In short, our model predicts that cash-in-advance financing fosters the export participation of firms.

We test this prediction using unique survey data for German firms. These data provide a precise measure of cash-in-advance received by firms which is the share of sales paid to a firm before it delivers its product to the customer. In order to deal with endogeneity with regard to the firm's financing choice, we instrument the use of prepayments by firms with product-customer-specific information that is unrelated to the export decision of a firm. Our results indicate that firms that receive a positive amount of their sales in advance have a 27% higher probability to export than firms that do not receive prepayments. Likewise, a one percent increase in the share of sales received in advance increases the export probability by about 13%. We find that this effect is particularly strong for financially constrained firms.

Our contribution to the existing literature is twofold: this chapter is the first to explicitly investigate the effect of cash-in-advance financing on exporting in a theoretical framework. Secondly, we provide a direct empirical test of the positive effect of cash-in-advance financing on exporting. Our results obtained for German firms are particularly interesting because they imply that cash-in-advance financing can even be beneficial in an already well developed financial market.

The third chapter studies the impact of cash-in-advance financing on the export activities of firms during the recent financial crisis.[3] Deteriorated credit conditions have been cited as one cause for the sharp drop in trade in the aftermath of the financial crisis. However, recent empirical evidence suggests that a drop in global demand accounted for the largest part of the great trade collapse whereas financial conditions only played a minor role (Bricongne, Fontagné, Gaulier, Taglioni, and Vicard, 2012 or Eaton, Kortum, Neiman, and Romalis, 2011). One potential explanation for this finding is that firms

[3]This chapter is based on the article "Trade Credit Financing and Exporting during a Financial Crisis".

can resort to trade credit financing from unconstrained trading partners if bank money supply becomes scarce. Indeed, several studies document that trade credit financing increases relative to bank credit financing if credit conditions tighten (Bougheas, Mateut, and Mizen, 2006 or Love, Preve, and Sarria-Allende, 2007). However, only few studies explore the effect of trade credit financing on international trade during a financial crisis. This chapter provides complementary evidence on the effects of cash-in-advance financing on exporting.

We draw on the theoretical framework from the second chapter to study the impact of a financial shock on the export decision of firms. The shock is modeled as an increase in interest rates for external financing and an increase in demand uncertainty. Both changes decrease the profitability of exporting and force some firms to exit the export market. Moreover, the export volume of continuing exporters declines. However, the decline in the profitability of exporting is smaller for cash-in-advance financing firms because prepayments mitigate the increase in demand uncertainty. Thus, we find that firms that receive prepayments have a higher probability to export in the crisis and they experience a smaller drop in export volumes than firms without cash-in-advance.

For a sample of European and Central Asian firms, we estimate the effect of cash-in-advance financing on firms' export performance before and during the financial crisis of 2008-09. To account for non-random sorting into prepayment financing, we apply a non-parametric matching approach. We find that access to cash-in-advance financing fosters exporting more strongly in the crisis than in the pre-crisis period. Firms with prepayment financing have a 6% higher probability to export in the pre-crisis period than firms without access to cash-in-advance. During the crisis, prepayments increase the export probability of firms by 9%. Moreover, firms that receive prepayments in the crisis face a drop in export shares that is lower by 6 percentage points than the loss of firms that do not receive cash-in-advance.

Our analysis is the first to study the impact of prepayment financing on exporting during a financial crisis. Moreover, we explicitly control for non-random sorting of firms into cash-in-advance financing. Comparing matched pairs of firms that receive and do not receive prepayments we can identify a causal effect of cash-in-advance financing on firms'

export performance in the crisis. Our results support that prepayments can alleviate the adverse impact of tightened credit conditions in international trade.

In the last chapter, we empirically investigate the channels through which spillovers from FDI influence the production of highly sophisticated products by Indian firms.[4] Politicians give high priority to attracting FDI to developing countries since FDI is considered as "a major catalyst to development" (OECD, 2002, p.3). Foreign investors not only inject fresh money into an economy but they also bring along an inflow of foreign knowledge and technologies that can spill over to host country firms. One way through which knowledge spillovers can foster growth in developing countries is the facilitation of manufacturing highly sophisticated products by firms. Although the importance of FDI is uncontested, little is known on the impact of spillovers from FDI on the production of highly sophisticated products by firms. This chapter aims to fill this gap.

We compile a large firm-product panel dataset for Indian manufacturing firms which we supplement with information on the intensity of firms' contact to multinational enterprises. To identify firms that manufacture a highly sophisticated product, we use a product-specific sophistication index and rank products according to their extent of technological sophistication. Products that belong to the top quartile of the sophistication distribution are termed highly sophisticated products. Interestingly, less than half of all firms in our dataset produce a highly sophisticated product. Those that do, tend to be larger and more productive than firms that produce less sophisticated products.

We then test the influence of horizontal and vertical spillovers on firms' probability to manufacture a highly sophisticated product. Using a pooled probit model, we provide evidence that vertical spillovers increase a firm's probability to manufacture a highly sophisticated product via supplier linkages. An increase by 10 percentage points in the presence of multinational downstream firms raises a firm's probability to manufacture a highly sophisticated product by 5%. In contrast, we document a negative effect through customer linkages. An increase by 10 percentage points in the presence of multinational upstream firms leads to a 10% decline in the probability to manufacture a highly sophis-

[4]This chapter is based on the article "Product Sophistication and Spillovers from FDI", which is joint work with Stephan Huber from the University of Regensburg.

ticated product. We do not find robust evidence of positive horizontal spillovers. One explanation for these findings is that multinationals have an incentive to transfer their knowledge to suppliers but try to prevent technology leakage within their own industry. Multinational upstream firms can impede the production of highly sophisticated goods by Indian firms since these are not able to incorporate the more sophisticated inputs into their production process.

This chapter is the first to identify firms that engage in the production of highly sophisticated products. In addition, we provide evidence on the impact of spillovers from FDI on firms' manufacturing of highly sophisticated products. Our results imply that attracting FDI in downstream industries is desirable while the presence of multinational upstream firms can be impedimental.

Taking the four chapters together, this dissertation shows that access to trade credits and foreign knowledge strongly fosters the business activities of firms. Trade credits alleviate asymmetric information that deters firms from exporting. One way to increase the extension of trade credits between firms is the provision of trade credit insurance, for example. This helps unconstrained firms grant credit to financially constrained trading partners even though banks are not willing to lend. In developing countries, access to foreign knowledge is essential to master the production of highly sophisticated products. Attracting FDI can lead to an inflow of foreign knowledge which facilitates the production of highly sophisticated goods.

Chapter 1

Trade Credits and Bank Credits in International Trade: Substitutes or Complements?*

1.1 Introduction

The financing of international transactions is a very important determinant of international trade, as the recent financial crisis has forcefully shown. According to WTO Trade Statistics, world merchandise exports declined by 12% in 2009, whereas world GDP declined by only 2.5% (WTO, 2010). A lack of finance during 2009 has been blamed as one of the reasons for this pronounced decrease in global trade (Amiti and Weinstein, 2011).

Apart from internal finance, firms have two options for financing their international transactions. They can ask for a bank credit or they can make use of supplier credits, also called trade credits.[1] In the latter case, they delay paying their supplier, usually between 30 to 60 days. Supplier credits are typically more expensive than bank credits, with a real interest rate of 40% (Petersen and Rajan, 1997). *Prima facie* this suggests that supplier credits are expensive substitutes, only attractive for those firms that cannot obtain bank

*This chapter is based on joint work with Martina Engemann and Monika Schnitzer.

[1]In the prevailing literature, the term trade credit is often used interchangeably for a supplier credit and does not exclusively refer to the financing of an international trading transaction.

credit. Interestingly, supplier credits are used intensively by internationally active firms. About 40% of international transactions are financed via supplier credits (IMF, 2009). Internationally active firms are also larger and more productive than domestic ones, as firm-level studies confirm (see for example Bernard, Jensen, Redding, and Schott, 2007 for a survey). This raises the question why internationally active firms rely to such a large extent on supplier credits and how this relates to their use of bank credits. In this paper, we address this question both theoretically and empirically.

We start from the observation that firms active in international trade have higher financing needs than purely domestic firms. They generally have higher outlays (for example the establishment of a distribution network abroad) and there is a longer delay between the production of the goods and the payment. Moreover, cross-border transactions are considered to be more risky (for example due to exchange rate risk, different legal systems, and less knowledge about the foreign market and the foreign trading partner). Thus, internationally active firms and banks financing these firms face a high uncertainty. Banks encounter difficulties to judge the profitability of international transactions. These information asymmetries may hinder internationally active firms from obtaining bank credits. Most models of international trade consider a world without financial friction so that these facts are insufficiently taken into account. In our paper, we show that supplier credits can alleviate financial constraints as they can reduce information asymmetries via a quality signal. Therefore, supplier credits and bank credits are complements for financially constrained firms.

For this purpose, we develop a model of a potential exporter who needs external finance for the production of export goods. In a world without asymmetric information, bank credits are cheaper than supplier credits because banks are more efficient in providing credits. With asymmetric information, however, bank credits become more expensive, even prohibitively so. If this is the case, a supplier credit can provide a signal about the quality of the supplier which may lead to the additional provision of a bank credit. The uncertainty the bank faces is reduced, so the bank charges a lower interest rate for any complementary bank credit. Thus, the use of supplier credits can facilitate the provision of additional bank credits due to a reduction in uncertainty.

To test our signaling hypothesis, we analyze whether supplier credits and bank credits are complements or substitutes. We use the Business Expectations Panel of the ifo Institute for Economic Research. This is a panel data set for the years 1994 to 2009 which contains merged balance sheet data and data of the ifo Business Tendency survey for 3,974 German companies. The data includes information on trade accounts payable and receivable and on bank debt from the balance sheet data. Additionally, it includes variables indicating a firm's export status and whether a firm is financially constrained or not. Thus, we have a direct measure of financial constraints and can avoid the problems arising from indirect measures such as balance sheet information.[2]

We estimate the relation between supplier credits and bank credits with the two-step GMM estimator for panel data proposed by Arellano and Bond (1991). As bank credit influences supplier credit and vice versa, we face a reverse causality problem. Therefore, we assume sequential exogeneity and instrument supplier credit with its second lag. This is admissible because the second lag of supplier credit influences bank credit today, but bank credit today does not influence supplier credit two periods ago. The results indicate that bank credit and supplier credit are substitutes for financially unconstrained firms. For financially constrained firms, however, we find evidence that the two forms of credit tend to be complements. As our theory suggests, we find this effect to be even stronger for financially constrained exporters. Thus, our results confirm our theoretical predictions of the quality signal conveyed by supplier credit.

Our paper is related to three strands of the literature. First, it is related to the theoretical and empirical literature on trade credits. There are several theoretical articles which explain the existence and use of trade credits (see Fisman and Love, 2003 for a reviwe). Closest to our approach is the warranty for product quality theory by Lee and Stowe (1993). The authors argue that certain industries require trade credits as a guarantee for product quality, because the choice of trade credit terms offered by the supplier can serve as a signal of product quality. Klapper, Laeven, and Rajan (2012) find empirical evidence on the warranty for product quality hypothesis. This paper contributes to the literature by explaining the intensive use of supplier credits by internationally active firms. In

[2]See Fazzari, Hubbard, and Petersen (1988) and Kaplan and Zingales (1997) for an intensive discussion.

international trade, quality uncertainty is even higher. Therefore, we incorporate the warranty for product quality as a motivation for the extension of trade credit into our model of international trade. We show that supplier credits are an important financing tool for financially constrained exporters.

Second, we build on the literature on the relation between bank credit and trade credit. Up to now, papers which deal with the relation between bank credits and trade credits focus only on national transactions. Biais and Gollier (1997) develop a model where the firm that extends the trade credit signals its belief in the credit worthiness of the firm it provides with trade credit. This in turn helps the firm receiving the trade credit obtain additional bank credits.[3] Their argument requires that the trade partner has an information advantage relative to the bank. This seems to be at odds with the empirical evidence by Giannetti, Burkart, and Ellingsen (2011) who find that suppliers have no persistent informational advantage. In contrast to Biais and Gollier (1997), in our model we assume that the firm extending trade credit signals its own quality, which seems to be the more natural and realistic assumption.[4] A closely related paper is the one by Burkart and Ellingsen (2004) who develop a model in which trade credits and bank credits are substitutes for firms with unconstrained access to external finance, whereas firms that do not receive sufficient bank funding, use bank and trade credits complementary. Their reasoning for the complementary relationship is that lending goods is less prone to diversion than lending cash, which has been termed the diversion theory of trade credit financing. Banks are more willing to extend additional bank credit to trade credit receiving firms since these are less likely to commit moral hazard. We develop a different model, in which trade credits help to solve an adverse selection problem and provide empirical evidence of our results in addition.

[3]Aktas, de Bodt, Lobez, and Statnik (2012) show that supplier credits are a signal not only to lenders but also to investors. Fabbri and Menichini (2010) study the use of trade credits for rationed and non-rationed firms, arguing that suppliers not only have an information advantage over other creditors, but are also better in liquidating the assets in case of default.

[4]Huang, Shi, and Zhang (2011) set up a mechanism-design model in which they can show that when firms' production efficiency crosses a low threshold supplier credits and bank credits are substitutes. This is, according to the authors, almost always the case. In contrast, we find that supplier credits and bank credits can be complements and that this complementary effect is of special importance for financially constrained exporters.

Empirically, Gama and Mateus (2010) find that in general, bank credits and supplier credits are substitutes. For smaller and younger firms, the substitution and complementary hypothesis are not mutually exclusive, however. Their interpretation of this result is that supplier credits signal the creditworthiness of the small firm to the bank, which can increase its bank credit supply. The paper by Yang (2011) finds that supplier credits and bank credits are complements for financially constrained firms, where financial constraints are measured by a firm's bond rating status and its size. Hence, Yang (2011) also strengthens the complementary effect for smaller firms.[5] Additionally, Giannetti, Burkart, and Ellingsen (2011) find that trade credits help firms secure financing from relatively uninformed banks or get better deals from their banks. Thus, they also confirm the complementary relation of supplier credits and bank credits. We go beyond their analysis by focusing on exporters for whom we expect the information problem for banks to be even larger. In contrast to previous findings, we show that the complementary relationship between supplier credits and bank credits also holds for large firms. Most noteworthy, our results show that it is not a firm's size that determines the relation between supplier credits and bank credits, but whether a firm is financially constrained and whether it is internationally active.

The third strand of literature we build on deals with financial constraints in international trade. Manova (2012) shows that firms that are productive enough to export in the absence of financial constraints may not be able to do so if they are financially constrained. Bellone, Musso, Nesta, and Schiavo (2010) and Feenstra, Li, and Yu (2011) provide empirical evidence for the importance of financial constraints in international trade. While these studies focus only on bank credit as a source of external finance, other recent papers also add supplier credits to the analysis (Ahn, 2011; Antràs and Foley, 2011; Schmidt-Eisenlohr, 2012). These studies focus on the optimal choice of financing modes in international trade considering supplier credits. Our paper extends this literature by

[5]While the findings in Yang (2011) suggest that trade credit can alleviate financial constraints that are due to asymmetric information between banks and firms, the paper cannot explain the intensive use of supplier credits in international trade. As exporters are generally larger than non-exporters, they would be classified as unconstrained by Yang (2011). Our data allow us to look at financially constrained exporters using the self-reported measure of financial constraints. As predicted by our model, we find that financially constrained exporters are more likely to benefit from the positive signaling effect of supplier credits.

showing that supplier credits and bank credits are not necessarily substitutes among which exporters have to choose but can also be complements.

The remainder of this chapter proceeds as follows: In Section 1.2, we present the basic model and compare different forms of financing. Furthermore, we derive empirical hypotheses from the model. Section 1.3 presents the data and gives summary statistics. In Section 1.4, we explain the estimation strategy and provide empirical results. Finally, Section 1.5 draws a conclusion.

1.2 Theoretical Framework

1.2.1 Basic Setup

Consider a firm that decides whether or not to export depending on its productivity level.[6] The productivity level may differ across firms. The firm needs to buy inputs to produce its final good that it can sell on the foreign market at an exogenously given market price p.[7]

The firm has the following Cobb-Douglas production function

$$f(q_1, \bar{q}_2) = x = [(1+\beta)q_1]^{\frac{1}{2}} \bar{q}_2^{\frac{1}{2}}, \tag{1.1}$$

where x is the quantity produced and q_1 and $\bar{q}_2$ are the input factors. $\bar{q}_2$ is a fixed input requirement. It can be interpreted as machines the quantity of which cannot be adjusted in the short run. $(1+\beta)$ denotes the productivity level, where $\beta > 0$. Thus, an increase in the productivity level leads to a larger output given a fixed quantity of inputs.

The firm has to buy the inputs q_1 from a supplier at price p_1. Minimizing costs for a given x leads to variable costs of production $k(x) = p_1 \frac{x^2}{(1+\beta)\bar{q}_2}$. The variable costs are marginally increasing in the quantity produced and are decreasing in the firm's productivity level and the fixed input requirement. Furthermore, the firm faces fixed costs. The fixed costs

[6] Note that we do not take into account the firm's domestic activities.

[7] We assume that the effect of the firm's production decision on the market price is negligible.

consist of fixed input costs ($F = p_2\bar{q}_2$) on the one hand and fixed costs of exporting (F_{EX}) on the other hand. The fixed costs of exporting can stem from the establishment of a distribution network or the acquirement of knowledge about the foreign market, for example.

The input good is subject to a quality risk.[8] With probability σ the supplier produces a product which is of good quality at marginal production costs $\bar{c}$. With probability $(1-\sigma)$ she produces low quality, at marginal costs $\underline{c}$, where $\bar{c} > \underline{c}$. The final good of the exporter can be sold only if the input used in the production process is of good quality, which is in line with the O-ring theory (Kremer, 1993). The supplier knows her own quality, but the exporter does not.

The price to be paid for the input good, p_1, is determined in a bargaining procedure between the exporter and the input supplier. In the following, we assume that the exporter has all the bargaining power, which means that he can choose the input price p_1 and the supplier only can choose whether or not to supply the input.

Production takes place in period $t = 0$. This is when the exporter has to incur the variable and the fixed costs. The revenues of the international transaction are generated in period $t = 1$. We assume that the exporter has no internal funds, thus external finance is needed to bridge the time lag. Our assumption on the distribution of bargaining power implies that the financing need of the exporter is minimized. It is straightforward to extend our analysis to cases when this assumption is relaxed. In the following, we analyze different financing scenarios and derive the minimum productivity level necessary for successful exporting under the different financing scenarios.

1.2.2 Pure Bank Credit Financing

Consider first the case in which the firm asks the bank for a credit to cover the production costs. Like the exporter, the bank cannot judge the quality of the supplier. There is perfect competition in the banking sector. Thus, if the quality of the input good is

[8]For simplicity, we do not consider quality uncertainty with respect to the exporter.

unknown, it is necessary that

$$\sigma D(1 + r_B) = (1 + \bar{r}_B)D, \tag{1.2}$$

for the bank to break even. σ represents the probability that the input is of good quality such that the exporter generates positive revenues and repays his credit. D stands for the amount of credit demanded, $(1 + r_B)$ is the gross interest rate charged by the bank and $\bar{r}_B$ are the refinancing costs incurred by the bank. Therefore the gross interest rate charged by the bank amounts to

$$(1 + r_B) = \frac{(1 + \bar{r}_B)}{\sigma}. \tag{1.3}$$

It is increasing in the refinancing costs and the quality risk (decrease of σ).

The exporter's profit function then is

$$\pi_{EX}^{BC} = \sigma px - \sigma \frac{(1 + \bar{r}_B)}{\sigma} \left[p_1 \frac{x^2}{(1 + \beta)\bar{q}_2} + F + F_{EX} \right]. \tag{1.4}$$

The firm has expected revenues of σpx. The total costs are financed via a bank credit which is repaid with probability σ.

The exporter chooses the input price p_1 such that his profits are maximized. This implies choosing the smallest possible price p_1 that satisfies the incentive constraint of the high quality input supplier so that the input good is delivered:

$$p_1 q_1 - \bar{c} q_1 \geq 0. \tag{1.5}$$

Thus, the exporter pays $p_1 = \bar{c}$ to the supplier.

Maximizing the exporter's profits with respect to the quantity and plugging in p_1 yields

$$x^{BC} = \frac{\sigma p(1 + \beta)\bar{q}_2}{2\bar{c}(1 + \bar{r}_B)}. \tag{1.6}$$

Plugging this into the profit function and setting it equal to zero gives the minimum productivity level necessary for successful exporting with bank credit financing

$$(1+\beta)^{BC} \equiv \frac{4(1+\bar{r}_B)^2(F+F_{EX})\bar{c}}{(\sigma p)^2 \bar{q}_2}. \tag{1.7}$$

Firms with a productivity level $1+\beta \geq (1+\beta)^{BC}$ are able to export as they make at least zero profits. Firms with a productivity level smaller than the threshold level are not able to start exporting.

Doing simple comparative statics, it is easy to see that the higher the costs, the higher the productivity a firm has to have in order to break even. In contrast, the higher the market price, the higher the revenues, so that the productivity threshold is lower. Moreover, the higher the quality uncertainty the firm faces, the lower are the expected revenues and the higher the productivity level has to be in order to export successfully. In case of no information asymmetries, $\sigma = 1$, firms need to be less productive to enter the foreign market.

1.2.3 Full Supplier Credit and Bank Credit Financing

Firms with a productivity level below the minimum threshold necessary to afford bank credit financing may turn to supplier credit financing instead. The supplier delivers the input, but the potential exporter can pay for it later. Usually, the payment can be made up to 30 to 60 days after delivery. By definition, the maximum amount of supplier credit extended are the costs of the input good ($p_1 q_1$). The rest has to be financed via a bank credit. To capture the idea that banks are inherently more efficient in supplying credits, we assume that the refinancing costs of suppliers, $(1+\bar{r}_{SC})$, are higher, $(1+\bar{r}_{SC}) > (1+\bar{r}_B)$. Note that the refinancing costs $(1+\bar{r}_{SC})$ can also be interpreted as a measure of the financial constraint of the supplier.

Consider first the case where the supplier credit covers the total input good costs, $p_1 q_1$. In this case, the exporter conditions the payment of the input on the success of resale. Only if the final goods can be sold on the foreign market successfully, the exporter pays the supplier. Note that our assumption that the exporter has no internal funds to finance

production precludes paying the supplier if there are no revenues from selling the good on the export market. Consequently, only good suppliers have an incentive to participate in the transaction. For the good supplier to be willing to do so, it is necessary that

$$p_1 q_1 - \bar{c} q_1 (1 + \bar{r}_{SC}) \geq 0. \tag{1.8}$$

Thus, the exporter pays the supplier $p_1 = \bar{c}(1 + \bar{r}_{SC})$ if the export goods are successfully sold.

As only the good supplier participates in the transaction, the quality uncertainty is eliminated. The bank, therefore, sets $\sigma = 1$ and is willing to finance the fixed costs at the interest rate $(1 + \bar{r}_B)$.

The exporter's profit function then looks as follows

$$\pi_{EX}^{SC} = px - \bar{c}(1 + \bar{r}_{SC}) \frac{x^2}{(1+\beta)\bar{q}_2} - (1 + \bar{r}_B)(F + F_{EX}). \tag{1.9}$$

Applying the same procedure as before, we can derive the minimum productivity level necessary for successful exporting with supplier credit financing for the variable costs and bank credit financing for the fixed costs

$$(1+\beta)^{SC} \equiv \frac{4(1 + \bar{r}_B)(F + F_{EX})\bar{c}(1 + \bar{r}_{SC})}{p^2 \bar{q}_2}. \tag{1.10}$$

Comparing (1.10) with (1.7) yields that firms who cannot afford bank credit financing are able to obtain supplier credit financing for the full variable costs and bank credit only for the fixed costs if and only if

$$(1+\beta)^{SC} \leq (1+\beta) < (1+\beta)^{BC}.$$

Note that there exist parameter cases for which the supplier credit threshold is below the bank credit threshold if and only if

$$(1 + \bar{r}_{SC}) < \frac{(1 + \bar{r}_B)}{\sigma^2}. \tag{1.11}$$

This is summarized in the following Proposition.

Proposition 1 *The higher the quality uncertainty (lower σ), the more attractive is supplier credit financing relative to pure bank credit financing. Furthermore, the higher the refinancing costs of the supplier, the more expensive is supplier credit financing.*

1.2.4 Partial Supplier Credit Financing

Consider now the case where the exporter uses a supplier credit only for a fraction of the input costs, to save on the high interest rates of the supplier credit. In the following, we determine the minimum amount of supplier credit necessary to solve the adverse selection problem. The rest of the production costs has to be covered by a bank credit.

The timing of the game is as follows:

1. Nature determines the supplier's type, ($T \in \{G, B\}$). The supplier is of the good type ($T = G$) with probability σ and of the bad type ($T = B$) with probability $(1 - \sigma)$. The supplier learns her type.

2. The exporter chooses the amount of supplier credit as a fraction $\alpha(T)$ of the costs of the input good $\left(p_1 \frac{x^2}{(1+\beta)\bar{q}_2}\right)$ and chooses the price he pays for the input (p_1).

3. The bank observes the amount of supplier credit extended to the exporter by the supplier (but not the supplier's quality) and makes an offer to the exporter about an additional bank credit, choosing either a high $\left(\frac{1+\bar{r}_B}{\sigma}\right)$, a low $(1 + \bar{r}_B)$ interest rate, or no credit offer at all.

4. Depending on the decisions by the bank and the supplier, the firm decides whether to export or not in period $t = 0$.

5. In period $t = 1$, payoffs are realized.

Note that we assume that a fraction of the input costs can be paid later. Generally, the supplier credit equals the whole amount of an invoice, but the terms of payment vary, which means whether the invoice amount can be paid 30 or 60 days after delivery. It

is straightforward to reinterpret the fraction α as a temporal instead of a quantitative fraction.

The profit function of the supplier is

$$\pi_{SU}(T) = \begin{cases} \alpha p_1 q_1 - (\bar{c} q_1 - (1-\alpha) p_1 q_1)(1 + \bar{r}_{SC}) & \text{if } T = G \\ [(1-\alpha) p_1 q_1 - \underline{c} q_1] \, (1 + \bar{r}_{SC}) & \text{if } T = B. \end{cases}$$

The good supplier gets paid the fraction α ($0 \leq \alpha \leq 1$) of the input costs in period $t = 1$. This reflects the repayment of the supplier credit. The rest of the input costs is paid at delivery in $t = 0$. The difference between the production costs of the input and the amount paid at delivery, $(\bar{c} q_1 - (1-\alpha) p_1 q_1)$, has to be financed at the interest rate $(1 + \bar{r}_{SC})$.

The profit function of the bad supplier differs in that she never receives the rest of the purchasing price which is supposed to be paid later, because the exporter generates no revenues. If the bad supplier extends a supplier credit, she delivers the good and receives only the amount which has to be paid immediately at delivery in $t = 0$.

We consider two types of equilibria, separating and pooling equilibria. In a separating equilibrium, the exporter chooses the amount of supplier credit and the input price such that he effectively screens the supplier and only the good type participates in the transaction. In a pooling equilibrium, the amount of supplier credit and the input price are chosen such that both types participate in the transaction and so the type of the supplier is not revealed.

1.2.4.1 Separating Equilibrium

When does the supplier credit provide a credible signal that the input is of good quality? The signal is credible if the amount of supplier credit extended is large enough so that the supplier yields positive profits if she is of the good type and her profits equal zero if she is of the bad type. This guarantees that the bad type has no incentive to mimic the good type by granting a supplier credit. The amount of supplier credit necessary for a

credible signal is given by

$$(1-\alpha)p_1 \leq \underline{c} \qquad \Rightarrow \quad \alpha^{sep} \geq 1 - \frac{\underline{c}}{p_1}. \tag{1.12}$$

Furthermore, the participation constraint of the good supplier has to be fulfilled:

$$\alpha p_1 q_1 - (\bar{c}q_1 - (1-\alpha)p_1 q_1)(1+\bar{r}_{SC}) \geq 0. \tag{1.13}$$

From this we can derive

$$p_1 = \underline{c} + (\bar{c} - \underline{c})(1+\bar{r}_{SC}), \tag{1.14}$$

$$\alpha^{sep} = \frac{(\bar{c} - \underline{c})(1+\bar{r}_{SC})}{\underline{c} + (\bar{c} - \underline{c})(1+\bar{r}_{SC})}. \tag{1.15}$$

Consider the following belief structure of the bank. The bank believes that a supplier which extends a level of supplier credit of $\alpha \geq \alpha^{sep}$ is of the good type, $Pr(G|\alpha \geq \alpha^{sep}) = 1$, and a supplier which extends a level of supplier credit of $0 \leq \alpha < \alpha^{sep}$ is of the bad type, $Pr(G|0 \leq \alpha < \alpha^{sep}) = 0$. If the bank believes that the supplier is good, it sets $\sigma = 1$. If instead the bank believes that the supplier is of the bad type, it does not extend any bank credit at all. Using this belief structure of the bank, we can check whether there exists a separating equilibrium in which the good supplier extends a fraction $\alpha(G) = \alpha^{sep}$ of supplier credit and the bad supplier chooses not to extend a supplier credit at all, $\alpha(B) = 0$.

The profit function of an exporter who finances the costs via a supplier credit ($\alpha(G) = \alpha^{sep}$) and a bank credit has the following form

$$\pi_{EX}^{SC/BC} = px - [(1-\alpha^{sep})p_1(1+\bar{r}_B) + \alpha^{sep}p_1] \frac{x^2}{(1+\beta)\bar{q}_2} - (1+\bar{r}_B)(F + F_{EX}). \tag{1.16}$$

The exporter has higher expected revenues compared to a situation with pure bank financing because he knows that the supplier is of good quality. Additionally, the bank charges a lower interest rate as it believes that the supplier is of good quality and sets $\sigma = 1$.

Again, the exporter maximizes profits with respect to the quantity. Plugging the optimal quantity into the exporter's profits and setting it equal to zero, we obtain the minimum productivity level necessary to export successfully with a combination of supplier credit and bank credit financing:

$$(1+\beta)^{SC/BC} \equiv \frac{4(1+\bar{r}_B)(F+F_{EX})\left[\underline{c}(\bar{r}_B-\bar{r}_{SC})+\bar{c}(1+\bar{r}_{SC})\right]}{p^2\bar{q}_2}. \tag{1.17}$$

Proposition 2 *For firms with* $(1+\beta) \geq (1+\beta)^{SC/BC}$ *there exists a separating perfect Bayesian equilibrium in which only the good supplier extends supplier credits and the bank charges the low interest rate as it believes in the quality signal. The strategies and beliefs of this separating equilibrium are given by*
$[(\alpha(G)=\alpha^{sep}, \alpha(B)=0)$*, (gives bank credit at interest rate* $(1+\bar{r}_B)$*, gives no bank credit),* $Pr(G|\alpha \geq \alpha^{sep})=1$ *and* $Pr(G|0 \leq \alpha < \alpha^{sep})=0]$.

Proof. See Appendix A.1. ■

For firms with a productivity level $(1+\beta) < (1+\beta)^{BC}$, who cannot afford a bank credit, supplier credit helps them overcome their financial constraints and realize the international transaction if and only if

$$(1+\beta)^{SC/BC} \leq (1+\beta) < (1+\beta)^{BC}.$$

Inserting the corresponding expressions (1.7) and (1.17), it is straightforward to see that there exist parameter cases for which the supplier credit threshold is below the bank credit threshold if the following condition holds

$$\underline{c}(\bar{r}_B-\bar{r}_{SC})+\bar{c}(1+\bar{r}_{SC}) < \frac{(1+\bar{r}_B)\bar{c}}{\sigma^2}. \tag{1.18}$$

This is summarized in the following Proposition.

Proposition 3 *Consider firms with* $(1+\beta) < (1+\beta)^{BC}$*. It is the more likely that the combination of supplier credit and bank credit yields a positive payoff for exporters who would not be able to receive pure bank financing*

(1) the lower the refinancing costs of the supplier ($\bar{r}_{SC}$),

(2) the higher the refinancing costs of the bank ($\bar{r}_B$),

(3a) if $(1+\bar{r}_{SC})\sigma^2 > (1+\bar{r}_B)$: the lower the difference in production costs of the suppliers,

(3b) if $(1+\bar{r}_{SC})\sigma^2 < (1+\bar{r}_B)$: the higher the difference in production costs of the suppliers,

(4) the higher the quality uncertainty (lower σ) and hence importance of the signal. For $\sigma = 1$, pure bank credit financing is cheaper than supplier credit financing.

In Appendix A.1, we provide a graphical illustration of different parameter combinations for which $(1+\beta)^{SC/BC} < (1+\beta)^{BC}$ holds.

We have shown that a supplier credit can ease financial constraints due to two mechanisms. First, there is the direct channel. Supplier credits provide the firm with liquidity. Consequently, the amount of credit which has to be financed by the bank is reduced. Additionally, there is the indirect channel of supplier credit. The supplier can signal her quality via the extension of supplier credit. The supplier delivers the good, but the firm needs only pay for it later. This means that in fact the exporter can condition the payment of the input good on the quality delivered. Accordingly, the risk of the transaction is reduced. Hence, the higher the risk of the transaction, the more attractive supplier credits become. As we have argued before, in our model suppliers can be national or international. However, supplier credits will be of higher importance for international suppliers as the uncertainty faced by the exporter and the bank will be higher than with a national supplier.

1.2.4.2 Pooling Equilibrium

Consider next the possibility of a pooling equilibrium where both suppliers give the same amount of supplier credit, $\alpha(G) = \alpha(B)$, with $0 \leq \alpha(T) < \alpha^{sep}$. In such a pooling equilibrium, the bank does not learn anything about the supplier's type. Hence, the same credit rate applies as in the case without supplier credit.

The exporter's profit function in a pooling equilibrium equals

$$\pi_{EX}^{pool} = \sigma p x - [(1-\alpha)p_1(1+\bar{r}_B) + \sigma\alpha p_1]\frac{x^2}{(1+\beta)\bar{q}_2} - (1+\bar{r}_B)(F+F_{EX}), \tag{1.19}$$

where the fraction of the input costs extended in form of supplier credit is $0 \leq \alpha < \alpha^{sep}$.

From the participation constraint of the good supplier we can derive that for a given α, the exporter sets the price p_1 in a pooling situation such that

$$\alpha p_1 q_1 \geq (\bar{c} - \underline{c})(1+\bar{r}_{SC}). \tag{1.20}$$

Furthermore, for both suppliers to extend the same amount of supplier credit it has to hold that

$$(1-\alpha)p_1 \geq \underline{c}.$$

We can again derive the minimum productivity level necessary for successful exporting:

$$(1+\beta)^{Pool} \equiv \frac{4(1+\bar{r}_B)(F+F_{EX})\left[\sigma(\bar{c}-\underline{c})(1+\bar{r}_{SC}) + \underline{c}(1+\bar{r}_B)\right]}{(\sigma p)^2 \bar{q}_2}. \tag{1.21}$$

Proposition 4 *For firms with* $(1+\beta) \geq (1+\beta)^{Pool}$ *there exists a pooling equilibrium with the following strategies*
$[(\alpha(G) = \alpha(B)$*, where* $0 \leq \alpha(T) < \alpha^{sep})$*, (gives bank credit at interest rate* $(1+\bar{r}_B)/\sigma$*, gives bank credit at interest rate* $(1+\bar{r}_B)/\sigma)$*,* $Pr(G|\alpha \geq \alpha^{sep}) = 1$*,* $Pr(G|0 \leq \alpha < \alpha^{sep}) = 0$ *and* $Pr(G|\alpha(G) = \alpha(B)) = \sigma]$.

Proof. See Appendix A.1. ■

For firms with a productivity level $(1+\beta) < (1+\beta)^{BC}$, i.e., who cannot afford a bank credit, supplier credit in a pooling equilibrium helps them to realize the international transaction if and only if

$$(1+\beta)^{Pool} \leq (1+\beta) < (1+\beta)^{BC}.$$

Using (1.7) and (1.21) we can show that there exist parameter cases for which the supplier credit threshold is below the bank credit threshold if and only if

$$\sigma(1 + \bar{r}_{SC}) < (1 + \bar{r}_B). \tag{1.22}$$

If this condition holds, firms are enabled to export using supplier credit even though it provides an uninformative signal. The uninformative signal does not reduce the uncertainty, however. Comparing the separating cutoff with the pooling cutoff yields that the parameter range for which there exists a separating equilibrium is larger than the parameter range for the pooling equilibrium. Comparing the expected profits of the exporter, supplier, and bank, we can derive that firms prefer playing the separating rather than the pooling equilibrium.

Proposition 5 *The separating equilibrium Pareto-dominates the pooling equilibrium.*

Proof. See Appendix A.1. ■

Thus, in our empirical predictions we restrict attention to the separating equilibrium.

1.2.5 Empirical Hypotheses

To sum up, our findings deliver the following hypotheses:

Hypothesis 1: In general, bank credit and supplier credit are substitutes.

Hypothesis 2: For financially constrained firms, supplier credit and bank credit are complements.

Hypothesis 3: The complementary effect is stronger for internationally active firms.

Our theoretical model illustrates the ambivalent nature of supplier credits. Proposition 1 implies that bank credit financing can be substituted for by supplier credits for the variable costs. Firms with a high enough productivity level can afford a bank credit to finance their international transaction. Therefore, they are not financially constrained. To them, supplier credits and bank credits are substitutes, as they have the option to finance the variable costs via a supplier credit or a bank credit (Hypothesis 1). Proposition

2 and 3 state that due to the reduction in risk, supplier credits can enable the extension of a bank credit for firms that are financially constrained, which otherwise could not afford pure bank credit financing. For these firms, supplier credits and bank credits can be complements (Hypothesis 2). Although we cannot directly test whether supplier credits provide a quality signal to the bank, we can test whether supplier credits lead to more bank credits for financially constrained firms. Since exporters have higher financing needs and generally face a higher uncertainty, the complementary effect of supplier credit financing should be particularly strong for exporters (Hypothesis 3).

1.3 Data and Summary Statistics

We use the Business Expectations Panel of the ifo Institute for Economic Research provided by the Economic and Business Data Center (EBDC). It contains balance sheet data and data of the ifo Business Tendency Survey for 3,974 German companies from the manufacturing sector for the years 1994 to 2009. The balance sheet data is taken from Amadeus and Hoppenstedt on a yearly basis. The ifo Business Tendency Survey is conducted on a monthly basis and contains mainly questions on the firms' business situation, expectations, and demand situation.[9] The panel is unbalanced. On average, firms are present for four years in the dataset. The balance sheet data includes information on trade accounts payable and receivable and on bank debt. Additionally, the ifo Business Tendency Survey contains variables indicating whether a firm exports or not and whether a firm is financially constrained or not.

Supplier Credit

Consistent with Petersen and Rajan (1997) and Fisman and Love (2003), we measure supplier credit taken by a firm via trade accounts payable scaled by total assets from the balance sheet data. Our measure of supplier credit can, thus, be interpreted as the ratio of total assets financed via interfirm loans.[10] We take the logarithm as trade

[9]For an overview of the collected variables, see Becker and Wohlrabe (2008) and for the methodological background of the survey, see Goldrian (2007).

[10]Scaling is necessary since the supplier credit volume of a firm is directly linked to its size and its sales volume. Furthermore, it allows us to abstain from price effect adjustments in each year.

accounts payable divided by total assets is highly skewed. The disadvantage of trade accounts payable is that they not only include voluntarily granted supplier credits but also delayed payments not agreed to by the supplier ex ante. One could argue that involuntarily extended supplier credits do not provide a quality signal. However, trade accounts payable are frequently used as a proxy for supplier credits and it is the best measure available to us.[11]

Bank Credit

The amount of bank credit a firm has is measured by the variable bank debt, which includes short-term and long-term debt. We also scale bank credit by total assets from the balance sheet data and take the logarithm.

Export Status

In the ifo Business Tendency Survey, firms are asked about their export status. From this we construct a dummy variable. As the firms are asked each month and we conduct our analysis on a firm-year basis, we collapse the data. We classify a firm as internationally active if it exports its product in at least two months per year.[12]

Financial constraints

The ifo Business Tendency Survey also contains two questions concerning the financial situation of a firm. In one question the firms are asked whether they are constrained in their production due to financial constraints (yes/no). The second question asks how the firms judge the willingness of banks to give credits to firms (cooperative/normal/restrictive). The latter question is general in nature. However, we argue that firms will answer this question based on their own experience and thus, the answer reflects their financial situation.[13] We combine both measures and classify a firm as financially constrained if

[11] Alternatively, we could take a binary variable indicating whether supplier credit financing is used by the firm. The underlying idea is that the extension of supplier credit provides the signal and that there is no linear effect such that more supplier credit received leads to more bank credit received. But the volume of trade accounts payable consists of several supplier credits from different suppliers, which all signal their quality. Consequently, there may indeed be a linear effect. Furthermore, we do not observe any zeros in our data since all firms have trade accounts payable in their balance sheet.

[12] Note that we cannot use export intensities as this information is not included in our data.

[13] These questions are not asked on a monthly basis. The question on whether the firm was constrained in production due to financial constraints is asked in January, April, July and October. The question on the willingness of banks to extend credits is asked in March and August.

it answers at least once a year that it is hindered in production due to financial constraints or that it judges the willingness of banks to extend credits as restrictive, or both. This variable, thus, provides us with a direct measure of financial constraints. Hence, we can overcome the problems raised by the discussion between Fazzari, Hubbard, and Petersen (1988) and Kaplan and Zingales (1997) concerning the use of indirect measures of financial constraints such as investment–cash flow sensitivities.

Other control variables

We control for the productivity of a company which we measure as the logarithm of sales over the number of employees (Helpman, Melitz, and Yeaple, 2004). Due to strong collinearity we do not simultaneously include the number of employees or sales. In a robustness check, however, we use the logarithm of sales instead of the productivity measure. Additionally, we include the log of the firm's tangible assets scaled by total assets (Gama and Mateus, 2010). Furthermore, we control for the sales growth of the firm to capture firm-specific growth prospects. A more detailed description of all variables can be found in Table A.1 in Appendix A.2

Panel A of Table 1.1 provides summary statistics for the variables used in our analysis.[14] The average number of employees per firm is 2,489. The share of firms that are exporting is 93%. The high export participation can be explained by the fact that primarily large firms are included in the dataset. The ifo Business Tendency Survey mainly addresses large firms. For large German firms, a share of exporters of about 80%-90% is reasonable (Burg, Dittrich, Vogel, and Wagner, 2009). 15% of the firms report that they are financially constrained. The share of trade accounts payable relative to total assets is 8%. In comparison, the share of bank credit relative to total assets is 17%. Thus, we see that firms use a larger share of bank credits to finance their costs. However, the share of trade accounts payable is also quite high compared to the bank credit share. Hence, supplier credit is a significant source of financing.[15] Comparing exporters to non-exporters in Panel B of Table 1.1, we find that exporters are significantly larger than non-exporters. This is the usual result stated in various studies (see (Bernard, Jensen, Redding, and

[14] These summary statistics are pooled over all sample years.

[15] Fisman and Love (2003) find a similar result for the share of trade accounts payable used in the US.

Table 1.1: Descriptive Statistics

Panel A: Summary Statistics on Firm Characteristics

	Mean	SD
Number of employees	2,489	10,999
Trade accounts payable (1000 Euros)	26,800	122,000
Bank credit (1000 Euros)	53,300	400,000
Tangible assets (1000 Euros)	74,100	185,000
Trade accounts payable/total assets (%)	8	6
Bank debt/total assets (%)	17	15
Tangible assets/total assets (%)	27	18
Salesgrowth (%)	28	630
Sales/number of employees	267,792	475,664
Share of exporters (%)	93	-
Share of financially constrained firms (%)	15	-

Panel B: Exporters vs. Non-Exporters

	Exporters	Non-Exporters	Mean Diff.
Number of employees	2,583	1,293	1,290***
Trade accounts payable/total assets (%)	8	8	0
Bank credit/total assets (%)	17	15	2
Tangible assets/total assets (%)	26	42	-16***
Salesgrowth (%)	30	4	26
Share of financially constrained firms (%)	15	20	-5

Panel C: Constrained vs. Unconstrained Exporters

	Constrained Exporters	Unconstrained Exporters	Mean Diff.
Number of employees	1,928	2,697	-769*
Trade accounts payable/total assets (%)	9	7	2***
Bank credit/total assets (%)	23	16	7***
Tangible assets/total assets (%)	25	26	-1
Salesgrowth (%)	8	34	-26

Panel A provides average firm characteristics pooled over all sample years. The number of observations is 1,720. Panels B and C provide mean comparison tests for various firm characteristics between exporters and non-exporters and financially constrained exporters and non-financially constrained exporters, respectively. ***, **, and * denote significance at 0.01, 0.05, and 0.10 levels, respectively.

Schott, 2007) for a survey) and is the basis for the selection into exporting theory modeled by Melitz (2003). We also see that slightly fewer exporters are financially constrained than non-exporters. 15% of the exporters report being financially constrained compared to 20% of the non-exporters. However, there is no difference in the use of trade accounts payable relative to total assets between exporters and non-exporters. But when we com-

pare financially constrained exporters to non-financially constrained exporters in Panel C of Table 1.1, we find that financially constrained exporters use a significantly higher share of trade accounts payable than non-financially constrained exporters at the 1% significance level. This finding supports the theoretical results of our model. Those firms which do not receive bank credit in the first place and are thus financially constrained, use supplier credit. Furthermore, supplier credit financing is even more important for internationally active firms. This explains the difference in the use of supplier credit between financially constrained exporters and non-financially constrained exporters.

Note that we have a missing data problem both in the survey data as well as in the balance sheet data. As mostly large firms answer the ifo Business Tendency Survey and have balance sheet data available our empirical analysis focuses on large firms. Therefore, we do not claim to have a representative sample of German manufacturing firms overall, but of large German manufacturing firms.

1.4 Estimation Strategy and Results

1.4.1 The Effect of Supplier Credit on Bank Credit for Financially Constrained and Unconstrained Firms

To test the hypotheses derived above, we analyze the effect of supplier credit on bank credit. The first hypothesis considers the general relation between bank credit and trade credit and the second hypothesis focuses on the effect of supplier credit on bank credit for financially constrained firms. To analyze the relationship between both financing modes for financially constrained and unconstrained firms, the corresponding estimation equation is

$$BC_{it} = \beta_0 + \beta_1 SC_{it} + \beta_2 constrain_{it} + \beta_3 SC_{it} * constrain_{it} + \boldsymbol{\beta_4 x_{it}} + \eta_i + \lambda_t + \epsilon_{it}. \quad (1.23)$$

Our dependent variable is the share of bank credit in total assets of firm i in period t (BC_{it}). Supplier credit is the explanatory variable of interest (SC_{it}). $constrain_{it}$

is a dummy variable indicating whether a firm is financially constrained or not. We also include an interaction term of supplier credit received and the financial constraints dummy. The variable $\mathbf{x_{it}}$ includes a vector of control variables. As control variables, we use firm productivity, sales growth, a dummy whether the firm is exporting, and tangible assets. Furthermore, we control for firm fixed effects (η_i) and time fixed effects (λ_t).

As bank credit influences supplier credit and vice versa, we face a reverse causality problem. Given its total financing needs, the firm decides simultaneously on how much to finance via bank credit and how much to finance via supplier credit. If the firm does not get enough or any bank credit at all, it will approach its supplier and ask for a supplier credit instead. Vice versa, if the firm gets supplier credit, this might enable it to get an additional bank credit. We estimate this equation with the two-step generalized method of moments (GMM) estimator for panel data proposed by Arellano and Bond (1991). We use the finite sample correction of the asymptotic variance estimates derived by Windmeijer (2005). Generally, the two-step GMM estimator uses heteroskedasticity-robust standard errors, but in small samples the estimated standard errors tend to be too small. This is due to the presence of estimated parameters in the weight matrix.

We assume sequential exogeneity and instrument supplier credit with its second lag, that is supplier credit received two years ago, which is the Anderson and Hsiao (1982) estimator. In addition, we also apply its second and third lag (supplier credit received two and three years ago) which is the Arellano and Bond (1991) estimator and allows to exploit more of the available moment conditions. This is admissible because supplier credit received two years ago (SC_{it-2}) influences bank credit today (BC_{it}), but bank credit received today does not influence supplier credit received two years ago. Like this, instrumenting SC_{it} with SC_{it-2} and SC_{it-3} solves our simultaneity problem. SC_{it-2} is strongly correlated with SC_{it} (correlation coefficient of 0.82), thus it is relevant. Furthermore, SC_{it-2} has an influence on BC_{it} only via SC_{it}. Additionally, we use all the right-hand-side variables as instruments, except for the financial constraints dummy. As we would argue that the amount of bank credit the firm receives depends on whether the firm feels financially constrained but the reverse is also plausible, we instrument the

financial constraints dummy also by its second and third lag, as well as the interaction term of supplier credit and the financial constraints dummy.

The Anderson and Hsiao (1982) and the Arellano and Bond (1991) estimators use first-differences. Thus, we account for the fact that the relation between bank credit and supplier credit might be a spurious relationship attributed to unobservable specific heterogeneity among firms. The two-step GMM estimator is only consistent if there is no second-order serial correlation of the errors. We provide a direct test of the second-order residual serial correlation coefficient proposed by Arellano and Bond (1991). Furthermore, we also use the Hansen test of over-identifying restrictions to test the validity of our instruments. The Hansen test can be weakened by instrument proliferation. Therefore, instead of using one instrument for each time period, variable and lag distance, we use one instrument for each variable and lag distance. The idea is that the moment conditions are summed over the years for each lag distance. Another study which uses this technique is, among others, Beck and Levine (2004).

The fact that we have an unbalanced panel does not prevent the use of the two-step GMM estimator. Arellano and Bond (1991) argue that no fundamental changes occur provided that a minimal number of continuous time periods is available for each firm. This is the case in our dataset. The average number of years in which the firms in our sample report is four. The maximal number of years is 13. However, in order to avoid losing observations we use the orthogonal deviations transformation instead of first-differencing as proposed by Arellano and Bover (1995). Instead of subtracting the previous observation, the orthogonal deviations transformation subtracts the average of all available future observations. Like differencing, this removes fixed effects, but it preserves the sample size in panels with gaps.

In equation (1.23), we expect supplier credit as such to have a negative effect on bank credit and the interaction term of supplier credit and the financial constraints dummy to have a positive effect. In this estimation, we cannot separately identify the different motives for the use of supplier credit and their effects on the use of bank credit. Certainly, there is the positive effect on bank credit included in the volume of supplier credit due

to the signal, but this effect probably does not compensate for the general substitution effect.

Table 1.2: The Relationship between Bank Credits and Supplier Credits

	BC	BC	BC	BC
	(1)	(2)	(3)	(4)
SC	-3.981*	-4.626**	-3.849**	-4.101*
	(2.311)	(2.331)	(1.682)	(2.215)
tangibles	1.215	1.457*	1.216**	1.291
	(0.788)	(0.856)	(0.603)	(0.797)
salesgrowth	-0.020	-.0215	-0.0181	-0.0191
	(0.0199)	(0.0193)	(0.0141)	(0.0151)
constrain	7.689*	7.359*	6.684*	6.252
	(4.321)	(3.964)	(3.507)	(3.822)
constrain*SC	2.118	1.9763		
	(1.385)	(1.315)		
constrain*SC*EXP			1.854**	1.720*
			(0.9371)	(1.044)
EXP	-0.454	-0.479	-0.3056	-0.3137
	(0.737)	(0.7258)	(0.6639)	(0.6877)
labprod	1.183	1.409*	1.116*	1.223
	(0.804)	(0.832)	(0.569)	(0.767)
year dummies	yes	yes	yes	yes
Observations	1720	1720	1720	1720
No. of companies	410	410	410	410
No. of instruments	23	20	25	21
Lags used	2,3	2	2,3	2
AR(1)	0.005	0.007	0.002	0.005
AR(2)	0.290	0.288	0.199	0.248
AR(3)	0.989	0.774	0.824	0.909
Hansen	0.851		0.953	

In columns 1 and 3, we use the two-step GMM estimator with Windmeijer finite sample corrected standard errors using the second and the third lag as instruments for the endogenous variables. In columns 2 and 4 we only use the second lag as instrument. ***, **, and * denote significance at 0.01, 0.05, and 0.10 levels, respectively.

In column 1 of Table 1.2, the results of the two-step GMM estimator are provided using Windmeijer finite sample corrected standard errors where we use the second- and the third lag as instruments for the endogenous variables. As explained above, we collapse the instruments and use orthogonal deviations. This gives us a sample of 1,720 observations for 410 companies and we use 23 instruments. We find that for financially unconstrained firms the share of supplier credits used indeed has a negative influence on the share of

bank credits used which is significant at the 10% level. As both measures are in logs the coefficient indicates that 1% more supplier credit leads to 4% less bank credit. This finding confirms our first hypothesis. Furthermore, we find weak support for our second hypothesis. The coefficient of the interaction term of the share of supplier credit used and the financial constraints dummy is positive. It is marginally significant with a p-value of 0.126. This indicates that although bank credit and supplier credit are substitutes for unconstrained firms, supplier credit has a positive impact on bank credit for financially constrained firms.

The coefficient of the variable tangible assets is positive as one would expect, though insignificant. Tangible assets can serve as collateral and hence should enable firms to get more bank credit. Salesgrowth is negative but its effect is close to zero. The dummy indicating whether a firm feels financially constrained has a large positive coefficient, which is significant at the 10% level. This is surprising as one would expect that firms that feel financially constrained should get less bank credit. However, this reasoning only considers the supply of bank credit and not the demand for bank credit. It may be that financially constrained firms are those firms that have a lot of investment possibilities and therefore a higher demand for bank credit. The export dummy has a negative coefficient which is insignificant. Being an exporter reduces the amount of bank credit you have. This can reflect the higher risk due to international transactions which reduces the willingness of banks to extend credit. Additionally, although internationally active firms usually need to finance more investments and transactions, they also generally have higher profits and can use them to build up internal funds. The coefficient of productivity is positive, which implies that more productive firms can get more bank credit as they are supposed to be more reliable creditors.

In column 2 of Table 1.2, we conduct the same estimation with only the second lag as instrument for the endogenous variables. The coefficients change slightly in size but the signs remain the same. Now, the coefficient of supplier credit is significantly negative at the 5% significance level. The coefficient of tangible assets also becomes significant at the 10% significance level. The financial constraints dummy remains significantly positive at the 10% level. The coefficient of supplier credit for financially constrained firms remains

positive and marginally significant with a p-value of 0.133. Furthermore, the coefficient of labor productivity becomes significant at the 10% level.

The test for serial correlation in both specifications shows that we have first-order serial correlation of the errors but no second-order or third-order serial correlation. Hence, the Arellano-Bond (1991) estimator is consistent. This supports our sequential exogeneity assumption. The Hansen test of overidentifying restrictions for the specification in the first column is fulfilled for this set of instruments. The Null that the instruments as a group are exogenous cannot be rejected. We also test whether subsets of instruments are exogenous by using difference-in-Hansen statistics. We find that all subsets of instruments are exogenous. In column 2, we do not report the Hansen test of overidentifying restrictions as the system is just identified. Thus, we can conclude that we have an indication for the signaling effect of supplier credit in our data. Although supplier credits and bank credits are substitutes for unconstrained firms, they are complements for financially constrained firms.

1.4.2 The Importance of Supplier Credit for Internationally Active Firms

Bellone, Musso, Nesta, and Schiavo (2010) and Feenstra, Li, and Yu (2011) show that financial constraints play an important role in international trade. This is the case because the costs and the risks faced by firms are higher in international transactions. Therefore, supplier credits, as an additional source of finance, are especially vital in international trade. We now test whether the complementarity between supplier credit and bank credit for financially constrained firms is particularly important for internationally active firms (Hypothesis 3). We use the following estimation equation

$$\begin{aligned} BC_{it} =& \gamma_0 + \gamma_1 SC_{it} + \gamma_2 constrain_{it} + \gamma_3 EXP_{it} + \gamma_4 SC_{it} * constrain_{it} * EXP_{it} \\ &+ \boldsymbol{\gamma_5 \mathbf{x_{it}}} + \eta_i + \lambda_t + \nu_{it}. \end{aligned} \tag{1.24}$$

This equation only differs from equation (1.23) in the triple interaction term we add instead of the interaction term between SC_{it} and $constrain_{it}$. We interact supplier credit

used with the dummy for whether a firm is financially constrained and a dummy indicating export status. Thus, γ_4 displays the effect of supplier credit on bank credit for financially constrained exporters. γ_1 is the effect of supplier credit on bank credit for non-financially constrained firms, both exporters and non-exporters and financially constrained non-exporters. We could also include the interaction term of supplier credit and the financial constraints dummy. This would then explicitly capture the group of financially constrained non-exporters. However, due to the high share of exporters and the small share of financially constrained firms in our data this group is so small such that it does not make sense to include it separately. Similarly, we do not add the interaction term of financial constraints and export status, as we see in our data that the within-variation is very small and thus is mainly captured by taking the first differences. Furthermore, we are interested in comparing the group of financially constrained exporters to all other firms. Following our model, we also do not add an interaction term for supplier credits for unconstrained exporters as unconstrained exporters are able to obtain bank credit in the first place without relying on the signal extended by supplier credit. Again, we also use the interaction terms lagged twice or three times as instruments.

In column 3 of Table 1.2, the share of supplier credit used again has a significantly negative effect on the share of bank credit used (5% significance level). The coefficient of supplier credit for financially constrained exporters is significantly positive at the 5% significance level. Thus, the signaling effect of supplier credit seems to be significant for financially constrained exporters which confirms our third hypothesis. The underlying theoretical argument is that for exporters the uncertainty is higher and thus the signaling effect is more important. For those exporters with a very high productivity level that nevertheless get bank credit financing, the signal provided by supplier credits is of no great importance. For those exporters with a lower productivity level whose bank credit financing is constrained, however, the signaling effect of supplier credit plays a significant role. The coefficient of tangible assets has a significantly positive effect on bank credit at the 5% significance level. The financial constraints dummy remains significantly positive at the 10% significance level as does labor productivity.

The results using only the second lag as instruments shown in column 4 are similar. The coefficient of supplier credit is significantly negative at the 10% significance level. Furthermore, the effect of supplier credit for financially constrained exporters remains significantly positive at the 10% significance level. The tests for serial correlation and the Hansen test for overidentification again yield that the estimator is consistent and the instruments are valid.

1.4.3 Robustness Checks

Using sales over employees is the best productivity measure we can use. Alternatively, we rerun the estimations using the logarithm of sales of a firm as a proxy for its size (Desai, Foley, and Hines, 2006). In Table A.2 in Appendix A.2 the results are shown. The signs remain the same for all coefficients. Only the size of the coefficients differs slightly. In columns 1 and 2, one sees that the effect of supplier credit as such remains significantly negative. The effect of supplier credit for financially constrained firms is positive, but insignificant. However, the estimation results in column 3 also support our results obtained using our productivity measure. Again, supplier credit for financially constrained exporters has a positively significant effect at the 5% significance level. In column 4, this effect is also positive but insignificant, with a p-value of 0.159. The tests for serial correlation and the Hansen test for overidentification are again fulfilled.

In a second robustness check, we scale trade accounts payable and bank debt by total liabilities instead of total assets. Hence, we consider the effect of the importance of supplier credits considering the whole amount of external finance on the importance of bank credits in the financing portfolio. As bank credits and supplier credits are not the only forms of external finance this effect can again be positive or negative. In columns 1 and 2 of Table A.3 in Appendix A.2, the substitutive relation between supplier credits and bank credit is confirmed. The coefficient of supplier credit for financially constrained firms is positive but insignificant. In columns 3 and 4, we again find supportive evidence for the positive effect of supplier credits for financially constrained exporters.

Summing up all results, we have seen that the share of supplier credit used has a negative effect on the share of bank credit used for financially unconstrained firms (Hypothesis 1). However, if we only look at financially constrained firms, the share of supplier credit used tends to positively affect the share of bank credit used, although the overall effect is still negative, but less so (Hypothesis 2). This positive effect seems to play a more significant role, though, for financially constrained exporters. The coefficient of the interaction term is positively significant. (Hypothesis 3). The empirical results, therefore, provide supporting evidence for our theoretical model.

1.5 Conclusion

Supplier credits are an important financing tool, especially for internationally active firms. This is surprising given that supplier credits are generally considered to be more expensive than bank credits, with an annual real interest rate of 40% or higher. We show that even though supplier credits can involve high implicit interest rates, they are attractive to financially constrained exporters. Supplier credits not only provide additional liquidity to a firm, but they serve as a signal of the quality of purchased intermediates. Access to supplier credit financing is particularly relevant for firms that cannot afford to export if only pure bank financing is available. They use supplier credits complementary to bank credits. In contrast, firms that can export with pure bank financing do not necessarily rely on supplier credit financing. To them, bank credits and supplier credits are substitutes. We confirm our predictions for a sample of German manufacturing firms.

Chapter 2

How Trade Credits Foster Exporting*

2.1 Introduction

Aggravated trade finance conditions have been suggested as one of the reasons why trade flows collapsed in the wake of the 2008-2009 financial crisis as well as in past crises (Amiti and Weinstein, 2011). Indeed, a great part of all trade transactions are supported by some form of trade finance (Auboin, 2009). Surprisingly, though, the main part of trade finance takes the form of trade credits, which are considered a particularly expensive form of financing: implicit annual trade credit interest rates can amount to up to 40% (Petersen and Rajan, 1997). Trade credits are extended bilaterally between firms and exist in the form of supplier credits and cash-in-advance. Cash-in-advance (CIA) refers to payments made in advance by the buyer of a good to the seller. In contrast, a supplier credit is granted from the seller of a good to the buyer such that the payment of the purchasing price can be delayed for a certain period of time.[1] Why trade credits are so prevalent in international trade, despite their high cost, has been little studied so far.

*This chapter is based on joint work with Martina Engemann and Monika Schnitzer.

[1]In the literature, the term trade credit is sometimes used for credits extended by a bank to support a trade transaction. When using the term trade credit, we exclusively refer to inter-firm credits that are extended between firms without any financial intermediation.

This chapter aims at closing this gap. We argue that international transactions are inherently subject to more uncertainty than domestic transactions and that trade credits serve as a quality signal that helps reduce this high uncertainty. In our analysis, we focus on CIA financing and provide a rationale for the use of expensive trade credits to finance international trade. For this purpose, we develop a model of financially constrained firms that need outside finance to be able to export. Financial constraints arise from asymmetric information problems that deter less productive firms from exporting if only bank financing is available. Access to CIA reduces the asymmetric information problem and thus promotes the export participation of firms that are constrained in their access to traditional bank financing.

We test our prediction with data from the Business Environment and Enterprise Performance Surveys (BEEPS) for German firms in 2004. This dataset is ideal for our purposes since it contains data on the use of CIA and the export activity of firms. We find that firms that receive CIA from their trading partners have on average a 27% higher probability to export than firms that do not receive CIA financing. Likewise, a 1% increase in CIA financing increases the export probability of firms on average by 13%. We find that the export fostering effect of CIA is particularly strong for financially constrained firms.

The contribution of this chapter is twofold. First, we are the first to explicitly analyze the effects of CIA financing on international trade in a theoretical framework. In our model, we show that the productivity threshold to profitably export is lower if a firm is provided with CIA by its foreign trading partner. Second, using survey data, we can provide direct evidence of the beneficial effects of CIA financing on exporting. In the survey, firms report how much of their sales are paid in advance by customers. Thus, we need not rely on proxies for CIA availability such as trade payables from balance sheet data. Since the use of CIA by firms is very likely related to unobserved firm characteristics we apply an instrumental variable approach to establish a causal effect of CIA financing on exporting. Accounting for endogeneity, we find that CIA availability strongly fosters the export participation of firms. In addition, we analyze the differential impact of CIA financing on exporting for firms that are constrained in their access to finance. We find that firms

that have higher financing needs and firms that experience difficulties in accessing bank finance more strongly benefit from CIA financing in terms of their export participation.

Our analysis is related to two strands of literature. First, it builds on the literature on trade credits such as Lee and Stowe (1993). In Lee and Stowe (1993), firms extend trade credits to signal product quality to their (domestic) customers which is the so called warranty by quality hypothesis of trade credit financing.[2] This signaling motive should hold *a fortiori* for international transactions that suffer from an even higher degree of uncertainty. As we show in our model, even though trade credits are intrinsically more costly than bank credits, this disadvantage is more than compensated for by the reduction of uncertainty, so financially constrained firms benefit from access to trade credits. Biais and Gollier (1997) develop a model where the firm that extends the trade credit signals its belief in the creditworthiness of the firm it provides with trade credit. Their argument requires that the trade partner has an information advantage relative to the bank. Giannetti, Burkart, and Ellingsen (2011), however, find that the trading partners have no persistent informational advantage. In contrast to Biais and Gollier (1997), in our model we assume that the firm extending CIA signals its own quality, which seems to be a more natural and realistic assumption. Furthermore, this literature focuses on supplier credits. Instead, we analyze CIA. This is especially interesting since Mateut (2012), for example, shows that prepayment financing is intensively used by French firms. Thus, CIA, similar to supplier credit financing, provides an alternative to bank-intermediated trade finance.

Only recently has the literature on trade credits taken international transactions into its focus, investigating the optimal choice of trade credit. In Schmidt-Eisenlohr (2012)'s model, financial market characteristics and contractual environments of both the foreign and domestic market influence the choice of trade credit by firms. Similarly, Antràs and Foley (2011) study how a firm's choice of using CIA versus supplier credit depends on the extent of contractual frictions in the foreign trading partner's country. The authors find empirical support using data from a large US exporting firm. Ahn (2011) investigates

[2]Another study on the warranty by quality hypothesis was simultaneously developed by Long, Malitz, and Ravid (1993). In a more recent paper, Klapper, Laeven, and Rajan (2012) provide empirical evidence of the quality signaling motive for a small sample of US and European firms.

which side of the transaction should provide a trade credit and finds that it should be the trade partner that has the larger amount of collateral. Furthermore, he provides an explanation for how a lack of trade finance could have contributed to the drop in global trade during the financial crisis. Olsen (2011) focuses on the role of banks in international trade. He shows that by issuing letters of credit, banks can help to overcome enforcement problems between exporters and importers. Glady and Potin (2011) provide empirical evidence on the importance of letters of credit when country default risk is high. While the focus of these papers is primarily on the choice of the trade credit form as a function of the level of uncertainty, we focus instead on the rationale for using CIA as an alternative or as a complement to cheaper bank financing. We show how CIA solves both a moral hazard and an adverse selection problem for an exporter. Hence, we find that CIA fosters international trade.

The second strand of literature explores the influence of financial constraints on exporting behavior. Chaney (2007) and Manova (2012) show that financial constraints can prevent less productive firms from exporting in a Melitz (2003) -type model. Feenstra, Li, and Yu (2011) argue that exporters are more severely affected by financial constraints than domestic firms, due to the higher risks and longer financing periods in international trade. Firm-level studies confirm the adverse effect of financial constraints on exporting (see for example Minetti and Zhu, 2011, Muûls, 2008, and Buch, Kesternich, Lipponer, and Schnitzer, 2010). We add CIA to the choice of financing instruments for an internationally active firm. Whereas some firms cannot profitably export if only bank financing is available, we show that with the help of CIA, financially constrained firms can also export.

The rest of the chapter is organized as follows: In Section 2.2, we develop a model for an exporter receiving CIA. Section 2.3 introduces the dataset and provides summary statistics. In Section, 2.4 we set out the empirical strategy to test our model predictions and present our results. Section 2.5 concludes.

2.2 Theoretical Framework

Consider a two-period economy, $t = 0, 1$, in which a firm considers whether to produce for the foreign market.[3] When producing the quantity x in $t = 0$, a firm faces the convex cost function $k = \frac{x^2}{2(1+\beta)}$. $(1 + \beta)$ denotes the productivity level of the firm so that more productive firms produce at lower variable costs, $\beta > 0$. Following the current literature, we characterize a firm by its productivity level which determines its decision to become internationally active (Melitz, 2003). Additionally, the firm has to incur a fixed cost F_{Ex} associated with foreign market entry, for example costs related to the establishment of a distribution network or market research in the foreign market. At the end of $t = 0$, the firm sells its good at price p in the foreign market to an importing firm. In $t = 1$, the importing firm can resell the good to final customers in the foreign market at the exogenous market price $\hat{p}$ and generate revenues.

We assume that the exporting firm does not possess any internal funds and has to finance all costs of production externally in $t = 0$, before any revenues are generated. The importing firm does not possess any cash, either, to pay for the exporter's good. There are two possibilities of how payment by the importer to the exporter can occur: either after delivery in $t = 1$, as soon as the importer has generated own revenues, or upfront before the exporter starts to produce. In the former scenario, the exporter has to finance all production costs via a bank credit. In the latter scenario, the importer has to access external finance to be able to pay in advance. We do not consider payment at delivery (at the end of $t = 0$) because this implies that both trading partners have to use costly external finance instead of only one of the partners. Therefore, payment at delivery is strictly dominated.

When payment occurs after delivery, the exporter faces two sources of uncertainty. The first one is an adverse selection problem with regard to the importer's type. With probability μ, $0 < \mu < 1$, the importer is of high quality (H) and so is able to successfully market the exporter's good in the foreign market. With probability $(1 - \mu)$, the importer

[3] Since we are interested only in whether a firm can export or not, we exclude domestic transactions from our analysis.

is of low quality (L) which means that positive revenues cannot be generated and hence the exporter is not paid.

Second, a moral hazard problem can occur, due to the long distances in international trade and difficulties of tracing the importer's behavior. Instead of selling the good in the foreign market, the importer can divert the good and derive a private payoff of ϕx, blaming adverse market conditions for not generating positive revenues. To fix ideas, we assume that the market demand for the exporter's good in the foreign market is uncertain: demand in the foreign market is positive with probability λ, $0 < \lambda < 1$ and it is zero with probability $(1 - \lambda)$. No revenues are generated in the latter case and the importer cannot repay the exporter, even if he is of high quality. We assume that diverting the good is inefficient, $0 < \phi < \lambda\hat{p}$. Whether or not the high-quality importer diverts the good depends on the price he is supposed to pay to the exporter in case of successfully marketing the good. The low-quality importer always diverts the good since he cannot successfully market it.[4] Hence, positive export revenues are generated only if the importer is of high quality, market demand is positive, and the high-quality importer does not divert the good.[5]

2.2.1 Pure Bank Credit Financing

In the following, we consider the case in which payment occurs after delivery and the exporter has to apply for a bank credit to finance all costs of production. The bank credit can be repaid only if the importer pays for the goods as agreed on. This depends on the type of the importer, the demand in the foreign market, and the decision whether to divert or resell the good. To prevent problems related to moral hazard, for each unit of x sold to the high-quality importer, the exporting firm demands a price p such that

$$\lambda(\hat{p}x - px) \geq \phi x.$$

[4] Including moral hazard is necessary to have type uncertainty in our model. Without any possibility to divert the good, a low-quality importer would not take part in trade.

[5] Araujo and Ornelas (2007) also model type uncertainty of exporters and importers in international trade. They focus on improvements in institutional quality to overcome asymmetric information.

The high-quality importer's expected revenues from selling the good and repaying the exporter in case of positive market demand must be at least as high as the gain from diversion. We assume that the exporter has full market power in setting the price for the good, so p is given by

$$p = \hat{p} - \frac{\phi}{\lambda}. \tag{2.1}$$

Assuming instead that the importer has some, but less than full, market power changes our results only quantitatively but not qualitatively.

Banks operate under perfect competition and make zero profits. The bank faces the same uncertainty as the exporter concerning the quality type of the importer and the market risk, so credit repayment by the exporter is uncertain. For simplicity, we assume that there is no asymmetric information with regard to the exporter's quality. For the bank to break even, the following condition has to hold:

$$\lambda\mu D(1 + r_B) = (1 + \bar{r}_B)D,$$

where D stands for the amount lent by the bank which is repaid with probability $\lambda\mu$, that means if the importer is of high quality and market demand is positive. The bank's expected revenues have to be equal to the refinancing costs of the bank. $(1 + r_B)$ denotes the gross interest rate the bank charges and $(1+\bar{r}_B)$ refers to the gross refinancing interest rate of the bank. The collateral in case of non-repayment is normalized to 0. Solving for $(1 + r_B)$ yields the gross interest rate the bank requires to break even:

$$(1 + r_B) = \frac{(1 + \bar{r}_B)}{\lambda\mu}. \tag{2.2}$$

The higher the certainty about the foreign market demand and the importer quality, the lower the interest rate the bank demands. In the case of complete certainty, $\lambda = \mu = 1$, the bank demands exactly its gross refinancing rate. With pure bank credit financing the exporter faces the following profit function:

$$\pi_{Ex}^{BC} = \lambda\mu px - (1 + \bar{r}_B)\left(\frac{x^2}{2(1 + \beta)} + F_{Ex}\right). \tag{2.3}$$

The exporter receives expected revenues of $\lambda\mu px$ and finances the total costs of production via a bank credit. The exporter repays the amount borrowed only in case of positive revenues ($\lambda\mu$) and is charged an interest rate that takes into account the risk of the international transaction. Maximizing the exporter's profit function with regard to x, we can derive the optimal quantity exported with pure bank credit financing:

$$x_{Ex}^{BC} = \frac{(1+\beta)}{\frac{1+\bar{r}_B}{\lambda\mu}} \left(\hat{p} - \frac{\phi}{\lambda} \right). \tag{2.4}$$

Plugging (2.4) into the exporter's profit function (2.3) and setting the profit equal to zero yields the minimum productivity level required to make at least zero profit:

$$(1+\beta)_{Ex}^{BC} \equiv \left(\frac{1+\bar{r}_B}{\lambda\mu} \right)^2 \frac{2F_{Ex}}{\left(\hat{p} - \frac{\phi}{\lambda} \right)^2}. \tag{2.5}$$

Firms with a productivity level $(1+\beta) < (1+\beta)_{Ex}^{BC}$ are not able to export since at this level of uncertainty, they are unable to break even.[6] We refer to these firms as **financially constrained** implying that they are not productive enough to export with pure bank financing. A similar concept is used in Manova (2012) where imperfect financial contract enforcement abroad precludes less productive firms from exporting. Better contractual enforcement, which can be seen as a reduction in uncertainty, leads to a lower export threshold.

In our model, the productivity threshold is lower, the lower the uncertainty with regard to the type of the foreign customer (higher μ) and positive market demand (higher λ). It decreases with lower refinancing costs incurred by the bank and increases with higher fixed costs of exporting. Firms that can charge a higher price p, for example if the moral hazard problem is less severe (lower ϕ), can be relatively less productive to start exporting since their expected revenues are higher.

[6] The idea of varying thresholds for different financing options is also found in Mateut, Bougheas, and Mizen (2006) and Burkart and Ellingsen (2004) who focus on trade credit extension without reference to international transactions.

2.2.2 Pure Cash-in-Advance Financing

Next, we consider payment before delivery. If the exporter can enforce advance payment of the total invoice before production takes place in $t = 0$, moral hazard and adverse selection can be eliminated completely. Low-quality importers reveal their type by not agreeing to pay in advance and problems related to moral hazard are irrelevant from the exporter's point of view. Moreover, an additional bank credit is not needed as the total costs of production can be paid out of the revenues received up-front.

When paying the invoiced amount in advance, the importer faces refinancing costs of $(1 + \bar{r}_{Im})$. We assume that $\bar{r}_{Im} > \bar{r}_B$ since banks are specialized financial intermediaries and are more efficient in providing credits. We can interpret $\bar{r}_{Im}$ as a measure of the financial constraint of the importer, which means that the higher is $\bar{r}_{Im}$, the less able is the importer to provide CIA. Recall our assumption that the exporter has full bargaining power. Hence, with pure CIA financing, the exporter demands a price $\tilde{p}$ such that the importer just breaks even:

$$\lambda\hat{p}x - \tilde{p}x(1 + \bar{r}_{Im}) = 0.$$

Consequently,

$$\tilde{p} = \frac{\lambda\hat{p}}{(1 + \bar{r}_{Im})}. \tag{2.6}$$

The exporter's profit function with pure CIA financing is

$$\pi_{Ex}^{CIA} = \tilde{p}x - \left(\frac{x^2}{2(1+\beta)} + F_{Ex}\right). \tag{2.7}$$

This leads to

$$(1+\beta)_{Ex}^{CIA} \equiv \left(\frac{1 + \bar{r}_{Im}}{\lambda}\right)^2 \frac{2F_{Ex}}{\hat{p}^2}. \tag{2.8}$$

Comparing the minimum productivity level required for pure CIA financing to the one for pure bank credit financing, we find that pure CIA financing requires a higher minimum productivity level if

$$(1 + \bar{r}_{Im})(\lambda\hat{p} - \phi) > \lambda\hat{p}\frac{(1 + \bar{r}_B)}{\mu}. \tag{2.9}$$

The above condition is fulfilled if the refinancing costs of the importer are high relative to the refinancing costs of the bank. If $\bar{r}_{Im}$ is high, firms that cannot export in the case of pure bank credit financing still cannot export with pure CIA financing, either. This is due to the fact that the higher the refinancing costs the lower the price $\tilde{p}$ exporters can demand for their goods. In contrast, if the adverse selection problem is acute (low μ), pure CIA financing is attractive for financially constrained firms because the elimination of the adverse selection problem is very valuable. To simplify our presentation, in the following we restrict attention to parameter cases where pure CIA is more expensive than pure bank credit financing, that means condition (2.9) is fulfilled. This seems to be the most relevant case since full prepayments are very rare in practice.

2.2.3 Partial Cash-in-Advance and Bank Credit Financing

Consider now a combination of bank credit and CIA where only a fraction α of the invoice payment is made in advance. This enables the importing firm to save some of the high refinancing costs while it still allows the exporter to solve the adverse selection and the moral hazard problem. The payment made in advance is used to pay a part of the total production costs, the rest is financed via bank credit.

The fraction paid in advance can now serve as a signal of the importer's quality type to the bank and the exporter. Three cases can occur after observing a certain α: first, if the bank believes that the importing firm is of high quality ($Prob(H) = 1$), it will provide an additional bank credit at a lower interest rate to the exporting firm. Second, if the bank believes that the importer is of low quality ($Prob(H) = 0$), it will not provide any bank credit at all because the exporter is not able to repay the bank when trading with a low-quality importer. Third, if the bank cannot infer the quality type from the amount paid in advance ($Prob(H) = \mu$), it will demand the same interest rate as in the case of pure bank credit financing.

The timing of the game is as follows:

1. Nature determines the importer's quality where $Prob(H) = \mu$ and $Prob(L) = (1 - \mu)$. The importer learns its type.

2. In $t = 0$, the exporting firm specifies a price $\check{p}$ for the good to be exported and demands CIA payment of a fraction α of the total amount from the importer. The importer decides whether to extend the fraction α in advance or not, depending on the importer's type.

3. The bank observes the CIA payment by the importer in $t = 0$ and decides on additional bank credit.

4. After observing the decisions made by the importer and the bank, the firm decides whether to produce and export or not.

5. In $t = 1$, pay-offs are realized.

We consider two types of equilibria in this game, separating and pooling equilibria. In a separating equilibrium, an informative signal is given, in a pooling equilibrium the signal sent by the importer is not informative. Proposition 1 describes the separating perfect Bayesian equilibrium that maximizes the exporter's pay-off. The first bracket contains the importers' strategies, the second bracket contains the strategies of the bank. The equilibrium and off-equilibrium beliefs are stated in the last two brackets.

Proposition 1 *There exists a separating perfect Bayesian equilibrium with*

$$\Big[\Big(\alpha^H = \alpha^{Sep}, \alpha^L = 0\Big), \Big(\frac{1+\bar{r}_B}{\lambda}, NoBC\Big), Prob\Big(H|\alpha \geq \alpha^{Sep}\Big) = 1,$$
$$Prob\Big(H|0 \leq \alpha < \alpha^{Sep}\Big) = 0\Big],$$

where $\alpha^{Sep} = \frac{\phi/(1+\bar{r}_{Im})}{\hat{p}+\frac{\phi}{(1+\bar{r}_{Im})}-\frac{\phi}{\lambda}}$ *and the price demanded for the exported good is* $\check{p} = \hat{p} - \frac{\phi}{\lambda} + \frac{\phi}{(1+\bar{r}_{Im})}$. *In this separating equilibrium, the high-quality importer extends the share* $\alpha^H = \alpha^{Sep}$ *in advance and the low-quality importer chooses not to extend CIA at all. When observing* $\alpha = \alpha^{Sep}$, *the bank updates its belief according to Bayes' Rule such that* $Prob\Big(H|\alpha = \alpha^{Sep}\Big) = 1$ *and extends additional bank credit at a lower interest rate,* $\frac{1+\bar{r}_B}{\lambda}$. *When observing* $\alpha = 0$, *the bank's belief is* $Prob\,(H|\alpha = 0) = 0$ *and it denies additional bank credit.*

Proof. See Appendix B.1. ■

In the separating equilibrium, the exported quantity x^{Sep} and the minimum productivity threshold for exporting $(1+\beta)_{Ex}^{Sep}$ equal:

$$x_{Ex}^{Sep} = \frac{(1+\beta)}{1+\bar{r}_B}\left[\lambda\hat{p} - \phi + \frac{\phi(1+\bar{r}_B)}{(1+\bar{r}_{Im})}\right], \tag{2.10}$$

$$(1+\beta)_{Ex}^{Sep} \equiv \frac{2(1+\bar{r}_B)^2 F_{Ex}}{\left[\lambda\hat{p} - \phi + \frac{\phi(1+\bar{r}_B)}{(1+\bar{r}_{Im})}\right]^2}. \tag{2.11}$$

Firms with a productivity level lower than $(1+\beta)_{Ex}^{Sep}$ cannot export since they have negative expected profits. As before, the productivity threshold increases with higher fixed costs and higher bank refinancing costs. It also increases with higher importer refinancing costs and a higher marginal benefit from diversion. In addition, we consider the following pooling equilibrium.

Proposition 2 *There exists a pooling perfect Bayesian equilibrium with*

$$\left[\alpha^{Pool}, \left(\frac{1+\bar{r}_B}{\lambda\mu}\right), Prob\left(H|\alpha = \alpha^{Pool}\right) = \mu, Prob\left(H|\alpha < \alpha^{Pool}\right) = 0,\right.$$

$$\left. Prob\left(H|\alpha > \alpha^{Pool}\right) \in [0,1]\right],$$

where $\alpha^{Pool} = \frac{\phi/(1+\bar{r}_{Im})}{\hat{p}+\frac{\phi}{(1+\bar{r}_{Im})}-\frac{\phi}{\lambda}}$ *and the price demanded by the exporter is* $\check{p} = \hat{p} - \frac{\phi}{\lambda} + \frac{\phi}{(1+\bar{r}_{Im})}$. *In this pooling equilibrium, both high- and low-quality importers extend the same share of CIA. The bank is unable to infer the type of the importer from this signal and sticks to its ex-ante belief,* $Prob(H) = \mu$. *It extends additional bank credit at the interest rate* $\frac{1+\bar{r}_B}{\lambda\mu}$.

Proof. See Appendix B.1. ■

For the pooling equilibrium in which $\alpha^{Pool} = \frac{\phi/(1+\bar{r}_{Im})}{\hat{p}+\frac{\phi}{(1+\bar{r}_{Im})}-\frac{\phi}{\lambda}}$, we can derive the following production quantity and productivity threshold:

$$x_{Ex}^{Pool} = \frac{(1+\beta)}{1+\bar{r}_B}\left[\mu(\lambda\hat{p} - \phi) + \frac{\phi(1+\bar{r}_B)}{(1+\bar{r}_{Im})}\right], \tag{2.12}$$

$$(1+\beta)_{Ex}^{Pool} \equiv \frac{2(1+\bar{r}_B)^2 F_{Ex}}{\left[\mu(\lambda\hat{p} - \phi) + \frac{\phi(1+\bar{r}_B)}{(1+\bar{r}_{Im})}\right]^2}. \tag{2.13}$$

Comparing the minimum productivity thresholds in the different financing scenarios, we derive the following proposition.

Proposition 3 *The productivity thresholds can be uniquely ranked:*

$$(1+\beta)_{Ex}^{Sep} < (1+\beta)_{Ex}^{Pool} < (1+\beta)_{Ex}^{BC}.$$

Thus, we can identify four groups of firms. (1) Firms with $(1+\beta) \geq (1+\beta)_{Ex}^{BC}$ *can export in every financing scenario. (2) Firms with* $(1+\beta)_{Ex}^{Pool} \leq (1+\beta) < (1+\beta)_{Ex}^{BC}$ *can export if CIA is given, either in the separating or the pooling equilibrium. (3) Firms with* $(1+\beta)_{Ex}^{Sep} \leq (1+\beta) < (1+\beta)_{Ex}^{Pool}$ *can export only in the separating equilibrium if the signal via CIA is informative. (4) Firms with* $(1+\beta) < (1+\beta)_{Ex}^{Sep}$ *cannot export at all.*

Proof. See Appendix B.1. ■

Figure 2.1 gives a graphical representation of the ranking of the productivity thresholds for the three different financing options. Proposition 3 implies that if CIA financing is available, financially constrained firms in the second and third group can export that would not have been able to do so with pure bank financing only. These firms benefit

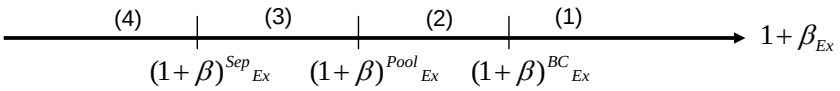

Figure 2.1: Ranking of Export Productivity Thresholds

from the availability of CIA. Firms in the fourth group cannot export even if CIA is available. Firms in the third group depend on an informative signal that eliminates the adverse selection problem. Therefore, these firms play the separating perfect Bayesian equilibrium. In contrast, firms in the second group have a high enough productivity level to export even if the adverse selection problem is not eliminated and can export under both equilibria. However, they cannot export with pure bank financing only. This is due to the fact that incentives for opportunistic behavior are stronger without CIA so that an exporter has to set a lower price for his good to prevent moral hazard by the importer. Firms in the first group do not depend on CIA availability since they are productive

enough to export with pure bank financing only. Interestingly, even these firms which have access to bank financing prefer to use partial CIA. This is shown in the following proposition.

Proposition 4 *Even if firms are able to export using pure bank financing, i.e., if* $(1+\beta) \geq (1+\beta)_{Ex}^{BC}$*, they prefer partial CIA financing to pure bank financing.*

Proof. See Appendix B.1. ■

Even very productive firms generate strictly lower expected profits with pure bank financing than with partial CIA financing. This is due to the fact that any small amount of CIA provided reduces the importer's incentive to divert the good. Consequently, the exporter can set a higher price and generate higher expected profits from partial CIA financing.

Proposition 5 *Firms with* $(1+\beta) \geq (1+\beta)_{Ex}^{Pool}$ *can export under both the separating and the pooling equilibrium. They prefer to play the separating (pooling) equilibrium if quality uncertainty is low (high) and the importer's refinancing costs are high (low). The higher the productivity of the firm, the greater the parameter space in which the pooling equilibrium is preferred by the exporters.*

Proof. See Appendix B.1. ■

If the importer's refinancing costs are high, the exporter's expected profits are higher in the separating equilibrium since the informative signal compensates for the relatively lower price firms receive from the importer. In contrast, expected profits are higher in the pooling (separating) equilibrium if uncertainty is high (low). This result seems counterintuitive at first. However, it is due to the fact that trade with an informative signal takes place with probability μ only. With probability $(1-\mu)$ the importer is of low quality and hence not willing to send the informative signal which means that the transaction does not take place. An uninformative signal in a pooling equilibrium is sent by both types of importers, instead. Therefore, firms prefer receiving at least a small (uninformative) share of CIA upfront than receiving nothing if it is very likely that they trade with a low-quality importer (low μ). This effect is reinforced for more productive firms since more productive firms have lower production costs and can better absorb

losses when trading with a low-quality importer. To summarize, what emerges from our model is the following.

Prediction

The availability of CIA increases the profitability of exporting and hence increases the probability of exporting, in particular for financially constrained firms.

CIA is beneficial to firms since it reduces uncertainty with regard to foreign trading partners and it makes moral hazard less attractive to the firm paying in advance. Both effects increase the profits from exporting which implies that all firms prefer to use a combination of CIA and bank credit. However, considering a firm's ability to export, the provision of CIA is particularly beneficial to financially constrained firms since these firms cannot export in the absence of CIA. Therefore, we expect the positive effect of CIA on the export probability of firms to work mainly through the effect of financially constrained firms.

2.3 Data and Summary Statistics

To test our prediction, we use data from the Business Environment and Enterprise Performance Survey (BEEPS) on 1,196 German firms in 2004. BEEPS was developed jointly by the European Bank for Reconstruction and Development and the World Bank Group to analyze the business environment of firms and to link it with firm performance. In 2004, cross-sectional data on German firms was collected. By using stratified random sampling, a high representativeness of the sample is achieved. Specifically, the sample is designed so that the population composition with regard to sectors, firm size, ownership, foreign activity, and location is captured.[7] In Table B.1 in Appendix B.2 the decomposition of firms according to sectors can be found for our sample. Panel A of Table 2.1

[7]Sectors included in the sample are mining and quarrying, construction, manufacturing, transportation, storage and communications, wholesale, retail and repairs, real estate, renting, and business service, hotels and restaurants, and other community, social and personal activities. Sectors that are subject to government price regulation and prudential supervision like banking, electric power, rail transport, and water and waste water are excluded.

provides average sample characteristics. The median number of 12 employees per firm and the median of expected sales of 1,200,000 Euro in the sample correspond quite well to the German population averages: according to data from the Statistical Yearbook for the Federal Republic of Germany, the average number of employees is 13 and average sales amount to 1,230,000 Euro in Germany in 2004 (Federal Statistical Office, 2007).

The main advantage of this dataset is that it provides us with a precise measure of the use of CIA by firms. More specifically, firms are asked what percentage of their sales' in value terms were paid before delivery from their customers over the last 12 months. Thus, we do not have to rely on a proxy such as trade payables which is often used in the trade credit literature when only balance sheet data is available. However, we cannot single out CIA related to exporting activities compared to domestic activities since transaction level data is not available in the survey. Thus, we restrict our analysis to linking the overall use of CIA by firms to their export participation decision. Data on the exporting activities by firms is given in terms of export shares of total sales which ranges from 0% to 90% in our dataset. We classify a firm as an exporter if it sells a positive amount of its sales abroad. A detailed description of all variables included in our analysis can be found in Table B.2 in Appendix B.2.

About 16% of all firms generate a positive share of their sales abroad (Panel A of Table 2.1), a share that is slightly higher than the population average which is 12% (Haunschild, Hauser, Günterberg, Müller, and Sölter, 2007). A look at the average use of CIA in the sample reveals that more than one third of all firms receive prepayments from their customers. In contrast, the mean share of prepayments received is rather low: on average, only 7% of total sales in value terms is paid by customers before delivery. This implies that the remaining part, about 93% of total sales, is either paid on time or after delivery by customers. The low average share of use of CIA may reflect the high refinancing costs for the extending firms.

Panel B of Table 2.1 displays differences in CIA use by exporters versus non-exporters. Strikingly, exporters distinctly use CIA more extensively than non-exporters. About 44% of all exporters receive a positive share of their sales in advance, whereas only 34% of all non-exporters obtain advance payment. The average share of CIA received is very similar

Table 2.1: Descriptive Statistics

Panel A: Summary Statistics on Firm Characteristics

	Mean	Median	SD	Obs.
Sales (1,000 Euros)	15,862	1,200	88,486	1,135
Age	19.4	14	16.7	1,196
Number of employees	85.8	12	443.3	1,195
Share of exporters (%)	16	-	-	188
Share of firms receiving CIA (%)	35	-	-	418
Share of CIA received (%)	7	0	16	1,196
LogLabprod	4.76	4.61	0.77	1,135
CompNum	3.51	4	1.03	1,196
ForPressure (%)	28.0	-	-	1,196
Univeduc (%)	12.36	5	20.58	1,195
Foreign (%)	9.0	-	-	1,196
PublicInfo (%)	27.4	-	-	1,184
Specificity	2.2	2	0.95	1,196

Panel B: Exporters vs. Non-Exporters

	Exp	Obs.	Non-Exp	Obs.	Mean Diff.
Share of firms receiving CIA (%)	43.5	188	33.7	1,008	9.8***
Share of CIA received (%)	7.4	188	7.2	1,008	0.2
Sales (1,000 Euros)	66,971	177	6,419	958	60,552***
LogSize	4.06	188	2.42	1,008	1.64***
LogAge	3.0	188	2.61	1,008	0.39***
LogLabprod	5.0	177	4.7	958	0.3***
Foreign (%)	37.0	188	4.0	1,008	33.0***
Lowest size quartile					
Share of firms receiving CIA (%)	33.3	24	27.9	305	5.4
Second-lowest size quartile					
Share of firms receiving CIA (%)	52.4	21	28.5	291	23.9**
Second-highest size quartile					
Share of firms receiving CIA (%)	48.3	29	34.8	230	13.5
Highest size quartile					
Share of firms receiving CIA (%)	43.0	114	48.4	182	-5.4

Panel A provides average firm characteristics. Panel B displays results from mean difference tests of firm characteristics for exporters vs. non-exporters using Welch's formula to allow for unequal variances in both groups (Welch, 1947). Firms are defined as exporters if they sell a positive share of their sales abroad. ***, **, and * represent mean differences significant at the 1%, 5% and 10% level, respectively.

for both groups and only marginally higher for exporters. Since our data does not allow us to determine whether CIA is used to finance a domestic or an export transaction, we are concerned that the higher use of CIA by exporters is simply driven by the significantly larger size of exporters in terms of number of employees and scope of operations. We therefore split firms into size quartiles according to their number of employees and check whether exporters still use CIA more extensively than non-exporters within the same size quartiles. We find that within the same size quartile, relatively more exporters than non-exporters receive CIA payments except within the highest size quartile. Note that the low number of exporters in each size quartile makes it difficult to observe significant positive differences although the differences are quite large. Other well-known characteristics of exporters are reflected in the data as well: exporters are older, have higher sales per worker (labor productivity), and rather tend to be foreign owned.

These descriptive statistics suggest that CIA financing plays a very important role for internationally active firms. Our theoretical model provides an explanation for these findings which we put to an empirical test in the following section.

2.4 Empirical Analysis

2.4.1 Empirical Strategy

Our main prediction from our theoretical model states that access to CIA financing facilitates entry into exporting since asymmetric information problems are reduced. This effect should be predominantly driven by the higher export performance of financially constrained firms since unconstrained firms can export even in the absence of CIA. As stated in our model, a firm is able to participate in exporting if it generates positive profits from exporting, $\pi_{Ex} > 0$. The firm's profits from exporting depend on the financing options available to the firm, partial CIA versus pure bank financing, its own productivity level as well as other firm characteristics. Thus, we rewrite π_{Ex} as

$$\pi_i^* = \alpha + \beta_1 CIArec_i + \beta_2 LogLabprod_i + \gamma \mathbf{C_i} + \epsilon_i, \tag{2.14}$$

where $CIArec$ measures firm i's use of CIA financing. We employ two measures of CIA financing. The first is a binary indicator, $DCIArec$, equal to 1 if the firm receives a positive amount of CIA and equal to 0 otherwise. In this case, the firm receives its sales either on time or after delivery which implies that the firm has to rely on other sources of financing such as bank credit financing. The second is the log percentage share of total sales received in advance, $LogCIArec$. A lower value of $LogCIArec$ implies that the firm has to rely on other financing sources to a greater extent. Log labor productivity, $LogLabprod$, is defined as the log of sales over employees and proxies for the firm's own level of efficiency. Additional firm-level controls that influence the export decision of a firm are included in the vector $\mathbf{C}$. ϵ denotes the error term. We do not observe the true profits from exporting π^* of a firm, but its export status Exp. It is defined as a binary indicator equal to 1 if the firm generates positive profits from exporting and 0 otherwise:

$$Exp_i = \begin{cases} 1, & \text{if } \pi_i^* > 0 \\ 0, & \text{if } \pi_i^* \leq 0. \end{cases} \tag{2.15}$$

Assuming a standard normal distribution of ϵ we can write firm i's probability to export as:

$$\begin{aligned} Prob(Exp_i = 1) &= Prob(\alpha + \beta_1 CIArec_i + \beta_2 LogLabprod_i + \gamma \mathbf{C_i} + \epsilon_i > 0) \\ &= \Phi(\alpha + \beta_1 CIArec_i + \beta_2 LogLabprod_i + \gamma \mathbf{C_i}), \end{aligned} \tag{2.16}$$

where Φ denotes the standard normal cumulative distribution function of the error term. According to our model, the availability of CIA increases the profits from exporting π^* and thus, we expect the effect of CIA on the export probability to be positive, $\beta_1 > 0$. The same holds true for the productivity level of the firm, $\beta_2 > 0$. A simple test of our hypothesis can be conducted via regressing Exp on $CIArec$ and further controls. The estimated coefficient β_1 is unbiased if we can assume that whether a firm receives CIA (or how much CIA it receives) is assigned randomly across firms. However, this assumption is very likely not to hold true due to unobserved factors that affect both the export decision of a firm and the decision whether to use CIA financing. Consider for example uncertainty with regard to the importer's type, captured by the parameter μ in our

model. Higher uncertainty with regard to the trading partner's ability to repay hinders entry into exporting since exporting becomes less profitable. But, higher uncertainty makes the use of CIA more attractive in order to alleviate asymmetric information. Consequently, not controlling for the level of uncertainty may lead to a downward bias of our results. A second example is manager motivation. More motivated managers may be more successful in leading their enterprises into exporting and they may also be more able to enforce CIA payment from their customers. Thus, omitted manager motivation can lead to an upward bias of our results. We address endogeneity in our key variable by employing two instruments that are unrelated to the export decision of a firm but influence CIA financing.

To find suitable instruments that strongly influence whether a firm receives CIA payment from its customers but that are unrelated to the export decision, we make use of information on the relationship between firms and their customers. The first instrument comes from a question on the sources that firms use to acquire new customers. In the survey, firms are asked whether trade fairs and other public sources of information are not, slightly, fairly, very, or extremely important sources of information about new customers to the firm. We construct the dummy $PublicInfo$, which is equal to 1 if the firm indicates that trade fairs and other public sources of information are extremely important sources of information about new customers. This is true for about 27% of firms in our dataset. $PublicInfo$ proxies for the closeness between firms and their customers. Firms that deem information collected and made available by official authorities as extremely valuable very likely experience difficulties in acquiring new customers. These firms should be more likely to ask for CIA (or for a higher share of sales paid in advance) to be compensated for the difficulties in finding the customers. $PublicInfo$ can also be seen as a proxy for the range of applications that the product can be used for. Firms that produce goods that can be used for a smaller range of applications usually tend to face a smaller circle of potential customers than firms that produce widely applicable goods. Consequently, they have to exert more effort to find new customers which makes using CIA more attractive. We do not expect the closeness between firms and customers to directly impact on the export decision of firms. If the degree of closeness to customers influences a firm's export decision, the observed influence would be very likely negative

since less knowledge on customers should rather impede exporting than facilitate it. IV estimation in that case would then lead to a lower and thus more conservative estimate for the effect of CIA on exporting.

The second question addresses the specificity of the main product or service sold by the firm. Firms are asked how their customers react if the firm raises the price of its main product or service line by 10%. Possible responses are: (i) customers buy from competitors, (ii) customers continue to buy at much lower quantities, (iii) customers continue to buy at slightly lower quantities, or (iv) customers continue to buy from the firm in the same quantities as before. Out of these answers, we construct the ordinal variable $Specificity$ that measures the price elasticity of demand that the firm faces or, in other words, the bargaining power that the firm has vis-à-vis its customers. $Specificity$ takes the value 1 if (i) is chosen by the firm, 2 if (ii) is chosen, and so forth. A higher value of the variable indicates a higher bargaining power or a lower elasticity of demand. We expect a positive relationship between $Specificity$ and the use of CIA. A low elasticity of demand reflects a high specificity of the good or service sold such that customers depend on the input. Consequently, these customers have a higher incentive to comply with CIA requirements by the firm. Mateut (2012) provides empirical evidence on the relationship between goods' characteristics and customer prepayments for French firms. She finds that downstream firms that sell a differentiated good receive larger prepayments from their customers than firms that sell standardized goods.

Since a high market bargaining power may also reflect the competitiveness of the firm, we are worried that our instrument does not only capture the specificity of the relationship between firm and customers but that it might also pick up the degree of competition the firm faces. Low competition can allow firms to raise prices without losing customers and enable firms to enter the export market more easily since they obtain higher profits. Therefore, we directly control for the level of competition that the firm experiences in the national and the international market. This ensures that $Specificity$ only captures customer dependence with regard to product characteristics and thus is exogenous to the export decision of a firm. Firms that produce very specific goods should be more able to

enforce CIA payment but producers of more specific goods should not be more likely to export than producers of less specific goods, once the competition level is controlled for.

Since our first measure $DCIArec$ for use of CIA financing is binary, we apply the recursive bivariate probit model to estimate the effect of CIA on export participation in our first specification. Given valid instruments, the recursive bivariate probit model allows to determine the causal effect of a potentially endogenous binary regressor on a binary dependent variable. Specifically, it simultaneously estimates two probit models via maximum likelihood. The first equation models the effect of the binary endogenous regressor and potential controls on the outcome. The second equation models the endogenous regressor as a function of potential instruments and potential controls. The error terms of both equations are assumed to be correlated due to unobserved factors, for example manager motivation. The causal effect of the binary endogenous regressor can be estimated if instruments are available that strongly influence the endogenous regressor but are exogenous to the outcome equation.[8] In our case, we jointly estimate the export probability and the probability of a firm to receive CIA by its customers. The first equation is given in (2.16). The second equation describes the probability to receive CIA as follows:

$$\begin{aligned} Prob(DCIArec_i = 1) &= Prob(a + \mathbf{b_1 Z_i} + b_2 LogLabprod_i + \mathbf{cC_i} + u_i > 0) \\ &= \Phi(a + \mathbf{b_1 Z_i} + b_2 LogLabprod_i + \mathbf{cC_i}), \end{aligned} \tag{2.17}$$

where u is assumed to be standard normally distributed. ϵ and u are jointly normally distributed with mean zero, a variance of 1, and a correlation coefficient of ρ. Alternatively, we can estimate the causal effect of CIA on exporting via a two-stage-least-squares (2SLS) linear regression model. This approach loosens the restrictive assumptions on the joint distribution of the error terms but it does not take into account the binary nature of both the dependent variable and the endogenous regressor.

$\mathbf{Z}$ denotes our set of instrumental variables, $PublicInfo$ and $Specificity$. By jointly estimating equation (2.16) and (2.17) via maximum likelihood we can identify a causal

[8] The recursive bivariate probit model is also used by Minetti and Zhu (2011) to address potential endogeneity in a trade context.

effect of the use of CIA on the export participation of a firm. We employ our instruments consecutively and also jointly in one specification.

In addition, we apply the continuous measure of CIA received, $LogCIArec$ to measure the intensity of CIA financing. In doing so, we replace equation (2.17) with the following reduced form specification:

$$LogCIArec_i = a + \mathbf{b_1 Z_i} + b_2 LogLabprod_i + \mathbf{c_2 C_i} + v_i. \tag{2.18}$$

Equation (2.16) and (2.18) are jointly estimated via maximum likelihood under the assumption that $\epsilon, v \sim N(\mathbf{0}, \sum)$ and $\sigma_{11} = 1$.

$\mathbf{C}$ contains several control variables that influence the export decision of firms and are commonly used in the literature. We follow Minetti and Zhu (2011) and control for reputation and size effects by including the log of firms' age, $LogAge$, and the log number of employees, $LogSize$. Moreover, the percentage of the workforce with a university education or higher, $Univeduc$, is added to control for human capital effects. Older and larger firms are usually expected to have a higher export probability, as well as firms that possess a more highly educated workforce. We take the competitive environment of the firm into account by controlling for the degree of national and international competition that the firm faces. $CompNum$ gives the number of national competitors of the firm which can take values from 0 to 4 where 4 is coded as 4 or more competitors in the national market. $ForPressure$ captures the extent of foreign competition. It is defined as a binary indicator equal to 1 if the firm states to be fairly or very much influenced by competition from foreign competitors when making key decisions with regard to developing new products, services or entering new markets. It is equal to 0 if foreign pressure is not at all or only slightly important to the decision process of the firm. The influence of competition on the export decision is ambivalent. On the one hand, stronger competition may deter firms from entering the export market. On the other hand, it might hint at the existence of a larger market and growth opportunities to the firm by going international. The inclusion of both controls ensures that our instrumental variable $Specificity$ only reflects the specificity of the firm-customer relationship and no competition effects. Last but not least, we control for foreign ownership since foreign owned firms are more likely

to export (Greenaway, Guariglia, and Kneller, 2007). *Foreign* is a dummy equal to 1 if at least 10% of the firm are owned by a foreign entity. Sector specific effects are included in all specifications, as well.

2.4.2 The Effect of Cash-in-Advance Financing on Export Participation

Table 2.2 provides the results from estimating the effect of CIA financing, measured as a binary indicator, on the export participation decision of firms. In the first column, we consider CIA received as randomly granted to firms by their customers and estimate equation (2.16) via a simple probit model. The effect of $DCIArec$ on the probability to export is positive and highly significant. To grasp the economic impact of positive CIA received, we calculate the average marginal effect for $DCIArec$ on the export probability: on average, firms that receive a positive amount of their sales in advance from their customers have a 6% higher probability to export than firms that either receive the payment on time or after delivery of their goods or services. With regard to the other estimates, we confirm prior findings of the literature. Larger and more productive firms have a higher export probability, as well as foreign owned firms and firms equipped with a more highly educated workforce. In contrast, older firms do not participate significantly more often in exporting. The effect of the number of domestic competitors is positive but not significant, either. Instead, we find a strong positive influence of pressure from foreign competitors on the export participation decision of firms. Firms indicating that pressure from foreign competitors is fairly or very important when making key decisions about developing new products or entering new markets have a higher probability to export. This may reflect growth opportunities available in the foreign market and firms making use of scale effects.

In columns 2 and 3, we jointly estimate equations (2.16) and (2.17), taking into account potential endogeneity of our key regressor. To instrument the use of CIA by firms, we employ $PublicInfo$ in column 2, which indicates whether the firm regards information on new customers acquired from trade fairs and other public sources as extremely important.

Table 2.2: Effect of $DCIArec$ on Export Participation - Simple and Bivariate Probit Model

	Probit	Bivariate probit		Bivariate probit		Bivariate probit	
	Exp	DCIArec	Exp	DCIArec	Exp	DCIArec	Exp
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
DCIArec	0.402***		1.301***		1.404***		1.504***
	(0.124)		(0.413)		(0.301)		(0.258)
LogAge	0.025	-0.127**	0.046	-0.135**	0.065	-0.126**	0.052
	(0.087)	(0.058)	(0.082)	(0.058)	(0.080)	(0.058)	(0.079)
LogSize	0.205***	0.131***	0.146***	0.137***	0.129***	0.128***	0.125***
	(0.041)	(0.029)	(0.053)	(0.029)	(0.047)	(0.029)	(0.045)
LogLabprod	0.326***	0.085	0.267***	0.110**	0.252***	0.0890*	0.246***
	(0.080)	(0.053)	(0.080)	(0.053)	(0.076)	(0.053)	(0.074)
Univeduc	0.008*	0.008***	0.002	0.008***	0.004	0.008***	0.001
	(0.004)	(0.002)	(0.004)	(0.002)	(0.004)	(0.002)	(0.004)
CompNum	0.015	-0.015	0.014	0.002	0.020	0.009	0.013
	(0.058)	(0.039)	(0.054)	(0.039)	(0.053)	(0.040)	(0.052)
ForPressure	0.747***	-0.043	0.695***	0.011	0.667***	-0.023	0.660***
	(0.121)	(0.093)	(0.131)	(0.093)	(0.126)	(0.094)	(0.123)
Foreign	1.358***	-0.099	1.273***	-0.134	1.248***	-0.099	1.213***
	(0.171)	(0.144)	(0.195)	(0.142)	(0.182)	(0.144)	(0.181)
PublicInfo		0.283***				0.278***	
		(0.087)				(0.084)	
Specificity				0.130***		0.130***	
				(0.044)		(0.043)	
AME/ATE	0.057		0.220		0.248		0.275
(SE) / SD	(0.018)		0.153		0.161		0.169
Observations	1,070	1,124		1,135		1,124	
$\hat{\rho}$		-0.550*		-0.620***		-0.681***	
Log-Likelihood	-274.0	-966.4		-975.5		-961.7	

Sector fixed effects are included in all regressions. Heteroskedastic robust standard errors are in parentheses. In column 1, we provide the average marginal effect of $DCIArec$ on exporting. In columns 3, 5, and 7 we calculate the average treatment effect of $DCIArec$ on exporting. ***, **, and * denote significance at 0.01, 0.05, and 0.10 levels, respectively.

The instrument highly significantly enters the equation for use of CIA. As conjectured, firms with a high demand for officially collected information on new customers are more likely to require CIA payment. Younger firms are more likely to use CIA reflecting that these firms probably do not have built up a reputation with banks and are more constrained in their access to traditional forms of finance. The size of a firm increases its likelihood to receive CIA. Both findings are in line with results for CIA use by French firms (Mateut, 2012). In addition, we find that firms with a more highly educated workforce also tend to use CIA financing more often. In column 3, the estimates for equation (2.16) are displayed. We observe a strong and positive influence of CIA received on the export participation decision of firms. Calculating the average treatment effect of CIA received

on the export probability of firms, we find that CIA financing increases the likelihood of firms to export by 22%.[9] The effect has more than tripled compared to the simple probit model estimate (6%). The Wald test of zero correlation between ϵ and u yields a significant negative correlation $\hat{\rho}$ at the 10% level suggesting that we cannot consider the use of CIA by firms as exogenous. Thus, not accounting for omitted variables greatly underestimates the true effect of CIA financing on exporting. A potential reason is omitted variable bias due to unobserved customer uncertainty which negatively impacts on exporting but makes CIA financing more necessary. The main findings for our other covariates basically hold true except that we fail to find a significant positive influence of a more highly skilled workforce.

In column 4, we use $Specificity$ as instrument which gauges the firm's bargaining power with regard to enforcing CIA payment from its customers. We expect firms with increasing bargaining power (decreasing price elasticity) to be more likely to enforce CIA payments from their customers. Looking at the results in column 4, we find that this is indeed the case. $Specificity$ has a strong and positive impact on firms' probability to receive CIA suggesting that the higher the bargaining power of the firm, the more likely it is to receive CIA. Exogeneity of the use of CIA can be rejected at the 1% level. The effect of advance payments on the exporting decision of firms increases when instrumented with pricing power information. On average, receiving CIA raises the export participation of firms by about 25%.

In the last specification, we use both instruments jointly to increase the precision of our estimates. Both instruments are again highly significant and exogeneity of our key regressor is strongly rejected. Making use of a larger part of the exogenous variation in $DCIArec$ leads to a decrease in the estimated standard errors in column 7 and to an even higher effect on exporting: receiving CIA increases the probability to export by 27%.

Next, we provide the results when measuring use of CIA as continuous variable in log percentage shares of total sales in Table 2.3. Instead of the bivariate probit model, we estimate equation (2.16) and (2.18) jointly via an instrumental variable probit model. We

[9]The average treatment effect of CIA received on exporting is given by the following formula in Wooldridge (2010), p. 594: $\Phi(\alpha + \beta + \gamma\mathbf{C_i}) - \Phi(\alpha + \gamma\mathbf{C_i})$.

Table 2.3: Effect of *LogCIArec* on Export Participation - Simple and IV Probit

	Probit	IV probit		IV probit		IV probit	
	Exp	LogCIArec	Exp	LogCIArec	Exp	LogCIArec	Exp
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
LogCIArec	0.107**		0.552***		0.691***		0.635***
	(0.043)		(0.204)		(0.074)		(0.098)
LogAge	0.013	-0.127**	0.059	-0.133**	0.094	-0.122**	0.072
	(0.086)	(0.060)	(0.078)	(0.060)	(0.062)	(0.060)	(0.070)
LogSize	0.210***	0.111***	0.114	0.115***	0.036	0.107***	0.075
	(0.040)	(0.029)	(0.084)	(0.029)	(0.059)	(0.029)	(0.059)
LogLabprod	0.331***	0.081	0.215*	0.102*	0.113	0.085	0.164*
	(0.080)	(0.056)	(0.118)	(0.056)	(0.083)	(0.056)	(0.086)
Univeduc	0.008*	0.008***	0.0002	0.008***	-0.001	0.008***	-0.001
	(0.004)	(0.002)	(0.005)	(0.002)	(0.003)	(0.002)	(0.003)
CompNum	0.016	-0.032	0.023	-0.014	0.034	-0.001	0.022
	(0.058)	(0.042)	(0.051)	(0.043)	(0.042)	(0.042)	(0.046)
ForPressure	0.747***	-0.056	0.607***	-0.003	0.418***	-0.024	0.514***
	(0.121)	(0.098)	(0.207)	(0.097)	(0.162)	(0.097)	(0.161)
Foreign	1.334***	0.018	1.044***	-0.013	0.714***	0.013	0.869***
	(0.170)	(0.162)	(0.361)	(0.159)	(0.274)	(0.161)	(0.268)
PublicInfo		0.292***				0.254***	
		(0.096)				(0.094)	
Specificity				0.154***		0.163***	
				(0.046)		(0.041)	
AME	0.015		0.100		0.146		0.125
(SE)	(0.006)		(0.055)		(0.027)		(0.030)
Observations	1,070	1,059	1,059	1,070	1,070	1,059	1,059
$\hat{\rho}$		0.140		0.002***		0.004***	
Log-Likelihood	-276.1	-2,073		-2,090		-2,064	

Sector fixed effects are included in all regressions. In column 1, 3, 5, and 7 we provide the average marginal effect of *LogCIArec* on exporting. Heteroskedastic robust standard errors are in parentheses. ***, **, and * denote significance at 0.01, 0.05, and 0.10 levels, respectively.

employ the same set of instruments in turn. When neglecting endogeneity in $LogCIArec$, we observe a small positive and significant effect on the export probability of firms. A 1% increase in the share of CIA received leads to a 2% increase in the export probability. Considering only the exogenous variation in our key regressor instead leads to more precise and larger coefficients that are highly significant: a 1% increase in the share of CIA received on total sales raises firms' export participation probability between 10% and 15%, depending on the set of instruments. However, $Publicinfo$ seems to be a rather weak instrument for $LogCIArec$. Applying it as single instrument in column 2, we cannot reject exogeneity of our key regressor which points to a weak instrument. Therefore, our preferred specification is the last specification in which we use both instruments jointly.

To ensure that the considerable increase in the estimated effect of CIA financing on exporting does not stem from non-linearities underlying the recursive bivariate or the instrumental probit model, we additionally provide the results from 2SLS estimations in Tables B.3 and B.4 in Appendix B.2. The effect of *DCIArec* on exporting is even larger when estimated via 2SLS in Table B.3. Moreover, the magnitude of the effect varies widely from an insignificant point estimate of 24% to an increase by 77%. These findings clearly illustrate that 2SLS is less suited for estimating the effect of a binary endogenous regressor on a binary outcome since it neglects the binary nature of both endogenous variables. One consequence is that predicted probabilities of export participation can lie outside the unit interval. Minetti and Zhu (2011) note that this shortcoming also affects the first stage if the share of firms with an outcome of 1 is rather low, as it is the case in our setting, since only about one third of all firms receive CIA. This may also explain why the first stage F-Statistic is below the recommended value of 10 (Staiger and Stock, 1997) although both instruments enter the first stage highly significantly and although the Hansen test statistic confirms that the overidentifying restrictions are valid. Therefore, estimation via the recursive bivariate probit model seems to be more appropriate to us.

When using the continuous measure of CIA received by firms as key regressor in Table B.4, the 2SLS results come closer to the estimates of the instrumental variable probit model and also the first stage F-Statistic improves. The estimated effects vary widely, though: a 1% increase in the share of CIA received leads to an increase in the export probability between 13% and 22%. The Hansen test statistic again confirms that the overidentifying restrictions are valid.

Taken together, our results strongly support our hypothesis that CIA financing fosters the export participation at the firm level. If we do not control for potential endogeneity, the effect of CIA on exporting is considerably smaller hinting at a downward bias due to omitted variables that jointly influence the export and CIA taking decision of firms. Applying instruments that account for non-random use of CIA by firms we establish a statistically and economically meaningful effect of CIA financing on exporting.

2.4.3 The Effect of Cash-in-Advance Financing on the Export Participation of Financially Constrained Firms

So far, we have assumed that the effect of CIA financing on the export participation decision of firms is constant across firms. According to our model, we expect the positive effect of CIA financing to be driven mainly through the effect for financially constrained firms since unconstrained firms can export even in the absence of CIA. In this subsection, we explicitly test for heterogeneous effects of CIA financing on exporting for constrained and unconstrained firms. We apply several different concepts that express firms' difficulties in accessing bank credits and their financial needs. In doing so, we rely on the specification with the continuous measure of CIA as key regressor (equations (2.16) and (2.18)) because the recursive bivariate probit model becomes less computationally feasible if the number of observations drops. Furthermore, we use the specification including both instrumental variables since it provides us with the most precise and efficient estimates. The results of this exercise can be found in Table 2.4.

We first split firms according to the number of employees with the median number of employees as cutoff. Assuming that smaller firms experience stronger difficulties in securing bank finance, we expect a stronger fostering effect of CIA on the export probability for firms below the median size level. The results in Table 2.4, row 1 and 2, confirm our conjecture and suggest that the effect of CIA on the export participation is mainly driven by small firms: small firms that experience a 1% increase in CIA shares can increase their export probability by about 16%. In constrast, larger firms do not significantly benefit from additional CIA financing.

We then divide firms according to their access to bank financing in rows 3 and 4. The survey allows to identify firms that do not receive a bank loan although they have a positive demand for it. In the survey, firms are asked whether they recently obtained a bank loan. Firms that state that they do not currently possess a bank loan are asked to state the reasons: potential answers are no need for a loan, downturn of the loan application, or discouragement from applying for the loan for several reasons. We follow Hainz and Nabokin (2012) and divide firms into two subgroups according to their demand

Table 2.4: Effect of *LogCIArec* on Export Participation - Different Subgroups, IV Probit

Exp	Coeff. *LogCIArec*	SE	AME	SE	Obs.
Heterogeneity according to Access to Finance					
LogSize					
(1) below median	0.778***	(0.046)	0.156	(0.023)	503
(2) above median	0.258	(0.421)	0.048	(0.085)	549
Firms with demand					
(3) and no access to loan	0.952***	(0.129)	0.266	(0.064)	71
(4) and access to loan	0.593***	(0.147)	0.115	(0.041)	723
Heterogeneity according to Financing Needs					
Material input growth					
(5) below median	0.540*	(0.300)	0.081	(0.073)	738
(6) above median	0.609***	(0.155)	0.141	(0.045)	313
(7) Manufacturing, Mining, and Construction	0.800***	(0.050)	0.204	(0.024)	443
(8) Services	0.489**	(0.198)	0.083	(0.048)	681

Instruments applied: PublicInfo, Specificity

Sector fixed effects are included in all regressions except for the last two sample splits according to the firm's main economic activity. Heteroskedastic robust standard errors are in parentheses. ***, **, and * denote significance at 0.01, 0.05, and 0.10 levels, respectively.

and access to credit. In doing so, we only consider firms that state a demand for credit, which is true for 78% of all firms in our sample. We then split these firms according to whether they currently possess a loan or not. Firms that do not possess a loan have either faced a downturn of their application or did not apply for a loan because they were discouraged from applying due to high interest rates, burdensome application procedures or because they thought the loan application would be turned down anyways. We expect firms that do not possess a loan but have a demand for a loan to benefit more from additional CIA financing than firms whose loan application was successful. Our results strongly confirm this conjecture: firms that require external finance but do not obtain a bank loan can raise their export probability by about 27% if CIA received increases

by 1%. In contrast, the partial effect for firms with access to a bank loan is only half of that for firms without access. This strongly points to substitutional CIA financing by customers in order to facilitate entry into exporting.

To gauge the extent of firms' financial needs, we next split the sample according to the real growth rate of material input costs. Firms with above median material input cost growth very likely require additional financing to cover their higher input costs. We expect these firms to benefit more strongly from additional CIA financing. Firms with above median input cost growth experience a rise in their export probability by about 14% for every 1% increase in CIA financing, row 6. In contrast, the average marginal effect for low cost growth firms is smaller and only marginally statistically significant, row 5.

Finally, we analyze heterogeneous effects across different sectors. We lump together firms from the manufacturing sector, mining, and construction and compare them to firms from the service sector. We expect the former to benefit more from CIA financing since manufacturing and construction goods rather tend to be capital intensive goods that have higher financing requirements than services. We find that the marginal effect of 1% increase in CIA financing on the export probability more than doubles when moving from service to non-service firms (rows 7 and 8). Thus, the strong effect of CIA financing on firms' export decision is mainly driven by firms in presumably more capital intensive sectors.

2.5 Conclusion

Our findings strongly suggest that CIA financing between firms can be highly beneficial. CIA can serve as a credible signal of quality and reduce part of the high uncertainty in international trade. This in turn can help to alleviate financial constraints experienced by firms in international trade despite higher implied costs. If external funds are not sufficiently available, firms can still overcome financial frictions if other firms redistribute their funds in form of CIA. We confirm our predictions for a sample of German firms. Although the German credit market is rather well-developed, German firms greatly benefit

from access to CIA financing in terms of their export participation. We expect the positive effects of CIA financing to be especially relevant in a situation of global monetary contractions when firms experience severe difficulties in obtaining bank-intermediated trade finance. An analysis of this relationship is carried out in the following chapter.

Chapter 3

Trade Credit Financing and Exporting during a Financial Crisis

3.1 Introduction

Recent evidence suggests that financial constraints only played a minor part in the great trade drop following the financial crisis 2008-09. The leading role is attributed to a global decline in demand (Bricongne, Fontagné, Gaulier, Taglioni, and Vicard, 2012 and Eaton, Kortum, Neiman, and Romalis, 2011), especially the decline in demand for durable and investment goods (Behrens, Corcos, and Mion, 2012). Studies that find an economically significant and negative impact of tightened credit conditions on international trade do so in particular for sectors that intensively rely on external financing and are thus more affected by a liquidity squeeze (Chor and Manova, 2012 and Iacovone and Zavacka, 2009). Considering the financial nature of the crisis and the high financing needs in international trade, a low impact of financial factors is puzzling. One potential explanation for this finding is that firms can resort to inter-firm financing if traditional bank lending becomes more restrictive. According to the redistribution hypothesis by Meltzer (1960), financially sound firms redirect financial funds to financially constrained trading partners when money supply by banks declines. Indeed, several studies document that trade credit financing increases relative to bank credit financing if credit conditions tighten (Bougheas,

Mateut, and Mizen, 2006 and Love, Preve, and Sarria-Allende, 2007). Thus, given that some firms still possess sufficient financial funds, the negative impact of tightened credit conditions can be mitigated. However, evidence on how trade credit financing affects the international activities of firms during a financial crisis is scarce.

This chapter aims to fill this gap and explores the influence of cash-in-advance (CIA) financing on the export activities of firms during the financial crisis 2008-2009. To derive predictions of the effect of CIA on exporting during a crisis, we build on the theoretical framework developed in Chapter 2. We introduce a financial shock to the model that increases the costs of external financing and the uncertainty with regard to foreign market demand. Both shifts decrease the profitability of exporting and thus induce a rise in the productivity threshold for exporting. Consequently, fewer firms are able to export in a financial crisis and those that do, export less than in the pre-crisis period. However, we can show that the increase in the productivity cut-off is smaller for CIA financed export transactions than for bank credit financed transactions. Similarly, the export volume of CIA financing firms decreases by less than the respective volume of bank credit financing firms. The reason for this is that the increase in uncertainty can be partly mitigated via CIA financing. In contrast, firms that finance their export transaction with a bank loan are fully affected by higher uncertainty. Thus, our model predicts that CIA financing becomes even more attractive to firms in the crisis than in the pre-crisis period since it softens the adverse crisis effect on exporting.

Our empirical analysis is based on the third and fourth round of the Business Environment and Enterprise Performance Survey (BEEPS) conducted in 2005 and 2009. The survey covers firm-level information on 1,935 firms from 27 European and Central Asian (ECA) countries. It provides us with a precise measure of CIA use by firms, the percentage of sales received before the delivery of the main good or service. In addition, firms report the share of sales that is sold abroad so that we can compare the export performance of firms over time and link it to their use of CIA. A first glance at CIA financing reveals that prepayments strongly increase during the crisis. In 2009, more firms receive prepayments and they receive a higher average share of sales in advance than in 2005. This finding

supports the redistribution hypothesis according to which trade credit financing rises when bank lending becomes more restrictive.

To test whether CIA financing more strongly fosters the export participation of firms in the crisis than in the pre-crisis period, we estimate the effect of CIA on the export participation of firms in 2005 and 2009, respectively. In doing so we rely on a matching approach since matching controls for non-random selection of firms into prepayment financing. By comparing the export performance of matched pairs of firms, we can identify a causal effect of CIA financing on firms' export activities. We find that firms that receive prepayments have a 6% higher probability to export in 2005 compared to firms that lack CIA financing. In 2009, the positive effect of CIA financing increases to 9%. Thus, CIA financing more strongly fosters the export participation of firms in the crisis than in the pre-crisis period. To test whether CIA financing softens the negative crisis impact on export shares, we compare the change in export shares of firms that receive CIA in the crisis with the change in export shares of firms that do not receive CIA in the crisis. Our results imply that the decrease in export shares is smaller by 6 percentage points for firms that receive CIA in 2009. Taken together, our results lend support to the redistribution hypothesis. In the crisis, CIA financing does not dry up for our sample of firms and the rechanneling of financial funds between firms strongly benefits exporting.

The contribution of this chapter is twofold. First, it is the first to study the effects of CIA financing on exporting during a crisis. The existing literature exclusively addresses the effects of supplier credit financing on international trade during a crisis. Considering access to CIA, instead, is particularly interesting because prepayments are intensively used by firms across all industries and provide an alternative to bank credit financing. Moreover, prepayments precisely capture trading partners' willingness to redistribute funds because customers actively decide whether to extend a prepayment or not. In contrast, a firm can extort a supplier credit by simply overstretching the payment period. Second, our study identifies the effect of redistributional CIA financing at the firm level. Other studies predominantly rely on pre-crisis industry measures of trade credit use to mitigate endogeneity with regard to the financing choice of a firm. These measures fail

to capture the immediate impact of trade credit financing at the firm level, though. To account for selection into CIA financing we apply non-parametric matching. This allows us to determine a causal effect of CIA financing on firms' export activities before and during the crisis.

This chapter relates to two different strands of literature. The first strand considers the redistribution of supplier credit financing to credit constrained firms in times of financial distress. A seminal paper is Meltzer (1960) who observes that in times of monetary tightening cash abundant US firms grant prolonged payment periods to their customers. Wilner (2000) provides a theoretical foundation for this finding. In his model, unconstrained firms extend trade credit to financially constrained customers in order to sustain the business relationship.[1] Nilsen (2002) and Bougheas, Mateut, and Mizen (2006) provide evidence that especially small firms increase their reliance on trade credit financing in times of a more restrictive monetary policy. Ahn (2011) explicitly considers trade credit extended in international transactions. He argues that internationally extended trade credits are the first to be cut in a crisis since international trade is more risky than domestic trade. His paper provides a rationale for the anecdotal evidence of declining trade finance during the recent financial crisis (Auboin, 2009). Further empirical evidence is mixed. Love, Preve, and Sarria-Allende (2007) use accounts payable to proxy supplier credit received for a set of Asian firms. They document an increase in supplier credit financing during the Asian financial crises of the 1990s. In contrast, Love and Zaidi (2010) observe declining trade credit financing for a different sample of Asian firms during the same crisis. Kestens, Van Cauwenberge, and Bauwhede (2011) also find declining accounts payable for Belgian firms during the subprime crisis. We complement the literature by providing first insights into CIA financing during the crisis. For our sample of European and Central Asian firms, we observe an increased willingness of customers to fund their trading partners which contradicts the anecdotal evidence of declining trade finance.

The second strand of literature considers the effects of trade finance on international trade in a financial crisis. Chor and Manova (2012) find support that *ceteris paribus* industries

[1] He assumes that some firms are not affected by the liquidity squeeze and thus are able to extend trade credit.

with a higher pre-crisis use of supplier credit export more to the US during the recent financial crisis. Amiti and Weinstein (2011) analyze the effects of bank intermediated trade finance in the Asian banking crises of the 1990s. For a sample of Japanese firms, they observe a strong positive correlation between the financial health of the main bank of a firm and the firm's export performance. Levchenko, Lewis, and Tesar (2010) and Iacovone and Zavacka (2009), however, do not detect a significant fostering effect of access to trade credit on US exports and imports during past crises and the recent subprime crisis. Coulibaly, Sapriza, and Zlate (2011) analyze Asian firm-level data and find that exporters use less trade credit in the recent crisis and also have lower sales than purely domestically active firms. They take this as incidence of declining trade due to a lack of trade finance. Our analysis complements the literature by providing firm-level evidence on the effects of CIA financing. We find that CIA financing fosters the export participation in particular during the crisis. Moreover, firms provided with an increase in prepayments can cushion the negative crisis effects on export shares. The paper closest to ours in methodology is Felbermayr, Heiland, and Yalcin (2012) who use a matching approach to determine the causal effect of public export credit guarantees on sales and employment of German firms during the subprime crisis. They find that firms provided with public export insurance generate higher sales and employment during the 2008-09 crisis.

The remainder of this chapter is organized as follows. In section 3.2, we present our theoretical considerations on the impact of CIA financing during a crisis and derive testable hypotheses. Section 3.3 describes the data used in our analysis and provides summary statistics. Section 3.4 explains our empirical strategy. In section 3.5, we present our results and discuss their robustness. Section 3.6 concludes.

3.2 The Role of Cash-in-Advance Financing in a Financial Crisis

3.2.1 Model Setup

We build on our results derived in Chapter 2 to infer the differential impact of CIA financing on firms' export activities in a financial crisis. Recall that a firm considers whether to sell its goods to a foreign market. Exporting the quantity x requires financing the variable costs, $k = \frac{x^2}{2(1+\beta)}$, and the fixed costs, F_{Ex} of production. $(1+\beta)$ denotes the productivity level of the firm. When selling x to a foreign importer, the exporter faces uncertainty with regard to the success of the export transaction. First, only with probability μ, $0 < \mu < 1$, the importer is of high quality and so is able to successfully market the exporter's good in the foreign market. With probability $(1-\mu)$, he is of low quality which means that positive revenues cannot be generated and hence the exporter is not paid by the importer. Second, demand in the foreign market is positive with probability λ, $0 < \lambda < 1$, and it is zero with probability $(1-\lambda)$. In the former case, the high-quality importer can resell the exporter's good at the exogenously given market price $\hat{p}$. No revenues are generated in the latter case and the importer cannot repay the exporter, even if he is of high quality. Therefore, diversion of the good becomes attractive which is captured by the private benefit ϕ that the importer derives, where $0 < \phi < \lambda\hat{p}$. The lower λ the more attractive is diversion to the high quality importer and the more severe the moral hazard problem faced by the exporter. The low-quality importer always diverts the good since he is not able to successfully market the good and generate revenues from reselling it.

The exporter does not possess any internal funds and has to finance the total costs of exporting externally. The financing can be provided by a bank in form of a bank credit or by the importer in form of a prepayment. In the latter case, complementary bank credit is needed since the amount paid in advance covers only a part of the total costs. The gross refinancing rate of the bank is $(1+\bar{r}_B)$ and the gross refinancing rate of the importer is $(1+\bar{r}_{Im})$ when paying in advance. We assume that $\bar{r}_{Im} > \bar{r}_B$, since the bank

is more efficient in providing credit than the importer. Despite its higher costs, CIA financing is attractive to the exporter because CIA provides a signal on the importer's quality type. In Chapter 2, we show that there exists a separating equilibrium in which the high quality importer pays part of the purchasing price in advance and the low-quality importer chooses not to extend CIA. In this equilibrium, the CIA payment eliminates the adverse selection problem with regard to the foreign importer's type.[2]

The firm is able to sell its goods abroad if $(1+\beta)$ lies above a certain threshold, $(1+\beta)_{Ex}$, which is derived from the zero-profit condition for exporting. The following expressions give the respective productivity cut-offs for exporting with pure bank financing and for exporting with CIA financing:

$$(1+\beta)_{Ex}^{BC} = \left(\frac{1+\bar{r}_B}{\lambda\mu}\right)^2 \frac{2F_{Ex}}{\left(\hat{p}-\frac{\phi}{\lambda}\right)^2}, \tag{3.1}$$

$$(1+\beta)_{Ex}^{CIABC} = \left(\frac{1+\bar{r}_B}{\lambda}\right)^2 \frac{2F_{Ex}}{\left[\hat{p}-\frac{\phi}{\lambda}+\frac{\phi(1+\bar{r}_B)}{\lambda(1+\bar{r}_{Im})}\right]^2}. \tag{3.2}$$

The first term in each expression denotes the gross refinancing interest rate of the bank adjusted for the level of uncertainty. If pure bank credit financing is chosen, demand and type uncertainty persist; thus the interest rate paid for a bank credit equals $\left(\frac{1+\bar{r}_B}{\lambda\mu}\right)$. If CIA combined with bank credit financing is chosen, the adverse selection problem is eliminated but uncertainty with regard to demand in the foreign market persists. The second term in each expression captures the fixed costs of exporting weighted by the price the exporter receives for the export good. In the case of pure bank credit financing, the exporter demands $\hat{p}$ less a discount, $\frac{\phi}{\lambda}$, from the importer. The discount accounts for the benefit that the importer can derive from diverting the good and is adjusted for uncertain market demand. With combined CIA financing, problems related to moral hazard can be alleviated. If part of the purchasing price is paid in advance by the importer, diversion of the purchased good becomes less attractive compared to selling it and lowers incentives

[2]In this analysis, we restrict our attention to the separating equilibrium. Our main results are unaffected when considering the pooling equilibrium.

for moral hazard. This allows the exporter to raise the price of the exported good (or decrease the discount) by $\frac{\phi}{\lambda}\frac{(1+\bar{r}_B)}{(1+\bar{r}_{Im})}$.

The export volumes in both scenarios are given by the following expressions:

$$x_{Ex}^{BC} = \frac{(1+\beta)}{\frac{1+\bar{r}_B}{\lambda\mu}}\left(\hat{p} - \frac{\phi}{\lambda}\right), \tag{3.3}$$

$$x_{Ex}^{CIABC} = \frac{(1+\beta)}{\frac{1+\bar{r}_B}{\lambda}}\left[\hat{p} - \frac{\phi}{\lambda} + \frac{\phi(1+\bar{r}_B)}{\lambda(1+\bar{r}_{Im})}\right]. \tag{3.4}$$

Comparing the cut-offs and export volumes in each financing scenario it is easy to see that

$$(1+\beta)_{Ex}^{CIABC} < (1+\beta)_{Ex}^{BC} \quad and \quad x_{Ex}^{BC} < x_{Ex}^{CIABC}.$$

The productivity threshold to export profitably is lower with CIA than with pure bank credit financing and the exporter can export a higher volume if the importer pays in advance. The underlying mechanism is that the elimination of type uncertainty and the alleviation of moral hazard increase the profitability of exporting. Thus, CIA fosters exporting at the extensive and intensive margin: less productive firms are able to export and exporters can export higher volumes.

3.2.2 A Financial Crisis Scenario

We now consider an adverse financial shock to the economy. The shock is modeled as a tightening of credit conditions and as a drop in global demand. Tightened credit conditions are captured by an increase in the gross interest rates of external financing, $(1+\bar{r}_B)$ and $(1+\bar{r}_{Im})$. The drop in demand is reflected by an increase in the probability $(1-\lambda)$ of zero demand for the exporter's good in the foreign market. A drop in demand makes moral hazard more attractive to the importer since the importer's expected profit from selling the exporter's goods decreases. Doing simple comparative statics, it is easy to see that an increase in the gross interest rate $(1+\bar{r}_B)$ and the probability of zero demand $(1-\lambda)$ induces a rise in both productivity thresholds. A rise in the importer's refinancing costs $(1+\bar{r}_{Im})$ leads to an increase in the cut-off for combined CIA financing

but does not affect the export cut-off with bank financing:

$$\frac{\partial(1+\beta)^{i}_{Ex}}{\partial(1+\bar{r}_B)} > 0, \qquad \frac{\partial(1+\beta)^{i}_{Ex}}{\partial(1-\lambda)} > 0, \qquad \frac{\partial(1+\beta)^{CIABC}_{Ex}}{\partial(1+\bar{r}_{Im})} > 0, \qquad \frac{\partial(1+\beta)^{BC}_{Ex}}{\partial(1+\bar{r}_{Im})} = 0,$$

where i denotes the financing mode, $i \in \{BC, CIABC\}$. Likewise, the financial shock leads to a decrease in export volumes:

$$\frac{\partial x^{i}_{Ex}}{\partial(1+\bar{r}_B)} < 0, \qquad \frac{\partial x^{i}_{Ex}}{\partial(1-\lambda)} < 0, \qquad \frac{\partial x^{CIABC}_{Ex}}{\partial(1+\bar{r}_{Im})} < 0, \qquad \frac{\partial x^{BC}_{Ex}}{\partial(1+\bar{r}_{Im})} = 0.$$

A financial shock decreases the profitability of exporting and forces the least productive firms to exit the export market. Those that export, export lower volumes than in the pre-crisis period. This holds true irrespective of the financing mode. We next assess how the adverse financial shock affects exporting with pure bank financing relative to exporting with combined CIA financing. This allows us to infer in which financing mode exporting becomes more restrictive during the financial crisis. We define the relative ease to enter the export market, B, as the ratio of the productivity thresholds:

$$B = \frac{(1+\beta)^{BC}_{Ex}}{(1+\beta)^{CIABC}_{Ex}} = \frac{\left(\hat{p} - \frac{\phi}{\lambda} + \frac{\phi(1+\bar{r}_B)}{\lambda(1+\bar{r}_{Im})}\right)^2}{\mu^2\left(\hat{p} - \frac{\phi}{\lambda}\right)^2}. \tag{3.5}$$

The total derivative of (3.5) with regard to $(1+\bar{r}_B)$, $(1+\bar{r}_{Im})$, and $(1-\lambda)$ then gives us the crisis-induced change in the relative export threshold:

$$dB = \frac{\partial B}{\partial(1+\bar{r}_B)} d(1+\bar{r}_B) + \frac{\partial B}{\partial(1+\bar{r}_{Im})} d(1+\bar{r}_{Im}) + \frac{\partial B}{\partial(1-\lambda)} d(1-\lambda).$$

Inserting the corresponding partial derivatives yields:

$$dB = \frac{2\left(\lambda\hat{p} - \phi + \frac{\phi(1+\bar{r}_B)}{(1+\bar{r}_{Im})}\right)\frac{\phi}{(1+\bar{r}_{Im})}}{\mu^2\left(\lambda\hat{p} - \phi\right)^2}\left(d(1+\bar{r}_B) + \frac{\hat{p}(1+\bar{r}_B)}{(\lambda\hat{p}-\phi)} d(1-\lambda) - \frac{(1+\bar{r}_B)}{(1+\bar{r}_{Im})} d(1+\bar{r}_{Im})\right).$$

If $dB > 0$, the productivity threshold with pure bank financing increases by more than the respective cut-off with CIA financing and *vice versa*. $dB > 0$ requires that

$$d(1-\lambda)\frac{\hat{p}}{(\lambda\hat{p}-\phi)} > \frac{d(1+\bar{r}_{Im})}{(1+\bar{r}_{Im})} - \frac{d(1+\bar{r}_B)}{(1+\bar{r}_B)}. \tag{3.6}$$

The left-hand-side expression in (3.6) denotes the increase in demand uncertainty weighted by the relative attractiveness of moral hazard. Recall that $\hat{p}$ is the price the importer receives from selling the exporter's good in the foreign market and $(\lambda\hat{p}-\phi)$ is the importer's expected surplus from selling the good over diversion. The lower $(\lambda\hat{p}-\phi)$, the more attractive is moral hazard and the more severe is the increase in uncertainty for a given $\hat{p}$. The right-hand-side expresses the growth differential of both refinancing interest rates. Thus, exporting with bank financing becomes relatively more restrictive than exporting with CIA financing if the increase in the attractiveness of moral hazard outweighs the growth differential in the refinancing rates of the importer and the bank.

From a theoretical perspective, the results derived by Wilner (2000) lend support that $dB > 0$ holds. Wilner (2000) determines the optimal trade credit contract between trade creditors and their trading partners. He shows that trade credit interest rates are higher than bank interest rates, but trade credit interest rates actually decrease when banks are forced to increase bank credit interest rates. The reason is that trade creditors want to ensure the continuation of business relations with trading partners that are in financial distress. Nilsen (2002) assumes that trade credit interest rates are constant so that trade credit financing becomes relatively cheaper when bank interest rates rise. Both results imply that the right-hand-side of (3.6) is negative. Since $d(1-\lambda)(\lambda\hat{p}-\phi) > 0$, this means that $dB > 0$ holds.

Empirical evidence on the development of $(1+\bar{r}_B)$ and $(1+\bar{r}_{Im})$ also suggests that (3.6) is fulfilled. Mapping $(1+\bar{r}_B)$ and $(1+\bar{r}_{Im})$ to financial market interest rates, the refinancing rate of the bank is best reflected by the money market interest rate at which banks can access liquidity from other banks or a central bank. The importer's refinancing rate, in turn, is best described by the retail lending rate to non-financial corporations. The European Central Bank (2009), for example, analyzes the development of retail lending rates for non-financial corporations and money market interest rates. They observe that between 2003 and 2009 both rates tend to move closely together since banks pass through an increase in their own refinancing rate to retail lending rates. This holds true even during the crisis. Generally, the adjustment of retail lending rates is rather sluggish

implying that retail lending rates increase by less than the refinancing costs of banks.[3] Co-movement of both rates is also observed by Égert, Crespo-Cuaresma, and Reininger (2007) for five Central and Eastern European countries. Thus, the growth differential in retail lending rates and banks' refinancing rates is either negative or close to zero.

Doing the same exercise for the change in the relative export volume, $X = \frac{x_{Ex}^{BC}}{x_{Ex}^{CIABC}}$, we derive the following expression:

$$dX = \frac{\mu \frac{\phi}{(1+\bar{r}_{Im})}}{\left(\lambda\hat{p} - \phi - \phi\frac{(1+\bar{r}_B)}{(1+\bar{r}_{Im})}\right)^2}\left(d(1+\bar{r}_{Im})\frac{(1+\bar{r}_B)(\lambda\hat{p}-\phi)}{(1+\bar{r}_{Im})} - d(1-\lambda)\hat{p}(1+\bar{r}_B) - d(1+\bar{r}_B)(\lambda\hat{p}-\phi)\right).$$

If $dX < 0$, then the export volume with pure bank credit financing decreases by more than the respective volume with combined CIA financing and *vice versa*. $dX < 0$ requires the same condition to hold true as for $dB > 0$:

$$d(1-\lambda)\frac{\hat{p}}{(\lambda\hat{p}-\phi)} > \frac{d(1+\bar{r}_{Im})}{(1+\bar{r}_{Im})} - \frac{d(1+\bar{r}_B)}{(1+\bar{r}_B)}. \tag{3.7}$$

Applying the same arguments from above, (3.7) is likely to hold since the interest rate increase in retail lending rates tends to be slightly smaller than the increase in the refinancing costs of banks.

Taken together our results imply that the importance of combined CIA financing for exporting increases in the crisis. More firms crucially depend on CIA financing to export in the crisis because export participation with pure bank credit financing becomes relatively more restrictive. Moreover, the export volume of continuing exporters decreases by less if CIA is available. The reason is that the change in the relative attractiveness of both financing modes is primarily driven by the increase in demand uncertainty. An increase in the rates of external financing does not substantially change the relative attractiveness of both financing modes. Tightened moral hazard, however, can be better compensated by firms that receive CIA. Firms that finance their export transaction via a bank credit have to fully account for the decrease in foreign market demand via decreasing the purchase price to $\hat{p} - \frac{\phi}{\lambda+d\lambda}$, where $d\lambda < 0$. In contrast, CIA financing firms decrease the price by less than bank credit financing firms to $\hat{p} - \frac{\phi}{\lambda+d\lambda} + \frac{\phi(1+\bar{r}_b+d\bar{r}_b)}{(1+\bar{r}_{Im}+d\bar{r}_{Im})}$ because a CIA

[3]Reasons for a sluggish adjustment of retail lending rates by banks are for example menu costs and long-term relationships with customers (Égert, Crespo-Cuaresma, and Reininger, 2007).

payment lowers the importer's incentive for moral hazard. We summarize our findings in the following hypotheses:

Hypothesis 1: *In a financial crisis, CIA financing has a stronger fostering effect on the export probability of firms than in the pre-crisis period.*

Hypothesis 2: *Firms that have access to CIA financing in a financial crisis experience a less severe decline in export volumes.*

In the following, we take our hypotheses to an empirical test.

3.3 Data and Summary Statistics

3.3.1 Database

For our analysis, we use firm-level panel data from the third and fourth round of the Business Environment and Enterprise Performance Surveys (BEEPS). The panel comprises data on 1,935 firms from 27 countries in the ECA region in 2005 and 2009. A list of all countries included in the analysis can be found in Table C.1 in Appendix C. The surveys were conducted by the European Bank of Reconstruction and Development and the World Bank in 2005 and 2008-2009 and gather information on the ease of developing and maintaining a business in these countries. In addition, income and expenditure statements as well as traditional balance sheet data are provided. The universe of sectors comprises the manufacturing sector, retail services, and other services (wholesale, services of motor vehicles, communication, transportation, and construction). Excluded are the agricultural, financial, real estate, and the public sector. Table C.2 in Appendix C provides the sectoral decomposition of firms. The surveys make use of stratified random sampling along the strata sector, firm size, and region to enhance the representativeness of the sample. Concerning sectors, the sample is stratified along the manufacturing sector, retail trade, and other services. Size strata entail small firms (5 to 19 employees),

medium-sized firms (20 to 99 employees), and large firms (at least 100 employees). To ensure regional representativeness, firms from urban and rural areas are included.[4]

Most important for our analysis is information on prepayment use and the international activities of firms. In the survey, firms are asked what percentage of their total annual sales of goods or services they are paid for by their customers before delivery (CIA received). In contrast to other studies, we do not have to rely on trade credit proxies from balance sheet data but can employ a precise measure of CIA received at the firm level. Firms also indicate the percentage of their sales that is generated at home and abroad. From this information we infer the export status of a firm as well as the extent of its export activities. We refer to a firm as exporter in a certain year if it sells a positive share of its sales abroad. Unfortunately, our dataset does not allow us to deduce whether CIA is received for a domestic or an international transaction. This kind of detailed information is usually only available in transaction level data. Therefore, we restrict our analysis to inferring the relationship between overall CIA received by firms and their export activities.

Studying the effects of CIA financing on the export activities of firms from transition countries during the financial crisis is particularly insightful because trade credits are an important financing source in countries with a weaker banking system. Fisman and Love (2003) find that in countries with less developed financial institutions those industries that intensively rely on trade credit financing have a higher growth in value added than industries with a less intensive use of trade credits. Figure 3.1 displays the ratio of private credit over GDP for six exemplarily chosen countries from our dataset as well as the average ratio of all 27 ECA countries. France and Germany are included as benchmark countries. Despite a rapid expansion of the banking sector, financial development still lacks behind in the ECA countries. The "average" ECA country exhibits a ratio of private credit over GDP that is well below the average for Germany or France, even though some countries, for example Estonia, have caught up lately.[5] In Figure 3.2, we plot the average

[4]We have to bear in mind that we only observe surviving firms in the panel. Firms that discontinued operations between the first and the second year of the survey are no longer included in the panel. Please refer to http://www.ebrd.com/pages/research/analysis/surveys/beeps.html for further information on the sampling scheme and the treatment of survey non-response.

[5]Data on financial development measured as the extension of private credit by banks over GDP come from Beck, Demirgüç-Kunt, and Levine (2000).

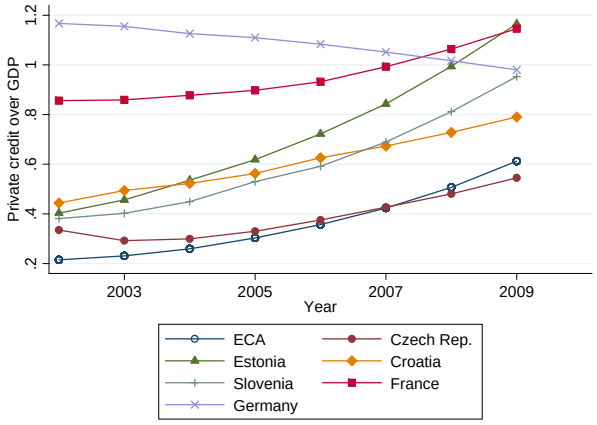

Figure 3.1: Private Credit over GDP for Selected Countries, 2002-2009

share of CIA received in each ECA country against private credit over GDP. For our sample of 27 ECA countries, we observe a negative correlation between CIA use and financial market development. This supports the hypothesis that trade credit financing becomes more important the less financially developed a country is.

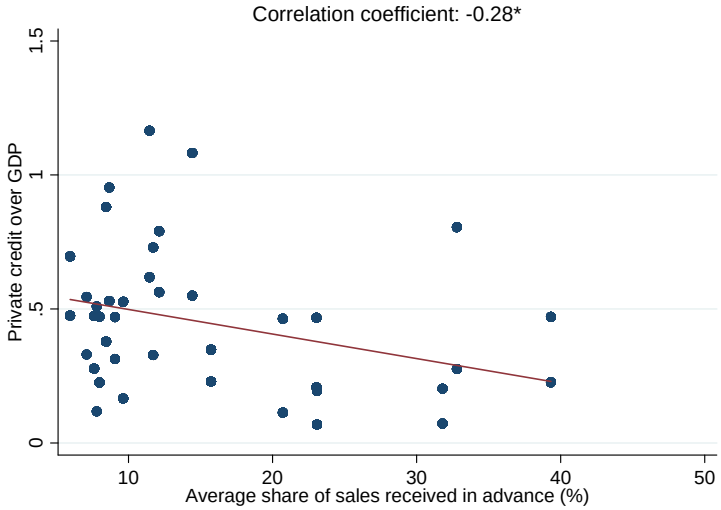

Figure 3.2: Average Share of CIA Received versus Private Credit over GDP for 27 ECA Countries, 2005 and 2009

3.3.2 Summary Statistics

Table 3.1 presents summary statistics on firm characteristics in 2005 and 2009. The average amount of firm sales and the number of employees increase within the four year period from 2005 to 2009. The share of exporting firms slightly drops from 26% to 22%

Table 3.1: Summary Statistics on Firm Characteristics, 2005 and 2009

	2005			2009			
	Mean	SD	Obs	Mean	SD	Obs	Mean Diff.
Sales (1,000 USD)	610	3,407	1,465	2,450	19,700	1,443	1,840***
Number of employees	99.9	302.5	1,934	111.6	894.4	1,927	11.7
Share of exporters (%)	25.9	-	1,933	22.0	-	1,930	-3.9***
Export share (%)	40.1	32.7	501	39.6	33.7	425	-0.5
Export share, 2005 exporters (%)	40.1	32.7	501	27.1	34.4	499	-13.0***

The mean difference test on average firm characteristics is conducted using Welch's formula to allow for unequal variances in both groups (Welch, 1947). Sales are reported in local currency units in the survey and are converted to nominal USD with exchange rate data from the IMF's International Financial Statistics Database.

in 2009 but the average export share remains constant at 40%. This contrasts previous findings in the literature which state a loss at the intensive margin of exporting but not at the extensive margin (see for example Behrens, Corcos, and Mion, 2012 and Bricongne, Fontagné, Gaulier, Taglioni, and Vicard, 2012 for firm-level evidence from Belgium and France). If we merely consider the export performance of firms that were exporting in 2005, we uncover a large loss at the intensive margin: the average export share drops from 40% to 27%.

In order to better understand the export dynamics during the crisis, we divide firms into four categories according to their export status. The results can be found in Table 3.2. The first group consists of firms that do not export in both years which we call never-exporters. These firms comprise the largest group in our sample. Firms that export in both years are termed always-exporters, they make up the second largest group. Stoppers are firms that export in 2005 but no longer in 2009. The smallest share of firms consists of so called starters which export in 2009 but not in 2005.[6] Always-exporters are clearly the strongest performing firms. They are unaffected by the crisis in terms of their average export share, almost half of their sales are generated abroad in both years. In contrast, stoppers sell on average only one third of their sales abroad in 2005. Starters sell even less abroad than stoppers indicating that these firms have not been exporting for a long time. Since less firms start exporting in 2009 than firms stop exporting, we observe a small loss at the extensive margin. Average shares exported by both groups do not differ

[6]This terminology is used for illustrative purposes. Since we observe firms in two years only, the classification does not need to hold over the whole life of these firms.

Table 3.2: Exporter Categories 2005 and 2009

	Never	Always	Stopper	Starter
Export status (2005/2009)	0/0	1/1	1/0	0/1
Share of firms (%)	67.4	15.3	10.6	6.7
Mean export share (2005/2009) (%)	0/0	45.4/45.8	32.6/0	0/25.5

by much, thus the overall loss at the intensive margin is negligible. The decomposition of firms according to exporter category illustrates that exporters from ECA countries react to the crisis via export exit instead of adjusting the scope of exporting: about 40% of firms that are exporting in 2005 do not export in 2009 anymore. One explanation for this finding might be that due to the rather late opening to international trade, exporters from ECA countries are younger, smaller and less experienced than firms from France and Belgium, for example. Thus, they do not have scope to adjust prices further down or to lower their output but are forced to exit the export market.

Next, we document changes in CIA financing in the crisis year. Figure 3.3 depicts the

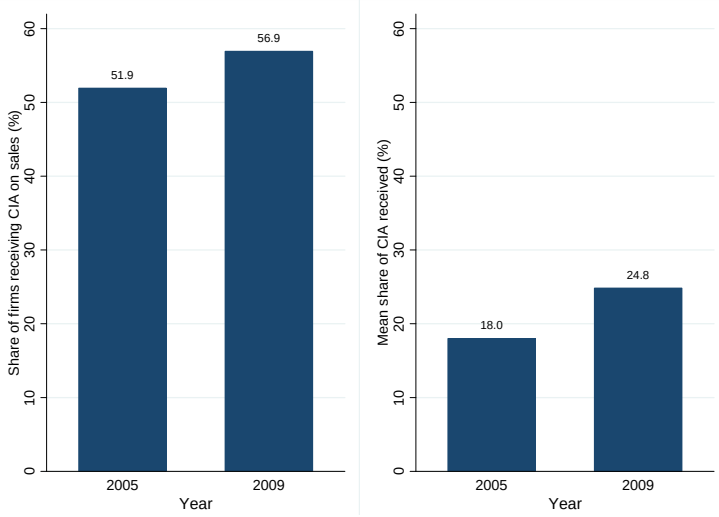

Figure 3.3: Use of CIA by Firms, 2005 and 2009

share of firms that receive CIA financing from customers as well as the average share of CIA received in both years. In 2009, the share of active CIA users increases from 52% to 57% and the average share of sales received in advance rises from 18% to 25%. Both increases are statistically significant at the 1% level as displayed in Panel A of Table C.3 (Appendix C). The increase in CIA financing contradicts the anecdotal evidence of a

decline in trade finance in the aftermath of the financial crisis (Auboin, 2009) and rather supports Meltzer's (1960) redistribution hypothesis. Since advance payments unlike supplier credits cannot be extorted from trading partners, increases in CIA financing reflect the increased willingness of financially sound firms to redistribute their funds. Generally, the average use of CIA by firms in the ECA countries is surprisingly high. For a sample of German firms in 2005, we find that only about 35% of all firms receive CIA and the average share of CIA received amounts to 7% (Table 2.1, Chapter 2). The intensive use of CIA in the ECA countries supports the hypothesis that trade credit financing is especially relevant in countries with an on average less developed banking system.

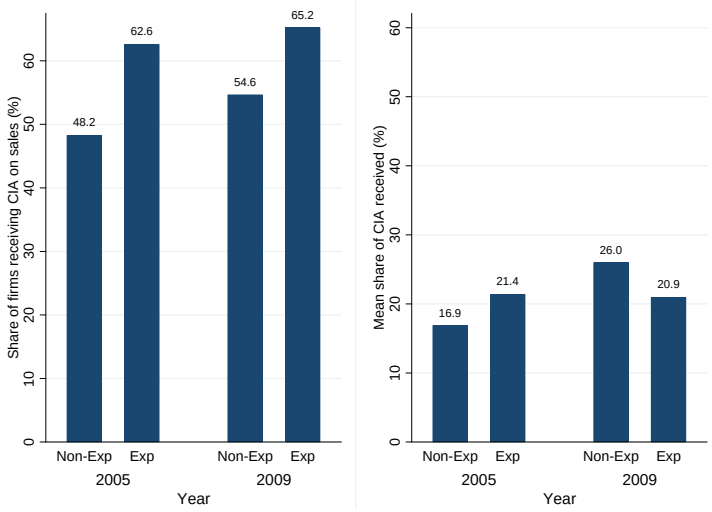

Figure 3.4: Use of CIA by Exporters versus Non-Exporters, 2005 and 2009

Figure 3.4 plots the average use of CIA by export status. More exporters use CIA than purely domestically active firms in 2005 and 2009. The average share of CIA received is higher for exporters than for non-exporters in 2005, whereas in 2009, the picture is reversed. This does not imply that CIA financing drops for internationally active firms, though. A closer look reveals that the mean share of CIA received by exporters remains constant over time. In fact, the difference between both years is not statistically significant (see Panel B of Table C.3, Appendix C). Non-exporters, however, increase CIA financing significantly which hints at non-random sorting of firms into CIA financing. Non-exporters usually tend to be smaller, less productive, and less resilient to liquidity squeezes such that they might increasingly resort to CIA financing during a crisis. All in all, our findings do not support Ahn's (2011) predictions according to which trade

credit financing decreases in particular for internationally active firms. In the crisis, both exporters and non-exporters rely more intensively on CIA financing than in the pre-crisis period, although the increase is more pronounced for non-exporters. These descriptive findings illustrate that prepayments are an important financing tool for firms and that the redistribution of funds in form of CIA financing takes place during the crisis.

3.4 Empirical Methodology

3.4.1 Motivation for Non-Parametric Estimation

A simple test of the first hypothesis can be conducted by regressing the export status of a firm in each year on a dummy that indicates access to CIA financing. Comparing the magnitude of both effects then allows determining whether CIA has a stronger fostering effect in the crisis period. Likewise, Hypothesis 2 can be tested by regressing the change in export volume between 2005 and 2009 on the CIA status of a firm.

However, this approach suffers from two methodological problems. First, there might be selection into CIA financing. Prepayments from customers cannot be considered as randomly assigned since firms are likely to sort into CIA financing according to observed and unobserved firm characteristics (compare Chapter 2). If non-random sorting occurs, simple OLS estimates are up- or downward biased. Second, the functional form of the relationship between export participation and CIA financing can be misspecified. Not accounting for non-linear relationships between CIA financing and other covariates also yields biased estimates (Blundell, Dearden, and Sianesi, 2005). In our setting, we expect CIA to have a different impact in the crisis compared to the pre-crisis period and we also expect a heterogeneous effect of CIA across different firm characteristics, such as firm size for example. In the previous chapter, we find that the effect of CIA financing on the export probability of firms is stronger for smaller firms and firms that are restricted in their access to traditional bank financing.

A straightforward solution to the first problem is to apply an instrumental variable (IV) approach and make use of the exogenous variation in CIA financing. However, in constrast

to the cross-sectional dataset of German firms used in Chapter 2, this panel dataset does not provide convincing instruments such as supplier-customer specific information. Moreover, IV estimation is less fit to solve the second problem and account for non-linear relationships.[7] To overcome both concerns, we resort to non-parametric estimation via matching.

Matching mimics the ideal experiment, to compare the export decision of a firm when it receives CIA with its export decision had it not received CIA. Matching accounts for non-random selection of firms into CIA financing by finding a suitable control group of firms that do not receive CIA. It has several advantages compared to traditional IV estimation and is now widely applied in trade settings.[8] In contrast to regression analysis, it does not impose any functional form assumption. Moreover, linear models usually estimate the average treatment effect (ATE), the effect of the treatment on the outcome of a firm that has average sample characteristics. Non-parametric matching, instead, allows calculating the average treatment effect on the treated (ATT). The ATT is more informative since it gives the effect on the outcome of a firm that has average sample characteristics of the *treated* subsample. In addition, matching allows estimating the effect only over the region of common support where sufficient overlap in firm characteristics between treated and untreated firms is given. If estimation of the CIA effect on exporting includes observations that strongly differ in the distribution of firm characteristics, the estimate is also biased (Stuart, 2010).

3.4.2 The Matching Estimator Approach

The basic idea of the potential outcome framework by Roy (1951) and Rubin (1974) is to compare the effect of a treatment on the outcome of a treated individual with the individual's outcome had it not received the treatment. The formal representation of the underlying model follows Caliendo and Kopeinig (2008). Let D be the treatment indicator where $D_i = 1$ denotes treatment of individual i and $D_i = 0$, otherwise. $Y_i(D_i)$

[7] Taking non-linear relationships into account requires the estimation of a fully interacted model. However, in an IV setting this is often infeasible due to data constraints.

[8] See for example Baier and Bergstrand (2009) or Egger, Egger, and Greenaway (2008) who estimate the effect of trade agreements on trade flows via a matching approach.

refers to the potential outcome of i given its treatment status. $Y_i(1)$ is i's outcome with treatment and $Y_i(0)$ is the outcome without treatment. The key parameter of interest is the population average treatment effect for the treated (ATT):

$$\tau_{ATT} = E\left[Y(1)|D=1\right] - E\left[Y(0)|D=1\right]. \tag{3.8}$$

The first term denotes the expected outcome of all individuals when receiving treatment. The second term denotes the expected outcome of the same individuals had they not received the treatment. However, usually only $E\left[Y(1)|D=1\right]$ and $E\left[Y(0)|D=0\right]$, the expected outcome of the treated when receiving treatment and the outcome of the untreated when untreated, are observed. The counterfactual, $E\left[Y(0)|D=1\right]$, the outcome of the treated had they not received the treatment, cannot be observed. Comparing $E\left[Y(1)|D=1\right]$ to $E\left[Y(0)|D=0\right]$, as OLS estimation does, can result in a biased ATT:

$$\begin{aligned} &E\left[Y(1)|D=1\right] - E\left[Y(0)|D=0\right] = \\ &\tau_{ATT} + E\left[Y(0)|D=1\right] - E\left[Y(0)|D=0\right]. \end{aligned} \tag{3.9}$$

The estimate of τ_{ATT} is unbiased only if

$$E\left[Y(0)|D=1\right] - E\left[Y(0)|D=0\right] = 0.$$

If the treated and untreated groups are dissimilar and have different average outcomes even in the absence of treatment, the estimate of τ_{ATT} is biased due to self-selection into treatment.

Since the ideal experiment is usually infeasible, matching treated and untreated observations can help overcome the self-selection bias. Matching mimics the counterfactual, $E\left[Y(0)|D=1\right]$ by finding a suitable control group of untreated individuals that is (almost) identical to the treated group in terms of its characteristics, $\mathbf{X}$. If individuals are identical except that some receive treatment and others do not, then treatment can be considered as randomly assigned and the outcome of an individual is independent of its treatment status given observable characteristics $\mathbf{X}$. This is stated in the conditional

independence or unconfoundedness assumption:

$$Y(0), Y(1) \perp\!\!\!\perp D|\mathbf{X}, \forall \mathbf{X}. \tag{3.10}$$

However, finding treated and untreated individuals with exactly the same values for all characteristics in $\mathbf{X}$ can become infeasible if $\mathbf{X}$ is highly dimensional. According to Rosenbaum and Rubin (1983), it is sufficient to compare untreated and treated individuals that have the same propensity to receive treatment based on their covariate characteristics. The propensity to receive treatment conditional on covariates is called the propensity score, $P(D = 1|\mathbf{X}) = P(\mathbf{X})$ and unconfoundedness given the propensity score is sufficient:

$$Y(D = 0), Y(D = 1) \perp\!\!\!\perp D|P(\mathbf{X}), \forall \mathbf{X}. \tag{3.11}$$

Furthermore, overlap between the treated and untreated control group has to be imposed. The common support assumption ensures that enough treated and untreated individuals of the same characteristics $\mathbf{X}$ exist that have the same propensity to receive the treatment:

$$0 < P(D = 1|\mathbf{X}) < 1. \tag{3.12}$$

If (3.11) and (3.12) hold, the treatment effect on the outcome for the treated can consistently be estimated by comparing the outcomes for the treatment group and its matched control group:

$$\tau_{ATT}^{PSM} = E_{P(\mathbf{X})|D=1} \left\{ E\left[Y(1)|D = 1, P(\mathbf{X})\right] - E\left[Y(0)|D = 0, P(\mathbf{X})\right] \right\}. \tag{3.13}$$

The quality of the matching estimates critically hinges on the assumption in (3.11) that selection into treatment is based on observables. The assumption is violated if heterogeneity due to unobserved factors remains. Stuart (2010), however, notes that matching not only controls for heterogeneity in observables but also in unobservables that are related to the observable characteristics. Therefore, the only bias that remains comes from unobservables that are unrelated to observable characteristics and this bias is generally considered to be rather small (Baier and Bergstrand, 2009). Thus, we are confident that our estimation strategy is a valid alternative in this setting and delivers a causal estimate.

3.4.3 Application of the Matching Estimator Approach

3.4.3.1 Hypothesis 1 - The Effect of Cash-in-Advance Financing on Export Participation in the Crisis

To test our first hypothesis, we estimate the ATT of CIA financing on the export probability in each year. We then compare the magnitude of the effects in both years to determine whether CIA has a stronger impact on the export probability in 2009. The ATT is given by

$$\begin{aligned}\tau_{ATT,t} = E_{P(\mathbf{X_t})|DCIA_t=1} \{ & E\left[Exp_t(1)|DCIA_t = 1, P(\mathbf{X_t})\right] \\ & - E\left[Exp_t(0)|DCIA_t = 0, P(\mathbf{X_t})\right]\}, \end{aligned} \tag{3.14}$$

where $t \in \{2005, 2009\}$ and Exp_t is the export status of firm i in year t. The treatment is $DCIA_t$, a dummy equal to 1 if the firm receives a positive amount of its sales in year t in advance and 0 otherwise. Treated and untreated firms are matched according to their propensity to receive CIA conditional on observable, contemporaneous firm covariates $\mathbf{X_t}$.

In a first step, we estimate the propensity of a firm to receive CIA in each year via the following probit model:

$$\begin{aligned}Pr\{DCIA_{it} = 1\} = & \Phi\{h(LogSize_{it}, LogAge_{it}, Ownerconc_{it}, \\ & Foreign_{it}, Iso_{it}, Transobs_{it}, Weak_{it}, \lambda_s, \mu_c)\}. \end{aligned} \tag{3.15}$$

We include a variety of covariates that influence whether a firm receives CIA and whether it exports. A list of all variables employed in our empirical analysis can be found in Table C.4 in Appendix C. To control for size and reputation effects, we use $LogSize$, the log number of employees, and $LogAge$, the log number of years since the firm began operations. Larger and older firms are more likely to export (Minetti and Zhu, 2011) but the effect on receiving CIA is ambiguous. On the one hand, larger and older firms are more likely to receive CIA because they have built up a higher reputation and have a

higher bargaining power. On the other hand, smaller and younger firms are in more need of CIA since they more likely lack access to other forms of financing.

We also include two variables that capture ownership effects. *Ownerconc* denotes the share owned by the largest owner of the firm. Cole (2010) finds that a firm is less likely to use trade credit financing if its largest owner exerts more control over the firm. The reason is that a larger owner bears the costs of trade credit financing on a larger part of the ownership. If the ownership share falls, the costs of trade credit financing are split more evenly across owners and thus trade credit financing becomes more attractive. In addition, we control for foreign ownership which is expected to positively impact on a firm's export probability (Greenaway, Guariglia, and Kneller, 2007). $Foreign$ is a dummy equal to 1 if more than 50% of the firm is owned by a foreign private individual, company or organization.

Iso indicates whether a firm possesses an internationally recognized quality certificate. Firms that signal higher quality are expected to export more and also to receive CIA more easily from their customers. $Transobs$ is a dummy equal to 1 if the firm faces moderate, major or very severe obstacles in transportation of its goods and it is 0 if it faces no or minor obstacles. Difficulties experienced in transportation are suspected to impede exporting, but to increase the probability to use CIA. According to the transaction cost theory of trade credit use by Ferris (1981), firms hedge against uncertainty in transportation via trade credit financing. If the delivery of goods is uncertain due to long distances so is the delivery of money. Standardized payments can alleviate transportation risks. $Weak$ controls for the firm's assessment of its legal environment. The dummy is equal to 1 if the firm considers its legal court system not able to enforce its decisions. The effect of $Weak$ can go in both directions. Firms that suffer from low legal enforcement should be more likely to insist on CIA financing in order to alleviate uncertainty. However, they can be less likely to receive CIA if the trading partner fears not to be able to enforce the delivery of the good (Antràs and Foley, 2011).

In an alternative specification, we control for log labor productivity of a firm instead of the log number of employees as a robustness check. *LogLabprod* is defined as total sales converted in USD over the number of employees. Due to construction, firm size and

labor productivity are highly multicollinear and do not carry independent information. Note also that we lose observations when including *LogLabprod* since data on sales are not available for all firms in both years. λ_s and μ_c denote a set of sector and country dummies to control for sector and country specific shocks in each year.

We use the predicted probability to receive CIA, $\hat{p}_i$, from (3.15) to find matched pairs of firms with and without CIA financing.[9] We employ three different matching algorithms: nearest neighbor matching with four neighbors and replacement, radius matching with a caliper of 0.01, and kernel density matching.[10] Four nearest neighbor (4 NN) matching compares the outcome of each treated observation to the unweighted average outcome of the four closest observations in terms of propensity score. Radius matching allows limiting the maximum difference in propensity scores for treated and untreated matches so that matched controls are not too far away from the treated observations. We choose a rather conservative caliper of 0.01, which means that the propensity to receive CIA for untreated controls is allowed to differ by 1 percentage point from the respective propensity of the treated firm. With kernel density matching, untreated control observations are weighted according to their propensity difference such that controls further away receive lower weights. This leads to more precise estimates but the average matching quality can be lower since also more dissimilar controls are used. For this reason, we again choose a rather conservative bound of 0.01 as maximum distance.

The calculation of ATTs adds variance from including the estimated rather than the true propensity score. This can lead to biased standard errors. Rubin and Thomas (1996) and Rubin and Stuart (2006) find that not accounting for the additional variation usually results in larger standard errors and wider confidence intervals than when using the true

[9] A different method to find a suitable control group is covariate distance matching as suggested by Abadie, Drukker, Leber Herr, and Imbens (2004). Covariate matching finds controls by minimizing the distance in terms of covariate characteristics between treated and untreated observations. If the number of covariates is high, distance matching, as for example Mahalanobis matching, is infeasible and can even lead to an increase in bias (Stuart, 2010). Since we include a large number of country and industry dummies, we do not apply this technique.

[10] We also tried nearest neighbor matching with one neighbor. This matching method is considered to ensure a high matching quality since every treated individual is compared to its most similar neighbor (the observation with the most similar propensity to receive treatment). This comes at the cost of reduced efficiency, though, since a large number of (untreated) observations is not taken into account when estimating the ATT (Stuart, 2010). For our specifications, this method did not achieve sufficient reduction in bias, thus we do not provide the corresponding results.

score. Therefore, unadjusted standard errors can be considered conservative estimates of the true standard errors in the case of nearest neighbor matching. For radius and kernel matching, we calculate bootstrapped robust standard errors since bootstrapping is valid for asymptotically linear estimators (Abadie and Imbens, 2008).

3.4.3.2 Hypothesis 2 - The Effect of Cash-in-Advance Financing on the Intensity of Exporting in the Crisis

According to Hypothesis 2, we expect firms that receive CIA financing in the crisis period to suffer from a smaller drop in export volumes. We test our hypothesis by applying a difference-in-difference matching approach. Difference-in-difference matching allows estimating the effect of a change in CIA financing on the change in the export performance of firms. The ATT is given by:

$$\tau_{ATT}^{DiffPSM} = E_{P(\mathbf{X_{2005}})|SwitchCIA=1}\{E\left[\Delta ExpS(1)|SwitchCIA=1, P(\mathbf{X_{2005}})\right] - E\left[\Delta ExpS(0)|SwitchCIA=0, P(\mathbf{X_{2005}})\right]\}. \quad (3.16)$$

Our treatment $SwitchCIA$ is a dummy equal to 1 if a firm does not receive CIA in 2005 but receives CIA in 2009. It is equal to 0 for firms that do not receive CIA in either year. We thus only consider firms that do not rely on CIA financing during stable monetary times. Firms that either receive CIA in both years or that receive CIA financing in 2005 but not in 2009 are discarded. In doing so, we can test whether those firms that receive redistributional CIA financing in 2009 can soften the negative crisis impact on their export intensity compared to firms that do not switch to CIA.

The outcome is the change in export shares $\Delta ExpS = ExpS_{2009} - ExpS_{2005}$. We use the export share reported by firms (in percent) rather than the exported volume because this frees us from adjusting for inflation and currency differences across the 27 different countries. Moreover, scaling removes common shocks that affect domestic and international sales to the same extent, as for example a drop in demand or cost increases. By taking the first difference of the outcome variable, we get rid of unobserved factors that are

assumed to be constant over time, such as motivation of the manager to acquire outside funding.[11]

The propensity to switch to CIA financing is estimated using the firm-level covariates from above but taken at their pretreatment value in 2005 (Heinrich, Maffioli, and Vázquez, 2010). Matching is performed via the same matching algorithms as outlined above and standard errors are adjusted via bootstrapping in the case of radius and kernel matching.

3.5 Empirical Results

3.5.1 Hypothesis 1

3.5.1.1 Selection into Cash-in-Advance Financing and Matching

We first discuss the results from estimating selection into CIA financing by firms in each year. The first two columns of Table 3.3 summarize the results for our main specification with *LogSize* in 2005 and 2009, respectively (Probit 1). In the third and fourth column, we control for *LogLabprod* instead of *LogSize* (Probit 2). We provide the average marginal effects since the raw coefficients are not straightforward to interpret. We find a strong and positive influence of size and labor productivity on the propensity to receive CIA in both years. For example, a 1% increase in size (labor productivity) raises the probability of a firm to receive CIA by 3% (5%) in 2005. A positive effect of size on prepayments is also observed by Mateut (2012) for a sample of French firms. Controlling for labor productivity yields a better model fit in terms of the Log Likelihood statistic but the number of observations drops due to missing sales values. Consistent with Cole (2010), *Ownerconc* has a negative influence. Foreign owned firms have an 8% to 11% higher probability to receive CIA than domestic firms, but the effect only holds in 2009. This finding may reflect that foreign owned firms have better access to CIA financing from their foreign parent company when bank lending becomes scarce. In 2005, possessing a

[11] Cross-sectional matching makes the stronger assumption that all differences between the treatment and control group are captured by observable covariates. Difference-in-difference matching, instead, explicitly allows for time invariant differences to exist between treated and untreated units.

Table 3.3: Hypothesis 1: Average Marginal Effects for Selection into CIA Financing in 2005 and 2009

	Probit 1		Probit 2	
	$DCIA_{2005}$	$DCIA_{2009}$	$DCIA_{2005}$	$DCIA_{2009}$
	(1)	(2)	(3)	(4)
LogSize	0.0304***	0.0486***		
	(0.00934)	(0.00967)		
LogLabprod			0.0735***	0.0420***
			(0.0189)	(0.0106)
LogAge	-0.00439	-0.0206	0.0264	0.0122
	(0.0192)	(0.0244)	(0.0196)	(0.0254)
Ownerconc	-0.000802**	-0.000170	-0.000907**	-3.44e-05
	(0.000408)	(0.000488)	(0.000447)	(0.000515)
Foreign	0.0130	0.0813*	0.0307	0.110**
	(0.0402)	(0.0473)	(0.0444)	(0.0510)
Iso	0.0878**	-0.0608*	0.0986**	0.00727
	(0.0348)	(0.0323)	(0.0385)	(0.0334)
Transobs	0.0810**	0.0570**	0.110***	0.0669**
	(0.0324)	(0.0261)	(0.0367)	(0.0277)
Weak	-0.0460*	0.0463*	-0.0650**	0.0350
	(0.0246)	(0.0250)	(0.0280)	(0.0268)
Observations	1,658	1,465	1,268	1,278
Pseudo R^2	0.132	0.133	0.149	0.134
Log Likelihood	-996.2	-866.3	-747.2	-751.4
Sector FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes

Columns 1 to 4 report average marginal effects. In columns 1 and 2, *LogSize* is used to control for the size of a firm, in columns 3 and 4, *LogLabprod* is used, instead. Robust standard errors are in parentheses. ***, **, and * denote significance at 0.01, 0.05, and 0.10 levels, respectively.

quality certification, Iso, facilitates access to CIA as conjectured. The positive average marginal effect of $Transobs$ is in line with the transaction cost theory of trade credit use postulated by Ferris (1981). Firms that face obstacles in transportation have a 6% to 11% higher propensity to receive CIA financing. Last but not least, we observe a negative correlation between contractual enforcement, $Weak$, and the probability to receive CIA in 2005 as rationalized by Antràs and Foley (2011). In 2009, however, the effect reverses and becomes weakly positive significant in one specification. The ambiguous direction of influence may reflect intensified sorting of firms into CIA financing in the crisis year. Firms that experience weak legal enforcement may require CIA more often in the crisis year to hedge against the increased level of uncertainty.

Table 3.4: Hypothesis 1: Testing for Covariate Balancing before and after 4 NN Matching in 2005 (Probit 1)

	$DCIA = 1$		$DCIA = 0$		% bias red.	t-statistic	
	Before	After	Before	After		Before	After
LogSize	3.52	3.50	2.90	3.58	87.4	8.02***	-0.97
LogAge	2.61	2.60	2.54	2.60	96.2	2.06**	0.08
Ownerconc	71.89	72.04	76.88	71.79	94.9	-3.51***	0.18
Foreign	0.119	0.117	0.087	0.120	90.8	2.10**	-0.19
Iso	0.180	0.174	0.099	0.178	95.4	4.77***	-0.21
Transobs	0.163	0.164	0.135	0.156	72.2	1.55	0.43
Weak	0.298	0.298	0.363	0.280	71.3	-2.85***	0.86

Estimates are based on comparing mean covariate characteristics of the treatment and control group before and after matching. The matching algorithm applied is nearest neighbor matching with 4 neighbors for all firms in 2005, Probit 1. Covariate balancing for sector and country dummies is achieved but not reported. ***, **, and * denote significance at 0.01, 0.05, and 0.10 levels, respectively.

Next, we calculate the predicted probabilities of firms to receive CIA for each specification in each year. We then match treated and untreated firms based on their propensity to receive CIA. To check whether propensity score matching achieves sufficient covariate balancing between treatment and control observations, we exemplarily compare the mean covariate characteristics of treated and untreated firms before and after 4 NN matching in 2005 (Table 3.4). Before matching, CIA receiving firms are significantly different from their counterparts. They tend to be larger, older, and foreign owned and their main owner exerts less control. After matching, a substantial reduction in the difference of the covariate means is achieved. In fact, none of the mean differences is significantly different from zero anymore. Matching thus eliminates a substantial amount of heterogeneity among treated and untreated firms. In order to save space, we only display two adequate test statistics in Table C.5 in Appendix C for all other matching procedures. First, the average standardised percentage bias gives the percentage difference of the average covariate means for the treated and untreated sub-samples before and after matching. A low value after matching indicates overall sufficient covariate balancing.[12] Second, a high matching quality is reflected in a high p-value from the likelihood-ratio test of joint insignificance of all covariates in explaining the propensity score. After matching,

[12]The formula of the standardised percentage bias for covariate X_l, $l = 1, .., M$, is $SB(X_l) = 100 * \left(\bar{X}_{l,D=1} - \bar{X}_{l,D=0}\right) / \left(\sqrt{\left(V_{D=1}(X_l) - V_{D=0}(X_l)\right)/2}\right)$ (see Rosenbaum and Rubin, 1985). The average standardised percentage bias is the simple mean over all covariate biases: $ASB = \frac{1}{M}\sum_{l=1}^{M} SB(X_l)$.

covariate characteristics should have no power in explaining the likelihood to receive CIA of firms. According to both test statistics, all matching algorithms perform very well in finding similar pairs of treated and untreated firms.

3.5.1.2 Effect of Cash-in-Advance Financing on Export Participation

Table 3.5 provides the estimated causal effect of CIA financing on the export probability of firms in 2005 and 2009. Consider for example Probit 1 and 4 NN matching in 2005. The estimated ATT of 0.0601 implies that in 2005 the average firm that receives CIA has a 6% higher probability to export than a firm that does not receive CIA. Radius and kernel matching yield similar treatment effects of 6.5% and 6.0%, respectively. The Probit 2 specification reports effects around 7% for radius and kernel matching and an insignificant estimate for 4 NN matching. In 2009, the effect of CIA financing on the export participation of firms is highly significant in all specifications. The average CIA receiving firm has a 7.6% to 8.9% higher probability to export than a comparable firm without CIA. For 4 NN matching, the ATT in 2009 is higher by more than 2 percentage points than the corresponding effect in 2005. This corresponds to a 35% increase in the magnitude of the effect. The differential impact between both years is slightly smaller for radius and kernel matching ranging from 1.1 to 1.9 percentage points. The difference is higher for the second probit specification which also provides a better fit for the model of selection into CIA financing. Overall, the matching results lend support to our first hypothesis. CIA has a positive impact on the export participation of firms and the effect is particularly strong in the crisis period.

As a comparison, we provide the corresponding estimates when selection into CIA financing by firms is not taken into account (Table 3.6). We run a weighted least squares regression of export status on the treatment and all other covariates in each year where we use the estimated propensity scores from 4 NN matching as inverse weights (see Hirano, Imbens, and Ridder, 2003). Treated observations receive a weight of 1 and control observations receive a weight of $\frac{\hat{p}_i}{1-\hat{p}_i}$. That allows us to directly compare the results from the linear model to matching because we use the same set of firms as in the matching approach and weight the observations accordingly. The main difference is that we do

Table 3.5: Hypothesis 1: ATT of $DCIA$ on Export Participation in 2005 and 2009

Matching Estimator	Outcome	Treatment	Year	Probit 1		Probit 2	
4 NN	*Exp*	*DCIA*	2005	0.0601**	(0.0279)	0.0555	(0.0345)
			2009	0.0813***	(0.0293)	0.0856***	(0.0309)
Radius (caliper 0.01)			2005	0.0647**	(0.0280)	0.0686**	(0.0326)
			2009	0.0757***	(0.0265)	0.0876***	(0.0305)
Epan. kernel			2005	0.0597**	(0.0281)	0.0696**	(0.0294)
(bandwidth 0.01)			2009	0.0755***	(0.0264)	0.0885***	(0.0294)
All observations			2005	1,651		1,259	
Treated observations				861		644	
All observations			2009	1,448		1,269	
Treated observations				827		739	

Estimation is done for the common support region only to ensure sufficient overlap between treated and untreated individuals. Standard errors are in parentheses. Bootstrapped robust standard errors are calculated for radius and kernel matching. ***, **, and * denote significance at 0.01, 0.05, and 0.10 levels, respectively.

not control for selection into CIA financing and we impose a linear functional form in the regression model. Generally, the estimated effect of CIA on export participation is larger in 2005 and smaller in 2009 than the corresponding matching results. The average CIA treatment effect on exporting via weighted least squares is 6.7% in 2005 and 5.2% in 2009 for the Probit 1 specification whereas 4 NN matching yields 6.0% and 8.1%. Thus, weighted least squares regression overestimates the true effect in the pre-crisis year and underestimates the true effect in the crisis year by more than 2 percentage points. The upward bias in 2005 can be attributed to non-random selection of stronger, high-performing firms that are more able to enforce CIA payment from their customers. These firms are also more likely to export, thus the impact of CIA is overstated. In contrast, during a financial crisis, customers redistribute their funds to their most dependent and financially constrained suppliers that are less likely to export. That exerts a downward pressure on the effect of $DCIA$ in 2009.

3.5.1.3 Sensitivity Analysis

The results for Hypothesis 1 critically hinge on the assumption that we can eliminate all bias between the treated and untreated observations given our observed covariates. We therefore test whether our results are robust to the inclusion of additional variables that control for the transparency of the firm and its growth opportunities. We include

Table 3.6: Hypothesis 1: Effect of $DCIA$ on Export Participation in 2005 and 2009, Weighted Least Squares

	Exp_{2005}	Exp_{2009}	Exp_{2005}	Exp_{2009}
	(1)	(2)	(3)	(4)
DCIA	0.0668***	0.0517**	0.0752***	0.0648**
	(0.0223)	(0.0257)	(0.0256)	(0.0283)
LogSize	0.0636***	0.0520***		
	(0.00962)	(0.00930)		
LogLabprod			0.0551***	0.0239**
			(0.0199)	(0.0111)
LogAge	-0.0113	-0.00598	0.0330*	0.00344
	(0.0193)	(0.0237)	(0.0197)	(0.0252)
Ownerconc	-0.000607	-8.51e-05	-0.00107**	-0.000579
	(0.000383)	(0.000516)	(0.000429)	(0.000583)
Foreign	0.193***	0.0756	0.294***	0.0805
	(0.0417)	(0.0499)	(0.0459)	(0.0563)
Iso	0.0721*	0.0774**	0.108***	0.138***
	(0.0374)	(0.0328)	(0.0398)	(0.0353)
Transobs	0.0128	0.0503*	0.0267	0.0432
	(0.0321)	(0.0271)	(0.0364)	(0.0297)
Weak	0.00105	0.0363	-0.0113	0.0222
	(0.0242)	(0.0258)	(0.0288)	(0.0293)
Observations	1,651	1,448	1,259	1,269
R^2	0.319	0.314	0.328	0.291
Sector FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes

The table reports the results from a propensity score weighted least squares regression of export status on CIA received and various covariates in 2005 and 2009. The weights come from 4 NN matching. Heteroskedastic robust standard errors are given in parentheses. ***, **, and * denote significance at 0.01, 0.05, and 0.10 levels, respectively.

a dummy equal to 1 if the firm has its annual financial statements checked and certified by an external auditor. An external validation of the firm's financial situation signals trustworthiness to customers which should positively impact on the firm's likelihood to obtain CIA. Furthermore, we control for the increase in the number of employees over the last three years. Firms with higher growth opportunities may require additional CIA to finance their transactions and they may also seem more attractive to customers. Panel A of Table C.6 in Appendix C provides the results for this exercise. Covariate balancing is achieved in all specifications but not reported. We find that our results are largely robust in terms of significance and magnitude. Including further controls even raises the

magnitude of the effect of CIA financing on the export participation of firms in 2009 and reduces its effect in 2005.

Since CIA financing should be particularly beneficial to firms that experience difficulties in access to bank financing, we control for the degree of financial constraints in the following robustness check. *Fincons* is a dummy equal to 1 if the firm reports that access to finance is a major or very severe obstacle to the operations of the firm. It is equal to 0 for firms that tick no obstacle, a minor obstacle or a moderate obstacle.[13] However, reverse causality may run from the export decision of a firm to the degree of financial constraints that it experiences (Minetti and Zhu, 2011). To mitigate this concern, we use the lagged value of *Fincons* from 2005 and only report the results for the year 2009. Panel B of Table C.6 in Appendix C confirms that our results are robust to controlling for the financial constraints as experienced by the firm.

3.5.2 Hypothesis 2

3.5.2.1 Effect of Switching to Cash-in-Advance Financing on the Change in Export Shares

We first discuss the results for selection into CIA financing in 2009 as reported in Table 3.7. The most important determinant for switching to CIA financing in 2009 is the size of a firm and its labor productivity (columns 1 and 2, respectively). Firms with a 1% higher number of employees in 2005 have a 4% higher probability to switch to CIA financing in 2009. A 1% higher level of labor productivity in 2005 increases the switching probability by 7%. In addition, foreign owned firms have a higher probability to switch to CIA financing (column 2). Matching leads to a sufficient bias reduction in average covariate means for all matching algorithms and across both specifications (see Table C.7 in Appendix C). After matching, treated and untreated controls do no longer differ in observable characteristics.

[13] Access to finance refers to the availability and cost, interest rates, fees, and collateral requirements that the firm faces.

Table 3.7: Hypothesis 2: Average Marginal Effects for Switching to CIA Financing in 2009

	Probit 1	Probit 2
	$SwitchCIA$	$SwitchCIA$
	(1)	(2)
LogSize05	0.0396***	
	(0.0139)	
LogLabprod05		0.0665**
		(0.0293)
LogAge05	-0.00932	0.0470
	(0.0357)	(0.0364)
Ownerconc05	-0.000563	-0.000930
	(0.000615)	(0.000687)
Foreign05	0.0949	0.150**
	(0.0633)	(0.0710)
Iso05	-0.0113	-0.0438
	(0.0604)	(0.0693)
Transobs05	-0.0680	-0.0647
	(0.0508)	(0.0599)
Weak05	0.0101	-0.00937
	(0.0367)	(0.0421)
Observations	755	589
Pseudo R^2	0.134	0.133
Log Likelihood	-450.8	-352.2
Sector FE	Yes	Yes
Country FE	Yes	Yes

Robust standard errors are in parentheses. ***, **, and * denote significance at 0.01, 0.05, and 0.10 levels, respectively.

Table 3.8 provides the ATT from $SwitchCIA$. Firms that switch to CIA have a 5 to 7 percentage points higher export share than firms that do not receive CIA in 2009. The results from applying the second probit specification are less precise, probably due to a drop in observations. To better understand the meaning of the treatment effect, we provide an example for the case of 4 NN matching. The average treatment effect of 7% (Probit 1) implies that firms that switch to CIA financing in 2009 face a loss in average export shares that is lower by 7 percentage points than the loss of firms that do not receive CIA in either year. The average drop in export shares is 1.2 percentage points for the treated group whereas control firms experience a loss in export shares of 8.2 percentage points. In Table 3.9, we compare the effect of $SwitchCIA$ obtained via matching to its counterpart from a weighted least squares estimation where the weights

Table 3.8: Hypothesis 2: ATT of $SwitchCIA$ in 2009 on the Change in Export Share

Matching estimator	Outcome	Treatment	Probit 1	Probit2
4 NN	$\Delta ExpS$	$SwitchCIA$	6.9598***	4.6766**
			(2.0496)	(2.3759)
Radius (caliper 0.01)			5.2226**	1.7221
			(2.5226)	(2.6777)
Epan. kernel			5.7071**	2.1207
(bandwidth 0.01)			(2.5232)	(2.7171)
All observations			744	577
Treated observations			336	259

Estimation is done for the common support region only to ensure sufficient overlap between treated and untreated individuals. Standard errors are in parentheses. Bootstrapped robust standard errors are calculated for kernel and radius matching. ***, **, and * denote significance at 0.01, 0.05, and 0.10 levels, respectively.

come from 4 NN matching. The estimated effect for $SwitchCIA$ from the weighted least squares regression in the first column is lower by more than 3 percentage points and only marginally significant. Consequently, not controlling for selection into CIA financing in 2009 leads to a downward bias of the true effect on the change in exports shares. This finding is in line with the downward bias in the effect of CIA on export participation in 2009 as observed above and can be explained via the redistribution hypothesis by Meltzer (1960). During a financial squeeze, predominantly weaker, less resilient firms tend to sort into CIA financing which might also be more likely to experience a stronger drop in export shares. All in all, our results strongly support our second hypothesis: the adverse effects of a credit crunch on firms' export share can be softened if there are still some deep pocket firms that redistribute their financial funds to their trading partners via CIA.

3.5.2.2 Sensitivity Analysis

In our main specification, we only consider firms that do not receive CIA in the first year. In doing so, we neglect firms that already receive CIA in 2005. As a robustness check, we re-estimate the effect of a change in CIA financing on the change in export shares considering all firms. We define the treatment $IncrCIA$, which is equal to 1 if a firm receives at least the same or a higher share of its sales in advance in 2009 than in 2005.

Table 3.9: Hypothesis 2: Effect of $SwitchCIA$ on the Change in Export Share, Weighted Least Squares

	$\Delta ExpS$	$\Delta ExpS$
	(1)	(2)
SwitchCIA	3.597*	3.951*
	(2.016)	(2.312)
LogSize_{05}	-1.801**	
	(0.899)	
LogLabprod_{05}		-2.550
		(2.774)
LogAge_{05}	4.646**	3.344
	(2.117)	(2.164)
Ownerconc_{05}	0.0303	0.0550
	(0.0314)	(0.0361)
Foreign_{05}	-13.54*	-25.43***
	(6.962)	(6.943)
Iso_{05}	1.745	0.788
	(3.088)	(3.037)
Transobs_{05}	-0.766	2.825
	(2.747)	(3.494)
Weak_{05}	1.187	1.217
	(1.962)	(2.435)
Observations	744	577
R^2	0.180	0.325
Sector FE	Yes	Yes
Country FE	Yes	Yes

The table reports the results from a propensity score weighted least squares regression of change in export shares on $SwitchCIA$ in 2009 and various pre-treatment covariates. The weights come from 4 NN matching. Heteroskedastic robust standard errors are given in parentheses. ***, **, and * denote significance at 0.01, 0.05, and 0.10 levels, respectively.

It is defined to be 0 for firms that experience a decrease in their share of CIA received over the same period. Firms with constant or increased CIA financing should face a lower decline in export shares than firms that experience a decline in CIA in the crisis year. We estimate the effect for the full sample of firms and for exporting firms only.

The results are given in Table C.8 in Appendix C. Covariate balancing is achieved for all covariates but results are not reported. The ATT of $IncrCIA$ is positive and significant in all but two specifications. Generally, firms that receive at least as much or more CIA financing in 2009 than in 2005 experience a 3 percentage points smaller decline in export

shares than firms that face a decrease in CIA financing (columns 1 and 2). If we consider exporters only, the effect more than doubles since we discard all never-exporters that face a zero change in their export share regardless of the change in CIA. Exporters that receive the same or a higher share of their sales in advance can soften the drop in export shares by about 6% compared to exporters that face a decrease (Probit 1). The results obtained in the last column seem to be less reliable since the number of observations drops. All in all, the effect of an increase in CIA financing also holds when we consider the full sample of firms or exporters only.

A further concern is that difference-in-difference matching assumes common time trends in covariates across the treated and untreated observations (Felbermayr, Heiland, and Yalcin, 2012). If time trends differ across both groups, then these differences can drive the change in the outcome variable and lead to a biased effect of the treatment. For example, if firms that switch to CIA financing in 2009 experience a higher productivity growth than firms that do not switch to CIA, these firms may also face a smaller decline in export shares. To mitigate this concern, we apply the regression-adjusted matching estimator as suggested by Heckman, Ichimura, and Todd (1997). We run a weighted least squares regression of $\Delta ExpS$ on the treatment $SwitchCIA$ and the covariates in first differences. The weights are obtained from the precedent matching process as described above. Robustness of our results with regard to different time trends is given if we still find a significant effect of our treatment on the outcome when controlling for different time trends. Table C.9 in Appendix C provides the corresponding treatment effects. The estimated treatment effects are significant although the magnitude of the coefficient is slightly different. All in all, the positive effect of $SwitchCIA$ is not driven by differences in time trends and provides strong evidence that CIA financing can alleviate the negative crisis impact on the intensive margin of exporting.

3.6 Conclusion

This chapter provides insights into how CIA financing shapes the international activities of firms from 27 European and Central Asian countries during the recent financial crisis.

In contrast to the prevailing assumption that trade credit financing dropped during the 2008-2009 crisis, we document a rise in prepayment financing for our sample of firms. We find strong support that CIA financing fosters export participation during the crisis and that redistributional CIA financing can alleviate the negative crisis impact on the export share of firms. One particular advantage of interfirm financing is that firms are often better able to judge their trading partners in terms of credit worthiness than banks since they have gained better insights during their business relationship. Consequently, if banks are more reluctant to extend credit in times of crisis, liquid firms can step in and provide sufficient financing to their trading partners.

Chapter 4

Product Sophistication and Spillovers from FDI*

4.1 Introduction

Politicians give high priority to attracting foreign direct investment (FDI) to developing countries. In India for example, foreign investors are exempted from customs duty and enjoy tax holidays up to 100% (UNCTAD, 2000). One reason for the grant of generous concessions is that FDI is considered to have a positive impact on economic growth in developing countries. FDI does not only inject fresh capital into an economy but it is often accompanied by an inflow of human capital, knowledge, and technology that spills over to host country firms. One particular channel through which spillovers from FDI foster growth in developing countries is the facilitation of manufacturing highly sophisticated products (Woo, 2012). As has been recently shown by Hausmann, Hwang, and Rodrik (2007), shifting the production from less to more sophisticated goods spurs technological change and thus leads to faster growth in developing countries.

Although a large body of literature addresses the importance of attracting FDI, little is known on how the presence of multinational enterprises (MNEs) is related to firms' manufacturing of highly sophisticated products. This chapter is the first to empirically

*This chapter is based on joint work with Stephan Huber.

investigate the channels through which spillovers from FDI influence the manufacturing of highly sophisticated products by firms. We argue that contact between MNEs and local firms sets free knowledge spillovers that help local firms manufacture technologically challenging products. In our analysis, we consider spillovers through horizontal and vertical linkages with multinational firms. For a sample of Indian manufacturing firms, we provide evidence that the presence of multinational downstream firms increases the probability of local Indian firms to manufacture a highly sophisticated product via vertical backward linkages. In contrast, a higher presence of multinational upstream firms decreases the manufacturing of highly sophisticated products via vertical forward linkages.

For our empirical analysis, we compile an unbalanced panel of 6,530 Indian manufacturing firms from 2001 to 2010. The data are taken from the Prowess database, which collects annual information on the financial performance of publicly listed and unlisted Indian firms. We use information on foreign ownership participation to calculate measures of horizontal and vertical FDI spillovers at the industry level. Following Javorcik (2004), spillovers are proxied by the intensity of contact between local firms and MNEs within and across industries. Horizontal spillovers are captured by the extent of multinational presence in each industry. Vertical backward spillovers refer to the intensity of contact between downstream multinational customers and local suppliers. Vertical forward spillovers are proxied by the intensity of contact between upstream multinational suppliers and local downstream firms. Data on the intensity of contact between upstream and downstream industries are taken from the OECD input-output tables for India.

In addition to foreign ownership, Prowess reports detailed information on the products manufactured by the Indian firms. This allows us to identify firms that produce highly sophisticated products. To determine the sophistication level of products, we employ the product-specific sophistication index by Hausmann, Hwang, and Rodrik (2007). For each product, the index measures the average technology level that a country must have in order to successfully export the product. The technology level is proxied by the average GDP per capita of all countries that export the product, weighted by their revealed comparative advantage. A product is more sophisticated if on average richer countries

have a revealed comparative advantage in the product. Data on the GDP per capita of countries are taken from the World Development Indicator database. Disaggregated country-product-level export data come from the international trade database BACI. As highly sophisticated products (HSPs), we term those products that belong to the top quartile of the sophistication distribution.

A first glance at the data reveals that about 40% percent of all firms produce at least one product that has a top quartile sophistication level. Comparing firms that manufacture HSPs to firms that produce goods from the lower end of the sophistication distribution, we observe that the former are significantly larger, older, and more productive than the latter. Moreover, we find that output generated from selling HSPs is rather low and only accounts for about 23% of total sample output. The low prevalence of HSPs in India distinctly reflects the higher difficulties associated with manufacturing more technically complex products in a developing country.

We use a pooled probit model to investigate the impact of horizontal and vertical FDI spillovers on a firm's probability to manufacture a HSP. We observe strong evidence of positive FDI spillovers through backward linkages. An increase in backward spillovers by 10 percentage points raises the probability of a firm to manufacture a HSP by 5%. In contrast, we do not find robust evidence of positive horizontal spillovers. These findings point to the fact that MNEs try to prevent technology leakage to competitors within the same industry. Instead, they have an incentive to transfer their knowledge to local suppliers in order to get access to more sophisticated inputs. The presence of multinational upstream firms induces a strong negative effect on a firm's probability to manufacture a HSP. An increase by 10 percentage points in forward linkages reduces a firm's probability to manufacture a HSP by 10%. One explanation for this finding is that Indian firms do not benefit from access to more sophisticated foreign inputs because the technology gap between these inputs and their final output good is too large. If MNEs' intermediate inputs are too sophisticated to be incorporated into the production process of local firms, Indian firms are driven out of the production of more sophisticated final goods. The negative effect of forward linkages is less strong for more productive Indian firms, though. This indicates that more productive firms are better able to use inputs from

MNE's since the technology gap is smaller for them. Overall, we find the spillover effects to be particularly strong for domestic firms without foreign ownership participation.

The contribution of this chapter is twofold. First, we are among the first to provide evidence on firms' manufacturing HSPs in a developing economy. Using a product-specific sophistication index, we can identify and portray those firms that manufacture HSPs. Our findings clearly reflect that HSPs are associated with higher technological requirements and are thus not very prevalent in India. Second, we are the first to provide direct evidence that FDI fosters HSP manufacturing in India. Due to our rich dataset, we can distinguish the effect of horizontal and vertical spillovers from FDI on a firm's probability to manufacture a HSP. Our results imply that attracting FDI in downstream industries is desirable whereas the presence of multinational firms in upstream industries can impede the manufacturing of HSPs by Indian firms.

This chapter builds on two different strands of literature. First, it builds on the literature on product sophistication and economic development. According to Stokey (1988) and Young (1991), the production of sophisticated goods sets free knowledge and learning-by-doing spillovers which spur growth. The spillovers are the stronger the more sophisticated the goods are which implies that enduring growth requires the introduction of increasingly sophisticated products. Hausmann, Hwang, and Rodrik (2007) develop a theoretical model in which the production of highly sophisticated products shifts out the technological frontier of a country and thus spurs growth. They also provide cross-country evidence on the positive impact of export sophistication on growth in developing countries. Jarreau and Poncet (2012) observe the same relationship between the sophistication level of exports by Chinese provinces and their growth rate. Our study complements the literature by providing micro-level evidence on HSP manufacturing. We are aware of only one study by Hunt and Tybout (1998) that portrays the manufacturing of highly sophisticated products by Colombian and Moroccan plants. Hunt and Tybout (1998) also observe a positive correlation between product sophistication and firm total factor productivity, for example. However, they use the number of technicians employed by a plant to identify firms that manufacture HSPs. We, instead, directly infer the sophisti-

cation level of a product. Our measure of product sophistication thus reflects differences in technological requirements of products and is unrelated to firm characteristics.

Second, we relate to the literature on spillovers from FDI. A large part of the literature focuses on the impact of FDI on firm-level productivity. Rodriguez-Clare (1996) and Markusen and Venables (1999) provide a theoretical foundation for positive FDI spillovers on firm-level productivity through backward linkages. Empirical evidence on productivity gains through contact to multinational firms remains ambiguous and critically hinges on the data available (see Görg and Strobl, 2001 for a meta-analysis on the subject). Studies that only consider horizontal spillovers from FDI often find negative or insignificant effects on the productivity of domestic firms (see for example Aitken and Harrison, 1999 for evidence on Venezuelan firms and Konings, 2001 for evidence on Romania, Bulgaria, and Poland). Blalock and Gertler (2008), Schoors and Van Der Tol (2002), and Javorcik (2004) differentiate between horizontal and vertical FDI spillovers and provide evidence of positive spillovers via backward linkages in Indonesia, Hungary, and Lithuania, respectively. The only study that addresses the effect of FDI on product sophistication does so at the product-country level. For a sample of 105 countries, Harding and Javorcik (2011) find that the unit values of export products increase if these products belong to sectors targeted by FDI promotion. However, they fail to find the same effect if product sophistication is measured via the Hausmann, Hwang, and Rodrik (2007) index. Our analysis extends the existing literature by providing evidence of FDI spillovers on the product sophistication of Indian firms. Differentiating between horizontal and vertical FDI spillovers, we find strong evidence of positive spillovers via backward linkages and a negative effect through forward linkages.

The remainder of this chapter is organized as follows. Section 4.2 provides an overview on how spillovers from FDI influence the manufacturing of HSPs through different linkages. Section 4.3 describes the datasets used in this analysis and reports summary statistics. In Section 4.4, we portray the manufacturing of HSP by Indian firms. Section 4.5 discusses our empirical strategy and presents the corresponding results. Section 4.6 concludes.

4.2 Potential Channels of FDI Spillovers and Their Effect on Product Sophistication

To guide our empirical analysis, we elaborate on the potential channels through which spillovers from FDI can influence the manufacturing of HSPs. Our discussion relies on the theoretical framework in Hausmann and Rodrik (2003) that describes the choice of an entrepreneur whether to produce a technology intensive good in a developing economy.

In the model by Hausmann and Rodrik (2003), entrepreneurs can choose whether to invest in the traditional sector or in the modern sector. The traditional sector consists of a homogeneous good whose cost of production is commonly known. The modern sector consists of differentiated goods, each of which requires the adaption of a particular technology that is already used in developed countries. The cost of producing a modern sector good is discovered only after production. Uncertainty about the production costs of a modern sector good can stem from two sources. First, the technology of the modern sector good may be unknown to the entrepreneur. Second, even if the technology is known, the entrepreneur may have to make certain adaptions in order to establish the product in her local market. For example, she may need to adjust the technology to different raw materials available in her home country or she may need to conduct additional quality controls. Thus, the entrepreneur has to engage in a costly learning process to discover whether she is able to successfully produce and market the good. If the new product is introduced successfully into the economy, it is prone to emulation from other entrepreneurs. The reason is that the original entrepreneur is not able to secure her adaption of the modern good via patents since the adjustment usually is too small to receive patent protection (Evenson and Westphal, 1995). This reduces its profitability to the entrepreneur who first introduces the product to the economy. Briefly, the returns from introducing a more sophisticated good cannot completely be internalized by entrepreneurs whereas they bear the full costs of the new investment. Consequently, due to uncertainty about the success and danger of emulation, entrepreneurs may choose too little investment in more sophisticated goods.

The presence of MNEs can impact on a firm's choice whether to produce a more sophisticated product because FDI changes the access to foreign knowledge and technologies in a developing country. As Harding and Javorcik (2011) note, MNEs may have already engaged in the cost discovery process of adapting new products. If their knowledge spills over to local firms, cost uncertainty is reduced and the production of more technologically advanced products is facilitated.

Spillovers from MNEs to local firms can evolve through three different channels. First, spillovers can flow from multinationals to local firms within the same industry. Well-cited examples for positive horizontal spillovers are learning-by-observation and worker turnover. Local firms learn how to produce a more sophisticated product by simply observing the production techniques of MNEs in the same industry. Furthermore, workers that have previously been employed by multinationals can transfer their acquired knowledge when switching to a local firm. The effect of horizontal spillovers is limited, though, since MNEs have an incentive to prevent technology leakage via patenting their technologies or via paying higher wages to limit the knowledge outflow (Blalock and Gertler, 2008). Within-industry presence of multinationals can also lead to a negative competition effect on local firms. Multinationals are usually assumed to be more skill-intensive and more productive than local firms and thus they are better able to produce more sophisticated goods. Consequently, competition might crowd out local firms from the production of HSPs. A crowding out effect also occurs if multinationals are favored in access to credit so that local firms lack the necessary funds to engage in the costly adaption process (Javorcik, 2008).

Second, vertical backward spillovers can occur between multinational downstream firms and local upstream firms via supplier linkages. Even though preventing technology leakage is preferable within the own industry, multinationals have an incentive to transfer their knowledge to local suppliers. Consider for example an Indian steel manufacturer that is selling steel bars for the use in water pumps. An MNE engaging in the construction of airplane wings requires flat rolled steel sheets, instead. Producing steel sheets is more technologically advanced since it requires the handling of special steel rolling machines. In order to source the flat steel sheets locally, the multinational company can provide

training services to suppliers on how to use the specific machines and on how to combine existing production techniques. The magnitude of the effect of backward spillovers depends on the extent to which multinationals source locally. If inputs are predominantly acquired from abroad, positive backward spillovers are limited in size (Javorcik, 2008).

Third, knowledge spillovers can flow from multinational suppliers to local customers via vertical forward linkages. Access to highly sophisticated inputs from multinationals allows local downstream firms to produce highly sophisticated outputs. Considering the example from above, flat steel sheets can only be produced if the specific rolling machines are available to Indian firms. In addition, multinational upstream firms can provide training to downstream customers on how to use the machines. The effect of positive forward spillovers depends on the availability of sophisticated inputs before the entry of multinational downstream firms. If highly sophisticated inputs are accessible via imports, forward spillovers are limited (Javorcik, 2008). Moreover, the technological gap between local and multinational firms plays a decisive role. If the technological gap is too large, local firms cannot make use of inputs provided by multinationals in their production process. This can also entail a negative effect if local inputs are crowded out by multinational inputs and local final good producers no longer have access to suitable inputs.

4.3 Data and Summary Statistics

We combine three different datasets in order to conduct our empirical analysis. Data on Indian manufacturing firms come from the Prowess database. To construct the spillover measures, we use data on the industry-wise sale and purchase relationships from the OECD input-output tables for India. Finally, we exploit disaggregated data on country level export flows from CEPII-BACI to calculate the product sophistication index.

4.3.1 Firm-Level Data - Prowess

The Prowess database is collected by the Centre for Monitoring the Indian Economy (CMIE) and provides firm-level information on listed and unlisted Indian enterprises.[1] The database performs quite well in terms of comprehensiveness. According to CMIE, the output of manufacturing firms covered in the database accounts for about 80% of total Indian manufacturing output. Identity indicators comprise *inter alia* the incorporation year, the ownership type, the share of equity held by foreign investors, and the place of business. The industry classification is based on ISIC Rev. 4 up to the 4-digit level. Data on financial statements include total sales, exports, the wage bill, total assets, and raw material expenditures. One drawback is that information on the number of employees per firm is available for very few firms only. Most important to our analysis is that Prowess provides information on the products manufactured by Indian firms. Due to the 1956 Companies Act, Indian firms have to make information available on the sales, capacities, and production quantities of their products.

We compile a firm-level panel data set of 6,530 manufacturing firms for the period 2001 to 2010. We choose 2001 as a start year since data on the equity capital held by foreign investors is available only from 2001 onwards. The panel is unbalanced and the number of firms observed in each year ranges between 3,900 and 5,000. The total number of firm-year observations amounts to 45,297. On average, a firm is present in the dataset for 7 out of 10 years. Table 4.1 provides average firm characteristics for the entire sample period. Data on income and expenditures are in million Rupees. Following Goldberg, Khandelwal, Pavcnik, and Topalova (2010), we deflate all monetary variables by either the Indian industry specific wholesale price index (sales and exports) or the Indian overall wholesale price index (all other). The average firm age is 25 in our sample and firms produce on average 2 products.

[1] Prowess has already been used in various research projects. See for example Goldberg, Khandelwal, Pavcnik, and Topalova (2009) for evidence on how trade liberalization affects the import of new inputs by Indian firms or Franco and Sasidharan (2010) for evidence of FDI spillovers on the export participation of Indian firms.

Table 4.1: Summary Statistics, 2001 - 2010

Variable	Mean	Std. Dev.	Observations
Age	24.82	17.91	45,234
Number of products	2.22	1.88	45,297
Sales	21.39	240.91	40,364
Wage bill	0.64	3.88	40,545
Total assets	16.80	143.96	41,688
Raw material expend.	8.92	93.49	38,809
LogTFP	0.0047	0.52	38,200
Exports	6.11	67.96	18,818
Privately Indian owned (%)	90.70		41,081
Foreign owned (%)	5.88		2,662
State owned (%)	3.42		1,554
Foreign equity share (%)	6.04	16.52	16,452

Sales, the wage bill, total assets, raw material expenses, and exports are in million Rupees. Sales and the export volume are deflated by the Indian industry specific wholesale price index and all other monetary values are deflated by the Indian overall wholesale price index.

Data on sales, the wage bill, total assets, and raw material expenditures are reported by most firms in each year. $LogTFP$ proxies for the productivity level of a firm. It is the residual from an OLS regression of sales on the wagebill, raw material expenditures and total assets proxying for the capital of firms:

$$Log(Sales)_i = \alpha_0 + \beta_1 LogWagebill_i + \beta_2 LogRawMatExp_i + \beta_3 LogTotalAssets_i + \epsilon_i,$$

where i denotes the firm. Since we want to allow for different input coefficients across industries, we perform industry-wise regressions.[2] $LogTFP$ can only be calculated for 38,200 observations since not all firms report on raw material expenditures. A list of all variables included in the analysis can be found in Table D.3 in Appendix D.2. Information on exports is only available for firms that export a positive amount (18,818 firm-year observations). More than 90% of all firms are privately Indian owned, about 6% are foreign owned and the remaining share is state owned.[3] For publicly listed companies,

[2]We also experimented with a semi-parametric productivity measure obtained via the Levinsohn-Petrin algorithm (Levinsohn and Petrin, 2003) that corrects for endogeneity in the firm's choice of production inputs due to unobserved shocks. Our main results remain unchanged when we use a more sophisticated measure of productivity. However, the Levinsohn-Petrin measure is more data-demanding and relies on the assumption that there is no entry and exit of firms. Since our panel is unbalanced, we decided to use a simpler measure of productivity.

[3]Prowess makes use of internal information to classify firms according to their ownership status but does not provide further information on the classification system.

Prowess provides the share of equity held by foreign investors which is on average 6%. We perform a consistency check on ownership information by comparing the ownership type, as indicated by Prowess, with the share of equity held by foreign investors. For government and Indian owned listed firms the average share of equity held by foreigners is below 10% and for listed firms classified as foreign owned, the average share lies above 50% (data not reported in Table 4.1).

4.3.2 Industry Linkages - OECD Input-Output Tables

We use data from the OECD input-output tables for India to construct the measures of FDI linkages. The input-output tables describe economy-wide consumption and supply relationships between producers and consumers. For India, data are available for two time periods, the early 2000 and the mid 2000 period.[4]

We follow Javorcik (2004) in constructing proxies for horizontal and vertical spillovers from FDI. Horizontal spillovers within each industry are defined as

$$Horizontal_{jt} = \left[\sum_{i,i \in j} ForeignShare_{it} * Y_{it} \right] / \sum_{i,i \in j} Y_{it}, \tag{4.1}$$

where i, j, and t are firm-, industry-, and time-specific subscripts. $ForeignShare_{it}$ is the percentage of equity held by foreign investors in firm i at time t and Y_{it} denotes the total sales of the firm. $Horizontal_{jt}$ thus is the sales weighted average of foreign equity held in industry j at time t. It proxies spillovers from the intensity of contact between foreign investors in industry j and local firms. Foreign presence in industry j rises if the average foreign equity share in the industry or the output of firms with foreign participation increases.

Vertical backward spillovers stem from the intensity of contact between suppliers and multinational customers in downstream industries. They are proxied by the degree of foreign presence in industries to which firms in industry j supply. $Backward_{jt}$ is defined

[4]For further information on the OECD input-output tables please refer to `http://www.oecd.org/trade/input-outputtables.htm` and Ahmad and Yamano (2006). The data for India can be accessed at `http://stats.oecd.org/Index.aspx?DataSetCode=STAN\_IO\_TOTAL\#`.

as

$$Backward_{jt} = \sum_{k,k\neq j} \alpha_{jk} * Horizontal_{kt}, \tag{4.2}$$

where α_{jk} denotes the share of output of industry j that is supplied to industry k and is calculated from the OECD input-output tables for India. Following Javorcik (2004), we calculate α_{jk} excluding output of industry j that is used for final consumption but including intermediate products. Moreover, the within-industry supply share α_{jj} is not included in (4.2) since within-industry spillover effects are already taken up by $Horizontal_{jt}$. Increases in backward spillovers to industry j can stem from a rise in relative supply to downstream industries with foreign presence or from a rise in foreign presence in downstream industries.

Last but not least, vertical forward spillovers originate from the contact between local downstream firms and multinational suppliers in upstream industries. They are proxied by the degree of foreign presence in industries from which industry j consumes inputs. $Forward_{jt}$ is defined as

$$Forward_{jt} = \sum_{m,m\neq j} \sigma_{jm} \left[\frac{\left[\sum_{i,i\in m} ForeignShare_{it} * (Y_{it} - X_{it})\right]}{\left[\sum_{i,i\in m} (Y_{it} - X_{it})\right]} \right], \tag{4.3}$$

where σ_{jm} is the share of inputs that industry j consumes from industry m. The within-industry consumption share σ_{jj} is not included in (4.3). Firm-level exports X_{it} are subtracted from firm-level output since exports cannot be consumed by industry j. Forward spillovers to industry j increase if relative consumption from industries with foreign presence rises or if foreign presence in upstream industries rises. Three remarks on the calculation of the FDI linkage measures are in order. First, note that we use the industry-wise supply and consumption shares from the early (mid) 2000 period to construct our spillover variables for the years 2001 to 2005 (2006 to 2010). Our spillover measures vary at the industry-year level because firm-year specific information on $ForeignShare_{it}$, Y_{it}, and X_{it} is added. Second, since the OECD input-output tables are based on ISIC Rev. 3, we convert the 24 2-digit manufacturing industries at ISIC Rev. 4 in Prowess to the corresponding ISIC Rev. 3 categories. Table D.2 in Appendix D.1 provides the correspondence between both classifications and the share of firms in each industry. Third,

Table 4.2: Summary Statistics on FDI Spillovers by Industry in 2010

Code	Industry	ForeignShare (%)	Horizontal (%)	Backward (%)	Forward (%)
C1516	Food, beverages, tobacco	2.51	4.13	1.47	0.55
C171819	Textiles, textile products, leather and footwear	1.61	2.29	1.48	1.53
C23	Coke, refined petroleum products and nuclear fuel	4.28	0.92	1.63	0.26
C24	Chemicals and chemical products	5.87	11.57	1.75	0.63
C25	Rubber and plastics products	4.12	4.13	5.23	5.75
C26	Other non-metallic mineral products	8.29	4.78	0.69	0.93
C27	Basic metals	1.72	5.21	6.42	0.80
C28	Fabricated metal products, exc. machinery and equipment	3.19	4.01	8.80	3.95
C29	Machinery and equipment n.e.c.	11.60	11.88	6.90	3.15
C303233	Office, accounting and computing machinery; Radio, television and communication equipment; Medical, precision and optical instruments	13.21	6.43	3.76	3.77
C31	Electrical equipment	7.13	21.17	3.47	3.74
C34	Motor vehicles, trailers and semi-trailers	38.25	39.07	1.30	3.72
C35	Other transport equipment	6.97	9.66	2.97	4.00
C3637	Manufacturing n.e.c; recycling	1.45	0.26	2.09	1.83

The code in column 1 corresponds to the classification in the input-output database of the OECD. The industries C30, C32, and C33 are combined into one industry since they correspond to one ISIC Rev.4 industry at the 2-digit level. The industries C20 and C2122 are not represented in our database.

data on $ForeignShare_{it}$, the equity participation by foreign investors, is available for publicly listed firms only (16,452 firm-year observations). If we use information from publicly listed firms only, we disregard almost two thirds of our observations. In order to calculate consistent spillover measures, we supplement $ForeignShare_{it}$ by information on the ownership type of firms as defined by Prowess. We consider firms that are classified as privately Indian or government owned to have 0% foreign equity and privately foreign owned firms to have 100% foreign equity. We provide a robustness check of our main results with regard to this assumption.

Table 4.2 reports summary statistics on the share of foreign equity in each industry and the spillover measures for the last year of our sample. Our measures strongly vary across industries. The average share of foreign equity held in firms is highest in the motor vehicles industry (38.3%) and lowest in the manufacturing and recycling industry (1.5%). If we weight foreign equity held in each industry by output, the ranking is similar. Horizontal spillovers in 2010 are highest in the motor vehicles industry and lowest in manufacturing and recycling. Backward spillovers are comparatively smaller in size and

range from a high 8.8% in fabricated metal products to a low 0.7% in other non-metallic mineral products. Firms in the fabricated metal industry supply to industries in which the average share of foreign equity held is 8.8%. They have the most intense contact to multinational downstream enterprises. In contrast, forward linkages are highest in the rubber and plastics product industry (5.8%). Firms in this industry very intensively consume inputs from multinational upstream enterprises. Very low contact to multinational upstream firms can be observed in the coke and petrol industry (0.3%).

4.3.3 Product Sophistication

To determine the sophistication level of products, we adapt the product-specific sophistication index from Hausmann, Hwang, and Rodrik (2007).[5] The index measures the average implied technology level of a product. The implied technology level of product k is proxied by the weighted average GDP per capita of those countries that export product k. The weights reflect the revealed comparative advantage that each country has in product k. A product is associated with a higher (lower) sophistication level if on average richer (poorer) countries have a revealed comparative advantage in the product. Put differently, the index represents the technology requirements that a country must meet in order to successfully export the product. The level of sophistication of product k is defined as

$$S^k = \sum_i \underbrace{\left(\frac{x_i^k / X_i}{\sum_i (x_i^k / X_i)} \right)}_{weight\ \varpi_i^k} Y_i, \tag{4.4}$$

where Y_i is the GDP per capita of country i. x_i^k denotes country i's export volume of product k and X_i is the total export volume of country i. The weights ϖ_i^k are variants of Balassa's Revealed Comparative Advantage (RCA) Index and add up to one. The weights ensure that the sophistication ordering of the products is not biased by country

[5]The sophistication index in Hausmann, Hwang, and Rodrik (2007) is called $PRODY$ and has been used by Jarreau and Poncet (2012) or Harding and Javorcik (2011), for example.

Table 4.3: Top and Bottom Sophisticated Products

Top 3 Products

SITC code	S in USD	Description
515	26,309	Organo-inorganic compounds, heterocyclic compounds, nucleic acids and their salts, and sulphonamides
344	26,049	Petroleum gases and other gaseous hydrocarbons, n.e.s.
514	23,356	Nitrogen-function compounds

Bottom 3 Products

SITC code	S in USD	Description
286	976	Uranium or thorium ores and concentrates
284	1,103	Nickel ores and concentrates; nickel mattes, nickel oxide sinters and other intermediate products of nickel metallurgy
264	1,357	Jute and other textile bast fibres, n.e.s., raw or processed but not spun; tow and waste of these fibres (including yarn waste and garnetted stock)

SITC categories are defined at the Rev. 3 3-digit level.

size.[6] Data on GDP per capita in constant 2005 USD stem from the World Development Indicators database. Data on product-level exports come from the CEPII-BACI database which is constructed from UN-Comtrade data. We use disaggregated export data at the 3-digit SITC Rev. 3 level which comprises 259 product categories. To get a time consistent indicator, we take the average level of GDP per capita and exports by each country over the time span of 2000 to 2010. This diminishes disturbing influences from wars and business cycle fluctuations, as well as industrial and technological developments over time. Consistent data on GDP per capita and the corresponding export flows is available for 175 countries. Table 4.3 provides the three most and least sophisticated products according S. The top sophisticated product is organo-inorganic compounds with an average sophistication level of 26,309 USD. Organo-inorganic compounds are intensively exported by Ireland, for example. In contrast, the least sophisticated product is uranium ores with an average sophistication level of 976 USD. Uranium ores make up a substantial share of Nigerian exports, one of the world's poorest countries.

[6]Assume for example that both the US and Ecuador export bananas. Since the US is larger in market size than Ecuador, its export volume of bananas might be larger than that of Ecuador. However, bananas certainly take a larger share in Ecuador's exports than in the US exports. Not controlling for a country's RCA in exporting bananas might thus lead to a higher sophistication level for bananas simply because they are exported (to a small extent) by a rich country.

We use the index to determine the sophistication level of the products manufactured by the Indian firms. The product classification of CMIE cannot directly be linked to any standard international classification. Therefore, we reclassify all products according to the SITC 3-digit classification. We manage to identify 82% of all firm-product-year observations which account for 88% of total output. For the remaining share, the information provided on the products is not sufficient in order to assign a sophistication level. We also experimented with a more disaggregated classification at the 4- and 5-digit level. However, as products become more disaggregated the reclassification becomes more imprecise and we managed to identify less than half of all observations. Although the 3-digit level is comparatively aggregate, we are confident that the 259 different product categories still provide sufficient scope for variation in the activities of firms. A more detailed description of the product reclassification to SITC Rev. 3 3-digit can be found in Appendix D.1.

In the following analysis, we refer to firms that produce at least one product from the top quartile of the sophistication distribution as HSP manufacturers.

4.4 Portrait of Product Sophistication in India

In this section, we describe the economic prevalence and the characteristics of HSP manufacturers in India. We first illustrate the industry-wise distribution of HSP manufacturing. Figure 4.1 shows that there is substantial variation in the manufacturing of HSPs across different industries. Firms that manufacture at least one HSP are present in each industry but they are not homogeneously spread across industries. The share of HSP manufacturers ranges from a low 5% in the textiles industry to a high 92% in the motor vehicles industry. This is plausible given that producing textiles requires a lower average technology level than producing cars.

As Panel A of Table 4.4 shows, only 42% of all firms produce a HSP at least once over the entire sample period. The majority of firms never produce a single HSP. Interestingly, HSP manufacturers generate more than two thirds of total sample output and they also produce on average a larger number of products than firms that never manufacture a HSP.

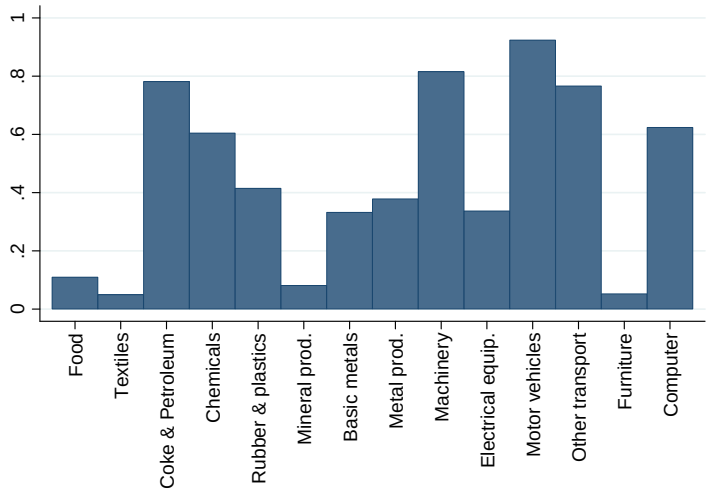

Figure 4.1: Share of HSP Manufacturers across Industries, 2001-2010

Table 4.4: Prevalence of HSP Manufacturing in India

Panel A: Output by HSP Manufacturers vs. Never-HSP Manufacturers

Type of firm	Num. of firms	Share of firms (%)	Share of output (%)	Mean num. of products	Mean num. of HSPs
Never-HSP manuf.	3,775	57.8	27.9	1.8	0
HSP manuf.	2,755	42.2	72.1	2.7	1.5
Total	6,530	100	100		

Panel B: Output of HSP Manufacturers by Product Type

Type of product	Share of products (%)	Share of output (%)
No HSP	46.0	68.6
HSP	54.0	31.3
Total	100	100

Half of all products produced by HSP manufacturers actually are HSPs, the other half is made up of less sophisticated products. Although these firms dominate manufacturing output, only one third of their output stems from HSPs (Panel B of Table 4.4). The remaining two thirds are generated from the sale of less sophisticated products. Hence, less than a quarter of total output is derived from the sale of HSPs in India. Figure 4.2 plots the share of output that is derived from the sale of HSPs over time. It increases from about 20% in 2001 to 23.5% in 2005 and then drops to 22%, following the financial crisis. These findings clearly indicate that manufacturing HSPs is not yet very prevalent among Indian manufacturing firms. One explanation is the high uncertainty in the profitability of these products. Since they require the investment in unknown technologies and are prone to emulation, only few firms engage in their production. A further issue is that demand

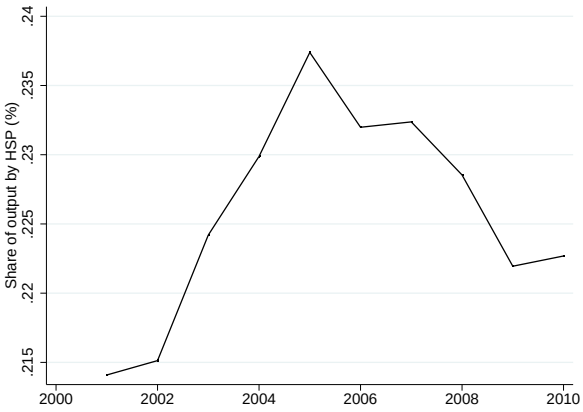

Figure 4.2: Share of Output Generated by the Sale of HSPs 2001-2010

for HSPs in India may still be low. This could also explain why rather large firms produce HSPs: only firms that generate sufficiently high returns from other activities can bear the risky investment because they can better cover potential losses from HSPs by other income generating products. We next compare the characteristics of HSP manufacturers to non-HSP manufacturers. The results in Panel A of Table 4.5 suggest the existence of HSP manufacturer premia: firms that produce HSPs are distinctly different in all reported firm characteristics. They are significantly older, larger in terms of sales and the wage bill, and they are more productive. This is in line with the theoretical predictions by Bernard, Redding, and Schott (2009) who derive that firms sort into the production of more complex goods according to their productivity. In their theoretical framework, the production of high-technology goods entails higher fixed and lower variable costs than the production of traditional low-technology goods. Consequently, only the most productive firms produce more complex goods because they can better cover the higher fixed costs of high-technology products. We also observe that these firms have a significantly higher probability to export and they are more often foreign owned. Exporters benefit from access to a larger market abroad which can be more attractive for selling top sophisticated products. Foreign owned firms usually have better access to more advanced technologies facilitating the cost discovery process as described by Hausmann and Rodrik (2003).

In Panel B of Table 4.5, we test whether HSP manufacturing firms are already stronger performers one year before they first produce a HSP. Specifically, we compare firms that add a HSP to their product basket in the year prior to the addition to firms that never

Table 4.5: Characteristics of HSP Manufacturers

Panel A: HSP Manufacturers vs. Non-HSP Manufacturers

	HSP manuf.	Obs.	Non-HSP manuf.	Obs.	Mean diff.
LogAge	3.02	18,053	2.95	27,136	0.77***
LogSales	1.02	16,412	0.64	23,952	0.38***
LogWagebill	-1.98	16,465	-2.65	24,080	0.67***
LogTFP	0.01	15,736	-0.001	22,464	0.011***
Foreign owned	0.08	18,104	0.04	27,193	0.04***
ForeignShare (%)	8.10	7,396	4.36	9,056	3.74***
Export Prob. (%)	56.3	16,412	40.0	23,953	16.3***
Number of products	3.31	18,104	2.18	27,193	1.12***

Panel B: HSP Upgraders vs. Never-HSP Manufacturers in Year before Upgrade

	HSP Upgrad.	Obs.	Never-HSP manuf.	Obs.	Mean diff.
LogAge	2.76	323	2.91	25,781	-0.15***
LogSales	0.86	291	0.55	22,589	0.31***
LogWagebill	-2.48	285	-2.71	22,385	0.23**
LogTFP	0.02	277	-0.01	20,851	0.03
Foreign owned	0.06	326	0.04	25,835	0.02
ForeignShare (%)	4.57	92	4.15	7,427	0.42
Export Prob. (%)	44.0	291	38.2	22,592	5.8**
Number of products	2.54	326	2.11	25,835	0.43***

Panel A display results from a mean difference test of firm characteristics for firms that produce a HSP vs. firms that do not produce a HSP in the same year. We use Welch's formula to allow for unequal variances in both groups (Welch, 1947). Panel B displays results from a mean difference test of firm characteristics for upgraders vs. never-HSP manufacturers in the year before upgrading to a HSP. Upgraders denote firms that do not produce a HSP in $t-1$ but do so in t. ***, **, and * represent mean differences significant at the 1%, 5% and 10% level, respectively.

produce a HSP. In our dataset, only about 330 firms start to produce a HSP between 2001 and 2010.[7] In the year prior to the upgrade, these firms tend to be larger in terms of sales, the wage bill and the overall number of products sold than firms that never manufacture a HSP. Moreover, they exhibit a higher export probability. Interestingly, firms that upgrade to HSP manufacturing tend to be younger which is at odds with the significantly higher age of HSP manufacturers observed above. The lower age probably reflects non-linearities such that firms above a certain age do not upgrade to the manufacturing of HSPs anymore.

One might be concerned that our classification of firms in HSPs and non-HSP manufacturers simply reflects the distinction between multi-product and single-product firms.

[7] We use product-firm information from the year 2000 to observe whether a firm adds a HSP in 2001.

Table 4.6: HSP Manufacturers and Multi-Product Firms

Type of firm	Num. of HSPs	Mean num. of total products	Share of observations (%)	Share of MP firms (%)
Never-HSP manuf.	0	2.1	55.7	54.0
HSP manuf.	0	2.8	4.3	66.6
	1	2.4	25.7	55.0
	2-13	5.0	14.3	100
Total			100	

Naturally, manufacturing a HSP and being a multi-product firm is highly correlated since HSP manufacturers produce on average more than one product. However, as Table 4.6 shows, more than half of all firms that never produce a HSP sell more than one product and are thus multi-product firms. Similarly, more than half of all HSP manufacturers that produce at most one HSP are multi-product firms. Therefore, we are confident that we do not simply capture multi-product firm characteristics when classifying firms according to the sophistication of their activities.

Overall, we find strong evidence that HSP manufacturers outperform firms that do not manufacture a HSP. They dominate manufacturing output, but the output by HSPs is rather low which may be due to the higher costs and uncertainty associated with producing more complex products. In the following, we analyze whether contact to MNEs can foster HSP manufacturing by firms via spillovers through horizontal and vertical linkages.

4.5 The Impact of FDI Spillovers on Product Sophistication

4.5.1 Empirical Strategy and Results

To examine the relationship between the manufacturing of HSPs and knowledge spillovers from FDI, we employ the following regression model:

$$Prob(HSP_{ijst} = 1) = \Phi(\alpha_0 + \beta_1 Horizontal_{jt} + \beta_2 Backward_{jt} + \beta_3 Forward_{jt} + \beta_4 ForeignShare_{ijst} + \gamma \mathbf{C_{ijst}} + \delta HHI_{jt} + \alpha_t + \alpha_j + \alpha_s) \quad (4.5)$$

Our dependent variable HSP is a binary indicator equal to 1 if firm i active in industry j and operating in state s produces at least one product in year t that belongs to the top quartile of S. $Horizontal$, $Backward$, and $Forward$ denote our measures of FDI spillovers as defined above. Additionally, we control for the share of equity held by foreigners in the firm, $ForeignShare$. We expect a positive influence of $ForeignShare$ on the manufacturing of HSPs. Foreigners with a higher stake in a local firm have a higher incentive to pass their knowledge and technologies to the firm such that it produces a more sophisticated output and earns higher profits. $\mathbf{C}$ is a vector of firm-level controls and comprises the log age of a firm, $LogAge$, the log wage bill, $LogWagebill$, and log total factor productivity, $LogTFP$. We expect a positive effect of age, size and productivity on the probability to manufacture a HSP since older, larger, and more productive firms are better able to cover the higher fixed costs and to bear the higher risk of producing more complex products. We also include the Herfindahl index HHI to control for industry concentration. HHI is defined as the sum of squared market shares of all firms operating in a particular industry. A higher value indicates higher concentration and thus weaker competition. The effect of HHI on product sophistication is ambiguous: on the one hand, stronger concentration generates larger profits which can be used to invest in the production of a more sophisticated good. On the other hand, higher concentration and thus weaker competition can impede the manufacturing of HSPs because firms have no incentive to innovate and produce HSPs. Gorodnichenko, Svejnar, and Terrell (2010), for

example, find a negative effect of higher concentration on innovation by firms in transition countries.

We cluster standard errors at the industry-year level because our key regressors of interest vary at the industry-year level. Not correcting for dependencies in the error terms of observations within the same grouping can lead to a downward bias in the estimated standard errors. This in turn can entail spurious inferences on the relationship between a micro unit outcome and more aggregated regressors (Moulton, 1990). Moreover, we include fixed effects for years, industries, and Indian states. Equation (4.5) is estimated via a pooled probit model for all observations between 2001 and 2010. By including industry and state dummies, we rule out that the effect of our spillover measures on HSP manufacturing is driven by the presence of multinational enterprises in more (or less) attractive industries and regions. We estimate our baseline specification for the full sample of firms and for domestically owned firms only since spillovers should be particularly relevant for firms with very low access to foreign knowledge and technologies. To identify domestically owned firms, we use the ownership classification as provided by Prowess.

4.5.1.1 Baseline Results

Table 4.7 provides the results from estimating equation (4.5) for the full sample (column 1) and domestically owned firms only (column 2). We report average marginal effects instead of the parameter coefficients since the latter are less informative in terms of the magnitude of the effects.

We find a small positive effect of *Horizontal* on the likelihood of a firm to produce a HSP (column 1). An increase by 10 percentage points in within-industry presence of multinational firms raises the likelihood of a firm to produce a HSP by 0.6%. Vertical backward spillovers, in contrast, strongly influence a firm's participation in HSP manufacturing through supply chains. An increase by 10 percentage points in foreign presence in downstream industries raises the likelihood of a firm to produce a HSP on average by 5%. This finding points to positive spillovers from multinational customers to local Indian suppliers via knowledge and technology transfers. So far, positive effects of backward

Table 4.7: Effect of FDI Spillovers on the Probability to Manufacture a HSP

	HSP			
	All firms	Domestic	All firms	Domestic
	(1)	(2)	(3)	(4)
Horizontal	0.000621*	0.000487	0.000656*	0.000480
	(0.000333)	(0.000340)	(0.000380)	(0.000387)
Backward	0.00457***	0.00435**	0.00460***	0.00431**
	(0.00154)	(0.00170)	(0.00164)	(0.00175)
Forward	-0.0111**	-0.00951**	-0.0126**	-0.0112**
	(0.00436)	(0.00450)	(0.00498)	(0.00500)
LogTFP	0.00931**	0.0127***	-0.00523	-0.00780
	(0.00465)	(0.00485)	(0.00631)	(0.00652)
LogTFP*Forward			0.00765***	0.0106***
			(0.00291)	(0.00294)
ForeignShare	-0.000203**		-0.000186*	
	(8.92e-05)		(9.49e-05)	
LogAge	0.0217***	0.0157***	0.0210***	0.0150***
	(0.00358)	(0.00365)	(0.00334)	(0.00341)
LogWagebill	0.0254***	0.0248***	0.0248***	0.0241***
	(0.00141)	(0.00154)	(0.00108)	(0.00117)
HHI	2.38e-06	9.35e-06	1.22e-06	8.22e-06
	(1.86e-05)	(2.11e-05)	(1.76e-05)	(1.89e-05)
Observations	36,858	34,632	36,858	34,632
Log-Likelihood	-18,598	-17,397		
Pseudo R^2	0.256	0.256		
R^2			0.304	0.302

Columns 1 and 2 provide average marginal effects from a pooled probit model. Columns 3 and 4 provide the coefficients from a pooled linear probability model including the interaction between *Forward* and *LogTFP*. Time, industry, and state fixed effects are included. Standard errors are clustered at the industry-year level. ***, **, and * denote significance at 0.01, 0.05, and 0.10 levels, respectively.

linkages have only been established on firm productivity (Javorcik, 2004, Blalock and Gertler, 2008, and Schoors and Van Der Tol, 2002). Interestingly, the effect of *Forward* is negative and twice as large as the effect of backward spillovers. Firms that consume from industries with a 10 percentage points higher foreign presence have a 10% lower probability to manufacture a HSP. This seems counterintuitive given that access to better inputs from foreign firms should lead to more sophisticated outputs (Rodriguez-Clare, 1996). One explanation for the negative impact of *Forward* is that intermediate inputs provided by multinational firms are probably not fit for use by local firms. If the technology gap between multinational firms and local Indian firms is too large, Indian firms will

not be able to successfully transform more sophisticated inputs into more sophisticated outputs. The crowding-out effect is aggravated if intermediate inputs from multinational firms replace other inputs. In that case, local Indian firms do not have access to suitable inputs anymore and cease the production of sophisticated final goods.

The average marginal effect of $ForeignShare$ is negative. Consequently, firms with a higher share of equity held by foreign investors are less likely to produce a product from the top quartile of the sophistication distribution. Although the magnitude of the effect is very small, this is counterintuitive since foreign investors that hold a higher stake in an Indian firm are expected to have a higher incentive to transfer their knowledge to the firm. However, this finding can reflect cost-saving motives of FDI: foreign investors invest in Indian firms in order to produce less sophisticated, intermediate products at lower costs which are then exported back to the home country of the investor. This does not contradict positive backward spillovers, though. A downstream multinational textile firm may still require highly sophisticated textile machines from a local supplier even though it produces a less sophisticated output (t-shirts for example).

The other firm-level covariates have the expected effect on HSP manufacturing: older, larger, and more productive firms are more likely to produce a HSP. For example, an increase in $LogTFP$ by 10% increases a firm's probability to produce a HSP by 9%. A higher industry concentration is associated with a higher probability to manufacture a HSP but the effect is not significantly different from zero. The corresponding results for domestically owned firms in column 2 are similar in magnitude and significance except for $Horizontal$ which is no longer significant. Overall, the results suggest that the effect of spillovers is mainly driven by domestically owned firms. This is plausible given that these firms should be more strongly affected by contact to multinational companies than foreign owned firms.

In columns 3 and 4, we include an interaction term between $Forward$ and $LogTFP$ to test whether spillovers through forward linkages depend on a firm's productivity level. More productive firms might be better able to make use of foreign inputs and thus might be less harmed by the presence of multinational upstream firms. In order to interpret the interaction term, we neglect the binary nature of our dependent variable and use a linear

probability model instead. The interaction term is indeed positive and highly significant whereas the base effect of $Forward$ remains negative. This confirms that the effect of access to foreign inputs depends on the firm's productivity level. The more productive the firm, the less it is affected by the technology gap to foreign multinational upstream firms. In terms of magnitude, the positive effect from a 1% increase in productivity almost outweighs the negative impact of a 1 percentage point higher presence of multinational suppliers.

Overall, our results provide strong evidence of spillovers between local Indian firms and multinational firms. Indian firms benefit from contact to multinational downstream firms. Firms that intensively supply to multinational customers have a higher probability to produce a HSP since they gain access to foreign knowledge and expertise via supplier linkages. In contrast, the effect of contact to multinational suppliers depends on the productivity level of firms. Low-productivity firms are hurt by intense presence of upstream firms whereas more productive firms can make better use of inputs supplied by foreign firms.

4.5.1.2 Upgrading to the Manufacturing of Top Sophisticated Products

We next analyze spillover effects on a firm's likelihood to upgrade to HSP manufacturing. Upgrading firms are defined as firms that do not produce a top sophisticated product in $t-1$ but do so in all consecutive periods $t, t+1, \ldots$. For this analysis, we only compare upgrading firms to firms that never produce a HSP over the whole sample period. We thus disregard firms that produce a HSP in every year of their occurrence in the sample. Our dependent variable is $UpHSP$, a binary indicator equal to 1 if the upgrading firm produces a HSP. It is 0 for firms that never produce a HSP and for upgraders in the pre-switch year. Since the number of upgraders is very small in our dataset (about 5% non-zero observations), we apply a complementary log-log (clog-log) model in our estimation. The clog-log model is preferable if the distribution of the dependent variable is not symmetric but highly skewed to one outcome which is the case in our application.[8]

[8]The following model is fitted by clog-log forms: $Prob(y = 1|\mathbf{x}) = 1 - exp\{-exp(\mathbf{x}'\beta)\}$. Our results are not affected by the model choice. Probit and linear probability models yield similar results.

Table 4.8: Effect of FDI Spillovers on the Probability to Upgrade to HSP Manufacturing

	UpHSP			
	All firms	Domestic	All firms	Domestic
	(1)	(2)	(3)	(4)
Horizontal	0.000368	0.000159	0.000363	0.000155
	(0.000354)	(0.000364)	(0.000360)	(0.000369)
Backward	0.00259**	0.00271**	0.00247**	0.00253**
	(0.00103)	(0.00113)	(0.00104)	(0.00115)
Forward	-0.00282	-0.00315	-0.00271	-0.00296
	(0.00257)	(0.00270)	(0.00257)	(0.00271)
ForeignShare	-9.36e-05		-9.97e-05	
	(6.77e-05)		(6.86e-05)	
LogAge	-0.00806***	-0.00752***	0.0604***	0.0646***
	(0.00169)	(0.00152)	(0.0151)	(0.0161)
$LogAge^2$			-0.0123***	-0.0129***
			(0.00267)	(0.00289)
LogWagebill	0.00808***	0.00828***	0.00885***	0.00906***
	(0.00105)	(0.00108)	(0.00102)	(0.00105)
LogTFP	-0.00309	-0.00204	-0.00419*	-0.00324
	(0.00235)	(0.00241)	(0.00244)	(0.00252)
HHI	-2.28e-05	-2.65e-05	-2.20e-05	-2.54e-05
	(1.71e-05)	(1.81e-05)	(1.74e-05)	(1.84e-05)
Observations	21,538	20,586	21,538	20,586
Zero Obs. 20494	20,494	19,604	20,494	19,604
Non-zero Obs.	1,044	982	1,044	982
Log-Likelihood	-3,705	-3,490	-3,689	-3,473

Columns 1 to 4 provide average marginal effects obtained from a clog-log model. Time, industry, and state fixed effects are included. Standard errors are clustered at the industry-year level. ***, **, and * denote significance at 0.01, 0.05, and 0.10 levels, respectively.

The average marginal effects displayed in Table 4.8 strongly point to positive spillovers via backward linkages. An increase in *Backward* by 10 percentage points increases a firm's likelihood to switch to HSP manufacturing by about 3% (column 1). The effect is similar for domestically owned firms only, column 2. We do not observe statistically significant effects from horizontal or forward spillovers, though. Thus, switching to HSP manufacturing mainly works through contact to foreign customers that require more sophisticated intermediate inputs from Indian firms. This seems plausible given that it is certainly more difficult to switch to producing final than intermediate HSPs. We do not observe a significant impact of total factor productivity. Consequently, contacts to multinational downstream firms seem to be more important than a firm's own level of

efficiency. The effect of size is positive and highly significant as observed above. In contrast, younger firms seem to be more likely to switch to HSP manufacturing which is at odds with the positive age effect on HSP (Table 4.7). We therefore add the square of $LogAge$ to the specification in columns 3 and 4 to allow for a non-linear age effect. The results suggest that older and thus more experienced firms tend to switch to HSP manufacturing but after passing the age of 12 years, firms do not switch to HSP manufacturing anymore.

4.5.2 Sensitivity Analysis

4.5.2.1 Extent of HSP Manufacturing

Regarding our previous analysis, two concerns need to be addressed. First, classifying firms into HSP and non-HSP manufacturers according to the top quartile of S, we do not observe continuous sophistication upgrading by firms. Spillovers may not only induce firms to produce one product of the top sophistication distribution, but also to gradually upgrade their production from products at the lower end to products further up the sophistication distribution. In order to observe continuous sophistication changes, we thus construct the dependent variable $LogEXS_{it}$, which measures the extent of product sophistication by each firm:

$$LogEXS_{it} = Log\left(\sum_{k}^{K} \frac{Sales_{ikt}}{\sum_{k}^{K} Sales_{ikt}} S_k\right). \tag{4.6}$$

$LogEXS$ is defined as the log average sophistication level of all products $k = 1, ...K$ produced by each firm i in year t, weighted by the sales share of each product.

Second, analyzing the probability of firms to produce a HSP, we are limited in our ability to control for a variety of unobserved factors that could both drive the decision of a firm whether to produce a HSP and the location decisions of foreign investors. Thus, we are worried that the relationship between our spillover measures and HSP manufacturing at the firm level might not be the result of pure knowledge spillovers but is driven by omitted influences. One source of potential bias are unobserved firm-

fixed effects that can affect both the location decision of multinationals and a firm's probability whether to produce a HSP. The effect of *Backward*, for example, is upward biased if multinational firms decide to locate in industries which predominantly consume from firms that have the highest management quality, assuming that better management fosters HSP manufacturing. Furthermore, multinationals might decide to invest more over time in those industries which consume or supply from industries that have a higher expected growth of HSP manufacturers. To mitigate these concerns, we follow Javorcik (2004) and run a regression of $LogEXS$ on our spillover measures and firm-level covariates in first and second differences. We additionally include time and industry fixed effects. Differencing eliminates firm-fixed effects such as managerial ability. Additional industry fixed effects account for the fact that the attractiveness of industries in terms of HSP manufacturing can change over time (see Javorcik, 2004, p. 616). Thus, we control for the fact that foreign investors gravitate towards industries that are supplied or sell to industries with an increasing level of product sophistication. Our specification in first differences is as follows:

$$\begin{aligned}\Delta LogEXS_{ijt} =& \alpha_0 + \beta_1 \Delta Horizontal_{jt} + \beta_2 \Delta Backward_{jt} + \beta_3 \Delta Forward_{jt} + \\ & \beta_4 \Delta ForeignShare_{ijt} + \gamma \mathbf{\Delta C_{ijt}} + \delta \Delta HHI_{jt} + \alpha_t + \alpha_j + \epsilon_{ijt}. \end{aligned} \tag{4.7}$$

The identification of β_1 to β_3 comes from within-industry changes in the spillover measures over time.

Finally, one last concern is that idiosyncratic shocks can occur that stimulate a firm's probability to manufacture a HSP. If multinationals tend to locate close to firms that experience such a shock in order to benefit from better inputs or increased selling opportunities, the effects of our spillover measures are biased. However, it is unlikely that multinationals are able to react to short term shocks experienced by Indian firms given that foreign investment usually involves longsome preparation and high transaction costs and fees (Blalock and Gertler, 2008).

Table D.4 in Appendix D.2 reports the corresponding results. In line with our results obtained above, backward linkages strongly foster the manufacturing of more sophisti-

cated products. An increase in the presence of multinational downstream firms by 10 percentage points increases the average product sophistication level of a firm by almost 20%. In contrast to our previous results, the negative effect of *Forward* is not significantly different from zero. This implies that a negative effect from *Forward* linkages is only observed for the top quartile of the sophistication distribution whereas gradual sophistication upgrades are not impeded by multinational presence in upstream industries. In addition, we observe a highly significant positive effect of firm size. A 10% increase in firm size leads to a 2% rise in average product sophistication. One notable difference is the small negative effect of *Horizontal* when allowing for a longer time lag (columns 3 and 4). Firms in industries with a high presence of multinational investors produce on average less sophisticated products than firms in industries with a lower presence. This result clearly points to within-industry crowding out effects by competition from multinational companies. Since multinational firms usually tend to be not only more skill-intensive but also more productive, they crowd out less efficient Indian firms which are prevented from product upgrading.

These findings strengthen that contact to foreign customers is particularly beneficial to Indian firms. Positive knowledge spillovers from multinational customers allow local suppliers producing one of the top sophisticated products and they also foster gradual sophistication upgrading.

4.5.2.2 Robustness Checks

Finally, we perform a series of robustness checks to test the sensitivity of our main results concerning the spillover measures, the financial situation of a firm, and the exclusion of different subsets of firms. The first robustness check regards the calculation of our spillover measures. *Horizontal*, *Backward*, and *Forward* hinge on the definition of the share of equity held by foreign investors. Since information on foreign equity share is available for publicly listed firms only, we assume that firms denoted as Indian owned by Prowess have a foreign equity share of 0% and firms classified as foreign owned are foreign owned by 100%. To test the restrictiveness of this assumption, we recalculate our spillover measures using only the information on foreign equity shares of publicly listed

firms. The three linkage variables thus exclusively capture spillovers from publicly listed multinationals. We re-estimate (4.5) for the full set of firms and domestically owned firms only, both for HSP manufacturers and upgraders to HSP manufacturing. Note that we cannot include *ForeignShare* since we would lose all observations from unlisted firms. Instead, we include a dummy that denotes foreign ownership. The average marginal effects displayed in Table D.5 in Appendix D.2 are similar in terms of significance and magnitude to the results obtained from our baseline specifications. The main difference is that some effects are less precisely estimated due to a lower variation in our spillover measures.

Second, in our main specification for HSP manufacturing and upgrading to HSP, we have not controlled for the liquidity situation of the firm. We would expect, though, that more liquid firms have a higher probability to produce HSPs and to upgrade to HSP manufacturing since they can better cover the higher investment costs. We therefore control for the liquidity ratio of the firm which is defined as the ratio of current assets minus current liabilities over total assets. Since we are worried that reverse causality may run from HSP manufacturing to the financial situation of a firm, we include the first lag of *LiqRatio* in order to mitigate this problem. Table D.6 in Appendix D.2 suggests that controlling for the liquidity ratio does not greatly change our main results. *LiqRatio* is positive in three out of four regressions but it is not significant.

Third, the effect of spillovers on the manufacturing of HSPs might be driven by certain groups of firms. Consider for example the coke and petroleum industry. Due to the construction of the index, most of the firms that produce petrol and coke products would be classified as HSP manufacturers because these products tend to have a high sophistication level. If multinationals tend to locate in India in order to benefit from cheaper access to oil from Indian suppliers, the positive effect of *Backward* would not truly reflect knowledge spillovers but also cost saving motives. To rule this out, we re-estimate our baseline specification for HSP manufacturers and for upgraders excluding firms located in the petrol and coke industry.

Furthermore, our results could be flawed from including firms in industries that enjoyed long-term absence of patent protection. Between 1970 and 2005 the food, the chemicals,

and the pharmaceuticals industry were not subject to intellectual property rights protection. In 2005, the Patent Amendments Act ended the freedom of patent protection in order to comply with TRIPs requirements. 35 years of absence in patent protection have led to a very low presence of multinational companies in the chemicals and pharmaceuticals industry. This in turn enabled reverse engineering of Western pharmaceuticals by local Indian firms and greatly boosted the Indian pharmaceuticals industry.[9] We exclude firms from patent free industries to check whether our results change if we only consider industries that were relatively more restricted in making use of already developed technologies.

Finally, Blalock and Gertler (2008) raise the concern that spillover effects could be mainly driven by exporting firms. Multinational firms probably tend to choose local suppliers that also sell their products to foreign markets assuming that this reflects a higher quality of the goods sold by these firms. Firms that have access to export markets are also more likely to invest in HSP production since they benefit from larger sales opportunities. In order to rule out bias from exporting firms, we re-estimate our main specification with non-exporting firms only.

Table D.7 in Appendix D.2 provides the corresponding results for HSP manufacturing (columns 1 to 3) and upgrading to HSP manufacturing (columns 4 to 6) in all three subsamples. To save space, we do not display the results for domestically owned firms only. Our results are basically unchanged in terms of magnitude and significance when excluding petrol and coke producing firms. The effect of $Horizontal$ on HSP is weakly positive, backward spillovers strongly positively affect the likelihood to produce a HSP and forward spillovers are associated with a significant negative effect. Upgraders are exclusively influenced by spillovers through backward linkages. Interestingly, the backward spillover effect increases slightly in magnitude when dropping out the former patent free industries. This finding illustrates that firms benefit more strongly from foreign knowledge when located in industries in which copying foreign technologies was more restricted. Finally, excluding exporting firms leads to less precise estimates since the number of firms drops considerably but our main results hold. The most notable change is a switch in

[9] By now, India is the world's fourth largest producer of pharmaceuticals in volume terms. See Greene (2007) for a more detailed overview of patent protection and the Indian chemical industry.

sign for *ForeignShare*. The effect of the firm's own equity share held by foreigners is still close to zero but it is positive for non-exporting firms. This confirms our prior assumption that the negative effect of foreign equity participation is driven by firms that predominatly produce less sophisticated products for foreign markets. Purely domestically active firms indeed benefit from foreign knowledge within the own corporation.

4.6 Conclusion

In this chapter, we have shown that knowledge spillovers from multinational enterprises to local firms can greatly impact on product sophistication in India. Local firms benefit the most from contact to multinational customers since downstream firms have a higher incentive to transfer their knowledge and technologies to upstream suppliers than to rivals in the same industry. In contrast, a higher presence of multinational upstream firms can lead to less HSP manufacturing in downstream industries. Indian firms are probably not able to integrate inputs from multinationals into their production process and are probably driven out of the production of more sophisticated final goods. Therefore, policies should aim at attracting multinational downstream firms in order to foster the structural transformation process from producing less to more sophisticated products. Our empirical analysis has to remain silent on the underlying mechanisms of how access to foreign technologies alters the product choices of firms. Therefore, a theoretical model is warranted that considers the production decisions of firms with respect to presence of foreign technology via horizontal and vertical linkages.

Appendices

A Appendix to Chapter 1

A.1 Theoretical Appendix

Proof of Proposition 2:

Given the belief of the bank, $Pr(G|\alpha \geq \alpha^{sep}) = 1$ and $Pr(G|0 \leq \alpha < \alpha^{sep}) = 0$, both suppliers have no incentive to deviate. The exporter sets α, p_1 and q_1. Given p_1 and q_1, the good supplier could choose a higher α, but he has no incentive to do so, since $\frac{\partial \pi_{SU}(G)}{\partial \alpha} < 0$.

$$\frac{\partial \pi_{SU}}{\partial \alpha} = [\underline{c} + (\bar{c} - \underline{c})(1 + \bar{r}_{SC})]\, q_1 - [\underline{c} + (\bar{c} - \underline{c})(1 + \bar{r}_{SC})]\, q_1(1 + \bar{r}_{SC}) < 0$$

Likewise, the good type has no incentive to lower α, as the exporter would not obtain a bank credit then and the export transaction does not take place which means that the supplier would make losses.

The bad type does not have an incentive to choose $0 < \alpha(B) \leq \alpha^{sep}$, because the transaction does not take place as the bank does not give a bank credit and hence she makes losses. For $\alpha(B) = \alpha^{sep}$, the supplier still makes zero profits and thus has no incentive to deviate to α^{sep}.

The bank updates its belief according to Bayes' rule and sets $\sigma = 1$ when $\alpha = \alpha^{sep}$. If $\alpha = 0$, the bank updates its belief according to Bayes' rule and sets $\sigma = 0$ and hence denies a credit. Thus, $[(\alpha(G) = \alpha^{sep}, \alpha(B) = 0)$, (gives bank credit at interest rate $(1 + \bar{r}_B)$, gives no bank credit), $Pr(G|\alpha \geq \alpha^{sep}) = 1$ and $Pr(G|0 \leq \alpha < \alpha^{sep}) = 0]$ is a perfect Bayesian equilibrium.

Illustration of Proposition 3:

Note that condition (1.18) requires the suppliers' refinancing costs not to be too high,

$$\bar{r}_{SC} < \frac{(1 - \sigma^2)\bar{c} + \bar{r}_B(\bar{c} - \sigma^2 \underline{c})}{\sigma^2(\bar{c} - \underline{c})},$$

and the adverse selection problem to be severe

$$\sigma^2 < \frac{(1+\bar{r}_B)\bar{c}}{\underline{c}(\bar{r}_B - \bar{r}_{SC}) + \bar{c}(1+\bar{r}_{SC})}.$$

In Figure A.1, the shaded area gives all the parameter combinations satisfying (1.18).

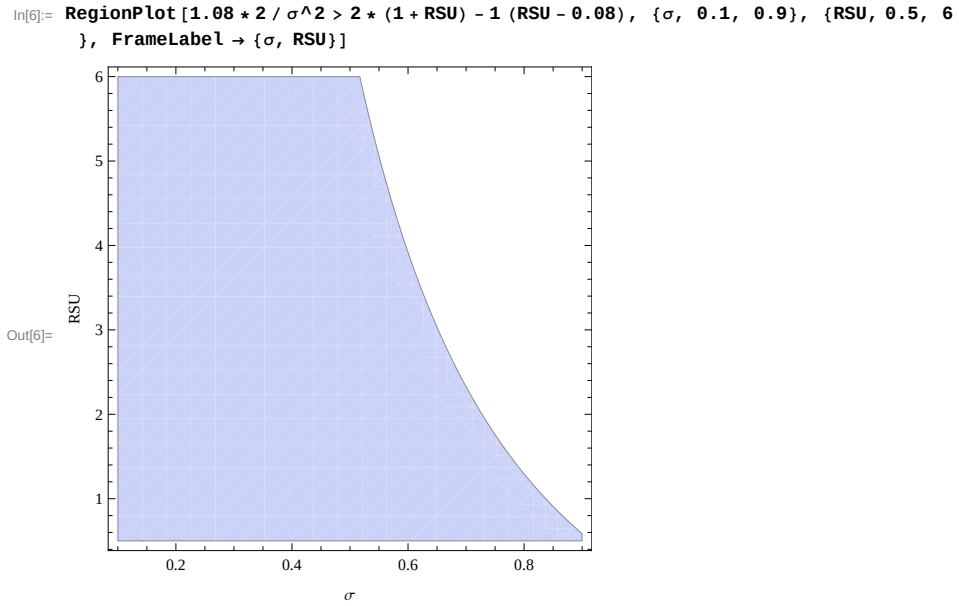

Figure A.1: Graphical Illustration of Proposition 3

This shows by example that the parameter set for which $(1+\beta)^{SC/BC} < (1+\beta)^{BC}$ is non-empty. In fact, for reasonable parameter constellations the productivity threshold for supplier credit and bank credit financing is almost always below the one for pure bank credit financing.

Proof of Proposition 4

Given the belief of the bank $Pr(G|\alpha \geq \alpha^{sep}) = 1$, $Pr(G|0 \leq \alpha < \alpha^{sep}) = 0$ and $Pr(G|\alpha(G) = \alpha(B)) = \sigma$ both suppliers have no incentive to deviate. They will not deviate to a higher α as their profits decrease in α (see above). Furthermore, they will not unilaterally decrease α as they will not get any bank credit then. Thus, in this case the bank does not learn anything.

Proof of Proposition 5

Comparing equation (1.17) with equation (1.21), we can derive that the minimum productivity level in the separating equilibrium lies below the one in the pooling equilibrium:

$$\frac{4(1+\bar{r}_B)(F+F_{EX})\left[\underline{c}(\bar{r}_B-\bar{r}_{SC})+\bar{c}(1+\bar{r}_{SC})\right]}{p^2\bar{q}_2} < \frac{4(1+\bar{r}_B)F\left[\sigma(\bar{c}-\underline{c})(1+\bar{r}_{SC})+\underline{c}(1+\bar{r}_B)\right]}{(\sigma p)^2\bar{q}_2}$$

$$\sigma^2(\bar{c}-\underline{c})(1+\bar{r}_{SC})+\sigma^2\underline{c}(1+\bar{r}_B) < \sigma(\bar{c}-\underline{c})(1+\bar{r}_{SC})+\underline{c}(1+\bar{r}_B).$$

Firms with a productivity level $(1+\beta) \in \left[(1+\beta)^{pool}, (1+\beta)^{BC}\right]$ if $(1+\beta)^{pool} < (1+\beta)^{BC}$, can play both the separating or the pooling equilibrium. To say which equilibrium they prefer, we have to compare the expected profits of both equilibria. In the separating equilibrium, only the good suppliers participate. Therefore, we have to multiply the profits of the separating equilibrium with the probability that the supplier is good (σ). Only if the supplier is good are the costs incurred and the revenues realized. In the pooling equilibrium, both types of suppliers participate. The pooling equilibrium is never played by the exporter if:

$$\sigma\pi_{EX}^{sep} > \pi_{EX}^{pool}$$

$$(1-\sigma)(1+\bar{r}_B)(F+F_{EX}) > \frac{1}{2}p\sigma\left[x^{pool}-x^{sep}\right].$$

This is always fulfilled, as the quantity produced by the exporter is always smaller in the pooling equilibrium than in the separating equilibrium. Thus, the separating equilibrium Pareto-dominates the pooling equilibrium. Playing the pooling equilibrium only has disadvantages. The exporter incurs the fixed costs and pays part of the variable costs to the supplier but does not get any revenues from selling its products if the supplier is of bad quality. It can still be better than using only bank credit financing as the exporter only pays a part of the variable costs and not the whole variable costs to the supplier.

Every pooling equilibrium where $0 \leq \alpha(T) < \alpha^{sep}$ is Pareto-dominated by the separating equilibrium independent of beliefs. Furthermore, there does not exist any other pooling equilibrium with $\alpha > \alpha^{sep}$ as the bad supplier always makes negative profits.

A.2 Empirical Appendix

Table A.1: Description of Variables

Outcome variable	
BC	Logarithm of bank debt divided by total assets
BCliab	Logarithm of bank debt divided by total liabilities
Independent endog. regressors	
SC	Logarithm of trade accounts payable divided by total assets
SCliab	Logarithm of trade accounts payable divided by total liabilities
constrain	0/1 dummy whether firms feel financially constrained or not This is the case if either the question whether the firm is constrained in its production due to financial constraints is answered with "yes" or if the question on how the firm judges the willingness of banks to give credits to firms is answered with "restrictive".
Independent exog. regressors	
EXP	0/1 dummy whether firm exports its product at least 2 months in a year
labprod	Productivity of a firm measured as Log(sales/employees)
sales	Logarithm of sales
salesgrowth	Sales of period t divided by sales of period $t-1$ minus 1, $((\text{sales}_t/\text{sales}_{t-1})\text{-}1)$
tangibles	Logarithm of tangible assets divided by total assets

Table A.2: Robustness Check: Sales as Size Measure

	BC	BC	BC	BC
	(1)	(2)	(3)	(4)
SC	-3.431*	-4.145**	-3.572**	-3.896**
	(1.889)	(2.024)	(1.417)	(1.871)
tangibles	0.946	1.184*	1.003**	1.101*
	(0.615)	(0.698)	(0.491)	(0.641)
salesgrowth	-0.027	-0.0307*	-0.0277*	-0.0293*
	(0.0184)	(0.0185)	(0.0147)	(0.016)
constrain	7.212*	6.651*	6.336**	5.724
	(4.218)	(3.953)	(3.131)	(3.567)
constrain*SC	1.876	1.611		
	(1.332)	(1.307)		
constrain*SC*EXP			1.6548**	1.424
			(0.8354)	(1.0100)
EXP	-0.495	-0.548	-0.3792	-0.4058
	(0.738)	(0.734)	(0.6883)	(0.708)
sales	1.321	1.635*	1.383**	1.538*
	(0.815)	(0.908)	(0.609)	(0.817)
year dummies	yes	yes	yes	yes
Observations	1,720	1,720	1,720	1,720
No. of companies	410	410	410	410
No. of instruments	23	20	25	21
Lags used	2,3	2	2,3	2
AR(1)	0.003	0.007	0.001	0.004
AR(2)	0.327	0.327	0.233	0.263
AR(3)	0.812	0.912	0.706	0.829
Hansen (p-value)	0.832		0.970	

In columns 1 and 3, we use the two-step GMM estimator with Windmeijer finite sample corrected standard errors using the second and the third lag as instruments for the endogenous variables. In columns 2 and 4, we only use the second lag as instrument. ***, **, and * denote significance at 0.01, 0.05, and 0.10 levels, respectively.

Table A.3: Robustness Check: Scaling Supplier and Bank Credit by Total Liabilities

	BCliab	BCliab	BCliab	BCliab
	(1)	(2)	(3)	(4)
SCliab	-3.549**	-3.657**	-3.102**	-3.881**
	(1.720)	(1.633)	(1.291)	(1.532)
tangibles	1.153*	1.195*	1.008**	1.270**
	(0.634)	(0.856)	(0.498)	(0.609)
salesgrowth	-0.020	-0.020	-0.017	-0.019
	(0.013)	(0.012)	(0.012)	(0.013)
constrain	3.395	4.093	4.458*	3.479
	(4.009)	(3.214)	(2.663)	(2.764)
constrain*SCliab	1.121	1.186		
	(1.350)	(1.091)		
constrain*SCliab*EXP			1.356*	0.993
			(0.813)	(0.905)
EXP	0.309	0.332	0.271	0.352
	(0.335)	(0.338)	(0.321)	(0.344)
labprod	1.037*	1.063*	0.839	1.124**
	(0.609)	(0.589)	(0.442)	(0.552)
year dummies	yes	yes	yes	yes
Observations	1,720	1,720	1,720	1,720
No. of companies	410	410	410	410
No. of instruments	23	20	25	21
Lags used	2,3	2	2,3	2
AR(1)	0.005	0.005	0.002	0.003
AR(2)	0.330	0.340	0.305	0.292
AR(3)	0.998	0.869	0.754	0.785
Hansen (p-value)	0.666		0.656	

In columns 1 and 3, we use the two-step GMM estimator with Windmeijer finite sample corrected standard errors using the second and the third lag as instruments for the endogenous variables. In columns 2 and 4, we only use the second lag as instrument. ***, **, and * denote significance at 0.01, 0.05, and 0.10 levels, respectively.

B Appendix to Chapter 2

B.1 Theoretical Appendix

Proof of Proposition 1

Consider the strategies and beliefs specified in Proposition 1. For these strategies and beliefs to form a separating perfect Bayesian equilibrium, the following conditions have to hold. Recall that $\check{p}$ denotes the price the exporter demands for the good.

$$
\begin{aligned}
&(1)\ \lambda\hat{p}x - \alpha^H\check{p}x(1+\bar{r}_{Im}) - \lambda(1-\alpha^H)\check{p}x \geq 0\\
&(2)\ -\alpha^L\check{p}x(1+\bar{r}_{Im}) \geq 0\\
&(3)\ \lambda\hat{p}x - \alpha^H\check{p}x(1+\bar{r}_{Im}) - \lambda(1-\alpha^H)\check{p}x \geq -\alpha^L\check{p}x(1+\bar{r}_{Im})\\
&(4)\ -\alpha^L\check{p}x(1+\bar{r}_{Im}) \geq -\alpha^H\check{p}x(1+\bar{r}_{Im}) + \phi x\\
&(5)\ \lambda\hat{p}x - \alpha^H\check{p}x(1+\bar{r}_{Im}) - \lambda(1-\alpha^H)\check{p}x \geq -\alpha^H\check{p}x(1+\bar{r}_{Im}) + \phi x.
\end{aligned}
$$

Conditions (1) and (2) describe the participation constraints of the high- and the low-quality importer when extending the share α of the purchasing price $\check{p}x$ in advance. Conditions (3) and (4) are the incentive compatibility constraints of both importer types. Condition (5) rules out moral hazard by the high-quality importer guaranteeing that the high-quality importer breaks even when paying an informative amount of CIA. It is easily verified that by choosing

$$
\alpha^H = \alpha^{Sep} = \frac{\phi/(1+\bar{r}_{Im})}{\hat{p} + \frac{\phi}{(1+\bar{r}_{Im})} - \frac{\phi}{\lambda}}, \quad \alpha^L = 0, \quad \textit{and} \quad \check{p} = \hat{p} - \frac{\phi}{\lambda} + \frac{\phi}{(1+\bar{r}_{Im})},
$$

all five conditions are fulfilled in such a way that the exporter's pay-off is maximized.

If the bank observes the share $\alpha = \alpha^{Sep}$ given in advance, it updates its belief according to Bayes' Rule such that $Prob(H|\alpha^{Sep}) = 1$ and extends additional bank credit at the cheaper interest rate $\frac{(1+\bar{r}_B)}{\lambda}$. If $\alpha \leq \alpha^{Sep}$, the bank's best response is to deny bank credit, as otherwise $\pi_B < 0$ because its updated belief is that it faces the low-quality importer.

The high-quality importer's best response is to choose $\alpha^H = \alpha^{Sep}$ and the low-quality importer's best response is to set $\alpha^L = 0$. The high-quality importer does not deviate to $0 \leq \alpha < \alpha^{Sep}$ since the bank does not extend any bank credit in this case, $Prob\left(H|0 \leq \alpha < \alpha^{Sep}\right) = 0$. Thus, the export transaction does not take place and the high-quality importer pays the amount of CIA in vain, $\pi^H_{Im} \leq 0$. The high-quality type does not have an incentive to set $\alpha > \alpha^{Sep}$, because given $\check{p}$ and x^{Sep}_{Ex}, the importer makes negative profits when extending a higher amount of CIA. Hence, the high-quality importer does not have an incentive to deviate from α^{Sep}.

The low-quality importer does not have an incentive to choose $0 < \alpha^L < \alpha^{Sep}$, since the bank does not extend an additional bank credit in this case and $\pi^L_{Im} \leq 0$. Neither does it choose $\alpha^L \geq \alpha^{Sep}$ since $\pi^L_{Im} \leq 0$, as well.

Derivation of x^{Sep}_{Ex} and $(1+\beta)^{Sep}_{Ex}$

In the separating equilibrium, the exporter's profit function with partial CIA and bank credit financing is

$$\pi^{Sep}_{Ex} = \alpha^{Sep}\check{p}x + \lambda(1-\alpha^{Sep})\check{p}x - \lambda\frac{(1+\bar{r}_B)}{\lambda}\left(\frac{x^2}{2(1+\beta)} + F_{Ex} - \alpha^{Sep}\check{p}x\right) - \alpha^{Sep}\check{p}x. \quad \text{(B.1)}$$

Part of the total invoice amount is received with certainty up-front, the rest is received with probability λ in $t = 1$. The amount paid in advance is used to pay a part of the total costs of production, the rest is financed via bank credit. Bank credit is available at a lower interest rate since uncertainty with regard to the importer's quality type has vanished.

Combining $\alpha^{Sep} = \frac{\phi/(1+\bar{r}_{Im})}{\hat{p}+\frac{\phi}{(1+\bar{r}_{Im})}-\frac{\phi}{\lambda}}$ and $\check{p} = \hat{p} - \frac{\phi}{\lambda} + \frac{\phi}{(1+\bar{r}_{Im})}$ to maximize the exporter's profit given in (B.1), we can derive the optimal quantity exported and the minimum productivity level necessary for exporting:

$$x^{Sep}_{Ex} = \frac{(1+\beta)}{1+\bar{r}_B}\left[\lambda\hat{p} - \phi + \frac{\phi(1+\bar{r}_B)}{(1+\bar{r}_{Im})}\right],$$

$$(1+\beta)_{Ex}^{Sep} \equiv \frac{2(1+\bar{r}_B)^2 F_{Ex}}{\left[\lambda\hat{p} - \phi + \frac{\phi(1+\bar{r}_B)}{(1+\bar{r}_{Im})}\right]^2}.$$

Proof of Proposition 2

Consider the strategies and beliefs specified in Proposition 2. For these strategies and beliefs to form a pooling perfect Bayesian equilibrium, the following conditions have to hold.

$$\begin{aligned}
&(1)\ \lambda\hat{p}x - \alpha^{Pool}\check{p}x(1+\bar{r}_{Im}) - \lambda(1-\alpha^{Pool})\check{p}x \geq 0\\
&(2)\ -\alpha^{Pool}\check{p}x(1+\bar{r}_{Im}) + \phi x \geq 0\\
&(3)\ \lambda\hat{p}x - \alpha^{Pool}\check{p}x(1+\bar{r}_{Im}) - \lambda(1-\alpha^{Pool})\check{p}x \geq -\alpha\check{p}x(1+\bar{r}_{Im})\\
&(4)\ -\alpha^{Pool}\check{p}x(1+\bar{r}_{Im}) + \phi x \geq -\alpha\check{p}x(1+\bar{r}_{Im})\\
&(5)\ \lambda\hat{p}x - \alpha^{Pool}\check{p}x(1+\bar{r}_{Im}) - \lambda(1-\alpha^{Pool})\check{p}x \geq -\alpha^{Pool}\check{p}x(1+\bar{r}_{Im}) + \phi x,
\end{aligned}$$

where α denotes any share of CIA extended by the importer except α^{Pool}. It is easily verified that with the share $\alpha^{Pool} = \frac{\phi/(1+\bar{r}_{Im})}{\hat{p}+\frac{\phi}{(1+\bar{r}_{Im})}-\frac{\phi}{\lambda}}$ and $\check{p} = \hat{p} - \frac{\phi}{\lambda} + \frac{\phi}{(1+\bar{r}_{Im})}$ the participation constraints and the incentive compatibility constraints are satisfied for both types of importers and the pay-off of the exporter is maximized. Note that only for $\alpha^{Pool} = \frac{\phi/(1+\bar{r}_{Im})}{\hat{p}+\frac{\phi}{(1+\bar{r}_{Im})}-\frac{\phi}{\lambda}}$ and $\check{p} = \hat{p} - \frac{\phi}{\lambda} + \frac{\phi}{(1+\bar{r}_{Im})}$ the exporter can set the profits of both importer types equal to 0.

Neither type of importer has an incentive to deviate from $\alpha^{Pool} = \frac{\phi/(1+\bar{r}_{Im})}{\hat{p}+\frac{\phi}{(1+\bar{r}_{Im})}-\frac{\phi}{\lambda}}$. They will not deviate to $\alpha > \alpha^{Pool}$ since, given the price $\check{p}$ for the exporter's good, importer profits decrease in α. Furthermore, they will not unilaterally decrease α as the transaction will not take place then. This holds independently for any equilibrium belief of the bank, $Prob\left(H|\alpha > \alpha^{Pool}\right) \in [0,1]$ since $\check{p}$ is given. For $Prob\left(H|\alpha > \alpha^{Pool}\right) = 1$, the bank offers the cheaper bank credit to the exporter. However, the exporter will charge the same price and thus the high-quality type does not have an incentive to deviate to $\alpha^H > \alpha^{Pool}$. For $Prob\left(H|\alpha > \alpha^{Pool}\right) = 0$, the bank does not extend any bank credit and the transaction does not take place. For every belief $Prob\left(H|\alpha > \alpha^{Pool}\right) \in [0,1]$, the exporter will charge the same price. Hence, neither the high-quality importer nor the

low-quality importer has an incentive to deviate to $\alpha^H > \alpha^{Pool}$.

Derivation of x_{Ex}^{Pool} and $(1+\beta)_{Ex}^{Pool}$

In the pooling equilibrium with $\alpha^{Pool} = \alpha^{Sep}$, the bank has the belief $Prob(H|\alpha^{Pool}) = \mu$ and $(1+r_B) = \frac{(1+\bar{r}_B)}{\lambda\mu}$. The price for the export good is given by $\check{p}$. The exporter's profit function with partial CIA and bank credit financing is

$$\begin{aligned}\pi_{Ex}^{Pool} =& \alpha^{Pool}\check{p}x + \lambda\mu(1-\alpha^{Pool})\check{p}x - \lambda\mu\frac{(1+\bar{r}_B)}{\lambda\mu}\left(\frac{x^2}{2(1+\beta)} + F_{Ex} - \alpha^{Pool}\check{p}x\right) \\ & - \alpha^{Pool}\check{p}x. \end{aligned} \tag{B.2}$$

The optimal quantity exported and the minimum productivity level required for exporting are

$$x_{Ex}^{Pool} = \frac{(1+\beta)}{1+\bar{r}_B}\left[\mu(\lambda\hat{p} - \phi) + \frac{\phi(1+\bar{r}_B)}{(1+\bar{r}_{Im})}\right],$$

$$(1+\beta)_{Ex}^{Pool} \equiv \frac{2(1+\bar{r}_B)^2 F_{Ex}}{\left[\mu(\lambda\hat{p} - \phi) + \frac{\phi(1+\bar{r}_B)}{(1+\bar{r}_{Im})}\right]^2}.$$

Proof of Proposition 3

A comparison of (2.11) with (2.13), reveals that $(1+\beta)_{Ex}^{Sep} < (1+\beta)_{Ex}^{Pool}$ since $\mu < 1$. Similarly, from comparing (2.13) with (2.5) we find that $(1+\beta)_{Ex}^{Pool} < (1+\beta)_{Ex}^{BC}$ since $0 < \frac{\phi(1+\bar{r}_B)}{(1+\bar{r}_{Im})}$. Therefore,

$$(1+\beta)_{Ex}^{Sep} < (1+\beta)_{Ex}^{Pool} < (1+\beta)_{Ex}^{BC}.$$

Proof of Proposition 4

Firms in the first category can export with pure bank credit financing or combined CIA financing. Partial CIA financing allows the exporter to charge a higher price than in the

case of pure bank financing. It is straightforward to see that

$$p < \check{p}.$$

A higher price leads to higher expected revenues and higher expected profits since the total costs of production remain constant.

Consider for example the case of partial CIA financing in the pooling equilibrium. The exporter faces the same type uncertainty as with pure bank financing and pays the same bank interest rate. However, the exporter receives a higher price from partial CIA financing and therefore makes higher profits than with pure bank financing.

Proof of Proposition 5

Whether exporters with $(1+\beta) \geq (1+\beta)_{Ex}^{Pool}$ prefer to play the pooling or the separating equilibrium depends on the expected profits in both equilibria. A transaction with an informative signal in the separating equilibrium occurs with probability μ since with probability $(1-\mu)$ the importer is of low quality and is not willing to extend an informative signal. Thus, expected profits in the separating equilibrium amount to $\mu\pi_{Ex}^{Sep}$. A transaction with an uninformative signal in the pooling equilibrium always takes place since every importer type is able to provide the uninformative fraction of CIA. Exporting firms in the first and second group receive a higher payoff in a separating equilibrium if

$$\mu\pi_{Ex}^{Sep} > \pi_{Ex}^{Pool}.$$

This is fulfilled if

$$2\left(1-\mu\right)\left(1+\bar{r}_B\right)^2 F_{Ex} > (1+\beta)\left[\left[\mu\left(\lambda\hat{p}-\phi\right)+\phi\frac{1+\bar{r}_B}{1+\bar{r}_{Im}}\right]^2-\mu\left[\lambda\hat{p}-\phi+\phi\frac{1+\bar{r}_B}{1+\bar{r}_{Im}}\right]^2\right]. \qquad \text{(B.3)}$$

For given values of $(1+\beta)$ and μ, (B.3) holds if

$$1+\bar{r}_{Im} > \pm\sqrt{\frac{\phi^2(1+\bar{r}_B)^2}{\frac{2(1+\bar{r}_B)^2 F_{Ex}}{(1+\beta)}+\mu\left(\lambda\hat{p}-\phi\right)}}.$$

We can rule out the negative value since $(1+\bar{r}_{Im}) \in [1,\infty)$. Thus, there exists a unique threshold of $(1+\bar{r}_{Im})$.

For given values of $(1+\beta)$ and $(1+\bar{r}_{Im})$, (B.3) holds if

$$\mu > \frac{(1+\bar{r}_B)^2(1+\beta)\phi^2 - 2F_{Ex}(1+\bar{r}_B)^2(1+\bar{r}_{Im})^2}{(1+\bar{r}_{Im})^2(1+\beta)(-\hat{p}\lambda+\phi)^2}.$$

Consequently, these exporters prefer playing the separating perfect Bayesian equilibrium if quality uncertainty is low (high μ) and the importer's refinancing costs are high. They prefer playing the pooling perfect Bayesian equilibrium if quality uncertainty is high (low μ) and the importer's refinancing costs are low.

Note further that for given values of μ and $(1+\bar{r}_{Im})$, (B.3) holds if

$$(1+\beta) < \frac{2\,(1-\mu)\,(1+\bar{r}_B)^2 F_{Ex}}{\left[\left[\mu\,(\lambda\hat{p}-\phi)+\phi\frac{1+\bar{r}_B}{1+\bar{r}_{Im}}\right]^2 - \mu\left[\lambda\hat{p}-\phi+\phi\frac{1+\bar{r}_B}{1+\bar{r}_{Im}}\right]^2\right]}.$$

Thus, the pooling equilibrium becomes more preferable, the higher the productivity of the firm.

B.2 Empirical Appendix

Table B.1: Decomposition of Firms according to Sectors

Sector	Number of firms	Share of firms (%)
Mining and quarrying	10	0.84
Construction	239	19.98
Manufacturing	221	18.48
Transportation, storage and communication	73	6.10
Wholesale, retail trade, and repairs	267	22.32
Real estate, renting and business services	244	20.40
Hotels and restaurants	66	5.52
Other services	76	6.35
Total	1,196	100

Table B.2: Description of Variables

Outcome variable	
Exp	0/1 dummy for firms that sell a positive share of their sales abroad
Independent endog. regressors	
DCIArec	0/1 dummy for firms that receive a positive share of their sales before delivery of the products or services
LogCIArec	Log percentage share of total sales received before delivery of the products or services
Independent exog. regressors	
LogAge	Log firm age in years
LogSize	Log number of full-time employees
LogLabprod	Log(total sales/number of employees)
CompNum	Number of competitors in the national market with regard to the main product line or main line of services (range 0, 1, 2, 3, or 4 and more, coded as 4)
ForPressure	0/1 dummy for firms for which pressure from international competitors is fairly or very important when making key decisions about their business with regard to developing new products or services and markets
Univeduc	Percentage of workforce that has a university education or higher
Foreign	0/1 dummy for firms of which 10% or more is foreign owned
Instruments	
PublicInfo	0/1 dummy for firms for which trade fairs and other public sources of information are extremely important as potential source about new customers
Specificity	Ordinal variable that is equal to: *1* for firms whose customers buy from competitors instead if the firm raises the price of the main product line or main service line by 10% *2* for firms whose customers continue to buy from the firm but at much lower quantities if the firm raises the price of the main product line or main service line by 10% *3* for firms whose customers continue to buy from the firm but at slightly lower quantities if the firm raises the price of the main product line or main service line by 10% *4* for firms whose customers continue to buy from the firm in the same quantities if the firm raises the price of the main product line or main service line by 10%

All variables are measures or projected estimates of firm characteristics for the year 2004.

Table B.3: Effect of $DCIArec$ on Export Participation - 2SLS

	2SLS		2SLS		2SLS	
	DCIArec	Exp	DCIArec	Exp	DCIArec	Exp
	(1)	(2)	(3)	(4)	(5)	(6)
DCIArec		0.236		0.774**		0.438**
		(0.233)		(0.392)		(0.206)
LogAge	-0.0422**	0.0129	-0.0448**	0.0388	-0.0415**	0.0214
	(0.0203)	(0.0164)	(0.0201)	(0.0267)	(0.0203)	(0.0174)
LogSize	0.0475***	0.0299**	0.0501***	0.00234	0.0469***	0.0198
	(0.0103)	(0.0145)	(0.0103)	(0.0229)	(0.0103)	(0.0137)
LogLabprod	0.0310	0.0391**	0.0391**	0.0175	0.0318*	0.0317**
	(0.0189)	(0.0152)	(0.0191)	(0.0232)	(0.0190)	(0.0159)
Univeduc	0.00290***	0.000305	0.00286***	-0.00104	0.00282***	-0.000305
	(0.000801)	(0.000845)	(0.000777)	(0.00138)	(0.000790)	(0.000832)
CompNum	-0.00463	0.00400	-0.000142	0.00923	0.00234	0.00488
	(0.0140)	(0.00855)	(0.0142)	(0.0132)	(0.0143)	(0.00977)
ForPressure	-0.0140	0.144***	0.00308	0.147***	-0.00712	0.145***
	(0.0333)	(0.0260)	(0.0333)	(0.0350)	(0.0333)	(0.0284)
Foreign	-0.0320	0.342***	-0.0455	0.371***	-0.0325	0.348***
	(0.0516)	(0.0452)	(0.0508)	(0.0591)	(0.0515)	(0.0484)
PublicInfo	0.0966***				0.0941***	
	(0.0326)				(0.0328)	
Specificity			0.0376**		0.0372**	
			(0.0152)		(0.0153)	
Observations	1,124	1,124	1,135	1,135	1,124	1,124
R^2	0.060	0.322	0.059	-0.484	0.065	0.123
F-Stat		36.05		19.27		28.99
1^{st} Stage F-Stat	8.76		6.09		7.57	
Hansen J-Stat					1.84	
χ^2 p-value					(0.1753)	

Sector fixed effects are included in all regressions. Heteroskedastic robust standard errors are in parentheses. ***, **, and * denote significance at 0.01, 0.05, and 0.10 levels, respectively.

Table B.4: Effect of *LogCIArec* on Export Participation - 2SLS

	2SLS		2SLS		2SLS	
	LogCIArec	Exp	LogCIArec	Exp	LogCIArec	Exp
	(1)	(2)	(3)	(4)	(5)	(6)
LogCIArec		0.0702		0.216**		0.130**
		(0.0691)		(0.0987)		(0.0585)
LogAge	-0.117**	0.0112	-0.124**	0.0310	-0.114*	0.0181
	(0.0585)	(0.0154)	(0.0582)	(0.0220)	(0.0585)	(0.0162)
LogSize	0.123***	0.0325***	0.130***	0.0131	0.121***	0.0247**
	(0.0283)	(0.0124)	(0.0284)	(0.0166)	(0.0282)	(0.0117)
LogLabprod	0.0825	0.0406***	0.107*	0.0246	0.0852	0.0347**
	(0.0547)	(0.0145)	(0.0552)	(0.0192)	(0.0549)	(0.0151)
Univeduc	0.00871***	0.000379	0.00850***	-0.000660	0.00841***	-0.000160
	(0.00237)	(0.000784)	(0.00229)	(0.00110)	(0.00233)	(0.000750)
CompNum	-0.0349	0.00536	-0.0208	0.0136	-0.0103	0.00737
	(0.0420)	(0.00902)	(0.0424)	(0.0130)	(0.0422)	(0.0101)
ForPressure	-0.0853	0.147***	-0.0309	0.156***	-0.0611	0.150***
	(0.0955)	(0.0259)	(0.0952)	(0.0323)	(0.0956)	(0.0277)
Foreign	0.000447	0.334***	-0.0289	0.342***	-0.00142	0.334***
	(0.153)	(0.0451)	(0.151)	(0.0540)	(0.153)	(0.0481)
PublicInfo	0.325***				0.316***	
	(0.0947)				(0.0948)	
Specificity			0.135***		0.131***	
			(0.0444)		(0.0447)	
Observations	1,124	1,124	1,135	1,135	1,124	1,124
R^2	0.063	0.333	0.061	-0.177	0.071	0.188
F-Stat		36.30		24.49		31.03
1^{st} Stage F-Stat	11.76		9.20		10.33	
Hansen J-Stat					1.78	
χ^2 p-value					(0.1818)	

Sector fixed effects are included in all regressions. Heteroskedastic robust standard errors are in parentheses. ***, **, and * denote significance at 0.01, 0.05, and 0.10 levels, respectively.

C Appendix to Chapter 3

Table C.1: Decomposition of Firms according to Countries

Country	Number of Firms	Share of Firms (%)
Albania	17	0.88
Armenia	99	5.12
Azerbaijan	106	5.48
Belarus	71	3.67
Bosnia	63	3.26
Bulgaria	118	6.10
Croatia	50	2.58
Czech Republic	17	0.88
Estonia	66	3.41
FYROM	87	4.50
Georgia	68	3.51
Hungary	62	3.20
Kazakhstan	77	3.98
Kyrgyz Republic	71	3.67
Latvia	57	2.95
Lithuania	45	2.33
Moldova	128	6.61
Montenegro	5	0.26
Poland	79	4.08
Romania	92	4.75
Russia	57	2.95
Serbia	111	5.74
Slovakia	33	1.71
Slovenia	57	2.95
Tajikistan	67	3.46
Ukraine	120	6.20
Uzbekistan	112	5.79
Total	1,935	100

Table C.2: Decomposition of Firms according to Sectors

Sector	Number of Firms	Share of Firms (%)
Manufacturing	801	41.40
Retail services	366	18.91
Other services	768	39.69
Total	1,935	100

Table C.3: Mean Difference Test on Mean Use of CIA, 2005 and 2009

Panel A: Development of Overall CIA Use

	2005	2009	Difference
Share of firms receiving CIA (%)	52.0	57.0	5.0***
Mean share of CIA received (%)	18.0	24.6	6.6***

Panel B: Differences in CIA Use by Exporters and Non-Exporters, 2005-2009

		Exporters	
	2005	2009	Difference
Share of exporters receiving CIA (%)	62.6	65.2	2.6
Mean share of CIA received (%)	21.4	20.9	-0.5
		Non-Exporters	
	2005	2009	Difference
Share of non-exporters receiving CIA (%)	48.2	54.6	6.4***
Mean share of CIA received (%)	16.9	26.0	9.1***

Panel A provides results from mean difference tests of CIA use in the pre-crisis and the crisis year. Welch's formula is used to allow for unequal variances in both groups (Welch, 1947). Panel B provides results from mean difference tests of CIA use in the pre-crisis and the crisis year according to exporter status. ***, **, and * denote significance at 0.01, 0.05, and 0.10 levels, respectively.

Table C.4: Description of Variables

Outcome variables	
Exp	Dummy equal to 1 if firm sells a positive amount of its sales abroad and 0 otherwise
ΔExpS	First difference of export share (%) between 2009 and 2005
Binary treatment indicators	
DCIA	Dummy equal to 1 if firm receives a positive amount of its sales before delivery of the good and 0 otherwise
SwitchCIA	Dummy equal to 1 if firm switches from no CIA in 2005 to a positive share of CIA received in 2009 and 0 if firm does not receive CIA in either year
IncrCIA	Dummy equal to 1 if firm receives the same or a higher share of CIA in 2009 compared to 2005 and 0 if it receives a lower share
Covariates	
Foreign	Dummy equal to 1 if more than 50% of the firm is owned by a foreign private individual, company or organization and 0 otherwise
Iso	Dummy equal to 1 if firm has an internationally recognized quality certificate and 0 otherwise
LogAge	Log firm age
LogLabprod	Log [Sales (converted in USD) / number of full-time employees]
LogSize	Log number of full-time employees
Ownerconc	Ownership share held by largest owner of the firm (%)
Transobs	Dummy equal to 1 if transport is a moderate, major or very severe obstacle to the current operations of the firm and 0 if transport is no or a minor obstacle
Weak	Dummy equal to 1 if firm tends to disagree or strongly disagrees that the court system is able to enforce its decisions and 0 if firm agrees or tends to agree that the court system is able to enforce its decisions
Additional controls for robustness checks	
Audit	Dummy equal to 1 if firm has its financial statements checked by an external auditor and 0 otherwise
Emplgrowth	Growth rate of employees over the last three years
Fincons_{2005}	Dummy equal to 1 if access to finance in 2005 (availability and cost, interest rates, fees, and collateral requirements) is a major or very severe obstacle to the business of the firm and 0 if access to finance is no, a minor, or a moderate obstacle

Table C.5: Hypothesis 1: Assessment of Matching Quality for Probit 1 and 2

Matching Estimator	Treatment	Year	Average % bias		$p > \chi^2$		Specification
			Before	After	Before	After	
4 NN	*DCIA*	2005	11.1	2.7	0.000	0.996	Probit 1
		2009	10.0	3.4	0.000	0.982	Probit 1
		2005	11.8	3.6	0.000	0.995	Probit 2
		2009	9.9	3.3	0.000	0.910	Probit 2
Radius (caliper 0.01)		2005	11.1	2.1	0.000	1.0	Probit 1
		2009	10.0	2.9	0.000	1.0	Probit 1
		2005	11.8	3.3	0.000	0.999	Probit 2
		2009	9.9	3.1	0.000	0.991	Probit 2
Epan. kernel		2005	9.4	1.8	0.000	1.0	Probit 1
		2009	7.9	2.2	0.000	1.0	Probit 1
		2005	11.8	3.3	0.000	0.999	Probit 2
		2009	8.9	2.3	0.000	0.991	Probit 2

The average (standardised) percentage bias is defined as $ASB = \frac{1}{M}\sum_{l=1}^{M} SB(X_l)$, where $SB(X_l) = 100 * \left(\bar{X}_{l,D=1} - \bar{X}_{l,D=0}\right) / \left(\sqrt{\left(V_{D=1}(X_l) - V_{D=0}(X_l)\right)/2}\right)$ for covariate X_l, $l = 1, .., M$ (Rosenbaum and Rubin, 1985). A low value of this statistic indicates good matching quality. The p-value is derived from the likelihood-ratio test of joint insignificance of all regressors in a regression of the predicted propensity score on all covariates. Joint insignificance after matching indicates a high matching quality.

Table C.6: Robustness Check Hypothesis 1: Adding Controls

Panel A: Adding Audit and Emplgrowth

Matching estimator	Outcome	Treatment	Year	Probit 1		Probit 2	
4 NN	*Exp*	*DCIA*	2005	0.0581**	(0.0293)	0.0307	(0.0358)
			2009	0.1023***	(0.0304)	0.1123***	(0.0323)
Radius (caliper 0.01)			2005	0.0657**	(0.0307)	0.0686**	(0.0326)
			2009	0.1020***	(0.0265)	0.0876***	(0.0305)
Epan. kernel			2005	0.0645**	(0.0321)	0.0578	(0.0356)
(bandwidth 0.01)			2009	0.0993***	(0.0252)	0.0953***	(0.0316)
All observations			2005	1,595		1,235	
Treated observations				831		636	
All observations			2009	1,379		1,204	
Treated observations				789		701	

Panel B: Adding $Fincons_{2005}$ in 2009

Matching estimator	Outcome	Treatment	Year	Probit 1		Probit 2	
4 NN	*Exp*	*DCIA*	2009	0.0899***	(0.0299)	0.1023***	(0.0318)
Radius (caliper 0.01)			2009	0.0668**	(0.0291)	0.0876***	(0.0305)
Epan. kernel (bandwidth 0.01)			2009	0.0755***	(0.0264)	0.0989***	(0.0308)
All observations			2009	1,398		1,221	
Treated observations				798		709	

Estimation is done for the common support region only to ensure sufficient overlap between treated and untreated individuals. All matching algorithms sufficiently reduce bias between treated and untreated observations (statistics not reported). Standard errors are in parentheses. Bootstrapped robust standard errors are calculated for radius and kernel matching. ***, **, and * denote significance at 0.01, 0.05, and 0.10 levels, respectively.

Table C.7: Hypothesis 2: Assessment of Matching Quality for Probit 1 and 2

Matching estimator	Treatment	Average % bias		$p > \chi^2$		Specification
		Before	After	Before	After	
4 NN	*SwitchCIA*	11.4	3.7	0.000	1.0	Probit 1
		11.7	3.6	0.000	1.0	Probit 2
Radius (caliper 0.01)		11.4	3.3	0.000	1.0	Probit 1
		11.7	2.7	0.000	1.0	Probit 2
Epan. kernel		11.4	3.5	0.000	1.0	Probit 1
		10.4	1.6	0.000	1.0	Probit 2

Table C.8: Robustness Check Hypothesis 2: ATT of *IncrCIA* on the Difference in Export Share

					Exporters only	
Matching estimator	Outcome	Treatment	Probit 1	Probit 2	Probit 1	Probit 2
4 NN	$\Delta ExpS$	*IncrCIA*	3.4101**	2.8961*	6.800*	8.5095*
			(1.3917)	(1.6992)	(3.8190)	(4.7503)
Radius (caliper 0.01)			3.1864**	2.7846*	6.2389	9.8935*
			(1.4648)	(1.448)	(3.7890)	(5.5556)
Epan. kernel			3.1102**	3.0439**	5.6828	10.5127*
(bandwidth 0.01)			(1.5094)	(1.4705)	(3.7998)	(5.6699)
All observations			1,612	1,227	494	382
Treated observations			1,132	878	304	237

Estimation is done for the common support region only to ensure sufficient overlap between treated and untreated individuals. Standard errors are in parentheses. Bootstrapped robust standard errors are calculated for kernel and radius matching. ***, **, and * denote significance at 0.01, 0.05, and 0.10 levels, respectively.

Table C.9: Robustness Check Hypothesis 2: Regression-Adjusted Matching

ATT of SwitchCIA			
Matching Estimator	Treatment	Probit 1	Probit2
4 NN	*SwitchCIA*	5.0423**	6.214**
		(2.4176)	(3.0406)
Radius (caliper 0.01)		4.7543**	7.0873**
		(2.3675)	(3.0998)
Epan. kernel		4.7543**	7.0873**
(bandwidth 0.01)		(2.3675)	(3.0998)
All observations		580	392
Treated observations		257	173

Estimates for ATTs are based on a weighted least squares regression of $\Delta ExpS$ on the treatment and the covariates in first differences. The weights are derived from the precedent matching process of each specification. Robust standard errors are in parentheses. ***, **, and * denote significance at 0.01, 0.05, and 0.10 levels, respectively.

D Appendix to Chapter 4

D.1 Description of the Product Classification

In the database, product names as reported by the firms are assigned a 20-digit code based on an internal classification system by CMIE. In fact, one product code is usually linked to several different product names in the database. We first standardize product names according to their internal code. Since we are only interested in the products a firm actually manufactures, we delete product codes that refer to retail trading activities, rental income and other services performed. In doing so, we eliminate 316 different products. We next allocate each product code the corresponding SITC 3-digit category in order to determine the sophistication level of a product. This task was performed manually by a research assistant. We double checked the reclassification and sorted out inconsistencies. Table D.1 provides an example of the concordance between the 20-digit internal code and the SITC Rev. 3 classification. Product names often differ in spelling (Fishing net vs. Fish net) or are more or less precise (Conveyors vs. Discharge Conveyor). We manage to classify 82% of all firm-product-year observations in our subsample at the 3-digit level. These account for 88% of total product output. For the remaining share of 12% of total output we cannot determine the corresponding concordance because sufficient information on the type of the product is not available. Assigning products to the 4- or 5-digit level would certainly be more satisfactory and better reflect single products compared to a more aggregate classification. However, given that we only observe the often rather uninformative names of the products this is infeasible without sacrificing the precision of our concordance.

Table D.1: Example of Reclassification from CMIE Codes to SITC Categories

CMIE product code	Name of products	3-digit	SITC description
14040501000000000000	Conveyor systems Conveyors Crusher Feed Conveyor Discharge Conveyor	744	Mechanical handling equipment, and parts thereof, n.e.s.
69907080100000000000	Fishing net Fish net Fish Knitted Fabrics Fishnet Fabrics	657	Special yarns, special textile fabrics and related products

Table D.2: Correspondence between ISIC Rev. 4 and ISIC Rev. 3 for Manufacturing Industries

ISIC Rev. 4 (2-digit)		ISIC Rev. 3 (2-digit)		I-O cat.	% firms
Code	Manufacture of	Code	Name		
10	Food products	15	Food products, beverages		
11	Beverages	15	Food products, beverages	C1516	13.10
12	Tobacco products	16	Tobacco		
13	Textiles	17	Textiles		
14	Wearing apparel	18	Textile products	C171819	14.06
15	Leather and related products	19	Leather and footwear		
16	Wood, wood and cork products, exc. furniture	20	Wood and products of wood and cork	C20	0
17	Paper and paper products	21	Pulp, paper, paper products	C2122	0
18	Printing and reproduction of recorded media	22	Printing and publishing		
19	Coke and refined petroleum products	23	Coke, refined petroleum, nuclear fuel	C23	0.98
20	Chemicals and chemical products	24	Chemicals and chemical products	C24	21.63
21	Pharmaceuticals, medic., chem., and botan. products	24	Chemicals and chemical products		
22	Rubber and plastics products	25	Rubber and plastics products	C25	6.52
23	Other non-metallic mineral products	26	Other non-metallic mineral products	C26	4.59
24	Basic metals	27	Basic metals	C27	11.14
25	Fabricated metal products, exc. machinery and equipment	28	Fabricated metal products exc. machinery and equipment	C28	3.56
26	Computer, electronic and optical products	30	Office, accounting and computing machinery	C30	
		32	Radio, television and communication equipment	C32	3.89
		33	Medical, precision and optical instruments	C33	
27 (exc. 2570)	Electrical equipment	31	Electrical machinery and apparatus n.e.c	C31	4.45
2750	Domestic appliances	29	Machinery and equipment n.e.c	C29	7.18
28	Machinery and equipment n.e.c.	29			
29	Motor vehicles, trailers and semi-trailers	34	Motor vehicles, trailers and semi-trailers	C34	0.32
30	Other transport equipment	35	Other transport equipment	C35	6.76
31	Furniture	36	Manufacturing n.e.c		
32	Other manufacturing	36		C3637	1.82
33	Repair and installation of machinery and equipment	37	Recycling		
Total					100

The industries captured by the OECD input-output tables are based on 23 2-digit ISCI Rev. 3 categories but have already been aggregated to 18 industries. From the 18 industries defined in the OECD input-output tables we combined industries C30, C32, and C33 into one industry since these three industries correspond to one ISIC Rev.4 industry (code 26).

D.2 Empirical Appendix

Table D.3: Description of Variables

Outcome variables	
HSP	Dummy equal to 1 if firm produces at least one product from the top quartile of the sophistication distribution and 0 otherwise
UpHSP	Dummy equal to 1 if firm switches from the production of a less sophisticated product to producing a HSP. It is equal to 0 for firms that never manufacture a HSP.
LogEXS	Log average product sophistication level of firm
Spillover measures	
Horizontal	Extent of presence of multinational companies in own industry
Backward	Extent of presence of multinational companies in downstream industries
Forward	Extent of presence of multinational companies in upstream industries
Other variables	
Exports	Export volume of firm
Foreign	Dummy equal to 1 if firm is owned by a foreign entity and 0 otherwise
ForeignShare	Share of equity held by foreign investors
HHI	Herfindahl index of industry concentration
LogAge	Log age of firm
LiqRatio	Liquidity ratio of firm, defined as current assets less current liabilities over total assets
LogRawMatExp	Log raw material expenditures of firm
LogSales	Log sales of firm
LogTFP	Log total factor productivity of firm, calculated as residual from industry-wise OLS regressions of LogSales on LogWagebill, LogRawMatExp, and LogTotalAssets
LogTotalAssets	Log total assets of firm
LogWagebill	Log wage bill of firm

Table D.4: Effect of FDI Spillovers on extent of HSP Manufacturing - First and Second Differences

	$LogEXS$			
	First differences		Second differences	
	All firms	Domestic	All firms	Domestic
	(1)	(2)	(3)	(4)
Horizontal	-0.00258	-0.00288	-0.00601**	-0.00662**
	(0.00223)	(0.00243)	(0.00238)	(0.00254)
Backward	0.0198***	0.0173**	0.0187**	0.0148*
	(0.00750)	(0.00837)	(0.00774)	(0.00804)
Forward	-0.0130	-0.0112	-0.0215	-0.0199
	(0.0195)	(0.0210)	(0.0158)	(0.0167)
LogTFP	-0.0267	-0.0214	0.0241	0.0209
	(0.0436)	(0.0447)	(0.0461)	(0.0477)
ForeignShare	0.00113		0.00197**	
	(0.000732)		(0.000959)	
LogAge	-0.137	-0.142	-0.129	-0.138
	(0.118)	(0.124)	(0.0943)	(0.102)
LogAge^2	-0.0239	-0.0413	0.00576	0.00283
	(0.0688)	(0.0698)	(0.0394)	(0.0415)
LogWagebill	0.164***	0.166***	0.169***	0.174***
	(0.0252)	(0.0260)	(0.0249)	(0.0258)
HHI	-0.000166*	-0.000169*	-0.000145	-0.000160
	(8.95e-05)	(9.73e-05)	(0.000101)	(0.000104)
Observations	31,590	29,668	26,071	24,482
R^2	0.006	0.006	0.009	0.010

This table provides results from regressions in first (columns 1 and 2) and second (columns 3 and 4) differences. Standard errors are clustered at the industry-year level and time fixed effects are included. ***, **, and * denote significance at 0.01, 0.05, and 0.10 levels, respectively.

Table D.5: Effect of FDI Spillovers from Publicly Listed Firms

	HSP		$UpHSP$	
	All firms	Domestic	All firms	Domestic
	(1)	(2)	(3)	(4)
Horizontal	-0.00120	-0.000730	-0.000465	-0.000261
	(0.00127)	(0.00135)	(0.00105)	(0.00103)
Backward	0.00722*	0.00694*	0.00591**	0.00709***
	(0.00393)	(0.00420)	(0.00256)	(0.00269)
Forward	-0.0125***	-0.0108**	-0.00283	-0.00422
	(0.00439)	(0.00449)	(0.00269)	(0.00289)
LogAge	0.0221***	0.0157***	-0.00806***	-0.00752***
	(0.00358)	(0.00365)	(0.00171)	(0.00153)
LogWagebill	0.0249***	0.0248***	0.00809***	0.00828***
	(0.00143)	(0.00154)	(0.00106)	(0.00108)
LogTFP	0.00852*	0.0125**	-0.00305	-0.00205
	(0.00467)	(0.00486)	(0.00234)	(0.00240)
Foreign	0.00249		-0.0100	
	(0.00776)		(0.00619)	
HHI	-3.52e-06	5.65e-06	-2.92e-05*	-3.15e-05*
	(1.91e-05)	(2.12e-05)	(1.59e-05)	(1.70e-05)
Observations	36,858	34,632	21,538	20,586
Log-Likelihood	-18,600	-17,398	-3,705	-3,489

Columns 1 and 2 provide average marginal effects obtained from a pooled probit model. Columns 3 and 4 provide average marginal effects obtained from a clog-log model. Time, industry, and state fixed effects are included. Standard errors are clustered at the industry-year level. ***, **, and * denote significance at 0.01, 0.05, and 0.10 levels, respectively.

Table D.6: Controlling for the Liquidity Situation of a Firm

	HSP		*UpHSP*	
	All firms	Domestic	All firms	Domestic
	(1)	(2)	(3)	(4)
Horizontal	0.000508	0.000406	0.000632	0.000509
	(0.000337)	(0.000379)	(0.000460)	(0.000442)
Backward	0.00353**	0.00304*	0.00317**	0.00296**
	(0.00167)	(0.00175)	(0.00147)	(0.00149)
Forward	-0.0102**	-0.00835*	-0.00324	-0.00338
	(0.00484)	(0.00496)	(0.00277)	(0.00287)
ForeignShare	-0.000160	-0.000274	-9.57e-05	-6.41e-05
	(9.80e-05)	(0.000333)	(7.40e-05)	(0.000317)
LogAge	0.0227***	0.0158***	-0.0111***	-0.0103***
	(0.00365)	(0.00381)	(0.00191)	(0.00177)
LogWagebill	0.0263***	0.0258***	0.00809***	0.00831***
	(0.00152)	(0.00171)	(0.00115)	(0.00114)
LogTFP	0.0118**	0.0156***	-0.00362	-0.00242
	(0.00479)	(0.00497)	(0.00272)	(0.00275)
L.LiqRatio	0.000702	-0.00471	0.00302	0.00207
	(0.00752)	(0.00772)	(0.00444)	(0.00438)
HHI	9.50e-07	1.23e-05	-1.90e-05	-1.91e-05
	(1.85e-05)	(2.13e-05)	(1.85e-05)	(1.91e-05)
Observations	33,250	31,197	19,268	18,411
Log-Likelihood	-16,872	-15,768	-3,426	-3,224

Columns 1 and 2 provide average marginal effects obtained from a pooled probit model. Columns 3 and 4 provide average marginal effects obtained from a clog-log model. *L.LiqRatio* denotes the lagged liquidity ratio of a firm. Standard errors are clustered at the industry-year level. ***, **, and * denote significance at 0.01, 0.05, and 0.10 levels, respectively.

Table D.7: Effect of FDI Spillovers for Different Subsets of Firms

	HSP			*UpHSP*		
	No coke	No food & chem.	No exp.	No coke	No food & chem.	No exp.
	(1)	(2)	(3)	(4)	(5)	(6)
Horizontal	0.000548*	0.000673**	-0.000392	0.000363	0.000462	-0.000422
	(0.000321)	(0.000283)	(0.000543)	(0.000357)	(0.000378)	(0.000754)
Backward	0.00497***	0.00603***	0.00547*	0.00249**	0.00380***	0.00472***
	(0.00157)	(0.00153)	(0.00308)	(0.00103)	(0.00113)	(0.00178)
Forward	-0.0120***	-0.0141***	-0.0149***	-0.00275	-0.00438	-0.00682*
	(0.00431)	(0.00418)	(0.00574)	(0.00257)	(0.00282)	(0.00356)
ForeignShare	-0.000250***	-8.67e-05	0.000655***	-9.52e-05	-3.07e-05	0.000428***
	(8.82e-05)	(0.000122)	(0.000201)	(6.78e-05)	(8.31e-05)	(7.63e-05)
LogTFP	0.00912*	0.0141**	0.0122**	-0.00320	-0.000793	0.00309
	(0.00469)	(0.00582)	(0.00554)	(0.00234)	(0.00258)	(0.00315)
LogAge	0.0208***	0.0202***	0.0152**	-0.00809***	-0.00766***	-0.00552**
	(0.00356)	(0.00389)	(0.00593)	(0.00169)	(0.00224)	(0.00240)
LogWagebill	0.0261***	0.0274***	0.00469*	0.00823***	0.0114***	0.00534***
	(0.00145)	(0.00132)	(0.00268)	(0.00105)	(0.000963)	(0.00117)
HHI	-1.04e-05	1.13e-05	-2.25e-05	-2.07e-05	-1.90e-05	-1.99e-05
	(1.97e-05)	(1.70e-05)	(2.41e-05)	(1.70e-05)	(1.63e-05)	(1.59e-05)
Observations	36,503	24,328	16,221	21,477	14,402	10,347
Log-Likelihood	-18,422	-11,610	-7,807	-3,696	-2,416	-1,456

Columns 1 to 3 provide average marginal effects obtained from a pooled probit model. Columns 4 to 6 provide average marginal effects obtained from a clog-log model. Time, industry, and state fixed effects are included. Standard errors are clustered at the industry-year level. ***, **, and * denote significance at 0.01, 0.05, and 0.10 levels, respectively.

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