The Effect of Cash-in-Advance Financing on Exporting during the Recent Financial Crisis - Firm Level Evidence from Europe and Central Asia

Katharina Eck[a,*]

[a] *Bavarian Graduate Program in Economics, University of Munich, Akademiestr. 1/III, 80799 Munich, Germany, katharina.eck@lrz.uni-muenchen.de*

Abstract

Trade credits are an important financing tool for firms and even more so for internationally active firms. In times of restrictive bank lending redistributional trade credit financing from financially sound to credit rationed firms can alleviate financial constraints. Thus, during a financial crisis, access to trade credit financing should become even more important for internationally active firms. In this paper, we analyze the effect of cash-in-advance financing on exporting activities of firms during the recent financial crisis. For a sample of European and Central Asian firms, we first explore how cash-in-advance financing is affected by the crisis. We then test whether cash-in-advance financing alleviates the negative impact of the crisis on the export activities of firms. We find evidence for a positive impact of cash-in-advance financing on exporting which is more pronounced in the crisis period.

Keywords: trade credit, trade crisis, BEEPS

JEL: F10, F14, G01, G32

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[*] The author would like to thank the Bavarian Graduate Program in Economics for financial support. The author particularly thanks Inga Heiland, Katrin Peters, Erdal Yalcin, and several seminar participants at LMU Munich and the BGPE Research Workshop for helpful comments and suggestions.

August 2012

1. Introduction

The literature on trade credit financing has established three facts on credits that are extended bilaterally between firms. First, trade credits are an important financing tool for firms. Up to one fourth of total assets in firms' balance sheets is estimated to consist of trade credits (Bougheas, Mateut, and Mizen, 2006) and trade credits constitute more than half of firms' total debt (Kohler, Britton, and Yates, 2000). Second, inter-firm financing is particularly pronounced in international trade. Up to 90% of international trade is conducted via some form of trade (credit) finance (The International Trade Center, 2009) and internationally active firms rely more intensively on trade credits than their domestic counterparts (Eck, Engemann, and Schnitzer, 2011). Third, trade credit financing becomes especially important during times of restrictive bank money supply. According to the redistribution hypothesis by Meltzer, 1960, financially sound firms rechannel financial funds to trading partners that are denied bank financing.[1] Trade credits can take the form of granting a prolonged payment period to customers, so called supplier credit and paying (part) of the purchase price in advance to sellers, so called cash-in-advance. Wilner, 2000 and Nilsen, 2002 find that the reallocation of funds via trade credit financing rises in times of a more restrictive monetary policy.

During a financial crisis, when money supply by banks becomes very restrictive, it is unclear what happens to trade credit financing. Following the redistribution hypothesis, we expect trade credit financing to rise since the reallocation of funds becomes even more important to less liquid firms. However, if most firms are affected by the financial squeeze, not only bank financing but also trade credit financing may dry up. Firms as well as banks possess limited funds to lend and with rising uncertainty about future financing possibilities, even very liquid firms may hesitate to extend trade credit to their trading partners. This scenario matches anecdotal evidence on a decline in trade (credit) financing which has been listed as one cause why trade dropped so sharply in the aftermath of the financial crisis 2008-2009 (Auboin, 2009).

In this paper, we use unique survey data on firms from Europe and Central Asia in 2005 and 2009 to analyze how cash-in-advance financing affects firms' export activities during the recent financial crisis. In our sample, cash-in-advance (CIA) refers to the percentage of sales that a firm is paid in advance before it delivers its good or service. Prepayment financing is especially relevant for exporters since it alleviates asymmetric information problems with regard to unknown trading partners (Eck et al., 2011). In our analysis, we first explore how CIA financing provided by customers is affected by the crisis. Second, we study whether CIA financing can alleviate the negative crisis

[1] See e.g. Burkart and Ellingsen, 2004 for a theoretical underpinning and Petersen and Rajan, 1997 for empirical evidence on the redistribution hypothesis.

effects on firms' exporting activities. Specifically, we test whether CIA fosters the export probability (extensive margin) and the export share (intensive margin) of firms and whether this effect becomes more pronounced in the crisis. Third, we determine the impact of a crisis induced change in CIA financing on firms' export shares. We find that CIA financing significantly rises in the crisis period and that CIA financing particularly fosters exporting in the crisis.

The contribution of this paper is twofold. First, it is the first paper to provide firm level evidence on how CIA financing is affected by the recent financial crisis. So far, the literature exclusively focuses on crisis effects on supplier credit (SC) financing by firms. Considering changes in CIA financing is interesting for two reasons. First, prepayment financing is intensively used by firms across industries (Mateut, 2012) and provides, like SC financing, an alternative to bank credit financing. Thus, firms' access to CIA has to be taken into account when gauging the effect of a monetary tightening on firms. Second, CIA financing is better suited to test the redistribution hypothesis than SC financing. Changes in CIA financing more precisely capture trading partners' willingness to redistribute their funds since CIA is voluntarily extended by customers. In contrast, firms can grant themselves SC by simply overstretching their payment period.

Second, we are the first to assess how CIA financing affects the exporting activities of firms during the financial crisis. Existing studies solely address the effects of SC financing on firms' trading activities during the crisis. Furthermore, these studies predominantly rely on pre-crisis SC measures defined at the industry level. In doing so, potential reverse causality between a firm's export decision and its use of SC financing is to be mitigated. These measures can describe the relationship between time-invariant industry use of SCs and exports but they fail to capture the immediate firm level impact of trade credit financing as well as crisis induced changes in trade credit financing. We, instead make use of firm level variation in access to CIA financing during and before the crisis. To account for selection into CIA financing by firms, we apply a matching technique. This procedure allows us to capture the contemporaneous effect of access to CIA financing on firms' exporting activities in 2009 and 2005. Since we use the same set of firms in both years, we can compare the magnitude of both effects and infer whether CIA financing is particularly beneficial during the crisis. Furthermore, we can analyze the effect of a change in CIA financing on the export performance of firms.

To guide our empirical analysis, we use a theoretical framework developed in Eck et al., 2011 to determine the impact of CIA financing on exporting during a financial crisis. In the model, firms depend on external finance to fund their export transactions, either pure bank credit financing or CIA financing combined with bank credit financing. We introduce the financial crisis as a shock that raises the costs of obtaining external finance and that intensifies asymmetric information problems. As a consequence, exporting becomes more difficult in the sense that the productivity threshold to profitably export rises. Therefore, fewer firms are able to export and those that do, export less than in the pre-crisis period. However, the productivity threshold to export profitably with CIA financing increases by less than the respective cut-off with pure bank credit financing. This implies that the importance of CIA financing for exporting relative to pure bank financing rises in the crisis since a larger share of firms crucially depends on CIA to export. Likewise, exported volumes decrease by less if CIA financing is available. Therefore, we expect the positive impact of CIA financing on the export probability and the exported volumes of firms to be stronger in the crisis than in the pre-crisis period. Moreover, we expect those firms that dispose of constant or increased supply of CIA to suffer a smaller loss in exported volumes than firms facing a decrease.

For our empirical analysis, we use the third and fourth round of the Business Environment and Enterprise Performance Survey (BEEPS) conducted by the European Bank of Reconstruction and Development and the World Bank in 2005 and 2009. The survey covers firm-level information on 1,935 firms from 27 European and Central Asian (ECA) countries in both years. The dataset provides us with a precise measure of CIA use by firms, the percentage of sales a firm receives before it delivers its good. In addition, data on firms' export activities is available for both years so that we can compare the export performance of firms over time and link it to access to CIA financing. For our sample of firms, we reject a decline in trade credit financing. We observe that the share of exporters using CIA slightly increases in 2009 and exporters receive on average the same share of sales in advance than in 2005. For non-exporters, we even document a significant increase in CIA financing.

In the empirical part, we exploit the panel structure of our dataset to test whether CIA financing particularly fosters exporting in the crisis period. We use predefined firm level characteristics to match CIA receiving firms to a subset of non-CIA receiving firms in both years. Assuming that selection into CIA financing is based on these observable firm characteristics, we then calculate the average treatment effect of CIA on the extensive and intensive margin of exporting for CIA receiving firms. We find that firms that receive CIA have a 6% to 7% higher probability to export in 2005 compared to firms that lack CIA financing. In 2009, this effect increases to 7% to 10% implying that in the crisis CIA financing is more important at the extensive margin of exporting. At the intensive margin of exporting, we find no significant effect of receiving CIA on exported shares in 2005. In 2009, however, CIA financing greatly fosters export shares: exporters that receive CIA have a 41% to 48% higher export share than exporters without CIA. We then analyze whether an increase in CIA financing softens the negative crisis impact on export shares. We compare the loss in export shares of firms that receive at least as much or more CIA financing in 2009 than in

2005 to the loss of firms that suffer a decrease in CIA financing. Our results show that firms provided with constant or increased CIA financing in 2009 experience on average a 20% smaller loss in export shares. Taken together, our results lend support to the redistribution hypothesis. The rechanneling of financial funds between firms does not die down in the crisis and strongly benefits firms' exporting activities. Consequently, in order to promote exports during a crisis, it may be worthwhile to think about adequate instruments that incentivize deep pocket firms to extend CIA during a crisis. While banks may hesitate to lend to certain firms, trading partners are often better able to judge the firm and thus may be more willing to lend. Offering prepayment insurance to CIA extending firms can be one way to ensure sufficient liquidity provision and to stabilize exports in a crisis.

Our paper relates to two different strands of literature. The first strand is concerned about the redistribution of SC financing to credit constrained firms. Meltzer, 1960 observes that cash abundant firms grant prolonged payment periods to their customers in times of monetary tightening. Bougheas et al., 2006 provide a theoretical framework in which credit rationed firms use SCs as substitute for bank credits. For a sample of UK firms, they show that this effect is particularly strong when bank credit interest rates are high. In contrast, Ahn, 2011 considers trade credit extended to support international transactions. He argues that internationally extended trade credits are the first to be cut in a crisis since international trade financing is more risky than domestic trade financing. Love, Preve, and Sarria-Allende, 2007 use accounts payable to proxy SC received for a set of Asian firms. They document an increase in SC financing during the Asian financial crises of the 1990s but a decrease for the post-crises years. In contrast, Love and Zaidi, 2010 note a decrease for their sample of Asian firms during the same crisis. Kestens, Van Cauwenberge, and Bauwhede, 2011 also find declining accounts payable of Belgian firms during the subprime crisis. We complement the literature by looking at changes in CIA financing during a crisis. For our sample of firms, we observe an increased willingness of customers to fund their trading partners. Moreover, we do not confirm a drop in trade credit financing for internationally active firms. CIA financing increases for non-exporters in the crisis year and CIA financing by exporters remains on its high pre-crisis level.

The second strand of literature considers the effects of trade finance on international trade in a financial crisis. Chor and Manova, 2010 find support that industries with a higher pre-crisis use of SCs experience higher exports to the US during the recent financial crisis. Levchenko, Lewis, and Tesar, 2010 and Iacovone and Zavacka, 2009, however, do not find a significant fostering effect of access to trade credit on US exports and imports during past crises and the recent subprime crisis. The results of Coulibaly, Sapriza, and Zlate, 2011 support Ahn, 2011. They look at 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 evidence for declining trade due to a lack of trade finance. The paper closest to ours is Felbermayr, Heiland, and Yalcin, 2012 who use a difference-in-difference 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 and the effect is stronger during the crisis. We also employ matching techniques to overcome endogeneity problems in studying the effect of access to CIA financing on exports at the firm level. We find that CIA financing fosters the exporting activities of firms and in particular during the crisis period. Moreover, firms provided with an increase in CIA financing can cushion the negative crisis effects on export shares.

The remainder of the paper is organized as follows. In section 2 we present our theoretical considerations on the impact of CIA financing during a crisis and derive testable hypotheses. Section 3 describes the data used in our analysis and provides summary statistics. Section 4 explains our empirical strategy. In section 5 we lay out our results and present robustness checks. Section 6 concludes.

2. Hypotheses on the role of Cash-in-Advance financing in a financial crisis

2.1. The model

We rely on earlier work by Eck et al., 2011 to infer the differential impact of CIA financing on firms' exporting activities in a financial crisis. In the model, firms depend on external finance to fund their export transactions. The financing of the variable and fixed costs of exporting can be provided by a bank in form of bank credit and by the firm's trading partner (the importer) who pays part of the purchasing price in advance. In this case, complementary bank credit is needed since the amount paid in advance covers only a part of the total costs.

Selling the good 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. Second, 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. Therefore, diversion of the good becomes attractive which is captured by a private benefit ϕ that the importer derives.[2]

[2]The low-quality importer always diverts the good since he is not able to successfully market the good and generate revenues from reselling it.

In the model, a firm is able to sell its goods abroad if its productivity level lies above a certain threshold. The productivity cut-off is derived from the zero-profit condition for exporting and it depends on the financing mode chosen. The cut-offs to export with pure bank financing and with combined CIA financing are given by:

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

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

The first term of each cut-off denotes the gross refinancing interest rate of the bank, $(1+\bar{r}_B)$, adjusted for the level of uncertainty. If pure bank credit financing is chosen, moral hazard and adverse selection persist; thus the interest rate paid for bank credit equals $\frac{1+\bar{r}_B}{\lambda\mu}$. If CIA combined with bank credit financing is chosen the adverse selection problem can be eliminated completely because the amount paid in advance serves as a signal of the importer's quality type: only high-quality importers are able to pay CIA. Market uncertainty persists.[3] The second term in (1) and (2) gives the fixed costs of exporting, F_{Ex}, weighted by the price the exporter receives for the export good. $\hat{p}$ denotes the exogenous market price at which the importer can resell the exporter's good. In the case of pure bank credit financing, the exporter demands $\hat{p}$ less a discount, $\frac{\phi}{\lambda}$, from the importer, where $0 < \phi < \lambda\hat{p}$. The discount accounts for the benefit derived from diversion adjusted for uncertain market demand. With combined CIA financing, problems related to moral hazard can be alleviated, though not perfectly. Paying part of the purchasing price in advance makes diversion of the purchased good less attractive compared to selling it and lowers incentives to commit moral hazard. This allows the exporter to raise the price of the exported good (or decrease the discount) by $\frac{\phi}{\lambda}\frac{(1+\bar{r}_B)}{(1+\bar{r}_{CIA})}$, where $(1+\bar{r}_{CIA})$ is the gross refinancing rate of the importer in order to extend CIA.

The exported volumes in both scenarios are given by the following expressions

$$x_{Ex}^{BC} = \frac{(1+\beta)}{\frac{1+\bar{r}_B}{\lambda\mu}}\left(\hat{p}-\frac{\phi}{\lambda}\right) \tag{3}$$

$$x_{Ex}^{CIABC} = \frac{(1+\beta)}{\frac{1+\bar{r}_B}{\lambda}}\left[\hat{p}-\frac{\phi}{\lambda}+\frac{\phi(1+\bar{r}_B)}{\lambda(1+\bar{r}_{CIA})}\right] \tag{4}$$

where $(1+\beta)$ refers to the productivity level of the firm. Comparing the cut-offs and exported volumes in each financing scenario it is easy to see that the productivity threshold to export is lower with CIA financing than with pure bank credit financing

[3]For simplicity, we restrict our analysis to the case in which the amount of CIA received from the foreign importer is sufficiently high to infer his quality type (separating equilibrium).

and exported volumes are higher in the case of CIA financing:

$$(1+\beta)_{Ex}^{CIA,BC} < (1+\beta)_{Ex}^{BC} \quad and \quad x_{Ex}^{BC} < x_{Ex}^{CIA,BC} \tag{5}$$

Consequently CIA financing enables less productive firms to start exporting and to export higher volumes.

2.2. A financial crisis scenario

We now consider an adverse financial shock to the economy. Specifically, we model it as a simultaneous increase in the gross interest rates for external financing, $(1+\bar{r}_B)$ and $(1+\bar{r}_{CIA})$, and an increase in uncertainty. This manifests in an increase in the probability $(1-\lambda)$ of zero demand in the foreign market and can be interpreted as moral hazard becoming more attractive to the importer. Similarly, adverse selection tightens in the crisis: high-quality type firms may become more reluctant to spend money on input or final good purchases whereas low-quality type importers that do not intend to resell the exporter's good are unaffected by the crisis. Thus, the share of offers coming from low-quality types, $1-\mu$, increases compared to "serious" offers from high-quality types.

Doing simple comparative statics, it is easy to see that both productivity thresholds increase in the crisis. A rise in $(1+\bar{r}_B)$ and a decrease in λ increases both cut-offs. The cut-off for combined CIA financing increases with a rise in $(1+\bar{r}_{CIA})$, whereas the bank credit cut-off increases with a drop in μ:

$$\frac{\partial(1+\beta)_{Ex}^{i}}{\partial(1+\bar{r}_B)} > 0 \qquad \frac{\partial(1+\beta)_{Ex}^{i}}{\partial(1-\lambda)} > 0 \quad where \quad i = BC, CIABC \tag{6}$$

$$\frac{\partial(1+\beta)_{Ex}^{CIABC}}{\partial(1+\bar{r}_{CIA})} > 0 \qquad \frac{\partial(1+\beta)_{Ex}^{BC}}{\partial(1-\mu)} > 0 \tag{7}$$

Likewise, the exported volume decreases:

$$\frac{\partial x_{Ex}^{i}}{\partial(1+\bar{r}_B)} < 0 \qquad \frac{\partial x_{Ex}^{i}}{\partial(1-\lambda)} < 0 \quad where \quad i = BC, CIABC \tag{8}$$

$$\frac{\partial x_{Ex}^{CIABC}}{\partial(1+\bar{r}_{CIA})} < 0 \qquad \frac{\partial x_{Ex}^{BC}}{\partial(1-\mu)} < 0 \tag{9}$$

Thus, in a financial crisis, exporting in both financing modes becomes more difficult at both margins. In a next step, we want to determine in which financing mode exporting becomes more difficult to assess the importance of combined CIA financing relative to pure bank credit financing in the crisis. To do so, we infer how the crisis affects the productivity cut-off with bank financing relative to the cut-off with CIA financing.

The relative productivity threshold B is defined as:

$$B = \frac{(1+\beta)_{Ex}^{BC}}{(1+\beta)_{Ex}^{CIABC}} = \frac{\left(\hat{p} - \frac{\phi}{\lambda} + \frac{\phi(1+\bar{r}_B)}{\lambda(1+\bar{r}_{CIA})}\right)^2}{\mu^2\left(\hat{p} - \frac{\phi}{\lambda}\right)^2} \tag{10}$$

To determine the impact of the crisis on the relative cut-off we take the total derivative of (10) with regard to changes in the refinancing rates and uncertainty:

$$dB = \underbrace{\frac{\partial B}{\partial(1+\bar{r}_B)}}_{>0}\underbrace{d(1+\bar{r}_B)}_{>0} + \underbrace{\frac{\partial B}{\partial(1+\bar{r}_{CIA})}}_{<0}\underbrace{d(1+\bar{r}_{CIA})}_{>0} + \underbrace{\frac{\partial B}{\partial \lambda}}_{<0}\underbrace{d\lambda}_{<0} + \underbrace{\frac{\partial B}{\partial \mu}}_{<0}\underbrace{d\mu}_{<0} > 0 \tag{11}$$

From (11), we find that in the crisis the productivity threshold with pure bank financing increases by more than the threshold with combined CIA financing except for very extreme increases in $(1+\bar{r}_{CIA})$ (Proof TBD). Therefore, exporting with pure bank credit financing becomes relatively more difficult in the crisis. Doing the same analysis for the relative export volume, $X = \frac{x_{Ex}^{BC}}{x_{Ex}^{CIABC}}$, we find that the exported volume with pure bank credit financing decreases by more than the exported volume with combined CIA financing:

$$dX = \underbrace{\frac{\partial X}{\partial(1+\bar{r}_B)}}_{<0}\underbrace{d(1+\bar{r}_B)}_{>0} + \underbrace{\frac{\partial X}{\partial(1+\bar{r}_{CIA})}}_{>0}\underbrace{d(1+\bar{r}_{CIA})}_{>0} + \underbrace{\frac{\partial X}{\partial \lambda}}_{>0}\underbrace{d\lambda}_{<0} + \underbrace{\frac{\partial X}{\partial \mu}}_{>0}\underbrace{d\mu}_{<0} < 0$$

Figures 1 and 2 graphically depict the changes in the cut-offs and exported volumes.

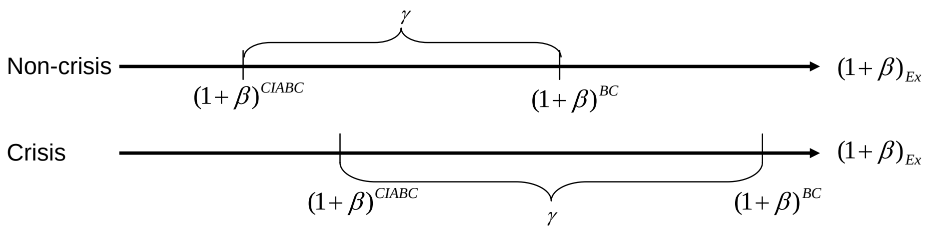

Figure 1: Crisis induced changes in the productivity threshold for different financing modes

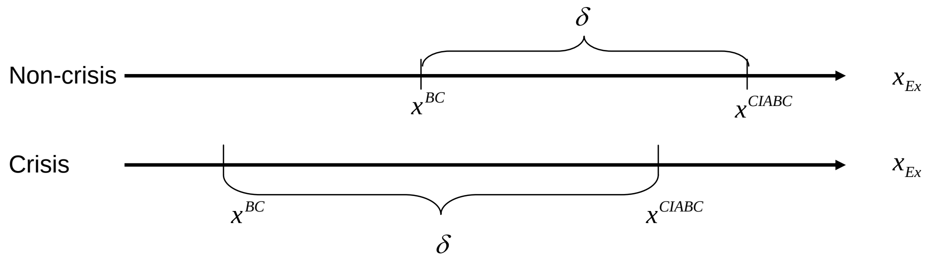

Figure 2: Crisis induced changes in the export volume for different financing modes

If we assume that the productivity level of firms is uniformly distributed then the range γ of firms for which CIA financing is essential to profitably export expands in the crisis. This is due to the fact that the increase in uncertainty can be better compensated by firms that receive CIA. Tightened adverse selection only affects pure bank credit financing since low-quality importers do not extend CIA. Tightened moral hazard affects all exporters, but CIA financed firms to a lesser extent since advance payment lowers incentives for moral hazard. A rise in $(1 + \bar{r}_B)$ more adversely affects pure bank credit financing firms since they pay the higher interest rate on a larger part of the credit. Relative gains can compensate for an increase in $(1 + \bar{r}_{CIA})$ that only affects CIA financed firms as long as the increase is not too large. Consequently, the "comparative advantage" that CIA receiving firms have above non-receiving firms, i.e. they need to be less productive to start exporting, grows stronger during a financial crisis. Likewise, the relative difference δ between exported volumes with pure bank credit financing and with combined CIA financing increases in a financial crisis. From these findings we derive our first hypothesis on the relative importance of CIA financing:

Hypothesis 1 - Crisis Relevance: *Firms that receive CIA have a higher export probability and export more. This effect magnifies in the crisis period.*

Our finding with regard to the effect of CIA on the exported volume also implies that exported volumes decrease by less if firms receive CIA in the crisis. The literature on redistributional trade credit financing states that firms switch to (more) trade credit financing to alleviate financial constraints in times of a monetary tightening (Bougheas et al., 2006). These two findings taken together, we expect firms that receive at least as much or even more CIA financing in the crisis than before to face a smaller loss in exported volumes. In contrast, firms that suffer a loss in CIA financing are expected to face a larger loss. This is summarized in our second hypothesis:

Hypothesis 2 - Redistribution: *Firms that receive at least as much or more CIA financing in the crisis than in the pre-crisis period face a lower drop in exported volumes.*

Note that our predictions do not contradict the results by Ahn, 2011 who claims that an adverse financial shock leads to a drop in trade credit financing and in turn to a decline of international trade. We do not predict how the amount of CIA financing changes in a financial crisis. According to our analysis, an increase in CIA financing is desirable from the point of view of receiving firms since more firms depend on CIA financing in the crisis period. However, we do not predict how CIA giving firms behave. We focus on the aspect that firms that receive CIA financing are comparably better off in terms of their export performance and that this effect magnifies in the crisis. Furthermore, those firms that benefit from a redistribution of funds from their (more liquid) trading partners can alleviate the adverse crisis effects compared to firms that suffer a decrease in CIA financing.

3. Data and summary statistics

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 Survey (BEEPS). The survey covers data on 1,935 firms from 27 countries in the ECA region in 2005 and 2009.[4] It was conducted by the European Bank of Reconstruction and Development and the World Bank in 2005 and 2008-2009. The survey gathers information on the ease of developing and maintaining a business in different sectors in these countries and also provides basic firm-level information. Only firms with at least five full-time employees are captured in the survey. The universe of sectors comprises manufacturing, construction, services, transport, storage, and communication. Excluded are the agricultural, financial, real estate and the public sector. Stratified random sampling along the strata industry, firm size, and region was used to enhance representativeness of the sample.[5]

Most important to our analysis is information on prepayment use and the international activities of firms. In the survey, firms are asked what percent of their total annual sales of goods or services they are paid for before delivery (CIA received) by their customers. Therefore, we can rely on a precise measure of contemporaneous CIA received at the firm level. Additionally, firms 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 exporting activities. Unfortunately, our dataset does not allow us to deduce the nature of CIA financing, i.e. whether it is used for a domestic or international transaction. This kind of detailed information is usually only available for 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 exporting activities of firms from transition countries during the crisis is particularly insightful for two reasons. First, while several studies analyze the trade contraction of Western European countries with great detail (see Behrens, Corcos, and Mion, 2011 and Bricongne, Fontagné, Gaulier, Taglioni, and Vicard, 2012 for evidence on Belgium and France) evidence on how the trading activities of firms from the ECA region are affected by the crisis is rare. This

[4] A list of all countries included in the analysis can be found in Table 1 in the Appendix.

[5] Please refer to http://www.ebrd.com/pages/research/analysis/surveys/beeps.shtml for further information on the sampling scheme.

is all the more surprising since the crisis hit these countries as hard as their Western neighbors. Looking at data on growth of GDP and growth of exports and services from the World Development Indicator Database, we find that in 2009, 70% of all the countries in our dataset experienced a negative GDP growth with -5% being the median GDP growth and -18% being the maximum negative growth rate (Latvia). Almost 90% experienced a negative growth of exports and services with a median growth rate of -11% and a maximum negative growth of -22% (Ukraine). This is in line with the decline experienced by high income countries such as France and Germany: Germany's GDP and exports of goods and services contracted by -5% and -14%, respectively, in the same period. France experienced a drop by -3% and -12%, respectively.[6] Figure 3

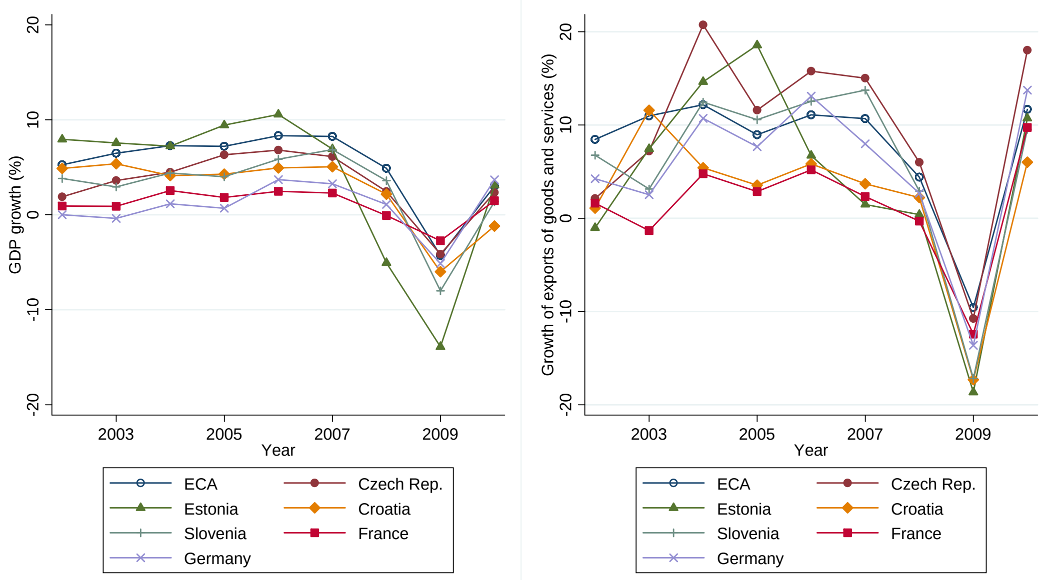

Figure 3: Annual growth rates of GDP and exports and services for selected countries, 2002-2010

depicts the changes in GDP and exports between 2002 and 2010 for the composite of all ECA countries, four exemplarily chosen countries from the dataset (Czech Republic, Estonia, Croatia, and Slovenia), and France and Germany as benchmark countries. The overall decline in GDP and exports of the ECA countries follows the pattern for Germany and France. Some countries such as Estonia and Slovenia have faced an even stronger drop in economic activity.

Second, trade credit financing is particularly relevant in countries with a weaker banking system. Fisman and Love, 2003 find that industries that intensively rely on trade credit financing have a higher growth in value added in countries with less developed financial institutions. After the break up of the Soviet Union, most former member countries started to reform their banking system. The single so called monobank was

[6]Data on GDP and export growth rates is taken from the Worldbank's World Development Indicator Database and can be accessed at: http://databank.worldbank.org/data/Home.aspx

replaced by new independent banks that exclusively focused on private banking. The implementation of the national monetary policy was transferred to different entities, instead (Tang et al., 2000). However, despite a rapid expansion of the banking sector, financial development still lacks behind in the ECA countries: as Figure 4 illustrates, 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, e.g. Estonia, have caught up lately.[7]

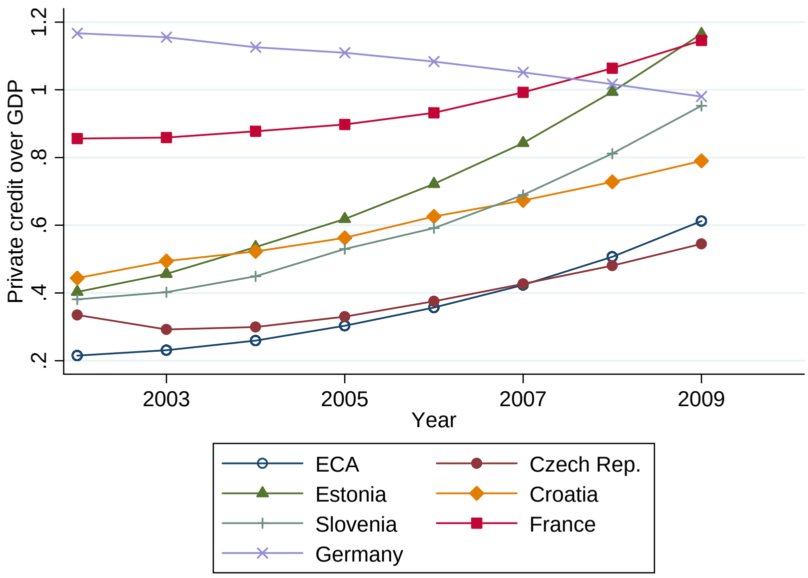

Figure 4: Private credit over GDP for selected countries, 2002-2009

In Figure 5, we plot country level average shares of CIA received against private credit over GDP for the ECA countries from our sample pooled over both years. We find a negative correlation indicating that CIA financing is more intensively used in those countries that have a comparably less developed financial system.

3.2. Crisis effects on exporting and CIA financing

We next present summary statistics for our key variables of interest. Table 2 reports average firm characteristics in 2005 and 2009. Average 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% in 2009 but the average share of sales sold abroad stays at around 40%. This is in contrast with the previous literature which finds a crisis-induced loss at the intensive margin of exporting but not at the extensive margin (see e.g. Behrens et al., 2011 and Bricongne et al., 2012 for evidence on firms from Belgium and France). If we merely consider the export performance of firms

[7]Data on financial development measured as the extension of private credit by banks over GDP comes from Beck et al., 2000.

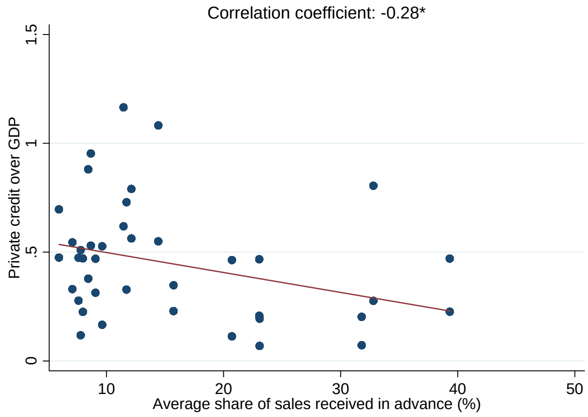

Figure 5: Average share of CIA received on sales versus private credit over GDP for 27 ECA countries, 2005 and 2009

that are already exporting in 2005, we uncover a large loss at the intensive margin: in 2009, the average share exported drops from 40% by 13 percentage points to 27%. To better understand the export dynamics during the crisis, we divide firms into four categories according to their export status in both years. The results can be found in Table 3. The first group consists of never-exporters, i.e. firms that do not export in both years; these firms comprise the largest group in our sample. Second, we term firms that export in both years as always-exporters, they make up the second largest group. Stoppers are firms that export in 2005 but do not export in 2009 anymore. Last but not least, the smallest share of firms consists of so called starters which export in 2009 but not in 2005.[8] 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 are less strong performing and also less resilient firms. They sell on average only one third of their sales abroad in 2005. Starters sell even less on average than stoppers which may indicate that these firms have not been exporting for a long time. Since less firms start to export in 2009 than firms that stop, we observe a small loss at the extensive margin. Average shares exported by both groups do not differ by much, thus the overall loss at the intensive margin is negligible. The decomposition of firms according to exporter category illustrates that weaker exporters from ECA countries react to the crisis via export exit as opposed to 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 in exporting than firms from France

[8]This terminology is used for illustrative purposes only. Given that we observe firms in only two years, the classification does not necessarily hold over the whole life of these firms.

and Belgium, for example. Thus, they do not have scope to adjust prices further down or to lower their output and are rather forced out of the export market.

In a next step, we document changes in CIA financing in the crisis year. Figure 6

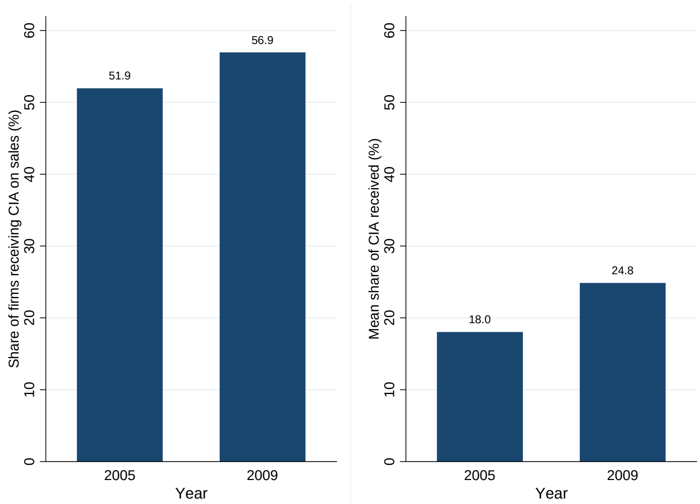

Figure 6: CIA use by firms, 2005 and 2009

depicts the share of firms that receives CIA financing from customers as well as the average share of CIA received by firms in both years. In the crisis year, we observe an increase in CIA financing by firms. Not only does the share of active CIA users increase from 52% to 57% but firms also raise the average share of sales received in advance from 18% to 25%. Both increases are statistically significant at the 1% level (see Table 4). These outcomes are surprising for two reasons. First, the increase in CIA financing for our sample contradicts the anecdotal evidence of a decline of trade finance in the aftermath of the financial crisis (see e.g. Auboin, 2009). Firms from the ECA region benefit from a moderate rise in CIA availability which supports Meltzer, 1960's redistribution hypothesis. Since CIA is a purely voluntarily extended form of trade credit financing, we are confident that our results reflect the increased willingness of financially sound firms to redistribute their funds.

Second, 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% (see Eck et al., 2011). The intensive use of CIA in the ECA countries supports the hypothesis that trade credit financing is especially relevant in countries with a less developed banking system.

We next examine average CIA use by exporters versus non-exporters in Figure 7. A firm is classified as exporter if it sells a positive share of its sales abroad.

We find that more exporters use CIA than non-exporters. In the crisis year, the share of firms that receives CIA rises in both groups, but more so for non-exporters. In 2005, exporters receive a higher average share of CIA than non-exporters, but in 2009,

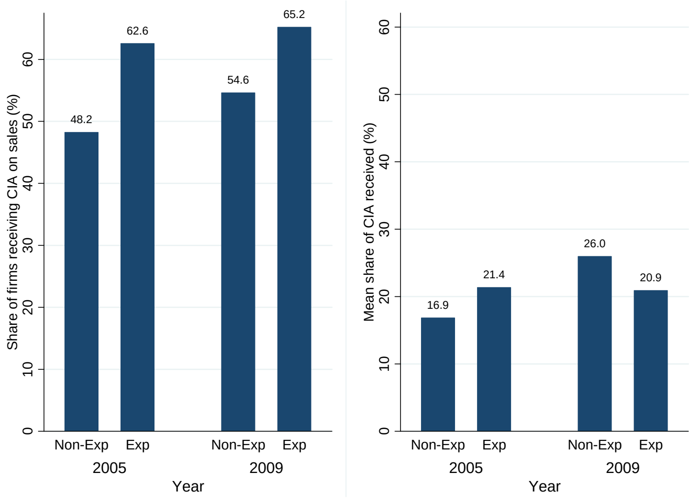

Figure 7: CIA use by exporters versus non-exporters, 2005 and 2009

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 stays constant over time. In fact, the difference is not statistically significant (see Table 4). Non-exporters, however, increase CIA financing significantly which reflects that purely domestically active firms are usually less productive and also less resilient to liquidity squeezes. Therefore, they particularly benefit from redistribution of funds via CIA financing. Our findings do not support Ahn, 2011's predictions according to which trade credit financing decreases in particular for internationally active firms.

4. Empirical methodology

4.1. Motivation for non-parametric estimation of CIA effects on exporting

Following previous work (Eck et al., 2011), a first test of Hypothesis 1 can be conducted via a simple OLS regression of the form:

$$y_{it} = \alpha_0 + \beta_1 Crisis_t + \beta_2 CIArec_{it} + \beta_3 Crisis_t * CIArec_{it} + \gamma \mathbf{X_{it}} + \epsilon_{it} \tag{12}$$

The dependent variables are Exp_{it}, a dummy equal to 1 if firm i sells a positive amount of its sales abroad in year t (extensive margin of exporting) and $LogExpS_{it}$, the log export share of total sales (intensive margin). We use the export share instead of exported volumes to avoid adjustments for currency differences and inflation rates in different countries. $Crisis_t$ is a dummy equal to 1 if t = 2009 and $CIArec_{it}$ is a dummy equal to 1 if the firm receives a positive amount of its sales before delivery of the good. $\mathbf{X_{it}}$ denotes a vector of firm specific controls intended to influence the exporting behaviour of firms. We choose firm size, labor productivity, firm age, and ownership concentration to control for size and reputation effects. Furthermore, we include a foreign ownership dummy, a dummy whether the firm has an internationally recognized quality certificate to account for product quality differences, a dummy that indicates obstacles in transportation hindering exporting, and a dummy to indicate whether the firm considers its own court system as weak in terms of legal enforcement. ϵ_{it} denotes the error term.[9]

According to our first hypothesis, we expect the financial crisis to induce a drop in exporting at both margins, $\beta_1 < 0$. Firms that receive CIA in 2005 have a higher probability to export and export a higher share of their sales, $\beta_2 > 0$. The fostering effect of CIA is predicted to be stronger in 2009, $\beta_3 > \beta_2$. Thus, the negative crisis effect can be softened for firms that receive CIA financing from their trading partners.

Table 6 provides the results from estimating (12) via OLS. The crisis exerts a negative influence on the export probability of firms although the effect is only significant when we use log labor productivity instead of firm size (column (2)). The export share decreases by 34% (i.e. $1 - e^{-0.41} = 0.337$) in the crisis (column (3)). Moving to our key variable of interest, we find that firms that receive CIA in the non-crisis period can increase their probability to export by 8-9% compared to non-CIA receiving firms. However, in the crisis firms do not additionally benefit from access to CIA financing. The coefficient of the interaction term between $CIArec$ and $Crisis$ is negative and insignificant. Turning to exported volumes scaled by total sales, we detect the opposite effect: receiving CIA is beneficial in the crisis period but harmful in the non-crisis period. In fact, receiving CIA in 2005 is associated with a 21% lower export share for exporters, whereas in the crisis, exporters with access to CIA have a 53% higher export share.

These results seem counterintuitive and hint at selection into CIA financing by firms. In our previous work, we argue that CIA financing is attractive to all firms, not only to financially constrained or less productive firms. Therefore, all firms have an incentive to apply for CIA financing. In stable monetary times, we do not expect selection of firms into CIA financing according to unobserved characteristics. However, during a financial crisis this no longer needs to hold true. As observed in the summary statistics, predominantly non-exporting firms which are usually considered to be smaller and less productive increase their use of CIA during the crisis. If overall money supply becomes short, the redistribution hypothesis claims that selection of less financially sound, less productive firms into CIA financing takes places: trading partners react to the shortness of funds by redistributing CIA financing predominantly to their most important or most indigent suppliers according to relationship specific characteristics that are unobserved by the econometrician. If selection into CIA financing takes place during the crisis,

[9]For a more detailed description of the variables employed in our analysis, please refer to Table 5.

then simple OLS estimates of the effect of CIA financing on exporting will be biased. A straight forward solution to this problem would be to apply an instrumental variables approach. However, without further information on supplier-customer specific relations it is difficult to find a suitable instrument that influences whether a firm receives CIA from its trading partner but that is unrelated to the firm's exporting performance. Therefore, we resort to nonparametric estimation via matching to test our hypotheses and to receive unbiased estimates of the effect of CIA financing during the crisis.

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 an individual with the effect on the individual's outcome had it not received the treatment. The representation of the model in this subsection 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. $Y_i(D_i)$ refers to the outcome of i. The key parameter of interest is the population average treatment effect for the treated (ATT). It is given by the average difference in outcome with and without treatment:

$$\tau_{ATT} = E\left[Y(1)|D=1\right] - E\left[Y(0)|D=1\right] \tag{13}$$

However, in reality 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 $E\left[Y(0)|D=1\right]$, i.e. the outcome of the treated had they not received treatment, cannot be observed. Comparing $E\left[Y(1)|D=1\right]$ to $E\left[Y(0)|D=0\right]$ instead, as estimation via simple OLS does, can result in a biased ATT:

$$E\left[Y(1)|D=1\right] - E\left[Y(0)|D=0\right] = \tau_{ATT} + E\left[Y(0)|D=1\right] - E\left[Y(0)|D=0\right] \tag{14}$$

As (14) implies, an unbiased estimate of τ_{ATT} is received only if $E\left[Y(0)|D=1\right] - E\left[Y(0)|D=0\right] = 0$. If there is self-selection into treatment, i.e. the treated and untreated groups are dissimilar and would have had different average outcomes even in absence of treatment, the estimate of τ_{ATT} is biased.

Since the ideal experiment, in this application observing the export activity of a firm with and without CIA financing, is infeasible, matching treated and untreated observations can help to 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 firms are identical except that some receive treatment and others do not, then treatment can be considered as randomly assigned and the outcome of a firm is independent of treatment given observable characteristics $\mathbf{X}$. This is stated in the conditional independence or unconfoundedness assumption:

$$Y(0), Y(1), \perp\!\!\!\perp D|\mathbf{X}, \forall \mathbf{X} \tag{15}$$

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:

$$Y(0), Y(1), \perp\!\!\!\perp D|P(\mathbf{X}), \forall \mathbf{X} \tag{16}$$

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 treatment:

$$0 < P(D = 1|\mathbf{X}) < 1 \tag{17}$$

If (16) and (17) hold, the treatment effect on the outcome for the treated can consistently be estimated via comparing the outcomes for the treatment group and its matched control group:

$$\tau_{ATT}^{PSM} = E_{P(\mathbf{X})|D=1} \left\{ E\left[Y(1)|D = 1, P(\mathbf{X})\right] - E\left[Y(0)|D = 0, P(\mathbf{X})\right] \right\} \tag{18}$$

4.3. Application of the matching estimator approach

4.3.1. Crisis relevance of CIA financing - Hypothesis 1

To test whether CIA financing has a stronger positive impact on the exporting activities of firms in the crisis period (Hypothesis 1), we estimate for each year the average treatment effect of CIA financing on the exporting activities of those firms that receive CIA, $\tau_{ATT,t}$. Since we use the same panel of firms in each year, we can compare the magnitude of the effects in both years to determine whether CIA has a stronger fostering impact in 2009. $\tau_{ATT,t}^{PSM}$ is given by:

$$E_{P(\mathbf{X_t})|CIArec_t=1} \left\{ E\left[y_t(1)|CIArec_t = 1, P(\mathbf{X_t})\right] - E\left[y_t(0)|CIArec_t = 0, P(\mathbf{X_t})\right] \right\} \tag{19}$$

where $t \in \{2005, 2009\}$ and y_t is either Exp_t or $LogExpS_t$. Treated and untreated individuals are matched according to their propensity to receive CIA conditional on observable, contemporaneous firm covariates $\mathbf{X_t}$.

In a first step, the probability model of receiving CIA is estimated via a probit model of the following form:

$$Pr\{CIArec_{it}=1\} = \Phi\{h(LogSize_{it}, LogAge_{it}, Ownerconc_{it}, Foreign_{it}, Iso_{it}, Transobs_{it}, Weak_{it}, \lambda_s, \mu_c)\} \tag{20}$$

Stuart, 2010 suggests including strictly exogenous covariates that influence both the outcome and the treatment to estimate the propensity score. We include the following covariates:

> $LogSize$, the log number of employees controls for size effects. Larger firms should have a higher export performance. The effect on receiving CIA is unclear: larger firms may be more likely to receive CIA to finance their larger transactions but smaller firms may be in more need of CIA and therefore be more likely to receive support by their trading partners.
>
> $LogLabprod$ is defined as total sales converted in USD over the number of employees. We use log labor productivity as a substitute for log size to control for the efficiency level of the firm when estimating extensive margin effects. In doing so, we lose observations since sales data is not available for all firms in both years. Since the number of exporters is already small in our sample, we do not use this specification when estimating intensive margin effects.
>
> $LogAge$ refers to the log number of years since the firm began operations. Older firms are expected to have a higher export performance but the effect on CIA is again ambiguous: Older firms can be more likely to receive CIA due to reputational effects but younger firms might be more in need of additional financing.
>
> $Ownerconc$ denotes the share owned by the largest owner of the firm. Cole, 2010 states 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 its ownership. With a falling ownership share costs decrease and trade credit financing becomes more attractive.
>
> $Foreign$ is a dummy equal to 1 if more than 50% of the firm is owned by a foreign private individual, company or organization. Foreign owned firms have better access to foreign markets and should also be more likely to receive CIA from their foreign parent company.

Iso denotes 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 indicates that it faces moderate, major or very severe obstacles in transportation of its goods. Obstacles 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 trade credit financing is used by trading partners to hedge against uncertainty in transportation. If the delivery of goods is uncertain due to long distances so is the delivery of money. Standardized payments (late or in advance, depending on the nature of the transaction) 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. Schmidt-Eisenlohr, 2010 and Antràs and Foley, 2011 predict that firms in countries with a weaker legal enforcement are less likely to receive advance payment.

Finally, we include sector and country dummies, λ_s and μ_c.[10]

In a next step, we use the estimated propensity score $\hat{p}_i$ from (20) to match firms with and without CIA financing in our dataset. We employ several different matching algorithms: nearest neighbor matching with one and four neighbors with replacement, kernel density matching and radius matching with a caliper of 0.02. Nearest neighbor matching with one neighbor 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 efficency, though, since a large number of (untreated) observations is not taken into account when estimating the ATT (Stuart, 2010). Therefore, we also apply four nearest neighbor matching which 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 0.02, i.e. the

[10] A different method to find a suitable control group is covariate distance matching as suggested by Abadie, Drukker, Leber Herr, and Imbens, 2001. Covariate matching finds controls by minimizing the distance in terms of covariate characteristics between treated and untreated individuals. 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 cannot apply this technique.

propensity to receive CIA for untreated controls is allowed to differ by 2 percentage points from the respective propensity of the treated individual. 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 average matching quality can be lower since also more dissimilar controls are used.

When calculating ATTs, variance is added 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 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, 2008). In addition, we follow an estimation approach suggested by Hirano, Imbens, and Ridder, 2003. We use the estimated propensity scores from four nearest neighbor matching as inverse weights to run a weighted least squares regression of export performance on the treatment and all other covariates in each year. Treated observations receive a weight of 1 and control observations receive a weight of $\frac{\hat{p_i}}{1-\hat{p_i}}$. This method can be considered as a compromise between matching and OLS since it provides correct standard errors but does not fully control for selection. Note that nonparametric matching is a very data hungry approach and the increased variance generated by nearest neighbor matching impedes finding significant ATTs. Therefore, our rather small sample works against us in finding significant treatment effects.

4.3.2. Redistributional effects of CIA financing - Hypothesis 2

According to Hypothesis 2, we expect firms that receive (more) CIA financing in the crisis period to suffer from a smaller drop in exported volumes. We test this hypothesis by applying a difference-in-difference matching approach. In particular, we analyze the effect of treatment $CIArecP$ on the growth rate of export shares, $\Delta LogExpS$. $CIArecP$ is equal to 1 if a firm receives the same or a higher share of CIA on its sales in 2009 than in 2005. It is defined to be 0 if the share of CIA decreases within the same period. By taking the first difference of the outcome variable we get rid of unobserved factors that stay constant over time, such as motivation of the manager to acquire outside funding, similar to a fixed effects regression. Cross-sectional matching makes the stronger assumption that all differences between 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. The ATT of redistributional CIA financing in the crisis on the export share growth rate is given as:

$$\tau_{ATT}^{DiffPSM} = E_{P(\mathbf{X_{2005}})|CIArecP=1}\left\{E\left[\Delta LogExpS(1)|CIArec=1, P(\mathbf{X_{2005}})\right] \right.$$
$$\left. -E\left[\Delta LogExpS(0)|CIArecP=0, P(\mathbf{X_{2005}})\right]\right\} \quad (21)$$

The propensity to receive treatment is estimated using firm level covariates from the pretreatment period 2005 (Heinrich et al., 2010). In addition to the above mentioned covariates, matching on pretreatment covariates allows us to also control for financial constraints experienced by firms in 2005. Financial constraints adversely affect the exporting behaviour of firms (Manova, 2012, Minetti and Chun Zhu, 2011) and financially constrained firms benefit from CIA financing (Eck et al., 2011). Financial constraints are captured by $Fincons$, a dummy variable equal to 1 if the firm states that access to finance (availability and cost, interest rates, fees, and collateral requirements) is a major or very severe obstacle to the operations of the firm in 2005. Moreover, we capture the innovativeness of a firm by including the dummy $Newprod$ which is equal to 1 if the firm has introduced new products or services within the last three years. In both cases, using a contemporaneous measure might lead to reverse causality since firms that export more might have higher financing needs and therefore be more likely to indicate that they are financially constrained. Likewise, firms that intend to increase their exports might do so by innovating. Pretreatment matching alleviates both concerns.

Matching is performed via the same matching algorithms as stated above and standard errors are adjusted via bootstrapping in the case of radius and kernel matching.

5. Results

5.1. Results for Hypothesis 1

5.1.1. Selection into CIA financing

Table 7 summarizes the results from estimating equation (20) for different subsets of our sample. In column (1) and (2), we estimate selection into CIA financing in 2005. In columns (3) and (4), selection into CIA financing in the crisis year 2009 is estimated. In column (2) and (4), we use $LogLabprod$ instead of $LogSize$ to control for the efficiency level of a firm. Note that due to data unavailability, we lose observations in this specification. Columns (5) and (6) provide the results in 2005 and 2009 for exporting firms only.

We find a strong and positive influence of $LogSize$ and $LogLabprod$ on the propensity to receive CIA when considering the full sample of firms in both years. This is in line with findings for a sample of UK firms by Mateut, 2012, the only study that explicitly deals with selection into prepayment financing by firms. In general, controlling for the labor productivity of firms instead of size yields a better fit of the model in terms of the Log Likelihood statistic but the number of observations drops. If we only consider exporters, the presumably largest and most productive firms, size does not play a role anymore in determining access to CIA. $Ownerconc$ has a negative influence, implying that firms of which the largest owner exerts more control *ceteris paribus* have a lower probability to use CIA financing consistent with Cole, 2010. But the effect is only significant in 2005. Foreign owned firms are more likely to receive CIA financing in the crisis, but only in 2009. This finding may reflect that foreign owned firms increasingly resort to CIA financing provided by their foreign parent companies when overall money supply becomes scarce. In 2005, possessing a quality certification, Iso, facilitates access to CIA as conjectured. In 2009, however, there is weak incidence that certified firms are less likely to receive CIA. During the crisis, trading partners probably redistribute their funds to weaker, smaller firms that cannot afford an ISO certificate. The coefficient of $Transobs$ is positive connoting that firms that face obstacles in transportation have a higher propensity to receive CIA financing. This is in line with the transaction cost theory of trade credit use postulated by Ferris, 1981. Last but not least, we observe a negative correlation between contractual enforcement, $Weak$, and the probability to receive CIA in 2005 as rationalized by Schmidt-Eisenlohr, 2010 and 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.

These results taken together hint at selection into CIA financing according to observed and unobserved firm characteristics, in particular during the crisis period. In 2005, customers decide on CIA financing from a rational perspective: CIA is more likely being given to larger and more trustworthy firms. In 2009, however, unobserved factors seem to play a more important role: less trustworthy firms and firms less well protected by jurisdiction receive CIA financing. Furthermore, relationship specific aspects seem to increase in relevance. Foreign owned firms make use of the connection to their foreign parental company and customers are likely to favor giving CIA to their most important or most dependent suppliers in the crisis. To account for selection into CIA financing we thus proceed by matching treated and untreated firms according to their propensity to receive CIA financing in each year.

5.1.2. Crisis induced effects of CIA financing on exporting

To verify 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 four nearest neighbor matching in 2005 (Probit 1 specification) in Table 8. Before matching, CIA receiving firms are significantly different from their counterparts. They tend to employ a larger number of workers, are older, their main owner exerts less control, and they are rather foreign owned. Furthermore, they are more likely to possess an internationally recognized quality certificate and they tend to experience less likely weak court systems. After matching, however, 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. The outcome assures that matching can reduce a substantial amount of heterogeneity among treated and untreated firms and allows us to estimate a causal effect from CIA financing on the exporting activities of firms.

To save space, we display only two adequate statistics to verify covariate balancing for all other matching specifications in Table 9. 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.[11] In addition, high matching quality is signalled by a high p-value from the likelihood-ratio test of joint insignificance of all covariates explaining variation in the pscore. After matching, covariate characteristics should have no power in explaining the pscore if firms with the same propensity to receive CIA are indeed very similar in terms of covariate characteristics. According to these statistics, all matching algorithms except for nearest neighbor matching with one neighbor perform very well. The low matching quality of one nearest neighbor matching may be due to the fact that the group of untreated firms is rather small in our sample which makes it difficult to find one very close neighbor. Using the unweighted average of four neighbors instead improves the matching quality considerably. We therefore treat results obtained from one nearest neighbor matching with caution.

Table 10 provides the estimated causal effects of CIA financing on the export probability of firms in 2005 and 2009. Except for the results from nearest neighbor matching, we find that the estimated ATTs are very similar across different matching algorithms and across both probit specifications in 2005. We find that firms that receive CIA financing from their customers in 2005, have a 6% to 7% higher probability to be exporting than comparable firms without CIA. Matching reduces the average treatment effect of CIA by almost 2 percentage points compared to the simple OLS estimates of 7.3% and 9.1% in 2005 (Table 6). The treatment effects closest in magnitude to the OLS results stem from the weighted least squares regressions in which observations are

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

weighted according to their treatment probability. Nearest neighbor matching with one neighbor performs poorly in 2005. The ATT in the first specification is very imprecisely estimated, probably because of the lower number of observations employed by one nearest neighbor matching. The ATT from Probit 2 overestimates the true effect due to the bad matching quality.

In 2009, we find a larger effect of CIA financing than in 2005. Firms that receive CIA in 2009 have a 7% to 10% higher probability to export than comparable firms without CIA. The differential impact between both years is especially pronounced if we consider the second probit specification controlling for log labor productivity instead of size which also provides a better fit for the model of selection into CIA financing (see the Log Likelihood statistic in Table 7). Again, the results from the propensity score weighted regression come closer to the benchmark OLS results. The effect in 2009 is slightly smaller than in 2005 which matches the OLS estimates of a negative (though insignificant) effect of CIA financing in the crisis period.

Turning to the results for the intensive margin of exporting in Table 11, we find that CIA financing has a negative, but insignificant effect on the exported share of exporters in 2005. Consequently, controlling for selection into CIA financing eliminates the significant negative influence of CIA on export shares in 2005 as reported by the simple OLS benchmark. In contrast, in the crisis year CIA financing strongly fosters exporting. Exporters that receive CIA in 2009 have 41% to 48% (i.e. $e^{0.34} = 1.405$, $e^{0.39} = 1.477$) higher export shares than comparable exporters without CIA. Again, the ATT obtained via matching is considerably lower than the OLS CIA crisis effect of 54% ($e^{0.43} = 1.537$).

To sum up, we find support for our first hypothesis using matching techniques. CIA financing fosters entry into exporting and its beneficial impact increases during the financial crisis. At the intensive margin, we find a considerable positive effect of CIA financing on the exported share of firms in the crisis year. Exporters that receive financing from their customers can greatly increase their relative exports. In 2005, however, exporters do not benefit from additional CIA financing.

5.2. Results for Hypothesis 2: Redistributional effects of CIA financing

We first analyze selection into redistributional CIA financing in 2009. The results are given in Table 12. Probit specifications 4 and 5 include the same pretreatment covariates as before, in specification 6 and 7 we additionally control for financial constraints experienced by firms, *Fincons*, and their innovativeness, *Newprod*. We find that smaller or less productive firms have a significantly higher probability to receive the same or a higher share of CIA in 2009. This is in line with empirical evidence by Nilsen, 2002 and Bougheas et al., 2006 who observe that in times of tight monetary policy it is particularly small firms that increase their use of trade credit financing.

Firms suffering from transportation obstacles in 2005 were less likely to benefit from additional CIA financing. Firms that experienced weak legal enforcement increased their use of CIA financing in the crisis, which matches the Probit 1 results in 2009 from above. *Fincons* is positively correlated as expected, but the effect is not significant. In contrast, very innovative firms are less likely to resort to additional CIA financing in 2009. In terms of goodness of fit, Probit 5 and 7 outperform the specifications controlling for the number of employees, however the estimates suffer from a greater variance and are less precise. Controlling for financial constraints and the innovativeness of the firm in 2005 leads to a lower Log Likelihood.

The matching quality of our four matching algorithms in specifications 4 to 7 is similar to the results obtained above. Nearest neighbor matching performs poorly except for one specification, all other matching algorithms reduce observable differences between treated and untreated observations almost perfectly (Table 9).

Table 13 provides the ATTs from redistributional CIA financing. One nearest neighbor matching gives unsatisfactory results that are either imprecisely estimated or that greatly overestimate the effect. Except for one specification, all other estimation procedures return significant effects. The results obtained for the Probit 4 specification are very similar across different matching algorithms. Firms that receive redistributional CIA in 2009 have an 18% to 20% higher export share. Probit 5 provides a better fit to the model of selection into redistributional CIA financing (Table 12) but due to a loss of observations, the ATT estimates are less precise and lie within a greater range (16% to 22%). The results obtained by propensity score weighted regressions come closest to the benchmark case, a simple OLS regression of the change in log export shares on the binary treatment indicator and the pretreatment covariates. The estimated treatment effect is higher when also controlling for financial constraints and the innovativeness of the firm. For Probit 6 the treatment effect lies between 18% and 24%, in Probit 7 between 16% and 22%. To better understand the meaning of the treatment effect, we provide one example for the case of Epanechnikov kernel matching which reports consistent treatment effects over all specifications. The average treatment effect of 19% (Probit 4 and 6) signifies that firms that received at least as much CIA financing in 2009 as in 2005 faced a 19% lower loss in average shares exported than firms that received a lower share of CIA in the same period. The average drop in export shares is 9% for the treated group and 28% for the group of matched controls. Interestingly, the OLS results yield a slightly lower treatment effect. This can be ascribed to the observation that it was mainly non-internationally active firms that raised their use of CIA financing (compare Figure 7) in the crisis. Therefore, when not controlling for selection into redistributional CIA financing the effect is downward biased by firms that do not lose export shares since they do not export. All in all, our results strongly support our second hypothesis: the adverse effects of a credit crunch on firms' exports can be softened if there are still some deep pocket firms that redistribute their financial funds to their trading partners via extending CIA.

5.3. Robustness checks

TBD

Results are robust to

- using different outcome variables: unrelated to CIA financing as desired (no effect).
- randomly assigned treatment (no effect).
- Results in 09 are not driven by starters, if we leave out starters: same effect

6. Conclusion

In this paper, we provide insights into how CIA financing shapes the international activities of firms from 27 European and Central Asian countries during the recent financial crisis. Contrary 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 fostered exporting activities in particular during the crisis and that redistributional CIA financing could alleviate the negative crisis impact on the export share of firms.

Therefore, one conclusion to draw from this analysis is that it can be worthwhile to think about how deep pocket firms can be incentivized to extend trade credit financing. 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 could step in and provide sufficient financing to their trading partners. A further advantage of trade credit financing is that it can be extended quickly and on a short-term basis to bridge financial gaps. One way to foster CIA supply by firms may be to provide specifically designed insurances that cover default by national and foreign trading partners that were provided with prepayments.

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Table 1: Decomposition of firms according to countries included in the sample

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
Georgia	68	3.51
Hungary	62	3.20
Kazakhstan	77	3.98
Kyrgyz	71	3.67
Latvia	57	2.95
Lithuania	45	2.33
Macedonia	87	4.50
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 number of firms	1,935	100

Table 2: Summary statistics on firm characteristics in 2005 and 2009

	2005			2009			
	Mean	SD	Obs	Mean	SD	Obs	Mean Difference
Sales (USD)	610,162	3,407,080	1,465	2,449,926	19,700,000	1,443	1,839,764***
Number of employees	99.9	302.5	1,934	111.6	894.4	1,927	11.7
Share of Exporters (%)	25.9	43.8	1,933	22.0	41.4	1,930	-3.9***
Av. share exported (%)	40.1	32.7	501	39.6	33.7	425	-0.5
Av. share exported, 2005 exporters(%)	40.1	32.7	501	27.1	34.4	499	-13.0***
Av. share of CIA rec. (%)	18.0	27.0	1,922	24.8	33.9	1,885	6.8***
Share of firms rec. CIA (%)	51.9	50.0	1,922	56.9	50.0	1,885	5.0***

The mean difference tests for average firm characteristics in 2005 and 2009 were conducted using Welch's formula to allow for unequal variances in both groups (Welch, 1947). Sales are given in local currency units in the survey and were converted into nominal USD using exchange rate data provided by the International Monetary Fund.

Table 3: Exporter categories 2005-2009

	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
Average export share (%) (2005/2009)	0/0	45.4/45.8	32.6/0	0/25.5

Classification of firms according to their export status in both years. Firms are classified as never-exporters if they do not export in both years. Firms are classified as always-exporters if they export in both years. Stoppers are firms that export in 2005 but not in 2009. Starters are firms that do not export in 2005 but export in 2009.

Table 4: Mean difference test on average CIA use, 2005-2009

Panel A: Development of overall CIA use

	Non-Crisis	Crisis	Difference
Av. share of CIA rec. (%)	18.0	24.6	6.6***
Share of firms receiving CIA (%)	52.0	57.0	5.0***

Panel B: Differences in CIA use by exporters and non-exporters, 2005-2009

	Exporters		
	Non-Crisis	Crisis	Difference
Av. share of CIA rec. (%)	21.4	20.9	-0.5
Share of exporters receiving CIA (%)	62.6	65.2	2.6
	Non-Exporters		
	Non-Crisis	Crisis	Difference
Av. share of CIA rec. (%)	16.9	26.0	9.1***
Share of exporters receiving CIA (%)	48.2	54.6	6.4***

Panel A provides results from mean difference tests of trade credit 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 5: Description of variables

Outcome variables	
Exp	0/1 dummy for firms that sell a positive amount of their sales abroad
$LogExpS$	Log share of sales that is generated abroad
$\Delta LogExpS$	Growth rate of export share over 2005-2009

Binary treatment indicators	
$CIArec$	0/1 dummy for firms that receive a positive amount of their sales before delivery of the good
$CIArecP$	0/1 dummy for firms that receive the same or a higher share of their sales before delivery of the good in 2009 compared to 2005

Covariates	
$Crisis$	0/1 dummy equal to 1 if $t = 2009$
$Fincons$	0/1 dummy whether the firm indicates that access to finance (availability and cost, interest rates, fees, and collateral requirements) is a major or very severe obstacle to its current operations
$Foreign$	0/1 dummy whether more than 50% of the firm is owned by a foreign private individual, company or organization
Iso	0/1 dummy whether the firm has an internationally recognized quality certificate
$LogAge$	Log firm age
$LogLabprod$	Log sales (converted in USD) over number of full-time employees
$LogSize$	Log number of full-time employees
$Newprod$	0/1 dummy whether firm has introduced new products or services within the last three years
$Ownerconc$	Share hold in firm by largest owner
$Transobs$	0/1 dummy whether transport is a moderate, major or very severe obstacle to the current operation of the firm
$Weak$	0/1 dummy whether the firm indicates that it tends to disagree or even strongly disagrees that the court system is able to enforce its decisions

Table 6: Effect of CIA financing on extensive and intensive margin of exporting via OLS, Hypothesis 1

	Exp	Exp	LogExpS
	(1)	(2)	(3)
Crisis	-0.0170	-0.0485**	-0.412***
	(0.0197)	(0.0228)	(0.158)
CIArec	0.0768***	0.0914***	-0.240*
	(0.0193)	(0.0224)	(0.124)
CIArec*Crisis	-0.0191	-0.0209	0.430**
	(0.0267)	(0.0304)	(0.184)
LogSize	0.0587***		0.0293
	(0.00585)		(0.0386)
LogLabprod		0.0142***	
		(0.00504)	
LogAge	-0.0158	0.0250*	0.0796
	(0.0128)	(0.0136)	(0.0678)
Ownerconc	-0.000528**	-0.00101***	0.00165
	(0.000254)	(0.000278)	(0.00168)
Foreign	0.185***	0.253***	0.391***
	(0.0278)	(0.0310)	(0.114)
Iso	0.0681***	0.111***	-0.0709
	(0.0213)	(0.0229)	(0.103)
Transobs	0.0140	0.0112	-0.0350
	(0.0164)	(0.0183)	(0.101)
Weak	0.00428	-0.00124	-0.0899
	(0.0142)	(0.0159)	(0.0922)
Constant	0.214**	0.323***	2.949***
	(0.0972)	(0.122)	(0.562)
Observations	3,124	2,546	774
R^2	0.286	0.278	0.190
Sector FE	Yes	Yes	Yes
Country FE	Yes	Yes	Yes

This table reports the estimated coefficients of various influences on firms' export activities via simple OLS. The dependent variable is an export decision dummy which is equal to 1 if the firm exports a positive amount in column (1) and (2). In column (3), the dependent variable is the log export share. In column (2), we include log labor productivity instead of log size to control for firm size effects. For the definitions of the independent variables please refer to Table 5. Robust standard errors are given in parentheses. ***, **, and * denote significance at 0.01, 0.05, and 0.10 levels, respectively.

Table 7: Probit model estimates for selection into CIA financing in 2005 and 2009

	Probit 1	Probit 2	Probit 1	Probit 2	Probit 3	Probit 3
	$CIArec_{2005}$	$CIArec_{2005}$	$CIArec_{2009}$	$CIArec_{2009}$	$CIArec_{2005}$	$CIArec_{2009}$
	(1)	(2)	(3)	(4)	(5)	(6)
LogSize	0.0802***		0.144***		0.0284	0.0109
	(0.0270)		(0.0293)		(0.0573)	(0.0650)
LogLabprod		0.269***		0.131***		
		(0.0532)		(0.0310)		
LogAge	-0.0117	0.0822	-0.0656	0.0458	0.0598	-0.233*
	(0.0556)	(0.0579)	(0.0722)	(0.0753)	(0.111)	(0.136)
Ownerconc	-0.00280**	-0.00296**	-0.000557	-0.000387	-0.00117	-0.00420
	(0.00118)	(0.00133)	(0.00145)	(0.00153)	(0.00269)	(0.00332)
Foreign	0.124	0.140	0.270*	0.350**	-0.110	0.607**
	(0.115)	(0.130)	(0.140)	(0.153)	(0.191)	(0.244)
Iso	0.260**	0.296**	-0.158*	0.0244	0.301*	-0.219
	(0.102)	(0.115)	(0.0958)	(0.099)	(0.173)	(0.199)
Transobs	0.234**	0.316***	0.188**	0.207**	0.365*	0.127
	(0.0941)	(0.109)	(0.0776)	(0.0829)	(0.193)	(0.178)
Weak	-0.133*	-0.189**	0.127*	0.099	-0.313**	0.0681
	(0.0714)	(0.0834)	(0.0741)	(0.0797)	(0.153)	(0.170)
Constant	-0.094	-1.629***	-0.851*	-1.459**	-0.771	-3.382
	(0.371)	(0.518)	(0.490)	(0.606)	(0.645)	(135.6)
Observations	1,660	1,269	1,462	1,275	422	331
Pseudo R^2	0.113	0.135	0.128	0.130	0.165	0.186
Log Likelihood	-1018	-760.7	-868.9	-753.4	-233.8	-174.6
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Exporters only	No	No	No	No	Yes	Yes

This table reports the estimated coefficients of various influences on the probability of a firm to receive CIA via a probit model. The dependent variable is a dummy equal to 1 if the firm receives a positive share of its sales in advance in 2005 (column (1) and (2)) and in 2009 (column (3) and (4)). In column (2) and (4) we control for log labor productivity instead of size of the firm. In column (5) and (6), selection into CIA financing is estimated for exporters only in 2005 and 2009. Robust standard errors are in parentheses. ***, **, and * denote significance at 0.01, 0.05, and 0.10 levels, respectively.

Table 8: Testing for covariate balancing before and after 4 NN matching in 2005, Probit 1 sepcification

	$CIArec = 1$		$CIArec = 0$		% reduc. bias	t-statistic	
	Before	After	Before	After		Before	After
LogSize	3.52	3.50	2.90	3.55	93.2	8.02***	-0.53
LogAge	2.61	2.60	2.53	2.58	66.3	5.08**	0.68
Ownerconc	71.8	72.00	76.9	70.8	76.6	-3.58***	0.85
Foreign	0.121	0.119	0.089	0.098	34.7	2.14**	1.41
Iso	0.180	0.177	0.099	0.199	72.1	4.76***	-1.20
Transobs	0.162	0.163	0.135	0.144	30.4	1.54	1.08
Weak	0.299	0.2982	0.363	0.280	71.8	-2.76***	0.82

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.

Table 9: Assessment of matching quality for Probit 1-7 specifications: average percentage bias and p-value of joint likelihood ratio test

Estimator	Year	Average % bias		$p > \chi^2$		Specification
		Before	After	Before	After	
1 NN matching	2005	11.5	3.8	0.000	0.631	Probit 1
	2005	11.9	4.5	0.000	0.615	Probit 2
	2005	14.2	10.1	0.000	0.009	Probit 3
	2009	10.8	5.5	0.000	0.017	Probit 1
	2009	10.3	5.0	0.000	0.010	Probit 2
	2009	12.4	10.5	0.000	0.033	Probit 3
		6.7	3.5	0.000	0.378	Probit 4
		7.4	6.1	0.000	0.001	Probit 5
		7.1	4.7	0.000	0.003	Probit 6
		7.8	5.4	0.000	0.016	Probit 7
4 NN matching	2005	11.5	3.0	0.000	0.993	Probit 1
	2005	11.9	4.1	0.000	0.940	Probit 2
	2005	14.2	4.5	0.000	0.995	Probit 3
	2009	10.8	2.7	0.000	0.997	Probit 1
	2009	10.3	3.1	0.000	0.991	Probit 2
	2009	12.4	8.0	0.000	0.954	Probit 3
		6.7	2.0	0.000	1.0	Probit 4
		7.4	3.0	0.000	0.989	Probit 5
		7.1	2.6	0.000	0.956	Probit 6
		7.8	2.9	0.000	0.997	Probit 7
Radius matching (caliper 0.02)	2005	11.5	1.9	0.000	1.0	Probit 1
	2005	11.9	3.4	0.000	1.0	Probit 2
	2005	14.2	4.1	0.000	1.0	Probit 3
	2009	10.8	2.3	0.000	1.0	Probit 1
	2009	10.3	2.4	0.000	1.0	Probit 2
	2009	12.4	7.1	0.000	0.990	Probit 3
		6.7	1.9	0.000	1.0	Probit 4
		7.4	2.2	0.000	1.0	Probit 5
		7.1	2.0	0.000	1.0	Probit 6
		7.8	2.2	0.000	1.0	Probit 7
Epanechnikov kernel matching	2005	11.5	1.6	0.000	1.0	Probit 1
	2005	11.9	3.1	0.000	1.0	Probit 2
	2005	14.2	3.7	0.000	1.0	Probit 3
	2009	10.8	2.0	0.000	1.0	Probit 1
	2009	10.3	2.3	0.000	1.0	Probit 2
	2009	12.4	6.3	0.000	0.999	Probit 3
		6.7	1.4	0.000	1.0	Probit 4
		7.4	2.0	0.000	1.0	Probit 5
		7.1	1.6	0.000	1.0	Probit 6
		7.8	2.0	0.000	1.0	Probit 7

This table displays two statistics to assess the matching quality for the four matching algorithms and all specifications (Probit 1 to 7). The average (standardised) percentage bias is the percentage difference of the sample means in the treated and non-treated sub-samples as a percentage of the square root of the average of the sample variances in the treated and non-treated groups (formula is taken from 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 high matching quality.

Table 10: Average CIA treatment effects on the treated for export probabilities

Estimator	Year	Probit 1		Probit 2	
1 NN matching	2005	0.0127	(0.0333)	0.0812*	(0.0418)
	2009	0.0329	(0.0337)	0.1***	(0.0375)
4 NN matching	2005	0.0566**	(0.0272)	0.0559	(0.0346)
	2009	0.0703**	(0.0285)	0.1010***	(0.0307)
Radius matching (caliper 0.02)	2005	0.0720***	(0.0244)	0.0704**	(0.0295)
	2009	0.0701***	(0.0273)	0.0889***	(0.0270)
Epanechnikov kernel matching	2005	0.0719***	(0.0248)	0.0687**	(0.0278)
	2009	0.0679**	(0.0270)	0.0834***	(0.0282)
PS weight. regression	2005	0.0730***	(0.0223)	0.0710**	(0.0251)
	2009	0.0537**	(0.0261)	0.0663**	(0.0283)
Observations	2005	1,656		1,269	
	2009	1,442		1,270	

Estimates for ATTs are based on various propensity score matching algorithms and on propensity score weighted regression. The binary treatment indicator in each year is $CIArec$, a dummy equal to 1 if the firm receives a positive amount of its sales in advance. The dependent variable is the export status of a firm in each year. 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 were calculated for kernel and radius matching *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 11: Average CIA treatment effects on the treated for log export shares

Estimator	Year	Probit 3	
1 NN matching	2005	-0.2455	(0.2139)
	2009	0.3924	(0.2500)
4 NN matching	2005	-0.2602	(0.1673)
	2009	0.3903*	(0.2166)
Radius matching (caliper 0.02)	2005	-0.2457	(0.1711)
	2009	0.3861*	(0.2154)
Epanechnikov kernel matching	2005	-0.2206	(0.1724)
	2009	0.3459*	(0.2102)
PS weight. regression	2005	-0.2260	(0.1397)
	2009	0.3400**	(0.1448)
Observations	2005	411	
	2009	310	

Estimates for ATTs are based on various propensity score matching algorithms and on propensity score weighted regression. The binary treatment indicator in each year is $CIArec$, a dummy equal to 1 if the firm receives a positive amount of its sales in advance. The dependent variable is the log export share of a firm in each year. 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 were calculated for kernel and radius matching *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 12: Probit model estimates for selection into increase in CIA financing between 2005 and 2009

	Probit 4	Probit 5	Probit 6	Probit 7
	$CIArecP$	$CIArecP$	$CIArecP$	$CIArecP$
	(1)	(2)	(3)	(4)
LogSize_{2005}	-0.0767***		-0.0691**	
	(0.0282)		(0.0293)	
LogLabprod_{2005}		-0.127**		-0.121**
		(0.0564)		(0.0571)
LogAge_{2005}	0.133*	0.0630	0.104	0.0560
	(0.0725)	(0.0749)	(0.0759)	(0.0765)
Ownerconc_{2005}	0.00138	0.00137	0.000861	0.00067
	(0.00122)	(0.00137)	(0.00125)	(0.0014)
Foreign_{2005}	0.0310	-0.0765	0.0500	-0.0668
	(0.116)	(0.131)	(0.118)	(0.132)
Iso_{2005}	-0.0697	-0.0754	-0.0323	-0.0353
	(0.101)	(0.114)	(0.103)	(0.116)
Transobs_{2005}	-0.156	-0.193*	-0.201**	-0.234**
	(0.0957)	(0.109)	(0.0984)	(0.112)
Weak_{2005}	0.171**	0.256***	0.169**	0.253***
	(0.0754)	(0.0887)	(0.0771)	(0.0906)
Fincons_{2005}			0.0753	0.0668
			(0.0969)	(0.111)
Newprod_{2005}			-0.225***	-0.226**
			(0.0755)	(0.0871)
Constant	0.177	0.854	0.341	0.986*
	(0.407)	(0.571)	(0.413)	(0.579)
Observations	1,617	1,236	1,558	1,188
Pseudo R^2	0.0523	0.0553	0.0568	0.0613
Log Likelihood	-932.0	-695.0	-892.5	-662.5
Sector FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes

This table reports the estimated probit coefficients of pretreatment firm characteristics on the probability of a firm to receive the same or a higher share of CIA

Table 13: Average CIA treatment effects on the treated for growth rate of export shares

Estimator	Probit 4	Probit 5	Probit 6	Probit 7
1 NN matching	0.1752	0.1612	0.3057***	0.0917
	(0.1117)	(0.1311)	(0.1150)	(0.1250)
4 NN matching	0.1900**	0.0965	0.2445***	0.2055*
	(0.0948)	(0.1100)	(0.0930)	(0.1108)
Radius matching (caliper 0.02)	0.2019***	0.1624*	0.2235***	0.1675*
	(0.0726)	(0.0973)	(0.0839)	(0.0972)
Epanechnikov kernel matching	0.1933***	0.1863*	0.1939**	0.1822*
	(0.0741)	(0.0974)	(0.0782)	(0.0983)
PS weight. regression	0.1843**	0.2204**	0.1838**	0.2204**
	(0.0737)	(0.0916)	(0.0752)	(0.0927)
Simple OLS regression	0.1803**	0.2022**	0.1925**	0.2135**
	(0.0754)	(0.0889)	(0.0759)	(0.0893)
Observations	1,610	1,223	1,551	1,177

Estimates for ATTs are based on various propensity score matching algorithms and on propensity score weighted regression. In addition, we provide corresponding results from a simple unweighted OLS rergression with heteroskedastic robust standard erros. The binary treatment indicator is $CIArecP$, a dummy equal to 1 if the firm in 2009 receives the same or a higher share of its sales in advance than in 2005. The dependent variable is the growth rate of export shares of a firm between 2005 and 2009. 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 were calculated for kernel and radius matching *** p<0.01, ** p<0.05, * p<0.1