Essays on Interconnected Markets

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A thesis submitted for the degree of
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This thesis consists of three essays that explore the dynamics of interconnected markets and examine the relationships between markets, investor behavior, and fundamental characteristics of the firm and the economy.

In the first essay, 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 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.

The second essay investigates the dynamics of commodity futures volatility. I derive the variance decomposition for the futures basis to show how unexpected excess returns result from new information about expected future interest rates, convenience yields, and risk premia. Using data on major commodity futures markets and global bilateral commodity trade, I analyze the extent to which commodity volatility is related to fundamental uncertainty arising from increased emerging market demand and macroeconomic uncertainty, and control for the potential impact of financial frictions introduced by changing market structure and index trading. I find that a higher concentration in the emerging market importers of a commodity is associated with higher futures volatility. Commodity futures volatility is significantly predictable using variables capturing macroeconomic uncertainty.

The third essay investigates the differential explanatory power of consumer (importing countries) and producer (exporting countries) risk in explaining the volatility of commodity spot premia and term premia using trade-weighted indices of GDP volatility. Using data for major commodity futures markets, bilateral commodity trade, exchange rates, and GDP for countries trading these commodities, I test hypotheses on the heterogeneous impact of consumer and producer shocks, potentially driven by differences in hedging preferences and investment planning horizons. Producer risk is significant for both short-dated and long-dated maturities, while consumer risk has greater explanatory power for the volatility of the term spread.

To my parents

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Abstract

This thesis consists of three essays that explore the dynamics of interconnected markets and examine the relationships between markets, investor behavior, and fundamental characteristics of the firm and the economy.

In the first essay, 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 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.

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The third essay investigates the differential explanatory power of consumer (importing countries) and producer (exporting countries) risk in explaining the volatility of commodity spot premia and term premia using trade-weighted indices of GDP volatility. Using data for major commodity futures markets, bilateral commodity trade, exchange rates, and GDP for countries trading these commodities, I test hypotheses on the heterogeneous impact of consumer and producer shocks, potentially driven by differences in hedging preferences and investment planning horizons. Producer risk is significant for both short-dated and long-dated maturities, while consumer risk has greater explanatory power for the volatility of the term spread.

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Chapter 1

Introduction

The research in this dissertation focuses on understanding the factors that explain predictability, excess volatility and comovement in international asset markets. It contributes to the body of literature examining the role of common investors across disparate asset markets, while also yielding novel insights into fundamental economic phenomena, which can produce heretofore unknown relationships between economic entities.

Enhancing our knowledge of such financial and fundamental relationships and the role played by these linkages during periods of crisis has become a major focus for practitioners and policy-makers worldwide. Recent financial crises have merely served to highlight the importance of conducting further rigorous research to deepen our understanding of the causes and consequences of interconnected economies, markets, firms, and investors.

The major contribution of this dissertation is contained in Chapters 2, 3, and 4. Each of these chapters is organized as a self-contained paper with its own literature review, model, data and methodology, and concluding sections, together with relevant appendices. Chapter 5 provides a concise overview of the main conclusions of this thesis.

In Chapter 2, we investigate the role played by the trade and credit links between suppliers and customers in transmitting financial shocks between international equity markets. In recent decades, periods of high financial volatility such as the Asian Currency crisis, the Russian crisis, and the recent global financial crisis have been accompanied by greater co-movement between stock markets around the world that is not entirely explained by changes in fundamentals.

Previous studies of such transmission channels have focused on changes to international investor portfolio holdings and bi-lateral trade links between countries. Several recent studies of domestic crisis transmission channels have analyzed the sales relationships along supplier-customer industry networks (Menzly and Ozbas, 2010a; Ahern, 2012; Kelly, Lustig, and Nieuwerburgh, 2013). In contrast, we investigate the role of trade credit exposure of firms 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 by the returns of their associated customer countries. This behavior is especially prevalent among firms with high levels of foreign sales, and is robust to a variety of controls for the state of the global economy, country and industry effects, and firm characteristics (e.g., size, leverage, liquidity, profitability, etc.)

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 high uninformed trading volume. We find supportive empirical evidence for these results.

Chapter 3, meanwhile, investigates the sources of fluctuations over time in commodity futures volatility. The second essay investigates the dynamics of commodity futures volatility. I derive the variance decomposition for the futures basis to show how unexpected excess returns result from new information about expected future interest rates, convenience yields, and risk premia. This motivates my empirical analysis of the volatility impact of economic and inflation regimes and commodity supply-demand shocks. Using data on major commodity futures markets and global bilateral commodity trade, I analyze the extent to which commodity volatility is related to fundamental uncertainty from increased emerging market demand and macroeconomic forecast uncertainty, while controlling for the potential impact of financial frictions introduced by changing market structure and commodity index trading.

Higher concentration in emerging market importers of a commodity is associated with higher futures volatility. I find that commodity futures volatility is significantly predictable using variables capturing macroeconomic uncertainty. I examine the conditional variation in the asymmetric relationship between returns and volatility, and how this relates to the futures basis and sensitivity to consumer and producer shocks. The analysis uses unexpected realizations and forecast disagreement in variables which capture fundamental and financial uncertainty to study their impact.

Chapter 4 investigates the differential explanatory power of consumer (importing countries) and producer (exporting countries) risk in explaining the volatility of commodity spot premia and term premia using trade-weighted indices of GDP volatility. I derive a variation of the decomposition in Campbell and Shiller (1988) and Campbell (1991) to decompose the unexpected variation in the commodity basis spread to its component sources. Using data for major commodity futures markets, bilateral commodity trade, exchange rates, and GDP for countries trading these commodities, I test hypotheses on the heterogeneous impact of consumer and producer shocks, potentially driven by differences in hedging preferences and investment planning horizons. Using rolling regressions, I attempt to identify significant variations in these relationships as the riskiness of the consuming and producing country set changes.

Producer risk is significant for both short-dated and long-dated maturities, while consumer risk has greater explanatory power for the volatility of the term spread. The analysis attempts to isolate the impact of explanatory variables on the volatility of spot premia (proxied as the one-month volatility) from their impact on futures volatility at different maturities along the term structure.

Chapter 2

Trade Credit and Cross-Country Predictable Firm Returns

Abstract[1]

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.

[1]This chapter is entirely based on work co-authored with Rui Albuquerque and Tarun Ramadorai

2.1 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.[2] 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 chapter 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,

[2]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).

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.[3]

We build a simple asset pricing model that delivers cross-predictability in returns driven by trade credit.[4] Our model uses three building blocks from two different streams of 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

[3]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).

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

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 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.[5] 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, 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.

[5]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.

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 chapter 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.

2.2 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.

2.2.1 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).[6] The model below shares many features of the model in Biais and Gollier (1997).[7] Each firm 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

[6]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.

[7]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.

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

$$D^P = \alpha P_{TC} \left(R^P\right)^{-1} S + (1-\alpha) S. \tag{2.1}$$

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

$$D^C = \bar{P}S - \alpha P_{TC} \left(R^C\right)^{-1} S - (1-\alpha) S, \tag{2.2}$$

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

$$\max_{P_{TC}} E\left[\left(D^P - S\right)^{\psi} \left(D^C - \left(\bar{P}S - S\right)\right)^{1-\psi}\right]. \tag{2.3}$$

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

$$P_{TC} = R^P + \psi\left(R^C - R^P\right). \tag{2.4}$$

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,

$$D^C = \left[\bar{P} - 1 + \alpha\left(1-\psi\right)\left(R^C - R^P\right)\left(R^C\right)^{-1}\right] S \tag{2.5}$$

and

$$D^P = \left[1 + \alpha\psi\left(R^C - R^P\right)\left(R^P\right)^{-1}\right] S. \tag{2.6}$$

Profits increase by the amount of shared surplus relative to a trade that does not involve trade credit.[8]

For notational simplicity, we transform dividends by letting

$$\alpha' \equiv \left(1 + \alpha\psi\left(R^C - R^P\right)\left(R^P\right)^{-1}\right)\left(\bar{P} - 1 + \alpha\left(1-\psi\right)\left(R^C - R^P\right)\left(R^C\right)^{-1}\right) \tag{2.7}$$

and specifying the date 2 customer dividend and the producer dividend to

[8] 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.

be, respectively,

$$D^C = \varepsilon^C + u^C \tag{2.8}$$

and

$$D^P = \alpha' D^C + \varepsilon^P + u^P. \tag{2.9}$$

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.

2.2.2 Investors and investor demands

In subsection 2.2.1, 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 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.[9]

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^2_{zi}, 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

[9] 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).

information.

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

$$\theta^i = \frac{\mathrm{E}^d\left[D^i - P^i\right]}{\gamma \mathrm{Var}^d\left[D^i - P^i\right]}. \tag{2.10}$$

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. (2.10), 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,

$$\begin{bmatrix} \eta^C \\ \eta^P \end{bmatrix} = \frac{1}{\gamma \sigma_{uP}^2} \begin{bmatrix} \frac{\sigma_{uP}^2 + \alpha'^2 \sigma_{uC}^2}{\sigma_{uC}^2}\left(\bar{D}^C - P^C\right) - \alpha'\left(\bar{D}^P - P^P\right) \\ \bar{D}^P - P^P - \alpha'\left(\bar{D}^C - P^C\right) \end{bmatrix}. \tag{2.11}$$

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'.

2.2.3 Equilibrium

The stock supply in the two markets z^C and z^P are random normal variables with zero means and variances σ_{zC}^2 and σ_{zP}^2, 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

$$z^C = \mu_C \eta^C + (1 - \mu_C)\, \theta^C \tag{2.12}$$

and

$$z^P = \mu_P \eta^P + (1 - \mu_P)\, \theta^P. \tag{2.13}$$

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

Proposition 2.1. *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 $\Pi^i \equiv P^i - b_{ii}\mathrm{E}^d\left(\bar{D}^i\right)$,

$$\Pi^C = (1 - b_{CC})\,\bar{D}^C - b_{CP}\left(\bar{D}^P - \mathrm{E}^d\left(\bar{D}^P\right)\right) - h_{CC}z^C - h_{CP}z^P \tag{2.14}$$

and

$$\Pi^P = (1 - b_{PP})\,\bar{D}^P - b_{PC}\left(\bar{D}^C - \mathrm{E}^d\left(\bar{D}^C\right)\right) - h_{PP}z^P - h_{PC}z^C. \tag{2.15}$$

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.

2.2.4 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,

$$\mathrm{E}\left[D^P - P^P | P^C\right] = \frac{\mathrm{Cov}\left(P^C, D^P - P^P\right)}{\mathrm{Var}\left(P^C\right)} P^C. \tag{2.16}$$

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 2.1 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. 2.1 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.[10]

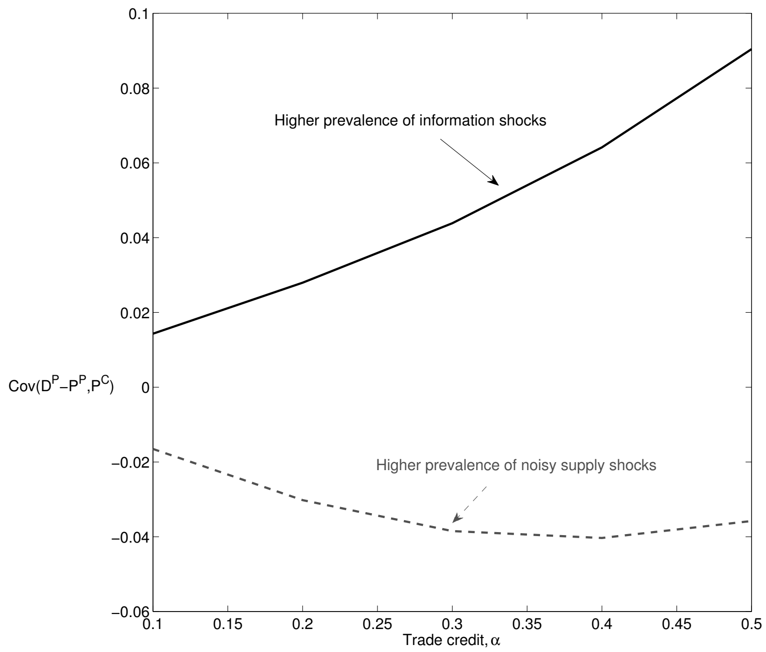

Figure 2.1: Cross-serial return covariance.
The figure plots the equilibrium value of $Cov\left(D^P - P^P, P^C\right)$ against several values of α'. The solid line has $\sigma^2_{zC} = 0.1$, and the dashed line has $\sigma^2_{zC} = 2.0$. The remaining parameters are $\sigma^2_{\varepsilon C} = 2.0, \gamma = 2.0$, $\mu_P = \mu_C = 0.5$, $\sigma^2_{\varepsilon P} = \sigma^2_{uC} = \sigma^2_{uP} = 1.0$, and $\sigma^2_{zP} = 0.1$.

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,

[10]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.

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. (2.11)). 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.

2.2.5 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 $\mathrm{E}\left[D^P D^C\right]$. α' is an increasing function of the producer firms' bargaining power, ψ.

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 2.1). 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.

2.2.6 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.

2.3 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.

2.3.1 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 Appendix displays robustness results with customer countries defined by the 3% and 7% alternative thresholds (Table 2.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 indices 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.

2.3.2 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.[11] 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. 2.A1 of the Appendix, 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[12] and factor returns that we employ for risk adjustment using MSCI country index return data.

[11]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 Appendix contains a comparison of the data coverage in this chapter with that in Fama and French (2012) and Hou, Karolyi, and Kho (2011).

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

2.3.3 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

$$ARTurnover_{i,t} = \frac{AR_{i,t}}{Sales_{i,t}}. \tag{2.17}$$

Table 2 shows descriptive statistics for the value-weighted index for the trade credit measure.[13] 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.

[13] 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 2.A1 of the Appendix shows descriptive statistics for the value-weighted index for net trade credit, and Table 2.A9 shows a summary of the results.

2.3.4 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*), and total liabilities (*WC03351*).[14] These variables are defined as

$$CashToAssets_{i,t} = \frac{Cash\&Equivalents_{i,t}}{TotalAssets_{i,t}}, \tag{2.18}$$

$$ShortTermDebtToAssets_{i,t} = \frac{ShortTermDebt_{i,t}}{TotalAssets_{i,t}}, \tag{2.19}$$

$$NetDebtToAssets_{i,t} = \frac{TotalDebt_{i,t} - Cash\&Equivalents_{i,t}}{TotalAssets_{i,t}}, \tag{2.20}$$

and

$$EquityMarketValueToBookValue_{i,t} = \frac{MarketCapitalization_{i,t}}{TotalAssets_{i,t} - TotalLiabilities_{i,t}}. \tag{2.21}$$

We are interested in assessing the extent to which trade credit mat-

[14]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 2.A10). Foreign sales data are unavailable for Chilean firms on Worldscope.

ters 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

$$ForeignSalesToTotal_{i,t} = \frac{ForeignSales_{i,t}}{Sales_{i,t}}. \tag{2.22}$$

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.[15] 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

$$EquityVolumeToMktCap_{c,t} = \frac{EquityTradingVolume_{c,t}}{TotalMarketCapitalization_{c,t}}. \tag{2.23}$$

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.

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

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

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.

2.4 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 2.3) 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.

2.4.1 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

$$FirmReturn_{i,t} = \sum_{j=1}^{J}\sum_{k=1}^{K}\left(CustomerReturn_{i,t-1}^{j} * TradeCredit_{i,t-1}^{k} * \hat{\alpha}_{j,k}\right) + \mathbf{Z_{i,t}}\hat{\beta} + \varepsilon_{i,t}. \tag{2.24}$$

Here, the dummy variable $CustomerReturn_{i,t-1}^{j}$ takes the value of one if firm i is in a producer country with an associated customer index in the j^{th} quintile in month $t-1$ and a value of zero otherwise. The dummy variable $TradeCredit_{i,t-1}^{k}$ takes the value of one if firm i is located in the k^{th} 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 j^{th} quintile, and in the k^{th} 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 (2.22) 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. (2.24) 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.

2.4.2 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).

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.[16] The table also shows that for firms with high foreign sales, both the within- and across-customer return quintile portfolio strategy yields larger and more significant returns than for firms with low foreign sales.

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 2.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

[16]In the Appendix, Table 2.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.

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. 2.1). 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 2.A5 repeats the same regressions but without controls. The results are unchanged.

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 2.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.

2.4.3 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.

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 indices, our results persist if we export-weight country index portfolios when constructing customer country-return indices, and they are robust to varying the 5% threshold (see Table 2.A8). Also, our predictability results are stronger when we winsorize the producer-country firm returns data at the 1^{th} and 99^{th} percentile points, which provides evidence that our results are not driven by extreme return observations.

In Table 2.A7 of the 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.[17] In the matrices shown in Table 8 (and Table 2.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

[17]In Table 2.A3 in the Appendix, we show the corresponding portfolio regression results with quintile-tercile sorts.

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).

2.5 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.

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 chapter. 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 chapter 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*		
Top - Bottom: With fixed effects					0.739	0.783	1.312		
					2.963	*3.119*	*4.281*		

	Without 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 - High					Low - High	
		Low trade credit	2	High trade credit	Without fixed effects	With fixed effects	Low trade credit	2	High trade credit	Without fixed effects	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		High Foreign Sales	
	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	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 - High					Low - High	
		Low trade credit	2	High trade credit	Without fixed effects	With fixed effects	Low trade credit	2	High trade credit	Without fixed effects	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		High emerging market stress	
	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	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*

2.6 Appendix

This Appendix provides the proof of Proposition 2.1 and the results in Subsection 2.2.5.

2.6.1 Proof of Proposition 2.1

Consider the equilibrium prices as given in the proposition:

$$P^C = \bar{D}^C - b_{CC}\left(\bar{D}^C - \mathrm{E}^d\left(\bar{D}^C\right)\right) - b_{CP}\left(\bar{D}^P - \mathrm{E}^d\left(\bar{D}^P\right)\right) - h_{CC}z^C - h_{CP}z^P \tag{2.25}$$

and

$$P^P = \bar{D}^P - b_{PP}\left(\bar{D}^P - \mathrm{E}^d\left(\bar{D}^P\right)\right) - b_{PC}\left(\bar{D}^C - \mathrm{E}^d\left(\bar{D}^C\right)\right) - h_{PP}z^P - h_{PC}z^C. \tag{2.26}$$

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:

$$\max_{\theta^i} \mathrm{E}^d\left[\exp^{-\gamma W_2^i}\right] \tag{2.27}$$

subject to

$$W_2^i = \theta^i\left(D^i - P^i\right). \tag{2.28}$$

The first order necessary and sufficient condition for this problem yields

$$\theta^i = \frac{\mathrm{E}^d\left[D^i - P^i\right]}{\gamma \mathrm{Var}^d\left[D^i - P^i\right]}. \tag{2.29}$$

Likewise, speculators from either country face the problem of

$$\max_{\eta^C,\eta^P} \mathrm{E}^s \left[\exp^{-\gamma W_2^i}\right] \tag{2.30}$$

subject to

$$W_2^i = \eta^C \left(D^C - P^C\right) + \eta^P \left(D^P - P^P\right). \tag{2.31}$$

This problem is solved by setting

$$\begin{bmatrix} \eta^C \\ \eta^P \end{bmatrix} = \gamma^{-1} V^{-1} \begin{bmatrix} \bar{D}^C - P^C \\ \bar{D}^P - P^P \end{bmatrix}, \tag{2.32}$$

where

$$V = \begin{bmatrix} \sigma_{uC}^2 & \alpha' \sigma_{uC}^2 \\ \alpha' \sigma_{uC}^2 & \sigma_{uP}^2 + \alpha'^2 \sigma_{uC}^2 \end{bmatrix} \tag{2.33}$$

which gives

$$V^{-1} = \frac{1}{\sigma_{uP}^2} \begin{bmatrix} \frac{\sigma_{uP}^2 + \alpha'^2 \sigma_{uC}^2}{\sigma_{Cu}^2} & -\alpha' \\ -\alpha' & 1 \end{bmatrix}. \tag{2.34}$$

After multiplying the two matrices, we obtain the expression in Eq. (2.11).

With the asset demands we can now solve for market clearing:

$$z^C = \mu_C \frac{1}{\gamma \sigma_{uP}^2} \left[\frac{\sigma_{uP}^2 + \alpha'^2 \sigma_{uC}^2}{\sigma_{Cu}^2} \left(\bar{D}^C - P^C\right) - \alpha' \left(\bar{D}^P - P^P\right)\right] + (1 - \mu_C) \frac{\mathrm{E}^d \left[D^C - P^C\right]}{\gamma \mathrm{Var}^d \left[D^C - P^C\right]} \tag{2.35}$$

and

$$z^P = \mu_P \frac{1}{\gamma \sigma_{uP}^2} \left[\bar{D}^P - P^P - \alpha' \left(\bar{D}^C - P^C\right)\right] + (1 - \mu_P) \frac{\mathrm{E}^d \left[D^P - P^P\right]}{\gamma \mathrm{Var}^d \left[D^P - P^P\right]}. \tag{2.36}$$

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):

$$0 = \mu_C \frac{1}{\gamma\sigma_{uP}^2} \frac{\sigma_{uP}^2 + \alpha'^2\sigma_{uC}^2}{\sigma_{Cu}^2} b_{CC} - \mu_C \frac{1}{\gamma\sigma_{uP}^2}\alpha' b_{PC} + (1-\mu_C)\frac{b_{CC}-1}{\gamma \mathrm{Var}^d\left[D^C - P^C\right]} \tag{2.37}$$

and

$$0 = \mu_C \frac{1}{\gamma\sigma_{uP}^2} \frac{\sigma_{uP}^2 + \alpha'^2\sigma_{uC}^2}{\sigma_{Cu}^2} b_{CP} - \mu_C \frac{1}{\gamma\sigma_{uP}^2}\alpha' b_{PP} + (1-\mu_C)\frac{b_{CP}}{\gamma \mathrm{Var}^d\left[D^C - P^C\right]}; \tag{2.38}$$

$$1 = \mu_C \frac{1}{\gamma\sigma_{uP}^2} \frac{\sigma_{uP}^2 + \alpha'^2\sigma_{uC}^2}{\sigma_{Cu}^2} h_{CC} - \mu_C \frac{1}{\gamma\sigma_{uP}^2}\alpha' h_{PC} + (1-\mu_C)\frac{h_{CC}}{\gamma \mathrm{Var}^d\left[D^C - P^C\right]} \tag{2.39}$$

and

$$0 = \mu_C \frac{1}{\gamma\sigma_{uP}^2} \frac{\sigma_{uP}^2 + \alpha'^2\sigma_{uC}^2}{\sigma_{Cu}^2} h_{CP} - \mu_C \frac{1}{\gamma\sigma_{uP}^2}\alpha' h_{PP} + (1-\mu_C)\frac{h_{CP}}{\gamma \mathrm{Var}^d\left[D^C - P^C\right]}; \tag{2.40}$$

$$0 = \mu_P \frac{1}{\gamma\sigma_{uP}^2} b_{PP} - \mu_P \frac{1}{\gamma\sigma_{uP}^2}\alpha' b_{CP} + (1-\mu_P)\frac{b_{PP}-1}{\gamma \mathrm{Var}^d\left[D^P - P^P\right]} \tag{2.41}$$

and

$$0 = \mu_P \frac{1}{\gamma\sigma_{uP}^2} b_{PC} - \mu_P \frac{1}{\gamma\sigma_{uP}^2} \alpha' b_{CC} + (1-\mu_P) \frac{b_{PC}}{\gamma \mathrm{Var}^d \left[D^P - P^P\right]}; \tag{2.42}$$

and

$$1 = \mu_P \frac{1}{\gamma\sigma_{uP}^2} h_{PP} - \mu_P \frac{1}{\gamma\sigma_{uP}^2} \alpha' h_{CP} + (1-\mu_P) \frac{h_{PP}}{\gamma \mathrm{Var}^d \left[D^P - P^P\right]} \tag{2.43}$$

and

$$0 = \mu_P \frac{1}{\gamma\sigma_{uP}^2} h_{PC} - \mu_P \frac{1}{\gamma\sigma_{uP}^2} \alpha' h_{CC} + (1-\mu_P) \frac{h_{PC}}{\gamma \mathrm{Var}^d \left[D^P - P^P\right]}. \tag{2.44}$$

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;

$$\mathrm{E}^d \left(\bar{D}^C | \Pi^C\right) = \frac{\mathrm{Cov}\left(\bar{D}^C, \Pi^C\right)}{\mathrm{Var}\left(\Pi^C\right)} \Pi^C = \beta^C \Pi^C \tag{2.45}$$

and

$$\mathrm{Var}^d \left(\bar{D}^C | \Pi^C\right) = \sigma_{\varepsilon C}^2 - \frac{\mathrm{Cov}\left(\bar{D}^C, \Pi^C\right)^2}{\mathrm{Var}\left(\Pi^C\right)}. \tag{2.46}$$

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:

$$\begin{aligned}\bar{D}^C - \mathrm{E}^d\left(\bar{D}^C\right) = &\left[1 - \beta^D\left(1 - b_{CC}\right)\right]\bar{D}^C + \beta^C b_{CP}\left(\bar{D}^P - \mathrm{E}^d\left(\bar{D}^P\right)\right)\\ &+ \beta^C h_{CC} z^C + \beta^C h_{CP} z^P \end{aligned} \tag{2.47}$$

and

$$\begin{aligned}\bar{D}^P - \mathrm{E}^d\left(\bar{D}^P\right) = &\left[1 - \beta^P\left(1 - b_{PP}\right)\right]\bar{D}^P + \beta^P b_{PC}\left(\bar{D}^C - \mathrm{E}^d\left(\bar{D}^C\right)\right)\\ &+ \beta^P h_{PP} z^P + \beta^P h_{PC} z^C. \end{aligned} \tag{2.48}$$

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

$$\bar{D}^C - \mathrm{E}^d\left(\bar{D}^C\right) = f_{cc}\bar{D}^C + f_{cp}\bar{D}^P + f_{czp}z^P + f_{czc}z^C \tag{2.49}$$

and

$$\bar{D}^P - \mathrm{E}^d\left(\bar{D}^P\right) = g_{pp}\bar{D}^P + g_{pc}\bar{D}^C + g_{pzc}z^C + g_{pzp}z^P. \tag{2.50}$$

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:

$$\begin{aligned}
\mathrm{Var}^d\left[D^i\right] &= \mathrm{Var}\left[D^i|\Pi^i\right] \\
&= \mathrm{Var}\left(u\right) + \mathrm{Var}^d\left[\bar{D}^i|\Pi^i\right] \\
&= \mathrm{Var}\left[D^i\right] - \frac{\mathrm{Cov}^2\left(\bar{D}^i, \Pi^i\right)}{\mathrm{Var}\left(\Pi^i\right)}. \qquad (2.51)
\end{aligned}$$

2.6.2 Proof of the results in Subsection 2.2.5

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 $\mathrm{E}\left[D^P D^C\right] = \alpha' \left(\sigma^2_{\varepsilon C} + \sigma^2_{uC}\right)$, 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 $\mathrm{E}\left[D^P D^C\right] = \alpha' \left(\sigma^2_{\varepsilon C} + \sigma^2_{uC}\right)$ 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 $\mathrm{E}\left[D^P D^C\right] = \alpha' \left(\sigma^2_{\varepsilon C} + \sigma^2_{uC}\right)$. Under our maintained assumptions, the solution to the asset pricing problem is the one in the main text. Fig. 2.1 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. (2.11), we obtain (setting α' to zero)

$$\begin{bmatrix} \eta^C \\ \eta^P \end{bmatrix} = \begin{bmatrix} \frac{\bar{D}^C - P^C}{\gamma \sigma^2_{uC}} \\ \frac{\bar{D}^P - P^P}{\gamma \sigma^2_{uP}} \end{bmatrix}. \tag{2.52}$$

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

$$z^C = \mu_C \frac{\bar{D}^C - P^C}{\gamma \sigma^2_{uC}} + \left(1 - \mu_C\right) \frac{\mathrm{E}^d\left[D^C - P^C\right]}{\gamma \mathrm{Var}^d\left[D^C - P^C\right]}. \tag{2.53}$$

Letting $\beta_0 = \mu_C / \gamma \sigma^2_{uC}$ and $\beta_1 = \left(1 - \mu_C\right) / \gamma \mathrm{Var}^d\left[D^C - P^C\right]$, and similarly to Proposition 2.1, we can write this expression as

$$P^C = \bar{D}^C - \frac{\beta_1}{\beta_0 + \beta_1}\left(\bar{D}^C - \mathrm{E}^d\left[D^C\right]\right) - \frac{1}{\beta_0 + \beta_1} z^C. \tag{2.54}$$

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,

$$\mathrm{E}^d\left[D^C\right] = \mathrm{E}\left[D^C | \Pi^C\right] \tag{2.55}$$

and

$$\mathrm{Var}^d\left[D^C - P^C\right] = \mathrm{E}\left[\left(D^C - \mathrm{E}\left[D^C|\Pi^C\right]\right)^2 |\Pi^C\right]. \tag{2.56}$$

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

$$\mathrm{E}^d\left[D^C\right] = \frac{\frac{\beta_0}{\beta_0+\beta_1}\sigma^2_{\varepsilon C}}{\left(\frac{\beta_0}{\beta_0+\beta_1}\right)^2 \sigma^2_{\varepsilon C} + \left(\frac{1}{\beta_0+\beta_1}\right)^2 \sigma^2_{zC}} \Pi^C \tag{2.57}$$

and

$$\mathrm{Var}^d\left[D^C - P^C\right] = \sigma^2_{\varepsilon C} + \sigma^2_{uC} - \frac{\beta_0^2 \sigma^4_{\varepsilon C}}{\beta_0^2 \sigma^2_{\varepsilon C} + \sigma^2_{zC}}. \tag{2.58}$$

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 2.1 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.

2.6.3 Additional tables and figures

Figure 2.A1

This 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.

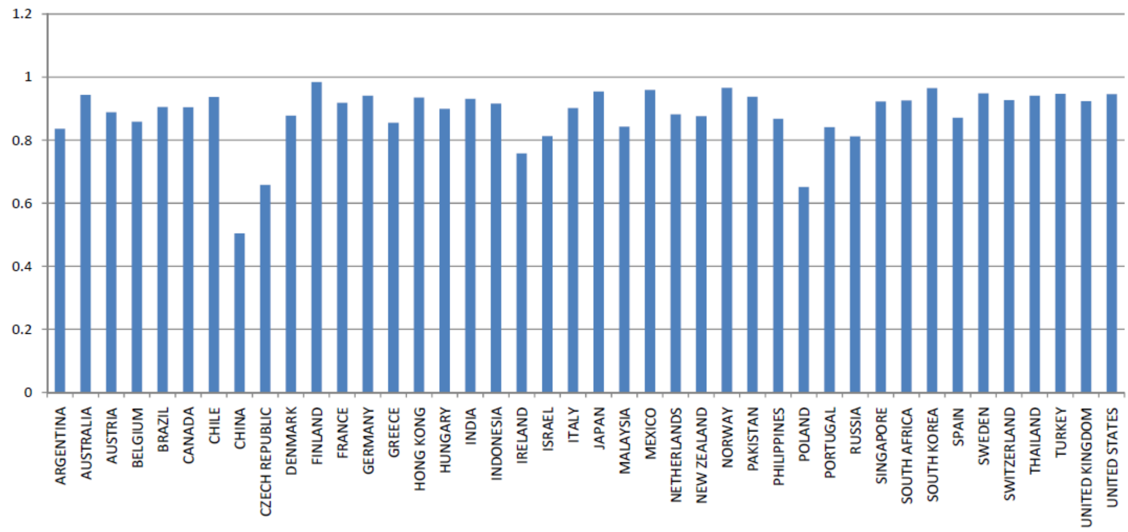

Table 2.A1
Country-Level Trade Credit Summary Statistics for Producer Countries

In this table we show summary statistics for two trade credit measures. Panel A shows descriptive statistics of (unfiltered) accounts receivable turnover by producer country and year. Panel B of this table shows descriptive statistics for the time series of the value-weighted cross-sectional mean of firms' *net trade credit* in countries classified at least once as a producer and have firm-level balance sheet data on Worldscope. Panel C shows descriptive statistics for the cross section of producer country trade credit each year. The "filtered" column corresponds to the summary statistics on this dataset with observations of firm-level accounts receivable turnover higher than 50 (5000%) filtered out. The trade credit ratios in this table are calculated from annual firm-level sales, accounts receivable, and accounts receivable data from 1992 to 2009.

Panel A: Summary statistics of (unfiltered) accounts receivable turnover by producer country and year

	By country						By year				
	Mean	Median	Std Dev	Min	Max		Mean	Median	Std Dev	Min	Max
Argentina	0.265	0.237	0.091	0.164	0.566	1992	0.238	0.211	0.115	0.078	0.745
Australia	0.201	0.186	0.052	0.142	0.318	1993	0.456	0.223	1.157	0.081	7.063
Austria	0.267	0.195	0.180	0.163	0.912	1994	0.268	0.210	0.154	0.102	0.912
Belgium	0.216	0.209	0.052	0.131	0.376	1995	0.235	0.210	0.083	0.110	0.486
Canada	0.269	0.215	0.133	0.169	0.617	1996	0.245	0.213	0.091	0.110	0.536
Chile	5.120	0.224	13.481	0.183	52.269	1997	1.656	0.230	8.552	0.126	52.269
China	0.504	0.432	0.336	0.188	1.722	1998	0.482	0.226	1.404	0.126	8.760
Czech Republic	0.462	0.195	0.883	0.116	3.632	1999	1.020	0.236	4.466	0.128	27.412
Denmark	0.287	0.221	0.266	0.179	1.349	2000	0.363	0.245	0.572	0.117	3.632
Finland	0.202	0.199	0.025	0.165	0.239	2001	0.228	0.217	0.068	0.095	0.439
France	0.257	0.252	0.029	0.195	0.317	2002	0.373	0.220	0.946	0.083	5.956
Germany	0.246	0.250	0.050	0.181	0.351	2003	0.721	0.201	3.038	0.075	18.692
Hong Kong	0.264	0.239	0.092	0.154	0.536	2004	0.222	0.215	0.078	0.124	0.454
Hungary	0.179	0.171	0.036	0.139	0.299	2005	0.268	0.206	0.261	0.116	1.722
Indonesia	0.171	0.154	0.057	0.110	0.338	2006	0.218	0.214	0.078	0.130	0.617
Ireland	0.176	0.178	0.023	0.144	0.216	2007	0.270	0.222	0.203	0.146	1.349
Israel	0.311	0.309	0.048	0.265	0.481	2008	0.380	0.206	0.926	0.106	5.827
Italy	0.352	0.340	0.073	0.271	0.513	2009	0.325	0.204	0.645	0.021	4.097
Malaysia	0.464	0.391	0.316	0.196	1.596						
Mexico	0.507	0.194	1.361	0.021	5.956						
Netherlands	0.155	0.147	0.027	0.125	0.236						
New Zealand	0.696	0.167	1.580	0.119	5.827						
Norway	0.206	0.195	0.038	0.162	0.295						
Pakistan	0.136	0.121	0.058	0.075	0.285						
Philippines	1.308	0.248	4.342	0.135	18.692						
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	0.286	0.261	0.060	0.206	0.408						
South Africa	0.209	0.176	0.088	0.122	0.438						
South Korea	0.224	0.209	0.054	0.157	0.340						
Spain	0.251	0.248	0.037	0.205	0.378						
Sweden	0.261	0.233	0.098	0.191	0.629						
Switzerland	0.212	0.213	0.015	0.189	0.244						
Thailand	0.191	0.162	0.076	0.106	0.365						
Turkey	0.597	0.220	1.614	0.162	7.063						
United Kingdom	0.181	0.182	0.020	0.156	0.224						

Panel B: Summary statistics of net trade credit time series by producer country

	Filtered					Unfiltered				
	Mean	Median	Std Dev	Min	Max	Mean	Median	Std Dev	Min	Max
Argentina	0.126	0.121	0.056	0.035	0.237	0.144	0.121	0.099	0.035	0.472
Australia	0.046	0.049	0.018	0.004	0.068	0.033	0.040	0.055	-0.089	0.150
Austria	0.149	0.096	0.164	0.056	0.741	0.149	0.096	0.164	0.056	0.741
Belgium	0.086	0.084	0.040	-0.008	0.150	0.086	0.084	0.040	-0.008	0.150
Canada	-0.015	-0.005	0.039	-0.107	0.035	-0.039	-0.010	0.157	-0.349	0.359
Chile	0.154	0.131	0.087	0.092	0.484	1.571	0.131	6.010	0.092	25.651
China	0.169	0.139	0.157	-0.058	0.649	-1.755	0.170	5.322	-18.952	0.649
Czech Republic	0.401	0.089	0.985	0.023	3.934	0.401	0.089	0.985	0.023	3.934
Denmark	0.143	0.147	0.030	0.092	0.218	0.067	0.147	0.333	-1.264	0.218
Finland	0.110	0.102	0.026	0.068	0.152	0.110	0.102	0.026	0.068	0.152
France	0.102	0.099	0.028	0.058	0.153	0.103	0.099	0.027	0.058	0.153
Germany	0.156	0.145	0.044	0.105	0.244	0.156	0.145	0.045	0.105	0.244
Hong Kong	0.081	0.127	0.099	-0.091	0.237	0.077	0.119	0.097	-0.091	0.237
Hungary	0.091	0.084	0.031	0.055	0.184	0.091	0.084	0.031	0.055	0.184
Indonesia	0.089	0.073	0.042	0.041	0.211	0.089	0.073	0.042	0.041	0.211
Ireland	0.075	0.074	0.023	0.039	0.125	0.075	0.074	0.023	0.039	0.125
Israel	0.189	0.188	0.046	0.135	0.346	0.189	0.188	0.046	0.135	0.346
Italy	0.140	0.151	0.041	0.068	0.237	0.140	0.151	0.041	0.068	0.237
Malaysia	0.211	0.207	0.080	0.097	0.421	0.105	0.207	0.495	-1.845	0.421
Mexico	0.075	0.078	0.055	-0.092	0.142	0.399	0.084	1.330	-0.092	5.724
Netherlands	0.067	0.068	0.011	0.047	0.087	0.067	0.068	0.011	0.047	0.087
New Zealand	0.032	0.065	0.123	-0.436	0.104	-1.209	0.059	5.246	-22.223	0.104
Norway	0.084	0.088	0.033	0.008	0.135	0.089	0.088	0.039	0.008	0.172
Pakistan	0.065	0.024	0.076	-0.004	0.242	0.065	0.024	0.076	-0.004	0.242
Philippines	0.065	0.063	0.042	-0.002	0.128	-0.051	0.050	0.391	-1.415	0.326
Poland	0.209	0.088	0.349	0.060	1.351	0.209	0.088	0.349	0.060	1.351
Portugal	0.083	0.089	0.033	-0.012	0.140	0.083	0.089	0.033	-0.012	0.140
Russia	0.193	0.160	0.136	0.046	0.537	0.193	0.160	0.136	0.046	0.537
Singapore	0.166	0.150	0.065	0.075	0.307	0.170	0.150	0.062	0.102	0.307
South Africa	0.060	0.045	0.062	-0.040	0.240	0.054	0.045	0.069	-0.074	0.240
South Korea	0.126	0.121	0.045	0.073	0.224	0.126	0.121	0.045	0.075	0.224
Spain	0.065	0.063	0.027	-0.007	0.113	0.065	0.063	0.027	-0.007	0.113
Sweden	0.141	0.132	0.040	0.064	0.223	0.163	0.134	0.101	0.064	0.534
Switzerland	0.137	0.142	0.019	0.103	0.164	0.137	0.142	0.019	0.103	0.164
Thailand	0.090	0.067	0.064	0.002	0.245	0.090	0.067	0.064	0.002	0.245
Turkey	0.121	0.123	0.026	0.068	0.170	0.426	0.123	1.296	0.068	5.617
United Kingdom	0.076	0.075	0.011	0.061	0.102	0.075	0.074	0.013	0.048	0.102

Panel C: Summary statistics of net trade credit for the cross-section of producer countries by year

	Filtered					Unfiltered				
	Mean	Median	Std Dev	Min	Max	Mean	Median	Std Dev	Min	Max
1992	0.119	0.109	0.112	-0.050	0.649	0.119	0.109	0.112	-0.050	0.649
1993	0.134	0.125	0.148	-0.052	0.854	0.303	0.125	0.939	-0.052	5.617
1994	0.168	0.113	0.240	-0.031	1.351	0.168	0.113	0.240	-0.031	1.351
1995	0.112	0.098	0.072	-0.042	0.307	0.112	0.098	0.072	-0.042	0.307
1996	0.115	0.112	0.056	0.010	0.267	0.119	0.113	0.056	0.010	0.267
1997	0.117	0.112	0.088	0.002	0.454	0.116	0.112	0.089	0.002	0.454
1998	0.109	0.099	0.105	-0.058	0.537	0.110	0.099	0.104	-0.058	0.537
1999	0.107	0.102	0.079	-0.091	0.301	0.740	0.094	4.222	-1.845	25.651
2000	0.222	0.099	0.634	0.002	3.934	0.224	0.110	0.635	-0.089	3.934
2001	0.109	0.102	0.061	0.007	0.276	0.107	0.109	0.069	-0.091	0.276
2002	0.113	0.111	0.069	-0.019	0.269	0.259	0.111	0.927	-0.197	5.724
2003	0.104	0.086	0.071	-0.022	0.359	0.105	0.086	0.072	-0.029	0.359
2004	0.104	0.089	0.066	-0.034	0.378	0.092	0.086	0.139	-0.626	0.378
2005	0.100	0.087	0.051	-0.035	0.218	-0.412	0.087	3.134	-18.952	0.472
2006	0.088	0.082	0.050	-0.107	0.172	0.037	0.082	0.260	-1.415	0.172
2007	0.103	0.094	0.080	-0.093	0.484	0.054	0.092	0.247	-1.264	0.484
2008	0.081	0.088	0.101	-0.436	0.234	-0.272	0.089	2.162	-13.052	0.234
2009	0.086	0.077	0.071	-0.092	0.267	-0.572	0.080	3.685	-22.223	0.359

Table 2.A2
Customer Momentum Strategy, Portfolio Regressions (trade credit quintiles)

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 receivables turnover). In Panel a, One factor and two factor correspond to alphas obtained from regressing returns of these indices on the world market return and world market plus country momentum, respectively. Panel B shows four factor regression results which include world market, country momentum, global HML, and a constructed trade credit factor on the RHS. 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-West method.

Panel A: One- and two--factor alpha

	One Factor (+MKT)						Two Factor (+MKT+MOM)					
	Low Trade Credit	2	3	4	High Trade Credit	Low - High	Low Trade Credit	2	3	4	High Trade Credit	Low - High
Bottom Customer	-0.144	0.250	0.028	-0.604	-1.370	1.226	-0.044	0.360	0.203	-0.584	-1.134	1.090
	-0.351	*0.655*	*0.060*	*-1.166*	*-2.364*	*2.770*	*-0.112*	*1.053*	*0.462*	*-1.201*	*-2.122*	*2.405*
2	-0.042	0.028	-0.055	0.412	-0.123	0.081	-0.003	0.120	0.000	0.477	-0.095	0.093
	-0.099	*0.075*	*-0.174*	*1.090*	*-0.250*	*0.175*	*-0.007*	*0.363*	*-0.001*	*1.324*	*-0.198*	*0.200*
3	0.712	0.524	0.105	0.204	0.034	0.678	0.807	0.574	0.192	0.189	0.092	0.715
	1.933	*1.626*	*0.323*	*0.707*	*0.078*	*1.461*	*2.233*	*1.823*	*0.574*	*0.643*	*0.190*	*1.417*
4	0.557	0.801	0.122	0.380	-0.633	1.190	0.513	0.831	0.098	0.371	-0.500	1.013
	1.683	*2.986*	*0.435*	*1.379*	*-1.489*	*2.773*	*1.666*	*2.993*	*0.319*	*1.332*	*-1.081*	*2.284*
Top Customer	1.163	0.693	0.550	0.289	0.120	1.043	1.226	0.795	0.640	0.427	0.226	0.999
	2.669	*1.770*	*1.378*	*0.669*	*0.194*	*2.216*	*2.640*	*2.082*	*1.563*	*0.942*	*0.348*	*2.184*
Top - Bottom	1.308	0.443	0.522	0.893	1.491		1.270	0.436	0.437	1.010	1.361	
	2.484	*1.041*	*0.922*	*1.565*	*1.932*		*2.261*	*1.020*	*0.760*	*1.694*	*1.769*	
Long low trade credit firms in top customer return countries, short high trade credit firms in bottom customer return countries					2.533		2.360					
					3.885		*3.640*					
Long high trade credit firms in top customer return countries, short low trade credit firms in bottom customer return countries					0.265		0.271					
					0.348		*0.343*					

Panel B: Four--factor alpha

	Four Factor (+MKT+MOM+HML+TC)					
	Low Trade Credit	2	3	4	High Trade Credit	Low - High
Bottom Customer	-0.322	0.140	0.138	-0.558	-1.149	0.826
	-0.858	*0.395*	*0.310*	*-1.167*	*-2.130*	*2.025*
2	-0.065	0.005	-0.023	0.564	0.255	-0.320
	-0.186	*0.018*	*-0.079*	*1.578*	*0.541*	*-0.760*
3	0.711	0.493	0.163	0.161	0.463	0.248
	1.867	*1.549*	*0.476*	*0.542*	*0.860*	*0.548*
4	0.152	0.447	-0.155	0.532	-0.363	0.516
	0.496	*1.818*	*-0.496*	*1.886*	*-0.823*	*1.504*
Top Customer	1.043	0.653	0.542	0.384	0.465	0.579
	2.287	*1.803*	*1.389*	*0.823*	*0.656*	*1.354*
Top - Bottom	1.366	0.513	0.404	0.942	1.614	
	2.361	*1.238*	*0.733*	*1.604*	*2.021*	

Long low trade credit firms in top customer return countries, short high trade credit firms in bottom customer return countries	2.192
	3.559
Long high trade credit firms in top customer return countries, short low trade credit firms in bottom customer return countries	0.787
	0.958

Table 2.A3
Customer Momentum Strategy, Portfolio Regressions (trade credit terciles)

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 terciles by trade credit (measured as AR Turnover). 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, respectively. The four factor regressions include a constructed trade credit factor on the RHS. 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-West method.

Panel A: Excess return and one-factor alpha

	Excess Return				One Factor (+MKT)			
	Low Trade Credit	2	High Trade Credit	Low - High	Low Trade Credit	2	High Trade Credit	Low - High
Bottom Customer	0.402	0.132	-0.772	1.174	0.168	-0.127	-1.034	1.202
	0.739	*0.224*	*-1.088*	*3.299*	*0.433*	*-0.300*	*-1.906*	*3.389*
2	0.185	0.286	0.261	-0.075	0.007	0.083	0.014	-0.007
	0.390	*0.633*	*0.464*	*-0.206*	*0.018*	*0.259*	*0.036*	*-0.020*
3	0.783	0.488	0.470	0.313	0.615	0.269	0.204	0.411
	1.775	*1.088*	*0.837*	*0.840*	*1.779*	*0.979*	*0.598*	*1.190*
4	0.928	0.630	-0.049	0.977	0.732	0.430	-0.303	1.035
	2.166	*1.530*	*-0.085*	*2.762*	*2.756*	*1.902*	*-0.897*	*3.006*
Top Customer	1.063	0.849	0.459	0.604	0.853	0.611	0.177	0.676
	2.080	*1.539*	*0.660*	*1.774*	*2.178*	*1.580*	*0.351*	*2.075*
Top - Bottom	0.661	0.717	1.231		0.685	0.738	1.212	
	1.593	*1.528*	*2.125*		*1.651*	*1.572*	*2.087*	

	Excess Return	One Factor (+MKT)
Long low trade credit firms in top customer return countries, short high trade credit firms in bottom customer return countries	1.835	1.888
	3.570	*3.700*
Long high trade credit firms in top customer return countries, short low trade credit firms in bottom customer return countries	1.231	1.212
	2.125	*2.087*

Panel B: Two- and three-factor alpha

	Two Factor (+MKT+MOM)				Three Factor (+MKT+MOM+HML)			
	Low Trade Credit	2	High Trade Credit	Low - High	Low Trade Credit	2	High Trade Credit	Low - High
Bottom Customer	0.281	0.019	-0.922	1.203	0.107	-0.027	-1.013	1.120
	0.796	*0.047*	*-1.862*	*3.320*	*0.312*	*-0.064*	*-1.921*	*2.996*
2	0.073	0.161	0.039	0.035	0.009	0.138	0.152	-0.144
	0.202	*0.561*	*0.102*	*0.096*	*0.026*	*0.478*	*0.357*	*-0.390*
3	0.690	0.319	0.261	0.429	0.638	0.288	0.340	0.298
	2.054	*1.099*	*0.712*	*1.217*	*1.876*	*0.960*	*0.714*	*0.821*
4	0.727	0.393	-0.256	0.983	0.457	0.278	-0.193	0.650
	2.805	*1.578*	*-0.694*	*2.797*	*1.642*	*1.120*	*-0.504*	*1.860*
Top Customer	0.945	0.683	0.325	0.620	0.897	0.584	0.368	0.530
	2.353	*1.764*	*0.618*	*1.868*	*2.218*	*1.524*	*0.643*	*1.548*
Top - Bottom	0.664	0.664	1.247		0.791	0.611	1.381	
	1.566	*1.385*	*2.102*		*1.810*	*1.234*	*2.256*	

	Two Factor	Three Factor
Long low trade credit firms in top customer return countries, short high trade credit firms in bottom customer return countries	1.868	1.910
	3.583	*3.547*
Long high trade credit firms in top customer return countries, short low trade credit firms in bottom customer return countries	1.247	1.381
	2.102	*2.256*

Panel C: Four-factor alpha

	Four Factor (+MKT+MOM+HML+TC)			
	Low Trade Credit	2	High Trade Credit	Low - High
Bottom Customer	0.006	-0.017	-0.912	0.917
	0.017	*-0.040*	*-1.841*	*2.857*
2	-0.052	0.149	0.295	-0.347
	-0.161	*0.520*	*0.834*	*-1.104*
3	0.548	0.300	0.519	0.029
	1.611	*0.994*	*1.277*	*0.112*
4	0.363	0.278	-0.079	0.442
	1.524	*1.099*	*-0.215*	*1.533*
Top Customer	0.836	0.578	0.454	0.382
	2.157	*1.530*	*0.787*	*1.221*
Top - Bottom	0.830	0.595	1.365	
	1.897	*1.196*	*2.219*	

Long low trade credit firms in top customer return countries, short high trade credit firms in bottom customer return countries	1.748
	3.372
Long high trade credit firms in top customer return countries, short low trade credit firms in bottom customer return countries	1.365
	2.219

Table 2.A4
Customer Momentum Strategy, Panel Regressions, Firms Reporting Foreign Sales Fields

Panel A of 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 levels, for the same base regression specification used in Table III, *for only the set of firms reporting foreign sales fields*. In Panel B, the pooled regression setup in Table III is further augmented with interactions on the ratio of firm foreign sales to total sales level. Table IV of the chapter shows results for the same specification, but with all 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, contemporaneous world market return, and industry and country fixed effects. 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.

Panel A: Baseline regression for only the set of firms reporting foreign sales fields

	Without Controls					With Controls				
	Low Trade Credit	2	High Trade Credit	Low - High		Low Trade Credit	2	High Trade Credit	Low - High	Low - High *With FE*
Bottom Customer	0.574	0.032	-0.663	1.237		-0.029	-0.558	-1.095	1.066	1.073
	3.088	*0.171*	*-2.897*	*6.056*		*-0.161*	*-2.891*	*-4.627*	*5.668*	*6.011*
2	0.193	0.417	0.297	-0.104		-0.336	-0.127	-0.124	-0.212	-0.207
	1.339	*2.663*	*1.550*	*-0.584*		*-1.970*	*-0.731*	*-0.618*	*-1.239*	*-1.224*
3	0.797	0.417	0.587	0.210		0.245	-0.163	0.104	0.141	0.127
	5.107	*2.483*	*2.981*	*1.145*		*1.377*	*-0.904*	*0.517*	*0.779*	*0.718*
4	0.948	0.615	0.105	0.843		0.416	0.077	-0.329	0.745	0.760
	5.867	*3.554*	*0.516*	*4.542*		*2.507*	*0.458*	*-1.634*	*4.461*	*4.581*
Top Customer	0.989	0.760	0.573	0.416		0.520	0.295	0.261	0.259	0.261
	5.483	*3.977*	*2.425*	*1.903*		*2.769*	*1.518*	*1.098*	*1.267*	*1.356*
Top - Bottom	0.415	0.728	1.236			0.549	0.853	1.356		
	1.601	*2.717*	*3.769*			*2.327*	*3.570*	*4.534*		
					With FE	0.482	0.803	1.294		
						2.033	*3.357*	*4.346*		

	Without Controls	With Controls	With Controls *With FE*
Long low trade credit firms in top customer return countries, short high trade credit firms in bottom customer return countries	1.652	1.615	1.555
	5.667	*5.938*	*5.912*
Long high trade credit firms in top customer return countries, short low trade credit firms in bottom customer return countries	-0.001	0.290	0.221
	-0.005	*1.080*	*0.841*

Panel B: Regression with foreign sales interaction

	Low Foreign Sales				High Foreign Sales			
	Low Trade Credit	2	High Trade Credit	Low - High	Low Trade Credit	2	High Trade Credit	Low - High
Bottom Customer	0.622	0.332	0.126	0.495	0.521	-0.170	-1.242	1.763
	3.049	*1.632*	*0.531*	*2.218*	*1.946*	*-0.698*	*-3.740*	*5.650*
2	0.762	0.626	0.474	0.288	-0.449	0.259	0.158	-0.606
	4.674	*3.518*	*2.227*	*1.390*	*-2.136*	*1.397*	*0.652*	*-2.387*
3	0.529	0.276	0.496	0.033	1.153	0.519	0.650	0.504
	3.076	*1.485*	*2.200*	*0.153*	*4.928*	*2.688*	*2.747*	*1.935*
4	0.666	0.612	0.752	-0.086	1.278	0.617	-0.330	1.608
	3.706	*3.184*	*3.380*	*-0.396*	*5.506*	*3.068*	*-1.242*	*5.929*
Top Customer	1.003	1.150	0.522	0.481	0.974	0.508	0.616	0.359
	5.189	*5.322*	*2.076*	*1.985*	*3.682*	*2.233*	*1.953*	*1.110*
Top - Bottom	0.381	0.818	0.396		0.453	0.678	1.858	
	1.358	*2.753*	*1.145*		*1.204*	*2.032*	*4.070*	
Long low trade credit firms in top customer return countries, short high trade credit firms in bottom customer return countries				0.877	2.216			
				2.859	*5.221*			
Long high trade credit firms in top customer return countries, short low trade credit firms in bottom customer return countries				-0.100	0.094			
				-0.307	*0.229*			

Table 2.A5

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 IV 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 IV to estimate return differences for firms with high levels of foreign sales. This table shows results with interactions for high foreign sales and high trading volume. Table V of the chapter shows results for the same specification, but with all 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, contemporaneous world market return, and industry and country fixed effects. 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
Bottom Customer	-1.696	-1.147	-3.281	1.584	2.707	1.108	1.182	1.525
	-4.911	*-3.334*	*-7.556*	*3.960*	*6.921*	*3.188*	*2.455*	*3.319*
2	-2.639	-0.322	-1.754	-0.885	1.305	0.877	2.715	-1.410
	-7.974	*-1.241*	*-5.615*	*-2.463*	*5.190*	*3.403*	*7.640*	*-3.924*
3	0.359	-0.446	0.149	0.211	1.808	1.716	1.290	0.518
	1.146	*-1.631*	*0.469*	*0.609*	*5.392*	*6.266*	*3.674*	*1.331*
4	-0.470	-0.376	-2.240	1.770	3.049	1.833	2.233	0.816
	-1.453	*-1.441*	*-6.979*	*4.863*	*9.185*	*6.128*	*5.262*	*1.946*
Top Customer	0.233	-0.404	-0.904	1.137	1.553	1.704	2.290	-0.737
	0.677	*-1.318*	*-1.940*	*2.493*	*3.936*	*5.373*	*5.422*	*-1.613*
Top - Bottom	1.929	0.744	2.377		-1.154	0.596	1.108	
	3.959	*1.616*	*3.731*		*-2.076*	*1.266*	*1.733*	

	Low Volume	High Volume
Long low trade credit firms in top customer return countries, short high trade credit firms in bottom customer return countries	3.514	0.371
	6.344	*0.596*
Long high trade credit firms in top customer return countries, short low trade credit firms in bottom customer return countries	0.792	-0.417
	1.365	*-0.724*

Table 2.A6

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 III is further augmented with interactions for 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 as financial stress periods. We interact the financial stress indicator with the firm dummies included in Table III to estimate performance differences in and out of periods of financial stress with all of the control variables. Table VI of the chapter shows results for the same specification, but with all 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, contemporaneous world market return, and 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.

	Low EM Stress				High EM Stress			
	Low Trade Credit	2	High Trade Credit	Low - High	Low Trade Credit	2	High Trade Credit	Low - High
Bottom Customer	1.733	1.701	1.105	0.628	-2.218	-2.969	-4.480	2.262
	7.431	*7.987*	*4.554*	*2.965*	*-6.299*	*-7.551*	*-9.490*	*5.809*
2	1.386	1.673	1.841	-0.455	-2.185	-2.448	-2.885	0.701
	8.801	*9.389*	*9.039*	*-2.500*	*-5.588*	*-6.870*	*-7.045*	*1.877*
3	1.778	1.680	1.326	0.453	-1.164	-1.878	-1.186	0.022
	7.690	*8.088*	*5.184*	*2.131*	*-2.908*	*-5.381*	*-3.066*	*0.061*
4	1.985	1.856	1.694	0.291	-1.148	-1.770	-3.490	2.342
	9.038	*9.183*	*7.235*	*1.433*	*-3.348*	*-5.646*	*-8.650*	*6.755*
Top Customer	1.842	1.469	1.617	0.225	-0.400	-0.363	-1.801	1.401
	10.067	*7.470*	*6.376*	*1.032*	*-1.102*	*-0.917*	*-3.874*	*3.539*
Top - Bottom	0.109	-0.232	0.512		1.818	2.606	2.679	
	0.368	*-0.799*	*1.460*		*3.593*	*4.671*	*4.041*	

	Low EM Stress	High EM Stress
Long low trade credit firms in top customer return countries, short high trade credit firms in bottom customer return countries	0.737	4.080
	2.425	*6.850*
Long high trade credit firms in top customer return countries, short low trade credit firms in bottom customer return countries	-0.116	0.417
	-0.336	*0.715*

Table 2.A7
Customer Momentum Strategy, Panel Regression, Conditional on NBER Recessions

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 recessionary periods. The pooled regression setup in Table III is further augmented with interactions for an indicator for NBER recession months. In Panel A, we interact the recession indicator with the firm dummies included in Table III, to estimate performance differences in and out of periods of economic recession with all controlling variables other than fixed effects included. These include the firm-level variables 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 *"With FE"* show results with all controlling variables plus industry and country fixed effects. Panel B shows results for the same specification, with no additional controlling 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.

Panel A: Regression with interaction for NBER recession periods, with controls

	Not Recession					Recession				
	Low Trade Credit	2	High Trade Credit	Low - High	Low - High *With FE*	Low Trade Credit	2	High Trade Credit	Low - High	Low - High *With FE*
Bottom Customer	0.092	-0.256	-0.803	0.895	0.949	0.190	0.546	-1.910	2.100	2.125
	0.482	*-1.297*	*-3.262*	*4.576*	*5.087*	*0.430*	*1.358*	*-4.015*	*5.144*	*5.163*
2	-0.250	-0.217	0.031	-0.281	-0.235	1.269	1.885	0.633	0.635	0.682
	-1.596	*-1.274*	*0.160*	*-1.625*	*-1.370*	*2.263*	*3.759*	*1.186*	*1.350*	*1.463*
3	0.274	0.102	0.332	-0.058	0.005	2.067	0.487	-0.326	2.394	2.370
	1.428	*0.589*	*1.579*	*-0.324*	*0.026*	*2.154*	*0.614*	*-0.418*	*3.393*	*3.424*
4	0.536	0.236	-0.208	0.744	0.811	1.204	0.908	-0.478	1.682	1.687
	2.703	*1.275*	*-0.996*	*4.364*	*4.806*	*2.476*	*2.160*	*-0.935*	*3.663*	*3.683*
Top Customer	0.759	0.567	0.337	0.421	0.458	1.386	0.801	0.456	0.930	0.962
	4.350	*3.051*	*1.448*	*2.170*	*2.489*	*2.280*	*1.303*	*0.679*	*1.707*	*1.800*
Top - Bottom	0.667	0.823	1.140			1.196	0.255	2.366		
	2.680	*3.247*	*3.560*			*1.627*	*0.356*	*2.930*		
Top - Bottom *With FE*	0.624	0.802	1.114			1.218	0.310	2.381		
	2.507	*3.165*	*3.477*			*1.658*	*0.431*	*2.939*		

	Not Recession	Not Recession *With FE*	Recession	Recession *With FE*
Long low trade credit firms in top customer return countries, short high trade credit firms in bottom customer return countries	1.562	1.572	3.296	3.343
	5.465	*5.575*	*4.355*	*4.443*
Long high trade credit firms in top customer return countries, short low trade credit firms in bottom customer return countries	0.245	0.165	0.265	0.256
	0.849	*0.589*	*0.338*	*0.326*

Panel B: Regression with interaction for NBER recession periods, without controls

	Not Recession				Recession			
	Low Trade Credit	2	High Trade Credit	Low - High	Low Trade Credit	2	High Trade Credit	Low - High
Bottom Customer	1.000	0.637	-0.045	1.045	-3.774	-3.411	-5.879	2.104
	5.059	*3.235*	*-0.186*	*5.009*	*-6.498*	*-5.659*	*-9.444*	*4.309*
2	0.610	0.643	0.799	-0.189	-2.786	-2.188	-3.576	0.790
	4.251	*4.026*	*4.188*	*-1.085*	*-4.028*	*-3.543*	*-5.435*	*1.380*
3	1.176	1.041	1.166	0.009	-1.921	-3.429	-4.348	2.427
	6.913	*6.662*	*5.684*	*0.054*	*-1.863*	*-3.982*	*-4.934*	*3.079*
4	1.465	1.167	0.619	0.846	-2.814	-3.083	-4.730	1.916
	7.940	*6.733*	*3.000*	*4.708*	*-4.351*	*-5.374*	*-6.769*	*3.369*
Top Customer	1.634	1.440	1.055	0.578	-2.754	-3.283	-3.661	0.907
	10.114	*8.231*	*4.575*	*2.845*	*-4.057*	*-4.519*	*-4.805*	*1.486*
Top - Bottom	0.634	0.802	1.100		1.020	0.128	2.217	
	2.482	*3.046*	*3.304*		*1.142*	*0.136*	*2.252*	

	Not Recession	Recession
Long low trade credit firms in top customer return countries, short high trade credit firms in bottom customer return countries	1.678	3.124
	5.793	*3.392*
Long high trade credit firms in top customer return countries, short low trade credit firms in bottom customer return countries	0.056	0.113
	0.183	*0.118*

Table 2.A8

Customer Momentum Strategy, Panel Regression - Results with Changing Customer Set

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, at three threshold levels for inclusion in a producer’s major customer index (importing at least 3%, 5%, or 7% of the producer’s total exports). Panel A shows the results when the customer country index is equal-weighted. Panel B shows the results when the customer country index is export-weighted. The results are from the same baseline pooled regression specification in Table III. This table shows results for panel regressions without controls and with all controlling variables including country and industry fixed effects. T-statistics (clustered by month-country-industry) are shown in italics below the coefficient estimates.

Panel A: Regressions with equal-weighted customer indices, at 3%, 5%, and 7% thresholds

		Without Controls				With All Controls			
Long Top Customer		Low Trade Credit		High Trade Credit		Low Trade Credit		High Trade Credit	
Short Bottom Customer		Low Trade Credit	High Trade Credit	Low Trade Credit	High Trade Credit	Low Trade Credit	High Trade Credit	Low Trade Credit	High Trade Credit
Threshold	3%	0.625	1.444	0.322	1.142	0.485	1.099	0.306	0.920
		2.484	*5.259*	*1.041*	*3.473*	*2.101*	*4.400*	*1.157*	*3.154*
	5%	0.681	1.857	0.063	1.238	0.739	1.837	0.214	1.312
	(Baseline)	*2.561*	*6.394*	*0.205*	*3.794*	*2.963*	*6.688*	*0.788*	*4.281*
	7%	0.832	1.840	0.293	1.301	0.912	1.817	0.454	1.358
		3.189	*6.381*	*0.997*	*4.082*	*3.552*	*6.443*	*1.629*	*4.390*

Panel B: Regressions with export-weighted customer indices, at 3%, 5%, and 7% thresholds

		Without Controls				With All Controls			
Long Top Customer		Low Trade Credit		High Trade Credit		Low Trade Credit		High Trade Credit	
Short Bottom Customer		Low Trade Credit	High Trade Credit	Low Trade Credit	High Trade Credit	Low Trade Credit	High Trade Credit	Low Trade Credit	High Trade Credit
Threshold	3%	0.379	1.333	-0.397	0.557	0.370	1.259	-0.312	0.577
		1.440	*4.505*	*-1.312*	*1.679*	*1.520*	*4.647*	*-1.175*	*1.925*
	5%	0.356	1.421	-0.244	0.822	0.417	1.396	0.008	0.987
		1.284	*4.529*	*-0.785*	*2.390*	*1.579*	*4.735*	*0.030*	*3.099*
	7%	0.419	1.265	-0.314	0.531	0.395	1.071	-0.189	0.486
		1.513	*4.033*	*-1.022*	*1.559*	*1.577*	*3.793*	*-0.694*	*1.570*

Table 2.A9
Customer Momentum Strategy, Panel Regression – Net Trade Credit as Trade Credit Measure

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 levels (*measured as net trade credit*), conditional on foreign sales level. The pooled regression setup in Table III is augmented with interactions on the ratio of firm foreign sales to total sales level. In Panel A, we interact the high foreign sales dummy with the firm dummies included in Table III, to estimate performance differences for firms conditional on foreign sales activity levels, with all controlling variables other than fixed effects included. These include the firm-level variables firm size (ranked within each country in each month), cash to assets, short-term debt to assets, net debt to assets, net trade credit ratio (trade credit measure), equity market value to book value, multinational firm dummy, lagged firm return, lagged customer country index return, lagged domestic industry return, and lagged country return. World market return is included to adjust for market risk. The row and columns *"With FE"* show results with all controlling variables plus industry and country fixed effects. Panel B shows results for the same specification, with no controlling variables. There are 692,346 firm-months in this panel regression. T-statistics (clustered by month-country-industry) are shown in italics below the coefficient estimates.

Panel A: Regression with foreign sales interaction, with controls

	Low Foreign Sales					High Foreign Sales				
	Low Trade Credit	2	High Trade Credit	Low - High	Low - High *With FE*	Low Trade Credit	2	High Trade Credit	Low - High	Low - High *With FE*
Bottom Customer	0.306	-0.266	-0.551	0.857	0.871	-0.236	-0.414	-2.010	1.774	1.805
	1.562	*-1.492*	*-2.728*	*4.510*	*4.621*	*-0.863*	*-1.613*	*-6.089*	*6.277*	*6.691*
2	0.111	0.049	0.344	-0.233	-0.260	-0.404	-0.184	-0.053	-0.352	-0.333
	0.585	*0.274*	*1.717*	*-1.221*	*-1.375*	*-1.766*	*-0.921*	*-0.223*	*-1.514*	*-1.434*
3	0.126	0.159	-0.158	0.284	0.317	0.381	-0.092	0.641	-0.260	-0.256
	0.622	*0.889*	*-0.773*	*1.412*	*1.597*	*1.602*	*-0.460*	*2.534*	*-1.076*	*-1.064*
4	0.332	0.312	1.597	-1.265	-1.210	0.707	-0.115	-0.485	1.192	1.216
	1.904	*1.869*	*7.831*	*-6.447*	*-6.205*	*2.972*	*-0.551*	*-1.754*	*4.584*	*4.693*
Top Customer	0.419	1.071	0.089	0.330	0.317	1.081	0.409	0.422	0.659	0.730
	2.074	*5.925*	*0.383*	*1.504*	*1.489*	*4.138*	*1.669*	*1.404*	*2.446*	*2.767*
Top - Bottom	0.113	1.337	0.640			1.317	0.823	2.432		
	0.409	*5.485*	*2.159*			*3.763*	*2.645*	*6.009*		
Top - Bottom *With FE*	0.062	1.268	0.616			1.268	0.771	2.343		
	0.224	*5.200*	*2.077*			*3.627*	*2.481*	*5.847*		

	Low Foreign Sales	Low Foreign Sales *With FE*	High Foreign Sales	High Foreign Sales *With FE*
Long low trade credit firms in top customer return countries, short high trade credit firms in bottom customer return countries	0.970	0.933	3.091	3.073
	3.491	*3.369*	*8.019*	*8.299*
Long high trade credit firms in top customer return countries, short low trade credit firms in bottom customer return countries	-0.217	-0.255	0.658	0.538
	-0.733	*-0.875*	*1.769*	*1.457*

Panel B: Regression with foreign sales interaction, without controls

	Low Foreign Sales				High Foreign Sales			
	Low Trade Credit	2	High Trade Credit	Low - High	Low Trade Credit	2	High Trade Credit	Low - High
Bottom Customer	0.721	0.247	0.101	0.620	0.224	0.090	-1.570	1.794
	3.402	*1.239*	*0.437*	*2.950*	*0.802*	*0.368*	*-4.881*	*5.900*
2	0.671	0.485	0.787	-0.117	-0.297	0.282	0.409	-0.706
	3.924	*2.909*	*3.619*	*-0.566*	*-1.358*	*1.519*	*1.741*	*-2.823*
3	0.552	0.502	0.133	0.419	0.699	0.487	1.259	-0.560
	2.943	*2.949*	*0.609*	*2.039*	*3.106*	*2.645*	*5.153*	*-2.244*
4	0.481	0.572	1.947	-1.467	1.263	0.445	-0.031	1.294
	2.513	*3.098*	*8.825*	*-6.772*	*5.458*	*2.234*	*-0.114*	*4.675*
Top Customer	0.748	1.609	0.488	0.261	1.286	0.657	0.612	0.675
	3.580	*8.205*	*1.985*	*1.131*	*4.960*	*2.852*	*2.054*	*2.337*
Top - Bottom	0.028	1.361	0.387		1.062	0.566	2.182	
	0.093	*4.865*	*1.152*		*2.785*	*1.691*	*4.999*	

	Low Foreign Sales	High Foreign Sales
Long low trade credit firms in top customer return countries, short high trade credit firms in bottom customer return countries	0.648	2.857
	2.084	*6.917*
Long high trade credit firms in top customer return countries, short low trade credit firms in bottom customer return countries	-0.233	0.388
	-0.717	*0.947*

Table 2.A10

Comparing the number of producer firms in this chapter with Fama and French (2012) and Hou, Karolyi and Kho (2011).

	This chapter	FF-2012	HKK-2011
Number of total countries in initial dataset	43 (37 producers)[1]	23 (advanced economies only)	49
Date range covered	January 1993 to March 2009	November 1989 to March 2011	July 1981 to December 2003
Number of total firms comprising producer set	33,915[2]	-	50,000
Number of firms with market capitalization data, and market cap above USD1M	32,430	-	-
Number of firms with basic Worldscope coverage	32,378 (with trade credit data coverage)	-	39,000
Number of firms in final producer set in default empirical specification with complete data coverage (for all controls included in Table III)	15,627	-	~27,000
Number of firms with foreign sales field coverage	9,367	-	-

[1] Estonia, Egypt, Colombia, Greece, Luxembourg, Morocco, Peru, Sri Lanka, Taiwan, Venezuela, and Zimbabwe never appear in the producer and customer sets or have significant data gaps, and are not included in the count of 43 countries.

[2] Customer countries never appearing in producer set: USA (~11,000 firms), Japan (~4,000), Brazil (~250), India (~900), Saudi Arabia, and Slovakia. Saudi Arabia and Slovakia do not have the necessary firm-level data coverage.

Chapter 3

Economic Uncertainty and Commodity Futures Volatility

Abstract

This chapter investigates the dynamics of commodity futures volatility. I derive the variance decomposition for the futures basis to show how unexpected excess returns result from new information about expected future interest rates, convenience yields, and risk premia. This motivates my empirical analysis of the volatility impact of economic and inflation regimes and commodity supply-demand shocks. Using data on major commodity futures markets and global bilateral commodity trade, I analyze the extent to which commodity volatility is related to fundamental uncertainty arising from increased emerging market demand and macroeconomic uncertainty, and control for the potential impact of financial frictions introduced by changing market structure and index trading. I find that a higher concentration in the emerging market importers of a commodity is associated with higher futures volatility. Commodity futures volatility is significantly predictable using variables capturing macroeconomic uncertainty.

3.1 Introduction

This chapter investigates the time-variation in commodity futures volatility and the factors explaining its dynamics. I analyze the impact of concentration and increased emerging market demand on commodity markets. This research builds on Bloom (2014), who presents evidence that emerging markets and recessionary periods are strongly associated with economic uncertainty, and Gabaix (2011), who shows the impact on aggregate volatility from power laws in size distributions. This chapter adds to the literature on what explains fluctuations in volatility (see, for example, Roll (1984); Schwert (1989); Engle and Rangel (2008); Gabaix (2011); Bloom (2014)), while also contributing to the current debate on commodity price dynamics and potential distortions arising from market frictions.[1] In particular, I examine how supply-demand shocks, macroeconomic uncertainty, and financial frictions are related to realized volatility in commodity futures markets.

Volatility dynamics are a key consideration in strategy formation for hedging, derivatives trading, and portfolio optimization. Moreover, producers and consumers benefit from understanding the factors explaining price fluctuations when evaluating real options embedded in investment choices (Schwartz, 1997). Distortions can lead to under- or overinvestment, and even transitory deviations from fundamentals can lead to the long-term misallocation of resources (see, for example, Bernanke (1983); Bloom, Bond, and Reenen (2007)). This is especially important when there are non-convex production

[1] For recent studies on factors affecting commodity markets, see, *inter alia*, US Senate Permanent Subcommittee on Investigations (2009, 2014); Tang and Xiong (2012); Singleton (2014); Basak and Pavlova (2013a,b), on commodity index and ETF trading and the involvement of banks in commodity markets, Etula (2013); Acharya, Lochstoer, and Ramadorai (2013) on broker-dealer capacity for risk taking, Kilian (2009); Chen, Rogoff, and Rossi (2010) on producer and consumer shocks, Roberts and Schlenker (2013) on changes to regulation.

functions and large fixed costs to entry and expansion (e.g., a copper producer considering the development of a new mine or a manufacturer considering the opening of a new factory that uses raw commodities as inputs). Uncertainty also increases the difficulty for both producers and consumers when formulating optimal hedging strategies, potentially leading to higher volatility in their cash flows. This can cause higher borrowing costs and lower debt in the presence of non-zero costs to bankruptcy and default, which can in turn lead to lower firm values. As such, understanding the relationship between volatility and economic factors is a first-order consideration. For commodities with derivative markets that are illiquid, opaque, or have little market depth or limited expirations, the findings in this chapter can provide a useful aid to price discovery, real option evaluation, and risk management for end-users as well as financial investors. A better understanding of these futures return dynamics also enables policy-makers to consider the impact of possible market intervention and evaluate regulatory options aimed at achieving a desired welfare objective.[2]

Using a reduced form model of a commodity market with power-law distributed consumers and producers, I present several hypotheses on how concentration and emerging market demand impacts commodity volatility, and test these in the data. When commodity supply and demand are dominated by a handful of countries, their shocks affect global commodity markets. Even in the case where trading partners face homogeneous shocks, the market concentration itself can have an impact on volatility. Heterogeneous consumers and producers may face supply-demand shocks with different variance. When the larger consumers are also riskier and more volatile (experience higher vari-

[2]Amartya Sen (*Poverty and Famines* (Oxford University Press, 1983)) and others, highlight the direct and potentially catastrophic consequences of commodity price dynamics.

ance shocks), their impact on market volatility is amplified through concentration. This is important when considering the impact of growing emerging market demand on commodity prices. Many of these markets are volatile, segmented, and pose non-diversifiable risks to hedgers and international investors (Bekaert and Harvey, 1997; Bloom, 2014).

I collate data on 22 major commodity futures markets and the global bilateral trade in the underlying commodities and analyze the extent to which commodity volatility is related to increased emerging market demand and other fundamentals such as inflation uncertainty, while controlling for financial frictions introduced by changing market structure and commodity index trading. A higher concentration in the emerging market importers of a commodity is associated with higher futures volatility. The results imply that a 1.00% gain in market concentration by developing country consumers is associated with a 1.19% increase in commodity futures volatility. I find predictability in commodity futures volatility using variables capturing macroeconomic uncertainty, with adjusted R-squared gains of over 10% over the baseline specification. Moreover, controlling for recession periods further increases the explanatory power of the main predictive regressions by over 13%. These reflect economically significant gains for an investor, particularly those engaged in hedging, in evaluating real options embedded in investment choices, or in trading portfolios of derivatives.

I derive the variance decomposition for futures, building on Working (1949); Campbell and Shiller (1988) and Campbell (1991), to show how unexpected changes to the excess basis return of a commodity future are driven by changes to the expectation of future interest rates, convenience yield (the net benefit of holding the underlying physical commodity) and risk premia.

These expectations are updated in response to new information about the future state of the economy (e.g., news on inflation and other variables related to the business cycle) and future commodity supply and demand (e.g., news about the economic health of commodity consumers and frictions to producer hedging). Similar to the analysis of stock market volatility by Engle and Rangel (2008), using this decomposition as the theoretical motivation, I examine the time-variation in the relationship between commodity volatility and shocks to relevant factors.

I find that there are significant fluctuations in both the realized volatility and the realized correlations of futures returns for the commodities analyzed in this study (e.g., Figures 3.1, 3.5, and 3.6). This is true at different horizons corresponding to different holding periods, and throughout the entire trading history of a contract (e.g., beginning in the 1960s for most grain commodities, April 1983 for crude oil, etc.). Large fluctuations in price and volatility occurred for the commodities in the sample even prior to the popularization of commodity index and ETF trading.[3] I analyze the determinants of this variation in volatility, selecting variables that capture the variation in global macroeconomic conditions, commodity supply-demand, and market frictions based on theory and past empirical studies on commodity risk premia (see, for example, Chen, Rogoff, and Rossi (2010); Hong and Yogo (2012) and Acharya, Lochstoer, and Ramadorai (2013)). I add to this from the literature on analyzing the determinants of the realized volatility of financial assets (see, for example, Roll (1984) for an early study on the volatility dynamics of a commodity derivative, Schwert (1989) on understanding the

[3]The "index financialization" period is commonly identified in the literature as beginning in January 2004 (Tang and Xiong, 2012; Hamilton and Wu, 2012; Singleton, 2014; Basak and Pavlova, 2013b).

time-variation in equity volatility, Engle and Rangel (2008) on relating low-frequency macroeconomic factors to realized volatility in global equity market indices, Gabaix (2011); Kelly, Lustig, and Nieuwerburgh (2013) on the granular origins of volatility, and Bloom, Bond, and Reenen (2007); Bloom (2009, 2014); Jurado, Ludvigson, and Ng (2014) on uncertainty and its relationship to volatility).

Global commodity markets have undergone major transformations in real economic demand and supply stemming from a sharp increase in demand from emerging market economies over the last two decades (see, for example, Figures 3.2 and 3.3). The speed and extent of this increase is larger compared to similar episodes of major global market transformation in recent history.[4] Emerging market economies have become increasingly significant players in many commodity markets. On the supply side, this has been the case for several decades for certain commodities. More recently, global demand has undergone significant changes. As can be seen from the data from UN Comtrade, countries that are not members of the OECD or G7 are now among the largest buyers in many key commodity markets. Developing and emerging market countries have more volatile economies and pose higher levels of legal, political, and economic policy uncertainty (Bekaert and Harvey, 1995, 1997, 2000; Bloom, 2014). Bernanke (1983); Bloom, Bond, and Reenen (2007); Bloom (2009) and others find that such uncertainty can lead to higher risk premia, lower investment levels, higher volatility, higher correlation levels, and deeper market distortions which last longer. Pastor and Veronesi (2011, 2013) show that such political uncertainty can lead to higher return volatility

[4]For instance, Japan's emergence as a global financial power post-World War II (1960-1970) was accompanied by slower, smaller market share changes in commodity markets compared with the change in China's share of the major commodity markets since 1990.

and correlation levels.[5]

Part of the recent debate on commodity price fluctuations attempts to distinguish between the impact on commodity futures markets from changing market structure and investor composition as opposed to changing macroeconomic fundamentals and supply-demand dynamics.[6] Several recent studies find in favor of the "financialization" or trader activity argument, citing, among other evidence, high commodity volatility and correlation (between crude oil prices and other financial markets) in the past decade (especially, after January 2004), when commodity index trading volumes increased substantially. However, I find that the commodity futures volatility observed during the past decade may in fact be largely in line with the high levels of futures volatility observed during past periods of financial crisis and geopolitical uncertainty. Similarly, correlation levels show significant time-variation over the full trading history of commodity futures (e.g., Figure 3.6).

The remainder of this chapter is organized as follows. The next section presents the research framework, including the theoretical motivation and empirical methodology underpinning this research. Section 3 describes the data and variables employed in the analyses. Section 4 presents the results from the main empirical analysis. The final section concludes.

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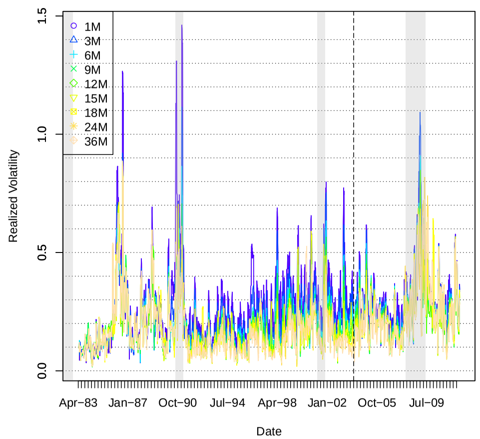
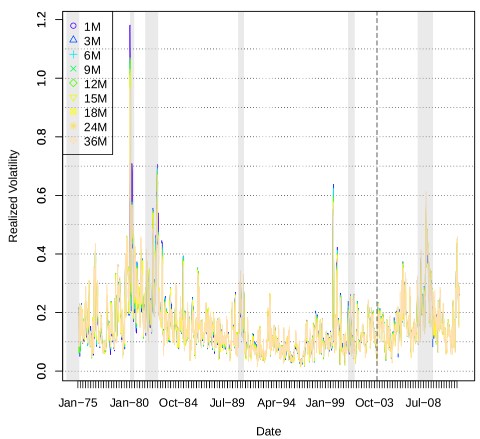
[5]Raghuram G. Rajan (*Fault Lines: How Hidden Fractures Still Threaten the World Economy* (Princeton University Press, 2010)) discusses the risks associated with different political, legal, and financial systems coming into contact with each other, and how this can generate uncertainty and increase the likelihood of financial market crises.

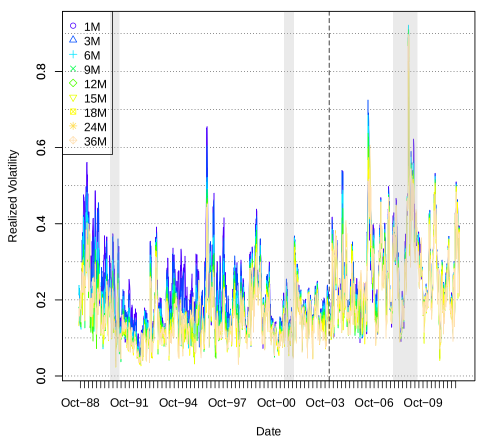
[6]See footnote 1.



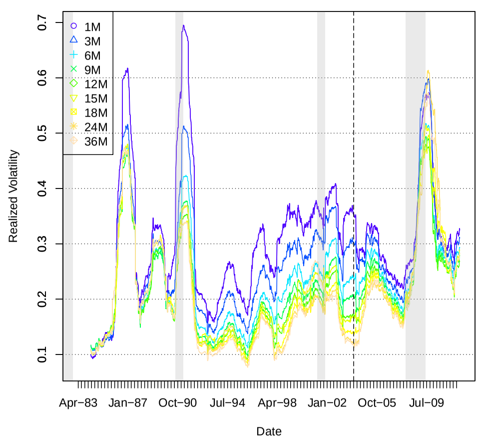
(a) Crude Oil - short-term volatility



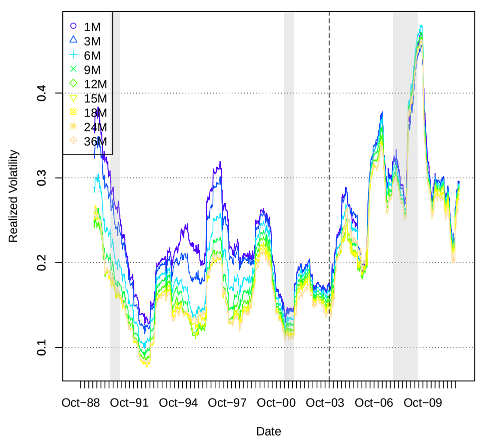
(b) Gold - short-term volatility



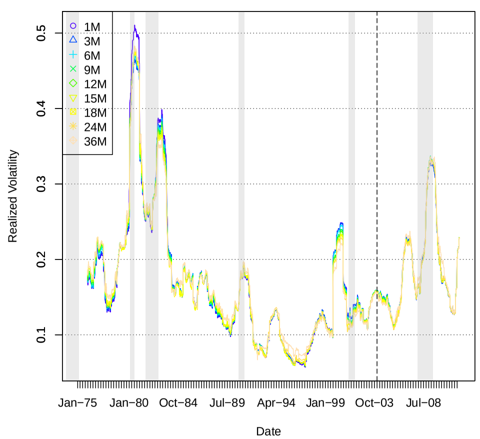
(c) Copper (HG) - short-term volatility



(d) Crude Oil - long-term volatility

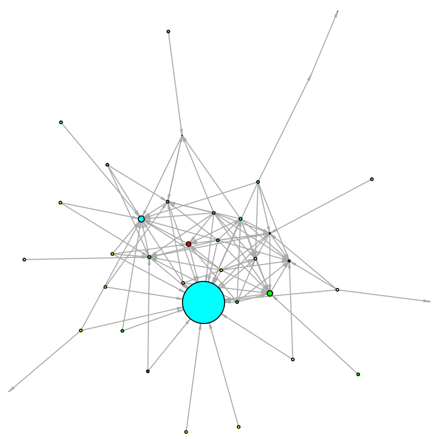


(e) Copper (HG) - long-term volatility

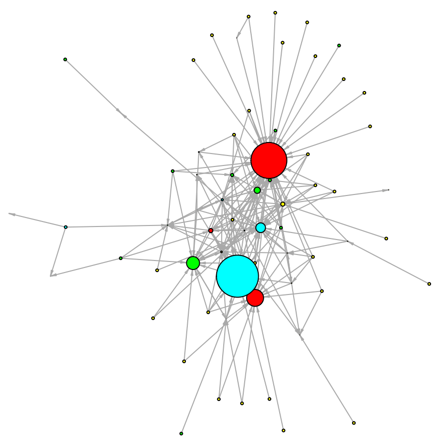


(f) Gold - long-term volatility

Figure 3.1: Time series of annualized rolling realized volatility at different horizons crude oil, natural gas, and gold. Time series of annualized rolling realized volatility at different horizons for 1M, 3M, ..., 36M futures using 3-day returns. Here, short-term volatility refers to the standard deviation for the previous month, while long-term volatility refers to the standard deviation for the previous twelve months. The shaded areas highlight the NBER recession periods. The dotted line marks January 2004.



(a) 1990 Imports



(b) 2007 Imports

Figure 3.2: Global copper imports network.

The vertex colors identify the country group: BRIC (red), non-OECD excluding BRIC (yellow), OECD excluding G7 (green), and G7 (blue). The relative size of a country vertex captures its total import value.

3.2 Research Framework

3.2.1 Commodity futures volatility

To understand the sources of variation in commodity futures returns, I build on present value models that show how changes in the current price of financial assets react to future changes to the underlying fundamentals. The stock variance decomposition presented in Campbell and Shiller (1988) and Campbell (1991) is widely used to identify the sources of financial asset volatility. This decomposition relates unexpected equity returns to news events that change expectations of future cash flows (stock dividends) and discount rates. Campbell and Ammer (1993) present the equivalent result for bond yields. A similar decomposition can be derived for commodity futures in terms of its basis. In order to understand this correspondence for a future on a storable commodity, begin with the no-arbitrage pricing formula for its futures price (Working, 1933, 1949; Kaldor, 1939; Brennan, 1958; Schwartz, 1997), $F_{t,T} = S_t e^{(r-y)(T-t)}$, where $F_{t,T}$ is the futures price at time t of a unit of the commodity delivered at time T, S_t is the spot price, r is the risk-free rate, and y is the convenience yield. Further, y can be decomposed into the "benefit" from holding the physical commodity, b, net of the storage (or carry) cost rate m, $y = b - m$; $r = \pi + \psi$, where π is the inflation rate and ψ the real interest rate. This decomposition and analysis that follow are applicable to any type of future, with the interpretation of y differing depending on the net benefit to holding the underlying asset, e.g., replace y with dividend yield d for stock futures or with the foreign currency interest rate r^f for currency futures.[7, 8]

Consider the discrete-time version of this formula, now with time-dependent r and y: the price at time t of a future expiring in n periods,

$$F_{n,t} = S_t \frac{(1+R_{n,t})^n}{(1+Y_{n,t})^n}, \tag{3.1}$$

$$(1+Y_{n,t}) = \left(\frac{1+B_{n,t}}{1+M_{n,t}}\right). \tag{3.2}$$

Denote the log price at time t of a future expiring in n periods as $f_{n,t}$ and the corresponding log spot price as s_t. Accordingly, the log price of the same future at time $t+1$ is $f_{n-1,t+1}$, now with $n-1$ periods to expiry, with an associated log spot price s_{t+1}. Define, $r_{n,t} \equiv \ln(1+R_{n,t}) = \pi_{n,t} + \psi_{n,t}$ and $y_{n,t} \equiv \ln(1+Y_{n,t}) = b_{n,t} - m_{n,t}$. Note that $r_{n,t}$ and $y_{n,t}$ are *per period* rates at time t, corresponding to the interest and convenience yield for the next n periods. Using this notation, I can define the basis, $p_{n,t}$,

$$f_{n,t} = s_t + n(r_{n,t} - y_{n,t}) \tag{3.3}$$

$$\begin{aligned} p_{n,t} &\equiv f_{n,t} - s_t \\ &= n(r_{n,t} - y_{n,t}), \end{aligned} \tag{3.4}$$

We can define the change in basis from t to $t+1$, $\delta_{n,t+1}$, and the return in

[7]This decomposition is exact for the forward price. Due to the mark-to-market gains and losses of the corresponding futures contract, differences can occur between the forward and future prices unless interest rates are deterministic.

[8]Several studies investigate the commodity convenience yield. Casassus and Collin-Dufresne (2005) nest several other models (including Gibson and Schwartz (1990) and Schwartz (1997)), concluding that convenience yield is increasing in the spot price, interest rates, and the extent to which the underlying commodity is used for production purposes.

excess of the cost-of-carry, $x_{n,t+1}$,[9]

$$\delta_{n,t+1} \equiv p_{n-1,t+1} - p_{n,t}, \tag{3.5}$$
$$= (n-1)(r_{n-1,t+1} - y_{n-1,t+1}) - n(r_{n,t} - y_{n,t}),$$
$$x_{n,t+1} \equiv \delta_{n,t+1} + (r_{1,t} - y_{1,t}), \tag{3.6}$$

Given that $p_{0,t} = 0$ for all t, solving (3.5) forward (for $p_{n,t}$, $p_{n-1,t+1}$, $p_{n-2,t+2}$, ..., $p_{1,t+n-1}$) till the maturity date $t+n$, and taking expectations at time t yields,

$$p_{n,t} = -\left[\delta_{n,t+1} + \delta_{n-1,t+2} + \ldots + \delta_{1,t+n}\right] \tag{3.7}$$
$$= -E_t \sum_{i=0}^{n-1} \delta_{n-i,t+i+1}. \tag{3.8}$$

Eq. (3.7) must hold ex post and ex ante, so taking its expectation yields Eq. (3.8). Substituting (3.8) back into (3.5) gives the decomposition,

$$\delta_{n,t+1} - E_t \delta_{n,t+1} = -(E_{t+1} - E_t) \sum_{i=1}^{n-1} \delta_{n-i,t+i+1}. \tag{3.9}$$

Eq. (3.6) can be substituted into (3.9) to obtain its unexpected change,

$$x_{n,t+1} - E_t x_{n,t+1} = (E_{t+1} - E_t) \left\{ \sum_{i=1}^{n-1} r_{1,t+i} - \sum_{i=1}^{n-1} y_{1,t+i} - \sum_{i=1}^{n-1} x_{n-i,t+i+1} \right\}. \tag{3.10}$$

[9] As discussed further in section 3.2.3, there can be deviations from the no-arbitrage condition due to non-diversifiable risks or market frictions such as producer hedging pressure and borrowing constraints (see, for example, (Keynes, 1930; Cootner, 1960; Hirshleifer, 1988, 1990; Roon, Nijman, Chris, and Veld, 2000; Acharya, Lochstoer, and Ramadorai, 2013)). $x_{n,t+1}$ also captures the part of the futures risk premia due to deviations from the expectations hypothesis in the interest rate term structure, as shown in Appendix 3.6.1, Eq. (3.38).

Eq. (3.10) means that, if there is an unexpected increase in the excess basis return, either expected future interest rates are higher, expected future convenience yields are lower, or future risk premia are lower. When the assumption that both the expectations hypothesis for the term structure of interest rates and the theory of storage hold exactly, $E\left[\delta_{n,t+1}\right] = y_{1,t} - r_{1,t}$ for all $n > 0$, the third summation (of expected future excess basis returns) in (3.10) is zero. When this assumption is relaxed, the decomposition captures the risk premia reflecting the maturity and spot risk in interest rates and convenience yields. If we further decompose the excess basis return, $x_{n,t+1}$, to separate out the excess return due to the interest rate term structure (i.e., due to deviations from the expectations hypothesis), we can characterize the excess return purely due to the convenience yield and commodity risk premia (see Eq. (3.39 and (3.40)) in Appendix 3.6.1.

The decomposition can be rewritten explicitly in terms of news events relating to convenience yield, the risk-free rate, and risk premia,

$$x_{n,t+1} - E_t x_{n,t+1} = \eta^r_{t+1} - \eta^y_{t+1} - \eta^x_{t+1}. \tag{3.11}$$

Eq. (3.11) shows that unexpected changes to the futures risk premium are due to innovations in the future expected convenience yields, interest rates, and excess basis returns. These expectations are updated in response to new information about the future state of the economy (e.g., the level and volatility of inflation and real interest rates) and commodity supply-demand (e.g., inventory levels and the economic health of consumers). A positive shock to future convenience yields (the net benefit from holding the underlying spot commodity) or risk premia has a negative effect on the futures risk premium. The volatility of the excess basis return is driven by unexpected news affecting interest rates, convenience yield, and risk premia. More explicitly, with correlated components,

$$
\begin{aligned}
Var(x_{n,t+1}) =& Var(\eta_t^r) + Var(\eta_t^y) + Var(\eta_t^x) \\
& -2Cov(\eta_t^r, \eta_t^y) - 2Cov(\eta_t^r, \eta_t^x) + 2Cov(\eta_t^y, \eta_t^x) \qquad (3.12)
\end{aligned}
$$

Engle and Rangel (2008) show that it is straightforward to model the unexpected return of a financial asset decomposed in this manner in terms of its stochastic volatility as,

$$
x_{n,t+1} - E_t x_{n,t+1} = \sigma_t \epsilon_t, \text{ where } \epsilon_t | \Omega_{t-1} \sim N(0,1). \qquad (3.13)
$$

Given (3.11) and (3.13), we see that the stochastic volatility, σ_t, is driven by news on the future state of the economy and commodity supply-demand that directly impact convenience yield and interest rates. Models commonly used to estimate σ_t for financial assets and their implementation for commodity futures in this study are discussed in section 3.3.2. Many studies attempting to understand equity risk premium dynamics decompose unexpected returns into K observable news sources or risk factors which affect expectations of future discount rates and cash flows to equity, i.e., for the unexpected excess equity return, $e_t - E_{t-1}e_t = \eta_t^d - \eta_t^r - \eta_t^e = \sum_{k=1}^{K} \beta_k \lambda_{k,t}$. The equivalent for commodities should use the appropriate information set given the decomposition in (3.11).

3.2.2 Producer and consumer impact on commodity market volatility

In this section, I illustrate how producer and consumer risks and concentrations can impact commodity market volatility, motivating my empirical approach to analyzing the effect of rapidly growing emerging market demand.

Consider a model where there are $p = 1, \ldots, P$ producers and $c = 1, \ldots, C$ consumers of a commodity. A producer p has market weight $w_{p,t}$ and a consumer has market weight $w_{c,t}$ with $\sum_{p=1}^{P} w_{p,t} = 1$ and $\sum_{c=1}^{C} w_{c,t} = 1$. The distribution of weights is power-law distributed, with a handful of consumers (producers) dominating the demand (supply) side. In this case, the idiosyncratic shocks to the trading parties matter in explaining market dynamics.[10] Similar to formulations in Acharya, Lochstoer, and Ramadorai (2013) and Ready, Roussanov, and Ward (2013), consumers have a downward-sloping demand curve for the commodity with price elasticity of demand ϵ, and face an idiosyncratic demand shock $A_{c,t}$ such that,

$$S_t = A_{c,t} \left(Q_{c,t}\right)^{-\frac{1}{\epsilon}} . \tag{3.14}$$

In the near-term, producers have a price-inelastic supply and face an idiosyncratic supply shock $B_{p,t}$, such that $Q_{p,t} = B_{p,t}$. Denote the log quantities and prices in lowercase, with $a_{c,t} \sim N(0, \sigma_{a_c})$ and $b_{p,t} \sim N(0, \sigma_{b_p})$. Given market clearing for the total change in supply and demand in this setting, $\sum_{p=1}^{P} w_{p,t} q_{p,t} = \sum_{c=1}^{C} w_{c,t} q_{c,t}$, I can derive the impact of consumer and pro-

[10] See, for example, Gabaix (2011) for an exposition of this principle applied to firm sizes and aggregate volatility.

ducer concentration on the variance of the commodity, $\sigma^2_{s,t}$,

$$\sigma^2_{s,t} = \beta_c \sum_{c=1}^{C} w^2_{c,t}\sigma^2_{a_c} + \beta_p \sum_{p=1}^{P} w^2_{p,t}\sigma^2_{b_p} + \eta_t. \tag{3.15}$$

Consider the case where all consumers and producers have the same distribution in their demand shocks, $a_{c,t} \sim N(0, \sigma_a)$ and supply shocks, $b_{p,t} \sim N(0, \sigma_b)$, respectively. Then, defining consumer and producer Herfindahls as $H_{c,t} = \sum_{c=1}^{C} w^2_{c,t}$ and $H_{p,t} = \sum_{p=1}^{P} w^2_{p,t}$, respectively, yields,

$$\sigma^2_{s,t} = \beta_c \sigma^2_a H_{c,t} + \beta_p \sigma^2_b H_{p,t} + \eta_t. \tag{3.16}$$

Eq. (3.16) shows that even with homogeneous shocks to demand and supply, consumer and producer market concentrations can have an impact on market volatility.[11]

Heterogeneous consumers and producers may face supply-demand shocks with different variance. When the larger consumers or producers are also riskier and more volatile (experience higher variance shocks), their impact on market volatility is amplified through concentration. This is important when considering the impact of growing emerging market trade on commodity prices.

Developing and emerging market countries have more volatile economies and greater uncertainty (Bekaert and Harvey, 1995, 2000; Bloom, 2014). We can consider consumers from emerging market, non-OECD countries as having demand shocks, $a_{c_{EM},t} \sim N(0, \sigma_{a_{EM}})$, while all others have demand shocks,

[11] This analysis is similar to those on the granular origins of aggregate volatility (see, for example, Gabaix (2011) on the impact of power-law distributed firm sizes on aggregate volatility and Acemoglu, Carvalho, Ozdaglar, and Tahbaz-Salehi (2012); Kelly, Lustig, and Nieuwerburgh (2013) on the supplier-customer network and size effects on volatility).

$a_{c,t} \sim N(0, \sigma_a)$, with $\sigma_{a_{EM}} > \sigma_a$. All idiosyncratic supply shocks remain uniform, $b_{p,t} \sim N(0, \sigma_b)$. Starting with Eq. (3.15), with $H_{c,t}^{EM} = \sum\limits_{c \in EM} w_{c,t}^2$,

$$\begin{aligned}
\sigma_{s,t}^2 =& \beta_c \sum_{c=1}^{C} w_{c,t}^2 \sigma_{a_c}^2 + \beta_p \sum_{p=1}^{P} w_{p,t}^2 \sigma_{b_p}^2 + \eta_t, \\
=& \beta_p \sigma_b^2 H_{p,t} \\
& + \beta_c \sigma_a^2 H_{c,t} + \beta_c \left(\sigma_{a_{EM}} - \sigma_a\right)^2 H_{c,t}^{EM} + \eta_t. \qquad (3.17)
\end{aligned}$$

In the near-term, producers are price-inelastic, with an essentially fixed supply and no unanticipated shocks ($\sigma_{b_p} = 0$). Under these conditions, the second term in Eq. (3.15) drops out, and producer concentration has no effect on commodity market volatility.

$$\begin{aligned}
\sigma_{s,t}^2 =& \beta_c \sum_{c=1}^{C} w_{c,t}^2 \sigma_{a_c}^2 + \beta_p \sum_{p=1}^{P} w_{p,t}^2 \sigma_{b_p}^2 + \eta_t, \\
\sigma_{s,t}^2 =& \beta_c \sum_{c=1}^{C} w_{c,t}^2 \sigma_{a_c}^2 + \eta_t, \qquad (3.18) \\
=& \beta_c \sigma_a^2 H_{c,t} + \beta_c \left(\sigma_{a_{EM}} - \sigma_a\right)^2 H_{c,t}^{EM} + \eta_t. \qquad (3.19)
\end{aligned}$$

These hypotheses capture the impact of the concentration and risks of producers and consumers on commodity markets. I empirically test several of the hypotheses related to consumer and producer impact on commodity volatility.

Denote the trade weights in commodity i of country j as,

$$w^I_{i,j,t} = \frac{ImportValue_{i,j,t}}{\sum\limits_{j=1}^{N} ImportValue_{i,j,t}}, \tag{3.20}$$

$$w^E_{i,j,t} = \frac{ExportValue_{i,j,t}}{\sum\limits_{j=1}^{N} ExportValue_{i,j,t}} \tag{3.21}$$

for imports and exports, respectively. Then, the measures of consumer concentration (of all countries and emerging market countries) are captured through Herfindahl indices and defined as,

$$H^C_{i,t} = \left[\sum_{j=1}^{N} \left(w^I_{i,j,t}\right)^2\right]^{\frac{1}{2}}, \tag{3.22}$$

$$H^{C\_EM}_{i,t} = \left[\sum_{j \in EM} \left(w^I_{i,j,t}\right)^2\right]^{\frac{1}{2}}, \tag{3.23}$$

respectively. The corresponding Herfindahl indices for producers, $H^P_{i,t}$ and $H^{P\_EM}_{i,t}$, are similarly defined using export weights. For notational simplicity, define $\lambda^E_{i,j,t} = \left(w^E_{i,j,t}\right)^2$ and $\lambda^I_{i,j,t} = \left(w^I_{i,j,t}\right)^2$.

Hypothesis 3.2.1. Concentration in the importing countries of commodity i impacts its futures volatility, $Vol_{i,t}$,

$$Vol_{i,t} = \mu_i + \beta_1 H^P_{i,t} + \beta_2 H^C_{i,t} + \mathbf{z}_t{}'\boldsymbol{\theta} + \eta_{i,t}, \tag{3.24}$$

where, $\mathbf{z}_t$ is a state vector of the relevant controls and $\boldsymbol{\theta}$ a vector of the coefficients.

$\beta_2 > 0$ in the specification in Eq. (3.24).

Hypothesis 3.2.2. Shocks to the major importers of commodity i impact its futures volatility, $Vol_{i,t}$,

$$Vol_{i,t} = \mu_i + \beta_1 \sum_{j=1}^{N} w_{i,j,t}^{E} \sigma_{j,t} + \beta_2 \sum_{j=1}^{N} w_{i,j,t}^{I} \sigma_{j,t} + \mathbf{z}_t{}' \boldsymbol{\theta} + \eta_{i,t}, \tag{3.25}$$

$\beta_2 > 0$ in the specification in Eq. (3.25).

Greater uncertainty and lower financial market development reduce the ability of commodity market participants (producers, consumers, and other investors) to insure against the risks of developing and emerging market countries (Bekaert and Harvey, 1995, 2000; di Giovanni and Levchenko, 2009; Pastor and Veronesi, 2011, 2013; Bloom, 2014).

Hypothesis 3.2.3. The relationship in hypotheses 3.2.1 and 3.2.2 is more significant for imports from countries that have higher policy uncertainty and lower financial openness (denoted EM countries).

$$Vol_{i,t} = \mu_i + \beta_1 H_{i,t}^{P} + \beta_2 H_{i,t}^{C} + \beta_3 H_{i,t}^{P\_EM} + \beta_4 H_{i,t}^{C\_EM} + \mathbf{z}_t{}' \boldsymbol{\theta} + \eta_{i,t}, \tag{3.26}$$

$$\begin{aligned} Vol_{i,t} = {} & \mu_i + \beta_1 \sum_{j=1}^{N} w_{i,j,t}^{E} \sigma_{j,t} + \beta_2 \sum_{j=1}^{N} w_{i,j,t}^{I} \sigma_{j,t} \\ & + \beta_3 \sum_{j=1}^{N} I_{[j \in EM]} w_{i,j,t}^{E} \sigma_{j,t} + \beta_4 \sum_{j=1}^{N} I_{[j \in EM]} w_{i,j,t}^{I} \sigma_{j,t} + \mathbf{z}_t{}' \boldsymbol{\theta} + \eta_{i,t}, \end{aligned} \tag{3.27}$$

$\beta_4 > 0$ in the specification in Eq. (3.26) and (3.27).

Hypothesis 3.2.4. In the short-term, producers hedge, have a fixed supply, and have no unanticipated supply shocks affecting commodity markets.
$\beta_1 = 0$ in the specifications in Eq. (3.24) and (3.25). $\beta_3 = 0$ in the specifications in Eq. (3.26) and (3.27).

The sensitivity of commodity futures to consumer and producer shocks will be highest when there is a scarcity or glut in the underlying commodity.

Such periods would be captured by periods of high absolute values of the futures basis ($HIGH\_BASIS$). Additionally, information about demand-side or supply-side pressure should be captured by the γ coefficient of a GJR-GARCH(1,1) fit of commodity futures daily returns (see Eq. 3.45 and related discussion in Appendix 3.6.2).

Hypothesis 3.2.5. The impact of shocks to the major importers of commodity i on its futures volatility, $Vol_{i,t}$, should be highest when the futures term structure exhibits a high basis.

$$\begin{aligned} Vol_{i,t} =& \mu_i + \beta_1 \sum_{j=1}^{N} w_{i,j,t}^{E} \sigma_{j,t} + \beta_2 \sum_{j=1}^{N} w_{i,j,t}^{I} \sigma_{j,t} + \mathbf{z}_t{}' \boldsymbol{\theta} + \beta_3 I_{[t-1 \in HIGH\_BASIS]} \\ &+ \beta_4 I_{[t-1 \in HIGH\_BASIS]} \sum_{j=1}^{N} w_{i,j,t}^{E} \sigma_{j,t} + \beta_5 I_{[t-1 \in HIGH\_BASIS]} \sum_{j=1}^{N} w_{i,j,t}^{I} \sigma_{j,t} + \eta_{i,t}, \end{aligned} \tag{3.28}$$

where, $HIGH\_BASIS = 1$ during periods when the absolute value of the futures basis is highest (i.e., when the basis is in the top or bottom quintile), and 0 otherwise.
$\beta_4 > 0$ and $\beta_5 > 0$ in the specification in Eq. (3.28).

Hypothesis 3.2.6. The impact of shocks to the major importers of commodity i on its futures volatility, $Vol_{i,t}$, should be highest when the asymmetric relationship between commodity volatility and returns is highest.

$$\begin{aligned} Vol_{i,t} =& \mu_i + \beta_1 \sum_{j=1}^{N} w_{i,j,t}^{E} \sigma_{j,t} + \beta_2 \sum_{j=1}^{N} w_{i,j,t}^{I} \sigma_{j,t} + \mathbf{z}_t{}' \boldsymbol{\theta} + \beta_3 I_{[t-1 \in HIGH\_GAMMA]} \\ &+ \beta_4 I_{[t-1 \in HIGH\_GAMMA]} \sum_{j=1}^{N} w_{i,j,t}^{E} \sigma_{j,t} + \beta_5 I_{[t-1 \in HIGH\_GAMMA]} \sum_{j=1}^{N} w_{i,j,t}^{I} \sigma_{j,t} + \eta_{i,t}, \end{aligned} \tag{3.29}$$

where, $HIGH\_GAMMA = 1$ during periods when the absolute value of the γ coefficient of conditional GJR-GARCH(1,1) fits of the commodity futures returns is highest (i.e., when γ is in the top or bottom quintile), and 0 otherwise.
$\beta_4 > 0$ and $\beta_5 > 0$ in the specification in Eq. (3.29).

I further examine the impact of demand and supply shocks on the conditional variation in the asymmetric relationship between commodity volatility and returns.

Hypothesis 3.2.7.

$$\begin{aligned}
Vol_{i,t} =& \mu + \alpha \left| r_{i,t-1} \right| + \beta Vol_{i,t-1} + \gamma_{i,t-1} I^{(+)}_{i,t-1} \left| r_{i,t-1} \right| + \mathbf{z}_{i,t-1}{}' \boldsymbol{\theta} + \eta_{i,t}, \\
\gamma_{i,t-1} =& \kappa_1 + \kappa_2 a_{i,t-1} + \kappa_3 b_{i,t-1},
\end{aligned} \tag{3.30}$$

where, $I^{(+)}_{i,t-1} = 1$ when $r_{i,t-1} > 0$, and 0 otherwise. $a_{i,t-1}$ and $b_{i,t-1}$ are demand and supply shocks, respectively. $\boldsymbol{\kappa} = [\kappa_1\ \kappa_2\ \kappa_3]$ denote regression coefficients. $\kappa_2 > 0$ and $\kappa_3 > 0$ in the specification in Eq. (3.30).

3.2.3 Impact of market frictions and limits to arbitrage

Deviations from the decomposition derived from no-arbitrage pricing conditions can occur for a variety of reasons in imperfect markets with frictions (e.g., information asymmetry or disagreement, limits to arbitrage via capital constraints) or due to the natural scarcity of the underlying asset, which is especially important for commodities, an asset class that has historically shown many episodes of market cornering and manipulation.[12] Such conditions can

[12]E.g., Haase and Zimmermann (2011) on the scarcity premium in commodity futures prices and Jovanovic (2013) on the possibility of bubbles in the prices of exhaustible commodities.

cause Eq. (3.1) to no longer hold exactly for all investors in the market. In Eq. (3.10), these deviations are captured in the third term.

The limits to arbitrage and its related literature look at standard theoretical asset pricing models with strong assumptions on the existence of perfect frictionless markets relaxed. Shleifer and Vishny (1997) show that since arbitrage in practice requires capital and is inherently risky, asset prices will diverge from fundamental values under a variety of possible conditions when informed arbitrageurs in the market are constrained from eliminating them. Gromb and Vayanos (2002) find that capital-constrained arbitrageurs may take more or less risk than in a situation where they face perfect capital markets, leading to equilibrium outcomes that are not Pareto optimal. Yuan (2005) uses a modified Grossman and Stiglitz (1980) framework where a fraction of informed investors face a borrowing constraint, which is a function of the risky asset price (the lower the price, the more constrained the investor), and shows that this can result in asymmetric price movements.

Garleanu, Pedersen, and Poteshman (2009) apply this reasoning to options markets, and consider the case where it is not possible to hedge equity option positions perfectly, leading to demand pressure having an impact on option prices. They show empirically with equity index and single stock data that this helps to explain asset pricing puzzles such as option volatility skewness and relative expensiveness, which are anomalies under the assumptions of the Black-Scholes-Merton model (Black and Scholes (1973), Merton (1973)).

Basak and Pavlova (2013a) model the impact on a stock market from institutional investors whose performance is measured against a benchmark equity index. As this results in institutional investors holding more index stocks than is otherwise optimal, there is demand pressure that boosts index stock prices (and not off-index stock prices). This amplifies the volatility of on-index stock prices and the correlations between them, as well as increasing overall market volatility.

The term financialization, in the context of commodities trading, is generally used to describe the increased noise and uninformed speculative trading (usually with no direct exposure to the underlying commodity) through a range of trading activities including index investment and financial portfolio hedging and rebalancing. Given market frictions, such trading can result in price volatility and correlation between markets to an extent that does not reflect underlying fundamentals (Pavlova and Rigobon, 2008; Basak and Pavlova, 2013a). Implicit in the financialization argument is the assumption that there are binding constraints on investors or other significant frictions such as information asymmetries that lead to the persistence of market inefficiencies despite the existence of some informed players in that market. Such frictions render markets incomplete. Under such conditions, financial innovation or the introduction of even redundant assets can change equilibrium allocations and market volatility and efficiency could increase or decrease. Equilibrium outcomes in markets where arbitrageurs are constrained can be inefficient or indeterminate under a range of common market conditions.[13]

Several recent studies examine the predictive relationships between commodities and other markets, and investigate the possible impact of financialization and investor characteristics on commodity markets. Tang and Xiong (2012) find that non-energy commodities have become increasingly correlated with oil prices, and that this relationship is stronger for constituent commodities of the SP-GSCI and DJ-UBS indices. They link this trend to

[13]See, for example, Cass (1992); Bhamra and Uppal (2006); Basak, Cass, Licari, and Pavlova (2008); Gromb and Vayanos (2010).

increased financialization, (mainly via the increased investment in popular commodity indices since the early 2000s), and conclude that the underlying mechanism driving this phenomenon differs from other episodes of commodity price shocks and increased correlation, such as the crisis periods during the 1970s. Singleton (2014) surveys the recent literature in an attempt to explain the impact of trader activity on the behavior of energy markets, particularly crude oil futures prices, and finds futures open interest has important predictive power for crude oil prices, confirming the finding in Hong and Yogo (2012).

Acharya, Lochstoer, and Ramadorai (2013) consider the effect of capital-constrained speculators in a commodity futures market, where producers trade due to hedging needs and link producer default risk to inventories and prices in energy markets. They find that when speculator activity is constrained or reduced, the impact of hedging demand increases, i.e., unconstrained speculator activity will assist the absorption of producer demand shocks. Etula (2013) also finds that the risk-bearing capacity of broker-dealers is predictive of commodity risk premia.

Based on the discussion above, I empirically test several hypotheses related to limits to arbitrage and the impact of trading activity on commodity markets. These test if the effects of “financialization" during the period from January 2004 had a discernible impact on market volatility. This requires that other (possibly more informed) market participants were constrained in their capacity to step in and engage in arbitrage trading to correct any mispricing. Any alternate explanation is that increased participation makes commodity markets more efficient and liquid, correcting any mispricings that may have existed previously due to limited participation and illiquidity.

If financialization increased access to commodity futures markets by participants such as hedge funds, the comovement between futures returns and large-scale trading activity and portfolio shocks of hedge funds may have increased to such an extent that cannot be absorbed by other market participants due to borrowing constraints, illiquidity, or other market friction that introduces limits to arbitrage.

Hypothesis 3.2.8. Shocks to hedge funds during the financialization period are associated with higher commodity futures volatility.

$$\begin{aligned} Vol_{i,t} =& \mu_i + \beta_1 HF\_RISK_{t-1} + \mathbf{z}_{t-1}{'}\boldsymbol{\theta} + \beta_2 I_{[t-1 \in IndexPeriod]} \\ &+ I_{[t-1 \in IndexPeriod]} * \mathbf{z}_{t-1}{'}\boldsymbol{\theta}^{INDEX} + \beta_3 I_{[t-1 \in IndexPeriod]} HF\_RISK_{t-1} + \eta_{i,t}, \end{aligned} \tag{3.31}$$

where HF_RISK_t denotes a proxy capturing hedge fund return activity. $\beta_3 > 0$ in the specification in (3.31).

3.3 Data and Variable Definitions

In this section, I describe the data used in the empirical analysis. I include a variety of factors that are potentially relevant for commodity prices based on theory and past empirical studies (see, among others, Hong and Yogo, 2012; Engle and Rangel, 2008; Bali, Brown, and Caglayan, 2014). Along the lines of the empirical analysis in Roll (1984) and Engle and Rangel (2008), I model the unexpected shocks to economic and financial variables that are potentially related to commodity prices and test the relationship between these variables and commodity futures volatility.

3.3.1 Price, returns and volatility

I use daily closing prices for commodity options and futures obtained from Barchart.com Inc. These commodities are categorized into four groupings (Energy, Grain, Metal, and Softs), traded on NYMEX (energy), COMEX (metal), CBOT (grain), CME, CSCE, and NYCE (softs) as shown in Table 3.1. Options price data, where available, begin on January 2, 2006. I extend futures data history prior to January 3, 2005 with data from Pinnacle Data Corp. Futures data go back further for most commodities, with the earliest being July 1959 for cotton, cocoa, and all commodities except rough rice in the grain grouping. To obtain the longest time period within a balanced panel without stale prices, the main regressions exclude natural gas, propane, rough rice, soybean oil, and orange juice futures.

I calculate commodity futures returns (from holding and rolling futures) at a fixed maturity point in the term structure (1, 3, 6, 9, 12, 15, 18, 24, and 36 months) using the methodology described in Singleton (2014), and generate realized volatility time series for 1, 3, 6, 12-month horizons using these fixed-term daily returns.

3.3.2 Volatility estimation

Several recent papers have studied the observed behavior of market implied and realized volatilities, and the variation in the volatility risk premium in equity and currency markets. Of these, Engle and Rangel (2008) and Engle, Ghysels, and Sohn (2013) analyze directly the impact of macroeconomic shocks on equity volatility within GARCH-type models that decom-

[14]Month codes: F - Jan | G - Feb | H - Mar | J - Apr | K - May | M - Jun |
N - Jul | Q - Aug | U - Sep | V - Oct | X - Nov | Z - Dec |

Table 3.1: Commodity Derivative Contract and Trade Classification Information

This table shows the 22 underlying commodities in the dataset, categorized into four market groupings (Energy, Metal, Grain, and Soft). The naming convention for a futures contract is [Contract code][Expiry month code][Last digit of expiry year], e.g., On 5 January 2005, the WTI Crude Oil futures contract expiring in December 2008 is ‘CLZ8’.[14]

<table>
<tr><th>Contract Code</th><th>Exchange Code</th><th>Traded Contract Months</th><th>Commodity Name</th><th>Futures Data Start</th></tr>
<tr><td>Energy</td><td></td><td></td><td></td><td></td></tr>
<tr><td>CL</td><td>NYMEX</td><td>All months</td><td>Crude Oil</td><td>03/30/1983</td></tr>
<tr><td>HO</td><td>NYMEX</td><td>All months</td><td>Heating Oil</td><td>11/14/1978</td></tr>
<tr><td>NG</td><td>NYMEX</td><td>All months</td><td>Natural Gas</td><td>04/04/1990</td></tr>
<tr><td>PN</td><td>NYMEX</td><td>All months</td><td>Propane</td><td>01/03/2005</td></tr>
<tr><td>Metal</td><td></td><td></td><td></td><td></td></tr>
<tr><td>GC</td><td>COMEX</td><td>G | J | M | Q | V | Z</td><td>Gold</td><td>12/31/1974</td></tr>
<tr><td>SI</td><td>COMEX</td><td>H | K | N | U | Z</td><td>Silver</td><td>06/12/1963</td></tr>
<tr><td>HG</td><td>COMEX</td><td>H | K | N | U | Z</td><td>Copper</td><td>01/03/1989</td></tr>
<tr><td>PA</td><td>NYMEX</td><td>H | M | U | Z</td><td>Palladium</td><td>01/03/1977</td></tr>
<tr><td>PL</td><td>NYMEX</td><td>F | J | N | V</td><td>Platinum</td><td>03/04/1968</td></tr>
<tr><td>Grain</td><td></td><td></td><td></td><td></td></tr>
<tr><td>W</td><td>CBOT</td><td>H | K | N | U | Z</td><td>Wheat</td><td>07/01/1959</td></tr>
<tr><td>C</td><td>CBOT</td><td>H | K | N | U | Z</td><td>Corn</td><td>07/01/1959</td></tr>
<tr><td>O</td><td>CBOT</td><td>H | K | N | U | Z</td><td>Oats</td><td>07/01/1959</td></tr>
<tr><td>S</td><td>CBOT</td><td>F | H | K | N | Q | U | X</td><td>Soybeans</td><td>07/01/1959</td></tr>
<tr><td>SM</td><td>CBOT</td><td>F | H | K | N | Q | U | V | Z</td><td>Soybean Meal</td><td>07/01/1959</td></tr>
<tr><td>BO</td><td>CBOT</td><td>F | H | K | N | Q | U | V | Z</td><td>Soybean Oil</td><td>07/01/1959</td></tr>
<tr><td>RR</td><td>CBOT</td><td>F | H | K | N | U | X</td><td>Rough Rice</td><td>08/20/1986</td></tr>
<tr><td>Soft</td><td></td><td></td><td></td><td></td></tr>
<tr><td>CT</td><td>NYCE</td><td>H | K | N | V | Z</td><td>Cotton</td><td>07/01/1959</td></tr>
<tr><td>OJ</td><td>NYCE</td><td>F | H | K | N | U | X</td><td>Orange Juice</td><td>02/01/1967</td></tr>
<tr><td>KC</td><td>CSCE</td><td>H | K | N | U | Z</td><td>Coffee</td><td>08/16/1972</td></tr>
<tr><td>SB</td><td>CSCE</td><td>H | K | N | V</td><td>Sugar</td><td>01/04/1961</td></tr>
<tr><td>CC</td><td>CSCE</td><td>H | K | N | U | Z</td><td>Cocoa</td><td>07/01/1959</td></tr>
<tr><td>LB</td><td>CME</td><td>F | H | K | N | U | X</td><td>Lumber</td><td>10/01/1969</td></tr>
</table>

pose volatility into short-term and long-term components, and identify several macroeconomic variables with significant impact on low and high-frequency equity volatility. Ang, Hodrick, Xing, and Zhang (2006, 2009) study the cross-sectional variation in risk premia and idiosyncratic volatility and find a significant positive relationship between the two. Campbell, Giglio, Polk, and Turley (2012) include stochastic volatility in an intertemporal CAPM framework and conclude that volatility risk is priced in US stocks and may explain stock return anomalies such as the value premium. Previous empirical studies on market volatility have mainly concentrated on the S&P500 index, individual US stocks, and currency markets for a variety of reasons including easy access to the relevant data, long time periods, liquidity, coverage in time-strike space (for implied volatility), etc. A similar systematic analysis of commodity volatility remains a potentially rich area for furthering our understanding of these markets.

A flexible, first-pass estimate for the volatility of an asset over a certain period is its realized volatility over that horizon. Similar to the convention for returns in Singleton (2014), I denote the d-day rolling return of the (fixed-term) f-month future of commodity i as $R_{i,t}^{fFdD}$. For example, the 5-day rolling return of the (fixed-term) 3-month commodity future at time t is denoted $R_{i,t}^{3F5D}$. Consequently, the realized volatility of d-day returns of the f-month commodity future at time t, over a horizon of m months, is defined as the annualized standard deviation over that period, $\sigma_{i,t} \approx Vol_{i,t}^{fFdDmM}$, where $d \in \{1, 3, 5, 21\}$ is the frequency in days of the return series used to construct the volatility series and the volatility horizon in months, $m \in \{1, 3, 6, 9, 12, 15, 18, 24, 36\}$, with a week, month, and year, defined as 5, 21, and 252 trading days, respectively.[15] The baseline panel regressions use the (non-overlapping) end-of-month (EOM) volatility of daily returns of the 1-month future, $Vol_{i,t} = Vol_{i,t}^{1F1DEOM}$ as the dependent variable, except where I explicitly state otherwise. The augmented Dickey-Fuller test (ADF) rejects the existence of a unit root in $Vol_{i,t}$ for all commodities in the sample (Table 3.A3 in the Appendix). The baseline predictive regressions take the form,

$$Vol_{i,t} = \mu + \alpha \left|r_{i,t-1}\right| + \beta Vol_{i,t-1} + \mathbf{z}_{i,t-1}{}'\boldsymbol{\theta} + \eta_{i,t}, \tag{3.34}$$

where $r_{i,t} = R_{i,t}^{1F21D}$, $\mathbf{z}_{i,t}$ is a vector of K (non-negative) explanatory variables, α, β, and the vector $\boldsymbol{\theta}$ denote regression coefficients. In Appendix 3.6.2, I discuss the related volatility models and empirical work that attempt to explain realized volatility with economic variables, which inform the framework of my analysis and its future extensions.

Table 3.2 shows summary statistics for the realized volatility of the commodity futures in this study. Panel A shows the mean and standard deviation of 1-month ("short-term") and 12-month ("long-term") realized volatility for the three maturity points on the futures curve (1M, 3M, and 12M). Plots of short-term and long-term realized volatility for the entire term structure are shown in Figures 3.1 and 3.5 for crude oil, copper, gold, natural gas, wheat,

[15] By this definition,

$$Vol_{i,t}^{fFdDmM} = \sqrt{\frac{252}{d}} \left[\frac{1}{N}\sum_{p=1}^{N} \left(R_{i,t-N+p}^{fFdD}\right)^2 - \left(\frac{1}{N}\sum_{p=1}^{N} R_{i,t-N+p}^{fFdD}\right)^2 \right]^{\frac{1}{2}}, \tag{3.32}$$

$$Vol_{i,t}^{1F1D1M} = \sqrt{\frac{252}{1}} \left[\frac{1}{21}\sum_{p=1}^{21} \left(R_{i,t-21+p}^{1F1D}\right)^2 - \left(\frac{1}{21}\sum_{p=1}^{21} R_{i,t-21+p}^{1F1D}\right)^2 \right]^{\frac{1}{2}}, \tag{3.33}$$

where $N = m * \frac{21}{d}$ is the number of d-day return periods in m months. The factor $\frac{252}{d}$ annualizes the volatility.

and lumber.

Table 3.2: Commodity Futures Volatility Summary Statistics
This table shows the summary statistics of volatility of daily returns for each commodity future at 1-month (1M), 3-month (3M) and 12-month (12M) maturities. This includes the mean and standard deviation of short-term (1-month) and long-term (12-month) realized volatility for the full trading history of each commodity until December 31, 2011 (see Table 3.1 for futures data start dates by commodity). The standard deviation is a measure of the volatility of volatility. In the Appendix, I show the same summary statistics by decade.

	Mean			Standard Deviation		
	1M	3M	12M	1M	3M	12M
Crude	30.054	26.531	22.033	16.249	13.670	11.775
Heating Oil	29.102	25.800	21.814	14.103	11.846	10.270
Natural Gas	44.508	34.208	20.631	19.003	13.614	10.150
Gold	16.966	16.846	16.617	9.991	9.460	9.095
Silver	28.114	26.830	26.122	15.884	12.785	12.449
Palladium	28.896	28.258	28.305	14.481	13.604	13.305
Platinum	24.005	23.520	23.049	13.261	11.432	10.760
Copper	25.295	24.794	21.629	11.214	11.228	11.06
Wheat	23.868	22.889	19.641	10.571	10.453	10.335
Corn	20.269	19.881	17.761	10.411	10.069	9.321
Oat	27.939	26.060	20.689	10.978	9.776	9.517
Soybeans	21.065	20.519	18.227	11.248	10.022	9.920
Soybean Meal	23.704	22.763	20.010	13.211	12.253	12.205
Soybean Oil	24.322	23.790	20.921	10.269	9.919	10.170
Cotton	23.584	21.767	16.582	10.118	8.684	8.764
Coffee	32.138	30.115	25.745	15.885	14.351	11.438
Sugar	38.880	35.493	27.793	18.477	13.884	13.416
Cocoa	29.285	27.959	24.283	9.565	9.126	8.186
Lumber	27.263	24.579	18.635	8.586	7.703	7.426

Relative to commodities in energy, grain and softs, precious metals broadly show little variation in average volatility by contract month. This is also evident in the figures plotting realized volatility for the futures terms structures over time (Figures in 3.1 and 3.5). This is indicative of parallel shifts to the forward curve being more common for metals than for commodities in other groups. For crude oil, natural gas, wheat, orange juice, and lumber, etc., the contracts in the nearer term are more volatile than longer-dated contracts. This difference is potentially a risk characteristic driven by underlying fundamentals - inventory, storability and the nature of the demand for a particular commodity. Relative to other commodity groups, metals are highly storable (dense and durable), easy to transport, and less exposed to supply-demand uncertainty due to weather or geopolitics. Casassus and Collin-Dufresne (2005), in addressing the disparities between the dynamics of convenience yields and futures term structure of crude oil and copper versus gold and silver, hypothesize that oil and copper have a primary function as inputs to production, whereas the latter two commodities are primarily stores of value. In this case, demand shocks driven by the prevailing economic conditions would drive price fluctuations in production commodities to a greater extent, and create greater variation along the term structure.

Table 3.3 shows that commodities generally exhibit volatility asymmetry in the opposite direction to equities, with significant gamma coefficients all negative. As documented by Bekaert and Wu (2000); Bollerslev and Todorov (2011) and others, equity indices tend to become more volatile as the price drops, to a greater extent than with index price increases, giving rise to positive gamma coefficients in GJR-GARCH(1,1) specifications. The causes commonly cited for this phenomenon in equities include financial and operating leverage effects, time-varying risk premia, and volatility feedback mechanisms. For commodities, volatility increases are generally larger with large price increases, and this effect merits further study. It appears likely that this effect is greater for commodities with increased inventory risk. In that case, such commodities would also show greater variation in the term structure of volatility.

Table 3.3: GARCH(1,1) and GJR-GARCH(1,1) Fits

This table shows the parameter and fit estimates of GARCH(1,1) and GJR-GARCH(1,1) models of commodity futures volatility, and for comparison, other financial data series. The first three rows show results from fitting daily log returns of the S&P 500 index, the FTSE 100 index, and the US-GBP exchange rate. Energy, Grain, Metal, Soft and All correspond to equal-weighted indices of the constituent commodity futures as shown in the grouping in Table 3.1. The LRT column shows the likelihood ratio test statistic (K - K'=1, critical value (at $\alpha = 0.05$) is 3.841). The series cover the period from September 1988 to December 2011, yielding 5,636 observations of daily log returns.

	GARCH (1,1)				GJR-GARCH(1,1)					LRT
	Omega	Alpha	Beta	LL	Omega	Alpha	Beta	Gamma	LL	
S&P 500	0.010	0.068	0.925	-7,692.3	0.017	0.010	0.918	0.117	-7,618.7	147.2
FTSE 100	0.018	0.086	0.904	-8,474.5	0.022	0.028	0.913	0.090	-8,434.9	79.2
USD-GBP	0.003	0.038	0.954	-4,890.1	0.003	0.032	0.953	0.011	-4,888.5	3.2
All Commodities	0.003	0.039	0.957	-6,339.4	0.002	0.045	0.959	-0.012	-6,337.4	4.0
Grain	0.017	0.069	0.923	-9,056.4	0.014	0.081	0.929	-0.032	-9,048.8	15.2
Metal	0.011	0.055	0.937	-8,107.8	0.010	0.062	0.938	-0.014	-8,106.1	3.4
Energy	0.052	0.073	0.917	-11678.0	0.051	0.076	0.919	-0.009	-11,677.0	2.0
Softs	0.035	0.057	0.913	-8,177.7	0.035	0.059	0.912	-0.003	-8,177.7	0.0

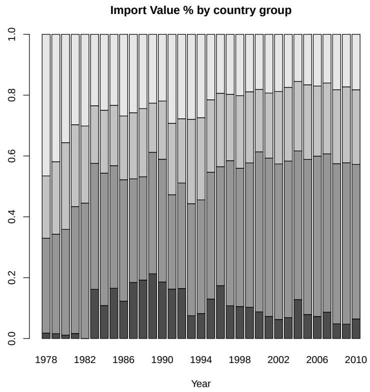
3.3.3 Commodity supply-demand

The main source of data used for global commodity trade flows is UN Comtrade. I match each of the commodity futures contracts in the study to a particular commodity code in UN Comtrade, determined as being most closely related to the underlying commodity. The commodity product classification used is the Standard International Trade Classification (SITC) Revision 2, in order to obtain the longest possible time series (see Appendix Table 3.A1). The global bilateral trade flow information for the matched commodity is the proxy used for the aggregate supply and demand for the commodity underlying the futures contracts. I document the changes to global commodity supply and demand since 1973 for these matched commodities.

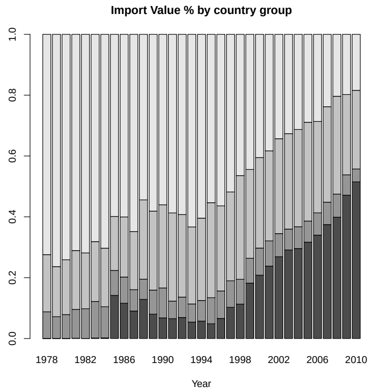
Figure 3.3 illustrates corresponding trends in trade by emerging countries in several commodities markets using annual UN Comtrade from 1978 to 2010. The figures show the trade value as a percentage of total world trade for BRIC, non-OECD excluding BRIC, OECD excluding G7, and G7 countries, for wheat, lumber, cotton, crude oil, copper, and aluminum. For most commodities in the dataset, the percentage of total world trade value for both imports and exports increased for BRIC countries and decreased for G7 countries during the past decade.

I construct measures of concentration and economic uncertainty for commodity consumers and producers for each commodity as defined in Eq. (3.22) and Eq (3.23). It is common that both the supply and demand side of global trade in a commodity are dominated by a handful of countries. As a result, it is possible to take the set of largest exporters and largest importers for each year to characterize the global supply and demand dynamics for each commodity. In constructing trade-weighted indices for producers (consumers) for a particular commodity as in (3.23) and (3.35), I take the set of (minimum five) countries that constitute at least 50% of the total global exports (imports) of that commodity when constructing the producer (consumer) index. In this case, $C\_HHI_{i,t} \approx H^{C}_{i,t}$, $C\_HHI\_EM_{i,t} \approx H^{C\_EM}_{i,t}$, $P\_HHI_{i,t} \approx H^{P}_{i,t}$, and $P\_HHI\_EM_{i,t} \approx H^{P\_EM}_{i,t}$. The empirical results are robust to the choice of these levels.

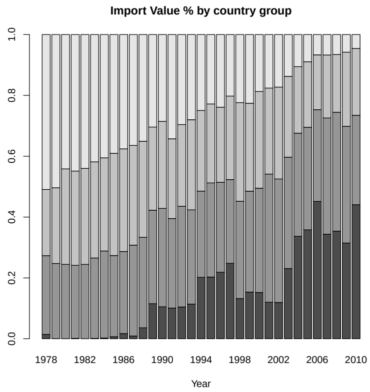
I obtain seasonally-adjusted quarterly GDP growth rate series using raw data from IMF International Financial Statistics (IFS). I discard any country without at least nine quarterly GDP observations and obtain a dataset of 81 countries. The GDP volatility for producers ($P\_VOL_{i,t}$) and consumers ($C\_VOL_{i,t}$) for commodity i at time t is constructed by averaging over the squared absolute value of the innovations from an AR(1) fit of all exporters and importers, respectively. For a country j, the trade weights are as defined



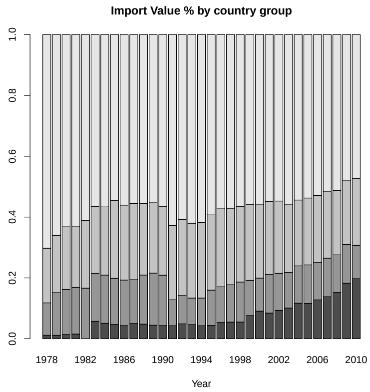
(a) Wheat



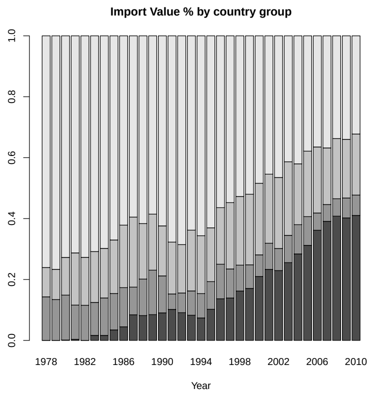
(b) Lumber



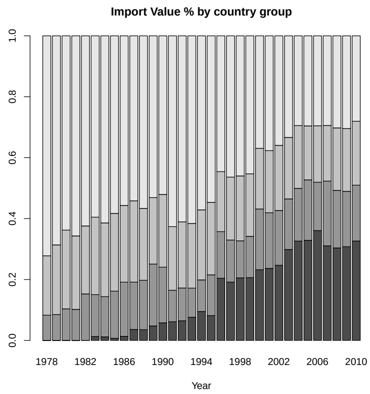
(c) Cotton



(d) Crude Oil



(e) Copper



(f) Aluminum

Figure 3.3: Time series of import value as a percentage of total world imports broken down by country group.

The four groups shown are, from the bottom (darkest to lightest shading): BRIC, non-OECD excluding BRIC, OECD excluding G7, and G7 countries, respectively.

in Eqs. (3.20) and (3.21).

$$\begin{aligned}\Delta log(GDP)_{j,t} =& \mu_j + \rho_j \Delta log(GDP)_{j,t-1} + \epsilon_{j,t}, \\ \sigma^2_{j,t} =& \frac{1}{4} \sum_{k=t-3}^{t} \left| \epsilon_{j,t} \right|^2, \\ C\_ \, VOL_{i,t} =& \left[\sum_{j=1}^{N} \left(w^I_{i,j,t} \right)^2 \sigma^2_{j,t} \right]^{\frac{1}{2}}. \end{aligned} \tag{3.35}$$

Building on findings that link commodity currency returns to commodity futures returns,[16] I construct producer and consumer FX volatility series as an explanatory variable: $P\_FX_{i,t} = \left[\sum_{j=1}^{N} \left(w^E_{i,j,t} \right)^2 x^2_{j,t} \right]^{\frac{1}{2}}$, and the corresponding series for $C\_FX_{i,t}$ for importers, where $x_{j,t}$ is the return at time t of the US dollar exchange rate of the country j currency. All exchange rate data are collated from Datastream and the Federal Reserve Board to obtain the longest available time series.

3.3.4 Market activity

I obtain information on the evolution of different types of traders (classified as commercial (hedger), non-commerical, spread, or non-reporting (small) traders) and their activity in commodity markets from the Commitment of Traders (COT) reports made available by the US Commodity Futures Trading Commission (CFTC). Figure 3.4 shows the variation in the type of traders holding outstanding long and short positions in commodities, from January

[16] Chen, Rogoff, and Rossi (2010) find that the exchange rates of countries which are the major exporters of commodities strongly predict world commodity prices, while the reverse relationship is weaker. They find some evidence that “commodity currency" returns Granger-cause global commodity futures returns. This has implications in terms of commodity price hedging, especially for commodities whose forward markets have reduced horizon and depth.

1986 or December 2011. While the fraction of commercial traders' (hedgers') positions has not changed markedly, the fraction of outstanding spread positions (which trade the basis) has increased substantially. Moreover, the imbalance in commercial positions generally appears to be the opposite of the imbalance in non-commercial positions.

The set of variables identified from previous work that examines the impact of speculator activity on commodity futures returns (Hong and Yogo, 2012; Acharya, Lochstoer, and Ramadorai, 2013) used as explanatory variables in $\mathbf{z}_{i,t}$ include changes to open interest and demand imbalance, e.g., using commercial ("hedger") position values collated by the CFTC, $HEDGER\_IMB_{i,t} = \frac{ShortOI_{i,t} - LongOI_{i,t}}{ShortOI_{i,t} + LongOI_{i,t}}$.[17]

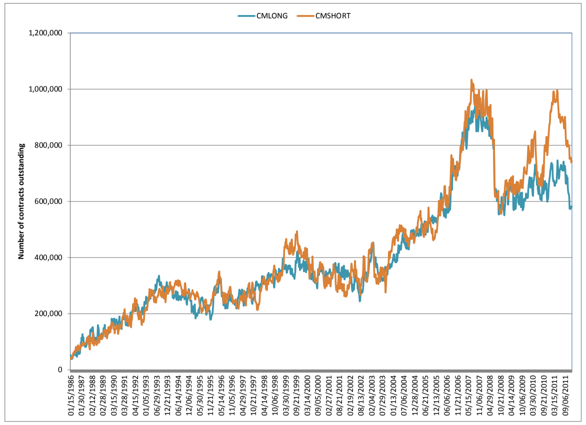
I use an indicator for the period beginning January 2004, commonly cited in previous work as the period showing index "financialization" (see, for example, Tang and Xiong, 2012; Singleton, 2014), as $IndexPeriod_t$, when testing for changes in the dynamics of volatility due to commodity index trading.

Finally, the state of the hedge funds industry is captured using the absolute value of the mean of monthly hedge funds returns (HF_RET_t) using hedge fund data collated from the Lipper-TASS, BarclayHedge, Morningstar, HFR and CISDM databases.

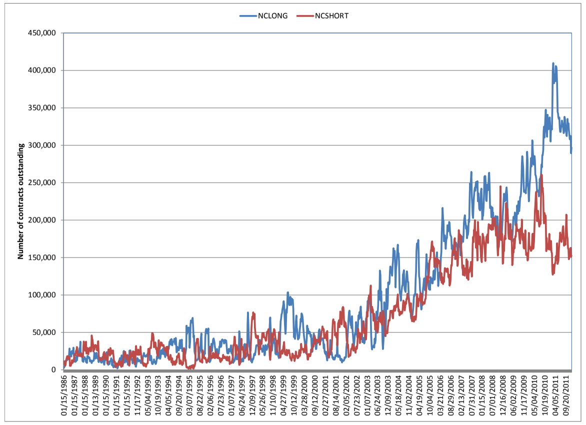
3.3.5 Macroeconomic uncertainty indicators

I use the IMF World Economic Outlook Database for aggregate economic variables, and the IMF Direction of Trade Statistics for country-to-country aggregate import/export data. Both of these sources provide data at an annual

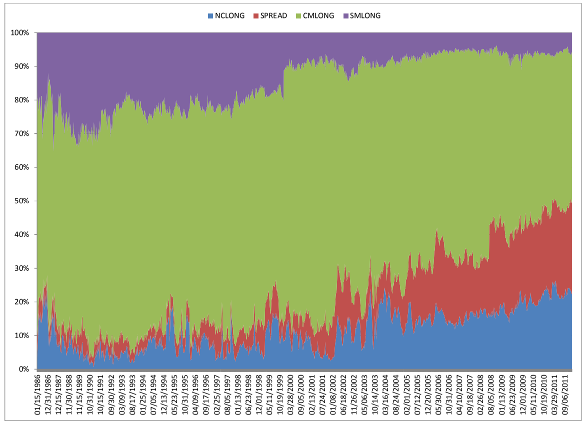
[17] Hong and Yogo (2012) investigate the power of futures open interest to predict commodity, currency, stock, and bond prices, and find open interest growth is more informative than other common alternatives as it is reflective of future economic activity.



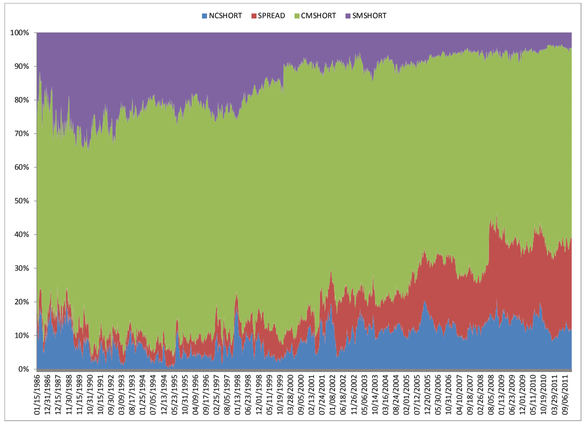
(a) Commercial (hedger) contracts



(b) Non-commercial contracts



(c) Breakdown by trader type - long positions



(d) Breakdown by trader type - short positions

Figure 3.4: The evolution of contract positions for Crude Oil futures broken down by trader type in CFTC Commitment of Traders (COT) reports.

frequency. All interest rates and exchange rates are from the Global Financial Database (GFD) and Datastream. Wherever necessary, World Bank classifications are used to group world economies.[18] The US GDP and CPI (quarterly) forecast statistics are from the Philadelphia Federal Reserve Bank's Survey of Professional Forecasters. Economic forecasts for other countries are from analyst forecasts collated in Bloomberg. US recession period data are from NBER.

The choice of variables used in constructing the macroeconomic uncertainty series is motivated by previous studies (Campbell and Shiller, 1988; Campbell, Giglio, Polk, and Turley, 2012; Bali, Brown, and Caglayan, 2014; Bloom, 2014). *INF_U* - US inflation from change in consumer price index. *INFFC_A* - Survey of Professional Forecasters, dispersion in next quarter CPI forecasts. *TERM_U* - Spread between 10-year and 3-month Treasury yields. *RREL_U* - Difference between 3-month Treasury yield and its 12-month geometric mean. *DEF_U* - Baa-Aaa (Moody's) rated corporate bond yield spread. *TED_U* - 1M LIBOR - 1M-T-Bill rates. *UNEMP_U* - US unemployment rate. *GDP_U* - US real GDP growth rate per capita. *CFNAI_U* - Chicago Fed Economic Activity Index. *RDIV_U* - Aggregate real dividend yield on S&P 500. *MKT_U* - S&P 500 index excess return. *VXO_A* - S&P 100 implied volatility index level.

These variables are available from January 1960 to the end of the sample period, except for CFNAI (from May 1967), TED (from January 1971) and VXO (from January 1986). X_U_t denotes the one period-ahead GARCH(1,1) volatility prediction of variable X made using all available observations up to time $t-1$ and X_A_t denotes the AR(1) forecast made using all available

[18]WB Country and Lending Groups Page (http://data.worldbank.org/about/country-classifications/country-and-lending-groups).

observations up to time $t - 1$.

3.4 Empirical Results

3.4.1 Consumer and producer impact

Table 3.4 shows the results of regressions using as explanatory variables consumer and producer trade-weighted indices that capture supply-demand uncertainty and vulnerability to shocks. Panel A shows the results with year-over-year changes of the Herfindahl indices. Panel B shows results with trade-weighted volatility indices of consumer and producer shocks. In Panel A, columns 1 to 3 show results from regressions including the change in the Herfindahl index of all major trading countries (HHI_ALL), without separating out non-OECD countries. Under all three regression specifications, only the consumer Herfindahl index has a positive significant coefficient with a t-statistic of 3.57, while the coefficient for producer concentration is not significant. This is in line with the predictions set forth in section 3.2.2. There is a significant impact on futures volatility from consumer concentration. Next, I consider the heterogeneity in shocks between the two groups, OECD and non-OECD.

Columns 4 to 6 in Table 3.4 show the same regressions with only non-OECD countries (HHI_EM), with the weights of OECD countries replaced with zero in the index. Again, the coefficient on the non-OECD consumer concentration index (CONS_HHI_EM) is the only one that is positive and significant, with a t-statistic of 6.38. The final three columns show the results when all four indices are included. The coefficient for CONS_HHI_EM remains essentially unchanged, with a t-statistic of 4.71. These results imply

Table 3.4: Commodity Futures Volatility - Producer and Consumer Uncertainty

This table shows results for the balanced panel regressions of 1-month volatility of the front-month futures return, Vol(t), as the dependent variable in regressions 1 through 9 in Panels A and B. The regressions shown in Panel A include year-over year changes to producer (exporter) and consumer (importer) concentration indices as the independent variables. The possible values of the HHI concentration indices range from 0 to 1, so that the change in the concentration index is between -1 and 1. Panel B regressions include the trade-weighted volatility indices for producer and consumer country shocks (to quarterly GDP). The results reported here are for all commodities over the entire period of the sample (262 months) for 4,454 commodity-month observations. All regressions include commodity and season (month) fixed effects. Return variables are in percentage. t-statistics clustered by month are shown in parenthesis below each coefficient estimate.

	1	2	3	4	5	6	7	8	9
Panel A: Changes to producer and consumer concentrations in global trade									
$\Delta PROD\_HHI\_ALL_{(t)}$	-0.138		-0.129				-0.235**		-0.228*
	(-1.415)		(-1.303)				(-2.032)		(-1.949)
$\Delta PROD\_HHI\_EM_{(t)}$				0.045		0.050	0.252		0.251
				(0.336)		(0.369)	(1.617)		(1.605)
$\Delta CONS\_HHI\_ALL_{(t)}$		0.365***	0.360***					0.009	-0.004
		(3.571)	(3.496)					(0.067)	(-0.032)
$\Delta CONS\_HHI\_EM_{(t)}$					1.192***	1.192***		1.183***	1.192***
					(6.383)	(6.391)		(4.653)	(4.709)
Adjusted R-squared	0.162	0.164	0.164	0.161	0.170	0.170	0.162	0.170	0.170
BIC	34,943.1	34,932.2	34,938.3	34,945.6	34,899.7	34,908.0	34,949.0	34,908.1	34,920.1
Panel B: Trade-weighted volatility indices of producer and consumer shocks									
$PROD\_VOL\_ALL_{(t)}$	0.094*		0.072				0.023		0.028
	(1.750)		(1.417)				(0.291)		(0.365)
$PROD\_VOL\_EM_{(t)}$				0.099**		0.082**	0.083		0.054
				(2.518)		(2.215)	(1.410)		(0.929)
$CONS\_VOL\_ALL_{(t)}$		0.165***	0.158***					0.113**	0.105**
		(3.589)	(3.614)					(2.567)	(2.495)
$CONS\_VOL\_EM_{(t)}$					0.462***	0.451***		0.405***	0.401***
					(6.327)	(6.375)		(6.190)	(6.150)
Adjusted R-squared	0.163	0.167	0.168	0.163	0.173	0.175	0.163	0.176	0.177
BIC	34,938.2	34,913.5	34,917.6	34,935.0	34,880.9	34,881.9	34,943.2	34,875.0	34,885.8

that a 1% gain in market concentration by developing country consumers is associated with a 1.19% gain in commodity futures volatility in this period. Regardless of the idiosyncratic variation within the two groups of consumers, controlling for the heterogeneity across the two groups allows us to capture the differential impact of emerging market countries on commodity volatility. These findings are in agreement with previous work that finds emerging markets pose greater uncertainty (Bloom, 2014). These results show how this uncertainty may affect commodity futures. These results showing the significance of non-OECD consumers are robust to using the level or change in HHI indices and the inclusion of year fixed effects.

Next, using conditional GJR-GARCH fits of commodity futures returns, I examine the time-variation in the asymmetric relationship between returns and volatility, and analyze how this relates to the commodity basis and sensitivity to consumer and producer shocks (hypothesis 3.2.6).

3.4.2 Macroeconomic uncertainty

Tables 3.5 to 3.8 show the results from balanced panel regressions of the (time, t) 1-month realized volatility of the front-month futures return over lagged (time, $t-1$) explanatory variables, as specified in Eq. (3.34). The volatility series are at a non-overlapping monthly frequency. The results shown are for the commodity groups: Energy, Metal, Grain, Softs, and All (of the 17 commodities in the sample, see section 3.3.1). The panel regressions all include commodity and seasonal (month-of-year) fixed effects, and t-statistics clustered by month are shown in parenthesis below each coefficient estimate. All regressions for a particular dependent variable include observations on the same dates, allowing for the comparison of information criterion.[19]

In Table 3.5, Panel A shows the baseline regressions with only lagged (time, $t-1$) volatility and lagged (absolute) return as explanatory variables (Vol and $Return$). This is similar in concept to a GARCH(1,1) formulation, broadly capturing the same information set at time $t-1$. The coefficients are positive and highly significant. This is similar to empirical observations of equity, bond and other financial markets. In Panel B, I include the variable $PositiveReturn$, which is the return series with negative values replaced with zero. This formulation is similar to a GJR-GARCH(1,1) specification (see Eq. (3.45)) and allows for the capture of any asymmetric affect on volatility from the direction of the lagged return. Similar to the model fits in Table 3.3, these results also show that, unlike in the case of equities (Bekaert and Wu, 2000), there is no unconditional directional bias in the relationship between lagged return and volatility for commodity futures. Given the information contained in this asymmetric effect on the concentration and direction of risk and investor demand (Bekaert and Wu, 2000; Bollerslev and Todorov, 2011; Garleanu, Pedersen, and Poteshman, 2009), the conditional variation in this relationship bears further study in the commodities space. In later analysis, I examine the impact of demand and supply shocks on the conditional variation in this relationship using the specification in Eq. (3.30).

In Table 3.6, I add the variables capturing macroeconomic uncertainty. This results in an adjusted R-squared gain of over 10% (for the Energy group)

[19] In the discussion of regression results that follow, model fit is considered using likelihood ratio tests, denoted LRT (Neyman and Pearson, 1933; Wilks, 1938; Engle, 1984), and Schwarz Bayesian information criteria (also known as the Bayesian information criterion), denoted BIC (Schwarz, 1978). LRT can be used to compare two nested models. More generally, a comparison using BIC is possible when the LHS dependent variable is exactly the same, even when two models do not nest. The standard errors shown in the panel regression results are clustered by month (Petersen, 2009).

Table 3.5: Commodity Futures Volatility - Panel Regression Results

This table shows the results for balanced panel regressions of (time, t) 1-month volatility of the front-month futures return, $Vol_{(t)}$, over lagged (time, $t-1$) volatility and (absolute) return. $PostiveReturn$ is the absolute return series of the front month future with the negative return months set to 0. The results reported here are for the groups Energy, Metal, Grain, Soft, and All commodities. All regressions include commodity and season (month) fixed effects. Return variables are in percentage. t-statistics clustered by month are shown in parenthesis below each coefficient estimate.

	Energy	Metal	Grain	Soft	All
Panel A: Baseline panel regression					
$(Intercept)$	20.671	6.765	10.213	16.249	11.335
	(4.571)	(5.084)	(7.897)	(8.419)	(10.582)
$\lvert Return_{(t-1)}\rvert$	0.617	0.416	0.227	0.371	0.391
	(4.074)	(3.321)	(3.137)	(4.119)	(6.781)
$Vol_{(t-1)}$	0.412	0.478	0.520	0.336	0.428
	(4.872)	(8.795)	(12.203)	(5.458)	(10.647)
Adjusted R-squared	0.343	0.437	0.419	0.252	0.395
Number of commodity-months	524	1,310	1,310	1,310	4,454
Panel B: Baseline panel regression allowing for asymmetric return effect					
$(Intercept)$	20.739	6.768	10.227	16.260	11.349
	(4.606)	(5.087)	(7.892)	(8.567)	(10.546)
$\lvert Return_{(t-1)}\rvert$	0.721	0.399	0.208	0.297	0.362
	(4.125)	(3.040)	(2.409)	(2.329)	(4.490)
$I_{[Return_{(t-1)}>0]} * \lvert Return_{(t-1)}\rvert$	-0.141	0.025	0.031	0.118	0.044
	(-0.733)	(0.145)	(0.313)	(1.094)	(0.525)
$Vol_{(t-1)}$	0.400	0.479	0.520	0.338	0.429
	(4.851)	(8.628)	(12.159)	(5.629)	(10.833)
Adjusted R-squared	0.343	0.436	0.419	0.253	0.395
Number of commodity-months	524	1,310	1,310	1,310	4,454
LRT statistic	1.60	0.20	0.20	3.20	1.40
$c[(K-K'=1),(\alpha=0.05)]=3.841$					

from the baseline specification in Table 3.5, Panel A. Other comparisons of model fit such as BIC and LRT also show a clear improvement for the commodities in the Energy, Metal, Grain, and All groups. The Softs group has the smallest gain in proportion of explained variation. The inclusion of economic controls consistently improves the adjusted R-squared and information criterion measures of model fit. $INFFC\_A$, $CFNAI\_U$ and $RDIV\_U$ have positive and significant coefficients in the regression including all commodities.[20] These results are in agreement with the implications of the derivation in section 3.2.1, which show that variation in commodity futures volatility arise due to changes to the expectations of future interest rates, convenience yield and risk premia. The inflation variables capture information about future interest rates and is informative of future economic and inflation regimes (David and Veronesi, 2013). Economic activity is related to the convenience yield (Casassus and Collin-Dufresne, 2005). The results including controls for recession periods (section 3.4.4) also capture the variation in risk premia associated with the business cycle. Moreover, these findings broadly confirm observations on the effects of uncertainty in other markets (Bloom (2014)).

It is difficult to contemporaneously explain, let alone predict, financial asset volatility using economic factors (see, for example, Roll (1984); Schwert (1989); Engle and Rangel (2008); Engle, Ghysels, and Sohn (2013)), even when model results and economic intuition posit a relationship between economic conditions and volatility. As such, the results in Table 3.6 constitute a step forward in our understanding of the factors that drive volatility.

Moreover, such predictive power is economically significant for a mean-

[20] See Table 3.A7 of the Appendix for the results of Granger causality tests, which show that the direction of predictive causality is from the economic uncertainty variables included here to commodity futures volatility, rather than vice versa.

Table 3.6: Commodity Futures Volatility and Macroeconomic Uncertainty

This table shows the results for balanced panel regressions of (time, t) 1-month volatility of the front-month futures return, $Vol_{(t)}$, over lagged (time, $t-1$) explanatory variables that capture macroeconomic uncertainty. These variables are the first four principal components of 11 lagged macroeconomic uncertainty series (Table 3.A4 and 3.A5 in the Appendix contain details of this PCA). The results reported here are for the groups Energy, Metal, Grain, Soft, and All commodities. All regressions include commodity and season (month) fixed effects. Return variables are in percentage. t-statistics clustered by month are shown in parenthesis below each coefficient estimate. The LRT row shows the likelihood ratio test statistic comparing the fit shown in Table 3.5.A to the current results.

	Energy	Metal	Grain	Softs	All
$PC1_{(t-1)}$	-2.166***	-1.030***	-0.890***	-0.630***	-0.952***
	(-4.975)	(-4.723)	(-4.991)	(-4.552)	(-6.934)
$PC2_{(t-1)}$	-1.356**	-0.417	0.037	0.380	-0.155
	(-2.139)	(-1.473)	(0.123)	(1.468)	(-0.759)
$PC3_{(t-1)}$	2.261***	0.538*	0.291	0.426*	0.586***
	(4.616)	(1.903)	(1.114)	(1.749)	(3.968)
$PC4_{(t-1)}$	1.188**	1.690***	1.513***	-0.320	0.977***
	(2.005)	(5.011)	(3.981)	(-0.997)	(4.489)
All predictors in Table 3.5	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.442	0.474	0.459	0.263	0.423
Number of commodity-months	524	1,310	1,310	1,310	4,454
LRT statistic	90.0	93.2	97.4	24.2	217.2
$c[(K-K'=4),(\alpha=0.05)]=9.488$					

variance investor (see, for example, Campbell and Thompson (2008); Inoue and Kilian (2004) and Moskowitz, Ooi, and Pedersen (2012) for further discussion on the value of time series predictability). An adjusted R-squared gain over the baseline model is useful for investors who have a non-zero "vega" exposure in their portfolio ($\frac{\delta V}{\delta \sigma} \neq 0$ in a portfolio with value V and volatility σ) as, in that case, predicting volatility allows for the prediction of portfolio and position values. This is important for any hedger or derivatives trader as the value of their portfolios and trading strategies is directly tied to the volatility of the traded assets.

For tractability, in the regressions that follow, I use the first four principal components to capture the variation of the 11 economic uncertainty series in the main regressions. Table 3.A4 of the Appendix presents the details of the principal component analysis. The panels in Table 3.A5 show the regressions results with varying numbers of principal components included.[21] In future work, I include uncertainty proxies directly based on work by Jurado, Ludvigson, and Ng (2014).

3.4.3 Hedging and trading activity

Table 3.7 shows the results once the variables capturing momentum and hedging activity (Hong and Yogo, 2012; Acharya, Lochstoer, and Ramadorai, 2013) are added to the specification in Table 3.6, which include the macroeconomic controls. While there is some improvement, there is no consistent gain in predictive power. Table 3.A6 of the Appendix shows the results without the inclusion of the macroeconomic controls. The regressions adding only economic uncertainty variables to the baseline specification as in Table

[21] See Bai and Ng (2002); Stock and Watson (2002) on selecting the appropriate number of factors.

3.6 perform better on the dimensions of adjusted R-squared and information criterion measures of model fit.

Table 3.7: Commodity Futures Volatility and Commodity Market Risk Factors

This table shows the results for balanced panel regressions of (time, t) 1-month volatility of the front-month futures return, $Vol_{(t)}$, over lagged (time, $t-1$) commodity market variables in addition to the macroeconomic uncertainty factors included in Table 3.6. The results reported here are for the groups Energy, Metal, Grain, Soft, and All commodities. All regressions include commodity and season (month) fixed effects. Return variables are in percentage. t-statistics clustered by month are shown in parenthesis below each coefficient estimate. The LRT row shows the likelihood ratio test statistic comparing the fit shown in Table 3.6 to the current results.

	Energy	Metal	Grain	Softs	All
$CMOM_{(t-1)}$	0.804	4.009***	0.503	-0.615	1.767***
	(0.681)	(3.538)	(0.561)	(-0.665)	(2.882)
$HEDGER\_OIG_{(t-1)}$	1.235	-0.177	0.282	0.774	0.320
	(1.245)	(-0.388)	(0.863)	(1.201)	(1.149)
$HEDGER\_IMB_{(t-1)}$	-0.153	-0.021	-0.069	-0.114	-0.089**
	(-0.806)	(-0.472)	(-0.786)	(-1.338)	(-2.328)
All predictors in Table 3.6	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.449	0.483	0.46	0.264	0.428
Number of commodity-months	524	1,310	1,310	1,310	4,454
LRT statistic	9.6	27.2	5.0	4.4	41.2
$c[(K-K'=3),(\alpha=0.05)]=7.815$					

Table 3.8 controls for hedge fund activity by including lagged hedge fund (absolute) return as an explanatory variable. HF_RET has a positive and significant coefficient of 0.421 with a t-statistic of 1.798, even after the inclusion of all proxies for economic uncertainty and hedging activity included in Table 3.7. The coefficient for grain commodities is the most significant, and this potentially links to the consequences of market changes related to the US Ethanol Mandate (Roberts and Schlenker, 2013). After interacting for the indicator for the "index period", I find that this positive relationship is limited to this period, when the coefficient is 1.085 with a t-statistic of 2.627.

However, given that this period overlaps significantly with a major recession, this identification in a smaller sample (starting in January 1995) is weak.

Table 3.8: Commodity Futures Volatility and Hedge Fund Activity
This table shows the results for balanced panel regressions of (time, t) 1-month volatility of the front-month futures return, $Vol_{(t)}$, over lagged (time, $t-1$) absolute value of the hedge fund industry mean return, in addition to all explanatory variables included in Table 3.7. The results reported here are for the groups Energy, Metal, Grain, Soft, and All commodities, from January 1995 to December 2010. All regressions include commodity and season (month) fixed effects. Return variables are in percentage. t-statistics clustered by month are shown in parenthesis below each coefficient estimate.

	Energy	Metal	Grain	Softs	All		
					1	2	3
$HF\_RET_{(t-1)}$	0.684	0.220	0.864***	0.106	0.421*	-0.223	0.120
	(1.435)	(0.611)	(2.585)	(0.428)	(1.798)	(-1.125)	(0.702)
$IndexPeriod_{(t)} * HF\_RET_{(t-1)}$						1.085***	
						(2.627)	
$Recession_{(t)} * HF\_RET_{(t-1)}$							1.615**
							(1.983)
All predictors in Table 3.7	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.451	0.473	0.440	0.250	0.416	0.422	0.427
Number of commodity-months	376	940	940	940	3,196	3,196	3,196

3.4.4 Time-variation

Table 3.9 shows the comparison of model fits, in addition to results with interactions for different time periods added to the specification in Table 3.7. In column 5, I interact for the NBER recession periods as in regression specification (3.36), and in column 6, I show the results from interacting with $IndexPeriod$ as in regression specification (3.37).

$$Vol_t = \mu_i + NBER\_Recession + \mathbf{z}_{t-1}{}'\boldsymbol{\theta} + NBER\_Recession * \mathbf{z}_{t-1}{}'\boldsymbol{\theta}^{REC} + \eta_t, \tag{3.36}$$

$$Vol_t = \mu_i + IndexPeriod + \mathbf{z}_{t-1}{}'\boldsymbol{\theta} + IndexPeriod * \mathbf{z}_{t-1}{}'\boldsymbol{\theta}^{INDEX} + \eta_t, \tag{3.37}$$

Interacting for $NBER\_Recession$ increases the model fit for all groups relative to the specification without the interaction with up to a 13.6% adjusted R-squared gain for Energy commodities. Commodities in the Grain and Softs groups show a better fit under $IndexPeriod$ interactions. Metal commodities show no significant difference between the two specifications, while Energy commodities have less explanatory power under the interaction with $IndexPeriod$. Next, I analyze the coefficients from rolling regressions in order to investigate the time-variation in commodity futures volatility.

3.5 Conclusions

This chapter conducts a systematic analysis in order to understand the dynamics of commodity futures volatility. I derive the variance decomposition for commodity futures to show how unexpected changes to the excess basis return is driven by changes to the expectation of future interest rates, convenience yield, and risk premia. These expectations are updated in response to news about the future state of the economy and future commodity supply and demand. I model time-varying commodity futures volatility and study the impact of variables that proxy for such economic uncertainty, while controlling for the impact of any frictions due to trading activity.

Using data for major commodity futures markets and global bilateral commodity trade, I analyze the extent to which commodity volatility is related to fundamentals that impact convenience yield and interest rates such as increased emerging market demand and inflation uncertainty, as well as financial frictions introduced by changing market structure and commodity index

Table 3.9: Commodity Futures Volatility during Different Time Periods

This table shows model fit measures for the balanced panel regressions of (time, t) 1-month volatility of the front-month futures return over lagged (time, t-1) explanatory variables under different specifications. Panel A shows the adjusted R-squareds, Panel B shows the Bayesian information criterion values, and Panel C shows the likelihood ratio statistic of the different models. Column 1 shows the fit measures from the regression specification in Table 3.5.A ("Baseline"), column 2 shows those from including all 11 macroeconomic uncertainty series on the RHS, column 3 shows those from Table 3.6 ("EU_PC 1-4"), and column 4 shows those from Table 3.7 ("Commodity market"'). Column 5 shows the results with all explanatory variables in Table 3.7 included, together with interactions for NBER recession periods; the last column shows the results with all explanatory variables in Table 3.7 included, together with interactions with $IndexPeriod$ (the indicator for the period subsequent to January 2004). The results reported here are for the groups Energy, Metal, Grain, Soft, and All commodities. All regressions include commodity and season (month) fixed effects.

	Baseline 1	Macro uncertainty 2	EU_PC 1-4 3	Commodity market 4	Interaction for recession periods 5	Interaction for $IndexPeriod$ 6
Panel A: Adjusted R-squared						
Energy	34.3	48.9	44.2	44.9	58.5	51.1
Metal	43.7	47.3	47.4	48.3	49.2	49.3
Grain	41.9	47.8	45.9	46.0	48.6	49.1
Softs	25.2	26.3	26.3	26.4	26.2	26.7
All	39.5	42.4	42.3	42.8	43.9	43.1
Panel B: Bayesian information criterion (BIC)						
Energy	4,136.6	4,057.1	4,071.6	4,080.8	3,983.6	4,069.7
Metal	9,760.8	9,733.7	9,696.2	9,690.7	9,728.9	9,727.6
Grain	9,306.6	9,256.4	9,237.8	9,254.3	9,252.7	9,239.6
Softs	10,210.0	10,251.1	10,214.4	10,231.6	10,295.9	10,287.9
All	33,500.9	33,351.5	33,317.3	33,301.3	33,285.9	33,353.4
Panel C: Likelihood ratio comparison (LRT)						
$K - K'$		$K_2 - K_1 = 10$	$K_3 - K_1 = 4$	$K_4 - K_2 = 3$	$K_5 - K_4 = 10$	$K_6 - K_4 = 10$
Critical value ($\alpha = 0.05$)		18.307	9.488	7.815	18.307	18.307
Energy		142.2	90.0	9.6	159.8	73.6
Metal		98.8	93.2	27.2	33.6	34.8
Grain		122.0	97.4	5.0	73.6	86.6
Softs		30.6	24.2	4.4	7.4	15.4
All		233.4	217.2	41.2	99.4	31.8

trading. A higher concentration in emerging market importers of a commodity is associated with higher futures volatility. I find significant predictability in commodity futures volatility using variables capturing macroeconomic uncertainty.

Such explanatory power can be economically significant for market participants (Campbell and Thompson, 2008; Inoue and Kilian, 2004). Investors who have volatility-sensitivity (a non-zero "vega" exposure) in their portfolios would especially benefit as in that case, predicting volatility allows for the prediction of portfolio and position values. This is important for any hedger or derivatives trader, as the value of their portfolios and trading strategies is directly tied to the volatility of the traded assets. Investors and end-users (commodity producers and consumers) in commodity markets benefit from understanding how the observed price behavior relates to the prevailing economic conditions. Uncertainty can lead to the long-term misallocation of resources as end-users evaluate real options in their investment decisions. Moreover, for many commodities with illiquid or short-dated derivatives markets of little depth, these findings can be a useful aid to price discovery and risk management.

This work builds on results discussed in Bloom (2014), which show that emerging markets and recessionary periods are strongly associated with economic uncertainty, and adapts work that studies the granular origins of volatility (Gabaix, 2011) and shows how the same principle can affect volatility in global markets. It is difficult to contemporaneously explain, let alone predict, financial asset volatility using factors reflecting economic conditions (Roll, 1984; Schwert, 1989; Engle and Rangel, 2008), even when model results and economic intuition posit such a relationship. As such, the results in this chapter constitute a step forward in our understanding of the factors that drive volatility. As global markets become increasingly interlinked, it is imperative to understand the impact of increased concentration and emerging market participation in commodity trade, and the manner and extent to which shocks propagate between markets.

3.6 Appendix

3.6.1 Components of the excess basis return

We can further decompose the excess basis return, $x_{n,t+1}$, in Eq. (3.10) to separate out the excess return due to the interest rate term structure and characterize the excess return purely due to convenience yield and commodity risk premia:

$$
\begin{aligned}
x_{n,t+1} \equiv& x^y_{n,t+1} - x^r_{n,t+1}, && (3.38)\\
x^y_{n,t+1} - E_t x^y_{n,t+1} =& (E_{t+1} - E_t)\left\{ -\sum_{i=1}^{n-1} y_{1,t+i} - \sum_{i=1}^{n-1} x^y_{n-i,t+i+1} \right\}, && (3.39)\\
x^r_{n,t+1} - E_t x^r_{n,t+1} =& (E_{t+1} - E_t)\left\{ -\sum_{i=1}^{n-1} \pi_{1,t+i} - \sum_{i=1}^{n-1} \psi_{1,t+i} - \sum_{i=1}^{n-1} x^r_{n-i,t+i+1} \right\}, && (3.40)
\end{aligned}
$$

where, $\pi_{1,t}$ is the 1-period inflation rate and $\psi_{1,t}$ is the 1-period real interest rate at time t. The derivation of (3.40) is discussed in Campbell and Ammer (1993).

3.6.2 Volatility models and extensions

In this appendix, I describe the realized volatility models that form the basis of the empirical analysis.

3.6.2.1 GARCH-type models

Drawing on previous work on equity market volatility (Engle and Lee, 1999; Engle and Gallo, 2008; Engle and Rangel, 2008), I use a GARCH-type model of volatility to check the robustness of the baseline regression analysis. A standard GARCH(1,1) process (Engle, 1982; Bollerslev, 1986) for a particular asset is defined as,

$$r_t = \mu_t + \sigma_t \varepsilon_t, \text{ where } \varepsilon_t | \Omega_{t-1} \sim N(0,1), \tag{3.41}$$

$$h_t = \omega + \alpha \varepsilon_{t-1}^2 + \beta h_{t-1}, \tag{3.42}$$

$$\sigma_t = \sqrt{h_t}. \tag{3.43}$$

It follows that the unconditional variance in the model will be $E\left[(r_t - E_{t-1}r_t)^2\right] = E\left[(r_t - \mu_t)^2\right] = \frac{\omega}{1-\alpha-\beta}$. In its simplest form, extensions to the standard GARCH(1,1) process that include K (weakly) exogenous lagged explanatory variables in $\mathbf{z_t}$, with $\boldsymbol{\xi}_t = \frac{\mathbf{z_t}}{E[\mathbf{z_t}]}$, take the form of GARCH-X(1,1),

$$\begin{aligned} g_t &= \omega + \alpha \varepsilon_{t-1}^2 + \beta g_{t-1} + {\boldsymbol{\xi}_t}' \boldsymbol{\theta}, \\ \sigma_t &= \sqrt{g_t}. \end{aligned} \tag{3.44}$$

Then the unconditional variance, $E\left[(r_t - E_{t-1}r_t)^2\right] = \frac{\omega + \gamma_1 + \ldots + \gamma_K}{1-\alpha-\beta}$.

Note that, unlike with equity (Bekaert and Wu, 2000; Bollerslev and Todorov, 2011), there is no direct equivalent to the firm leverage effect for commodities and risk can be concentrated in either direction depending on the shock to supply or demand. A model capturing asymmetry in a manner such as the GJR-GARCH model[22] may be useful for learning about the conditional demand- or supply-side pressures in a commodity market. As seen in Tables 3.3 and 3.5.B, for commodity futures, there is no unconditional asymmetric volatility effect when controlling solely for the sign of lagged returns.

3.6.2.2 Long-run and short-run volatility components

Consider the short-term and long-term components of the data-generating process within a framework similar to the models of equity volatility presented in Engle and Rangel (2008) and Engle, Ghysels, and Sohn (2013), differing only in terms of the definition of the slow-moving component of volatility.

$$\begin{aligned} r_t =& \mu_t + \sigma_t \varepsilon_t, \\ h_t =& (1-\alpha-\beta) + \alpha \frac{\varepsilon_{t-1}^2}{\tau_{t-1}} + \beta h_{t-1}, \\ \sigma_t =& \sqrt{\tau_t h_t}, \end{aligned} \tag{3.46}$$

where τ_t represents the long-term volatility component and, for a set of K lagged explanatory variables in $\mathbf{z_t}$, is defined,

$$\log \tau_t = m + \mathbf{z}_t{}'\boldsymbol{\theta}, \tag{3.47}$$

[22]From Glosten, Jagannathan, and Runkle (1993), a GJR-GARCH(1,1) process allows for an asymmetric return effect, and differs from the specification of GARCH(1,1) in (3.42) by the specification of h_t,

$$h_t = \omega + \alpha\varepsilon_{t-1}^2 + \gamma I_{t-1}^{(-)}\varepsilon_{t-1}^2 + \beta h_{t-1}, \tag{3.45}$$

where, $I_{t-1}^{(-)}$ is 1 when $\varepsilon_{t-1} < 0$, and 0 otherwise.

The size of the set of estimated parameters in the model, $\Theta = \{\mu, \alpha, \beta, m, \gamma_1, \ldots, \gamma_K\}$, is on the same order as the GARCH-X model presented in the previous section. In this model, the unconditional variance corresponds exactly to the low-frequency component as $E\left[(r_t - E_{t-1}r_t)^2\right] = \tau_t E[h_t] = \tau_t$.

Engle, Ghysels, and Sohn (2013), in their analysis of the macroeconomic determinants of equity market volatility, separately consider the impact of the level and volatility of two variables: inflation and industrial production growth. They find a significant impact from these macroeconomic variables even on daily volatility. Their model differs in the definition of τ in (3.47) by including multiple lags of each explanatory variable with an imposed weighting function. This limits the number of factors that can be included together as each adds three parameters to Θ.

In contrast, Engle and Rangel (2008), in their spline-GARCH specification (also differing solely in their definition of (3.47)), estimate τ non-parametrically using an exponential quadratic spline.

$$\tau_t = c \exp\left(w_0 t + \sum_{i=1}^{k} w_i ((t - t_{i-1})_+)^2 \right), \tag{3.48}$$

where $(t - t_i)_+ = \{t - t_i \text{ if } t > t_i, \text{ otherwise } 0\}$ and k is the optimal number of equally-spaced knots, selected using information criteria (AIC and BIC). This partitions the time series into k equally-spaced intervals, demarked by $\{t_0 = 0, t_1, \ldots, t_k = T\}$. The estimated time series of the slow-moving component (τ) is subsequently used as the dependent variable in an independent regression, with up to eleven explanatory variables in their model: economic development level, market capitalization, inflation level, GDP level and growth, market size (number of listed companies), and volatilities of the short term interest rate, exchange rate, GDP and inflation.

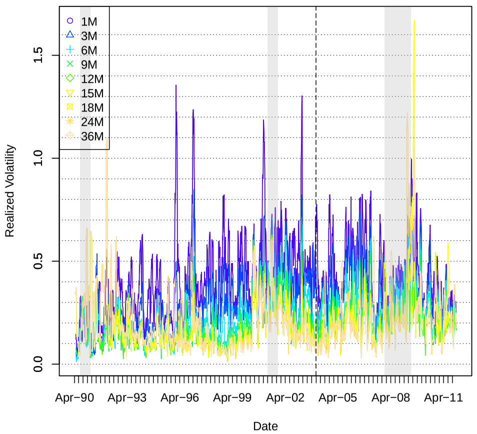
Correspondingly, I include a number of variables in my analysis that are potentially relevant for commodity markets in $\mathbf{z}$ that can capture the impact of macroeconomic uncertainty, supply-demand shocks, and trading activity.

3.6.3 Commodity Market Variation through Time

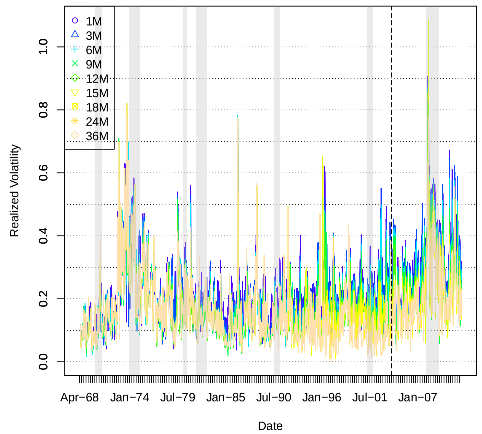
This section presents evidence of significant time-variation in volatility, correlations, and trends in emerging market commodities trade throughout the history of futures trading since the 1950s, which motivates the analysis presented in the rest of this chapter. There are extreme price movements over the entire term structure during the Global Financial Crisis, leading to sharp increases in the volatility exhibited during that period. From late 2001 to early 2007, there is a steady increase in cumulative return across all maturities. Figures 3.1 and 3.5 illustrate the difference in the estimated time-varying volatility depending on the term structure and holding period. The figures show the rolling 1-month and 12-month realized volatility for 1M, 3M, ..., 36M futures (3-day) returns for crude oil, natural gas, gold, copper, wheat, and lumber.

Table 3.A2 shows the mean and standard deviation of long-term (12-month) realized volatility of daily commodity futures returns over the the three decades: 1980-1989, 1990-1999, and 2000-2009.

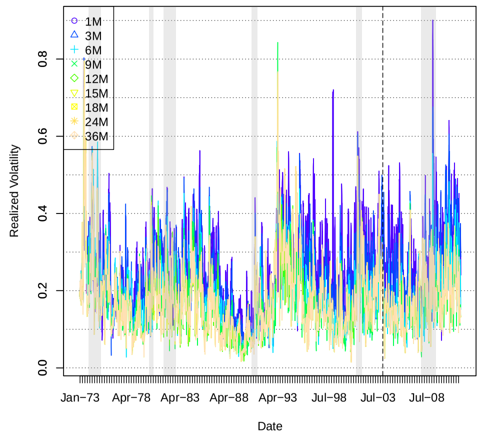
Figure 3.7 shows Chilean exports of copper for the period covered by the OECD STAN Bilateral Trade database. From the early 2000s, there is a sharp upturn in the percentage of exports to China, while the fraction of exports to G7 countries declines over the same period. Starting from near-zero, within less than two decades, the fraction of exports to China rises to 35.64% at the end of 2009, surpassing exports to all G7 countries combined.



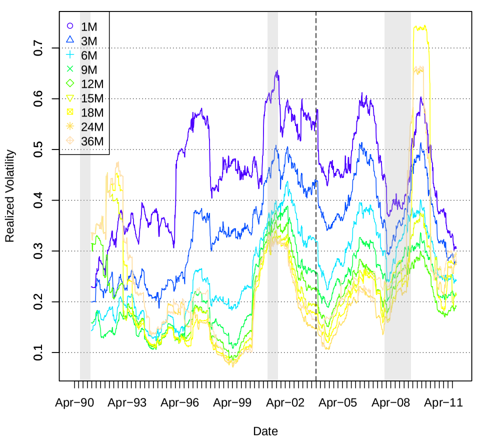
(a) Natural Gas - short-term volatility



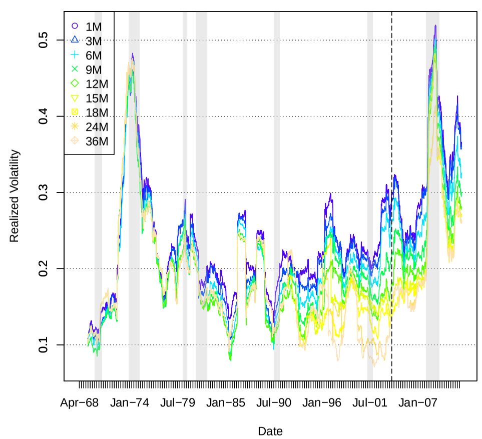
(b) Wheat - short-term volatility



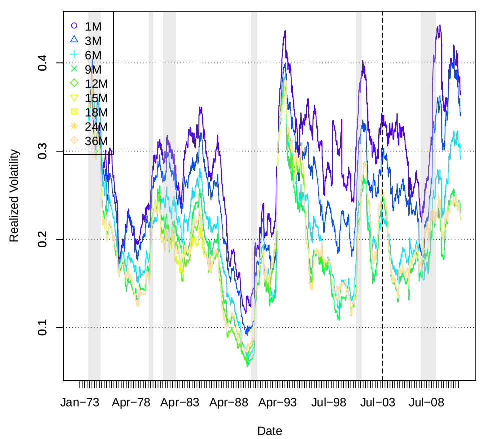
(c) Lumber - short-term volatility



(d) Natural Gas - long-term volatility



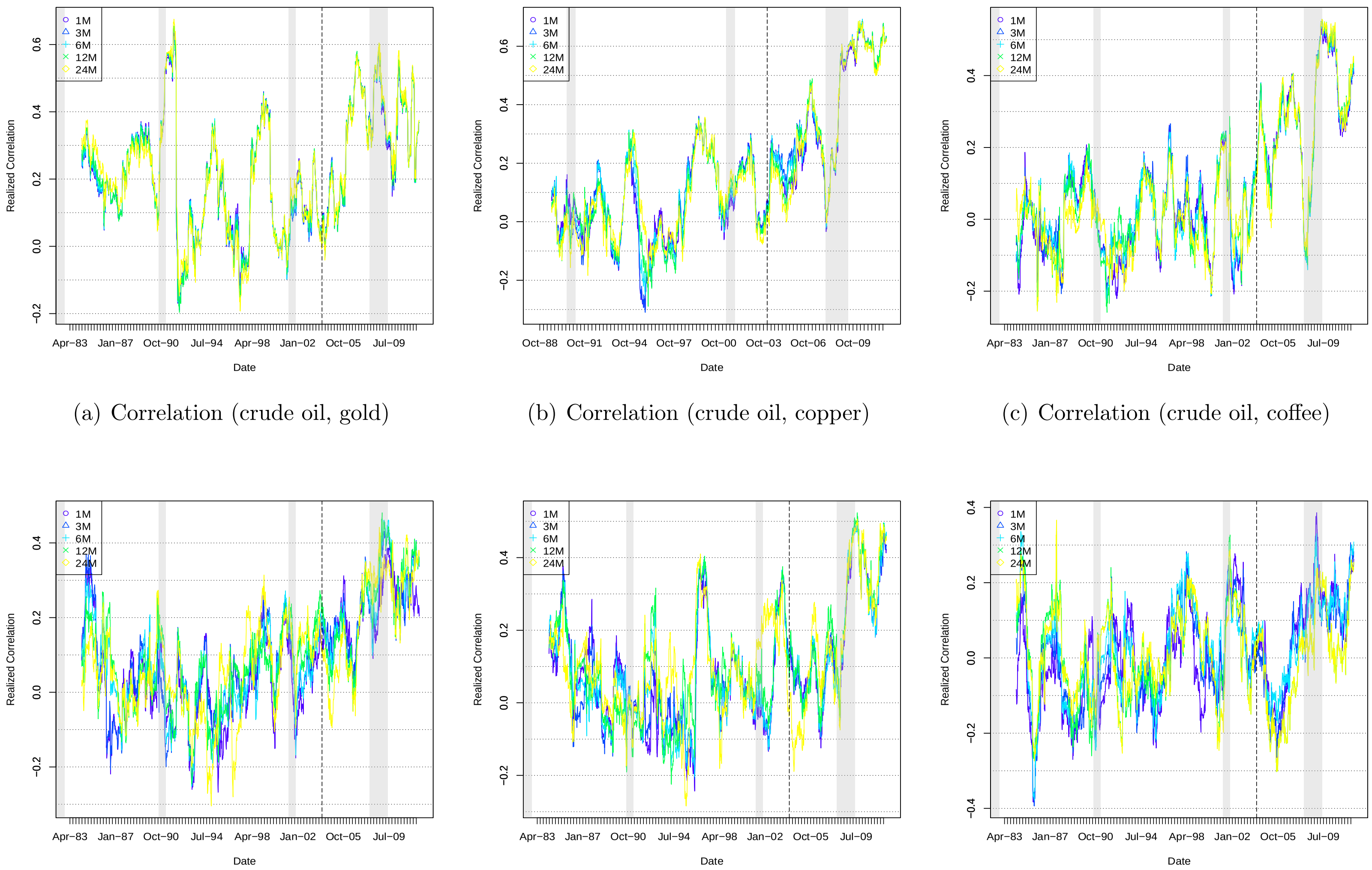
(e) Wheat - long-term volatility



(f) Lumber - long-term volatility

Figure 3.5: Time series of annualized rolling realized volatility at different horizons for copper, wheat, and lumber.

Time series of annualized rolling realized volatility at different horizons for 1M, 3M, ..., 36M futures using 3-day returns. Here, short-term volatility refers to the standard deviation for the previous month, while long-term volatility refers to the standard deviation for the previous twelve months. The shaded areas highlight the NBER recession periods. The dotted line marks January 2004.



(a) Correlation (crude oil, gold)

(b) Correlation (crude oil, copper)

(c) Correlation (crude oil, coffee)

(d) Correlation (crude oil, cotton)

(e) Correlation (crude oil, wheat)

(f) Correlation (crude oil, lumber)

Figure 3.6: Time series of the rolling 12-month pairwise correlation between returns of the crude oil 3-month future and gold, copper, coffee, cotton, wheat, and lumber futures returns.

Each date shows the corresponding correlation for the previous 12-month period calculated on 3-day returns. The shaded areas highlight NBER recession periods. The dotted line marks January 2004.

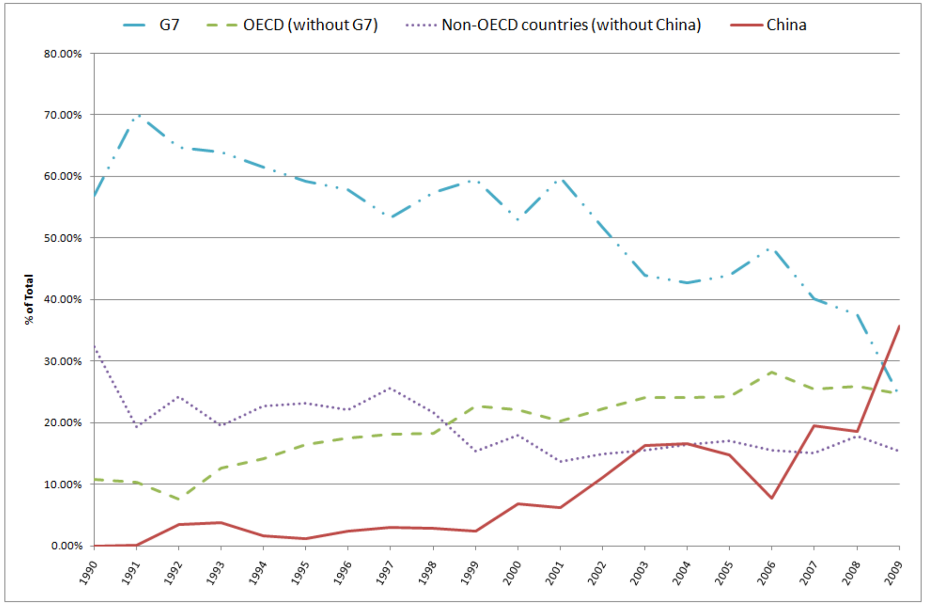
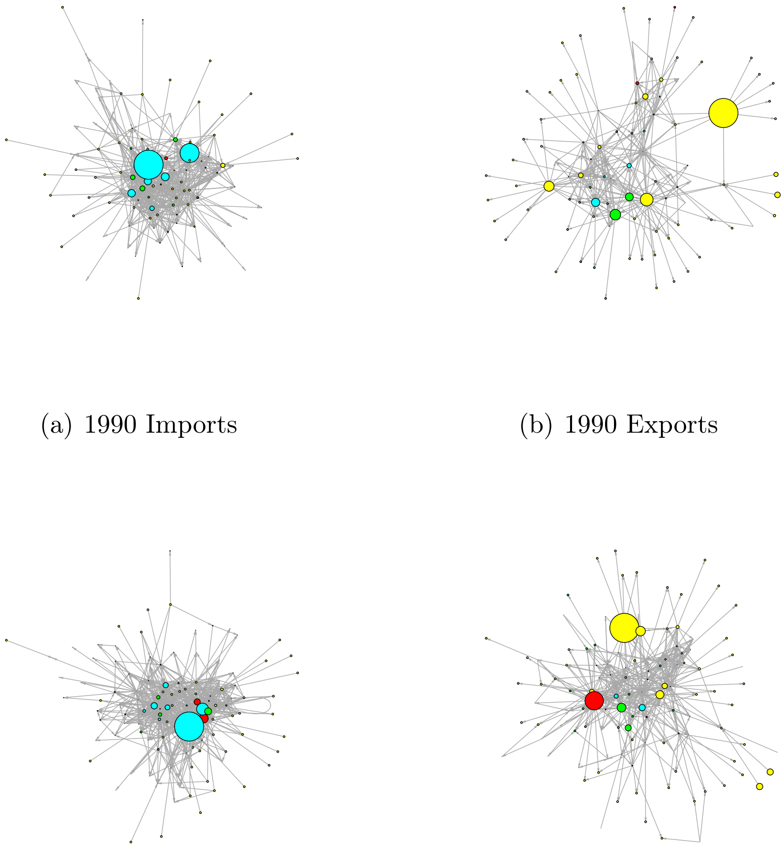


Figure 3.7: Breakdown of importers of Basic Metals from Chile from 1990 to 2009.

Chile exports close to a third of the world's copper, a key raw material in manufacturing. The four series displayed add up to 100% of Chilean exports of Basic Metals in a given year.



(a) 1990 Imports

(b) 1990 Exports

(c) 2007 Imports

(d) 2007 Exports

Figure 3.8: Global crude oil trade network.

The vertex colors identify the country group: BRIC (red), non-OECD excluding BRIC (yellow), OECD excluding G7 (green), and G7 (blue). The relative size of a country vertex captures its total import value.

3.6.4 Additional tables

Table 3.A1
Commodity description for the matched UN Comtrade reference

SITC Rev. 2 Code	Commodity Description
S2-041	Wheat and meslin, unmilled
S2-042	Rice
S2-044	Maize, unmilled
S2-0452	Oats, unmilled
S2-061	Sugar and honey
S2-071	Coffee and coffee substitutes
S2-072	Cocoa
S2-2222	Soya beans
S2-247	Other wood in the rough or roughly squared
S2-263	Cotton
S2-2871	Copper ore and concentrates; copper matte; cement copper
S2-2873	Aluminium ores and concentrates (including alumina)
S2-2890	Ores and concentrates of precious metals, waste, scrap
S2-333	Crude petroleum and oils obtained from bituminous minerals
S2-341	Gas, natural and manufactured
S2-4232	Soya bean oil

Table 3.A2

Commodity Futures Volatility - Long-term (12-month) Volatility Summary by Decade

This table shows the summary statistics of the volatility of daily returns for each commodity future at 1-month, 3-month and 12-month maturities, by decade (January 1980 to December 1989, January 1990 to December 1999, and January 2000 to December 2009) for long-term volatility.

	Mean									Std Dev								
Decade	1980-1989			1990-1999			2000-2009			1980-1989			1990-1999			2000-2009		
Maturity	1M	3M	12M	1M	3M	12M	1M	3M	12M	1M	3M	12M	1M	3M	12M	1M	3M	12M
Crude	25.839	23.948	23.028	30.485	24.688	18.793	36.011	32.416	25.988	16.110	13.450	12.117	13.027	9.417	7.447	8.805	8.460	7.867
Heat. Oil	25.268	23.102	21.964	30.360	24.643	19.605	36.949	33.174	26.496	10.946	8.995	7.883	10.642	8.489	7.951	5.601	5.968	5.744
Nat Gas	-	-	-	39.747	27.121	18.101	53.079	42.597	25.406	-	-	-	12.859	7.023	6.903	7.836	6.529	5.919
Gold	23.506	22.967	22.382	11.250	11.267	11.163	18.036	18.000	17.831	10.496	9.410	8.614	3.765	3.752	3.709	5.647	5.611	5.800
Silver	38.420	33.302	32.186	22.730	22.610	22.066	28.328	28.208	27.504	15.109	8.413	7.824	4.892	4.836	4.559	11.976	11.859	11.922
Copper	30.386	29.437	24.000	23.276	22.113	17.371	27.992	27.968	25.859	4.543	4.004	3.429	5.096	4.680	3.634	10.842	11.017	10.963
Pallad.	31.666	30.575	30.687	26.125	24.749	24.775	34.982	34.686	34.438	9.483	8.871	8.484	10.377	9.008	8.505	7.873	7.505	7.413
Platinum	33.548	32.330	31.062	16.875	16.768	16.464	25.249	23.367	23.260	9.896	8.384	7.924	3.471	3.556	3.361	10.508	7.609	7.265
Wheat	20.873	19.804	17.200	21.108	19.768	15.970	29.850	28.709	22.879	4.204	4.548	4.632	3.956	3.811	3.324	8.326	8.008	8.335
Corn	19.008	18.181	16.703	18.445	18.215	15.580	26.415	25.864	21.158	5.688	4.782	3.975	3.567	3.254	2.575	7.379	7.258	7.601
Oat	27.035	24.962	21.841	28.091	26.188	21.632	32.458	29.662	21.001	6.770	6.028	5.948	3.849	3.417	2.954	6.438	6.034	5.969
Soybean	21.495	21.253	19.011	18.401	18.348	15.569	25.621	24.468	20.913	5.726	5.001	4.052	3.013	2.864	2.134	8.416	6.351	6.646
SB Meal	22.889	22.326	20.083	19.507	19.390	16.854	26.792	26.107	22.907	5.787	5.363	4.827	4.308	4.337	3.096	6.659	6.315	6.508
SB Oil	24.719	24.172	20.961	19.320	18.986	16.513	24.946	24.513	21.779	4.510	4.302	3.677	2.148	2.112	1.901	6.457	6.298	6.295
Cotton	20.301	18.877	15.031	20.864	18.918	13.132	29.224	26.911	20.927	5.376	5.586	5.829	3.699	3.137	2.437	6.265	5.549	5.063
Coffee	29.221	26.508	21.251	39.319	37.577	30.557	36.087	35.147	29.933	10.241	8.530	6.848	10.986	10.890	7.663	8.651	8.652	7.001
Sugar	54.664	46.858	34.901	29.267	27.023	19.458	36.294	32.053	24.205	9.778	6.375	4.773	6.753	6.487	5.526	8.649	5.181	5.548
Cocoa	29.124	27.252	22.664	27.996	26.706	22.651	33.275	32.246	29.287	5.997	5.294	4.142	5.742	5.598	4.656	4.922	5.054	4.728
Lumber	25.759	23.791	17.027	27.614	23.343	19.557	30.525	25.883	19.747	4.896	4.820	4.345	7.317	6.714	6.356	5.079	4.343	3.736

Table 3.A3
Augmented Dickey-Fuller (ADF) Tests of Commodity Futures Volatility

This table shows the results from the Augmented Dickey-Fuller tests for unit roots in the commodity futures volatility time series used as dependent variables. In these tests, for a series x, Lag Order = trunc((length(x)-1)$^{1/3}$).

Commodity Code	Lag Order	DF Value	p-value
C	6	-5.236	0.010
CC	6	-3.772	0.021
CL	6	-5.072	0.010
CT	6	-3.856	0.017
GC	6	-4.508	0.010
HG	6	-4.120	0.010
HO	6	-4.602	0.010
KC	6	-4.519	0.010
LB	6	-3.643	0.030
O	6	-5.579	0.010
PA	6	-4.789	0.010
PL	6	-4.129	0.010
S	6	-4.883	0.010
SB	6	-4.659	0.010
SI	6	-4.475	0.010
SM	6	-4.168	0.010
W	6	-4.113	0.010

Table 3.A4
Description of Macroeconomic Uncertainty Variables

Panel A of this table shows the correlation between the uncertainty time series of the eleven macroeconomic variables used in this study for the period from January 1988 to December 2011. Panels B and C show the results of the principal components analysis of these factors. Section 3.3.5 in the chapter provides further description of each variable.

Panel A: Correlation Matrix of Macroeconomic Uncertainty Variables

	DEF_U	RREL_U	TERM_U	INF_U	RDIV_U	MKT_U	UNEMP_U	RGDP_U	CFNAI_U	VXO_A	INFFC_A
DEF_U	1.000										
RREL_U	0.138	1.000									
TERM_U	0.207	-0.078	1.000								
INF_U	0.771	0.179	0.133	1.000							
RDIV_U	-0.212	-0.159	-0.193	-0.005	1.000						
MKT_U	0.645	0.026	0.275	0.338	-0.003	1.000					
UNEMP_U	0.242	-0.180	0.392	0.177	-0.009	0.396	1.000				
RGDP_U	0.754	0.331	-0.009	0.629	-0.191	0.492	0.086	1.000			
CFNAI_U	0.753	0.335	-0.013	0.654	-0.197	0.474	0.083	0.840	1.000		
VXO_A	0.633	0.043	0.052	0.376	0.115	0.818	0.174	0.565	0.575	1.000	
INFFC_A	0.501	0.166	0.134	0.528	-0.209	0.264	0.251	0.520	0.555	0.251	1.000

Panel B: Summary of PCA of (Standardized) Macroeconomic Uncertainty Variables

	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9	PC10	PC11
Standard deviation	2.157	1.290	1.153	0.940	0.858	0.782	0.669	0.532	0.406	0.351	0.323
Proportion of variance	0.423	0.151	0.121	0.080	0.067	0.056	0.041	0.026	0.015	0.011	0.009
Cumulative proportion	0.423	0.574	0.695	0.775	0.842	0.898	0.939	0.964	0.979	0.991	1.000

Panel C: Factor loadings from PCA

	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9	PC10	PC11
DEF_U	-0.425	0.027	-0.012	0.014	-0.143	0.243	-0.219	0.255	-0.148	-0.248	-0.737
RREL_U	-0.122	-0.467	-0.148	-0.313	0.759	-0.158	-0.057	0.183	0.006	0.037	-0.084
TERM_U	-0.093	0.472	-0.443	-0.160	0.317	0.530	0.277	-0.285	0.047	0.057	-0.020
INF_U	-0.357	-0.080	-0.033	0.454	0.088	0.408	-0.296	0.369	0.077	0.211	0.459
RDIV_U	0.085	0.134	0.649	0.440	0.480	0.114	0.149	-0.203	-0.070	-0.161	-0.149
MKT_U	-0.335	0.330	0.237	-0.382	0.031	-0.117	0.114	0.262	-0.231	-0.500	0.421
UNEMP_U	-0.141	0.546	-0.188	0.200	0.215	-0.562	-0.462	-0.084	0.076	0.119	-0.065
RGDP_U	-0.401	-0.216	0.029	-0.021	-0.071	-0.033	-0.104	-0.569	-0.624	0.220	0.111
CFNAI_U	-0.405	-0.226	0.019	0.015	-0.075	-0.039	-0.047	-0.454	0.656	-0.365	0.074
VXO_A	-0.339	0.154	0.429	-0.312	-0.070	-0.051	0.219	0.099	0.285	0.647	-0.121
INFFC_A	-0.300	-0.069	-0.287	0.438	-0.032	-0.347	0.689	0.165	-0.069	-0.008	-0.056

Table 3.A5
Commodity Futures Volatility and Macroeconomic Uncertainty

This table shows the results for balanced panel regressions of (time, t) 1-month volatility of the front-month futures return over *lagged* (time, t-1) explanatory variables that capture macroeconomic uncertainty. The panels show, respectively, the results with the first six, one and three principal components of the 11 macroeconomic uncertainty series (Table 3.A4 in the Appendix contains details of this PCA). The results reported here are for the groups Energy, Metal, Grain, Soft, and All commodities. All regressions include Commodity*Season (month-of-year) fixed effects. Return variables are in percentage. *t*-statistics clustered by month are shown in italics below each coefficient estimate. The LRT row shows the likelihood ratio test statistic comparing the fit shown in Table 3.6 to the current results.

Panel A: Regressions using six principal components

	Energy	Metal	Grain	Softs	All
(Intercept)	28.543	7.468	11.583	16.907	12.337
	6.025	*6.379*	*9.786*	*8.880*	*13.293*
$\lvert Return_{(t-1)} \rvert$	0.474	0.428	0.201	0.369	0.383
	3.587	*3.852*	*2.860*	*4.225*	*7.200*
$Vol_{(t-1)}$	0.181	0.356	0.405	0.307	0.351
	3.001	*6.321*	*9.958*	*5.110*	*9.950*
$PC1_{(t-1)}$	-2.166	-1.035	-0.899	-0.637	-0.957
	-4.975	*-4.789*	*-5.153*	*-4.744*	*-7.052*
$PC2_{(t-1)}$	-1.354	-0.412	0.034	0.370	-0.158
	-2.143	*-1.460*	*0.112*	*1.420*	*-0.762*
$PC3_{(t-1)}$	2.262	0.544	0.295	0.430	0.591
	4.560	*1.936*	*1.132*	*1.761*	*4.021*
$PC4_{(t-1)}$	1.179	1.675	1.530	-0.293	0.981
	2.023	*4.933*	*4.059*	*-0.906*	*4.548*
$PC5_{(t-1)}$	*-0.070*	*-0.063*	*0.284*	*0.659*	*0.207*
	-0.071	*-0.178*	*0.734*	*2.172*	*0.781*
$PC6_{(t-1)}$	0.153	0.565	0.372	0.364	0.387
	0.119	*1.182*	*0.823*	*0.765*	*1.181*
Adjusted R-squared	0.440	0.474	0.460	0.264	0.423
Number of months	262	262	262	262	262
Number of commodity-months	524	1310	1310	1310	4454
K	21	24	24	24	36
Log likelihood	-1,973.1	-4,764.1	-4,534.9	-5,022.7	-16,508.9
AIC	3,990.3	9,578.2	9,119.8	10,095.4	33,091.9
BIC	4,084.0	9,707.7	9,249.2	10,224.8	33,328.8
LRT statistic [K – K’=6 | [(P = 0.05) =12.592]	90.20	96.20	100.40	28.20	222.60

Panel B: Regressions using one principal component

	Energy	Metal	Grain	Softs	All
(Intercept)	25.348	7.473	11.285	16.605	12.287
	5.448	*5.940*	*8.925*	*8.558*	*12.298*
$\|Return_{(t-1)}\|$	0.560	0.418	0.217	0.370	0.384
	4.095	*3.570*	*3.157*	*4.218*	*7.874*
$Vol_{(t-1)}$	0.270	0.399	0.444	0.317	0.368
	3.820	*7.197*	*11.088*	*5.272*	*11.472*
$PC1_{(t-1)}$	-1.807	-0.949	-0.834	-0.624	-0.930
	-4.366	*-4.259*	*-4.528*	*-4.629*	*-8.254*
Adjusted R-squared	0.398	0.457	0.444	0.262	0.416
Number of months	262	262	262	262	262
Number of commodity-months	524	1310	1310	1310	4454
K	16	19	19	19	31
Log likelihood	-1,994.7	-4,786.9	-4,556.7	-5,027.5	-16,540.2
AIC	4,023.5	9,613.7	9,153.3	10,095.0	33,144.4
BIC	4,095.9	9,717.3	9,256.9	10,198.5	33,349.2
LRT statistic [K – K'=1 | [(P = 0.05) =3.841]	47.00	50.60	56.80	18.60	160.00

Panel C: Regressions using four principal components

	Energy	Metal	Grain	Softs	All
(Intercept)	28.296	7.499	11.365	16.836	12.412
	6.233	*5.947*	*8.903*	*8.649*	*12.675*
$\|Return_{(t-1)}\|$	0.480	0.415	0.216	0.369	0.382
	3.562	*3.562*	*3.097*	*4.225*	*7.106*
$Vol_{(t-1)}$	0.195	0.394	0.441	0.313	0.363
	3.196	*7.187*	*10.922*	*5.234*	*10.267*
$PC1_{(t-1)}$	-2.124	-0.965	-0.839	-0.627	-0.942
	-5.065	*-4.433*	*-4.528*	*-4.545*	*-6.894*
$PC2_{(t-1)}$	-1.309	-0.376	0.061	0.372	-0.134
	-2.080	*-1.295*	*0.199*	*1.426*	*-0.641*
$PC3_{(t-1)}$	2.226	0.534	0.295	0.421	0.591
	4.460	*1.796*	*1.084*	*1.735*	*3.748*
Adjusted R-squared	0.437	0.460	0.444	0.263	0.419
Number of months	262	262	262	262	262
Number of commodity-months	524	1310	1310	1310	4454
K	18	21	21	21	33
Log likelihood	-1,975.8	-4,782.3	-4,555.4	-5,025.1	-16,528.9
AIC	3,989.7	9,608.5	9,154.7	10,094.2	33,125.9
BIC	4,070.6	9,722.4	9,268.6	10,208.1	33,343.5
LRT statistic [K – K'=3 | [(P = 0.05) =7.815]	84.80	59.80	59.40	23.40	182.60

Table 3.A6
Commodity Futures Volatility and Commodity Market Risk Factors – Without Macroeconomic Controls

This table shows the results for balanced panel regressions of (time, t) 1-month volatility of the front-month futures return over lagged (time, t-1) commodity market variables without including the macroeconomic uncertainty factors included in Table 3.6. The results reported here are for the groups Energy, Metal, Grain, Soft, and All commodities. All regressions include Commodity*Season (month-of-year) fixed effects. Return variables are in percentage. *t*-statistics clustered by month are shown in italics below each coefficient estimate. The LRT row shows the likelihood ratio test statistic, comparing the fit shown in the corresponding panel in Table 3.7 (which shows results for the same regression specification *with* controls for macroeconomic uncertainty) to the current results.

	Energy	Metal	Grain	Softs	All
(Intercept)	18.819	5.895	10.533	16.258	10.919
	4.776	*4.309*	*7.233*	*8.809*	*10.219*
$\lvert Return_{(t-1)} \rvert$	0.537	0.335	0.218	0.369	0.354
	3.572	*2.809*	*3.102*	*4.123*	*6.213*
$Vol_{(t-1)}$	0.384	0.447	0.491	0.332	0.407
	4.938	*8.516*	*11.146*	*5.364*	*10.654*
$CMOM_{(t-1)}$	2.078	5.300	1.540	0.175	2.623
	1.557	*4.419*	*1.801*	*0.185*	*4.057*
$HEDGER\_OIG_{(t-1)}$	1.158	-0.135	0.268	0.899	0.327
	1.070	*-0.293*	*0.836*	*1.434*	*1.145*
$HEDGER\_IMB_{(t-1)}$	-0.258	-0.035	-0.137	-0.156	-0.118
	-1.315	*-0.848*	*-1.560*	*-2.055*	*-3.357*
Adjusted R-squared	0.362	0.456	0.425	0.254	0.405
Number of months	262	262	262	262	262
Number of commodity-months	524	1310	1310	1310	4454
K	18	21	21	21	33
Log likelihood	-2,008.7	-4,787.6	-4,577.2	-5,033.2	-16,580.1
AIC	4,055.3	9,619.2	9,198.4	10,110.4	33,228.3
BIC	4,136.3	9,733.1	9,312.3	10,224.3	33,446.0
LRT statistic [K – K'=3 | [(P = 0.05) =7.815]	19.00	49.20	15.80	7.20	80.20

Table 3.A7
Granger Causality Tests

This table shows the results of bivariate Granger causality tests of commodity futures volatility and variables used in the predictive regressions. Panel A shows the predictive causality results for the macroeconomic uncertainty variables using the monthly volatility of commodity sector indices. Panel B shows the predictive causality results for the monthly volatility of commodity sector indices using the macroeconomic uncertainty variables. The p-values of the tests are shown in parenthesis below the test statistic (df1=258, df2=1).

Panel A: Bivariate Granger causality tests with commodity futures volatility as the cause variable

	Energy	Metal	Grain	Softs	All
PC1	0.307	2.242	2.096	0.053	1.966
	[0.580]	[0.136]	[0.149]	[0.819]	[0.162]
PC2	1.496	1.874	1.606	0.550	1.660
	[0.222]	[0.172]	[0.206]	[0.459]	[0.199]
PC3	4.043	1.044	0.014	0.077	0.799
	[0.045]	[0.308]	[0.905]	[0.782]	[0.372]
PC4	0.170	0.390	0.413	0.274	0.409
	[0.680]	[0.533]	[0.521]	[0.601]	[0.523]

Panel B: Bivariate Granger causality tests with commodity futures volatility as the effect variable

	Energy	Metal	Grain	Softs	All
PC1	17.508	8.943	6.896	13.566	10.303
	[0.000]	[0.003]	[0.009]	[0.000]	[0.001]
PC2	1.726	0.120	0.006	2.482	0.004
	[0.190]	[0.729]	[0.937]	[0.116]	[0.949]
PC3	6.385	0.549	0.240	1.786	2.173
	[0.012]	[0.460]	[0.625]	[0.183]	[0.142]
PC4	2.779	7.671	7.713	0.477	5.310
	[0.097]	[0.006]	[0.006]	[0.490]	[0.022]

Table 3.A8
Commodity Futures Volatility during Different Time Periods

This table shows the results for balanced panel regressions of (time, t) 1-month volatility of the front-month futures return over *lagged* (time, t-1) explanatory variables. Panel A shows the results of Chow tests (for recession and non-recession periods) for the mean ("Intercept"), the regression specification in Table 3.5 ("Base"), and the regression specification in Table 3.7 ("Economic and Commodity Market Risk Factors"). Panel B shows the Chow test results for a structural break for the "index financialization" period, for the same model specifications as in Panel A. Panels A and B show the Chow test statistic with the p-value below in italics. The results reported here are for the groups Energy, Metal, Grain, Soft, and All commodities. All regressions include commodity and season (month-of-year) fixed effects.

Panel A: Chow tests for structural break during recession periods

	Regression Specification	Energy	Metal	Grain	Softs	All
(1)	Intercept	142.552	103.286	88.841	8.462	230.265
		0.000	*0.000*	*0.000*	*0.004*	*0.000*
(2)	Base	8.195	5.553	4.448	1.719	8.125
		0.000	*0.000*	*0.000*	*0.031*	*0.000*
(3)	Economic and Commodity Market Risk Factors	17.078	2.155	4.962	1.297	5.907
		0.000	*0.008*	*0.000*	*0.202*	*0.000*
Number of commodity-months		524	1310	1310	1310	4454
Breakpoint		454	1135	1135	1135	3859

Panel B: Chow tests for structural break during "Index Period"

	Regression Specification	Energy	Metal	Grain	Softs	All
(1)	Intercept	4.720	125.259	261.014	2.062	198.874
		0.030	*0.000*	*0.000*	*0.151*	*0.000*
(2)	Base	1.757	4.901	8.942	1.989	6.280
		0.038	*0.000*	*0.000*	*0.008*	*0.000*
(3)	Economic and Commodity Market Risk Factors	4.332	2.212	6.707	1.911	4.235
		0.000	*0.001*	*0.000*	*0.005*	*0.000*
Number of commodity-months		524	1310	1310	1310	4454
Breakpoint		360	900	900	900	3060

Chapter 4

Term Structure Dynamics of Commodity Futures

Abstract

This chapter investigates the differential explanatory power of consumer (importing countries) and producer (exporting countries) risk in explaining the volatility of commodity spot premia and term premia using trade-weighted indices of GDP volatility. Using data for major commodity futures markets, bilateral commodity trade, exchange rates, and GDP for countries trading these commodities, I test hypotheses on the heterogeneous impact of consumer and producer shocks, potentially driven by differences in hedging preferences and investment planning horizons. Using rolling regressions, I attempt to identify significant variations in these relationships as the riskiness of the consuming and producing country set changes. Producer risk is significant for both short- and long-dated maturities, while consumer risk has greater explanatory power for the volatility of the term spread.

4.1 Introduction

This chapter aims to extend our understanding of the dynamics of the term structure of the realized volatility of commodity futures returns. I investigate whether it is possible to identify heterogeneous impact of consumer and producer shocks at shorter versus longer maturities by using commodity trade-weighted (import- or export-weighted) indices. I also attempt to isolate the impact of explanatory variables on the volatility of spot premia (proxied as the one-month volatility) from their relationship to futures volatility at different maturities along the term structure. I find that producer risk is significant for both short- and long-dated maturities, while consumer risk has greater explanatory power for the volatility of the term spread.

Extending the work in Watugala (2014), I derive a variation of the decomposition in Campbell and Shiller (1988) and Campbell (1991), to decompose the unexpected variation in the commodity basis spread to its component sources. I construct and test empirical hypotheses given the premise that there exist segmented hedging activity and heterogeneous complexity in forecasting done by producers and consumers. Consumers primarily hedge in the near term, while producers may hedge using both short- and long-term futures contracts. Speculators, defined as market participants who do not have a natural exposure to the physical commodity, take the opposite side of these trades, especially where there is an imbalance in fundamental (hedging) supply-demand. They demand risk premia for taking on (spot) price risk. Funding capacity constraints and limits to arbitrage can affect these futures markets (Acharya, Lochstoer, and Ramadorai, 2013).

Several studies have analyzed segmented activity along the term structure in bond markets (Cochrane and Piazzesi, 2005, 2008) and proposed models of investors with preferred habitats to understand the empirical findings in these markets (Vayanos and Vila, 2009). Several characteristics of commodity futures markets make their term structure intriguing. Consumers have a natural short exposure to a commodity. In the futures market, they wish to buy futures to hedge this exposure. They have greater uncertainty forecasting their future commodity needs, which increases further into the future. They tend to have more constrained hedging mandates. In contrast, producers have a natural long exposure to a commodity. In the futures market, they wish to sell futures to hedge this exposure. They are able to forecast commodity production with greater certainty further into the future and tend to have more sophisticated hedging mandates (as this is their main business line). Producers tend to have better storage capability.

This chapter tests several hypotheses. When speculators are constrained from taking the other side (of fundamental hedging activity), the relationship between hedging activity and commodity futures return dynamics is stronger. The shocks to consumers can be captured via shocks to real variables such as GDP or financial variables such as equity market return and bilateral exchange rates. When speculators are unconstrained, these hypothesized relationships should be less strongly identified in the data. Producer risks will similarly affect risk in commodity futures markets, with the relationships stronger for long-term commodity futures than short-term ones.

The findings on commodity futures in this work highlight the significant time variation in risk premia (both spot and term premia) and volatility in commodity futures markets. The extent of the cross-sectional variation within and across different commodity groups, and the difficulty in explaining this variation also hints at the problems related to considering commodities a homogeneous asset class. The differential impact of unexpected shocks to the economy, weather, supply-demand, liquidity, market concentration, and trading volume in different commodity markets, while perhaps dampened via financialization, remains a feature of these markets even during the past decade.

I collate data from several sources to characterize commodity supply and demand dynamics. In particular, I analyze recent data to identify changes due to changing demand centers, i.e., the rising importance of emerging market players in a variety of commodity markets. Additionally, I consider periods of heightened political risk and uncertainty separately to better delineate the direct impact of geopolitics on the underlying economics driving commodity supply, demand and prices. In addition to lagged import and export weighted exchange rate indices, the lagged trade-weighted indices of the financial openness measures of importing countries show predictive power for commodity premia at the short end of the futures curve. This provides some indication of the importance of the changing demand centers in global commodity markets.

I find evidence that commodities with greater inventory risk and relatively inelastic demand show greater variation in the term structure of volatility. Relative to commodities in energy, grain and softs, commodities in the metals group broadly show little variation in their average volatility by contract month. This is indicative of parallel shifts to the forward curve being more common for metals than for commodities in other groups. For commodities such as crude oil, wheat, and lumber, the contracts in the nearer term are more volatile than longer-dated contracts. This difference is potentially a risk characteristic driven solely by fundamentals - inventory, storability and the nature of the demand for a particular commodity. Relative to other commodity groups, metals are highly storable (dense and durable), easy to transport, and less exposed to uncertainty in supply-demand due to weather or geopolitics.

Several recent papers in the literature on commodity and currency markets motivate this study. Chen, Rogoff, and Rossi (2010) show that commodity currencies predict global commodity prices both in-sample and out-of-sample. Ferraro, Rogoff, and Rossi (2011) explore the contemporaneous relationship between oil prices and exchange rates. Koijen, Moskowitz, Pedersen, and Vrugt (2012) analyze strategies equivalent to the currency carry trade in other financial markets and find persistence in profitability.

The literature that attempts to explain the seemingly anomalous puzzle in international finance of persistent carry trade profits or the forward premium anomaly has explored several different perspectives. Several studies consider the impact of time-varying risk premia (Fama, 1984; Bekaert, 1996), global risk sharing or crash risk (Barro, 2006; Lustig, Roussanov, and Verdelhan, 2011; Burnside and Graveline, 2012; Mueller, Stathopoulos, and Vedolin, 2012). Verdelhan (2010) attempts to explain the puzzle within a model of investors with habit-based preferences. Froot and Ramadorai (2005) consider the variance decomposition of exchange rate returns, and find that short-term exchange rate fluctuations are related to flows, whereas long-term returns are related to fundamentals. Ang and Chen (2010) analyze the significance of yield curve predictors, and find useful explanatory power for excess currency returns.

Verdelhan (2012) introduces two factors, a carry factor and a global "dollar" factor, which together are more successful in explaining the variation in currency returns than previous such attempts. Similarly, Szymanowska, de Roon, Nijman, and van den Goorbergh (2013) find one factor that has significance in explaining the cross section of commodity spot premia and two factors that explain commodity term premia. These studies yield further questions regarding the economic underpinnings of such common risk factors, and the literature on identifying macroeconomic and financial variables that explain such global risk factors or have predictive power in explaining return variation attempts to understand these economic channels.

Ready, Roussanov, and Ward (2013) find that persistent heterogeneity in the goods production of countries, together with frictions introduced by the limited shipping capacity between countries, explain a substantial portion of currency carry trade profits. Countries that export basic commodities generally have higher interest rates, and countries that import basic commodities (and produce final goods) tend to have lower interest rates. In their model, shocks to global production are absorbed by the final goods producers due to limited shipping capacity, and hence, interest rates in commodity currencies are higher due to lower precautionary demand.

These studies, together with Bakshi, Panayotov, and Skoulakis (2011); Bakshi and Panayotov (2012); Cole and Obstfeld (1991); Fitzgerald (2012); Greenwood and Hanson (2013); Koijen, Moskowitz, Pedersen, and Vrugt (2012), and Lustig, Roussanov, and Verdelhan (2011, 2012), indicate that considering the relationship between these markets and associated frictions together could yield deeper insights into the common risks driving return variation.

The remainder of this chapter is organized as follows. The next section discusses the theoretical background and methodology underpinning this research. Section 3 describes the empirical implementation and data. I then present the results from the main empirical analysis in Section 4. The final section concludes with suggestions for future work.

4.2 Methodology

4.2.1 Futures term structure variation

I consider the deeper implications of the decomposition derived in Watugala (2014) for the futures term spread, which adapts the derivation in Campbell and Ammer (1993) for the term structure of bond yields.

Define $s_{n,t} \equiv y^*_{n,t} - y^*_{1,t}$, where $y^*_{n,t} = y_{n,t} - r_{n,t}$. Given $p_{n,t} = n(r_{n,t} - y_{n,t})$ and $p_{n,t} = -E_t \sum_{i=0}^{n-1} \delta_{n-i,t+i+1}$,

$$\begin{aligned} y^*_{n,t} &= \left(\frac{1}{n}\right) E_t \sum_{i=0}^{n-1} \delta_{n-i,t+i+1} \\ &= \left(\frac{1}{n}\right) E_t \sum_{i=0}^{n-1} (x_{n-i,t+i+1} + y^*_{1,t+i}). \end{aligned} \tag{4.1}$$

Given (4.1) and the definition of futures term spread $s_{n,t}$, the unexpected excess return can be decomposed into the unanticipated change in $y^*_{1,t}$ and the unexpected change in futures term spread:

$$\begin{aligned} x_{n,t+1} - E_t x_{n,t+1} =& - (n-1)(y^*_{n-1,t+1} - E_t y^*_{n-1,t+1}) \\ =& - (n-1)(E_{t+1} - E_t) \left[y^*_{1,t+1} + s_{n-1,t+1} \right]. \end{aligned} \tag{4.2}$$

Given the definition of $y^*_{1,t}$, it is straightforward to show that $y^*_{1,t+1} - E_t y^*_{1,t+1} = (E_{t+1} - E_t) \left[y_{1,t+1} - r_{1,t+1} \right]$. To derive the unexpected change in futures term spread, we start with (4.1) to relate futures term spread to expectations of future excess return and changes to the convenience yield of the front month future.

$$
\begin{aligned}
s_{n,t} \equiv & y^*_{n,t} - y^*_{1,t} \\
= & \left(\frac{1}{n}\right) E_t \sum_{i=0}^{n-1} (x_{n-i,t+i+1} + y^*_{1,t+i} - n y^*_{1,t}) \\
= & \left(\frac{1}{n}\right) \left(E_t \sum_{i=0}^{n-1} x_{n-i,t+i+1} \right) + E_t[-n y^*_{1,t} + y^*_{1,t} + (n-1) y^*_{1,t+1} - (n-2) y^*_{1,t+1} \\
& + \ldots + 3y^*_{1,t+n-3} - 2y^*_{1,t+n-3} + 2y^*_{1,t+n-2} - y^*_{1,t+n-2} + y^*_{1,t+n-1}] \\
= & \left(\frac{1}{n}\right) E_t \sum_{i=0}^{n-1} (x_{n-i,t+i+1} + (n-i-1) \Delta y^*_{1,t+i+1}).
\end{aligned} \tag{4.3}
$$

Then the unanticipated change in futures term spread can be derived as,

$$
\begin{aligned}
s_{n-1,t+1} - E_t s_{n-1,t+1} = & \left(\frac{E_{t+1} - E_t}{n-1}\right) \sum_{i=0}^{n-1} (x_{n-i,t+i+1} + (n-i-1) \Delta y^*_{1,t+i+1}) \\
= & \nu^x_{t+1} + \nu^y_{t+1} - \nu^r_{t+1}.
\end{aligned} \tag{4.4}
$$

When both the expectations hypothesis for the term structure of interest rates and the theory of storage hold exactly, the first term on the right hand side is zero, and innovations in futures term spread are driven by changes to expectations of future changes to front month convenience yield and short rates.

4.2.2 Measuring term structure variation

In order to empirically distinguish between the drivers of the variation in the level of commodity prices (spot premia) versus the variation in the slope of the futures curve (term premia), I consider the time series of orthogonal variation in 1M, 6M, and 12M futures; i.e., I run the following regressions to obtain three orthogonal time series:

$$ln(\sigma_{6,i,t}) = \alpha_6 + \beta_6^1 ln(\sigma_{1,i,t}) + \delta_{6,i,t}, \tag{4.5}$$

$$ln(\sigma_{12,i,t}) = \alpha_{12} + \beta_{12}^1 ln(\sigma_{1,i,t}) + \beta_{12}^6 \delta_{6,i,t} + \delta_{12,i,t}, \tag{4.6}$$

The regression analysis of commodity premia uses $r_{1,i,t}$, $\theta_{6,i,t}$, and $\theta_{12,i,t}$, where $\theta_{6,i,t} = \alpha_6 + \delta_{6,i,t}$ and $\theta_{12,i,t} = \alpha_{12} + \delta_{12,i,t}$. I use these series as dependent variables in regressions analyzing the predictive power of macroeconomic and financial variables chosen based on the existing literature.

It is also possible to characterize the term structure variation in volatility as a function F, similar to the basic setup for yield curves in Piazzesi (2010),

$$\sigma_{n,t}^2 = \sigma_{1,t}^2 F(n, \mathbf{z}_t), \tag{4.7}$$

where $F(1, \mathbf{z}_t) = 1$, $\mathbf{z}_t$ is a state vector capturing relevant factors, and $\sigma_{n,t}^2$ is the variance at time t of the future expiring in n periods. Whereas the focus of Watugala (2014) is on understanding the dynamics of the front month commodity futures volatility or level of volatility, the focus here is on analyzing the variation in the volatility differences along the futures curve.

$$\begin{aligned} F(n, \mathbf{z}_t) &= e^{\lambda_{n,t}}, \\ \lambda_{n,t} &= k_n^* + \mathbf{z}_t{}' \boldsymbol{\beta_n^*} + \varepsilon_{n,t}^*, \\ 2\left(\ln \sigma_{n,t} - \ln \sigma_{1,t}\right) &= \lambda_{n,t}, \\ s_{n,t} = \ln\left(\frac{\sigma_{n,t}}{\sigma_{1,t}}\right) &= k_n + \mathbf{z}_t{}' \boldsymbol{\beta_n} + \varepsilon_{n,t} \end{aligned} \tag{4.8}$$

In the empirical implementation of (4.8), I run regressions with $s_{6,t} =$

$\ln\left(\frac{\sigma_{6,t}}{\sigma_{1,t}}\right)$ and $s_{12,t} = \ln\left(\frac{\sigma_{12,t}}{\sigma_{1,t}}\right)$ as dependent variables. In this implementation, I use the simplest appropriate estimate of $\sigma_{1,t}$, $\sigma_{6,t}$, and $\sigma_{12,t}$: the time series of 1-month rolling realized volatility (standard deviation) of daily fixed term futures volatility at the required maturity. Table 4.2 shows the summary statistics for the relevant time series, while Table 4.5 presents results for the regressions using data for the entire date range available in this study, from September 1988 to December 2010. I also run rolling regressions with a 60-month window in order to understand the stability of the coefficients and to identify any clear regime shifts. Figures 4.2 to 4.5 present the coefficient values together with the 95% confidence intervals from these regressions.

4.2.3 Consumer and producer activity

For the supply-demand analysis, I match each of the commodity futures contracts in the study to a particular commodity code in UN Comtrade, determined to be most closely related to the underlying commodity (Table 4.1). The global bilateral trade flow information for the matched commodity is the proxy used for the aggregate supply and demand for the commodity underlying the futures contracts. I include measures of financial and macroeconomic uncertainty of commodity consumers and producers as explanatory variables in $\mathbf{z}_{i,t}$, via indices weighted by their fraction of world imports or exports, as appropriate. For a commodity i, the trade weight from country c in year t is $w^I_{i,c,t} = \frac{ImportValue_{i,c,t}}{\sum_{c=1}^{N} ImportValue_{i,c,t}}$ for imports and $w^E_{i,c,t} = \frac{ExportValue_{i,c,t}}{\sum_{c=1}^{N} ExportValue_{i,c,t}}$, for exports, where N is the total number of countries.

$$
\begin{aligned}
\Delta log(\lambda)_{j,t} =& \mu_j + \rho_j \Delta log(\lambda)_{j,t-1} + \epsilon_{j,t}, \\
\sigma^2_{j,t} =& \frac{1}{4} \sum_{k=t-3}^{t} |\epsilon_{j,t}|^2 , \\
C\_ VOL_{i,t} =& \left[\sum_{j=1}^{N} \left(w^I_{i,j,t} \right)^2 \sigma^2_{j,t} \right]^{\frac{1}{2}} ,
\end{aligned} \tag{4.9}
$$

where $\lambda_{c,t}$ can correspond to the equity market return, currency return, treasury yield spread, difference in financial openness, or political uncertainty in country c at time t, with Λ as [], $[EQ]$, $[FX]$, $[TY]$, $[FO]$, or $[PU]$ denoting volatility of GDP, equity market, exchange rate, treasury yield spread, financial openness, or political uncertainty indices, as appropriate. The volatility for producers ($P\_\Lambda\_VOL_{i,t}$) and consumers ($C\_\Lambda\_VOL_{i,t}$) for commodity i at time t is constructed by averaging over the squared absolute value of the innovations from an AR(1) fit of all exporters and importers, respectively. The empirical analysis uses these indices in regression specification as,

$$
Vol_{i,t} = \mu_i + \beta_1 P\_ VOL_{i,t} + \beta_2 C\_ VOL_{i,t} + \varepsilon_{1,t}. \tag{4.10}
$$

4.2.4 Data

A description of the 22 commodities in this study is in Table 4.1. The commodity price, trade, and returns data, together with the macroeconomic and financial variables used in this study are broadly the same as in Watugala (2014), and are described in detail therein. There are a few additions.

The Baltic Dry Index (shipping freight) data are from Bloomberg. I use a widely accessible measure of financial openness proposed by Chinn and

Ito (2008).[1] The exchange rate data are from Bloomberg where available, augmented with the historic exchange rate data for Euro area countries from the New York Federal Reserve Board. The US and Global Equity Market factors are from Kenneth French.[2] The political uncertainty measures are as introduced in Baker, Bloom, and Davis (2014). The measures of distance between countries are available from CEPII (Mayer and Zignago, 2011).

4.3 Empirical Results

4.3.1 The term structure of commodity futures volatility

Table 4.2, Panel A shows the summary statistics of fixed-term commodity futures volatility at 1-month, 6-month and 12-month maturities, grouped as Energy, Metals, Grains, Softs, and All commodities. The median, mean, and standard deviation of volatility clearly decreases as the maturity of the futures contract increases. This is in line with the idea that supply-demand shocks to the underlying commodity, which cannot be absorbed by current inventory levels, can impact futures prices in the near term. As there is time to adjust to changes to expectations regarding supply and demand at longer horizons, futures further out on the curve will exhibit fewer extreme price fluctuations, and hence, lower volatility.

Relative to commodities in energy, grain and softs, commodities in the metals group broadly show little (although still monotonically decreasing)

[1]The Chinn-Ito index (KAOPEN): http://web.pdx.edu/ ito/Chinn-Ito_website.htm.
[2]Kenneth French Data Library:
http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.
[3]Month codes: F - Jan | G - Feb | H - Mar | J - Apr | K - May | M - Jun |
N - Jul | Q - Aug | U - Sep | V - Oct | X - Nov | Z - Dec |

Table 4.1: Commodity Derivative Contract and Trade Classification Information

This table shows the 22 underlying commodities in the dataset categorized into four market groupings (Energy, Metal, Grain, and Soft). The naming convention for a futures contract is [Contract code][Expiry month code][Last digit of expiry year], e.g., On 5 January 2005, the WTI Crude Oil futures contract expiring in December 2008 is 'CLZ8'.[3]

Contract Code	Exchange Code	Traded Contract Months	Commodity Name	Futures Data Start
Energy				
CL	NYMEX	All months	Crude Oil	03/30/1983
HO	NYMEX	All months	Heating Oil	11/14/1978
NG	NYMEX	All months	Natural Gas	04/04/1990
PN	NYMEX	All months	Propane	01/03/2005
Metal				
GC	COMEX	G | J | M | Q | V | Z	Gold	12/31/1974
SI	COMEX	H | K | N | U | Z	Silver	06/12/1963
HG	COMEX	H | K | N | U | Z	Copper	01/03/1989
PA	NYMEX	H | M | U | Z	Palladium	01/03/1977
PL	NYMEX	F | J | N | V	Platinum	03/04/1968
Grain				
W	CBOT	H | K | N | U | Z	Wheat	07/01/1959
C	CBOT	H | K | N | U | Z	Corn	07/01/1959
O	CBOT	H | K | N | U | Z	Oats	07/01/1959
S	CBOT	F | H | K | N | Q | U | X	Soybeans	07/01/1959
SM	CBOT	F | H | K | N | Q | U | V | Z	Soybean Meal	07/01/1959
BO	CBOT	F | H | K | N | Q | U | V | Z	Soybean Oil	07/01/1959
RR	CBOT	F | H | K | N | U | X	Rough Rice	08/20/1986
Soft				
CT	NYCE	H | K | N | V | Z	Cotton	07/01/1959
OJ	NYCE	F | H | K | N | U | X	Orange Juice	02/01/1967
KC	CSCE	H | K | N | U | Z	Coffee	08/16/1972
SB	CSCE	H | K | N | V	Sugar	01/04/1961
CC	CSCE	H | K | N | U | Z	Cocoa	07/01/1959
LB	CME	F | H | K | N | U | X	Lumber	10/01/1969

Table 4.2: Commodity Futures Term Structure - Summary Statistics

This table shows the summary statistics of the term structure of commodity futures volatility by commodity group. Panel A shows the median, mean, and standard deviation of commodity futures at 1-month, 6-month, and 12-month fixed maturity term. σ_n is the 1-month standard deviation of the fixed term future at n-month maturity. In Panel B, the natural log of the ratio of realized volatility of the 6-month future over the 1-month future and the ratio of the natural log of realized volatility of the 12-month future over the 1-month future are shown multiplied by 100. These are measures of the percentage change in volatility along the futures curve. There are 268 months in this sample, from September 1988 to December 2010. The commodity groupings are as described in Table 4.1.

Panel A: Commodity futures volatility

	Median			Mean			Standard Deviation		
	σ_1	σ_6	σ_{12}	σ_1	σ_6	σ_{12}	σ_1	σ_6	σ_{12}
Energy	29.396	22.18	20.173	31.663	24.599	22.225	14.158	11.261	10.424
Metals	19.507	18.853	18.442	22.421	21.619	21.263	12.816	11.872	11.806
Grains	21.402	19.498	16.633	23.888	21.599	18.711	10.571	9.365	8.934
Softs	28.212	22.951	20.747	30.052	24.690	22.186	13.110	10.630	10.149
All	23.901	20.690	18.793	26.184	22.867	20.897	12.994	10.844	10.47

Panel B: Commodity futures volatility spreads

	Median		Mean		Standard Deviation	
	$ln(\sigma_6/\sigma_1)$	$ln(\sigma_{12}/\sigma_1)$	$ln(\sigma_6/\sigma_1)$	$ln(\sigma_{12}/\sigma_1)$	$ln(\sigma_6/\sigma_1)$	$ln(\sigma_{12}/\sigma_1)$
Energy	-25.18	-36.176	-26.278	-36.795	15.017	19.572
Metals	-1.089	-2.120	-3.171	-4.995	8.380	11.746
Grains	-7.984	-22.251	-9.868	-25.627	14.157	25.843
Softs	-14.797	-26.372	-20.809	-33.123	20.547	27.144
All	-8.059	-17.832	-13.047	-23.077	17.325	25.464

variation in average volatility by contract month. This is indicative of parallel shifts to the forward curve being more common for metals than for commodities in other groups. For crude oil, wheat, lumber, etc., the contracts in the nearer term are more volatile than the longer-dated contracts. This difference is potentially a risk characteristic driven solely by fundamentals - inventory, storability and the nature of the demand for a particular commodity. Relative to other commodity groups, metals are highly storable (dense and durable) and easy to transport, which potentially explains this result.

In Table 4.3, Panel A, I show the results of projecting 6-month (6M) fixed term futures volatility on contemporaneous 1-month (1M) futures volatility. If the 1M future is considered a measure of the level of the futures curve, this allows me to obtain the variation at the 6M point of the futures curve that is completely orthogonal to it, $\delta_{6,i,t}$, and study its dynamics. The adjusted R-squared of these regressions range from 0.76 for Softs to 0.97 for Metals. The highest standard deviation for $\delta_{6,i,t}$ is for Softs, corresponding to the highest variance unrelated to the 1M future. As expected, given Table 4.2 and the indication of parallel shifts to the futures curve dominating for this group, Metals show the lowest standard deviation in the variation at the 6M point unexplained by the 1M futures return.

Similarly, in Table 4.3, Panel B, the summary of the results for the regression in (4.6) shows that, after accounting for 1M and 6M futures volatility, the orthogonal variation in 12-month (12M) futures is small. The adjusted R-squared for these regressions are again lowest for the Softs group and highest for Metals.

These results are broadly in line with a principal component analysis of commodity futures curves, which shows that three components are important

Table 4.3: Commodity Futures Term Structure - Orthogonal Projections

Panel A shows the results of projections of 6-month futures volatility on 1-month future volatility and the summary statistics of the resulting time series of the 6-month futures variation that is orthogonal to the 1-month future. Panel B shows the results of projections of 12-month future volatility on 1-month and 6-month futures volatility, and the summary statistics of the resulting time series of the 12-month futures variation that is orthogonal to both 1-month and 6-month futures. In both Panel A and B, the regressions use the standardized natural log of volatility series. t-statistics clustered by month are shown in parenthesis under the regression coefficients. There are 268 months in this sample, from September 1988 to December 2010. The commodity groupings are as described in Table 4.1.

Panel A: Projection of 6-month futures volatility on 1-month futures volatility

$$ln(\sigma_{6,i,t}) = \alpha_6 + \beta_6^1 ln(\sigma_{1,i,t}) + \delta_{6,i,t}, \tag{4.11}$$
$$\theta_{6,i,t} = \alpha_6 + \delta_{6,i,t} \tag{4.12}$$

	α	β	Adjusted R-squared	Standard Deviation(θ_6)
Energy	-0.281 [-3.582]	1.005 [42.690]	0.867	0.150
Metals	0.051 [2.235]	0.972 [120.142]	0.974	0.083
Grains	0.110 [2.929]	0.932 [74.797]	0.889	0.139
Softs	-0.090 [-1.038]	0.965 [36.386]	0.765	0.205

Panel B: Projection of 12-month futures volatility on 1-month and 6-month futures volatility

$$ln(\sigma_{12,i,t}) = \alpha_{12} + \beta_{12}^1 ln(\sigma_{1,i,t}) + \beta_{12}^6 \delta_{6,i,t} + \delta_{12,i,t}, \tag{4.13}$$
$$\theta_{12,i,t} = \alpha_{12} + \delta_{12,i,t} \tag{4.14}$$

	α	β^1	β^6	Adjusted R-squared	Standard Deviation(θ_{12})
Energy	-0.275 [-8.019]	0.973 [94.360]	1.192 [38.108]	0.965	0.079
Metals	0.059 [6.868]	0.963 [329.918]	1.241 [22.602]	0.989	0.054
Grains	0.14 [2.877]	0.872 [54.607]	1.176 [19.157]	0.812	0.193
Softs	-0.316 [-5.457]	0.995 [59.325]	0.889 [23.713]	0.816	0.201

in capturing variation in the term structure, commonly identified in the literature as level, slope, and curvature (Geman, 2005). The first component (level) captures the major portion of the total variance.[4] In Table 4.4, I show the correspondence between these orthogonal projections and the three principal components characterizing the commodity volatility term structure. Figure 4.1 plots the loadings of the three principal components on 1M, 6M, and 12M maturity points on the term structure.

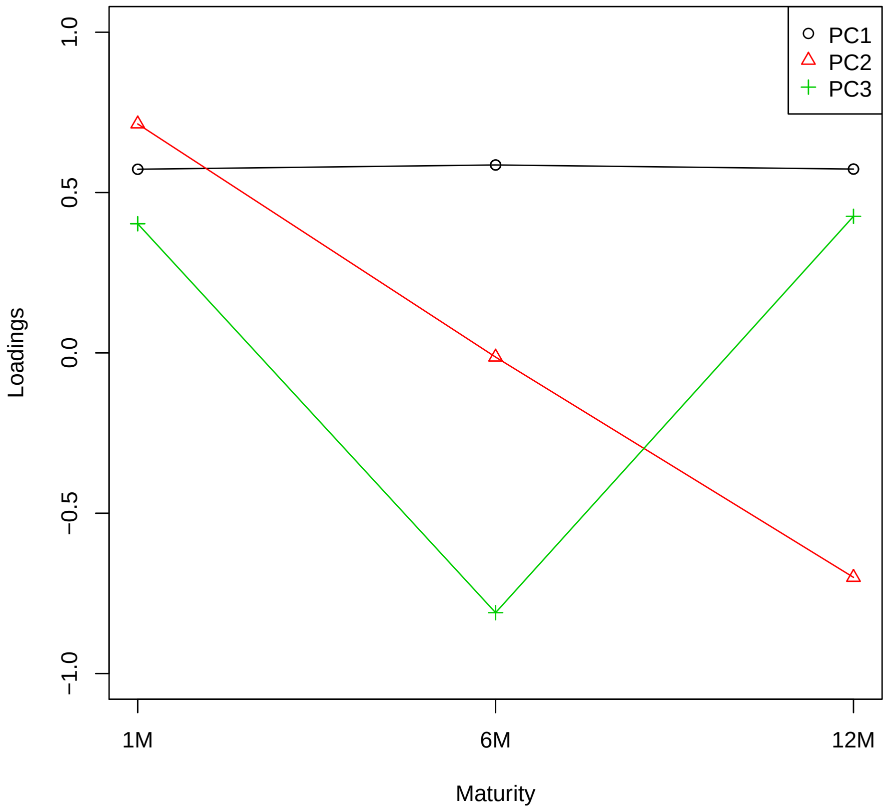


Figure 4.1: Principal component loadings along the term structure.
The figure shows the loads at each maturity of the three principal components describing the volatility of the commodities term structure.

[4]The proportion of variance explain by the three principal components in this analysis, level, slope, and curvature, are 94.33%, 4.24%, and 1.43%, respectively.

Table 4.4: Correlation between orthogonalized θ_n series and principal components

This table shows the correlation between orthogonalized θ_n series described in Table 4.2 and principal components of the 1M, 6M, 12M futures volatility. There are 268 months in this sample, from September 1988 to December 2010.

	$ln(\sigma_1)$	θ_6	θ_{12}
$PC1$	0.963	0.238	0.116
$PC2$	0.255	-0.673	-0.670
$PC3$	0.083	-0.689	0.702

While there may be drawbacks to this approach, including the absence of a directly tradeable equivalent to θ_6 and θ_{12}, it allows for the study of the variation in 1M, 6M, and 12M futures separately. The orthogonalization allows for the clear delineation of how common factors are related to commodity level or spot premia versus commodity term premia (at different points on the futures curve).

4.3.2 Consumer and producer impact

Table 4.5 shows the results of panel regressions with three variations to the specification in Eq. 4.10. The dependent variables are the 1M volatility ($l_1 = ln(\sigma_1)$), the 6M spread ($s_6 = ln(\sigma_6/\sigma_1)$), and the 12M spread ($s_{12} = ln(\sigma_{12}/\sigma_1)$). This analysis uses the trade-weighted volatility indices for producer and consumer country shocks to quarterly GDP as explanatory variables. These regressions all use the natural logarithm of all volatility variables, and all variables are standardized. The regressions include commodity and quarterly fixed effects. t-statistics clustered by month are shown in parenthesis below each coefficient estimate.

The first three columns of results show regressions with only the producer volatility index of shocks to GDP included, in addition to commodity and

Table 4.5: Commodity Futures Term Structure - Producer and Consumer Shocks

This table shows results from panel regressions including the trade-weighted volatility indices for producer and consumer country shocks (to quarterly GDP) as explanatory variables. The dependent variables are the 1M volatility ($l_1 = ln(\sigma_1)$), the 6M spread, and the 12M spread. The term spreads are defined as, $s_n = ln(\sigma_n/\sigma_1)$. The dependent and independent variables are standardized. There are 268 months in this sample, from September 1988 to December 2010. All regressions include commodity and quarterly fixed effects. t-statistics clustered by month are shown in parenthesis below each coefficient estimate.

	1			2			3		
	l_1	s_6	s_{12}	l_1	s_6	s_{12}	l_1	s_6	s_{12}
PROD_VOL	0.089***	-0.005	-0.035				0.086***	-0.002	-0.032
	(4.977)	(-0.246)	(-1.880)				(4.857)	(-0.127)	(-1.690)
CONS_VOL				-0.081	0.073	0.109***	-0.074	0.073	0.107***
				(-2.579)	(2.247)	(3.199)	(-2.359)	(2.217)	(3.077)
Adjusted R-squared	0.323	0.199	0.219	0.320	0.200	0.221	0.324	0.200	0.221
BIC	11,707.6	12,446.2	12,334.5	11,727.5	12,440.3	12,324.8	11,708.8	12,448.7	12,330.0

time fixed effects. Regressions under the second specification include only the consumer index as an explanatory variable, in addition to commodity and time fixed effects. The third set of results, shown in the final three columns, are from regressions including both producer and consumer trade-weighted volatility indices of shocks to GDP.

Increases to the volatility of producer shocks is associated with higher 1M volatility, which is identified as a level factor in this framework (see Table 4.4). These findings are robust to the inclusion of a variety of controls discussed in Watugala (2014). The volatility of consumer shocks is more significant further out on the futures curve, and remains robust to different specifications and sets of controls.

A potential limitation of this analysis arises from the imprecise nature of the mapping of commodity futures to the trade flows of the underlying. The exchange traded futures contracts in this study are written on underlying physical assets at specified grades, delivery locations, times of delivery, etc.

Table 4.6: Commodity Futures Term Structure - Producer and Consumer Shocks

This table shows results from panel regressions including the trade-weighted volatility indices for producer and consumer country shocks (to quarterly GDP) as explanatory variables. The dependent variables are the first three principal components characterizing the commodity volatility term structure, *level*, *slope*, and *curvature*. The dependent and independent variables are standardized. There are 268 months in this sample, from September 1988 to December 2010. All regressions include commodity and quarterly fixed effects. t-statistics clustered by month are shown in parenthesis below each coefficient estimate.

	4			5			6		
	level	*slope*	*curvature*	*level*	*slope*	*curvature*	*level*	*slope*	*curvature*
PROD_VOL	0.122***	0.028***	-0.003				0.119***	0.027***	-0.002
	(4.232)	(3.920)	(-0.635)				(4.139)	(3.759)	(-0.559)
CONS_VOL				-0.101	-0.038***	0.011	-0.091	-0.036***	0.011
				(-1.905)	(-3.463)	(1.788)	(-1.729)	(-3.239)	(1.770)
Adjusted R-squared	0.351	0.159	0.160	0.349	0.158	0.161	0.351	0.161	0.161
BIC	16,146.6	3,514.5	-1,345.3	16,161.5	3,520.3	-1,347.9	16,151.0	3,512.2	-1,339.9

The minutiae related to a specific futures contract, its market microstructure and the vagaries of delivering its underlying, can create frictions that are observable and significant in futures return dynamics, unrelated to the global bilateral supply and demand of the corresponding commodity. Moreover, many of the explanatory variables are only available at lower frequencies. The regressions are set up in such a way that these measurement errors introduce orthogonal noise in the variables, which reduces the significance of the regression coefficients compared to the case when precisely measured variables are available.

While non-OECD countries with greater economic uncertainty have always been the major producers of basic commodities, Watugala (2014) shows that, during the past couple of decades, these countries have also become major consumers. Although globalization and other changes have increased financial liberalization throughout the world, many major non-OECD commodity trading countries remain some of the least financially open.

4.3.3 Volatility term structure - predictive regressions

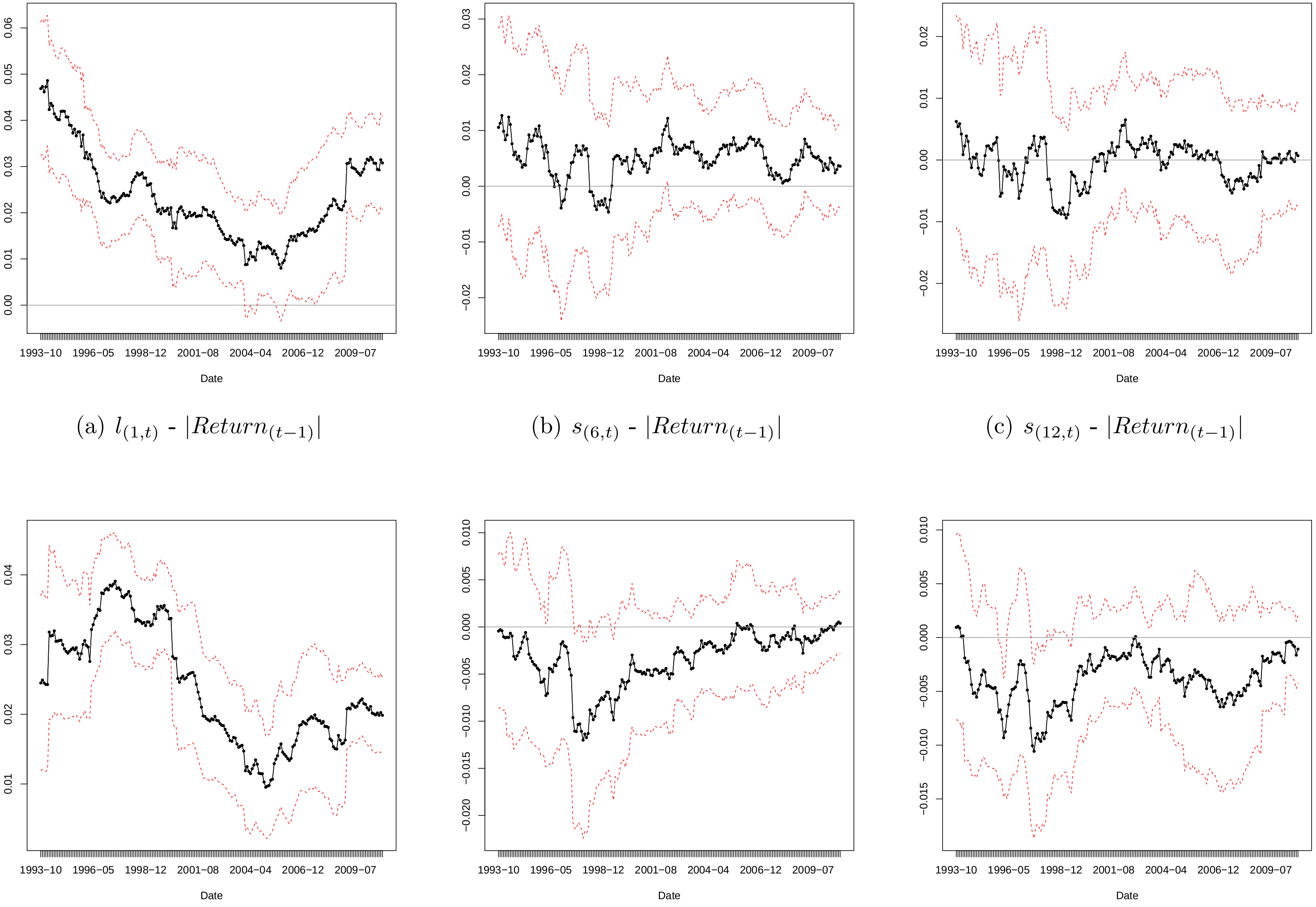
Table 4.7 shows model fit measures for the balanced panel regressions of (time, t) dependent variables over lagged (time, $t-1$) explanatory variables. The dependent variables for the regression results shown are the 1M volatility ($l_1 = ln(\sigma_1)$), the 6M spread, and the 12M spread, in addition to the first three principal components characterizing the commodity volatility term structure, *level*, *slope*, and *curvature*. The term spreads are defined as, $s_n = ln(\sigma_n/\sigma_1)$. Panel A shows the adjusted R-squareds, Panel B shows the F-test results of the nested models, and Panel C shows the Bayesian information criterion values. Column 1 shows the fit measures from the regression specification including the dependent variables used in Table 3.5.A ("Baseline"), column 2 shows those from including the variables used in Table 3.6 ("EU_PC 1-4"), column 3 shows those from including the variables used in Table 3.7 ("Commodity market"'), and column 4 adds the lagged trade-weighted indices, $PROD\_VOL$ and $CONS\_VOL$. The dependent and independent variables are standardized. All regressions include commodity and season fixed effects.

Figures 4.2 to 4.6 present the results of 60-month rolling regressions set up as specified in Eq. (4.8). These are balanced panel regressions of (time, t) dependent variables over lagged (time, $t-1$) explanatory variables. The dependent variables are the 1M volatility ($l_1 = ln(\sigma_1)$), the 6M spread, and the 12M spread. The term spreads are defined as, $s_n = ln(\sigma_n/\sigma_1)$. The dependent and independent variables are standardized. All regressions include commodity and season fixed effects. The solid black line shows the coefficients for baseline variables from 60-month rolling regressions. The dotted red lines capture the 95% confidence interval.

Table 4.7: Commodity Futures Volatility Term Structure

This table shows model fit measures for the balanced panel regressions of (time, t) dependent variables over lagged (time, $t-1$) explanatory variables. The dependent variables for the regression results shown are the 1M volatility ($l_1 = ln(\sigma_1)$), the 6M spread, and the 12M spread, in addition to the first three principal components characterizing the commodity volatility term structure, *level*, *slope*, and *curvature*. The term spreads are defined as, $s_n = ln(\sigma_n/\sigma_1)$. Panel A shows the adjusted R-squareds, Panel B shows the F-test results of the nested models, and Panel C shows the Bayesian information criterion values. Column 1 shows the fit measures from the regression specification including the dependent variables used in Table 3.5.A ("Baseline"), column 2 adds the dependent variables used in Table 3.6 ("EU_PC 1-4"), column 3 adds the variables used in Table 3.7 ("Commodity market"'), and column 4 adds the lagged trade-weighted indices, $PROD\_VOL$ and $CONS\_VOL$. All regressions include commodity and season fixed effects.

	Baseline 1	EU_PC 1-4 2	Commodity market 3	Trade-weighted indices 4
Panel A: Adjusted R-squared				
l_1	0.394	0.431	0.435	0.437
s_6	0.178	0.190	0.190	0.191
s_{12}	0.178	0.193	0.193	0.195
level	0.402	0.446	0.451	0.452
slope	0.126	0.139	0.139	0.142
curvature	0.157	0.163	0.163	0.163
Panel B: F-test				
l_1		72.738***	12.378***	9.957***
s_6		17.879***	1.272	3.201**
s_{12}		20.573***	1.851	7.615***
level		89.508***	15.091***	5.975***
slope		17.498***	1.631	9.119***
curvature		9.094***	0.807	0.373
Panel C: Bayesian information criterion (BIC)				
l_1	10,642.9	10,395.7	10,383.8	10,380.6
s_6	11,996.9	11,959.1	11,980.4	11,990.8
s_{12}	11,992.2	11,943.9	11,963.6	11,965.0
level	15,211.0	14,901.6	14,881.5	14,886.2
slope	3,116.8	3,080.7	3,101.0	3,099.4
curvature	-1,897.0	-1,899.9	-1,877.1	-1,861.1



(a) $l_{(1,t)}$ - $|Return_{(t-1)}|$

(b) $s_{(6,t)}$ - $|Return_{(t-1)}|$

(c) $s_{(12,t)}$ - $|Return_{(t-1)}|$

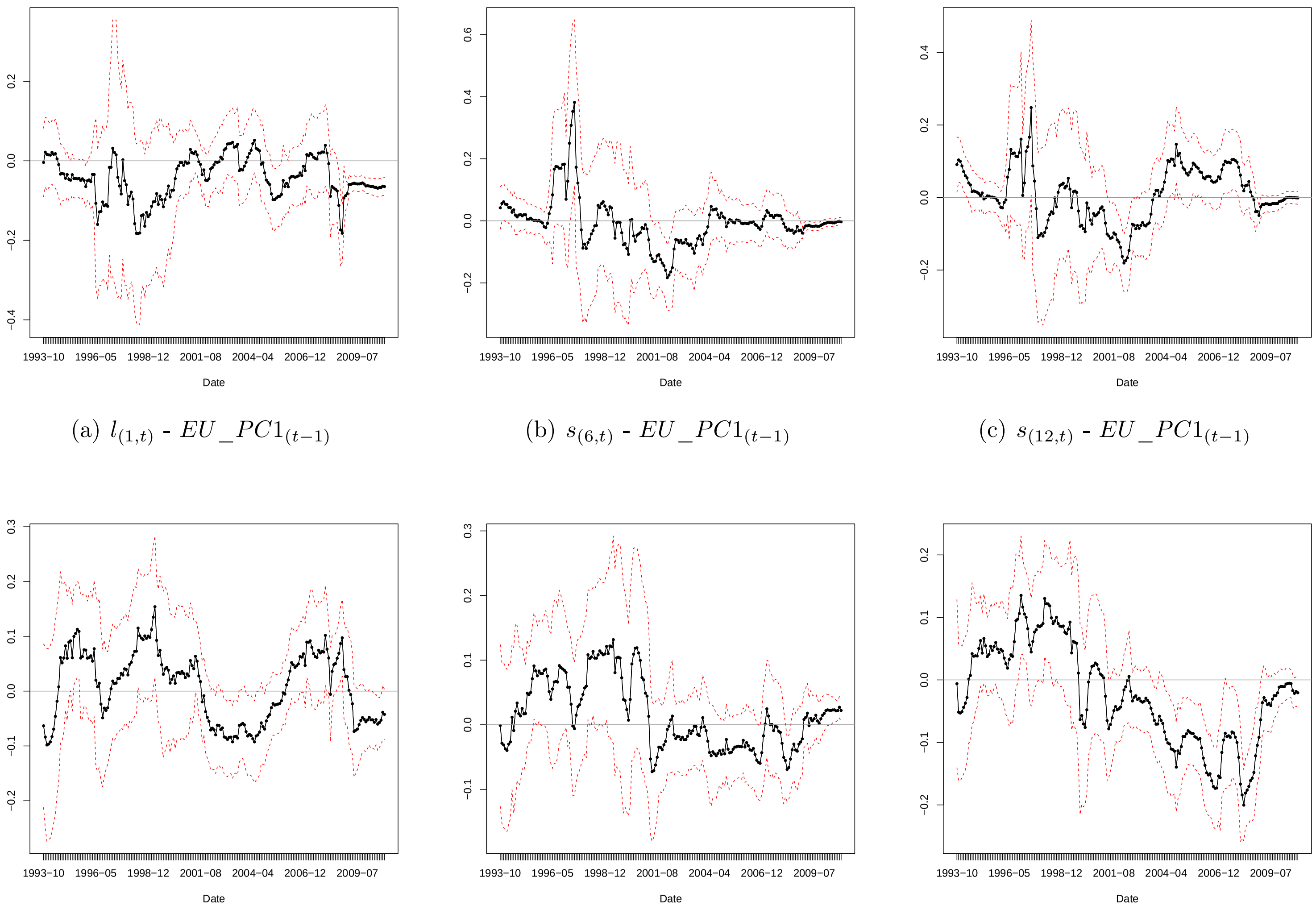
(d) $l_{(1,t)}$ - $Vol_{(t-1)}$

(e) $s_{(6,t)}$ - $Vol_{(t-1)}$

(f) $s_{(12,t)}$ - $Vol_{(t-1)}$

Figure 4.2: Results from the rolling regressions - the coefficients for variables in the baseline specification.

Panel regression results with lagged controls. The dependent variables are the 1M volatility ($l_1 = ln(\sigma_1)$), the 6M spread, and the 12M spread. The term spreads are defined as, $s_n = ln(\sigma_n/\sigma_1)$. The dependent and independent variables are standardized. The solid black line shows the coefficients for baseline variables from 60-month rolling regressions. The dotted red lines capture the 95% confidence interval.



(a) $l_{(1,t)}$ - $EU\_PC1_{(t-1)}$

(b) $s_{(6,t)}$ - $EU\_PC1_{(t-1)}$

(c) $s_{(12,t)}$ - $EU\_PC1_{(t-1)}$

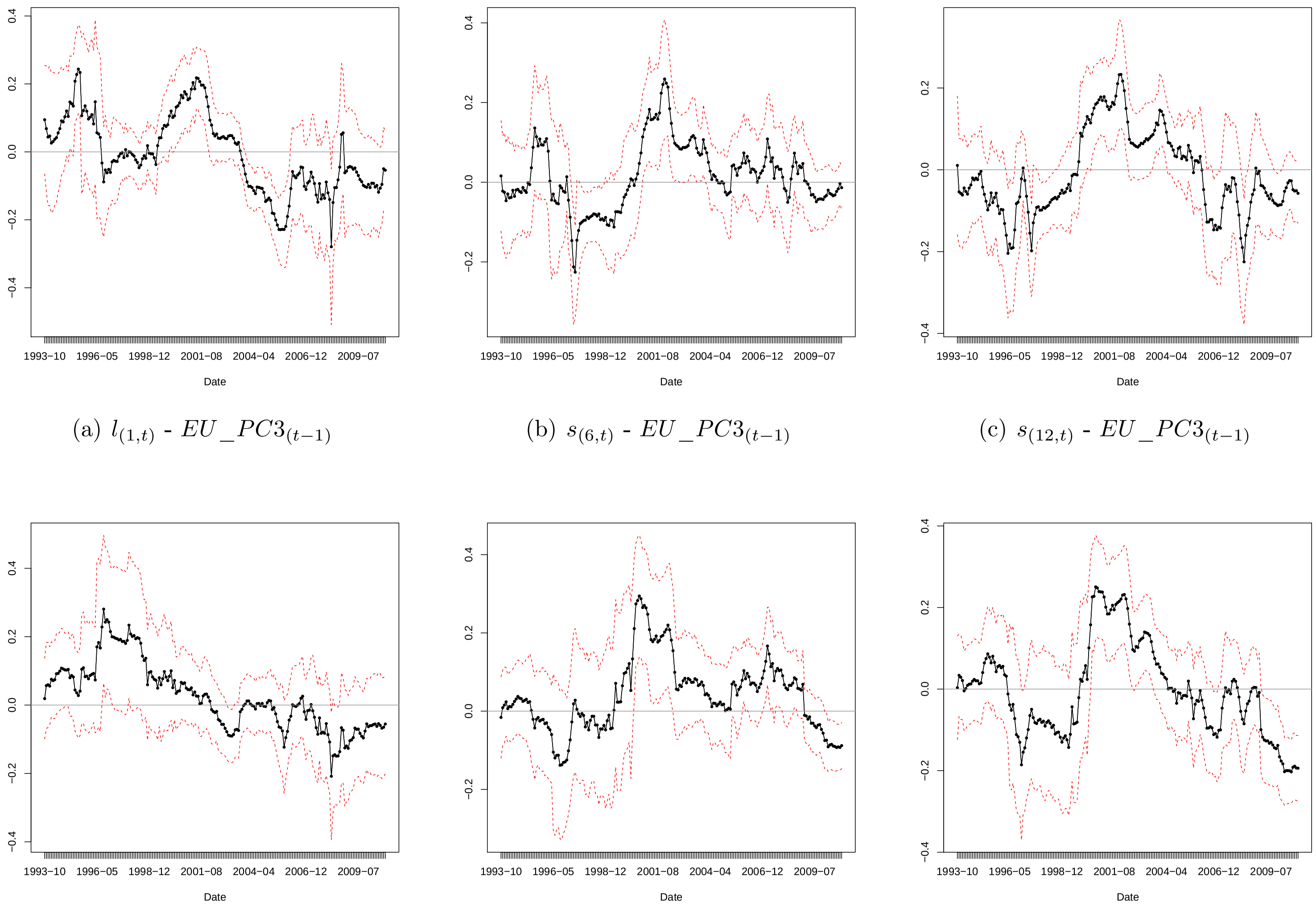
(d) $l_{(1,t)}$ - $EU\_PC2_{(t-1)}$

(e) $s_{(6,t)}$ - $EU\_PC2_{(t-1)}$

(f) $s_{(12,t)}$ - $EU\_PC2_{(t-1)}$

Figure 4.3: Results from the rolling regressions - the coefficients for the economic uncertainty variables.

Panel regression results with lagged controls. The dependent variables are the 1M volatility ($l_1 = ln(\sigma_1)$), the 6M spread, and the 12M spread. The term spreads are defined as, $s_n = ln(\sigma_n/\sigma_1)$. The dependent and independent variables are standardized. The solid black line shows the coefficients for baseline variables from 60-month rolling regressions. The dotted red lines capture the 95% confidence interval.



(a) $l_{(1,t)}$ - $EU\_PC3_{(t-1)}$

(b) $s_{(6,t)}$ - $EU\_PC3_{(t-1)}$

(c) $s_{(12,t)}$ - $EU\_PC3_{(t-1)}$

(d) $l_{(1,t)}$ - $EU\_PC4_{(t-1)}$

(e) $s_{(6,t)}$ - $EU\_PC4_{(t-1)}$

(f) $s_{(12,t)}$ - $EU\_PC4_{(t-1)}$

Figure 4.4: Results from the rolling regressions - the coefficients for the economic uncertainty variables.

Panel regression results with lagged controls. The dependent variables are the 1M volatility ($l_1 = ln(\sigma_1)$), the 6M spread, and the 12M spread. The term spreads are defined as, $s_n = ln(\sigma_n/\sigma_1)$. The dependent and independent variables are standardized. The solid black line shows the coefficients for baseline variables from 60-month rolling regressions. The dotted red lines capture the 95% confidence interval.

(a) $l_{(1,t)}$ - $HEDGER\_OIG_{(t-1)}$

(b) $s_{(6,t)}$ - $HEDGER\_OIG_{(t-1)}$

(c) $s_{(12,t)}$ - $HEDGER\_OIG_{(t-1)}$

(d) $l_{(1,t)}$ - $HEDGER\_IMB_{(t-1)}$

(e) $s_{(6,t)}$ - $HEDGER\_IMB_{(t-1)}$

(f) $s_{(12,t)}$ - $HEDGER\_IMB_{(t-1)}$

Figure 4.5: Results from the rolling regressions - the coefficients for the open interest and hedging imbalance variables. Panel regression results with lagged controls. The dependent variables are the 1M volatility ($l_1 = ln(\sigma_1)$), the 6M spread, and the 12M spread. The term spreads are defined as, $s_n = ln(\sigma_n/\sigma_1)$. The dependent and independent variables are standardized. The solid black line shows the coefficients for baseline variables from 60-month rolling regressions. The dotted red lines capture the 95% confidence interval.

(a) $l_{(1,t)}$ - $CMOM_{(t-1)}$

(b) $s_{(6,t)}$ - $CMOM_{(t-1)}$

(c) $s_{(12,t)}$ - $CMOM_{(t-1)}$

Figure 4.6: Results from the rolling regressions - the coefficients for the commodity market momentum variable.

Panel regression results with lagged controls. The dependent variables are the 1M volatility ($l_1 = ln(\sigma_1)$), the 6M spread, and the 12M spread. The term spreads are defined as, $s_n = ln(\sigma_n/\sigma_1)$. The dependent and independent variables are standardized. The solid black line shows the coefficients for baseline variables from 60-month rolling regressions. The dotted red lines capture the 95% confidence interval.

4.4 Conclusions

This chapter conducts a systematic analysis of the term structure variation in risk premia and volatility in commodity futures markets. I analyze the explanatory power of macroeconomic and financial shocks to understand the drivers of differences along the term structure and the changes over time. This work further analyzes the impact of explanatory variables on futures volatility at different maturities along the term structure or on the term volatility spread, beyond the impact on the volatility of spot premia.

I isolate the orthogonal variation in the volatility at three maturities (1M, 6M, and 12M) along the futures curve, and analyze the differences in the significance of different explanatory variables. I proxy for consumer or producer shocks using commodity trade-weighted (import- or export-weighted) volatility indices of GDP, equity market, interest rate spreads, exchange rates, and financial openness. This allows for the analysis of any differential impact of consumer and producer shocks at different maturities.

This heterogeneity can arise from a variety of channels, e.g., if consumers hedge at shorter horizons than producers who concentrate their activity in futures markets at longer maturities, and hence the variation at different maturities are driven by participants on different sides of the market for the underlying commodity. I find that producer risk is significant for both short- and long-dated maturities, while consumer risk has greater explanatory power for the volatility of the term spread.

Chapter 5

Conclusions

This thesis contributes to our understanding of how economic factors, market frictions, and limits to arbitrage can propagate and exacerbate shocks between markets through fundamental and financial transmission channels.

In the first essay, we use a dataset of all firms listed in the equity markets of 43 countries for which balance sheet data are available to test whether the use of trade credit by firms creates a link between customer stock returns and supplier stock returns across countries. We find a previously unknown channel which yields insights into how funding decisions at a microeconomic level, coupled with the financial market actions of asymmetrically informed investors, can propagate shocks internationally. We use both portfolio sorts and firm-level panel regressions to show that this empirical finding is robust to a variety of specifications and controls.

We model the decision of firms to engage in trade credit agreements as opposed to pure cash sales, and analyze how stock market investors in an international segmented markets setup can generate predictability between the equity markets of the customer firms and the supplier firms. Trade credit creates a fundamental correlation in the future dividend streams of customer and supplier firms, which is learned by informed international investors. This information asymmetry means that shocks to customer firms are not immediately revealed in the supplier firm stock prices, as uninformed investors cannot distinguish between information and noise shocks with certainty.

The second essay investigates the dynamics and sources of fluctuations over time of commodity futures volatility. In order to better understand the drivers of return variation in commodity futures markets, I derive the variance decomposition for the commodity futures basis to show how unexpected excess returns result from new information about the expected future interest rates, convenience yields, and risk premia. These expectations are updated in response to news about the future state of the economy and future commodity supply and demand. This motivates my empirical analysis of the volatility impact of economic and inflation regimes and commodity supply-demand shocks.

Using data on 22 major commodity futures markets and global bilateral commodity trade, I analyze the extent to which commodity volatility is related to fundamental uncertainty from increased emerging market demand and macroeconomic forecast uncertainty. I control for the potential impact of financial frictions introduced by changing market structure and commodity index trading.

Higher concentration in emerging market importers of a commodity is associated with higher futures volatility. I find that commodity futures volatility is significantly predictable using variables capturing macroeconomic uncertainty. I examine the conditional variation in the asymmetric relationship between returns and volatility, and how this relates to the futures basis and sensitivity to consumer and producer shocks. The analysis uses unexpected realizations and forecast disagreement in variables which capture fundamental and financial uncertainty to study their impact.

This essay also contributes to our understanding of the impact of "financialization" in commodity markets from the introduction of commodity indices and other financial products which granted easy direct access to futures markets to a new class of investors. In both rolling regressions and regressions with interactions for the time period commonly identified in the literature as the financialization period, the variables capturing financial frictions do not show increased significance in explaining realized volatility of commodity futures returns.

This work builds on results discussed in previous work that show emerging markets and recessionary periods are strongly associated with economic uncertainty, and adapts studies on the granular origins of volatility and shows how the same principle can affect volatility in global markets. As shown in the literature on explaining time-varying realized volatility, it is difficult to contemporaneously explain let alone predict financial asset volatility using factors reflecting economic conditions, even when model results and economic intuition posit such a relationship. As such, the results in this chapter constitute a step forward in our understanding of the factors that drive volatility.

As global markets become increasingly interlinked, it is imperative to understand the impact of increased concentration and emerging market participation in commodity trade, and the manner and extent to which shocks propagate between markets. Investors and end-users (commodity producers and consumers) in commodity markets benefit from understanding how the observed price behavior relates to the prevailing economic conditions. Uncertainty can lead to the long-term misallocation of resources as end-users evaluate real options in their investment decisions. Moreover, for many commodities with illiquid or short-dated derivatives markets of little depth, these findings can be a useful aid to price discovery and risk management.

In the third essay, I attempt to extend our understanding of the dynamics of the term structure of futures returns. I test whether it is possible to identify the impact of consumer hedging at shorter maturities and producer hedging at longer maturities by using commodity trade-weighted (import- or export-weighted) indices of equity returns, interest rates and exchange rates.

I also attempt to isolate the impact of these explanatory variables on the volatility of spot premia (proxied as the one-month volatility) from their impact on futures volatility at different maturities along the term structure. I find that shocks to producers are significant for both short- and long-dated maturities, while consumer shocks have greater explanatory power for the volatility of the term spread.

The findings on commodity futures in this work highlight the significant time variation in risk premia (both spot and term premia) and volatility in commodity futures markets. The extent of the cross-sectional variation within and across different commodity groups, and the difficulty in explaining this variation also hints at the problems in considering commodities a homogeneous asset class. The differential impact of unexpected shocks to the economy, weather, supply-demand, liquidity, market concentration, and trading volume in different commodity markets, while perhaps dampened via financialization, remains a feature of these markets, even over the past decade.

This thesis contributes to our knowledge of the fundamental underpinnings of interconnected markets and how agents acting in an environment with market frictions may alter the dynamics of markets in unexpected ways. Further research of this nature to deepen our understanding of such systems remains imperative, so that policy-makers and market participants can make more informed decisions that may mitigate, if not altogether preempt, future financial crises.

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