Trade Credit and International Return Comovement*

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Abstract

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Observers of international financial markets have long sought to understand why ostensibly local shocks to economic fundamentals such as the East Asian crisis of 1997, the Russian crisis of 1998 and the credit crisis of 2007 to 2009 have been accompanied by greater comovement between stock markets around the world. One important channel for comovement that has been identified from analysis of these episodes is the actions of financial intermediaries such as investment managers or banks,[1] and during these episodes, the apparent lack of comovement in fundamentals across markets has been cited as evidence of the intermediaries' role in causing contagion. In this paper, we analyze a source of comovement in international stock returns that arises from the comovement of fundamentals, and has been given rather less attention in the literature, namely, the role of trade credit links between firms in different countries.

Trade credit is an important source of financing for many firms (Mian and Smith, 1992, 1994). Further, it appears particularly important as a source of financing for firms that are bank credit constrained as suggested by evidence in Petersen and Rajan (1994a, 1997) (see also Biais and Gollier, 1997). We take these observations as our starting point, and hypothesize that trade credit between firms in different countries may be a transmission channel for local financial shocks. To do so, we build a simple asset pricing model that explores the implications of trade credit for the comovement of stock returns across firms in different countries and provide empirical evidence that is consistent with the model.

Our simple model consists of two countries with segmented stock markets each consisting of a representative firm. 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. We designate one firm/country as the consumer of outputs and the other firm/country as the producer. Trade credit implies that the dividends of the two firms will be correlated. The investment opportunities

[1] See, for example, Kaminsky and Reinhart (2000), Kaminsky, Lyons and Schmukler (2004), Broner, Gelos and Reinhart (2006), Boyer, Kumagai and Yuan (2006) and Jotikasthira, Lundblad and Ramadorai (2010) for empirical work, and Calvo (2005) and Pavlova and Rigobon (2008) for theory.

available to speculators imply that they trade for information motives and for rebalancing motives, with the latter driven by the induced correlation between the two stock markets' returns.

To see how the model works, consider a positive shock to fundamentals in the consumer 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 consumer country. If some information remains private, dividends will be higher than anticipated in prices, meaning that returns will be positive again in the future. This causes momentum in the consumer country's stock market.

In such an equilibrium, speculators increase their consumer country holdings, but rebalance 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 in order to induce them to buy, depressing the current price in the producer country. Since the two dividend processes are positively correlated, producer country dividends will also therefore be higher than anticipated in prices. Thus, the model predicts cross-asset serial correlation, i.e., stock returns in the producer country can be predicted from prior movements in consumer country returns. Higher trade credit leads to a stronger correlation across the two assets and hence, a stronger rebalancing motive. This comparative statics exercise suggests that when trade credit is higher, cross-asset serial correlation is also higher.

Our empirical analysis takes as its starting point the analysis of Rizova (2010), who provides empirical evidence in the international context that mimics the domestic analysis of Menzly and Ozbas (2010a). Rizova finds that high-exporting (or producer) countries' stock returns are predictable in advance using signals about their consumer countries' stock returns. We extend this analysis by classifying the firms within these country indices by their levels of trade credit (accounts receivable, accounts payable and a net trade credit measure that aggregates the two), and find that the predictable performance of producer countries' stock indices is driven by the cross-sectional variation in trade credit in a way that is consistent with the model. Within the bottom tercile of producer countries sorted by their consumer countries' past performance, a strategy that goes long low-trade credit firms and short high-trade credit firms generates significantly positive stock returns. Across terciles, 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 between 12 and 15% per annum depending on the method of risk adjustment. Importantly, we find that the trade credit dimension captures essentially all of the returns from the consumer-performance-prediction strategy. Put differently, we find evidence that the proximate driver of the cross-serial correlation in country index returns is the trade credit channel.[2]

We also check the robustness of these empirical results to double-sorting firms by our trade credit measures and other attributes that might be correlated with trade credit such as firm size and firm short-term debt levels. The return on the trading strategy implied by our model is, if anything, enhanced by the introduction of these controls. We formalize this use of controls in firm-level panel regressions to capture variation potentially caused by a range of country and firm-level attributes. The use of country and industry fixed effects, controls for local and world market returns, and controls for firm attributes such as size and short-term debt do not affect the performance of the strategy. However, we do find one interesting source of variation in the returns to the trading strategy implied by the model, namely that virtually all of these returns are garnered during periods of high financial stress in emerging markets. This suggests that a conditional version of our model would be an interesting extension to consider in future research.

Our theory and empirical results are related to the extensive literature on trade credit. Fisman and Love (2003) show that firms in countries with less developed financial markets appear to sub-

[2] It is worth noting here that within the top tercile of producer countries, the strategy that goes long high-trade credit firms and short low-trade credit firms generates marginally significant positive returns, whereas the model predicts that it should generate negative returns. We believe this weakness of the model derives from the assumption of linearity that is required to solve it. It is likely that trade credit, as a mechanism to manage and share contractual risks, is active mainly when consumer countries are underperforming.

stitute trade credit provided by their suppliers to finance growth. Demirguc-Kunt and Maksimovic (2001) consider the important role played by trade credit in emerging markets with under-developed legal systems and capital markets. Wilner (2000) and Cuñat (2007) suggest that trade credit could provide firms with a shield during financial distress, relative to credit from financial intermediaries. Many papers have also considered the link between credit rationing from formal financial markets and the extent to which firms engage in trade credit (Petersen and Rajan, 1994a, 1994b, 1997, Mian and Smith, 1992, and Biais and Gollier, 1997). Recent evidence on this channel is provided by Chor and Manova (2010), who show that industry sectors with low access to trade credit were most susceptible to credit market tightening during the recent financial crisis. Our focus relative to these papers is different in that we are primarily interested in the asset pricing implications of the trade credit links between firms. We find that these links seem to generate significant comovement between the stock returns of such connected firms. In this sense our paper is related to Choi and Kim (2005) who show that trade credit can serve as a mechanism to spread shocks when monetary policy is tightened. Their (empirical) analysis focuses on the U.S. market, whereas our focus is on international return comovement.

The remainder of the paper is organized as follows. Section 1 presents the model and theoretical predictions. Section 2 describes the empirical methodology employed. Section 3 describes the data. Section 4 discusses the results, and Section 5 concludes. The appendix contains the proof of the proposition in the model section.

1. A Simple Model of International Comovement

We present a simple model of international comovement, and in particular of cross-serial correlation in stock markets, due to portfolio rebalancing by some investors. The model has two dates, $t = 1, 2$ and two countries, a 'consumer' country labelled C and 'producer' country labelled P. Each country has one firm that pays a liquidating dividend at date 2. The firm in the consumer country generates a liquidating dividend of

$$D_t^C = \varepsilon_t^C + u_t^C.$$

The two shocks are assumed normally distributed with zero means and variances $\sigma^2_{\varepsilon C}$ and σ^2_{uC}, respectively.

We view trade credit as a mechanism through which a firm can manage or share risks using contractual business links with other firms. For example, a firm may increase its accounts receivables with customers in good times and increase its accounts payables with suppliers in bad times. The evidence is supportive of this view of trade credit: Petersen and Rajan (1997) find that more profitable sellers provide more trade credit; Nilsen (2002) finds that during monetary contractions small firms obtain more trade credit from their suppliers; Choi and Kim (2005) show that trade credit allows firms to absorb the effect of a credit contraction. Several theories state that trade credit arises from the design of long term contractual arrangements which allow firms to internalize inefficiencies due to costly trading in financial markets. According to Petersen and Rajan (1997), these long term arrangements give the supplier an "implicit equity stake in the customer." Their rationale is that trade credit favors riskier buyers, since trade credit terms are generally invariant to the credit quality of the buyer. If these buyers are also credit rationed, they will have more price elastic demand, making trade credit an effective form of price discrimination (this point can also be found in papers such as Meltzer, 1960, Schwartz and Whitcomb, 1979, Brennan et al., 1988, and Mian and Smith, 1982). Consequently, Petersen and Rajan argue that the supplier may have a long term interest in the survival of the buyer as it can collect current margins as well as margins on future sales.[3]

[3] In some cases trade credit can also be an efficient substitute for debt financing. For example, Schwartz (1974) proposed that the extension of credit goes from the financially stronger firm to the financially weaker. If trading partners are better informed than banks (Biais and Gollier, 1997, Emery, 1984, Smith, 1987, Brennan et al., 1988), they can take their place through trade credit. Alternatively, if sellers can repossess and better liquidate the goods

Following this reasoning, we assume that the firm in the producer country has dividends of

$$D_t^P = \alpha D_t^C + \varepsilon_t^P + u_t^P,$$

where $\alpha > 0$. We interpret the parameter α as the level of trade credit but note that α is also identified by the more standard role of the correlation between country dividends, i.e., $\mathrm{E}\left[D_t^P D_t^C\right] = \alpha\left(\sigma_{\varepsilon C}^2 + \sigma_{uC}^2\right)$. The main advantage of our reduced form approach is the simplicity with which we can analyze trade credit in an asset pricing model, letting us focus on the asset pricing implications of trade credit. The main limitation is that we leave unmodeled the agency decision to enter into trade credit arrangements.

Each country has a continuum of investors with unit mass. The fraction $1 - \mu_i$ of investors in country $i = C, P$ invests domestically only, and the fraction μ_i of investors in the same country invests in both countries. We label the μ_i investors as speculators and the rest of the local investors as domestic. This segmentation hypothesis has been used in many papers, most notably in Merton (1987), and there is empirical evidence to suggest that segmentation remains an important feature of international financial markets (see, for example, Bekaert et al. (2010)). It is consistent with the home bias in international equity portfolios and with other features of international investing (see Albuquerque et al., 2007) as well as with the existence of carry trade profits (see Jylha and Suominen, 2010).

Investors have constant absolute risk aversion of $\gamma > 0$ about their date-2 wealth, W_2, and start off with wealth $W_1 > 0$. Investors can also borrow and lend at the risk free rate r, which we normalize to $r = 0$. There is an exogenous, random supply of shares in each country, z^i, with

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 may represent better enforcement than cutting credit by a bank if the market for bank loans is more competitive or the bank is restricted by bankruptcy from doing so.

mean zero and variance σ_{zi}^2, with $i = C, P$. We solve for a rational expectations equilibrium where investors take prices as given when solving for their asset demands; in turn, 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. Speculators hold assets from both countries and have better information than domestic investors. For simplicity, we assume that speculators learn both shocks, ε^C and ε^P. Let $\bar{D}_t^C = \varepsilon_t^C$ and $\bar{D}_t^P = \alpha\varepsilon_t^C + \varepsilon_t^P$ and write:

$$
\begin{aligned}
D_t^C &= \bar{D}_t^C + u_t^C \\
D_t^P &= \bar{D}_t^P + \alpha u_t^C + u_t^P.
\end{aligned}
$$

This decomposition of dividends can be derived from a model where speculators receive signals about future dividends. In that setting, $\bar{D}_t^i$ is 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. That domestic investors learn from prices is an additional feature that separates this model from the model of investor inattention of Menzly and Ozbas (2010b). However, we maintain the assumption that domestic investors in each country invest only domestically, and learn only from local prices. Note that this assumption is not critical, as long as domestic investors do not become *fully* informed about the dividend process by observing foreign prices. As long as there is some asymmetric information, in the presence of noisy supply domestic investors would still be unable to perfectly learn the information of speculators and hence the mechanisms we highlight below would still prevail.

We now turn to the derivation of the equilibrium and refer the reader to the Appendix for details.

A. Investor asset demands and equilibrium prices

From the domestic investors' optimization problem, we obtain their local-asset demands, θ^i, for $i = C, P$:

$$\theta_t^i = \frac{\mathrm{E}_t^d\left[D_{t+1}^i - P_t^i\right]}{\gamma \mathrm{Var}_t^d\left[D_{t+1}^i - P_t^i\right]}.$$

The upperscript letter d means that the conditional moments use the information available to the domestic investors in the respective country. According to the asset demand, 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.

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

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

Speculators buy more of country's i 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 rebalancing effect that obtains because of the trade credit linkage. The size of the rebalancing effect is determined by the magnitude of trade credit α which also determines the positive conditional correlation between the two stocks.

The equilibrium in the C and P countries requires market clearing (z_t^C, z_t^P are the noisy supply levels in the two markets):

$$\begin{aligned} z_t^C &= \mu_C \eta_t^C + (1-\mu_C)\,\theta_t^C \\ z_t^P &= \mu_P \eta_t^P + (1-\mu_P)\,\theta_t^P. \end{aligned}$$

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

Proposition 1 *The date-1 stock market equilibrium is characterized by the following prices:*

$$\begin{aligned} P_t^C &= \bar{D}_{t+1}^C - b_{CC}\left(\bar{D}_{t+1}^C - \mathrm{E}_t^d\left(\bar{D}_{t+1}^C\right)\right) - b_{CP}\left(\bar{D}_{t+1}^P - \mathrm{E}_t^d\left(\bar{D}_{t+1}^P\right)\right) - h_{CC} z_t^C - h_{CP} z_t^P \\ P_t^P &= \bar{D}_{t+1}^P - b_{PP}\left(\bar{D}_{t+1}^P - \mathrm{E}_t^d\left(\bar{D}_{t+1}^P\right)\right) - b_{PC}\left(\bar{D}_{t+1}^C - \mathrm{E}_t^d\left(\bar{D}_{t+1}^C\right)\right) - h_{PP} z_t^P - h_{PC} z_t^C. \end{aligned}$$

The stock price in country i equals the present value of speculators' dividend forecast in that country, $\bar{D}_{t+1}^i$, adjusted for the presence of private information as illustrated by the forecast error made by domestic investors about the country's dividend, $\bar{D}_{t+1}^i - \mathrm{E}_t^d\left(\bar{D}_{t+1}^i\right)$, 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, $\bar{D}_{t+1}^j - \mathrm{E}_t^d\left(\bar{D}_{t+1}^j\right)$, for $j \neq i$, as well as the random supply in that foreign country. This last feature of equilibrium prices is due to the fact that the pricing in one market affects speculators' rebalancing trades in the other market. Specifically, if the forecast error in C is large and expected returns there are high then speculators may 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 $\Pi_t^i \equiv P_t^i - b_{ii}\mathrm{E}_t^d\left(\bar{D}_{t+1}^i\right)$ or

$$\begin{aligned}
\Pi_t^C &= (1-b_{CC})\,\bar{D}_{t+1}^C - b_{CP}\left(\bar{D}_{t+1}^P - \mathrm{E}_t^d\left(\bar{D}_{t+1}^P\right)\right) - h_{CC}z_t^C - h_{CP}z_t^P \\
\Pi_t^P &= (1-b_{PP})\,\bar{D}_{t+1}^P - b_{PC}\left(\bar{D}_{t+1}^C - \mathrm{E}_t^d\left(\bar{D}_{t+1}^C\right)\right) - h_{PP}z_t^P - h_{PC}z_t^C.
\end{aligned}$$

That is, Π_t^i serves as a noisy signal of $\bar{D}_{t+1}^i$ for domestic investors in country i. The conditional means and variances used by domestic investors to determine their asset demands have to be consistent with equilibrium prices and Π_t^i. For brevity we leave the construction of these moments to the Appendix, where we also show how to find the conditional forecast errors, $\bar{D}_{t+1}^i - \mathrm{E}_t^d\left(\bar{D}_{t+1}^i\right)$. This concludes the derivation of the equilibrium.

B. The cross-serial covariance in stock returns

In the Appendix we show that the equilibrium is characterized by a non-linear system of equations which can be solved numerically. We use comparative statics on the numerical equilibrium to study the properties of the theoretical cross-serial covariance $\mathrm{Cov}\left(P_t^C, D_{t+1}^P - P_t^P\right)$ (note that P_{t-1}^C is set to zero in order to interpret P_t^C as a return in our two-date model). This covariance constitutes the relevant moment for our hypothesis because its sign is the sign of the slope coefficient in a cross-predictability regression of producer country returns on consumer country returns. That is, in the model:

$$\mathrm{E}\left[D_{t+1}^P - P_t^P | P_t^C\right] = \frac{\mathrm{Cov}\left(P_t^C, D_{t+1}^P - P_t^P\right)}{\mathrm{Var}\left(P_t^C\right)} P_t^C.$$

The unconditional covariance indicates how producer country future returns co-move with consumer country current returns. Besides being interested in the sign of this covariance, we are also interested in how it changes with the size of trade credit, α.

First we describe how rebalancing trades and information trades affect this covariance. Consider good private information about consumer country dividends. When some, though not all, of this information is revealed in the stock price, the price increases. However, domestic investors have a positive forecast error and the price is below the expected value of dividends. This means that speculators would like to buy more of the domestic good and would like to rebalance their portfolio by selling in the producer country. Absent any dividend shocks in that market, the domestic consumers in the producer country are willing to absorb the speculator sales if the price drops. Hence, high returns in the consumer country forecasts high returns in the producer country.

Consider now the effect of rebalancing trades, which, say, come from a low supply realization. The presence of random supply acts as a confounding source of noise for domestic investors trying to learn the private information of speculators: Low supply drives prices up mimicking good private information. However, because dividends are not expected to be high in the future, expected returns must be low following a low supply realization, which leads to negative serial correlation in stock returns and negative cross-asset serial correlation.

The size of each of these effects is determined by 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 vice-versa, increasing σ^2_{zC} relative to $\sigma^2_{\varepsilon C}$ strengthens the effect of rebalancing trades.

Figure 1 graphically portrays these insights from the model. The solid line shows that a low σ^2_{zC} leads to a positive cross-asset covariance in equilibrium. Likewise, the dashed line in Figure 1 pertains to the cross-asset covariance computed across equilibria computed with a high σ^2_{zC}.[4] Moreover, the figure also shows that when σ^2_{zC} is low, i.e., along the solid line, higher trade credit may lead to a stronger correlation across the two assets. Intuitively, speculators care more about the rebalancing motive because the conditional correlation across the two assets is stronger (see equation 1). Good news in the consumer country still implies higher expected returns in the consumer

[4] 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 σ^2_{zC} lies in the fact that σ^2_{zC} does not affect the covariance in fundamentals as does $\sigma^2_{\varepsilon C}$, leaving this role exclusively to the trade credit parameter, α.

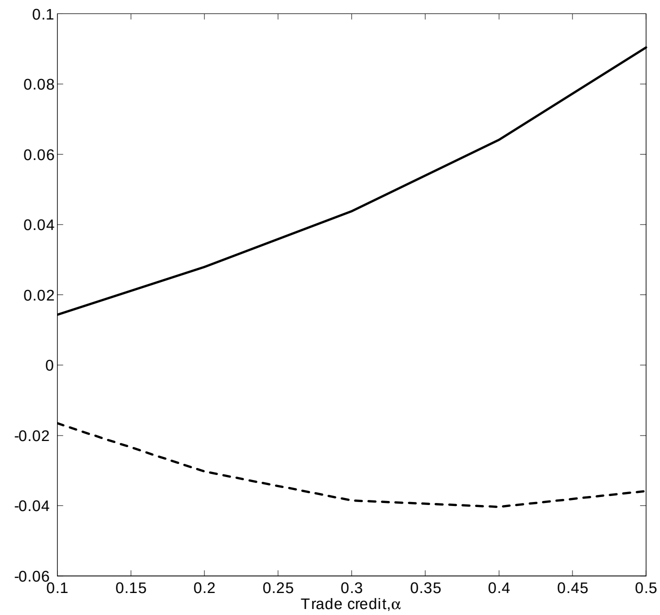

Figure 1: Cross-serial return covariance. The figure plots the equilibrium value of $Cov\left(D_{t+1}^{P} - P_{t}^{P}, P_{t}^{C}\right)$ against several values of α. The solid line has $\sigma_{zC}^{2} = .1$ and the dashed line has $\sigma_{zC}^{2} = 2$. The remaining parameters are $\sigma_{\varepsilon C}^{2} = 2, \gamma = 2$, $\mu_P = \mu_C = 0.5$, $\sigma_{\varepsilon P}^{2} = \sigma_{uC}^{2} = \sigma_{uP}^{2} = 1$ and $\sigma_{zP}^{2} = .1$.

country, but generates a stronger rebalancing stock sale in the producer country. Domestic investors in the producer country are only willing to accommodate these trades if the price is low enough, or if the expected return is high enough.

The linearity of the pricing rule and of stock returns required to solve the model with asymmetrically informed investors does not allow for trade credit to be state dependent. In line with the literature cited above, it is natural to think that trade credit is particularly responsive during periods of scarcity of funds, such as periods of monetary contractions (e.g., Nilsen, 2002) or credit contractions (e.g., Choi and Kim, 2005). In a richer model of trade credit it is plausible that the mechanism we describe above applies only when consumer country firms experience low returns, rather than in periods of both high and low consumer returns.

2. Empirical Methodology

Our empirical methodology to test the model takes as its starting point the analysis of Rizova (2010), who finds evidence of return predictability across economically linked countries. We concentrate our analysis on customer-producer relationships between countries. These relationships are identified using trade flows across countries. 'Producer' countries are those with greater than or equal to 20% of GDP in exports and their associated 'consumers' are those consuming 5% or more of the producers' exports in any given year. Each month, consumer countries are sorted into terciles based on their stock index performance and the subsequent monthly stock index performance of the producers linked to these consumers in the bottom, middle and top terciles is computed. Rizova conducts the analysis entirely at the country index level, and finds that there is an approximately 70 basis point per month difference between equal-weighted portfolios formed from the top and bottom terciles of producer country index returns (these country indices are value-weighted across firms in each country). Menzly and Ozbas (2010a) conduct a similar analysis for domestic stocks in the U.S. market. Rizova attributes her results to investor inattention, in the spirit of Menzly and Ozbas (2010b).

A. Testing the trade credit hypothesis

Our sample period extends from January 1993 to March 2009. We replicate Rizova's results over the sample period using the sample of firms for which we have corporate finance data (see below), and then customize the methodology to investigate the role of the direct, trade credit links between firms in different countries. Our approach is as follows: We gather firm-level data for the firms in each one of the producer and consumer countries, and compute several trade-credit ratios for each firm i in each year t. These ratios are:

$$\begin{aligned} ARTurnover_{i,t} &= \frac{AR_{i,t}}{TotalSales_{i,t}}, \\ APTurnover_{i,t} &= \frac{AP_{i,t}}{COGS_{i,t}}, \\ NetTradeCredit_{i,t} &= \frac{AR_{i,t} - AP_{i,t}}{TotalSales_{i,t}}, \end{aligned}$$

where AR is the accounts receivable amount and AP is the accounts payable amount at the end of the year, and $COGS$ is the cost of goods sold for the firm. Note that AR Turnover and AP Turnover used here correspond to the reciprocals of the standard accounting definition. Our next step is to create indices of firms *within* each of the terciles, sorted by these ratios.

Take, for example, the bottom tercile of customer countries in a given month in year t. We gather all of the firms in the associated producer countries, and then sort them by the three trade credit measures at the end of year $t-1$. We then create two value-weighted indices of stock returns from this firm level data, respectively for firms with higher and lower than the median trade credit measure. These indices are subsequently re-created each month as the countries in each of the terciles vary, using trade credit data that varies each year. Because we are unable to match firms engaged in trade credit across producer and consumer countries, the indices thus constructed can only be used as a proxy to portfolio exposure to the trade credit channel.

We then evaluate the performance of these trade-credit-sorted indices. If our theoretical model is correct, the predictability of stock returns in producer countries should be driven by the returns of the high-trade credit indices. Put differently, the cross-serial correlation that the model predicts should be higher as α increases, i.e., when trade credit measures are higher. Translated into a portfolio strategy, this implies that a portfolio which is long low-trade credit firms and short high-trade credit firms should have positive returns when consumer returns are low, and negative returns when consumer returns are high. Note that this is a strategy that operates *within* terciles sorted by consumer country returns.

Another trading strategy implied by the model uses the differences *across* terciles sorted by consumer country returns. This strategy consists of going long high-trade-credit firms in the high consumer return tercile, and short high-trade-credit firms in the low consumer return tercile. We also evaluate the returns to these long-short strategies.

One obvious criticism of our empirical approach is that trade credit may be correlated with other firm attributes that generate return spreads across firms. For example, if firm size is correlated with levels of trade credit, then our results could just be picking up a size effect in stock returns; and another potentially correlated attribute, namely, the level of short-term debt, is a well-known indicator of the financial fragility of a firm (see Rodrik and Velasco, 1999, for example, about the association of short-term debt levels with the impacts of financial crises). As a robustness check, therefore, we independently double-sort firms within the customer induced terciles by our trade credit measures and by these two firm attributes. This results in four portfolios of firms within each tercile, and we compare the returns across the dimensions of trade credit and each of the attributes. If our results are robust to this issue, then we would expect to see return spreads across the trade credit dimension within each of the bins sorted by size or short-term debt levels.

Finally, to permit more variables than just size and short-term debt to affect the returns of firms (and to account for the possibility that these attributes and others may simultaneously impact firm-level stock returns), we also re-run our analysis by stacking stock returns for all firm-months into a panel and regressing these returns on firm-level attributes, country-level fixed effects, and time-varying variables such as the world market return and country-index returns.

B. Risk adjustment

When we compute returns for the long-short portfolios, we also risk-adjust these returns to ensure that we are not picking up differences in systematic risk across the portfolios. We do so using three risk-adjustment models in addition to presenting excess return differences. All of these models are factor models of the form:

$$r_{p,t} - r_{f,t} = \alpha_p + \sum_{j=1}^{J} \beta_{p,j} F_{j,t} + \varepsilon_{p,t}.$$

Here, the excess returns on portfolio p are regressed on J factors. The first model sets $J = 1$, with the excess return on the MSCI world index (MKT) as the factor. The second model, with $J = 2$, adds a momentum (MOM) factor to the MSCI world index, this momentum factor is constructed from terciles of developed country returns, sorted by their past twelve month returns. The MOM factor is then obtained by subtracting the bottom tercile return from the top tercile return, and rebalancing monthly. Finally, the third model, with $J = 3$, adds a value factor (HML), which is constructed by sorting countries into terciles based on their value-weighted firm-level book-to-market ratios, and subtracting the bottom tercile portfolio returns from the top tercile's portfolio returns. Countries are equal-weighted within terciles in both MOM and HML factors.

Throughout the empirical analysis we employ Newey-West (1983) standard errors, which are robust to heteroskedasticity and autocorrelation, to assess the significance of portfolio returns.

3. Data

Our study employs balance sheet data, firm-level total return data, and country-level data from January 1993 to March 2009. We consider firms in the countries shown in Table I, where the classification into emerging and developed categories is as in Froot and Ramadorai (2008). The table shows all countries that are designated as producers (those with exports totalling $\geq 20\%$ of

GDP) and countries which are designated as their trade partners (consumers), who consume $\geq 5\%$ of these exports. There are 33 countries that we designate as producers, and a total of 42 countries that are either producers or consumers.[5] For the consumer countries, we included all countries for which we were able to find country index returns data from either MSCI or S&P/IFC. At the firm-level, we focus only on the industrial firms, filtering on the basis of the firm's general industry classification in Worldscope (we include firms from the following industries: consumer goods and services, health care, industrials, oil and gas, technology, telecommunications and utilities, and exclude firms from banking, insurance and other financial industries).

A. Price and Returns Data

Stock price, dividend and market capitalization data for all industrial firms in the producer countries are obtained from Worldscope. As return data are incomplete before January 1993 for several countries, we employ data after this period. Return data for Czech Republic, Hungary, Poland, Russia, Brazil and Israel is available beginning later, as shown in Table I. Table I also presents some summary statistics on monthly country index USD returns, and shows the number of unique industrial firms available per country over the entire period. 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 return data from Worldscope, removing data points showing monthly returns in excess of 1000% 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 Worldscope, and the corresponding MSCI country indices is high, as can be seen in Figure 2, which constructs

[5] To arrive at this final sample of producers, we first took all countries in the MSCI world and MSCI emerging markets indices, and then narrowed down the set by restricting the analysis to only those countries for which corporate finance data was available for firms on Worldscope. Applying the 20% of GDP criterion as described above results in the final set of 33 producers.

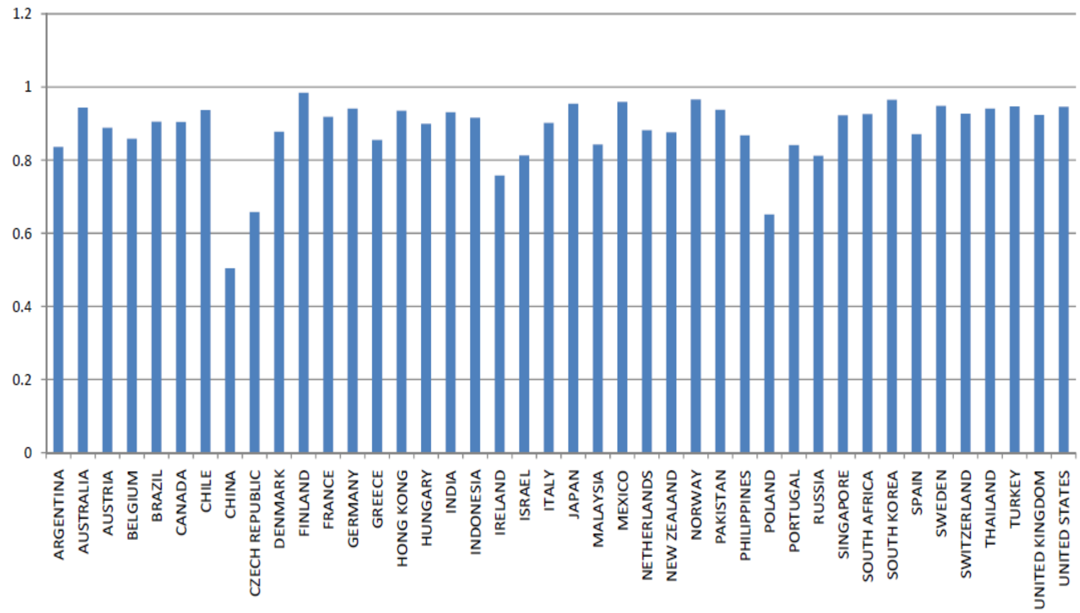

Figure 2: Correlations between MSCI and constructed indices. The figure shows the country-level correlations between the indices of industrial firms that we construct from Worldscope data and the MSCI indices where available for these countries.

these indices for all available countries in the data (not limited to the sample that we consider).

B. Accounting data

We use annual accounting data from Worldscope on Datastream for all firms in the producer set of countries identified in Table I. We obtain the following accounting variables at an annual frequency: accounts receivable (from trade), accounts payable (from trade), net sales, cost of goods sold (COGS), and short-term debt. Firm-level accounting data is unavailable in our data source for Egypt, Morocco, Columbia and Peru and hence, these drop out of the possible producer set in our analysis. Table II shows descriptive statistics for the value-weighted index for each of the measures defined in the empirical methodology section, namely, Net Trade Credit, AR Turnover and AP turnover. We filter extreme values above 50 in any of these ratios at the firm level, a procedure similar to previous studies such as Demirguc-Kunt and Maksimovic (2001). Table II shows descriptive statistics for value-weighted indices of the trade-credit measures for all possible producer countries. For developed countries, accounts receivable amounts to 22% of sales, and accounts payable amounts to 23% of COGS in any given year, taking the mean across the average values reported in the table. For the emerging markets, these values are 25% and 20% respectively, suggesting that there is no real difference between the developed and emerging countries along this dimension. However, there is substantial cross-sectional and time-series variation in the levels of AR and AP turnover, suggesting that there may be periods where these links between firms assume a great deal of importance.

C. Macroeconomic data

We obtain annual bilateral trade data from IMF Direction of Trade Statistics and annual GDP data from the IMF World Economic Outlook Database in order to classify countries as producers and trade partners. Our factor regressions use monthly USD T-Bill rates from the Kenneth French data library to calculate excess returns, and the factor returns that we employ for risk adjustment (described in the empirical methodology section) are all sourced from MSCI country indices.

4. Results

A. Calendar-time portfolio results

Table III presents the main results of the paper. Panel A of the table shows Rizova's (2010) results replicated in our dataset. In Panel A of Table III, as in her study, when producer countries are sorted into terciles based on their consumer countries' prior month stock returns, producer countries in the top tercile deliver higher average returns than those in the bottom tercile. However, unlike Rizova, we do not find that the difference between these tercile returns is statistically significant, either in the raw return difference, or in terms of differences in alpha estimated using the one, two and three factor models that we employ for risk-adjustment. This could be attributed to differences in the sample period employed (her data extends from 1981 to 2009, whereas ours begins in 1993), or in the set of firms employed to generate the return indices (we employ all industrial firms for which corporate finance information is available from Worldscope, and construct indices from these data rather than employing the MSCI indices directly).

Panel B of Table III applies the trade credit sort to the firm-level data within each of the terciles, and shows the value-weighted index returns of high and low trade credit producer firms. Within the bottom tercile (producer countries with consumers in the lowest tercile of stock returns), the table shows that firms with low net trade credit have average stock returns of approximately 50 basis points per month, while firms with high net trade credit have negative average stock returns of about -13 basis points per month. The difference, which is the return on a long-short portfolio *within* the bottom tercile, is statistically significant, at 64 basis points per month over the sample period, which translates to an annualized return of approximately 7.7%. Risk-adjusting using the factor models slightly increases this return to a statistically significant annualized level of 8.3% using the two-factor model (and even higher for the three-factor model).

Turning to the top tercile of consumer returns, the difference between low and high trade credit firms within this tercile is positive, although not statistically significant. However, the model would predict a *negative* difference between low and high trade credit firms when consumer returns are high. This suggests that the effect that we identify in the model, namely that there is a symmetric response in good and bad times for consumer firms, may not be the entire explanation. One explanation for the non-linearity we observe is that during bad times consumer firms are reluctant to pay AR's to their producers and may even be given additional better terms, whereas when times are good for consumer firms there is no higher payment of AR's to producers. Such an explanation creates a state dependence of trade credit on current returns that is difficult to model in our normal-exponential setting. Another possibility is that sorting into terciles based on consumer countries' returns does not capture the full picture. Conditional on positive returns for consumer countries, we might find results more fully consistent with the model. In other words, the top tercile that we capture may include periods in which consumer countries are doing poorly in absolute terms, but better in relative terms, and our results do not distinguish these cases as they currently stand.

In terms of long-short portfolio returns, a portfolio which is long low trade credit firms in the top tercile and short high trade credit firms in the bottom tercile of countries yields about 12% per annum irrespective of the method of risk adjustment. Figure 3 below plots the cumulative returns of this strategy, and contrasts this with the returns from Rizova's strategy and the cumulative world market returns over our sample period. Table III Panel B shows that the returns of this portfolio strategy are always statistically significant at the 5% level or better using the net trade credit measure. For the long-short portfolio favoured by the model, i.e., long top tercile high trade credit firms and short bottom tercile high trade credit firms, monthly excess returns are positive as expected but not statistically significant. Again, this evidence is consistent with the non-linearity described above. Importantly, it is also the case that the next two rows, i.e., long low trade credit top tercile and short low trade credit bottom tercile, and long high trade credit top tercile and short low trade credit bottom tercile returns are not statistically significant. This provides evidence that the cross-serial correlation across countries is driven by the trade credit channel, and emphasizes the role of the direct trade credit links between firms that we model.

Turning to the components of the net trade credit measure, it appears that the return is driven by accounts receivables rather than accounts payables. For AR turnover, the long top tercile low trade credit-short bottom tercile high trade credit return is also significantly positive, and the magnitude is higher than the net trade credit measure, at an annualized level of close to 14%. However, there are no significant effects for accounts payable. This suggests that the primary mechanism through which trade credit connects customer and producer firms, is that producer firms with high levels of accounts receivable are likely to be at-risk of their trading partners choking

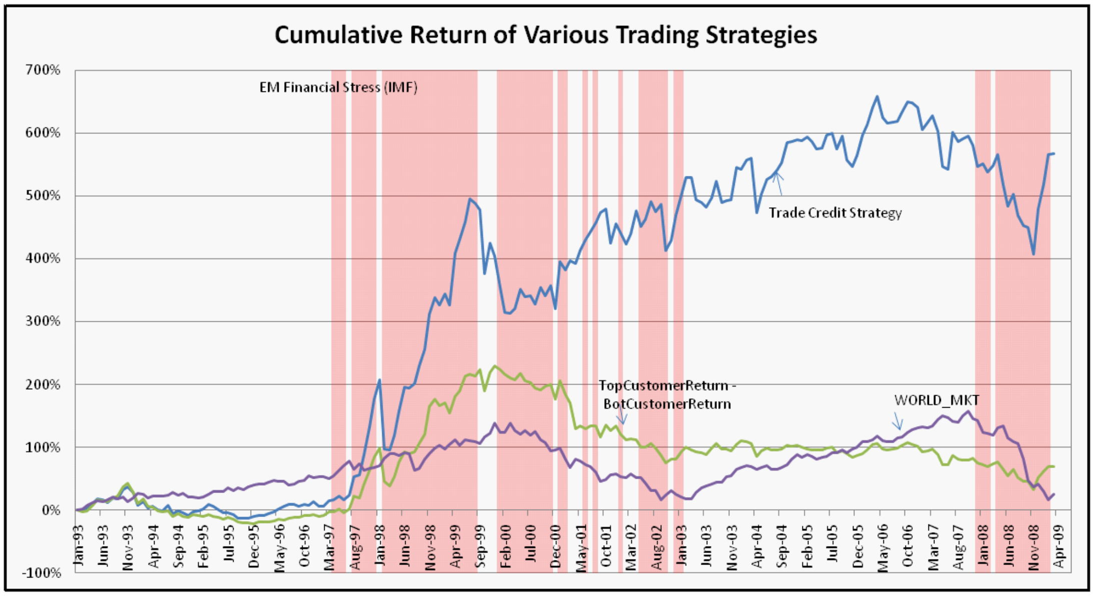

Figure 3: Cumulative returns of trade credit strategies. The figure shows the cumulative returns from our best strategy ('Trade Credit Strategy' long low trade credit firms in producer countries with high customer returns, and short high trade credit firms in producers with low customer returns); the strategy that simply uses consumer returns as a signal ('TopCustomerReturn-BotCustomerReturn', which is Rizova's strategy) and the cumulative world market return. The vertical bars indicate periods of emerging market financial stress as identified by the IMF.

off payment to them in bad times.

B. Calendar time portfolios with size and short-term debt

Table IV double sorts the firms within each customer momentum tercile by size and the trade credit measures. For ease of exposition, we present only the excess returns in each of the bins, but the results are broadly the same regardless of the method of risk adjustment employed. The table shows that in the bottom tercile of customer returns, it is always the case that the high trade credit firms underperform low trade credit firms, regardless of the size of the firms under consideration. As before, these results are primarily driven by AR turnover, and in three out of four cases in the net trade credit and AR turnover bins, these results are statistically significant at the 5% level or better. In the top tercile of customer country returns, there does not seem to be any distinguishable pattern of returns, and the differences between high and low trade credit firms are not statistically significant.

The long-short portfolio returns are computed at the bottom of the table, and show that in six of eight cases for the net trade credit and AR turnover measures, the returns are positive and statistically significant. Conditioning on size seems to improve the performance of these strategies, but they are not dependent on size. For AP turnover, the returns are now statistically significant when small firms in the top tercile with low trade credit are employed.[6]

Table V double sorts firms within each customer momentum tercile by the trade credit measures and by the level of short-term debt expressed as a percentage of sales. The table shows that the trade credit effect in the bottom tercile continues to persist even after controlling for the level of short-term debt that firms take on. In firms with low and high levels of short-term debt, the trade credit effects are clearly visible. There is also a perceptible impact of high levels of short-term debt on the performance of the portfolios. Firms with high levels of short-term debt have lower returns than those with low levels of short-term debt even after controlling for the level of trade credit. The magnitudes of the two effects (trade credit and short-term debt) are roughly similar in the bottom tercile of firms. It is also the case that the trade credit effect is much stronger for firms which also have high levels of short-term debt, suggesting that a strategy that conditions on both these firm attributes will perform better than one which considers these attributes separately. Indeed, the bottom of Table V shows that the long-short portfolio returns are highest when both the top tercile firms and the bottom tercile firms have high levels of short-term debt. The best strategy that conditions on both these attributes simultaneously uses AR turnover as the measure of trade credit, and yields a very high and statistically significant 21% per annum return over the sample period.

[6] Another interesting conclusion from the table is that small firms do seem to have higher average returns than large firms, as has been found in studies using U.S. data (see, for example, Fama and French, 1993), but the effect does not seem to be statistically strong, consistent with broader studies using international data such as Fama and French (1998).

C. Panel regression results

Table VI re-estimates the results in a pooled regression setting, allowing us to simultaneously control for the impacts of multiple conditioning variables. The pooled regressions employ between ~860,000 and 923,000 firm-months, and around 12,000 firms depending on the trade credit variable employed in the sorts. The first column of the table simply estimates the average return of firms from the top customer return and bottom customer return terciles (sorted in the previous month) just as in the calendar-time regression results. The regressions are run using weighted least squares, with each firm in a country weighted by its market-capitalization relative to all other firms in the same country. This is done so as to mimic the value-weighted country portfolios that we employ in our calendar-time portfolio estimation. The regression simply reconfirms that the baseline strategy of going long high-customer return countries and short low-customer return countries generates positive returns (positive coefficient on top customer return, negative coefficient on bottom customer return), however, as we found earlier, these are not statistically significant in our sample.

The next column of the table (column 2) uses AR turnover as the trade credit measure, and simply adds three dummy variables to the specification, which interact the top, medium and bottom customer return dummies with dummies that take the value of one whenever a firm has high trade credit (above the median, in the previous year across all firms). As we found earlier, the high-trade credit firms in the bottom customer return tercile have statistically significantly lower returns than their low-trade credit counterparts. Panel B of the table confirms that this effect exists in our panel estimation. Columns 3 and 4 of Table VI add in a number of controls. Column 3 adds the market capitalization and short-term debt level (both measured as fractional ranks across all firms in each country in each month to avoid issues of non-stationarity); lagged firm returns; the lagged country return; contemporaneous world market returns, and country-specific fixed-effects in estimation. Lagged one-month firm returns are estimated to have a negative and significant coefficient suggesting a short-term reversal in returns, and lagged one-month country returns are marginally statistically significant and positive, suggesting that there is some country-level stock return momentum. The world market return is estimated to have a highly statistically significant coefficient close to 1, suggesting that the world market model is a reasonable risk-adjustment method. However, despite all of these additions, Panel B of the table shows that the difference between low and high trade credit firms in the bottom tercile of consumer returns continues to be strong and statistically significant, at ~ 51 basis points per month or around 6% per annum in the column labeled '4.'

The cross-customer return tercile portfolio difference is also substantial (this portfolio goes long low trade credit firms with high customer returns and short high trade credit firms with low customer returns). Panel C of Table VI shows that this portfolio is estimated to have statistically significant annualized returns of around 14% per annum in the panel regression, which is close to the 12% figure detected earlier using the calendar time analysis.[7] This magnitude does reduce with the addition of controls in the panel regression, especially in the specification in which we add the country-index return on the right-hand side in addition to the world market return.[8] Panel C shows that the returns from the cross-customer return tercile portfolio strategy are about 6% per annum with the inclusion of the country index return, and less statistically significant. This reduction in the magnitude of the strategy's returns is interesting - and suggests that future investigation of whether trade credit levels can predict firms' beta variation in addition to variation in their outperformance relative to a benchmark model would be useful. Despite this reduction in the alpha of the trading strategy, it is worth noting that the coefficient on the interaction between bottom customer returns and high trade credit in Panel A of the table is highly statistically significant regardless of the

[7]The magnitude is slightly different across the two analyses because we employ a slightly different sample, i.e., we only pick firm-months for which accounts receivable turnover data is available. This minor variation causes the small difference in the two sets of results.

[8]We do so in order to control for the possibility that global capital markets are segmented (see, among others, Solnik, 1974, and Bekaert and Harvey, 1995).

introduction of these controls. This shows that the marginal impact of having high trade credit is negative, even after controlling for the contemporaneous country-index return.

Columns 5 through 8 of Table VI re-do the results using AP turnover and subsequently net trade credit as the variables employed to create the dummies. These columns echo the findings from the calendar-time portfolio analysis, namely that accounts receivables rather than accounts payable seem to be the main channel capturing cross-correlation. The net trade credit measure does reasonably well as a conditioning variable, but not as well as accounts receivable on its own. Taken together, the findings in Table VI provide strong support to the findings from the calendar-time portfolio analysis.

Table VII adds two dimensions to our results. The first is that we investigate the conditional performance of our trading strategy. The conditioning variable that we use is the IMF's emerging market financial stress index.[9] Unconditionally, the inclusion of the measure is not useful for predicting future stock returns of the producer firms in the panel regression, but when the indicator is interacted with the producer returns index separately for high and low trade credit firms, the results are quite striking. Essentially all of the negative effects of high trade credit occur during periods of emerging market stress - the dummy variable BottomCustomerReturn *HighTradeCredit is not statistically significant, while the variable BottomCustomerReturn *HighTradeCredit*Financial Stress is highly statistically significant and negative. This is virtually unchanged by the second dimension that Table VII adds, namely the inclusion of industry dummy variables into the regression. The invariance of the results to the addition of the industry dummies confirms 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. Rather, the performance of the strategy is driven almost completely by firm-level variation in trade-credit. Put differently, even within the

[9] The index, developed by Danninger et. al. (2009), comprises measures of exchange market pressure, emerging economy sovereign spreads, betas of banking stocks; stock price returns; and time-varying stock return volatility for 18 emerging markets.

same industry, we would expect to see variation across firms in the extent of their predictability by consumer returns, based solely on their different levels of trade credit.

5. Conclusion

We build a simple model of trade credit between firms in different countries, and derive asset pricing implications from the model which we then test on data from 55 countries over the 1993 to 2009 period. The model predicts that high levels of trade credit between firms in different countries should be associated with high levels of cross-serial correlation of their stock returns. Our empirical results provide strong support to the predictions of the theory, and suggest that trade credit is an important source of international stock return comovement. Yet, the model cannot explain the insignificant returns to the long low trade credit and short high trade credit portfolio strategy in the high tercile of consumer country returns. We view this as a shortcoming of the stylized/reduced form model of trade credit used in this paper that does not allow for trade credit to be state dependent. Future research should aim to endogenize the choice of trade credit, incorporating the relevant corporate frictions into asset pricing models.

The role of financial intermediaries such as banks and mutual funds in transmitting shocks across borders has been extensively studied, and the relationships between these intermediaries and the firms to which they lend has been the focus of significant attention. However, trade credit relationships between firms have not been given quite as much visibility in debates about the sources of the international propagation of shocks. Our results suggest that this channel may be equally important, and consequently our analysis raises interesting policy questions about the optimal structuring of trade credit agreements across borders.

Appendix

This Appendix provides the proof of the proposition in the text.

Proof of Proposition 1 . Consider the equilibrium prices as given in the proposition:

$$
\begin{aligned}
P_t^C &= \bar{D}_{t+1}^C - b_{CC}\left(\bar{D}_{t+1}^C - \mathrm{E}_t^d\left(\bar{D}_{t+1}^C\right)\right) - b_{CP}\left(\bar{D}_{t+1}^P - \mathrm{E}_t^d\left(\bar{D}_{t+1}^P\right)\right) - h_{CC}z_t^C - h_{CP}z_t^P \\
P_t^P &= \bar{D}_{t+1}^P - b_{PP}\left(\bar{D}_{t+1}^P - \mathrm{E}_t^d\left(\bar{D}_{t+1}^P\right)\right) - b_{PC}\left(\bar{D}_{t+1}^C - \mathrm{E}_t^d\left(\bar{D}_{t+1}^C\right)\right) - h_{PP}z_t^P - h_{PC}z_t^C.
\end{aligned}
$$

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

$$\max_{\theta^i} \mathrm{E}_t^d\left[\exp^{-\gamma W_{t+1}^i}\right]$$

subject to

$$W_{t+1}^i = W_t^i + \theta^i\left(D_{t+1}^i - P_t^i\right).$$

The first order necessary and sufficient condition for this problem yields

$$\theta^i = \frac{\mathrm{E}_t^d\left[D_{t+1}^i - P_t^i\right]}{\gamma \mathrm{Var}_t^d\left[D_{t+1}^i - P_t^i\right]}.$$

Likewise, speculators from either country face the problem of

$$\max_{\eta^C,\eta^P} \mathrm{E}_t^s\left[\exp^{-\gamma W_{t+1}^i}\right]$$

subject to

$$W_{t+1}^i = W_t^i + \eta^C\left(D_{t+1}^C - P_t^C\right) + \eta^P\left(D_{t+1}^P - P_t^P\right).$$

This problem is solved by setting

$$\begin{bmatrix} \eta^C \\ \eta^P \end{bmatrix} = \gamma^{-1}V_t^{-1}\begin{bmatrix} \bar{D}_{t+1}^C - P_t^C \\ \bar{D}_{t+1}^P - P_t^P \end{bmatrix},$$

where

$$V_t = \begin{bmatrix} \sigma_{uC}^2 & \alpha\sigma_{uC}^2 \\ \alpha\sigma_{uC}^2 & \sigma_{uP}^2 + \alpha^2\sigma_{uC}^2 \end{bmatrix}$$

which gives

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

After multiplying the two matrices we obtain the expression in equation (1). With the asset demands we can now solve for market clearing:

$$z_t^C = \mu_C\frac{1}{\gamma\sigma_{uP}^2}\left[\frac{\sigma_{uP}^2+\alpha^2\sigma_{uC}^2}{\sigma_{Cu}^2}\left(\bar{D}_{t+1}^C - P_t^C\right) - \alpha\left(\bar{D}_{t+1}^P - P_t^P\right)\right] + (1-\mu_C)\frac{\mathrm{E}_t^d\left[D_{t+1}^C - P_t^C\right]}{\gamma\mathrm{Var}_t^d\left[D_{t+1}^C - P_t^C\right]}$$

$$z_t^P = \mu_P\frac{1}{\gamma\sigma_{uP}^2}\left[\bar{D}_{t+1}^P - P_t^P - \alpha\left(\bar{D}_{t+1}^C - P_t^C\right)\right] + (1-\mu_P)\frac{\mathrm{E}_t^d\left[D_{t+1}^P - P_t^P\right]}{\gamma\mathrm{Var}_t^d\left[D_{t+1}^P - P_t^P\right]}.$$

Using the price functions to substitute for the values of P_t^i and combining terms associated with the various state variables $(\bar{D}_{t+1}^C - \mathrm{E}_t^d\left(\bar{D}_{t+1}^C\right), \bar{D}_{t+1}^P - \mathrm{E}_t^d\left(\bar{D}_{t+1}^P\right), z_t^C, z_t^P)$ we obtain eight equilibrium conditions (four from each market clearing condition):

$$\begin{aligned}
0 &= \mu_C \frac{1}{\gamma\sigma_{uP}^2} \frac{\sigma_{uP}^2 + \alpha^2\sigma_{uC}^2}{\sigma_{Cu}^2} b_{CC} - \mu_C \frac{1}{\gamma\sigma_{uP}^2} \alpha b_{PC} + (1-\mu_C) \frac{b_{CC} - 1}{\gamma \mathrm{Var}_t^d\left[D_{t+1}^C - P_t^C\right]} \\
0 &= \mu_C \frac{1}{\gamma\sigma_{uP}^2} \frac{\sigma_{uP}^2 + \alpha^2\sigma_{uC}^2}{\sigma_{Cu}^2} b_{CP} - \mu_C \frac{1}{\gamma\sigma_{uP}^2} \alpha b_{PP} + (1-\mu_C) \frac{b_{CP}}{\gamma \mathrm{Var}_t^d\left[D_{t+1}^C - P_t^C\right]}
\end{aligned}$$

$$\begin{aligned}
1 &= \mu_C \frac{1}{\gamma\sigma_{uP}^2} \frac{\sigma_{uP}^2 + \alpha^2\sigma_{uC}^2}{\sigma_{Cu}^2} h_{CC} - \mu_C \frac{1}{\gamma\sigma_{uP}^2} \alpha h_{PC} + (1-\mu_C) \frac{h_{CC}}{\gamma \mathrm{Var}_t^d\left[D_{t+1}^C - P_t^C\right]} \\
0 &= \mu_C \frac{1}{\gamma\sigma_{uP}^2} \frac{\sigma_{uP}^2 + \alpha^2\sigma_{uC}^2}{\sigma_{Cu}^2} h_{CP} - \mu_C \frac{1}{\gamma\sigma_{uP}^2} \alpha h_{PP} + (1-\mu_C) \frac{h_{CP}}{\gamma \mathrm{Var}_t^d\left[D_{t+1}^C - P_t^C\right]}
\end{aligned}$$

and

$$\begin{aligned}
0 &= \mu_P \frac{1}{\gamma\sigma_{uP}^2} b_{PP} - \mu_P \frac{1}{\gamma\sigma_{uP}^2} \alpha b_{CP} + (1-\mu_P) \frac{b_{PP} - 1}{\gamma \mathrm{Var}_t^d\left[D_{t+1}^P - P_t^P\right]} \\
0 &= \mu_P \frac{1}{\gamma\sigma_{uP}^2} b_{PC} - \mu_P \frac{1}{\gamma\sigma_{uP}^2} \alpha b_{CC} + (1-\mu_P) \frac{b_{PC}}{\gamma \mathrm{Var}_t^d\left[D_{t+1}^P - P_t^P\right]}
\end{aligned}$$

$$\begin{aligned}
1 &= \mu_P \frac{1}{\gamma\sigma_{uP}^2} h_{PP} - \mu_P \frac{1}{\gamma\sigma_{uP}^2} \alpha h_{CP} + (1-\mu_P) \frac{h_{PP}}{\gamma \mathrm{Var}_t^d\left[D_{t+1}^P - P_t^P\right]} \\
0 &= \mu_P \frac{1}{\gamma\sigma_{uP}^2} h_{PC} - \mu_P \frac{1}{\gamma\sigma_{uP}^2} \alpha h_{CC} + (1-\mu_P) \frac{h_{PC}}{\gamma \mathrm{Var}_t^d\left[D_{t+1}^P - P_t^P\right]}.
\end{aligned}$$

These equations can be used to solve for the eight unknowns: $b_{CC}, b_{CP}, b_{PC}, b_{PP}, h_{PC}, h_{PP}, h_{CC}, h_{CP}$. This is a non-linear system of equations because the conditional variances $\mathrm{Var}_t^d\left[D_{t+1}^P - P_t^P\right]$ and $\mathrm{Var}_t^d\left[D_{t+1}^C - P_t^C\right]$ depend on these price parameters as well. We turn to the calculation of these conditional variances now.

From the properties of conditional normal distributions:

$$\begin{aligned}
\mathrm{E}^d\left(\bar{D}_{t+1}^C | \Pi^C\right) &= \frac{\mathrm{Cov}\left(\bar{D}_{t+1}^C, \Pi^C\right)}{\mathrm{Var}\left(\Pi^C\right)} \Pi^C = \beta^C \Pi^C \\
\mathrm{Var}^d\left(\bar{D}_{t+1}^C | \Pi^C\right) &= \sigma_{\varepsilon C}^2 - \frac{\mathrm{Cov}\left(\bar{D}_{t+1}^C, \Pi^C\right)^2}{\mathrm{Var}\left(\Pi^C\right)}.
\end{aligned}$$

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:

$$\begin{aligned}
\bar{D}_{t+1}^C - \mathrm{E}_t^d\left(\bar{D}_{t+1}^C\right) &= \left[1 - \beta^D\left(1 - b_{CC}\right)\right] \bar{D}_{t+1}^C + \beta^C b_{CP} \left(\bar{D}_{t+1}^P - \mathrm{E}_t^d\left(\bar{D}_{t+1}^P\right)\right) \\
&\quad + \beta^C h_{CC} z_t^C + \beta^C h_{CP} z_t^P
\end{aligned}$$

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

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

$$\begin{aligned}\bar{D}^{C}_{t+1}-\mathrm{E}^{d}_{t}\left(\bar{D}^{C}_{t+1}\right) &= f_{cc}\bar{D}^{C}_{t+1}+f_{cp}\bar{D}^{P}_{t+1}+f_{czp}z^{P}_{t}+f_{czc}z^{C}_{t}\\ \bar{D}^{P}_{t+1}-\mathrm{E}^{d}_{t}\left(\bar{D}^{P}_{t+1}\right) &= g_{pp}\bar{D}^{P}_{t+1}+g_{pc}\bar{D}^{C}_{t+1}+g_{pzc}z^{C}_{t}+g_{pzp}z^{P}_{t}.\end{aligned}$$

We can now solve for five unconditional moments, $\mathrm{E}\left[\left(\bar{D}^{P}_{t+1}-\mathrm{E}^{d}_{t}\left(\bar{D}^{P}_{t+1}\right)\right)\left(\bar{D}^{C}_{t+1}-\mathrm{E}^{d}_{t}\left(\bar{D}^{C}_{t+1}\right)\right)\right]$, $\mathrm{Cov}\left(\bar{D}^{C}_{t+1},\Pi^{C}_{t}\right)$, $\mathrm{Cov}\left(\bar{D}^{P}_{t+1},\Pi^{P}_{t}\right)$, $\mathrm{Var}\left(\Pi^{P}_{t}\right)$ and $\mathrm{Var}\left(\Pi^{C}_{t}\right)$, from which we finally get the conditional variances:

$$\begin{aligned}\mathrm{Var}^{d}_{t}\left[D^{i}_{t+1}\right] &= \mathrm{Var}\left[D^{i}_{t+1}|\Pi^{i}\right]\\ &= \mathrm{Var}\left(u\right)+\mathrm{Var}^{d}\left[\bar{D}^{i}_{t+1}|\Pi^{i}\right]\\ &= \mathrm{Var}\left[D^{i}_{t+1}\right]-\frac{\mathrm{Cov}^{2}\left(\bar{D}^{i}_{t},\Pi^{i}\right)}{\mathrm{Var}\left(\Pi^{i}\right)}.\end{aligned}$$

■

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Table I
Country-Level Descriptive Statistics for Returns

This table presents summary data about the monthly return data employed in our dataset. The "Producer Set" shows the countries with export levels of ≥20% of GDP in any year in the sample period. The "Trade Partner Set" comprises those countries which consume ≥5% of these exports of the producers in any year. The descriptive statistics shown for corresponding country indices are for percentage monthly (value-weighted, simple) USD returns. For countries only in the trade partner set, these data are the corresponding MSCI country indices, and for all others, these indices are built from industrial-firm-level Worldscope data, and the total number of unique firms and the average number of firms per year used to construct these indices is presented in the columns.

Country	Region	Export (Customer) Links		Median	Mean	Std Dev	Total Num Firms	Average Num Firms	Data Begin Date
		Producer Set	Trade Partner Set						
Developed									
Japan	East Asia	N	Y	0.313	0.247	5.963	4053	3070	1/31/1993
Canada	North America	Y	Y	1.256	0.889	5.822	1657	1165	1/31/1993
United States	North America	N	Y	1.194	0.596	4.858	10034	6949	1/31/1993
Australia	Oceania	N	Y	1.504	1.020	6.708	1825	991	1/31/1993
New Zealand	Oceania	Y	N	1.123	1.001	6.686	123	81	1/31/1993
Denmark	Scandinavia	Y	Y	1.358	0.949	5.091	155	128	1/31/1993
Finland	Scandinavia	Y	Y	1.582	1.596	9.431	135	98	1/31/1993
Norway	Scandinavia	Y	Y	1.822	1.174	7.538	242	137	1/31/1993
Sweden	Scandinavia	Y	Y	1.801	1.164	8.514	467	257	1/31/1993
Austria	Western Europe	Y	Y	1.377	0.681	6.204	104	83	1/31/1993
Belgium	Western Europe	Y	Y	1.443	0.673	5.451	144	94	1/31/1993
France	Western Europe	Y	Y	1.311	0.815	6.220	238	168	1/31/1993
Germany	Western Europe	Y	Y	1.526	0.754	6.067	941	649	1/31/1993
Ireland	Western Europe	Y	Y	1.926	0.686	7.633	79	60	1/31/1993
Italy	Western Europe	Y	Y	0.610	0.713	6.862	293	189	1/31/1993
Netherlands	Western Europe	Y	Y	1.540	0.826	4.927	207	173	1/31/1993
Spain	Western Europe	N	Y	0.778	0.715	5.630	134	105	1/31/1993
Switzerland	Western Europe	Y	Y	1.053	0.927	4.388	220	170	1/31/1993
United Kingdom	Western Europe	Y	Y	0.816	0.637	4.405	2797	1925	1/31/1993
Emerging									
South Africa	Africa	Y	Y	1.100	0.887	7.742	509	380	1/31/1993
China	East Asia	Y	Y	-0.156	1.002	13.396	1360	724	1/31/1993
Hong Kong	East Asia	Y	Y	1.459	0.980	8.453	755	496	1/31/1993
South Korea	East Asia	Y	N	-0.358	1.259	12.851	1178	738	1/31/1993
Czech Republic	Eastern Europe	Y	Y	1.645	1.189	7.373	52	50	1/31/1996

Hungary	Eastern Europe	Y	Y	1.461	0.893	10.489	34	27	1/31/1994
Poland	Eastern Europe	Y	Y	0.986	0.627	10.681	300	130	1/31/1994
Russia	Eastern Europe	Y	Y	3.303	2.262	14.453	103	40	1/31/1997
Slovakia	Eastern Europe	N	Y	1.677	1.148	8.648			2.28.1997
Argentina	Latin America	Y	Y	0.657	0.573	8.895	52	47	1/31/1993
Brazil	Latin America	N	Y	2.881	2.064	13.446	185	136	8/31/1994
Chile	Latin America	Y	Y	0.983	1.023	7.184	110	96	1/31/1993
Mexico	Latin America	Y	N	1.929	0.871	9.153	118	94	1/31/1993
India	South Asia	N	Y	1.818	0.878	9.056			1/31/1993
Indonesia	Southeast Asia	Y	Y	1.421	1.000	12.673	253	123	1/31/1993
Malaysia	Southeast Asia	Y	Y	0.229	0.783	10.797	913	593	1/31/1993
Philippines	Southeast Asia	Y	N	0.195	0.474	9.972	117	92	1/31/1993
Singapore	Southeast Asia	Y	Y	1.161	0.688	8.635	597	342	1/31/1993
Thailand	Southeast Asia	Y	Y	-0.263	0.243	9.877	439	312	1/31/1993
Israel	Southwest Asia	Y	Y	1.374	0.913	8.058	122	95	1/31/1994
Saudi Arabia	Southwest Asia	N	Y	1.356	1.178	8.011			1/30/1998
Turkey	Southwest Asia	N	Y	3.176	2.474	16.744			1/31/1993
Portugal	Western Europe	Y	N	1.457	1.098	6.418	88	77	1/31/1993

Table II
Country-Level Trade Credit Summary Statistics for Producer Countries

This table shows descriptive statistics for the time series of the value-weighted cross-sectional means of the variables listed in the columns for each country in the possible producers set which have firm-level data available on Worldscope. These ratios are calculated from annual firm-level sales, cost of goods sold, accounts receivable and accounts payable data from 1992 to 2009.

Country	Region	Net Trade Credit			AR Turnover			AP Turnover		
		Median	Mean	Std Dev	Median	Mean	Std Dev	Median	Mean	Std Dev
Developed										
Canada	North America	-0.005	-0.014	0.039	0.193	0.197	0.023	0.390	0.425	0.128
New Zealand	Oceania	0.065	0.032	0.123	0.164	0.165	0.024	0.192	0.329	0.363
Denmark	Scandinavia	0.147	0.143	0.030	0.219	0.223	0.027	0.177	0.183	0.055
Finland	Scandinavia	0.102	0.110	0.026	0.199	0.202	0.025	0.134	0.136	0.018
Norway	Scandinavia	0.088	0.086	0.034	0.189	0.201	0.037	0.147	0.153	0.027
Sweden	Scandinavia	0.132	0.141	0.040	0.223	0.237	0.037	0.128	0.130	0.016
Austria	Western Europe	0.096	0.149	0.164	0.195	0.267	0.181	0.146	0.159	0.073
Belgium	Western Europe	0.084	0.086	0.040	0.209	0.209	0.035	0.168	0.208	0.095
France	Western Europe	0.099	0.103	0.028	0.250	0.256	0.029	0.253	0.242	0.033
Germany	Western Europe	0.145	0.156	0.044	0.249	0.245	0.050	0.149	0.144	0.026
Ireland	Western Europe	0.074	0.075	0.023	0.178	0.176	0.023	0.186	0.217	0.103
Italy	Western Europe	0.151	0.140	0.041	0.340	0.352	0.074	0.507	0.505	0.089
Netherlands	Western Europe	0.067	0.065	0.012	0.147	0.154	0.027	0.125	0.133	0.019
Switzerland	Western Europe	0.142	0.137	0.019	0.212	0.212	0.015	0.220	0.207	0.036
United Kingdom	Western Europe	0.075	0.076	0.011	0.181	0.178	0.016	0.205	0.210	0.070
Emerging										
South Africa	Africa	0.045	0.060	0.062	0.161	0.206	0.089	0.173	0.245	0.131
China	East Asia	0.139	0.165	0.154	0.359	0.362	0.156	0.255	0.428	0.578
Hong Kong	East Asia	0.126	0.081	0.099	0.239	0.241	0.048	0.214	0.243	0.082
South Korea	East Asia	0.121	0.126	0.045	0.209	0.224	0.054	0.131	0.133	0.017
Czech Republic	Eastern Europe	0.151	0.414	0.980	0.239	0.477	0.878	0.137	0.150	0.059
Hungary	Eastern Europe	0.084	0.092	0.031	0.171	0.179	0.036	0.153	0.156	0.051
Poland	Eastern Europe	0.088	0.209	0.349	0.203	0.241	0.124	0.168	0.195	0.076
Russia	Eastern Europe	0.159	0.192	0.136	0.230	0.312	0.190	0.252	0.295	0.143
Argentina	Latin America	0.121	0.127	0.057	0.235	0.245	0.051	0.215	0.218	0.021
Chile	Latin America	0.129	0.150	0.085	0.218	0.241	0.089	0.151	0.158	0.047
Mexico	Latin America	0.078	0.075	0.055	0.174	0.176	0.050	0.163	0.166	0.023
Indonesia	Southeast Asia	0.073	0.089	0.042	0.154	0.171	0.057	0.120	0.132	0.033
Malaysia	Southeast Asia	0.207	0.212	0.078	0.363	0.351	0.110	0.165	0.164	0.043
Philippines	Southeast Asia	0.063	0.065	0.042	0.229	0.233	0.048	0.270	0.300	0.112
Singapore	Southeast Asia	0.151	0.166	0.065	0.262	0.282	0.064	0.176	0.170	0.018
Thailand	Southeast Asia	0.067	0.090	0.064	0.162	0.191	0.076	0.182	0.212	0.114
Israel	Southwest Asia	0.189	0.197	0.061	0.309	0.318	0.056	0.201	0.219	0.061
Portugal	Western Europe	0.089	0.082	0.033	0.219	0.212	0.040	0.161	0.161	0.018

Table III
Customer Momentum Strategy, Trade Credit Sort

This table shows returns produced by the customer momentum strategy. Panel A shows baseline results where producer countries are sorted solely based on the returns in the previous month of their major customers (trade partners which purchase ≥5% of total exports of a producer country). The "Top" Customer Return index consist of countries in the top 30th percentile sorted by returns, the "Bottom" Customer Return index consists of countries in the bottom 30th percentile sorted by returns. Panel B shows the returns of indices derived from sorting firms in countries *within* Top and Bottom customer returns groups by whether they have above or below the median level of trade credit (measured by Net Trade Credit, AR Turnover, or AP Turnover). This creates 4 indices: Bottom Customer Return & Low Trade-Credit, Bottom Customer Return & High Trade-Credit, Top Customer Return & Low Trade-Credit, and Top Customer Return & High Trade-Credit. Excess Return is the average return over the sample period in excess of the monthly US T-Bill rate. One factor, two factor and three factor correspond to alphas obtained from regressing returns of these indices on the world market return; world market plus country momentum; and world market plus country momentum plus global HML. Percentage monthly (value-weighted, simple) USD returns are shown for the 4 regressions. Standard errors are shown within brackets below the return estimates, and computed using the Newey-West method.

Panel A: Baseline Results, no Trade Credit Sort

Regression	Excess Return	One Factor (+MKT)	Two Factor (+MOM)	Three Factor (+HML)
Top Customer	0.728	0.488	0.543	0.511
	[0.501]	[0.283]	[0.282]	[0.275]
Bottom Customer	0.281	0.037	0.167	0.110
	[0.529]	[0.403]	[0.362]	[0.418]
Top - Bottom	0.447	0.451	0.376	0.401
	[0.441]	[0.445]	[0.428]	[0.455]

Panel B: Benchmark Trade Credit Results

Trade Credit Measure →	**Net Trade Credit**				**AR Turnover**				**AP Turnover**			
Regression	Excess Return	One Factor (+MKT)	Two Factor (+MOM)	Three Factor (+HML)	Excess Return	One Factor (+MKT)	Two Factor (+MOM)	Three Factor (+HML)	Excess Return	One Factor (+MKT)	Two Factor (+MOM)	Three Factor (+HML)
Bottom Cust.												
Low TC	0.513 [0.525]	0.271 [0.417]	0.427 [0.382]	0.391 [0.426]	0.582 [0.506]	0.348 [0.399]	0.502 [0.368]	0.482 [0.401]	0.181 [0.533]	-0.048 [0.425]	0.078 [0.388]	-0.088 [0.431]
High TC	-0.127 [0.569]	-0.368 [0.438]	-0.264 [0.403]	-0.354 [0.479]	-0.281 [0.636]	-0.538 [0.496]	-0.427 [0.447]	-0.518 [0.553]	0.297 [0.553]	0.045 [0.417]	0.176 [0.370]	0.174 [0.434]
Difference	0.640 [0.304]	0.640 [0.303]	0.691 [0.335]	0.745 [0.380]	0.863 [0.354]	0.885 [0.347]	0.929 [0.363]	1.000 [0.439]	-0.116 [0.251]	-0.093 [0.241]	-0.099 [0.229]	-0.261 [0.242]
Top Cust.												
Low TC	0.910 [0.503]	0.688 [0.329]	0.723 [0.326]	0.647 [0.284]	0.892 [0.493]	0.670 [0.309]	0.721 [0.308]	0.715 [0.275]	0.738 [0.522]	0.494 [0.315]	0.639 [0.315]	0.527 [0.307]
High TC	0.574 [0.537]	0.322 [0.309]	0.389 [0.303]	0.416 [0.332]	0.549 [0.552]	0.294 [0.332]	0.368 [0.322]	0.358 [0.355]	0.711 0.503]	0.479 [0.293]	0.462 [0.284]	0.471 [0.283]
Difference	0.336 [0.296]	0.367 [0.299]	0.334 [0.279]	0.231 [0.278]	0.343 [0.273]	0.376 [0.272]	0.352 [0.251]	0.357 [0.291]	0.027 [0.214]	0.015 [0.214]	0.177 [0.192]	0.056 [0.232]
Long Top - Short Bottom												
Low TC - High TC	1.037 [0.494]	1.057 [0.501]	0.988 [0.486]	1.001 [0.511]	1.173 [0.526]	1.208 [0.530]	1.147 [0.504]	1.233 [0.557]	0.441 [0.475]	0.449 [0.478]	0.463 [0.467]	0.353 [0.504]
High TC - High TC	0.701 [0.494]	0.690 [0.495]	0.653 [0.480]	0.770 [0.535]	0.829 [0.541]	0.832 [0.546]	0.795 [0.525]	0.876 [0.599]	0.414 [0.455]	0.434 [0.461]	0.285 [0.435]	0.297 [0.454
Low TC - Low TC	0.397 [0.435]	0.417 [0.442]	0.296 [0.434]	0.256 [0.445]	0.310 [0.449]	0.323 [0.455]	0.219 [0.449]	0.233 [0.458]	0.557 [0.469]	0.542 [0.467]	0.561 [0.455]	0.615 [0.500]
High TC - Low TC	0.061 [0.506]	0.050 [0.507]	-0.038 [0.484]	0.025 [0.515]	-0.033 [0.488]	-0.053 [0.482]	-0.134 [0.462]	-0.124 [0.504]	0.530 [0.474]	0.527 [0.473]	0.384 [0.436]	0.559 [0.459]

Table IV
Customer Momentum Strategy, Size and Trade Credit Double Sort

This table independently double sorts the firms in the Top and Bottom Customer Return indices by their levels of trade credit, and their market capitalization levels. Firms in countries in the Top (Bottom) index are sorted each month into 4 groups based on whether they are above or below the median size and median trade credit level for all constituent firms in the Top (Bottom) index. Excess Return is in excess of the monthly US T-Bill rate. Excess Return is the average return over the sample period in excess of the monthly US T-Bill rate. One factor, two factor and three factor correspond to alphas obtained from regressing returns of these indices on the world market return; world market plus country momentum; and world market plus country momentum plus global HML. Percentage monthly (value-weighted, simple) USD returns are shown for the 4 regressions. Standard errors are shown within brackets below the return estimates, and computed using the Newey-West method.

Trade Credit Measure →		**Net Trade Credit**			**AR Turnover**			**AP Turnover**		
		Market Cap			Market Cap			Market Cap		
Bottom Customer Return		Low	High	Low-High	Low	High	Low-High	Low	High	Low-High
Trade Credit	Low	0.290 [0.581]	0.524 [0.524]	-0.234 [0.302]	0.319 [0.556]	0.598 [0.506]	-0.280 [0.288]	0.256 [0.589]	0.185 [0.541]	0.070 [0.267]
	High	0.103 [0.661]	-0.143 [0.567]	0.245 [0.298]	0.052 [0.675]	-0.307 [0.635]	0.359 [0.302]	0.109 [0.655]	0.304 [0.537]	-0.195 [0.313]
	Low-High	0.188 [0.209]	0.667 [0.317]		0.266 [0.243]	0.905 [0.361]		0.147 [0.195]	-0.119 [0.257]	

Top Customer Return		Low	High	Low-High	Low	High	Low-High	Low	High	Low-High
Trade Credit	Low	1.180 [0.616]	0.907 [0.504]	0.273 [0.277]	1.229 [0.560]	0.887 [0.495]	0.342 [0.252]	1.142 [0.586]	0.730 [0.521]	0.412 [0.304]
	High	1.095 [0.656]	0.560 [0.535]	0.535 [0.429]	1.055 [0.699]	0.518 [0.553]	0.536 [0.407]	1.150 [0.678]	0.709 [0.503]	0.441 [0.381]
	Low-High	0.086 [0.219]	0.347 [0.301]		0.174 [0.257]	0.369 [0.283]		-0.008 [0.176]	0.021 [0.220]	

Long Top – Short Bottom		Bottom Customer Return (High TC)			Bottom Customer Return (High TC)			Bottom Customer Return (High TC)		
		Low Mcap	High Mcap		Low Mcap	High Mcap		Low Mcap	High Mcap	
Top Customer Return (Low TC)	Low Mcap	1.078 [0.574]	1.323 [0.560]		1.177 [0.561]	1.536 [0.572]		1.033 [0.561]	0.838 [0.520]	
	High Mcap	0.804 [0.558]	1.050 [0.494]		0.835 [0.563]	1.195 [0.528]		0.621 [0.537]	0.426 [0.465]	

Table V

Customer Momentum Strategy, Short-Term Debt and Trade Credit Double Sort

This table independently double sorts the firms in the Top and Bottom Customer Return indices by their levels of trade credit, and their short-term debt levels (as a percentage of sales). Firms in countries in the Top (Bottom) index are sorted each month into 4 groups based on whether they are above or below the median size and median trade credit level for all constituent firms in the Top (Bottom) index. Excess Return is in excess of the monthly US T-Bill rate. Excess Return is the average return over the sample period in excess of the monthly US T-Bill rate. One factor, two factor and three factor correspond to alphas obtained from regressing returns of these indices on the world market return; world market plus country momentum; and world market plus country momentum plus global HML. Percentage monthly (value-weighted, simple) USD returns are shown for the 4 regressions. Standard errors are shown within brackets below the return estimates, and computed using the Newey-West method.

Trade Credit Measure →		**Net Trade Credit**			**AR Turnover**			**AP Turnover**		
		Short-term Debt			Short-term Debt			Short-term Debt		
Bottom Customer Return		Low	High	Low-High	Low	High	Low-High	Low	High	Low-High
Trade Credit	Low	0.516 [0.529]	0.302 [0.561]	0.214 [0.280]	0.629 [0.509]	0.220 [0.551]	0.409 [0.285]	0.395 [0.517]	-0.251 [0.631]	0.647 [0.306]
	High	0.265 [0.579]	-0.617 [0.622]	0.882 [0.368]	0.055 [0.685]	-0.655 [0.628]	0.710 [0.375]	0.585 [0.564]	-0.258 [0.573]	0.843 [0.346]
	Low-High	0.252 [0.357]	0.919 [0.326]		0.574 [0.463]	0.874 [0.274]		-0.189 [0.271]	0.006 [0.315]	
Top Customer Return		Low	High	Low-High	Low	High	Low-High	Low	High	Low-High
Trade Credit	Low	0.917 [0.506]	0.979 [0.589]	-0.063 [0.353]	0.878 [0.502]	1.121 [0.585]	-0.244 [0.349]	0.787 [0.527]	0.852 [0.611]	-0.065 [0.387]
	High	0.583 [0.603]	0.693 [0.549]	-0.110 [0.388]	0.594 [0.634]	0.570 [0.568]	0.024 [0.390]	0.807 [0.536]	0.775 [0.548]	0.032 [0.341]
	Low-High	0.334 [0.361]	0.287 [0.295]		0.284 [0.359]	0.551 [0.287]		-0.020 [0.277]	0.077 [0.296]	

Long Top – Short Bottom		Bottom Customer Return (High TC)			Bottom Customer Return (High TC)			Bottom Customer Return (High TC)		
		Low ST debt	High ST Debt		Low ST debt	High ST debt		Low ST debt	High ST debt	
Top Customer Return (Low TC)	Low ST debt	0.652 [0.503]	1.534 [0.558]		0.823 [0.540]	1.533 [0.550]		0.202 [0.464]	1.045 [0.518]	
	High ST debt	0.715 [0.553]	1.597 [0.608]		1.066 [0.669]	1.776 [0.626]		0.268 [0.570]	1.110 [0.616]	

Table VI
Customer Momentum Strategy, Panel Regression

This table shows pooled firm level return regressions using weighted least squares. We include dummies to indicate the customer return set a firm belongs to in a particular month (TopCustomerReturn, BotCustomerReturn), and in regressions 2 through 8 we interact these dummies with dummy variables indicating a firm's level of trade credit (above the median or High, and below the median, or Low) to find the excess return difference between low and high trade credit firms within a customer return set. We include lagged firm, lagged country returns, and firm size and short-term debt levels ranked within each country in each month. Both country and world market returns are included to adjust for market risk. Results are shown with different conditioning variables on the right hand side. T-statistics (clustered by month) are shown within brackets below the coefficient estimates.

Panel A: Regression results for firm returns

		AR Turnover			Net Trade Credit	
Regression	**1**	**2**	**3**	**4**	**7**	**8**
(Intercept)	0.008	0.007	-0.004	-0.015	-0.005	-0.017
	[1.566]	[1.572]	[-0.45]	[-1.584]	[-0.581]	[-1.702]
TopCustomerReturn	0.003	0.005	0.004	0.001	0.004	0.001
	[0.595]	[1.061]	[0.921]	[0.3]	[0.944]	[0.336]
BottomCustomerReturn	-0.003	0.002	0.002	0.001	0.001	0.001
	[-0.618]	[0.324]	[0.422]	[0.272]	[0.216]	[0.298]
TopCustomerReturn*HighTradeCredit		-0.004	-0.004	-0.003	-0.003	-0.002
		[-2.357]	[-2.517]	[-2.115]	[-1.957]	[-1.532]
MediumCustomerReturn*HighTradeCredit		0.000	0.000	-0.002	0.001	-0.001
		[0.183]	[0.125]	[-0.96]	[0.613]	[-0.348]
BottomCustomerReturn*HighTradeCredit		-0.009	-0.009	-0.005	-0.007	-0.004
		[-5.500]	[-5.618]	[-3.225]	[-4.35]	[-2.756]
Market Capitalization Rank			0.004	0.003	0.004	0.003
			[0.971]	[0.902]	[0.95]	[0.84]
Short-Term Debt Rank			-0.002	-0.001	-0.004	-0.003
			[-0.346]	[-0.23]	[-0.675]	[-0.613]
Lagged Firm Return			-0.032	-0.028	-0.030	-0.027
			[-3.54]	[-3.346]	[-3.297]	[-3.16]
Country Return				0.929		0.922
				[24.148]		[23.587]
Lagged Country Return			0.076	0.022	0.078	0.023
			[1.774]	[0.735]	[1.753]	[0.734]
World Market Return			1.094	-0.016	1.106	0.000
			[13.255]	[-0.247]	[13.056]	[-0.002]
Country dummies	No	No	Yes	Yes	Yes	Yes
Number of firms	12,724	12,724	12,724	12,724	12,245	12,245
Number of firm-months	923,315	923,315	923,315	923,315	860,584	860,584
Adjusted R-squared	0.000	0.001	0.146	0.330	0.149	0.331

Panel B: Estimates of the 'Within' Customer Return Tercile Long-Short Portfolio Return Based on Trade Credit

	AR Turnover			Net Trade Credit	
	2	**3**	**4**	**7**	**8**
Bottom Customer Returns					
Low TC – High TC	0.939%	0.928%	0.511%	0.686%	0.420%
	[5.500]	[5.618]	[3.225]	[4.350]	[2.756]
Top Customer Returns					
Low TC – High TC	0.369%	0.359%	0.290%	0.282%	0.214%
	[2.357]	[2.517]	[2.115]	[1.957]	[1.532]

Panel C: Estimates of the 'Across' Customer Return Tercile Long-Short Portfolio Return Based on Trade Credit

	AR Turnover			Net Trade Credit	
	2	**3**	**4**	**7**	**8**
Long Top Customer Low TC –	1.240%	1.135%	0.513%	0.997%	0.427%
Short Bottom Customer High TC	[2.052]	[2.184]	[1.274]	[1.837]	[1.001]

Table VII
Customer Momentum Strategy, Panel Regression, Conditional on Financial Stress

This table shows pooled regression results as in Table VI, conditional on emerging market financial stress, defined as any period where the IMF World Economic Outlook Financial Stress Indicator for an emerging market is above 1. This flags 65 out of 195 months in our sample period as financial stress periods. We interact the financial stress indicator with the firm dummies included in Table VI, to estimate performance in and out of periods of financial stress. Trade credit is defined using AR Turnover. The table also includes specifications which employ industry dummy variables. T-statistics (clustered by month) are shown within brackets below the coefficient estimates.

Regression	1	2	3
Intercept	-0.018 [-1.773]	-0.002 [-0.424]	-0.018 [-1.87]
FinancialStress	0.005 [0.699]	0.004 [0.635]	0.005 [0.702]
TopCustomerReturn	0.001 [0.269]	0.001 [0.321]	0.001 [0.257]
TopCustomerReturn* FinancialStress	0.000 [-0.020]	0.000 [-0.022]	0.000 [-0.026]
BottomCustomerReturn	0.001 [0.230]	0.001 [0.224]	0.001 [0.217]
BottomCustomerReturn* FinancialStress	0.000 [-0.005]	0.001 [0.067]	0.000 [-0.005]
TopCustomerReturn *HighTradeCredit	-0.001 [-0.456]	-0.001 [-0.513]	-0.001 [-0.599]
TopCustomerReturn *HighTradeCredit*Financial Stress	-0.006 [-1.687]	-0.006 [-1.554]	-0.006 [-1.633]
MediumCustomerReturn *HighTradeCredit	0.001 [0.589]	0.001 [0.689]	0.001 [0.430]
MediumCustomerReturn *HighTradeCredit*Financial Stress	-0.008 [-2.155]	-0.008 [-2.099]	-0.008 [-2.144]
BottomCustomerReturn *HighTradeCredit	-0.001 [-0.333]	-0.001 [-0.287]	-0.001 [-0.462]
BottomCustomerReturn *HighTradeCredit*Financial Stress	-0.013 [-3.650]	-0.013 [-3.513]	-0.013 [-3.596]
Market Capitalization Rank	0.003 [0.915]	0.003 [0.702]	0.002 [0.683]
Short-Term Debt Rank	-0.001 [-0.294]	0.001 [0.123]	-0.002 [-0.437]
Lagged Firm Return	-0.029 [-3.400]	-0.029 [-3.443]	-0.029 [-3.442]
Country Return	0.929 [23.969]	0.926 [23.795]	0.929 [23.965]
Lagged Country Return	0.023 [0.752]	0.021 [0.715]	0.023 [0.765]
World Market Return	-0.015 [-0.226]	-0.013 [-0.188]	-0.015 [-0.227]
Country dummies	Yes	No	Yes
Industry dummies	No	Yes	Yes
Number of firms	12,724	12,724	12,724
Number of firm-months	923,315	923,315	923,315
Adjusted R-squared	0.331	0.330	0.331