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Trade credit and cross-country predictable firm returns☆

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Abstract

We investigate the role of trade credit links in generating cross-border return predictability between international firms. Using data from 43 countries from 1993 to 2009, we find that firms with high trade credit located in producer countries have stock returns that are strongly predictable based on the returns of their associated customer countries. This behavior is especially prevalent among firms with high levels of foreign sales. To better understand this effect we develop an asset pricing model in which firms in different countries are connected by trade credit links. The model offers further predictions about this phenomenon, including stronger predictability during periods of high credit constraints and low uninformed trading volume. We find supportive empirical evidence for these predictions.

Keywords: international equity markets, trade credit, information asymmetry, customer-supplier relations, predictability
JEL: G12, G14, G15

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1. Introduction

During financial crises, stock market movements across the globe appear synchronized. To explain this observation, many have highlighted the role of direct economic links, such as trade flows, between countries.[1] Recent domestic evidence from the US shows that economic links not only explain contemporaneous correlations between firms' stock returns, but also provide useful information for predicting future firm-level stock returns [see, for example, Cohen and Frazzini (2008) and Menzly and Ozbas (2010a), who identify "upstream" and "downstream" firms in the US supply chain]. It is, therefore, natural to investigate whether such economic link-derived return predictability also exists between different countries, especially in light of the substantial interest in the sources of cross-border return correlations (see Karolyi and Stulz, 1996; Forbes and Rigobon, 2002; and Bekaert, Hodrick, and Zhang, 2009). Our contribution in this paper is to identify the role of an important economic connection between firms across countries that leads to such cross-border return predictability, namely, trade credit.

Trade credit represents a significant source of financing for many firms (see Mian and Smith, 1992; and Mian and Smith, 1994), in particular, those that are bank credit-constrained (see Petersen and Rajan, 1994a,b; and Petersen and Rajan, 1997), and those that operate in emerging markets with underdeveloped legal systems and capital markets (see Demirguc-Kunt and Maksimovic, 2001; and Fisman and Love, 2003). While a number of studies have pointed to international trade as a channel for the transmission of shocks (e.g., Eichengreen, Rose, and Wyplosz, 1996; Kaminsky and Reinhart, 2000; and Forbes, 2004), complementary evidence suggests that trade credit is enhanced during financial crises, further linking the economic prospects of firms at such times. For example, Wilner (2000); Cuñat (2007); Love, Preve, and Sarria-Allende (2007); and Coulibaly, Sapriza, and Zlate (2011) find that trade credit increases to provide firms with a shield during financial distress relative to credit from financial intermediaries, and Chor and Manova, 2010 show that industry sectors with low access to trade credit were most susceptible to credit market tightening during the 2007-2008 global financial crisis.[2]

We build a simple asset pricing model that delivers cross-predictability in returns driven by trade credit.[3] Our model uses three building blocks from two different streams of

[1] See, for example, Eichengreen, Rose, and Wyplosz (1996); Sachs, Tornell, and Velasco (1996); Eichengreen and Rose (1998); Rigobon (1998); Glick and Rose (1999); and Forbes (2004).

[2] A body of literature shows that trade credit can serve as a mechanism for spreading shocks when monetary policy is tightened (see Nilsen, 2002; and Choi and Kim, 2005).

[3] We use the term *trade credit* in the accounting sense of sales of goods or services that are paid for later by the customer and that are recorded as accounts receivable on the producer firm's balance sheet. Trade credit is not to be confused with trade finance, which normally arises as the result of the issuance of a letter

literature. From the corporate finance literature, we take the idea that trade credit arises as the extension of finance from financially stronger to financially weaker firms (e.g., Schwartz, 1974). From the international asset pricing literature, we borrow the assumption that asymmetric information exists in international capital markets between foreign and domestic investors (e.g., Gehrig, 1993; and Brennan and Cao, 1997), and the assumption that markets are, at least partially, segmented (e.g., Errunza and Losq, 1985; and Merton, 1987). Armed with these assumptions, we consider two countries with segmented stock markets each consisting of a representative firm. We designate one firm-country as the customer and the other firm-country as the producer. We model the correlation between the dividends of the two firms as rising with increases in trade credit and rising with the difference in the financing costs of the two firms. Each stock market is populated by domestic investors, who invest only in their local market, and by privately informed speculators, who invest in both markets. The investment opportunities available to speculators imply that they trade for information motives and for rebalancing motives, with the latter induced by the correlation between the two stock markets' returns.

To see how the model works, consider a positive shock to fundamentals in the customer country, about which speculators have private information. In equilibrium, some of this information flows to prices, causing a rise in the stock price of the customer country. If some information remains private, dividends would be higher than anticipated in prices, meaning that returns would be positive again in the future. In such an equilibrium, speculators increase their customer country holdings, bear more risk, and demand higher expected return, despite rebalancing their portfolios by selling some of their holdings in the producer country. When speculators sell on account of their rebalancing needs they have to concede some expected return to domestic investors in the producer country to induce them to buy, depressing the current price in the producer country. Thus, the model predicts cross-predictability, i.e., stock returns in the producer country can be predicted using prior movements in the customer country returns. Higher trade credit leads to a higher positive correlation across the two assets, and hence, a stronger rebalancing motive. This comparative statics exercise suggests that when trade credit is higher, cross-predictability is also higher.

The model delivers three main additional predictions regarding cross-predictability. First, cross-predictability is stronger when shocks to fundamentals dominate vis-à-vis shocks to rebalancing trades. Because shocks to rebalancing trades are associated with higher trading volume and lower cross-predictability, we hypothesize that cross-predictability is stronger when volume is lower. Second, cross-predictability is stronger when the difference in financing

of credit and is used to limit the risk to exporters of default by importers.

costs of the two firms is at its highest, i.e., when trading credit is most valuable. Third, the way trade credit drives predictability in stock returns has nonlinear effects, due to the reduced benefits of using trade credit when customer firms are doing well.

To empirically explore the role of trade credit in driving cross-country return predictability, we build on the strategy in Rizova, 2010. Rizova finds that high-exporting (producer) countries' stock market returns can be predicted using their major-importing (customer) countries' stock market returns. We modify her approach to further allow for the possibility of economic linkages between firms located in different countries. We estimate a baseline specification that allows for separate predictions of firm-level excess stock returns of producer firms with high and low levels of trade credit, and we find that the predictability is concentrated in high trade credit firms. We then further restrict the set of producer firms with high levels of trade credit to those with high levels of foreign sales, in consonance with economic intuition and our model's predictions for the highest levels of predictability based on the trade credit channel under investigation.

Our results are best illustrated as the returns on portfolio strategies. Within the bottom quintile of producer countries sorted by their customer countries' past performance, a strategy that goes long low-trade credit firms and short high-trade credit firms generates significantly positive stock returns. Across the quintiles of producer countries sorted by their customer countries' past performance, a strategy that goes long low trade credit firms in countries with high-performing customers and short high-trade credit firms in countries with poor-performing customers generates returns of around 14% per annum. While these returns are large and statistically significant, what is perhaps more important from the perspective of economic interpretation is our finding that the proximate driver of the cross-predictability of producer country stock returns by customer country returns is the trade credit channel. In other words, the trade credit channel appears to be the main reason for the predictability of producer country returns by customer country returns.[4] To ensure that our results are driven by the links between international firms, we verify that the cross-predictability we uncover is driven by firms with high levels of foreign sales. After controlling for high foreign sales, the cross-predictability operates as expected for producer countries experiencing high customer returns as well as for those experiencing low customer returns.

The returns to these trading strategies are robust to a variety of controls, which we employ in our firm-level panel regressions to capture variation potentially caused by a range of country, industry, and firm-level attributes. The use of country and industry fixed effects,

[4]This effect is distinct from that of Goto, Xiao, and Xu, 2011, who show that own accounts payables predict own returns. We control for the effect of lagged trade credit on its own in our predictive regressions, and we find that the cross-predictability effect is strong and statistically significant over and above this effect.

controls for lagged and contemporaneous local and world market returns, local industry returns, and firm-level controls such as the level of cash, firm size and book-to-market ratios, and short- and long-term debt do not affect the performance of the strategies. We also check the robustness of our empirical results by using different sorting procedures and by risk-adjusting in various ways. Finally, we employ a placebo test in which firm-level trade credit within an industry at each month is reassigned randomly across the firms in that industry during that month. We then repeat the empirical analysis and show that the strategy returns are not affected by conditioning on trade credit. The finding suggests that trade credit displays incremental explanatory power and gives further support to our identification strategy.

We test additional model predictions by inspecting cross-predictability during periods in which producer countries experience high trading volume relative to their market capitalization and by checking how the cross-predictability of stock returns operates during periods of financial stress when opportunities to access external capital markets are likely to be more unequal. We find that cross-predictability is significantly higher when our proxy for volume is low and that the cross-predictability of stock returns operates primarily in periods of financial stress. Virtually all of the returns from the buy-and-hold strategies are garnered during periods of high financial stress. We conclude that, consistent with the model, trade credit is particularly relevant as a mechanism for the international transmission of economic shocks during periods of financial stress, for firms with high foreign sales, and during periods with low trading volume. Finally, our results are particularly strong when customer returns are low, consistent with the nonlinear effects predicted by the model.

Our model constitutes a theoretical contribution providing a reliable identification of economic links by way of the trade credit channel. In particular, we model the effects on return predictability of the actions of agents who learn from prices, and, by introducing trade credit, we add firm-specific financial considerations to the modeling of cross-predictability. We are thus able to separate our story from the investor inattention view of Hong, Torous, and Valkanov (2007), Cohen and Frazzini (2008), and Menzly and Ozbas (2010a). While trade credit presumes long-term relations that are known by the market and can be subject to investor inattention [such as the customer-supplier links emphasized by Cohen and Frazzini, 2008], trade credit also emphasizes a financial link, which we test directly. By modeling firm-level operating fundamentals, we also offer a distinct framework for return correlations from that stemming from the constraints imposed on institutional investors (e.g., Brunnermeier and Pedersen, 2009; Hameed, Kang, and Viswanathan, 2010; and Bartram, Griffin, and Ng, 2012).

Shahrur, Becker, and Rosenfeld (2009) and Rizova (2010) find evidence of cross-country

return predictability at aggregate levels (i.e., across industry portfolios or country indices). Our analysis is distinguished from theirs by its emphasis on the firm-level predictability and its focus on a specific theoretically motivated mechanism. This emphasis allows for sharper inferences, enabling us to detect cross-border return predictability, which is substantially higher than that previously found in the literature. Moreover, we are able to provide insight on an important economic driver of aggregate cross-border return predictability. That is, we build a theoretical model to understand the role of trade credit and, thus, derive additional predictions that are supported by the data.

The remainder of this paper is organized as follows. Section 2 presents the model and theoretical predictions. Section 3 describes the data employed. Section 4 discusses the empirical strategy and results. Section 5 concludes. The Appendix contains the proofs of the results in section 2.

2. An asset pricing model with trade credit

We take two dates, $t = 1, 2$, and two countries: a customer country labeled C and a producer country labeled P, each with one firm. The customer-country firm buys from the producer-country firm. We first model the corporate finance part of the economies related to trade credit. We derive firm dividends and establish dividend correlation across countries, showing how trade credit affects this correlation. We then embed this model of dividends into an asset pricing model to derive predictions about stock returns.

2.1. Modeling trade credit

We adopt the prominent view in the literature that trade credit is the extension of finance from the financially stronger firm to the financially weaker (e.g., Schwartz, 1974).[5] The model below shares many features of the model in Biais and Gollier (1997).[6] Each firm

[5]Petersen and Rajan (1997) find evidence for this view by showing that more profitable sellers provide more trade credit. Nilsen (2002) shows that small firms obtain more trade credit from their suppliers during monetary contractions. Choi and Kim (2005) show that trade credit allows firms to absorb the effect of a credit contraction. Love, Preve, and Sarria-Allende (2007) find that trade credit provision increases after crises start.

[6]There are several variants to this view. If trading partners are better informed than banks (see Biais and Gollier, 1997; Emery, 1984; Smith, 1987; and Brennan, Maksimovic, and Zechner, 1988), they can substitute for the banks through trade credit. Alternatively, if sellers can repossess and better liquidate the goods upon default by the buyer than a bank can (Mian and Smith, 1992), then sellers would have an advantage in supplying credit to buyers vis-a-vis banks. Finally, if a buyer does not pay, the seller can choke the buyer by cutting additional supplies (provided buyer continues operating) and this could represent better enforcement than cutting credit by a bank if the market for bank loans is more competitive or if the bank is restricted by bankruptcy from doing so.

pays a liquidating dividend at date 2 that depends on the trade credit deal between them.

At date 2, the random normal quantity of goods S is traded between customer and producer. Customer and producer firms agree to trade the fraction α of goods at P_{TC} per unit paid at date 1 (trade credit) and the fraction $1-\alpha$ at the cash price of 1. The price P_{TC} is to be determined in equilibrium. The producer (customer) faces an opportunity cost of money of R^P (R^C) per unit. It is assumed that the producer firm is financially stronger, $R^C - R^P > 0$. Assuming no cost in producing goods for simplicity, the producer firm's date 2 dividend is

$$D^P = \alpha P_{TC} \left(R^P\right)^{-1} S + (1-\alpha) S. \tag{1}$$

The amount paid via trade credit is measured in date 2 units and must be discounted to reflect the opportunity cost of money. The customer firm's dividend is

$$D^C = \bar{P}S - \alpha P_{TC} \left(R^C\right)^{-1} S - (1-\alpha) S, \tag{2}$$

where $\bar{P}$ is some exogenous, reservation price at which the firm can sell its products.

The trade credit price P_{TC} is the outcome of Nash bargaining. To solve for the Nash bargaining solution, we have to specify the dividend to either firm if trade credit is not used. We assume that the producer firm's dividend absent trade credit presumes all sales are cash and equals S and, likewise, for the customer firm its dividend absent trade credit is $\bar{P}S - S$. Assigning the bargaining weight ψ to the producer, the date 1 choice of P_{TC} solves

$$\max_{P_{TC}} E\left[\left(D^P - S\right)^{\psi} \left(D^C - \left(\bar{P}S - S\right)\right)^{1-\psi}\right]. \tag{3}$$

From the necessary and sufficient first order condition, the solution to this problem is to set

$$P_{TC} = R^P + \psi \left(R^C - R^P\right). \tag{4}$$

The price of goods sold on credit is given by a threshold, R^P, which represents the opportunity cost of selling for cash and investing the money, plus the producer's bargaining fraction of the surplus from trade credit. This surplus internalizes the differential opportunity cost of money that each trading partner faces. The stronger financial firm lends money to the weaker firm at R^P by means of trade credit, and they both share the surplus of avoiding borrowing by the weaker firm at R^C.

Given the solution for P_{TC}, we derive the optimal dividends,

$$D^C = \left[\bar{P} - 1 + \alpha (1-\psi) \left(R^C - R^P\right) \left(R^C\right)^{-1}\right] S \tag{5}$$

and

$$D^P = \left[1 + \alpha\psi \left(R^C - R^P\right) \left(R^P\right)^{-1}\right] S. \tag{6}$$

Profits increase by the amount of shared surplus relative to a trade that does not involve trade credit.[7]

For notational simplicity, we transform dividends by letting

$$\alpha' \equiv \left(1 + \alpha\psi \left(R^C - R^P\right) \left(R^P\right)^{-1}\right) \left(\bar{P} - 1 + \alpha \left(1 - \psi\right) \left(R^C - R^P\right) \left(R^C\right)^{-1}\right) \tag{7}$$

and specifying the date 2 customer dividend and the producer dividend to be, respectively,

$$D^C = \varepsilon^C + u^C \tag{8}$$

and

$$D^P = \alpha' D^C + \varepsilon^P + u^P. \tag{9}$$

All four shocks $\varepsilon^C, u^C, \varepsilon^P$, and u^P are normally distributed with zero means and variances $\sigma^2_{\varepsilon C}, \sigma^2_{uC}, \sigma^2_{\varepsilon P}$, and σ^2_{uP}, respectively, and are independent of each other. Specifying two shocks, ε^C and u^C, in lieu of the random variable S, is arbitrary but useful later when we characterize investors' information sets. We add a stream of dividends to the producer firm unrelated to trading with the customer firm given by $\varepsilon^P + u^P$. The parameter α' incorporates the effect of trade credit and measures the covariance between country dividends, i.e., $\mathrm{E}\left[D^P D^C\right] = \alpha' \left(\sigma^2_{\varepsilon C} + \sigma^2_{uC}\right)$. The covariance α' is increasing with trade credit, α, and increasing in the spread $R^C - R^P$. The reason for the latter is that the larger spread increases the gains from trade credit for fixed α and the dividends to both firms.

2.2. Investors and investor demands

In subsection 2.1, we show how trade credit affects the covariance between dividends across countries. The covariance between dividends is an integral part of the asset pricing model that we build because it drives both hedging demands and information transmission.

Each country has a continuum of investors with unit mass. The fraction $1-\mu_i$ of investors

[7] Absent any cost to engage in trade credit, it would be optimal to set $\alpha = 1$. It is easy, but uninformative, to introduce a cost of trade credit convex in α and linear in S that would lead to an interior solution to α. Instead, we proceed with the assumption that α is a fixed parameter.

in country $i = C, P$ invests domestically only, and the fraction μ_i invests in both countries. We label the μ_i investors as speculators and the rest of the local investors as domestic.[8]

Investors have a constant absolute risk aversion of $\gamma > 0$ about their date 2 wealth, W_2. They can borrow and lend at the risk free rate that we normalize to zero. There is an exogenous, random supply of shares in each country, z^i, with mean zero and variance σ_{zi}^2, with $i = C, P$. We solve for a rational expectations equilibrium in which investors take prices as given when solving for their asset demands. The equilibrium price is such that total stock demand equals total stock supply.

The final aspect to consider in the model is the information available to each investor. Following an extensive literature in international finance that highlights the role of information asymmetries in explaining many stylized facts (e.g., Gehrig, 1993; and Brennan and Cao, 1997), we assume that speculators have better information than domestic investors [see, for example, Froot and Ramadorai (2008), for evidence to support this assumption]. For simplicity, speculators learn both shocks, ε^C and ε^P. Let $\bar{D}^C = \varepsilon^C$ and $\bar{D}^P = \alpha'\varepsilon^C + \varepsilon^P$. This decomposition of dividends can be derived from a model in which speculators receive signals about future dividends. In that setting, $\bar{D}^i$ is the speculators' expectation of the future dividend conditional on the signal, and u^i is the forecast error made by speculators. Domestic investors learn only from their local price as there is no additional public information.

Solving the domestic investors' optimization problem (see the Appendix for details), we obtain their local-asset demands, θ^i, for $i = C, P$,

$$\theta^i = \frac{\mathrm{E}^d\left[D^i - P^i\right]}{\gamma \mathrm{Var}^d\left[D^i - P^i\right]}. \tag{10}$$

Superscript d means that the conditional moments use the information available to the domestic investors in the respective country. According to the asset demand in Eq. (10), domestic investors in country i face a mean-variance trade-off and buy more of country i's stock if they expect a higher return for the same conditional variance.

From the speculators' optimization problem, we obtain η^i, their asset demand for country i's stock,

$$\begin{bmatrix} \eta^C \\ \eta^P \end{bmatrix} = \frac{1}{\gamma\sigma_{uP}^2} \begin{bmatrix} \frac{\sigma_{uP}^2 + \alpha'^2\sigma_{uC}^2}{\sigma_{uC}^2}\left(\bar{D}^C - P^C\right) - \alpha'\left(\bar{D}^P - P^P\right) \\ \bar{D}^P - P^P - \alpha'\left(\bar{D}^C - P^C\right) \end{bmatrix}. \tag{11}$$

[8]This segmentation hypothesis has been used in many papers, most notably in Errunza and Losq (1985) and Merton (1987). Empirical evidence suggests that segmentation remains an important feature of international financial markets (see, for example, Bekaert, Harvey, Lundblad, and Siegel, 2010). It is consistent with the home bias in international equity portfolios and with other features of international investing (see Albuquerque, Bauer, and Schneider, 2007) as well as with the existence of carry trade profits in foreign exchange (see Jylha and Suominen, 2011).

Speculators buy more of country i's stock if the expected return on the country's stock is high, or if the expected return on the other country's stock is low. The former trading motive is driven primarily by information, whereas the latter trading motive is a portfolio rebalancing effect that obtains because of the trade credit linkage. The size of the rebalancing effect is determined by the magnitude of trade credit as incorporated into α'.

2.3. Equilibrium

The stock supply in the two markets z^C and z^P are random normal variables with zero means and variances σ^2_{zC} and σ^2_{zP}, respectively, and independent from all other shocks. Random stock supplies are introduced to guarantee that the equilibrium price is not fully revealing and that some information remains private to speculators. Market clearing requires

$$z^C = \mu_C \eta^C + (1 - \mu_C)\, \theta^C \tag{12}$$

and

$$z^P = \mu_P \eta^P + (1 - \mu_P)\, \theta^P. \tag{13}$$

In the Appendix, we show that the stock markets clear with the following stock prices:

Proposition 1. *If a linear equilibrium exists, the date 1 stock market equilibrium is characterized by the following prices:*

$$P^C = \bar{D}^C - b_{CC}\left(\bar{D}^C - \mathrm{E}^d\left(\bar{D}^C\right)\right) - b_{CP}\left(\bar{D}^P - \mathrm{E}^d\left(\bar{D}^P\right)\right) - h_{CC} z^C - h_{CP} z^P$$

and

$$P^P = \bar{D}^P - b_{PP}\left(\bar{D}^P - \mathrm{E}^d\left(\bar{D}^P\right)\right) - b_{PC}\left(\bar{D}^C - \mathrm{E}^d\left(\bar{D}^C\right)\right) - h_{PP} z^P - h_{PC} z^C.$$

The constants b_{CC}, b_{PP}, b_{CP}, h_{CC}, h_{CP}, b_{PC}, h_{PP}, and h_{PC} are nonlinear functions of the model parameters.

The stock price in country i equals the present value of the speculators' dividend forecast in that country, $\bar{D}^i$, adjusted for the presence of private information as illustrated by the forecast error made by domestic investors about the country's dividend, $\bar{D}^i - \mathrm{E}^d\left(\bar{D}^i\right)$, as well as by the random supply of the country's stock. A positive forecast error means that prices are below future expected dividends provided $b_{ii} > 0$ because a fraction of investors

fails to recognize the ability of the stock to pay dividends. Country i's stock price also depends on the forecast error made by domestic investors in the foreign country about their own dividend, $\bar{D}^j - \mathrm{E}^d\left(\bar{D}^j\right)$, for $j \neq i$, as well as the random supply in that foreign country. This feature of equilibrium prices is due to the fact that the pricing in one market affects speculators' rebalancing trades in the other market. If the forecast error in C is large and if expected returns there are high, then speculators could sell in P for rebalancing purposes, forcing a lower price. Hence, $b_{PC} > 0$. Likewise, noisy supply in either market is likely to contribute to low prices, $h_{ii}, h_{ij} > 0$.

Given equilibrium prices, we can solve the learning problem of the domestic investors. After observing the equilibrium prices, domestic investors in country i learn $\Pi^i \equiv P^i - b_{ii}\mathrm{E}^d\left(\bar{D}^i\right)$,

$$\Pi^C = (1 - b_{CC})\,\bar{D}^C - b_{CP}\left(\bar{D}^P - \mathrm{E}^d\left(\bar{D}^P\right)\right) - h_{CC}z^C - h_{CP}z^P \tag{14}$$

and

$$\Pi^P = (1 - b_{PP})\,\bar{D}^P - b_{PC}\left(\bar{D}^C - \mathrm{E}^d\left(\bar{D}^C\right)\right) - h_{PP}z^P - h_{PC}z^C. \tag{15}$$

Π^i is a noisy signal for $\bar{D}^i$ for domestic investors in country i. The conditional means and variances used by domestic investors to determine their asset demands are consistent with equilibrium prices and Π^i. For brevity we leave the construction of these moments to the Appendix, where we also show how to find the conditional forecast errors, $\bar{D}^i - \mathrm{E}^d\left(\bar{D}^i\right)$. This concludes the construction of the equilibrium. In the Appendix we also show how the equilibrium can be solved numerically.

2.4. Cross-country return predictability

We now use comparative statics to study the properties of the theoretical covariance $\mathrm{Cov}\left(P^C, D^P - P^P\right)$. We focus on this moment, as it is most relevant for our empirical analysis. The sign of this covariance is the same as the sign of the slope coefficient in a cross-predictability regression of future producer-country returns on current customer-country returns. That is, in the model,

$$\mathrm{E}\left[D^P - P^P | P^C\right] = \frac{\mathrm{Cov}\left(P^C, D^P - P^P\right)}{\mathrm{Var}\left(P^C\right)} P^C. \tag{16}$$

Besides being interested in the sign of this covariance, we are interested in how it changes with the size of trade credit, α, and the financing cost difference, $R^C - R^P$.

We begin with an intuitive description of the way in which information-driven trades and portfolio rebalancing trades affect this covariance. As a first step, consider a situation in which good private information about future customer-country dividends emerges. If there were a perfectly efficient market in which information is fully impounded in the price, the price would immediately adjust upward and there would be no trading. However, in our model, in which information is not fully impounded into the price, there is a partial, not full, price increase. Recall from Proposition 1 that domestic investors' forecast error, $\bar{D}^C - \mathrm{E}^d\left(\bar{D}^C\right) > 0$, keeps the price from increasing up to the full present value of future dividends.

The partial price increase induces speculators, on account of their private information, to buy customer-country stock, increasing their holdings of these stocks. This increased holding triggers an additional effect. Because customer-country stock returns are conditionally positively correlated with producer-country stock returns, speculators rebalance their portfolios by selling some producer-country stock.

Absent any dividend shocks in the producer country, domestic investors in the producer country are willing to absorb these rebalancing-induced speculator sales only if the current price (future return) of producer-country stock drops (rises). Thus, in equilibrium, high returns in the customer country forecast high returns in the producer country.

Now consider a different situation in which an unexpectedly low supply realization in the customer country emerges. The presence of random supply constitutes noise, making it difficult for domestic investors trying to learn the private information of speculators, as low supply drives prices up in an identical fashion to good private information. The consequences of such a low supply shock are different from an information shock, however, because dividends are not expected to be high in the future. As a result, expected returns in the customer country must be low following a low supply realization. Speculators, therefore, would move to the producer country, thus bidding producer-country stock prices up, lowering producer-country expected stock returns. In such a situation, therefore, speculator rebalancing trades contribute to negative cross-asset serial correlation.

The relative importance of trades driven by noisy supply shocks and trades driven by information in affecting the covariance $\mathrm{Cov}\left(P^C, D^P - P^P\right)$ depends on the relative size of the variances $\sigma^2_{\varepsilon C}$ and σ^2_{zC}. Decreasing σ^2_{zC} relative to $\sigma^2_{\varepsilon C}$ strengthens the effect of information trades, and increasing σ^2_{zC} relative to $\sigma^2_{\varepsilon C}$ strengthens the effect of noisy supply–driven rebalancing trades.

Fig. 1 provides comparative statics along this dimension, derived from a numerical solution of the model. The solid line tracks the trade credit level–cross-predictability relation when σ^2_{zC} is low and shows that a positive cross-asset covariance can arise in equilibrium for

low values of σ^2_{zC}, holding all other parameters constant. The dashed line tracks the trade credit level–cross-predictability relation when σ^2_{zC} is high and shows that, in such cases, a negative cross-asset covariance can arise in equilibrium.[9]

[Insert Fig. 1 near here]

The solid line in the figure has a positive slope, which shows that, when σ^2_{zC} is low, higher levels of trade credit are associated with a stronger cross-predictability relation between the assets of the two countries. Intuitively, when speculators respond to information shocks pertaining to the customer country, a high level of α' (meaning that the conditional correlation across the two assets is stronger) creates stronger rebalancing motives in the stock of the producer country. This can be seen in Eq. (11)). Good news in the customer country still implies higher expected returns in the customer country, but generates a stronger rebalancing stock sale in the producer country because the two stocks have higher correlation. Domestic investors in the producer country are willing to accommodate these trades only if the price is sufficiently low and, thus, if the expected return is sufficiently high.

2.5. Nonlinear effects

In line with the trade credit literature, it is natural to think that the effect of trade credit depends nonlinearly on the state of the economy and, hence, on the level of customer country stock returns.

First, trade credit could serve as a particularly important mechanism for the transmission of shocks during periods when funding is scarce (e.g., Nilsen, 2002; and Choi and Kim, 2005), i.e., periods when $R^C - R^P$ is likely to be highest.

Second, consider the effect of the interest tax shield of debt. In good times, firms can use the interest expense on their debt as a shield against the taxation of profits, meaning that the relative benefit of using trade credit, i.e., the ability to consume credit at a rate in-between the borrowing costs of producer and customer firms, is lower. However, in bad times, when profits are lower, the interest tax shield motivation is reduced, and the benefit of trade credit will be highest.

Finally, during good times for consumer firms, their bargaining power could increase, leading to a decline in α' and a reduction in the covariance $\mathrm{E}\big[D^P D^C\big]$. α' is an increasing function of the producer firms' bargaining power, ψ.

[9] A similar picture arises if instead we let $\sigma^2_{\varepsilon C}$ determine the relative strengths of the rebalancing effect (low $\sigma^2_{\varepsilon C}$) and of the asymmetric information effect (high $\sigma^2_{\varepsilon C}$). However, our preference for using σ^2_{zC} here lies in the fact that σ^2_{zC} does not affect the covariance of fundamentals as does $\sigma^2_{\varepsilon C}$, leaving this role exclusively to the trade credit parameter, α.

While these nonlinear effects are clearly important, difficulties arise in directly incorporating them into our model. Our model embeds trade credit into an asset pricing equilibrium with asymmetrically informed investors. The model generates predictions for cross-country return predictability and shows that this predictability is related to the level of trade credit. However, the model does so in the context of an equilibrium linear price rule (see Proposition 1). This equilibrium linear pricing rule results from the standard assumptions of normality of shocks and exponential utility.

Departing from this standard framework is complex, but we outline one possible avenue to do so. Suppose that firm policies for the usage of trade credit follow a threshold rule. The threshold rule results in the covariance $\mathrm{E}\left[D^P D^C\right]$ equaling $\alpha'\left(\sigma^2_{\varepsilon C}+\sigma^2_{uC}\right)$ if ε^C is below a certain threshold and zero (no trade credit used) if ε^C is above this threshold.

Speculators observe ε^C, so they know the size of the true covariance $\mathrm{E}\left[D^P D^C\right]$. That is, speculators know when firms use trade credit and when they do not.

Assume that domestic investors believe that firms always use trade credit, i.e., that $\mathrm{E}\left[D^P D^C\right]=\alpha'\left(\sigma^2_{\varepsilon C}+\sigma^2_{uC}\right)$ always. Domestic investors also do not know that speculators' assessment of $\mathrm{E}\left[D^P D^C\right]$ varies with ε^C, but they do know that speculators could be using a different value for $\mathrm{E}\left[D^P D^C\right]$. The two groups agree to disagree in the usual sense.

The Appendix provides the solution of the model under these assumptions. The solution shows that when ε^C is low, and both investors believe $\mathrm{E}\left[D^P D^C\right]=\alpha'\left(\sigma^2_{\varepsilon C}+\sigma^2_{uC}\right)$, which corresponds to true firms' policies. Cross-country return predictability displays the properties in our baseline model and increases with trade credit.

However, when ε^C is high, and speculators and domestic investors agree to disagree on the size of the true covariance, the fact that $\alpha'=0$ for speculators removes their static hedging demand and, thus, the link between the two countries' stock returns. The Appendix shows that domestic investors' beliefs that $\mathrm{E}\left[D^P D^C\right]=\alpha'\left(\sigma^2_{\varepsilon C}+\sigma^2_{uC}\right)$ are irrelevant for the equilibrium. Cross-country return predictability is therefore zero in this case.

Under these assumptions, the model delivers a nonlinear prediction, that cross-country return predictability depends on trade credit only when customer country firms experience low returns.

2.6. Predictions

The model delivers several predictions regarding cross-country return predictability.

Prediction 1 Cross-country predictability in returns is positive due to trade credit.

Prediction 2 Cross-country predictability in returns increases in trade credit. This effect should be stronger when uninformed volume is low.

Because differences in financing costs enter multiplicatively with trade credit, $\alpha\left(R^C - R^P\right)$, we have Prediction 3.

Prediction 3 The effect of trade credit on cross-country predictability increases with $R^C - R^P$.

We test Prediction 3 using an index of financial stress in emerging countries as it is natural to assume that unequal access to credit across firms internationally is more likely in periods of financial stress (e.g., Nilsen, 2002; and Choi and Kim, 2005).

And, finally, because of the presence of nonlinear effects in trade credit, we have Prediction 4.

Prediction 4 The effect of trade credit on cross-country predictability is stronger for low customer country returns.

Our model shares several aspects with the model of investor inattention of Menzly and Ozbas (2010b), which builds on Cohen and Frazzini (2008) and, thus also shares some of the same predictions. Cross-predictability is linked to economic fundamentals in both models and is also related to the presence of uninformed investors (or inattentive investors in their model). However, the models are not observationally equivalent, as we highlight the role of trade credit in generating the association between economic fundamentals and also because trade credit ties our story uniquely to financial conditions. Our model assumes that domestic investors in each country learn only from local prices [in Menzly and Ozbas (2010b) investors do not learn from prices]. This assumption is not critical, however, as long as domestic investors do not become fully informed about the dividend process by observing foreign prices. The presence of noisy supply guarantees that domestic investors would be unable to perfectly learn the information of speculators even if they also observed foreign prices and, thus qualitatively the economic mechanism we highlight would be unaffected.

Finally, trade credit has important intertemporal dimensions absent in the model that result from established long-term relations between producers and customers (e.g., Petersen and Rajan, 1997). Arguably, such long-term relations should lead to stronger co-movement in fundamentals, in which case our results would be strengthened. However, long lived investors could be able to acquire more information, in which case our results would be weakened. These trade-offs are important for a quantitative evaluation of the mechanism but do not change its effects qualitatively.

3. Data and variable definitions

Our empirical goal is to assess the predictability of producer firms' stock returns using the stock returns of customer firms linked via trade credit. As we do not have detailed firm-level

data for each producer firm on its list of customers, we adopt an indirect approach, forming customer stock return indices based on aggregate international trade at a country level and trade credit at a firm level to predict the stock returns of firms in producer countries. We include a variety of controls to account for a range of country, industry, and firm-level attributes.

3.1. Producer and customer countries

We start with all the countries for which firm-level data are available on Worldscope for the period January 1993 to March 2009. We employ data beginning in 1993 because return (and accounting) data are significantly incomplete before January 1993 for a large number of firms across several countries. We identify producers and customers, and we do so annually, at the country level, using trade flows across countries. We obtain annual bilateral trade data from International Monetary Fund (IMF) Direction of Trade Statistics and annual gross domestic product (GDP) data from the IMF World Economic Outlook Database to classify countries as producers and customers. The producer countries in a given year are those in the top 75% by exports to GDP in the previous year. By using a relative benchmark, our approach minimizes the impact of trends in international trade on the size of the producer set and contributes to a better identification strategy. A producer country's associated customer countries are those responsible for at least 5% of the producer country's exports. The online Appendix displays robustness results with customer countries defined by the 3% and 7% alternative thresholds (Table A8). We utilize this classification of producer and customer countries at the firm level, predicting firm-level stock returns of firms in producer countries using an index of the previous month's returns of its major customer countries.

Table 1 shows the 43 countries that constitute the sum of all producer and associated customer countries (37 of these are designated as producers during at least one year of the study period and 36 appear as a major customer of a producer country at least once). We restrict ourselves to the set of firms with time series of available accounting data (sales, cost of goods sold, accounts receivable, etc.). The customer set is only limited by the availability of country equity market indexes from either MSCI or S&P/IFC. At the firm-level, we focus only on industrial firms, filtering on the basis of the firm's general industry classification in Worldscope.

[Insert Table 1 near here]

3.2. Price and returns data

We obtain total equity return data of all industrial firms in the producer countries from Datastream. Return data for Brazil, Czech Republic, Hungary, Israel, Poland, Russia, Saudi Arabia and Slovakia are available beginning later than January 1993, as shown in Table 1. Table 1 also presents summary statistics on monthly market capitalization-weighted country index US dollar returns and shows the number of unique industrial firms available per country over the entire period. Our data contain $15,627$ firms in 37 producer countries.[10] The column entitled 'Average number of firms' indicates how many stocks on average constitute the country index in each month. We filter out extreme values in the total return data from Datastream, removing data points showing monthly firm-level returns in excess of $1,000\%$ for any firm (there are very few such observations). The country indices are then constructed by weighting firms by their previous year-end market capitalization. The correlation between these country indices, which we construct with firm-level data from Datastream, and the corresponding MSCI country indices is high, as can be seen in Fig. A1, which constructs these indices for all available countries with returns data (not limited to the sample that we consider).

Our tests also use data on monthly US dollar Treasury bill rates sourced from the Kenneth French data library[11] and factor returns that we employ for risk adjustment using MSCI country index return data.

3.3. Trade credit measures

We construct a firm-level measure of trade credit as the ratio of accounts receivable to sales. We employ annual accounting data from Worldscope (via Datastream) for all firms in the producer set of countries identified in Table 1: accounts receivable (from trade) (*WC02051*) and sales (*WC01001*). Writing $AR_{i,t}$ for the dollar amount of accounts receivable for firm i in year t, trade credit is defined as

$$ARTurnover_{i,t} = \frac{AR_{i,t}}{Sales_{i,t}}. \tag{17}$$

[10] We include firms from the following industries: consumer goods and services, health care, industrials, oil and gas, technology, telecommunications, and utilities. We exclude firms from banking, insurance, and other financial industries. The online Appendix contains a comparison of the data coverage in this paper with that in Fama and French (2012) and Hou, Karolyi, and Kho (2011).

[11] `http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html`

Table 2 shows descriptive statistics for the value-weighted index for the trade credit measure.[12] We filter extreme values above 50 (5000%) in this ratio at the firm level, a procedure similar to Demirguc-Kunt and Maksimovic (2001). Table 2 shows descriptive statistics for both the time series and the cross-section of value-weighted indices of $ARTurnover$ for all possible producer countries, both filtered and unfiltered for extreme values. Using a similar classification of countries into emerging and developed as in Froot and Ramadorai (2008), accounts receivable amount to 22% of sales in any given year in developed countries, taking the mean across the average values reported in Table 2.A. For emerging markets, this value is 25%, suggesting that no real difference exists between developed and emerging countries along this dimension. However, substantial cross-sectional and time series variation exists in the level of $ARTurnover$, suggesting that there could be periods when these links between firms assume greater importance.

[Insert Table 2 near here]

3.4. Control variables

In our panel regressions, we use firm market capitalization (*WC08001*) as an independent variable to account for the potential impact of firm size driving firm returns. We scale the variable as a percentile rank between zero and one by country in each month to account for nonstationarity ($MarketCapitalizationRank_{i,t}$). We also include several variables to control for risk attributes (see Hou, Karolyi, and Kho, 2011) and for attributes that could contain information about a firm's financing situation such as trade credit, cash and equivalents (*WC02001*), short-term debt (*WC03051*), total debt (*WC03255*), total assets (*WC02999*),

[12] We replicate our analysis using net trade credit defined as the ratio of accounts receivable minus accounts payable (from trade) (*WC03040*) to sales. Data are filtered for extreme values above 50 and below −50. Table A1 of the online Appendix shows descriptive statistics for the value-weighted index for net trade credit, and Table A9 shows a summary of the results.

and total liabilities (*WC03351*).[13] These variables are defined as

$$CashToAssets_{i,t} = \frac{Cash\&Equivalents_{i,t}}{TotalAssets_{i,t}}, \tag{18}$$

$$ShortTermDebtToAssets_{i,t} = \frac{ShortTermDebt_{i,t}}{TotalAssets_{i,t}}, \tag{19}$$

$$NetDebtToAssets_{i,t} = \frac{TotalDebt_{i,t} - Cash\&Equivalents_{i,t}}{TotalAssets_{i,t}}, \tag{20}$$

and

$$EquityMarketValueToBookValue_{i,t} = \frac{MarketCapitalization_{i,t}}{TotalAssets_{i,t} - TotalLiabilities_{i,t}}. \tag{21}$$

We are interested in assessing the extent to which trade credit matters based on a firm's international sales exposure. We use foreign sales (*WC08731*) to classify a firm as having high foreign sales ($HighForeignSales_{i,t}$) using the ratio

$$ForeignSalesToTotal_{i,t} = \frac{ForeignSales_{i,t}}{Sales_{i,t}}. \tag{22}$$

We also control for the multinational status of the firm using a dummy variable, which flags the existence of nonzero foreign sales ($MultinationalDummy_{i,t}$).

We follow Campbell, Grossman, and Wang (1993) to construct a measure of uninformed trading volume in the stock market.[14] We obtain time series data for the trading volume from Datastream for each stock in each producer country in our study and aggregate these to obtain the stock market trading volume level $EquityTradingVolume_{c,t}$. For country c and time t, we classify periods of high uninformed volume ($HighTradingVolume_{c,t}$) in a country using the ratio

$$EquityVolumeToMktCap_{c,t} = \frac{EquityTradingVolume_{c,t}}{TotalMarketCapitalization_{c,t}}. \tag{23}$$

We use producer country trading volume due to its simplicity, noting that the effects of uninformed trading volume in the model coming from the producer or the consumer countries both lead to negative serial cross-predictability in returns.

[13] As the necessary firm-level accounting data are unavailable in our data source for Colombia, Egypt, Morocco, Peru, Saudi Arabia, and Slovakia, these drop out of the possible producer set in our analysis (Table A10). Foreign sales data are unavailable for Chilean firms on Worldscope.

[14] For other measures of uninformed volume, see Llorente, Michaely, Saar, and Wang (2002) and Gagnon and Karolyi (2009).

We obtain the IMF World Economic Outlook Financial Stress Indicator to identify periods of financial stress. The index, developed by Danninger, Balakrishnan, Elekdag, and Tytell (2009), has measures of exchange market pressure, emerging economy sovereign spreads, betas of banking stock, stock price returns, and time-varying stock return volatility for 18 emerging markets. We define these as any month in which the Financial Stress Indicator for any emerging market is above one, which flags 65 out of 195 months in our sample as financial stress periods.

4. Empirical strategy and results

A simple illustration of our approach could be instructive before presenting a full-blown description of our pooled regression model. At the beginning of each year, we identify the major customer countries (as described in section 3) for each producer country. We then construct an index of customer-country (value-weighted) stock returns for each producer country, which we refer to henceforth as the "customer indices." We sort these customer indices each month into quintiles based on their stock returns.

Consider the bottom quintile of customer indices thus sorted. The stock returns of firms located in the associated producer countries connected to these customer indices should on average be lower than those of firms in producer countries associated with the top quintile of customer indices if there is cross-country predictability.

To test our specific prediction, we next sort the producer firms within these quintiles sorted by customer indices, by their level of trade credit. Our model predicts that these firms, with high trade credit, located in producer countries that are linked to customer countries with low past returns, should on average have even lower stock returns.

4.1. Regression setup

In line with this intuitive description, to formally test our hypothesis, we estimate a pooled regression model that allows us to simultaneously control for the impact of multiple conditioning variables. The regressions are estimated using weighted least squares, with each firm weighted by its market capitalization relative to all other firms in the same trade credit group. This is done to be able to interpret the coefficients as the returns on value-weighted portfolios. The fully specified regression that we estimate is

$$FirmReturn_{i,t} = \sum_{j=1}^{J}\sum_{k=1}^{K}\left(CustomerReturn^{j}_{i,t-1} * TradeCredit^{k}_{i,t-1} * \hat{\alpha}_{j,k}\right) + \mathbf{Z_{i,t}}\hat{\beta} + \varepsilon_{i,t}. \tag{24}$$

Here, the dummy variable $CustomerReturn^{j}_{i,t-1}$ takes the value of one if firm i is in a producer country with an associated customer index in the jth quintile in month $t-1$ and a value of zero otherwise. The dummy variable $TradeCredit^{k}_{i,t-1}$ takes the value of one if firm i is located in the kth tercile of firms sorted by their levels of trade credit in month $t-1$ and a value of zero otherwise. Correspondingly, $\hat{\alpha}_{j,k}$ is the regression intercept for firms in a producer country with an associated customers index in the jth quintile, and in the kth tercile of firms sorted by their levels of trade credit.

$\mathbf{Z_{i,t}}$ is a vector of (a comprehensive set of) control variables. $\hat{\alpha}$ and $\hat{\beta}$ are vectors of regression coefficients, and $\varepsilon_{i,t}$ is the regression residual. In our estimation, standard errors are clustered by month-country-industry.

As per the intuitive example described above, an alternative way to view our test is through the lens of a portfolio strategy, i.e., a portfolio that is long low-trade credit firms and short high-trade credit firms should have positive returns when customer index returns are low and negative returns when customer index returns are high. This strategy operates within quintiles sorted by customer index returns. Yet another trading strategy uses the differences across quintiles sorted by customer index returns. This strategy consists of going long high-trade credit firms in the high customer return quintile and short high-trade credit firms in the low customer return quintile. We also evaluate the returns to these long-short strategies.

We conduct a sharper test of the predictions of our model, conditioning on producer firms' level of foreign sales. In our identification, the transmission channel is an overseas firm-link on account of trade credit. Hence, if our model is correct, firms with high foreign sales and high levels of trade credit should demonstrate the highest levels of predictability.

We therefore define $HighForeignSales_{i,t-1}$ as a dummy that takes the value of one if firm i has a $ForeignSalesToTotal_{i,t-1}$ ratio (22) in the top tercile for its country in the period $t-1$ and zero otherwise. We then interact the dummy variable $HighForeignSales_{i,t-1}$ with the $CustomerReturn^{j}_{i,t-1}$ and $TradeCredit^{k}_{i,t-1}$ dummies in the regression to capture the difference in intercepts between firm groups with high and low levels of foreign sales. As foreign sales data are not available for all firms in all countries, in the specifications in which we employ this variable, the sample size is reduced from 1,200,585 to 700,650 firm-month observations.

When presenting our regression estimates, we first show results from a stripped-down version of Eq. (24) which omits control variables $\mathbf{Z_{i,t}}$. In order to control for a range of firm attributes that could be correlated with firm-level expected returns, we follow Hou, Karolyi, and Kho (2011) and others and use a comprehensive set of firm characteristics in $\mathbf{Z_{i,t}}$, including cash-to-assets ($CashToAssets_{i,t-1}$), the market capitalization rank of the firm

within a country at each point in time ($MarketCapitalizationRank_{i,t-1}$), the market-to-book ratio ($EquityMarketValueToBookValue_{i,t-1}$) of the firm, the lagged one-month firm return and lagged customer index return as momentum controls (see also Jegadeesh and Titman, 1993), lagged country-industry return (see Cohen and Frazzini, 2008 and Menzly and Ozbas, 2010a), lagged country return, and contemporaneous world market return.

Trade credit could be correlated with other firm attributes that generate return spreads across firms; for example, if firm size is correlated with the use of trade credit, then our results could simply be picking up a size effect in stock returns. Another potentially correlated firm attribute, the level of short-term debt, is a well-known indicator of the financial fragility of a firm [see Rodrik and Velasco (2000), for example, on the association between short-term debt levels and the impacts of financial crises]. As a result, we also control for the value of the trade credit measure ($ARTurnover_{i,t-1}$), a dummy representing that the firm has operations in multiple countries ($MultinationalDummy_{i,t-1}$), short-term debt-to-assets ($ShortTermDebtToAssets_{i,t-1}$), and total net debt-to-assets ($NetDebtToAssets_{i,t-1}$). Finally, we add country and industry fixed effects into our estimation to soak up any potential variation arising from these sources.

4.2. Results

Table 3 presents the results of the baseline panel regression specification. In the first matrix, the specification uses no control variables beyond the interactions between trade credit and customer-index returns, which sort the firms into 15 groups in each period. Within the bottom customer-return quintile (firms in producer countries with customers in the lowest quintile of stock returns), the firms with low trade credit have average stock returns, which are approximately 1.2% per month higher than those with firms with high trade credit. This difference, which is the return on a long-short portfolio within the bottom customer-return quintile, is statistically significant and translates to an annualized return of approximately 14% (both the long and short legs of this strategy are significant).

[Insert Table 3 near here]

The second matrix in the table adds in the control variables. By and large, these controls display the expected signs, and we omit their presentation for space considerations. Despite these additional controls, the table shows that the difference between low- and high-trade credit firms in the bottom quintile of customer returns continues to be strong and statistically significant, at approximately 1.0% per month or around 13% per annum (excluding fixed effects). When industry fixed effects and country fixed effects are added, the results remain

strong and statistically significant. The invariance of the results to the addition of industry dummies indicates that the performance of our strategy is not merely driven by cross-industry variation in trade credit measures and time variation in the extent of this cross-industry variation. Instead, the performance of the strategy is driven almost completely by firm-level variation in trade credit. In other words, even within the same industry, we expect that variation across firms in trade credit levels would line up with the predictive ability of customer-country returns.

Table 3 also shows that, in the top quintile of customer returns, the difference between low- and high-trade credit firms within this quintile is positive. However, barring any nonlinear effects, we would expect a negative difference between low- and high-trade credit firms when customer returns are high. The reason is that when customer returns are high, positive cross-serial correlation should imply that producer firm returns would be high in the future, and particularly so if the level of trade credit is high. This finding also impacts the cross-quintile strategy when, instead of looking at the returns on the long-short portfolios within quintiles, we consider differences across quintiles sorted by customer country returns. This strategy consists of going long high-trade credit firms in the high customer return quintile and short high-trade credit firms in the low customer return quintile. It yields 1.2% per month without controls, and 1.3% once all controls with country and industry fixed effects are included. In the top quintile of customer returns, the difference between the low- and high-trade credit firms within this quintile is positive. Hence, the strategy yields higher returns (1.8% per month with fixed effects) if we go long in low-trade credit firms in the high customer return quintile and go short in high-trade credit firms in the low customer return quintile. This result, however, is not robust when we subsequently condition on foreign sales, consistent with the existence of nonlinear effects in trade credit that we discuss in our model.

In Table 4, we condition our strategy on firms' international exposure using the level of foreign sales. This helps us in our identification of the trade credit link between firms. We do this by further interacting the trade credit dummies with the high foreign sales dummy. The results of the long-short strategy within the bottom quintile of firms sorted by customer country returns are even stronger for firms with high foreign sales and are significant, with a monthly return of roughly 1.6% without fixed effects and 1.7% with fixed effects. Moreover, the returns to the same strategy applied to firms with low foreign sales are markedly smaller at 0.3% per month and are insignificant.[15] The table also shows that for firms with high foreign sales, both the within- and across-customer return quintile portfolio strategy yields

[15] In the online Appendix, Table A4, Panel A, reestimates the regressions in Table 3 on the smaller sample of 700,650 firm-months for which foreign sales data are available and shows that the same results we obtain in Table 4 are not due to a smaller sample.

larger and more significant returns than for firms with low foreign sales.

[Insert Table 4 near here]

Table 4 shows that, for high foreign sales firms, the strategy of going long high-trade credit firms in the high customer return quintile and short high-trade credit firms in the low customer return quintile delivers positive and significant returns (roughly 2.0% with fixed effects), as per our hypothesis. Only one of the legs in this strategy has significant returns. In contrast, the predictability result is weak for low foreign sales firms. Finally, there is a weaker asymmetric finding as the across strategy of going long low-trade credit firms in the high customer return quintile and short high-trade credit firms in the low customer return quintile delivers positive (roughly 2.4% with fixed effects) and significant returns for firms with high foreign sales. In the top customer quintile, we cannot reject that low-trade credit firms in the top customer quintile earn the same return as high-trade credit firms also in the top customer quintile. Table A4, Panel B, repeats the same regressions but without controls. The within and across quintile strategy results are essentially the same, with the strong and statistically significant predictability concentrated in firms with high foreign sales.

Table 5 tests the model prediction that the cross-predictability of stock returns depends on both trading volume and trade credit. Recognizing that other interpretations of this variable could exist (see, for example, Llorente, Michaely, Saar, and Wang, 2002), we identify periods during which stock trading volume is high relative to market capitalization as those in which there is high uninformed trading volume [see, for example, Campbell, Grossman, and Wang (1993) for a similar assumption]. Table 5 shows suggestive evidence in support of the model for firms with high foreign sales. The returns to both within and across strategies during periods of low trading volume in producer countries dominate the corresponding returns during high trading volume periods, as the model would predict if rebalancing trades dominated (see Fig. 1). When trading volume is low, the returns on this strategy are large and statistically significant. The returns rise to 3.5% per month with fixed effects and are statistically significant. The returns of going long high-trade credit and short low-trade credit conditional on being in the top customer quintile are about half as the same returns conditional on being in the bottom customer quintile, which is supporting evidence for nonlinear effects in the model. Table A5 repeats the same regressions but without controls. The results are unchanged.

[Insert Table 5 near here]

Table 6 tests the model prediction that investigates the conditional performance of our trading strategy during periods of financial stress in emerging countries where unequal access

to credit across firms internationally is more likely. The tests use the IMF emerging market (EM) financial stress index. Unconditionally, the inclusion of the measure is not useful for predicting future stock returns of the producer firms in the panel regression. However, when the indicator is interacted with the dummies for high- and low-trade credit firm groups, the results are strong and in line with model predictions. The table reports that our predictability result is larger during times of EM stress. The return performance in times of high EM stress is over four times that in times of low EM stress. Consistent with Prediction 3, this suggests that most of the gains from these strategies are made when access to external financing is more asymmetric. We show in Table A6 that the same regressions run without controls produce similar qualitative effects. Taken together, these results offer further empirical support to our model of trade credit as a mechanism for generating cross-country return predictability and international transmission of shocks, and they suggest that the channels that we identify in the model are potentially important.

[Insert Table 6 near here]

4.3. Robustness

We believe that the effects we find in the panel regressions are due to trade credit and cannot be explained by the included controls. We do not simply have an indicator variable for trade credit. We sort firms monthly by the level of trade credit to create a discrete variable that we use for our interaction terms, but we also include the level of trade credit, a continuous variable, as a control on the right-hand side of the regressions. Further, our panel regression results are essentially unchanged when we include controls for the three Fama and French factors, global momentum, and firms' earnings before interest, taxes, depreciation, and amortization (EBITDA)-to-sales ratio.

To further assess the reliability of our identification strategy, we perform a placebo test in which firm-level trade credit within an industry each month is reassigned randomly across the firms in that industry and month. We repeat the entire empirical analysis (sorting on customer country return, sorting on randomized trade credit, panel regressions with all controls, etc.) and show the results in Table 7. For ease of comparison, the first row ("Baseline Result") shows the baseline panel regression result with all controls shown in Table 3. The results from the randomization ("Placebo test result") are in the second line. We find that the strategy returns do not change conditional on high and low trade credit after that field is randomized, suggesting that randomized trade credit does not contain useful identification information, and gives further support to our identification strategy.

[Insert Table 7 near here]

In our regressions we value-weight stocks within each of the trade credit producer-country portfolios, as well as accounting for firm size on the right-hand side. This helps to ameliorate concerns that our results are driven by very small firms or by liquidity-related issues such as variation in transaction costs or stale prices. We also re-run our regressions after applying filters for firm size. We filter out the smallest 15% of firms by market capitalization in each country in each period and all firms with market capitalization less than $1 million and, separately, $10 million. The results are either unchanged or marginally stronger. Our results are also robust to variations in the construction of the customer-return portfolios. Over and above the standard equal-weights applied across country-return indexes, our results persist if we export-weight country index portfolios when constructing customer country-return indexes, and they are robust to varying the 5% threshold (see Table A8). Also, our predictability results are stronger when we winsorize the producer-country firm returns data at the 1th and 99th percentile points, which provides evidence that our results are not driven by extreme return observations.

In Table A7 of the online Appendix, we show that using National Bureau of Economic Research recession periods instead of the EM financial stress index gives similar results. Our predictability result is larger during recession periods. These findings are consistent with the model's prediction regarding predictability across periods of more asymmetric access to external credit.

Finally, Table 8 employs portfolio sorts instead of the panel regression methodology to check for possible nonlinearities, and it risk-adjusts the portfolio returns using high minus low (HML) and country momentum (MOM) in addition to the world market portfolio return (MKT). The HML factor is obtained from Fama and French international data, the MKT factor is the excess return of the MSCI World index over the three-month US T-bill rate, and the global (country-level) MOM factor is constructed as follows: At the end of each period t, countries (constituents of MSCI World index) are sorted into terciles based on the compounded local-currency return for the corresponding MSCI country index from $t-12$ to month $t-1$. MOM for period t is the return difference (in US dollar terms) between the top and bottom tercile (equal-weighted) portfolios. In this table, we show the results from portfolio regressions with both customer return and trade credit dimensions sorted into quintiles. In the panel regressions in Tables 3 to 7, we use quintile-tercile sorting as some specifications use multiple further levels of interactions, which can cause some grouping sizes to become very small when using the quintile-quintile sorting.[16] In the matrices shown

[16]In Table A3 in the online Appendix, we show the corresponding portfolio regression results with

in Table 8 (and Table A2), we display the results for regressions with no factors (excess return) and one (+MKT), two (+MOM), and three (+HML) factors included. We also add in a trade credit factor to correct for the possibility that trade credit itself could be a determinant of excess returns. To construct this factor, at each date we sort all firms by trade credit into terciles. We form value-weighted portfolios of these terciles, and the trade credit factor return is the high-low tercile portfolio return. The long-short portfolio strategy results are unaffected by the inclusion of these factors. The four-factor model displays the predicted nonlinear relation with the significance in predictability coming statistically strong only for firms in the bottom customer quintile. The evidence from the portfolio sorts and the evidence above provide a fundamentals-based channel for the effect captured by Rizova (2010).

[Insert Table 8 near here]

5. Conclusions

The role of financial intermediaries such as banks and mutual funds in transmitting shocks across borders has been extensively studied, and the relation between these intermediaries and the firms to which they lend has been the focus of significant attention. However, trade credit relation and other cash flow connections between firms across different nations have featured less prominently in debates on the sources of cross-border return predictability. We build a simple model of trade credit between firms in different countries and derive novel predictions pertaining to the role of trade credit, trading volume, and the costs of financing to cross-country firm-level predictability in stock returns, which we then test on our sample.

Our empirical results suggest that this channel could be equally important to that of financial intermediaries, showing that high-trade credit firms in producer countries experience significantly low returns when their customer countries' stock markets perform poorly. We find support for our identification by showing that this behavior is confined to firms with high foreign sales. We find additional support for the predictions of the model regarding the conditions under which the cross-predictability increases dramatically. Taken together, our model and empirical results provide support for the important role played by trade credit, a direct economic link between firms, in explaining cross-country return predictability. Our work suggests that future research would profitably focus on better understanding the role of these economic links.

quintile-tercile sorts.

Appendix A.

This Appendix provides the proof of Proposition 1 and the results in Subsection 2.5.

A.1. Proof of Proposition 1

Consider the equilibrium prices as given in the proposition:

$$P^C = \bar{D}^C - b_{CC}\left(\bar{D}^C - \mathrm{E}^d\left(\bar{D}^C\right)\right) - b_{CP}\left(\bar{D}^P - \mathrm{E}^d\left(\bar{D}^P\right)\right) - h_{CC}z^C - h_{CP}z^P \tag{25}$$

and

$$P^P = \bar{D}^P - b_{PP}\left(\bar{D}^P - \mathrm{E}^d\left(\bar{D}^P\right)\right) - b_{PC}\left(\bar{D}^C - \mathrm{E}^d\left(\bar{D}^C\right)\right) - h_{PP}z^P - h_{PC}z^C. \tag{26}$$

Domestic investors in country i learn $\Pi^i \equiv P^i - a_i - b_{ii}\mathrm{E}^d\left(\bar{D}^i\right)$, a noisy signal for $\bar{D}^i$ for domestic investors in country i. Using this information, a domestic investor in country i solves at date 1:

$$\max_{\theta^i} \mathrm{E}^d\left[\exp^{-\gamma W_2^i}\right] \tag{27}$$

subject to

$$W_2^i = \theta^i\left(D^i - P^i\right). \tag{28}$$

The first order necessary and sufficient condition for this problem yields

$$\theta^i = \frac{\mathrm{E}^d\left[D^i - P^i\right]}{\gamma \mathrm{Var}^d\left[D^i - P^i\right]}. \tag{29}$$

Likewise, speculators from either country face the problem of

$$\max_{\eta^C,\eta^P} \mathrm{E}^s\left[\exp^{-\gamma W_2^i}\right] \tag{30}$$

subject to

$$W_2^i = \eta^C\left(D^C - P^C\right) + \eta^P\left(D^P - P^P\right). \tag{31}$$

This problem is solved by setting

$$\begin{bmatrix} \eta^C \\ \eta^P \end{bmatrix} = \gamma^{-1}V^{-1}\begin{bmatrix} \bar{D}^C - P^C \\ \bar{D}^P - P^P \end{bmatrix}, \tag{32}$$

where

$$V = \begin{bmatrix} \sigma_{uC}^2 & \alpha'\sigma_{uC}^2 \\ \alpha'\sigma_{uC}^2 & \sigma_{uP}^2 + \alpha'^2\sigma_{uC}^2 \end{bmatrix} \tag{33}$$

which gives

$$V^{-1} = \frac{1}{\sigma_{uP}^2} \begin{bmatrix} \frac{\sigma_{uP}^2 + \alpha'^2\sigma_{uC}^2}{\sigma_{Cu}^2} & -\alpha' \\ -\alpha' & 1 \end{bmatrix}. \tag{34}$$

After multiplying the two matrices, we obtain the expression in Eq. (11). With the asset demands we can now solve for market clearing:

$$z^C = \mu_C \frac{1}{\gamma\sigma_{uP}^2} \left[\frac{\sigma_{uP}^2 + \alpha'^2\sigma_{uC}^2}{\sigma_{Cu}^2} \left(\bar{D}^C - P^C\right) - \alpha' \left(\bar{D}^P - P^P\right) \right] + (1-\mu_C) \frac{\mathrm{E}^d\left[D^C - P^C\right]}{\gamma \mathrm{Var}^d\left[D^C - P^C\right]} \tag{35}$$

and

$$z^P = \mu_P \frac{1}{\gamma\sigma_{uP}^2} \left[\bar{D}^P - P^P - \alpha' \left(\bar{D}^C - P^C\right)\right] + (1-\mu_P) \frac{\mathrm{E}^d\left[D^P - P^P\right]}{\gamma \mathrm{Var}^d\left[D^P - P^P\right]}. \tag{36}$$

Using the price functions to substitute for the values of P^i and combining terms associated with the various state variables $(\bar{D}^C - \mathrm{E}^d\left(\bar{D}^C\right), \bar{D}^P - \mathrm{E}^d\left(\bar{D}^P\right), z^C, z^P)$, we obtain eight equilibrium conditions (four from each market clearing condition):

$$0 = \mu_C \frac{1}{\gamma\sigma_{uP}^2} \frac{\sigma_{uP}^2 + \alpha'^2\sigma_{uC}^2}{\sigma_{Cu}^2} b_{CC} - \mu_C \frac{1}{\gamma\sigma_{uP}^2} \alpha' b_{PC} + (1-\mu_C) \frac{b_{CC} - 1}{\gamma \mathrm{Var}^d\left[D^C - P^C\right]} \tag{37}$$

and

$$0 = \mu_C \frac{1}{\gamma\sigma_{uP}^2} \frac{\sigma_{uP}^2 + \alpha'^2\sigma_{uC}^2}{\sigma_{Cu}^2} b_{CP} - \mu_C \frac{1}{\gamma\sigma_{uP}^2} \alpha' b_{PP} + (1-\mu_C) \frac{b_{CP}}{\gamma \mathrm{Var}^d\left[D^C - P^C\right]}; \tag{38}$$

$$1 = \mu_C \frac{1}{\gamma\sigma_{uP}^2} \frac{\sigma_{uP}^2 + \alpha'^2\sigma_{uC}^2}{\sigma_{Cu}^2} h_{CC} - \mu_C \frac{1}{\gamma\sigma_{uP}^2} \alpha' h_{PC} + (1-\mu_C) \frac{h_{CC}}{\gamma \mathrm{Var}^d\left[D^C - P^C\right]} \tag{39}$$

and

$$0 = \mu_C \frac{1}{\gamma\sigma_{uP}^2} \frac{\sigma_{uP}^2 + \alpha'^2\sigma_{uC}^2}{\sigma_{Cu}^2} h_{CP} - \mu_C \frac{1}{\gamma\sigma_{uP}^2} \alpha' h_{PP} + (1-\mu_C) \frac{h_{CP}}{\gamma \mathrm{Var}^d\left[D^C - P^C\right]}; \tag{40}$$

$$0 = \mu_P \frac{1}{\gamma \sigma_{uP}^2} b_{PP} - \mu_P \frac{1}{\gamma \sigma_{uP}^2} \alpha' b_{CP} + (1 - \mu_P) \frac{b_{PP} - 1}{\gamma \mathrm{Var}^d \left[D^P - P^P \right]} \tag{41}$$

and

$$0 = \mu_P \frac{1}{\gamma \sigma_{uP}^2} b_{PC} - \mu_P \frac{1}{\gamma \sigma_{uP}^2} \alpha' b_{CC} + (1 - \mu_P) \frac{b_{PC}}{\gamma \mathrm{Var}^d \left[D^P - P^P \right]}; \tag{42}$$

and

$$1 = \mu_P \frac{1}{\gamma \sigma_{uP}^2} h_{PP} - \mu_P \frac{1}{\gamma \sigma_{uP}^2} \alpha' h_{CP} + (1 - \mu_P) \frac{h_{PP}}{\gamma \mathrm{Var}^d \left[D^P - P^P \right]} \tag{43}$$

and

$$0 = \mu_P \frac{1}{\gamma \sigma_{uP}^2} h_{PC} - \mu_P \frac{1}{\gamma \sigma_{uP}^2} \alpha' h_{CC} + (1 - \mu_P) \frac{h_{PC}}{\gamma \mathrm{Var}^d \left[D^P - P^P \right]}. \tag{44}$$

These equations can be used to solve for the eight unknowns: b_{CC}, b_{CP}, b_{PC}, b_{PP}, h_{PC}, h_{PP}, h_{CC}, and h_{CP}. This is a nonlinear system of equations because the conditional variances $\mathrm{Var}^d \left[D^P - P^P \right]$ and $\mathrm{Var}^d \left[D^C - P^C \right]$ depend on these price parameters as well. We solve for the equilibrium by finding a numeric solution to this system of equations.

From the properties of conditional normal distributions;

$$\mathrm{E}^d \left(\bar{D}^C | \Pi^C \right) = \frac{\mathrm{Cov} \left(\bar{D}^C, \Pi^C \right)}{\mathrm{Var} \left(\Pi^C \right)} \Pi^C = \beta^C \Pi^C \tag{45}$$

and

$$\mathrm{Var}^d \left(\bar{D}^C | \Pi^C \right) = \sigma_{\varepsilon C}^2 - \frac{\mathrm{Cov} \left(\bar{D}^C, \Pi^C \right)^2}{\mathrm{Var} \left(\Pi^C \right)}. \tag{46}$$

These moments are harder to calculate than in more standard models of asymmetric information because domestic investors in each country do not form expectations about fundamentals in the other country. Specifically, the unconditional covariance between forecast errors is not an output from investor learning behavior. Using these moments and the definition of Π^i,

we can write the expressions for the forecast errors of each domestic investor:

$$\begin{aligned}\bar{D}^C - \mathrm{E}^d\left(\bar{D}^C\right) = &\left[1-\beta^D\left(1-b_{CC}\right)\right]\bar{D}^C + \beta^C b_{CP}\left(\bar{D}^P - \mathrm{E}^d\left(\bar{D}^P\right)\right)\\ &+\beta^C h_{CC} z^C + \beta^C h_{CP} z^P \end{aligned} \tag{47}$$

and

$$\begin{aligned}\bar{D}^P - \mathrm{E}^d\left(\bar{D}^P\right) = &\left[1-\beta^P\left(1-b_{PP}\right)\right]\bar{D}^P + \beta^P b_{PC}\left(\bar{D}^C - \mathrm{E}^d\left(\bar{D}^C\right)\right)\\ &+\beta^P h_{PP} z^P + \beta^P h_{PC} z^C. \end{aligned} \tag{48}$$

Solving this system of two equations in two unknowns (the forecast errors) gives

$$\bar{D}^C - \mathrm{E}^d\left(\bar{D}^C\right) = f_{cc}\bar{D}^C + f_{cp}\bar{D}^P + f_{czp}z^P + f_{czc}z^C \tag{49}$$

and

$$\bar{D}^P - \mathrm{E}^d\left(\bar{D}^P\right) = g_{pp}\bar{D}^P + g_{pc}\bar{D}^C + g_{pzc}z^C + g_{pzp}z^P. \tag{50}$$

We can now solve for five unconditional moments, $\mathrm{E}\left[\left(\bar{D}^P - \mathrm{E}^d\left(\bar{D}^P\right)\right)\left(\bar{D}^C - \mathrm{E}^d\left(\bar{D}^C\right)\right)\right]$, $\mathrm{Cov}\left(\bar{D}^C, \Pi^C\right)$, $\mathrm{Cov}\left(\bar{D}^P, \Pi^P\right)$, $\mathrm{Var}\left(\Pi^P\right)$, and $\mathrm{Var}\left(\Pi^C\right)$, from which we finally obtain the conditional variances:

$$\begin{aligned}\mathrm{Var}^d\left[D^i\right] &= \mathrm{Var}\left[D^i|\Pi^i\right]\\ &= \mathrm{Var}\left(u\right) + \mathrm{Var}^d\left[\bar{D}^i|\Pi^i\right]\\ &= \mathrm{Var}\left[D^i\right] - \frac{\mathrm{Cov}^2\left(\bar{D}^i, \Pi^i\right)}{\mathrm{Var}\left(\Pi^i\right)}. \end{aligned} \tag{51}$$

A.2. Proof of the results in Subsection 2.5

We solve the model in which investors agree to disagree on the true value of the covariance $\mathrm{E}\left[D^P D^C\right]$. We assume that firms' trade credit pattern is such that $\mathrm{E}\left[D^P D^C\right] = \alpha' \left(\sigma_{\varepsilon C}^2 + \sigma_{uC}^2\right)$, if $\varepsilon^C \leq \overline{\varepsilon}^C$ and $\mathrm{E}\left[D^P D^C\right] = 0$ otherwise. Because speculators observe ε^C, they know the true value of the covariance $\mathrm{E}\left[D^P D^C\right]$. We assume that domestic investors know the value of the covariance as perceived by the speculators but agree to disagree and believe that $\mathrm{E}\left[D^P D^C\right] = \alpha' \left(\sigma_{\varepsilon C}^2 + \sigma_{uC}^2\right)$ always. We also assume that domestic investors do not know that speculators' perception of the covariance $\mathrm{E}\left[D^P D^C\right]$ depends on ε^C. This last assumption eliminates a complicated inference problem.

Consider states of the world in which $\varepsilon^C \leq \overline{\varepsilon}^C$ and the true covariance is $\mathrm{E}\left[D^P D^C\right] = \alpha' \left(\sigma_{\varepsilon C}^2 + \sigma_{uC}^2\right)$. Under our maintained assumptions, the solution to the asset pricing problem is the one in the main text. Fig. 1 provides comparative statics on the equilibrium value of cross-country predictability, $\mathrm{E}\left[D^P - P^P | P^C\right]$.

Consider now states of the world in which $\varepsilon^C > \overline{\varepsilon}^C$ and the true covariance is $\mathrm{E}\left[D^P D^C\right] = 0$. Rewriting Eq. (11), we obtain (setting α' to zero)

$$\begin{bmatrix} \eta^C \\ \eta^P \end{bmatrix} = \begin{bmatrix} \frac{\bar{D}^C - P^C}{\gamma \sigma_{uC}^2} \\ \frac{\bar{D}^P - P^P}{\gamma \sigma_{uP}^2} \end{bmatrix}. \tag{52}$$

Solving the stock market equilibrium condition for country C (the derivations for country P are similar and are omitted):

$$z^C = \mu_C \frac{\bar{D}^C - P^C}{\gamma \sigma_{uC}^2} + (1 - \mu_C) \frac{\mathrm{E}^d \left[D^C - P^C\right]}{\gamma \mathrm{Var}^d \left[D^C - P^C\right]}. \tag{53}$$

Letting $\beta_0 = \mu_C / \gamma \sigma_{uC}^2$ and $\beta_1 = (1 - \mu_C) / \gamma \mathrm{Var}^d \left[D^C - P^C\right]$, and similarly to Proposition 1, we can write this expression as

$$P^C = \bar{D}^C - \frac{\beta_1}{\beta_0 + \beta_1} \left(\bar{D}^C - \mathrm{E}^d \left[D^C\right]\right) - \frac{1}{\beta_0 + \beta_1} z^C. \tag{54}$$

By construction, this price function solves for the stock market equilibrium. To complete the solution of the equilibrium, we need to solve for $\mathrm{Var}^d \left[D^C - P^C\right]$ to then solve for β_1. Domestic investors learn from prices the sum $\Pi^C = \frac{\beta_0}{\beta_0 + \beta_1} \bar{D}^C - \frac{1}{\beta_0 + \beta_1} z^C$, from which they construct their conditional moments,

$$\mathrm{E}^d \left[D^C\right] = \mathrm{E}\left[D^C | \Pi^C\right] \tag{55}$$

and

$$\mathrm{Var}^d\left[D^C - P^C\right] = \mathrm{E}\left[\left(D^C - \mathrm{E}\left[D^C|\Pi^C\right]\right)^2|\Pi^C\right]. \tag{56}$$

Using the properties of multivariate normal distributions, it is straightforward to show that

$$\mathrm{E}^d\left[D^C\right] = \frac{\frac{\beta_0}{\beta_0+\beta_1}\sigma^2_{\varepsilon C}}{\left(\frac{\beta_0}{\beta_0+\beta_1}\right)^2\sigma^2_{\varepsilon C} + \left(\frac{1}{\beta_0+\beta_1}\right)^2\sigma^2_{zC}}\Pi^C \tag{57}$$

and

$$\mathrm{Var}^d\left[D^C - P^C\right] = \sigma^2_{\varepsilon C} + \sigma^2_{uC} - \frac{\beta_0^2\sigma^4_{\varepsilon C}}{\beta_0^2\sigma^2_{\varepsilon C} + \sigma^2_{zC}}. \tag{58}$$

Having solved for $\mathrm{Var}^d\left[D^C - P^C\right]$, we can obtain β_1 and the price function. This concludes the derivation of the equilibrium. We have, therefore, shown that because the true $\alpha' = 0$, an equilibrium of the form described in Proposition 1 exists with $b_{CP} = h_{CP} = 0$. In this equilibrium, $\mathrm{E}\left[D^P - P^P|P^C\right] = 0$ trivially because P^C does not convey any information for producer country firms. Therefore, there is no cross-country return predictability.

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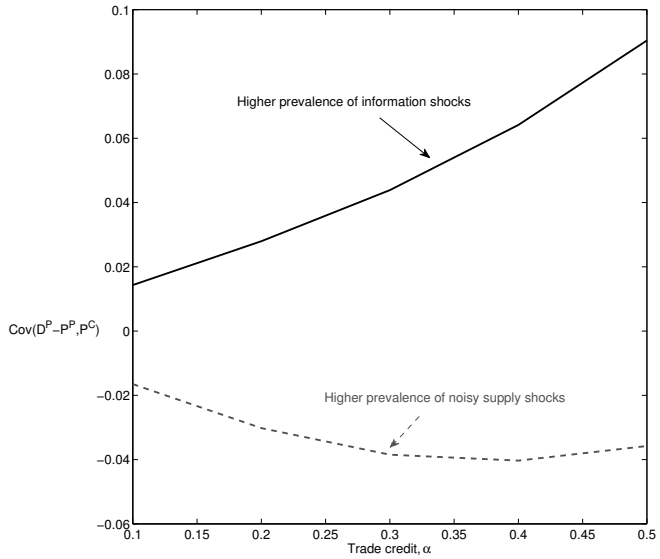

Fig. 1. Cross-serial return covariance. The figure plots the equilibrium value of $Cov\left(D^P - P^P, P^C\right)$ against several values of α'. The solid line has $\sigma^2_{zC} = 0.1$, and the dashed line has $\sigma^2_{zC} = 2.0$. The remaining parameters are $\sigma^2_{\varepsilon C} = 2.0, \gamma = 2.0$, $\mu_P = \mu_C = 0.5$, $\sigma^2_{\varepsilon P} = \sigma^2_{uC} = \sigma^2_{uP} = 1.0$, and $\sigma^2_{zP} = 0.1$.

Table 1
Country-level descriptive statistics for returns

This table presents summary statistics at the country-level of the monthly return data employed in the paper. The set of producers for a particular year is the top 75% of countries ranked by the exports to gross domestic product ratio over the previous year. For each producer and year, a set of countries is identified as its major customers (importing at least 5% of the producer's exports over the previous year). The set of producers and their customers is identified at the start of each year from 1993 to 2009. The table shows descriptive statistics for country indices using percentage monthly (market capitalization-weighted) US dollar–denominated simple returns. For countries that appear only as customers throughout the study period, these data are the corresponding MSCI country indices. For all others, these indices are built from industrial firm-level Worldscope data. The table presents the total number of unique firms and the average number of firms per year used to construct these indices.

Country	Region	Median	Mean	Standard deviation	Total number of firms	Average number of firms	Data Begin Date
Argentina	Latin America	0.657	0.573	8.895	52	47	1/31/1993
Australia	Oceania	1.504	1.020	6.708	1,259	337	1/31/1993
Austria	Western Europe	1.377	0.681	6.204	104	83	1/31/1993
Belgium	Western Europe	1.443	0.673	5.451	144	94	1/31/1993
Canada	North America	1.256	0.889	5.822	1,657	1,165	1/31/1993
Chile	Latin America	0.983	1.023	7.184	110	96	1/31/1993
China	East Asia	-0.156	1.002	13.396	1,360	724	1/31/1993
Czech Republic	Eastern Europe	1.645	1.189	7.373	52	50	1/31/1996
Denmark	Scandinavia	1.358	0.949	5.091	155	128	1/31/1993
Finland	Scandinavia	1.582	1.596	9.431	135	98	1/31/1993
France	Western Europe	1.311	0.815	6.220	238	168	1/31/1993
Germany	Western Europe	1.526	0.754	6.067	941	649	1/31/1993
Hong Kong	East Asia	1.459	0.980	8.453	755	496	1/31/1993
Hungary	Eastern Europe	1.461	0.893	10.489	34	27	1/31/1994
Indonesia	Southeast Asia	1.421	1.000	12.673	253	123	1/31/1993
Ireland	Western Europe	1.926	0.686	7.633	79	60	1/31/1993
Israel	Southwest Asia	1.374	0.913	8.058	122	95	1/31/1994
Italy	Western Europe	0.610	0.713	6.862	293	189	1/31/1993
Malaysia	Southeast Asia	0.229	0.783	10.797	913	593	1/31/1993
Mexico	Latin America	1.929	0.871	9.153	118	94	1/31/1993
Netherlands	Western Europe	1.540	0.826	4.927	207	173	1/31/1993
New Zealand	Oceania	1.123	1.001	6.686	123	81	1/31/1993
Norway	Scandinavia	1.822	1.174	7.538	242	137	1/31/1993
Pakistan	South Asia	-0.118	0.963	11.712	63	38	1/31/1993
Philippines	Southeast Asia	0.195	0.474	9.972	117	92	1/31/1993
Poland	Eastern Europe	0.986	0.627	10.681	300	130	1/31/1994
Portugal	Western Europe	1.457	1.098	6.418	88	77	1/31/1993
Russia	Eastern Europe	3.303	2.262	14.453	103	40	1/31/1997
Singapore	Southeast Asia	1.161	0.688	8.635	597	342	1/31/1993
South Africa	Africa	1.100	0.887	7.742	509	380	1/31/1993
South Korea	East Asia	-0.358	1.259	12.851	1,178	738	1/31/1993
Spain	Western Europe	0.778	0.715	5.630	132	81	1/31/1993
Sweden	Scandinavia	1.801	1.164	8.514	467	257	1/31/1993
Switzerland	Western Europe	1.053	0.927	4.388	220	170	1/31/1993
Thailand	Southeast Asia	-0.263	0.243	9.877	439	312	1/31/1993
Turkey	Southwest Asia	3.176	2.474	16.744	182	102	1/31/1993
United Kingdom	Western Europe	0.816	0.637	4.405	2,797	1,925	1/31/1993
Appearing only as customers							
Brazil	Latin America	2.881	2.064	13.446			8/31/1994
India	South Asia	1.818	0.878	9.056			1/31/1993
Japan	East Asia	0.313	0.247	5.963			1/31/1993
Saudi Arabia	Southwest Asia	1.356	1.178	8.011			1/30/1998
Slovakia	Eastern Europe	1.677	1.148	8.648			2/28/1997
United States	North America	1.194	0.596	4.858			1/31/1993

Table 2
Country-level trade credit summary statistics for producer countries

The values "By country" show descriptive statistics for the time series of the value-weighted cross-sectional mean of firms' trade credit (accounts receivables turnover) in countries classified at least once as a producer and have firm-level balance sheet data on Worldscope. The results "By year" show descriptive statistics for the cross section of producer-country trade credit by year. These summary statistics are with observations of firm-level accounts receivable turnover higher than 50 (5000%) filtered out. The trade credit sorts in the portfolio strategies in the rest of the paper use these filtered data. In Table A1, Panel A of the online Appendix, we show the corresponding statistics for the unfiltered data. The trade credit ratios are calculated from annual firm-level sales and accounts receivable data from 1992 to 2009.

	By country						By year				
Country	Mean	Median	Standard Deviation	Minimum	Maximum	Year	Mean	Median	Standard Deviation	Minimum	Maximum
Argentina	0.245	0.235	0.051	0.164	0.344	1992	0.237	0.211	0.116	0.078	0.745
Australia	0.180	0.174	0.025	0.142	0.224	1993	0.248	0.216	0.112	0.081	0.523
Austria	0.267	0.195	0.180	0.163	0.912	1994	0.268	0.210	0.154	0.102	0.912
Belgium	0.209	0.209	0.035	0.131	0.288	1995	0.235	0.210	0.083	0.110	0.486
Canada	0.197	0.193	0.024	0.166	0.242	1996	0.235	0.213	0.074	0.110	0.431
Chile	0.245	0.223	0.091	0.183	0.587	1997	0.249	0.226	0.104	0.126	0.690
China	0.366	0.359	0.158	0.182	0.745	1998	0.250	0.226	0.125	0.126	0.759
Czech Republic	0.462	0.195	0.883	0.116	3.632	1999	0.251	0.234	0.086	0.128	0.504
Denmark	0.223	0.219	0.027	0.179	0.298	2000	0.346	0.245	0.563	0.117	3.632
Finland	0.202	0.199	0.025	0.165	0.239	2001	0.224	0.214	0.069	0.095	0.439
France	0.256	0.250	0.029	0.195	0.317	2002	0.216	0.212	0.074	0.083	0.361
Germany	0.245	0.249	0.050	0.181	0.351	2003	0.211	0.201	0.070	0.075	0.390
Hong Kong	0.241	0.239	0.048	0.154	0.352	2004	0.210	0.208	0.063	0.124	0.438
Hungary	0.179	0.171	0.036	0.139	0.299	2005	0.210	0.204	0.047	0.116	0.309
Indonesia	0.171	0.154	0.057	0.110	0.338	2006	0.202	0.206	0.039	0.130	0.282
Ireland	0.176	0.178	0.023	0.144	0.216	2007	0.224	0.211	0.071	0.146	0.587
Israel	0.311	0.309	0.048	0.265	0.481	2008	0.206	0.200	0.050	0.106	0.340
Italy	0.352	0.340	0.073	0.271	0.513	2009	0.194	0.187	0.063	0.021	0.310
Malaysia	0.352	0.363	0.110	0.182	0.562						
Mexico	0.176	0.174	0.050	0.021	0.236						
Netherlands	0.155	0.147	0.027	0.125	0.236						
New Zealand	0.165	0.164	0.024	0.119	0.211						
Norway	0.199	0.189	0.036	0.162	0.295						
Pakistan	0.136	0.121	0.058	0.075	0.285						
Philippines	0.233	0.229	0.048	0.135	0.349						
Poland	0.241	0.203	0.124	0.162	0.602						
Portugal	0.212	0.219	0.040	0.105	0.280						
Russia	0.315	0.234	0.189	0.136	0.759						
Singapore	0.282	0.261	0.064	0.187	0.408						
South Africa	0.206	0.161	0.089	0.122	0.438						
South Korea	0.224	0.209	0.054	0.155	0.340						
Spain	0.251	0.248	0.037	0.205	0.378						
Sweden	0.237	0.223	0.036	0.191	0.316						
Switzerland	0.212	0.213	0.015	0.189	0.244						
Thailand	0.191	0.162	0.076	0.106	0.365						
Turkey	0.217	0.219	0.032	0.162	0.280						
United Kingdom	0.178	0.181	0.016	0.156	0.208						

Table 3
Customer momentum strategy, panel regressions

This table shows pooled firm level return (WLS) regressions. We include dummies to indicate the customer-return quintile a firm belongs to in a particular month and we interact these with dummy variables indicating a firm's level of trade credit (sorted into terciles) to find the excess return difference between low and high trade credit firms between particular customer-return sets. In the matrix on the left, we show the results from regressions without controls; the results on the right include controls. As control variables, we include lagged values of firm size (ranked within each country in each month), cash-to-assets, short-term debt-to-assets, net debt-to-assets, accounts receivables-to-sales (trade credit measure), equity market value-to-book value, multinational firm dummy, firm return, customer country index return, domestic industry return, country return, and contemporaneous world market return. The row and columns labeled "With fixed effects" show results with all these controlling variables plus industry and country fixed effects. There are 1,200,585 firm-months in this panel regression. *t*-statistics (clustered by month-country-industry) are shown in italics below the coefficient estimates.

		Without controls				With controls				
		Low trade credit	2	High trade credit	Low - High	Low trade credit	2	High trade credit	Low - High: Without fixed effects	Low - High: With fixed effects
Bottom customer		0.409	0.136	-0.766	1.176	0.073	-0.189	-0.973	1.047	1.098
		2.036	*0.679*	*-3.300*	*6.008*	*0.403*	*-1.024*	*-4.285*	*5.938*	*6.572*
2		0.190	0.292	0.258	-0.068	-0.079	0.025	0.088	-0.166	-0.117
		1.098	*1.678*	*1.291*	*-0.382*	*-0.468*	*0.148*	*0.462*	*-1.006*	*-0.725*
3		0.793	0.488	0.484	0.308	0.491	0.144	0.245	0.246	0.303
		3.846	*2.671*	*2.234*	*1.637*	*2.202*	*0.740*	*1.135*	*1.328*	*1.689*
4		0.935	0.641	-0.043	0.978	0.627	0.327	-0.236	0.863	0.926
		4.900	*3.639*	*-0.206*	*5.492*	*3.388*	*1.894*	*-1.201*	*5.395*	*5.877*
Top customer		1.091	0.855	0.472	0.619	0.862	0.621	0.376	0.486	0.525
		6.257	*4.526*	*2.056*	*3.143*	*4.628*	*3.170*	*1.626*	*2.602*	*3.014*
Top - Bottom	Without fixed effects	0.681	0.719	1.238		0.789	0.809	1.349		
		2.561	*2.607*	*3.794*		*3.165*	*3.219*	*4.402*		
	With fixed effects					0.739	0.783	1.312		
						2.963	*3.119*	*4.281*		

	Without no controls	With controls: Without fixed effects	With controls: With fixed effects
Long low trade credit firms in top customer-return countries, short high trade credit firms in bottom customer-return countries	1.857	1.836	1.837
	6.394	*6.588*	*6.688*
Long high trade credit firms in top customer-return countries, short low trade credit firms in bottom customer-return countries	0.063	0.303	0.214
	0.205	*1.077*	*0.788*

Table 4

Customer momentum strategy, panel regressions, conditional on foreign sales level

This table shows the estimates of the 'within' and 'across' customer-return quintile long-short portfolio returns for firms classified by their customer-index performance and trade credit levels, conditional on the foreign sales level. The pooled regression setup in Table 3 is augmented with interactions on the ratio of firm foreign sales to total sales level. We interact the high foreign sales dummy with the firm dummies included in Table 3 to estimate performance differences for firms conditional on foreign sales activity levels with all of the control variables. These include lagged values of firm size (ranked within each country in each month), cash-to-assets, short-term debt-to-assets, net debt-to-assets, accounts receivables-to-sales (trade credit measure), equity market value-to-book value, multinational firm dummy, firm return, customer country index return, domestic industry return, country return, and contemporaneous world market return. The row and columns labeled "With fixed effects" show results with all of the control variables plus industry and country fixed effects. In Table A4, Panel B of the online Appendix, we show results for the same specification, but without control variables. There are 700,650 firm-months in this panel regression. *t*-statistics (clustered by month-country-industry) are shown in italics below the coefficient estimates.

		Low Foreign Sales					High Foreign Sales				
		Low trade credit	2	High trade credit	Low - High: Without fixed effects	Low - High: With fixed effects	Low trade credit	2	High trade credit	Low - High: Without fixed effects	Low - High: With fixed effects
Bottom customer		0.024	-0.155	-0.269	0.292	0.261	-0.064	-0.807	-1.677	1.613	1.658
		0.130	*-0.827*	*-1.248*	*1.471*	*1.337*	*-0.241*	*-3.153*	*-4.869*	*5.448*	*5.932*
2		0.050	0.090	0.021	0.029	0.006	-0.756	-0.274	-0.215	-0.541	-0.501
		0.272	*0.482*	*0.101*	*0.144*	*0.032*	*-3.397*	*-1.369*	*-0.847*	*-2.253*	*-2.091*
3		0.040	-0.217	0.260	-0.219	-0.224	0.537	-0.107	0.017	0.521	0.504
		0.211	*-1.112*	*1.195*	*-1.024*	*-1.065*	*2.128*	*-0.523*	*0.066*	*2.040*	*1.996*
4		0.325	0.223	0.366	-0.041	-0.017	0.538	-0.002	-0.783	1.321	1.331
		1.940	*1.276*	*1.759*	*-0.212*	*-0.087*	*2.200*	*-0.011*	*-2.874*	*5.195*	*5.272*
Top customer		0.373	0.693	0.159	0.214	0.161	0.697	0.050	0.362	0.335	0.397
		1.929	*3.485*	*0.672*	*0.946*	*0.736*	*2.597*	*0.207*	*1.114*	*1.102*	*1.356*
Top - Bottom	Without fixed effects	0.349	0.849	0.428			0.761	0.857	2.039		
		1.369	*3.241*	*1.391*			*2.196*	*2.805*	*4.780*		
	With fixed effects	0.283	0.801	0.383			0.692	0.801	1.954		
		1.104	*3.055*	*1.248*			*1.993*	*2.628*	*4.629*		

	Low Foreign Sales: Without fixed effects	Low Foreign Sales: With fixed effects	High Foreign Sales: Without fixed effects	High Foreign Sales: With fixed effects
Long low trade credit firms in top customer-return countries, short high trade credit firms in bottom customer-return countries	0.642	0.544	2.374	2.350
	2.311	*1.978*	*5.930*	*6.163*
Long high trade credit firms in top customer-return countries, short low trade credit firms in bottom customer-return countries	0.135	0.123	0.426	0.296
	0.468	*0.435*	*1.127*	*0.796*

Table 5

Customer momentum strategy, panel regressions, conditional on volume

This table shows the estimates of the 'within' and 'across' customer-return quintile long-short portfolio returns for firms classified by their customer performance and trade credit level, conditional on volume and foreign sales level. The pooled regression setup in Table 4 is further augmented with interactions on the ratio of total stock trading volume to total equity market capitalization in the producer country. We interact the high trading volume dummy with the firm dummies included in Table 4 to estimate return differences for firms with high levels of foreign sales. The table shows results with interactions for high foreign sales and high trading volume, with all of the control variables. These include lagged values of firm size (ranked within each country in each month), cash-to-assets, short-term debt-to-assets, net debt-to-assets, accounts receivables-to-sales (trade credit measure), equity market value-to-book value, multinational firm dummy, firm return, customer country index return, domestic industry return, country return, and contemporaneous world market return. The row and columns labeled "With fixed effects" show results with all of the control variables plus industry and country fixed effects. In Table A5 of the online Appendix, we show results for the same specification, but without control variables. There are 694,899 firm-months in this panel regression. *t*-statistics (clustered by month-country-industry) are shown in italics below the coefficient estimates.

		Low Volume					High Volume				
		Low trade credit	2	High trade credit	Low - High		Low trade credit	2	High trade credit	Low - High	
					Without fixed effects	With fixed effects				Without fixed effects	With fixed effects
Bottom customer		-1.654	-1.354	-3.215	1.560	1.664	1.524	-0.193	0.006	1.518	1.491
		-4.948	*-4.060*	*-7.568*	*3.994*	*4.421*	*4.206*	*-0.584*	*0.013*	*3.503*	*3.522*
2		-1.562	-0.010	-1.055	-0.507	-0.439	-0.183	-0.542	0.996	-1.179	-1.148
		-4.738	*-0.039*	*-3.460*	*-1.511*	*-1.306*	*-0.694*	*-2.098*	*2.735*	*-3.339*	*-3.242*
3		0.114	-0.571	-0.453	0.567	0.563	0.872	0.599	0.554	0.318	0.328
		0.339	*-2.165*	*-1.389*	*1.623*	*1.624*	*2.531*	*2.224*	*1.599*	*0.847*	*0.880*
4		-0.661	-0.683	-2.386	1.725	1.746	1.841	0.858	1.404	0.438	0.471
		-2.273	*-2.608*	*-7.601*	*5.307*	*5.373*	*5.238*	*3.158*	*3.475*	*1.085*	*1.172*
Top customer		0.315	-0.617	-0.562	0.877	0.946	0.980	0.901	1.374	-0.393	-0.309
		0.910	*-1.949*	*-1.210*	*2.019*	*2.212*	*2.573*	*2.925*	*3.377*	*-0.918*	*-0.734*
Top - Bottom	Without fixed effects	1.969	0.737	2.653			-0.543	1.094	1.368		
		4.246	*1.704*	*4.390*			*-1.077*	*2.632*	*2.328*		
	With fixed effects	1.852	0.720	2.570			-0.543	1.000	1.257		
		3.943	*1.680*	*4.334*			*-1.073*	*2.387*	*2.137*		

	Low Volume		High Volume	
	Without fixed effects	With fixed effects	Without fixed effects	With fixed effects
Long low trade credit firms in top customer-return countries, short high trade credit firms in bottom customer-return countries	3.530	3.516	0.974	0.948
	6.681	*6.918*	*1.680*	*1.657*
Long high trade credit firms in top customer-return countries, short low trade credit firms in bottom customer-return countries	1.092	0.906	-0.150	-0.233
	1.987	*1.661*	*-0.291*	*-0.456*

Table 6

Customer momentum strategy, panel regression, conditional on financial stress

This table shows the estimates of the 'within' and 'across' customer-return quintile long-short portfolio return for firms classified by their customer performance and trade credit level, conditional on financial stress level. The pooled regression setup in Table 3 is further augmented with interactions for emerging market financial stress, defined as any period in which the IMF World Economic Outlook Financial Stress Indicator for an emerging market is above one. This flags 65 out of 195 months in our sample as financial stress periods. We interact the financial stress indicator with the firm dummies included in Table 3 to estimate performance differences in and out of periods of financial stress with all of the control variables. These include lagged values of firm size (ranked within each country in each month), cash-to-assets, short-term debt-to-assets, net debt-to-assets, accounts receivables-to-sales (trade credit measure), equity market value-to-book value, multinational firm dummy, firm return, customer country index return, domestic industry return, country return, and contemporaneous world market return. The row and columns labeled "With fixed effects" show results with all of the control variables plus industry and country fixed effects. In Table A6 of the online Appendix, we show results for the same specification, but without control variables. There are 1,200,585 firm-months in this panel regression. *t*-statistics (clustered by month-country-industry) are shown in italics below the coefficient estimates.

		Low emerging market stress					High emerging market stress				
		Low trade credit	2	High trade credit	Low - High: Without fixed effects	Low - High: With fixed effects	Low trade credit	2	High trade credit	Low - High: Without fixed effects	Low - High: With fixed effects
Bottom customer		0.337	0.323	-0.151	0.488	0.545	-0.542	-1.299	-2.714	2.172	2.236
		1.557	*1.600*	*-0.639*	*2.493*	*2.849*	*-1.844*	*-3.919*	*-6.120*	*6.109*	*6.445*
2		0.028	0.338	0.607	-0.580	-0.534	-0.329	-0.637	-0.998	0.669	0.729
		0.167	*1.821*	*2.905*	*-3.199*	*-2.940*	*-0.940*	*-1.977*	*-2.709*	*1.957*	*2.164*
3		0.453	0.328	0.082	0.371	0.412	0.577	-0.211	0.569	0.008	0.094
		2.059	*1.654*	*0.339*	*1.903*	*2.144*	*1.208*	*-0.543*	*1.396*	*0.019*	*0.239*
4		0.667	0.530	0.513	0.154	0.202	0.611	-0.020	-1.679	2.290	2.392
		2.951	*2.580*	*2.192*	*0.827*	*1.100*	*2.134*	*-0.075*	*-4.997*	*7.325*	*7.651*
Top customer		0.644	0.266	0.511	0.134	0.189	1.415	1.442	0.214	1.201	1.231
		3.428	*1.339*	*2.077*	*0.657*	*0.958*	*3.916*	*3.845*	*0.480*	*3.189*	*3.372*
Top – Bottom	Without fixed effects	0.308	-0.057	0.662			1.957	2.741	2.928		
		1.116	*-0.214*	*1.998*			*4.289*	*5.682*	*4.851*		
	With fixed effects	0.254	-0.096	0.609			1.909	2.735	2.914		
		0.922	*-0.360*	*1.845*			*4.232*	*5.700*	*4.842*		

	Low emerging market stress: Without fixed effects	Low emerging market stress: With fixed effects	High emerging market stress: Without fixed effects	High emerging market stress: With fixed effects
Long low trade credit firms in top customer-return countries, short high trade credit firms in bottom customer-return countries	0.796	0.798	4.129	4.145
	2.728	*2.752*	*7.436*	*7.588*
Long high trade credit firms in top customer-return countries, short low trade credit firms in bottom customer-return countries	0.174	0.065	0.756	0.678
	0.548	*0.208*	*1.470*	*1.348*

Table 7

Customer momentum strategy, panel regression - placebo test randomizing trade credit measure

This table shows the estimates of the within and across customer-return quintile long-short portfolio returns when the trade credit measure of firms is randomized within an industry each month. The "Baseline result" row shows the baseline panel regression results for the long-short portfolio strategy (same as in Table 3) for comparison. The "Placebo test result" shows the corresponding returns after randomizing the trade credit measure. The table shows results for panel regressions without controls and with all of the control variables including country and industry fixed effects. *t*-statistics (clustered by month-country-industry) are shown in italics below the coefficient estimates.

	Without controls				With all controls			
	Long top customer low trade credit		Long top customer high trade credit		Long top customer low trade credit		Long top customer high trade credit	
	Short bottom customer		Short bottom customer		Short bottom customer		Short bottom customer	
Regression	Low trade credit	High trade credit	Low trade credit	High trade credit	Low trade credit	High trade credit	Low trade credit	High trade credit
Baseline result	0.681	1.857	0.063	1.238	0.739	1.837	0.214	1.312
	2.561	*6.394*	*0.205*	*3.794*	*2.963*	*6.688*	*0.788*	*4.281*
Placebo test result	0.917	0.893	0.730	0.706	1.019	0.985	0.817	0.784
	3.368	*3.231*	*2.620*	*2.497*	*4.005*	*3.859*	*3.237*	*3.006*

Table 8
Customer momentum strategy, portfolio regressions

This table shows returns produced by the customer momentum strategy. We show the returns of indices derived from sorting firms into customer-return quintiles, then further sorting each quintile into quintiles by trade credit (measured as accounts receivable turnover). Excess return is the average return over the sample period in excess of the monthly US Treasury bill rate. Three factor corresponds to alphas obtained from regressing returns of these indices on the world market (MKT), country momentum (MOM), and global high minus low (HML). In Table A2 of the online Appendix, we also show the alphas obtained from regressing returns of these indices on one factor, two factors and four factors (world market plus country momentum plus global HML plus a constructed trade credit factor). We also show portfolio regression results for quintile-tercile sorts. These results show percentage monthly (market capitalization–weighted) US dollar–denominated simple returns. *t*-statistics are shown in italics below the return estimates and computed using the Newey and West method.

	Excess return						Three factor (+MKT+MOM+HML)					
	Low trade credit	2	3	4	High trade credit	Low - High	Low trade credit	2	3	4	High trade credit	Low - High
Bottom customer	0.091	0.486	0.290	-0.351	-1.101	1.192	-0.232	0.220	0.121	-0.618	-1.266	1.035
	0.161	*0.897*	*0.463*	*-0.526*	*-1.489*	*2.688*	*-0.600*	*0.638*	*0.269*	*-1.227*	*-2.205*	*2.057*
2	0.131	0.212	0.157	0.635	0.135	-0.004	-0.026	0.070	-0.022	0.481	0.063	-0.089
	0.273	*0.452*	*0.342*	*1.239*	*0.206*	*-0.009*	*-0.075*	*0.224*	*-0.074*	*1.324*	*0.109*	*-0.158*
3	0.883	0.703	0.333	0.439	0.315	0.567	0.766	0.563	0.166	0.099	0.223	0.544
	1.897	*1.633*	*0.670*	*0.875*	*0.513*	*1.175*	*2.039*	*1.742*	*0.490*	*0.324*	*0.348*	*0.876*
4	0.755	0.995	0.309	0.618	-0.361	1.117	0.242	0.528	-0.132	0.494	-0.519	0.762
	1.568	*2.355*	*0.727*	*1.226*	*-0.554*	*2.502*	*0.709*	*1.923*	*-0.412*	*1.769*	*-1.111*	*1.568*
Top customer	1.366	0.923	0.790	0.534	0.430	0.936	1.095	0.713	0.550	0.349	0.346	0.749
	2.500	*1.765*	*1.381*	*0.885*	*0.531*	*1.867*	*2.273*	*1.987*	*1.386*	*0.750*	*0.485*	*1.684*
Top - Bottom	1.275	0.437	0.501	0.885	1.531		1.327	0.493	0.429	0.966	1.613	
	2.397	*1.022*	*0.905*	*1.560*	*1.973*		*2.281*	*1.193*	*0.749*	*1.596*	*1.998*	

	Excess return	Three factor
Long low trade credit firms in top customer-return countries, short high trade credit firms in bottom customer-return countries	2.467	2.361
	3.729	*3.414*
Long high trade credit firms in top customer-return countries, short low trade credit firms in bottom customer-return countries	0.340	0.578
	0.439	*0.700*