# Essays in International Finance

by

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# Contents

# List of Tables

# List of Figures

*To my parents*

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# Declarations

This thesis is submitted to the University of Warwick in support of my application for the degree of Doctor of Philosophy. It has been composed by myself and has not been submitted in any previous application for any degree.

Chapters 2 and 3 are based on collaborative work with Pasquale Della Corte (Imperial College London Business School, Chapter 3), Dennis Reinhardt (Bank of England, Chapter 2) and Lucio Sarno (Cass Business School, Chapter 3). In both instances the writing and majority of the empirical analysis were undertaken by the author. In Chapter 2, Dennis Reinhardt also undertook some additional research analysis at the request of the author, using data which had to remain on site at the Bank of England. Moreover, George Gale and Boris Butt provided research assistance at the Bank of England, under the guidance of the author, to collect macroeconomic and financial data. In Chapter 3, Pasquale Della Corte also provided data on currency options collected from J.P. Morgan.

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[1] Della Corte, Pasquale, Steven J. Riddiough and Lucio Sarno (2014), "Currency Premia and Global Imbalances," Unpublished manuscript, The University of Warwick. [Submitted: Review of Financial Studies]

[2] Reinhardt, Dennis, and Steven J. Riddiough (2014), "The Two Faces of Cross-Border Bank Flows: An investigation into the links between global risk, arms-length funding and internal capital markets," *Bank of England Working Paper No. 498.*

# Abstract

This thesis studies the role of global risk within the context of international finance. In total, the thesis is composed of three essays. In Chapter 2, I investigate the impact of global risk on the cross-border flows of funding between banks. Specifically, I decompose gross cross-border bank-to-bank funding between arms-length (interbank) and related (intragroup) funding, and show that while interbank funding is withdrawn when global risk is high, intragroup funding remains stable during these periods, despite being more volatile on average. The results are in contradiction with theoretical predictions for the behavior of cross-border banking flows, and help explain why certain banking systems lost more cross-border bank-to-bank funding than others during the global financial crisis of 2008. In Chapter 3, I turn my attention to the currency market and show that global imbalances are a fundamental economic determinant of currency risk premia. I propose a factor that captures exposure to countries' external imbalances – termed the global imbalance risk factor – and show that it explains most of the cross-sectional variation in currency excess returns. The economic intuition of this factor is simple: net foreign debtor countries offer a currency risk premium to compensate carry trade investors willing to finance negative external imbalances.

Finally, in Chapter 4, I focus again on the currency market by investigating the fundamental source of variation in currency betas. Theoretical models of currency premia offer precise explanations for *why* currencies exhibit heterogeneous exposure (betas) to risk. Characteristic factors, constructed to reflect these 'beta predictions' of leading models of currency premia would, therefore, also be expected to explain the cross-section of currency portfolio returns. I find, however, that none of the factors can explain *any* of the cross-sectional spread in returns. Yet alternative non-theoretical characteristic factors, based on macroeconomic, financial and political risk, perform almost universally well in cross-sectional tests. But these factors can also be dismissed as explanations for heterogeneous currency betas, with a simple secondary test. The findings imply a need for a stricter empirical benchmark for assessing all theoretical models of currency premia. Moreover, by investigating currency betas, I show that standard empirical asset pricing techniques can filter out around 99% of spurious currency risk factors.

# Abbreviations

| | |
|---|---|
| **$AC_1$** | Autocorrelation 1-lag |
| **BIS** | Bank for International Settlements |
| **CBOE** | Chicago Board Options Exchange |
| **CC** | Colacito and Croce (2013) |
| **CIP** | Covered Interest Rate Parity |
| **DOL** | Dollar Risk |
| **EME** | Emerging Market Economy |
| **ER** | Exchange Rate |
| **FMB** | Fama-MacBeth Regressions |
| **FRED** | Federal Reserve Economic Data |
| **FX** | Foreign Exchange |
| **GDP** | Gross Domestic Product |
| **GMM** | Generalized Method of Moments |
| **HAC** | Heteroskedasticity and Autocorrelation Consistent |
| **HJ** | Hansen-Jagannathan |
| **$HML_{alt}$** | Non-Theoretical Characteristic Factor |
| **$HML_{FX}$** | Slope Risk |

**$\mathbf{HML_{NA}}$** Global Imbalance Risk

**$\mathbf{HML_{TM}}$** Theoretically-motivated Characteristic Factor

**$\mathbf{HML_{rnd}}$** 'Useless' Currency Factor

**IBLN** International Banking Locational Statistics by Nationality

**ICRG** International Country Risk Guide

**IFS** International Financial Statistics

**IMF** International Monetary Fund

**IR** Interest Rate

**Kurt** Kurtosis

**LRV** Lustig, Roussanov, and Verdelhan (2011)

**LM** Lagrange Multiplier

**MDD** Maximum Draw Down

**NBER** National Bureau of Economic Research

**NFA** Net Foreign Assets

**Obs** Observations

**OTC** Over the Counter

**$\mathbf{P_1}$** Portfolio 1

**$\mathbf{P_5}$** Portfolio 5

**PC** Principal Component

**PCA** Principal Component Analysis

**PRS** Political Risk Services

**RMSE** Root Mean Squared Error

**ROE** Return on Equity

**Sdev** Standard deviation

**SDF** Stochastic Discount Factor

**Skew** Skewness

**SR** Sharpe Ratio

**TCV** Theoretically-motivated Control Variable

**TED** Treasury-Eurodollar

**UIP** Uncovered Interest Rate Parity

**USD** U.S. Dollar

**V** Verdelhan (2010)

**VaR** Value at Risk

$\mathbf{VOL_{FX}}$ Currency Volatility Risk

**WDI** World Development Indicators

*"Our knowledge can only be finite, while our ignorance must necessarily be infinite"*

Karl Popper

# Chapter 1

# Introduction

"*War is the only proper school for a surgeon*"

Hippocrates, c.460 – 370 BC

## 1.1 The Benefits of a Financial Crisis

The global financial crisis, which began in the middle of 2007 and reached its apex in the winter of 2008, following the collapse of the investment bank Lehman Brothers, marks a defining point in the history of finance. It serves as a reminder that our ability to tame markets and perfectly share risk is still a distant prospect, only alive today in the theoretical domain. The once cherished belief among academics and policy makers that we were living the good life, in the world of a 'great moderation', belongs to a distant and seemingly naive past. But for all the pain and anguish that arises from a crisis, from the mass unemployment and sharp fall in output, to the loss of public provisions, one group arises from the rubble with an apparent treasure trove – the economists. The plethora of new and interesting observations which arise from a crisis provide the impetus for an explosion in research and new ways of thinking, as the process of 'creative destruction', usually synonymous with the grubby practicalities of capitalism, works itself into the ivory towers of academia.

That is not to say, however, that a financial or economic crisis is inherently 'good' for an economist, since it only acts as a reminder that we, as a group, are fallible and possess a still inadequate grasp of the economic machine. Yet, the machine is complex and dynamic and in a constant state of flux. Its evolution over time, combined with an inexhaustible array of feedback mechanisms, makes the modeling of its core functions and empirical identification of stable relationships a challenge of the highest magnitude, but one worth undertaking for the potential payoffs to science and human welfare. And here a crisis can, paradoxically, be helpful. In the same way that the tragedies of war have also provided the catalyst for improvements in medical knowledge, a financial crisis highlights the weaknesses within the economic system. By exploring what went wrong and, more importantly, what can go wrong – we may not gain control of the system, but we can garner a greater understanding of its inner workings and prevent, or at least mitigate against, future episodes of crisis.

This thesis brings together three essays which have at their root a story of global risk and crisis. In fact, in all three essays the global financial crisis provides the backdrop to the questions which I seek to address. The concepts of risk and crisis are inherently linked. If a crisis is the realization of the 'bad state' of the world, then a rise in global risk implies a greater probability of us finding ourselves in that 'bad state'. It therefore follows that by studying risk, one may help to contribute to our knowledge of weakness in the economic system and in some part mitigate the possibility that the 'bad state' of the world, manifesting itself as a crisis, is realized.

In each essay, the theme of 'global' risk is studied within the overarching framework of 'international' finance. To this author, the use of the term 'international finance' is something of an historical oddity. Today it seems cliché to describe the financial community as being interconnected or 'global'. The world is not defined by countries living isolated lives of autarky – an economic shock in one country is frequently transmitted to that of another, whether through the channel of financial contagion or economic interdependence. It seems therefore apparent that all finance is international by nature.

But the academic finance and economic communities are no less slaves to their historical legacy than other cultures. The U.S. centric approach to finance ebbs but remains strong. In the future the term 'international finance' will, no doubt, be a defunct term and quaint reminder of the discipline's origins. Yet, despite this short aside, my usage of the term 'international finance' is, throughout this thesis, in accord with the strictest common parlance. Each essay, to a greater or lesser degree, focusses on the cross-border flows of finance between countries and on the currencies one uses to transact overseas.

## 1.2 Background and Thesis Outline

During the recent crisis, banks around the world engaged in a wide-scale retrenchment in their lending to other banks. Fears and uncertainty over the health of borrowing banks' balance sheets often meant that the reward-to-risk ratio from lending overseas became too low to be tenable. This sudden stop in cross-border lending came at the end of a prolonged build up in bank-to-bank funding across borders, making the negative knock-on consequences for domestic credit expansion especially pronounced.

In fact, recent history shows that the growth in cross-border capital flows has been so rapid that the total value of flows far exceeds the value of countries' exports and imports. This growth in cross-border finance has called into question the traditional view of analyzing mismatches in trade and investment as a measure of a country's underlying riskiness. Highlighting this view, Maurice Obstfeld, in his keynote address at the American Economic Association annual meeting in 2012, titled his talk "Does the Current Account Still Matter?" and emphasized the need to look to the balance sheet mismatches of leveraged financial entities as a means to assess potential instability within a country's financial system.

Heading this message, Bruno and Shin (2014) have recently developed a model of cross-border funding between banks, which has at its core the leverage ratio of global banks. Periods of heightened global risk have been shown to lead to a reduction in global bank leverage, as banks actively manage their balance sheets, often in compliance with internal Value-at-Risk (VaR) targets (Adrian and Shin, 2010). The model of Bruno and Shin (2014) captures this mechanism by predicting that cross-border funding between banks will fall when global risk rises.

In Chapter 2, I challenge this theory, by arguing that cross-border funding between banks needs to be put under the microscope, since the aggregate international flow of funding between banks can be disaggregated into two distinct funding types. First, banks can lend overseas to 'arms-length' counterparties with whom the bank has no direct relations. Alternatively, a bank can lend to a related bank, within a banking group's 'internal capital market'. I refer to these two forms of funding as interbank and intragroup. Using a large panel of data on 25 banking systems from the Bank for International Settlements (BIS), I disaggregate cross-border funding between interbank and intragroup flows and show that the split has statistical, economic and theoretical importance.

When global risk is high or rising, interbank funding falls as predicted by the model of Bruno and Shin (2014), particularly to banks resident in emerging economies. On the other hand, intragroup funding, which accounts for almost half of all cross-border funding between banks, is found to be more volatile than interbank funding, but displays the opposite behavior in response to fluctuations in global risk. When global risk rises, intragroup funding expands and, when global risk is at an elevated level, intragroup funding remains stable.

These results have economic importance. Banking systems with a large share of interbank relative to intragroup funding experienced the largest withdrawals of funding by overseas banks during the global financial crisis. Even the United States, at the epicenter of the global financial crisis, experienced a relatively modest five percent withdrawal in funding by overseas banks, which can be largely explained by its heavy reliance on intragroup bank funding. In fact, by considering only the ratio of interbank to intragroup funding, I find that up to 45 percent of the change in cross-border funding between banks, during the global financial crisis, can be explained at country level.

To better understand the behavior of intragroup funding in response to global risk, I further disaggregate intragroup funding between flows to parent and foreign affiliate banks. I find that the increase in intragroup funding is principally to parent banks resident in advanced market economies, which use their foreign affiliates as a buffer against liquidity shocks during a period of heightened risk. Nonetheless, I find no robust evidence that foreign affiliates of global banks experience a reduction in funding from their parent bank during these periods. Moreover, foreign affiliates resident in emerging economies are shown to receive an inflow of intragroup funding when the average profitability of banks in their local economy is low, implying that emerging economies can benefit from a stabilizing foreign bank presence in the local economy. The results suggest a need for policy makers to monitor disaggregated funding, split between interbank and intragroup. Focussing on the aggregate figure, while implicitly assuming that both forms of funding will behave symmetrically following a rise in global risk, could lead to a misleading interpretation of the banking system's underlying vulnerability to funding withdrawals.

In addition to demonstrating a theoretical link between global risk and cross-border funding between banks, Bruno and Shin (2014) demonstrate a causal link between currency market movements and international banking flows. An appreciation of the local currency is shown theoretically to increase funding from overseas banks to banks resident in the local economy. In Chapter 2, I show the relationship between the currency market and banking flows holds across both interbank and intragroup funding, while in Chapter 3, I explore more deeply the relationship between aggregate international capital flows, of which international banking flows are a sub-component, and the currency market. In doing so, I try to understand the fundamental macroeconomic rationale, which lies behind currency risk premia and the empirical failure of Uncovered Interest Rate Parity (UIP).

One of the key debates in international finance relates to why the UIP condition fails to hold. Expressed simply, UIP states that the exchange rate between two countries should appreciate by the exact difference in the risk-free interest rates offered in those countries. For example, if the one-year interest rate is ten percent in Australia and one percent in Japan, then over the course of the following year UIP states that one would expect the Japanese yen to appreciate by nine percent against the Australian dollar. By doing so, an investor who decided to undertake a 'carry strategy', of borrowing in the low interest currency and lending in the high interest currency, would on average do no better than break even. Yet consistently the carry-trade investor has been shown empirically to profit from this apparently naïve strategy, raising one of the major puzzles in international finance commonly referred to as the 'forward premium puzzle'.

Whenever a theory is shown to consistently be at odds with reality, the first course of action is to investigate the assumptions which generated the model's predictions. In the case of UIP, two strong assertions lie at the heart of the theory. First, investors are assumed to have 'rational expectations', such that the way they form their expectations is consistent with the underlying data generating process. Second, investors are assumed to be 'risk neutral' and hence, do not require any compensation above the risk-free rate for holding risky securities. Any test of UIP is, in effect, a joint test of the hypotheses that investors are rational and risk neutral. Froot and Frankel (1989) provide an early example of an attempt to decompose deviations from UIP between forecast errors and compensation for risk. Their study and subsequent work (Chinn and Frankel, 2002; Cavaglia, Verschoor, and Wolff, 1994; Bacchetta, Mertens, and Van Wincoop, 2008) fail to show either a time-varying risk premium, or that errors in investor expectations are the only reason for the empirical failure of UIP.

Perhaps the most pragmatic view is one which accepts that both elements are likely important contributors; however, this in itself raises questions. First, why do investors systematically form biased forecasts of the future exchange rate? And second, what exactly is the time-varying source of risk compensation for? The first question remains open with multiple contending theories, including: learning (Lewis, 1989a,b), peso-problems (Evans and Lewis, 1995; Burnside, Eichenbaum, Kleshchelski, and Rebelo, 2011a), and slow reactions to news caused by ambiguity aversion (Ilut, 2012) or rational inattention (Bacchetta and Van Wincoop, 2010b). In Chapter 3, I delve into the second question and investigate the underlying macroeconomic explanation for why time-varying risk exists within the currency market and why carry trade investors find themselves exposed to this risk.

Recent evidence from Lustig, Roussanov, and Verdelhan (2011), suggests that a 'global' risk factor can explain the cross-section of currency excess returns. In other words, currencies seem to be exposed to a single source of time-varying risk. The approach adopted by Lustig et al. (2011) involves sorting currencies into portfolios based on their interest rate and follows a long tradition of sorting assets into portfolios, with Fama and French (1993) providing the seminal study for the equity market. The returns to these portfolios are then explained, or ‘priced’, using standard empirical asset pricing techniques, including the approach of Fama and MacBeth (1973) as well as the Generalized Method of Moments (GMM) technique of Hansen (1982). Yet, despite the encouraging evidence that a single source of time-varying risk may be responsible for explaining excess currency returns, the fundamental explanations for *what* the risk is, and *why* some currencies are more exposed to that risk are not provided.

To understand why, it is important to outline how Lustig et al. (2011) discover the ‘global’ risk factor. Specifically, the authors perform a statistical decomposition of currency portfolio returns, to reveal that two underlying principal components (PCs) can explain the majority of variation in returns. The first PC is a ‘level’ factor which all currencies are equally (approximately) exposed to. Since Lustig et al. (2011) perform their analysis with respect to the U.S. dollar (USD), the PC implies that all currencies tend to move up-or-down against the dollar simultaneously. The second PC is a ‘slope’ factor which currencies are heterogeneously exposed to. High-interest-rate currencies ‘load’ positively on the factor while low-interest-rate currencies ‘load’ negatively. This second principal component is of particular interest since it provides evidence that a unique ‘factor’, in the spirit of the Arbitrage Pricing Theory (APT) of Ross (1976), can be used to model currency returns by considering their exposure to this factor.

Of course, a fundamental concern with this type of work is that it relies principally on statistical methods without intrinsically offering a strong economic insight. Lustig et al. (2011) attempt to overcome this critique by forming return-based factors which capture the underlying PCs. To capture the first principal component, the authors take an equally weighted average of all five currency portfolio returns each month, a factor which they term *Dollar risk* ($DOL$). This factor has a correlation of over 99 percent with the first PC. To capture the second PC, the authors take the difference in returns between the highest- and lowest-interest-rate-sorted portfolios each month. This second factor is termed *Slope risk* ($HML_{FX}$) and correlates almost perfectly with the second PC.

The *Slope* factor, the difference in returns between high and low-interest-rate currencies, is effectively a carry strategy. In essence, the factor constructed by Lustig et al. (2011) tells us that when returns to the carry trade are low, global risk must be high and vice versa. But the fundamental questions surrounding the nature of risk and the macroeconomic rationale for why currencies are more or less exposed to that risk, remain open. To provide more clarity to the issue, in Chapters 3 and 4, I investigate the fundamental source of risk and exposure that carry-trade investors face.

To do so, in Chapter 3, I build on the recent theoretical developments of Gourinchas and Rey (2007), Gourinchas (2008) and Gabaix and Maggiori (2014), who demonstrate a link between countries' external accounts and currency market returns. Gourinchas and Rey (2007) show that a country's net foreign asset (NFA) position today – the difference between the total value of its foreign assets and liabilities – can be used to forecast future exchange rate movements. The finding implies that the NFA position of a country is a candidate 'state variable', which affects the conditional distribution of foreign exchange returns. Net debtor countries are more likely to experience a future exchange rate depreciation as a means to help rebalance the external account. In Gourinchas (2008), the finding is developed. Net debtor countries with a high share of foreign debt issued in foreign currency – a phenomenon known as 'original sin' (Eichengreen, Hausmann, and Panizza, 2002) – require the largest future currency depreciation, since a depreciation of the local currency *increases* the value of its foreign debt and hence causes a further deterioration of the external account. In Gabaix and Maggiori (2014), the authors develop a model which links currency premia with interest rates and net foreign assets. Dealers operating in money markets require a premium to compensate for imbalances in supply and demand within the foreign exchange market. Net debtor countries with high interest rates offer the highest expected return to incentivize a currency dealer to take on funding liquidity risk, by holding a position in those particular currencies.

To capture the predictions of these models, I construct a currency factor based on NFAs, which replaces *Slope* risk in the model of Lustig et al. (2011). The factor is easily constructed: first, I sort currencies into portfolios based on their NFA position in combination with the proportion of foreign debt held in foreign currency. Next, I take the difference in returns on the extreme portfolios each month. In one extreme are net debtors with the majority of foreign debt issued in foreign currency. This portfolio is considered the 'riskiest'. In the other extreme are net creditors with the majority of foreign debt issued in domestic currency. This portfolio is considered the 'safest'. The difference in returns between these portfolios forms the 'global-imbalance risk factor', which I denote $HML_{NA}$.

I find that the global imbalance risk factor can explain (or 'price') currency portfolio returns, hence offering a candidate macroeconomic explanation for the source of risk driving currency premia. The finding provides support to the view that carry-trade investors receive compensation for holding the currencies of debtor nations, which are expected to require a future currency depreciation to help stabilize their external account, following an external shock. The finding is not mechanically driven, and I show that the net foreign asset position of a country provides more information than interest rates regarding future exchange rate returns.

The findings are also shown to have practical implications. From a trading perspective, the factor provides an alternative method for constructing a risky currency portfolio, which has a similar Sharpe ratio to the carry trade but with lower overall volatility. Moreover, the strategy requires little modification, hence when rebalancing at yearly intervals, it provides a Sharpe ratio twice the size of the currency carry trade. The factor also helps make sense of recent currency market activity. Following the Federal Reserve Announcement in May 2013 that it would taper its bond buying programme, currencies with almost identical interest rates suffered asymmetric depreciations, yet the depreciations were consistent with the relative debtor status of the underlying countries.

Since the identification of the *Slope* factor by Lustig et al. (2011), a number of other alternative factors have been proposed, which help to provide greater insight into the mechanics behind this 'global' risk factor. These alternatives range from volatility, skewness and correlation risk (Menkhoff, Sarno, Schmeling, and Schrimpf, 2012; Rafferty, 2012; Mueller, Stathopoulos, and Vedolin, 2013) to 'downside' market risk (Lettau, Maggiori, and Weber, 2013). Yet one underlying issue with these alternative factors, at least to this author, is the lack of strong economic content, combined with an inability to explain *why* some currencies are more exposed to risk than others – currency betas remain a mystery. Empirically it may be the case, for example, that in months when volatility, skewness or correlations rise, the carry trade suffers. But that does not provide an explanation for why high-interest-rate currencies should be the most affected by those distributional changes.

The global imbalances factor, proposed in Chapter 3, offers one possible solution to this critique – risky currencies are those issued by countries with vulnerable external accounts. Yet other candidate explanations could also allow for the construction of a 'characteristic factor', whereby currencies are sorted into portfolios based on the characteristic which is conjectured to explain currency betas. These factors could perform equally well in explaining currency portfolio returns. Moreover, a recent line of literature has critiqued traditional empirical asset pricing by showing it fails to eliminate most candidate risk factors.

Lewellen, Nagel, and Shanken (2010), for example, present compelling evidence that explaining portfolio returns can be a relatively low hurdle, if the returns are characterized by a strong factor structure. This type of factor structure is present when currencies are sorted into portfolios by interest rates and, in every paper in which a new currency factor is proposed, this group of currency portfolios is invariable used. While we know that the second principal component (approximately

*Slope* risk) is, effectively, the 'true' global risk factor, Lewellen et al. (2010) demonstrate that it is possible for a factor with almost zero correlation with *Slope* risk to still have strong pricing power. In fact, Daniel and Titman (2012) find evidence that, for the more mature equity market literature, many leading factors which claim to price the 25 size-and-book-to-market portfolios (another set of portfolios with a strong factor structure) have approximately zero correlation with one another and hence, with the true factor. One possible concern, therefore, is that we could conceivably witness a similar factor proliferation in the currency market, whereby factors with seemingly no relationship with one another all claim encouraging levels of success.

I attempt to address these concerns in Chapter 4 and, in doing so, build on the findings of Chapter 3. To do so, I turn to recent consumption-based models of currency premia, which have shown great promise in providing theoretical explanations to various puzzles in international finance. But one feature of these models, which is widely overlooked, is the theoretical prediction each one makes relating to the fundamental drivers of currency betas. If we want to understand *why* high-interest-rate currencies are the riskiest, it seems appropriate to turn to the leading theoretical models of currency premia for potential answers, thus avoiding criticisms of 'data snooping' for factors which may show promise in explaining currency returns but, in light of the findings of Lewellen et al. (2010), demonstrate nothing more than a spurious relationship.

I focus on the external-habit model of Verdelhan (2010), the long-run risks model of Colacito and Croce (2013) and the variable rare disasters model of Farhi and Gabaix (2013). The three models cover the main branches, or variations, of the consumption-based model and provide a panorama of the leading theoretical models of currency premia in use today. Each of the models investigated in Chapter 4 provides a precise prediction as to why currencies have heterogeneous exposure to risk, by linking currency betas with a macroeconomic state variable. In the external habit model of Verdelhan (2010), countries whose representative agent is closest to their 'habit' (subsistence) level of consumption are the most risk averse, and therefore investors in those countries require the highest return from lending internationally. In the long-run risks model of Colacito and Croce (2013), countries with the largest share of world consumption are the riskiest because they are less able to share consumption risks with other countries. Finally, in the variable rare disasters model of Farhi and Gabaix (2013), countries most exposed to a global disaster – through experiencing the largest productivity fall following the shock – are the riskiest.

To capture the predictions of these models regarding currency betas, I construct 'characteristic factors' by sorting currencies into portfolios on the basis of the macroeconomic 'characteristic' which explains why certain currencies are more (or less) exposed to risk. These factors are then used to explain the cross-section of currency portfolio returns. If the models provide a robust explanation for currency betas, then the factors should perform comparably well to the *Slope* factor of Lustig et al. (2011) when pricing interest-rate-sorted currency portfolios. High-interest-rate currencies should 'load' positively on the factor, while low-interest-rate currencies should 'load' negatively.

Using a standard two-pass empirical asset pricing test, I find, however, that none of the factors can explain *any* of the cross-sectional spread in returns. In fact, the factors generate negative cross-sectional $R^2$ statistics, large pricing errors, large root-mean squared errors and exhibit low or negative correlations with *Slope* risk. The finding is made especially puzzling by the fact that the test assets exhibit a strong factor structure, which, as already noted, increases the likelihood that the factor performs well in empirical tests.

The finding raises questions over whether any fundamentally based variable can explain the variation in betas across currencies. To address this question, I perform a 'fishing' exercise whereby I arbitrarily construct 25 new non-theoretical characteristic factors using country-level data on macroeconomic, financial and political risks. Unlike the theoretical factors, these alternatives factors perform well in cross-sectional asset pricing tests. In particular, all macroeconomic factors are statistically 'priced' with a t-statistic in excess of 3.0, with associated cross-sectional $R^2$ between 60 and 80 percent. In total, 20 of the 25 factors are 'priced' and only a handful of political risk factors show weak pricing performance comparable to the theoretically grounded factors.

While none of the theoretically motivated factors were capable of explaining currency portfolio returns, a concern now arises that, even if they had been successful, pricing interest-rate-sorted portfolios is not a sufficiently high benchmark for assessing the performance of a new factor. I perform two exercises to address this concern. First, I change the set of test assets that the non-theoretical factors are asked to price. Specifically, if a factor really does capture a currency's exposure to risk (its beta), then it should also explain portfolios sorted by the characteristic itself. Next, I simulate 'useless' risk factors which contain no economic content, by randomly sorting currencies into portfolios. I test these 'useless' factors' ability to explain interest-rate-sorted portfolios and randomly generated currency portfolios, from which they were constructed.

I find that none of the 25 non-theoretical factors are priced when explaining currency portfolios sorted by the same characteristic as the factor itself. Moreover, I find that only 1.5 percent of all 'useless' factors can price both interest-rate-sorted portfolios *and* portfolios sorted by the same characteristic as the factor. I find, however, that the global imbalances factor, constructed in Chapter 3, *is* capable of passing both tests – strengthening the overall findings of Chapter 3.

Overall, the findings imply a need for a stricter benchmark for judging all new theoretical models of currency premia. Theoretical models should provide a precise prediction for the fundamental drivers of currency betas, which naturally lend themselves to the construction of a characteristic factor that should be capable of pricing both interest-rate-sorted and characteristic-sorted currency portfolios. Moreover, the findings offer support that, despite the recent series of critiques of empirical asset pricing, standard techniques *can* filter out around 99 percent of all spurious currency factors when currency betas are the primary focus of the study.

# Chapter 2

# The Two Faces of Cross-Border Banking Flows

## 2.1 Introduction

Cross-border funding between banks is a volatile and economically important source of cross-border finance (Gabriele, Boratav, and Parikh, 2000; Milesi-Ferretti and Tille, 2011).[1] During the global financial crisis this funding was quickly withdrawn at the *aggregate* level, leading policy makers and academics to focus their attention on cross-border banking flows, as well as the operations of global banks which play a key role in channeling this funding around the globe (Acharya and Schnabl, 2010; Shin, 2012; Giannetti and Laeven, 2012a,b; De Haas and Van Horen, 2012, 2013; Cerutti and Claessens, 2013; Ongena, Peydró, and Van Horen, 2013).[2]

Investigating *disaggregated* cross-border bank-to-bank funding could, however, provide richer insights, since the aggregate flow is the sum of two distinctive forms of funding, with potentially disparate behavior. First, there is *arms-length* (interbank) funding, that takes place between unrelated banks, and second, there is related (intragroup) funding that takes place between global banks and their foreign affiliates within an *internal capital market.* Cetorelli and Goldberg (2011) have documented that both forms of funding could be equally vulnerable to withdrawal

[1]In recent years efforts have been made at policy level to both understand and regulate these flows (see Hoggarth, Mahadeva, and Martin, 2010; Committee on International Economic Policy and Reform, 2012).

[2]Recent policy debate has centered on the 'Balkanization' of cross-border banking, including proposals to make affiliates of foreign-owned banks safer through holding more capital – potentially limiting the parent bank's ability to shift internal funding from one part of the group to another. See Goldberg and Gupta (2013) and Carney (2013) for recent discussions; see Federal Reserve Board (2014) for a description of the recently finalized rules that require large foreign affiliates operating in the U.S. to adhere to U.S. capital and liquidity rules.

following an international funding shock, or a period of elevated global risk.

Yet the two forms of funding have key differences. In particular, within an internal capital market, global parent banks have the power to shift liquidity from one corner of the banking group to another. Additionally, when lending internationally, banks have more information about their counterparties' overall riskiness, relative to banks lending at arms-length. The differences could influence the way the two flows behave in response to fluctuations in global risk. It is therefore possible that some countries' banking systems could be more insulated from heightened global risk than others, depending on (i) their mix of arms-length and related funding and (ii) the share of related funding held by global parent banks relative to foreign affiliates.

In this essay I make two broad contributions. First, I build on the cross-border banking literature by empirically studying the behavior of *disaggregated* cross-border bank-to-bank funding over time and across a large panel of countries. Next, focussing on global risk allows me to test precisely the theoretical predictions made by Bruno and Shin (2014), whose recent contribution has made significant strides towards building a framework for understanding cross-border bank-to-bank flows. In the empirical analysis, I sequentially decompose aggregate cross-border funding between banks, across 25 advanced and emerging market economies, using the Bank for International Settlements' (BIS) *International Banking Statistics* database. First, I split funding to banks in a particular country between interbank and intragroup and then, to paint a more detailed picture, I further disaggregate intragroup funding between flows to parent and foreign affiliate banks.[3,4]

At the first level of disaggregation between interbank and intragroup funding, I find that the split has statistical, theoretical *and* economic importance. A period of high and rising global risk aversion, such as that witnessed following the collapse of Lehman Brothers, results in markedly different behavior in ensuing interbank and intragroup flows. Specifically, intragroup funding, which makes up around half of all cross-border funding between banks, *rises* when global risk increases and is invariant to periods of high global risk. Interbank funding displays the opposite behavior and is withdrawn during periods of elevated global risk, with emerging economies being particularly vulnerable.

These findings, in part, contradict the recent theoretical predictions made

[3]Throughout this essay the term 'intragroup funding' refers to gross cross-border bank-to-bank funding within an internal capital market of a banking group, and the term 'interbank funding' refers to gross cross-border bank-to-bank funding conducted at arms-length.

[4]While the BIS database has been used extensively by researchers in this literature, the approach to decompose aggregate cross-border bank flows is unconventional. Cetorelli and Goldberg (2011), for example, is a related paper which adopts the more common approach of examining aggregate, bilateral flows, within the BIS database.

by Bruno and Shin (2014). Building on the Merton (1974) and Vasicek (2002) models of credit risk, the authors deduce that changes in global risk should drive *all* cross-border funding between banks.[5] When global risk is high, the model predicts that the leverage of global banks will fall, global liquidity will dissipate, and both interbank *and* intragroup funding will contract. However, my results indicate a need for policymakers to monitor *disaggregated* international funding between banks. Assuming that both forms of funding respond identically to fluctuations in global risk could result in a misleading assessment of a country's underlying financial stability. In fact, I find that considering each country's mix of interbank and intragroup funding alone can explain up to 45 percent of the change in cross-border bank-to-bank funding across countries during the global financial crisis.

At the second level of disaggregation, I show that increased intragroup funding during episodes of heightened risk is principally driven by global banks, headquartered in advanced economies, receiving funding from their foreign affiliates. In fact, I find that banking systems with a large share of global banks were relatively well insulated against funding withdrawals during the global financial crisis. The result supports the view expressed by Kohn (2008), that global banks may respond to an economic shock by using foreign affiliates as a source of liquidity, limiting liquidity pressures at home. In a related study, Cetorelli and Goldberg (2012b) analyze U.S. global banks, and find that during the global financial crisis, foreign affiliates resident in traditional funding locations were harvested for liquidity.[6] I find the result extends across advanced economies as well as periods outside the financial crisis. However, I do not find evidence of significantly reduced intragroup funding *to* foreign affiliates in either advanced or emerging economies during periods of high global risk.[7] In fact, I find that foreign affiliates resident in emerging economies experience an *increase* in intragroup funding, when the average profitability of banks in the local economy is low.

Additionally, by testing the predictions of Bruno and Shin (2014), I am able to provide a more nuanced examination of the relationship between cross-border banking flows and other financial and economic variables, which have been deduced theoretically to drive this funding. In particular, I show that liquidity

[5]At a more general level, it is well documented that capital flows are theoretically and empirically related to fluctuations in global risk (see e.g. Adrian and Shin, 2010; Bacchetta and Van Wincoop, 2010a; Forbes and Warnock, 2012; Fratzscher, 2012; Gourio, Siemer, and Verdelhan, 2013; Milesi-Ferretti and Tille, 2011).

[6]Cetorelli and Goldberg (2012a) demonstrate that within internal capital markets, funds are reallocated from foreign affiliates to U.S. parent banks, as a way for the parent bank to insulate itself against contractionary monetary policy in the United States.

[7]Likewise, Schnabl (2012) finds global banks maintained intragroup funding to their foreign affiliates resident in Peru in the year following the Russian financial crisis.

management within an internal capital market has links with both financial market prices and monetary policy. A depreciating currency for example, has been shown by Bruno and Shin (2014) to be theoretically linked to a reduction in subsequent cross-border bank-to-bank flows. I show the relationship holds across both interbank and intragroup funding. Moreover, I find evidence that global banks take advantage of higher interest rates in emerging economies by increasing intragroup funding to foreign affiliates resident in those economies.

The remainder of the chapter is organized as follows: in Section 2.2 I briefly review the literature on how interbank and intragroup funding could behave in response to fluctuations in global risk. In Section 2.3 I describe the theoretical framework which anchors the empirical analysis. In Section 2.4 I describe the data. I present empirical results in Section 2.5 and robustness analysis in Section 2.6. Finally, I conclude in Section 2.7. In Appendix A, I provide further robustness tests and additional supporting analyses.

## 2.2 Related Literature: Global Risk and Cross-Border Bank Flows

Cetorelli and Goldberg (2011) acknowledge that both interbank *and* intragroup funding could collapse in the event of bad economic news, while the model of Bruno and Shin (2014) predicts that both forms of funding will be withdrawn when global risk is high or rising. Exactly how the two flows behave in relation to different levels of global risk is, ultimately, an empirical question which I aim to shed light on in the empirical investigation. But first, I briefly review the literature on interbank and intragroup funding to describe the contrasting perspectives on how the two flows could react when global risk is high.

Interbank funding has been shown to act as a beneficial source of bank monitoring (Calomiris and Kahn, 1991; Calomiris, 1999) and to alleviate liquidity shocks caused by unexpected retail depositor withdrawals (Goodfriend and King, 1988). Given the increased 'sophistication' of interbank lenders relative to retail depositors, this funding could therefore remain stable when global risk is high, as the lending bank is unlikely to withdraw funding from healthy banks.

Yet, interbank flows may have a darker side. Indeed, Song and Thakor (2007) and Huang and Ratnovski (2011) document the high withdrawal risk of interbank funding. In fact, these authors argue that interbank funding could be *inefficiently* withdrawn when global risk is high, as a result of lending banks not having perfect information regarding the balance sheets of the banks they funded.

Moreover, Brunnermeier (2009) finds banks, worried about their own capital buffers, withdrew interbank funding during the financial crisis as insurance against future balance sheet shocks, *irrespective* of the counterparty's balance sheet.

Turning to intragroup funding, De Haas and Van Lelyveld (2010) find parent banks are likely to trade-off lending across countries to support their weakest subsidiaries, while Schnabl (2012) shows foreign affiliates in Peru continued to receive intragroup funding when global risk spiked following the Russian financial crisis. On the other hand, Correa, Sapriza, and Zlate (2011) find net intragroup funding of subsidiaries and branches in the U.S. *falls* when economic output in the United States is low, while Cetorelli and Goldberg (2012a,b) find that U.S. parent banks smooth economic shocks at home by channeling funding *from* their foreign affiliates. De Haas and Van Lelyveld (2014) also find evidence that, unlike previous crises, parent banks were unable to support their foreign affiliates during the recent global financial crisis.

Intragroup funding has also gained attention recently, following evidence that European foreign affiliates operating in the United States, borrowed in local money-markets to fund their parent bank headquartered in Europe (Bank for International Settlements, 2010). This particular funding stream was severely impacted by the global financial crisis (McGuire and Von Peter, 2009), implying that intragroup funding could be significantly affected by fluctuations in global risk, with both foreign affiliates and global parent banks vulnerable to potential funding withdrawals.

## 2.3 Theoretical Framework

I structure the empirical analysis using the theoretical framework developed by Bruno and Shin (2014). The authors model the total cross-border bank-to-bank funding that takes place between regional and global banks and provide a strong theoretically grounded rationale for *why* a link between global risk and cross-border bank-to-bank flows exists for both interbank and intragroup funding. It also supplies me with additional theoretically-grounded control variables, which should explain changes in cross-border bank-to-bank funding. In this section I briefly outline the model's key features and predictions.

### 2.3.1 The Model

In the model of Bruno and Shin (2014), total cross-border funding of regional banks by global banks is given by

$$L = \frac{E_G + E_R . \frac{1+l}{1+b} . \delta_G . \delta_R}{1 - \frac{1+l}{1+b} . \delta_G . \delta_R}, \tag{2.1}$$

where $E_G$ and $E_R$ are the book value of global and regional bank equity, $\frac{1+l}{1+b}$ is the ratio of the lending rate regional banks require from domestic borrowers ($l$), to the borrowing rate paid by global banks to borrow in global money markets ($b$), while $\delta_G$ and $\delta_R$ are the notional debt ratios of global and regional banks, measured as the ratio of total liabilities to total assets.

A rise in the debt ratio, by definition, decreases a firm's equity, hence the debt ratios can be viewed as measures of leverage. Specifically, the debt ratios of global and regional banks are given by $\frac{(1+b)M}{(1+f)L}$ and $\frac{(1+f)L}{(1+l)C}$, where $f$ is the funding rate charged by the global bank to the regional bank, and $M$ and $L$ represent the book value of global and regional bank liabilities, respectively.

I derive an approximation for the change in cross-border funding between banks, taking a first-order approximation of equation 2.1 with respect to changes in global bank leverage and the return on domestic bank book equity:

$$\Delta L \approx \frac{\partial L}{\partial E_R} \Delta E_R + \frac{\partial L}{\partial \delta_G} \Delta \delta_G, \tag{2.2}$$

$$= \gamma \left( \delta_G \Delta E_R + C \Delta \delta_G \right) \tag{2.3}$$

where in equation 2.3, $\gamma$ is equal to $\frac{\frac{1+l}{1+b}\delta_R}{1-\frac{1+l}{1+b}\delta_R\delta_G}$ and $C$ represents the total credit provided by regional banks, which is shown in the model to be equal to $\frac{E_G+E_R}{1-\frac{1+l}{1+b}.\delta_G.\delta_R}$. The equation applies equally to both interbank *and* intragroup funding.

### 2.3.2 Hypotheses

Equation 2.3 provides the framework for the empirical analysis. The main hypotheses that I derive from the model and investigate in the formal regression analysis are outlined below.

#### Fluctuations in Global Risk

According to equation 2.3, cross-border interbank and intragroup funding should be positively related to the level and change in global bank leverage $\delta_G$. Bruno and Shin (2014) and Adrian and Shin (2010) show that the VIX index – a measure of global risk – can be substituted in place of global bank leverage because changes in global risk *drive* global bank leverage. *Hence, when global risk is high and global bank leverage is low, both interbank and intragroup funding are predicted to contract.*

The rationale for this relationship is intuitive, and reflects the marking-to-market of assets by global banks. A rise in the value of bank assets, for example, corresponds to a fall in bank leverage.[8] I should therefore observe a negative empirical relationship between asset and leverage growth. But Adrian and Shin (2010) show the opposite to be true. This finding implies that global bank's actively manage their leverage, in response to fluctuations in asset prices. Indeed, Ang, Hodrick, Xing, and Zhang (2006) and Menkhoff, Sarno, Schmeling, and Schrimpf (2012) have shown that lower volatility is associated with a rise in risky asset prices, and so it follows that global banks borrow more when risk aversion falls, and invest the proceeds in other financial securities – including increased cross-border funding of other banks. In fact, Adrian and Shin (2010) argue that the active management is likely driven by value-at-risk (VaR) considerations, in which a decrease in volatility reduces a bank's VaR and incentivizes an expansion of the balance sheet.

Furthermore, in their empirical analysis, Bruno and Shin (2014) confirm the main predictions of their model using data on aggregate international bank-to-bank funding, replacing global bank leverage with the VIX index. The authors argue for the suitability of the VIX index as a proxy for global bank leverage based on two findings. First, in a bivariate regression, the lagged VIX index can explain a large portion of the variation in U.S. broker dealer leverage. Second, the residuals from the regression have no statistical significance in explaining international lending between banks. Moreover, focussing on the VIX – and global risk – is useful from a policy perspective, as a critical concern among policy makers is how capital flows react during periods of economic stress.

### Theoretically Motivated Control Variables

**Regional bank equity.** *The return on domestic bank book equity $E_R$, is predicted to be positively related to global funding between banks.* A rise in the value of a regional bank's book equity reduces the probability of the bank defaulting (the regional bank's leverage is lower). The reduction in default probability enables the regional bank to expand its borrowing capacity and hence absorb additional funding from global banks.

[8] As an example, if the starting balance sheet is split: Assets (\$100), Liabilities (\$90), Equity (\$10), then the leverage ratio is equal to \$100/\$10 = 10. A \$10 rise in the value of assets, when marked to market, reduces the leverage ratio to \$110/\$20 = 5.5.

**Interest-rate differentials.** *A rise in* $\frac{1+l}{1+b}$, *the ratio between individual country interest rates and global money market rates is predicted to be positively related to cross-border bank-to-bank funding.* The intuition is that an increase in a country's interest rate increases its income from lending, which in turn shifts the bank away from its default boundary, freeing up capacity to take on additional funding from global banks.

**Exchange rates.** Fluctuations in the foreign exchange market enter the model indirectly. Nonetheless, the model provides a key insight into the relationship between the currency market and global liquidity. *Specifically, the relationship between foreign exchange returns and cross-border lending between banks is predicted to be negative* (assuming foreign exchange rates are measured as the number of local currency units per U.S. dollar). A local currency appreciation reduces the value of U.S. dollar denominated liabilities of domestic corporations and increases the likelihood that they will be able to repay loans to regional banks. That reduces the probability of regional banks defaulting and expands their borrowing capacity.[9]

## 2.4 Data and Summary Analysis

### 2.4.1 Data Sources and Variable Definitions

**Banking flows data.** I collect data on cross-border bank-to-bank funding for advanced and emerging market economies from the Bank for International Settlements's (BIS) *International Banking Statistics* database. In total I consider 25 banking systems that report both interbank and intragroup cross-border banking flow data, consisting of 19 advanced market economies and 6 emerging market economies as classified by the BIS. The banking systems include (emerging economies in bold): Austria, Australia, Belgium, **Brazil**, Canada, **Chile**, Cyprus, Denmark, Germany, France, **India**, Ireland, Italy, Japan, Luxembourg, Netherlands, Norway, **South Africa**, **South Korea**, Spain, Sweden, Switzerland, **Turkey**, United Kingdom, and the United States. All cross-border bank-to-bank flow data are adjusted for the effects of exchange rate movements and I exclude data on offshore banking centers.[10]

Within the *International Banking Statistics* database, I make use of Locational Statistics by Nationality (IBLN). Funding is split between the flows to (i) 'related foreign offices', which I categorize as intragroup flows, and (ii) 'other

[9] The strength of this channel depends on the degree of currency mismatches on the corporate sector's balance sheet as an appreciation also reduces the value of dollar denominated assets.

[10] I exclude from the sample any country which does not report both interbank and intragroup flow data. I also exclude Finland as it only reports intragroup flows from 2010Q2 onwards.

banks', which I categorize as interbank flows. I calculate the percentage change in cross-border interbank and intragroup funding for each quarter between 1998Q1 and 2011Q4 for all 25 banking systems in the study.[11] For example, for the United States, I calculate cross-border intragroup funding as the summation of all intragroup *inflows* to banks resident in the United States from related banks elsewhere in the world and divide by the previous quarter *stock* of intragroup funding held by all banks (parents and foreign affiliates) resident in the United States.

Using information on the nationality of the parent bank (as contained in IBLN), I am able to disaggregate intragroup funding further, between funding to domestically owned parent banks, and funding to foreign affiliate banks. For example, in the case of the U.S., intragroup funding can be split between (i) cross-border flows to U.S. owned banks operating in the United States, which I classify as a flow to a parent bank headquartered in the U.S. and (ii) cross-border flows to non-U.S. owned banks (foreign affiliates) operating in the United States.[12]

As indicated, for the purposes of the empirical work I normalize quarterly interbank and intragroup flows by the previous quarter stock of interbank and intragroup funding, such that

$$\Delta L^j_{i,t} = \frac{\sum_{k=1}^{N} F^j_{i,k,t}}{\sum_{k=1}^{N} S^j_{i,k,t-1}} \times 100, \tag{2.4}$$

where $\Delta L$ is the normalized quarterly exchange rate adjusted change in either interbank or intragroup funding. $F$ denotes the *flow* of interbank or intragroup funding, reported by the BIS, while $S$ relates to the *stock* of interbank or intragroup funding. The subscript $i$ denotes whether the funding is interbank or intragroup, while $j = 1, 2, .., 25$, denotes the 25 BIS reporting countries who provide the BIS with both interbank and intragroup data on their resident banks, and $k = 1, 2, ..., N$, refers to the $N$ countries of ultimate bank origin which have banking operations in country $j$. That is, I sum all the cross-border funding which flows into a country $j$ across

[11] While the BIS makes some international banking data publicly available, due to confidentiality, the split between interbank and intragroup funding forms part of a restricted dataset not available to the public.

[12] The BIS does not currently report locational data on a bilateral basis. The BIS's bilateral data is only available for *aggregate* (interbank *plus* intragroup) funding. So it is not known, for example, if the British or German bank located in the U.S. is borrowing from its headquarters, or from another foreign affiliate elsewhere in the world. In fact, the BIS is currently expanding its dataset to include bilateral interbank and intragroup flows but at present insufficient data is available for the purposes of this study. I begin the sample in 1998, as key determinants of banking flows such as local equity growth are not available prior to this date. The data are reported on (i) an amount outstanding basis (the stock) and (ii) an exchange rate adjusted change basis (the flow).

all banks (local and foreign) resident in that country.

The overall result is a panel of normalized interbank and intragroup flows between 1998Q1 and 2011Q4. Note that the countries $k = 26, 27, ..., N$, do not report banking statistics to the BIS but do have global banks with operations abroad, significant examples include China and Russia.

The split of intragroup funding between parent and foreign affiliate banks is then given by,

$$\Delta L^{P}_{j,t} = \frac{F^{j}_{t}}{S^{j}_{t-1}} \times 100, \qquad \Delta L^{FA}_{j,t} = \frac{\sum\limits_{k=1,k\neq j}^{N} F^{j}_{k,t}}{\sum\limits_{k=1,k\neq j}^{N} S^{j}_{t-1}} \times 100 \tag{2.5}$$

where $\Delta L^{P}_{j,t}$ and $\Delta L^{FA}_{j,t}$ are the percentage changes in intragroup funding to parent and foreign affiliate banks, resident in country $j$ at time $t$. In the case of parent banks I record the flow $F$, when $k = j$. That is, the bank resident in country $j$ is also headquartered in country $j$. I normalize the change in funding by dividing by the previous quarter stock of intragroup funding held by parent banks headquartered in country $j$. In the case of foreign affiliates, I sum across all banks with operations in country $j$ that are owned by a bank outside country $j$.

**Economic and financial data.** I proxy for global risk using the VIX index from the Chicago Board Options Exchange (CBOE). The VIX index is a measure of U.S. stock market volatility, compiled from the prices of short-dated options on the S&P 500 index, and is often considered in academic and policy circles as an empirical proxy for global risk aversion.[13] In the robustness analysis I consider alternative measures of global risk. The return on resident banks' book equity (ROE) is measured as the median return on book equity (Net Income/Total Equity) across all banks resident in a particular economy, collected from the database compiled by Beck, Demirgüç-Kunt, and Levine (2000, 2009). The authors calculate the median bank book equity based on all foreign and domestic banks in an economy using data from *Bankscope*.[14]

Nominal foreign exchange rates against the U.S. dollar (USD) as well as money market rate data are collected at a quarterly frequency from the IMF's *In-*

[13]Recent papers which use the VIX index as a measure of global risk include, *inter alia*, Longstaff, Pan, Pedersen, and Singleton (2011), Bacchetta and Van Wincoop (2013), Forbes and Warnock (2012), and Fratzscher (2012).

[14]While *Bankscope* data is comprehensive, it does not have a 100 percent coverage of banks within an economy. The return on equity data, for example, does not take into consideration the return on equity of foreign *branches* since they are not required to hold any equity.

*ternational Financial Statistics* database. Other macroeconomic control data is collected from the IMF's *World Economic Outlook* database and includes the inflation rate, GDP growth rate and the change in the ratio of public debt to GDP. I also include annual domestic stock market volatility from the World Bank's *Global Financial Development* database. The dependent variables, $\Delta L_{i,j,t}$, $\Delta L^{P}_{j,t}$ and $\Delta L^{FA}_{j,t}$, as well as all country-specific independent variables are winsorized at 2.5 percent to limit the impact of outliers.[15]

### 2.4.2 Summary Statistics

In Table 2.1 I provide summary statistics for the period 1998Q1 to 2011Q4. The average quarterly percent change in interbank funding is 2.1 percent compared to 4.3 percent for intragroup funding. Intragroup funding to parents and foreign affiliates both grew at similar quarterly rates (5.2 percent and 4.0 percent, respectively). Perhaps surprising is the finding that the growth in intragroup funding is *more* volatile than interbank funding, indicating that global banks often make large shifts in internal funding with foreign affiliates. In Appendix Table A.3, I present correlations of macroeconomic and financial variables. I find the quarterly correlation between changes in the growth of interbank and intragroup funding is *negative* and statistically different from zero ($\approx -7\%$). All other correlations are low, mitigating concerns over multicollinearity.

In Table 2.2 I present statistics on the breakdown of cross-border bank-to-bank funding. In advanced economies, intragroup funding accounts, on average, for 42% of all cross-border bank funding. Around half (57%) of all intragroup funding is held by parent banks. In emerging economies the split between interbank and intragroup funding is tilted more towards interbank funding. On average, almost three-quarters of all cross-border borrowing by emerging economy resident banks is interbank. However for emerging economies, cross-border banking is relatively small, with total cross-border funding being on average only 7% of GDP, compared to over 100% for advanced economies.

In Figure 2.1, I present a breakdown of the average proportion of intragroup funding relative to total cross-border bank-to-bank funding between 1998 and 2011 for different BIS reporters. Due to data confidentiality I am unable to report specific country details on intragroup funding and hence, for the purposes of the figure, I anonymize countries. The funding models adopted across banking systems vary markedly. In a few banking systems, intragroup funding accounted, on average, for

[15] Winsorizing data involves setting all values at the extremes of the observed distribution equal to a pre-specified percentile. A 2.5 percent winsorization means all data below the $2.5^{th}$ percentile are set equal to the $2.5^{th}$ percentile and all data above the $97.5^{th}$ percentile are set equal to the $97.5^{th}$ percentile.

| Variable | Description | Source | Mean | Std.dev. | Min | Max | Obs. |
|---|---|---|---|---|---|---|---|
| *Cross-Border Bank-to-Bank Flows* | | | | | | | |
| Interbank Funding | Estimated exchange rate adjusted flow in cross-border interbank funding scaled by the stock of interbank funding (%). | BIS International Banking Statistics by Nationality (IBLN). | 2.06 | 11.37 | -23.03 | 33.35 | 1,178 |
| Intragroup Funding | Estimated exchange rate adjusted flow in cross-border intragroup funding scaled by the stock of intragroup funding (%). | BIS International Banking Statistics by Nationality (IBLN). | 4.20 | 16.88 | -30.95 | 58.27 | 1,178 |
| Intragroup Funding: Parent banks | Estimated exchange rate adjusted flow in parent cross-border intragroup funding scaled by the stock of parent intragroup funding (%). | BIS International Banking Statistics by Nationality (IBLN). | 5.18 | 23.59 | -40.73 | 100.0 | 964 |
| Intragroup Funding: Foreign Affiliates | Estimated exchange rate adjusted flow in affiliate cross-border intragroup funding scaled by the stock of affiliate intragroup funding (%). | BIS International Banking Statistics by Nationality (IBLN). | 4.00 | 19.43 | -41.67 | 72.50 | 975 |
| *Global Risk Appetite* | | | | | | | |
| VIX | Implied one-month volatility on the S&P 500 index. Monthly average of the log index value. | Bloomberg, authors' own calculations. | 3.06 | 0.34 | 2.40 | 4.07 | 1,400 |
| $\Delta$VIX | Change in the average log index value. | Bloomberg, authors' own calculations. | 0.00 | 0.22 | -0.33 | 0.85 | 1,400 |
| *Theoretically Motivated Controls* | | | | | | | |
| ROE | Average Return on Equity (Net Income/Total Equity). | Beck, Demirgüç-Kunt and Levine (2000) | 9.45 | 11.62 | -35.01 | 27.55 | 1,392 |
| FX Return | % Change in log end-of-period nominal exchange rate. U.S. dollar numéraire. | International Financial Statistics Database (IMF) | 0.00 | 0.06 | -0.21 | 0.62 | 1,400 |
| $\Delta$IR Spread | Change in the difference between domestic and the average of U.S. and U.K. money market rates. | International Financial Statistics Database (IMF) | 0.00 | 0.68 | -2.35 | 1.78 | 1,346 |
| *Other Macroeconomic and Financial Controls* | | | | | | | |
| Inflation | Annual inflation rate (%). | World Economic Outlook (IMF) | 2.93 | 2.67 | -0.33 | 13.24 | 1,400 |
| GDP Growth | Quarterly GDP growth (%). | World Economic Outlook (IMF) | 2.63 | 5.46 | -11.74 | 19.45 | 1,398 |
| $\Delta$Public Debt | Ratio to GDP (Annual, %). | World Economic Outlook (IMF) | 0.09 | 1.17 | -1.74 | 3.58 | 1,323 |
| Stock Volatility | 360-day standard deviation of returns on the national stock market index (Annual). | Global Financial Development Database (World Bank) | 26.24 | 11.36 | 12.39 | 59.62 | 1,332 |

**Table 2.1:** ***Descriptive Statistics: Banking, Macroeconomic and Financial Data.***

| Variable | Mean | Std.dev. | Min | Max | Obs. |
|---|---|---|---|---|---|
| *Full sample* | | | | | |
| Total external bank funding/total bank assets (%) | 22.6 | 11.8 | 5.2 | 73.5 | 555 |
| Total external bank funding/GDP (%) | 89.2 | 192.6 | 1.1 | 1,132.8 | 1,186 |
| Intragroup funding/total funding (%) | 42.2 | 25.2 | 0.1 | 97.4 | 1,186 |
| Intragroup funding of parents/intragroup funding (%) | 56.8 | 30.2 | 0.0 | 100.0 | 1,004 |
| *Advanced Economies* | | | | | |
| Total external bank funding/total bank assets (%) | 22.6 | 11.8 | 5.2 | 73.5 | 555 |
| Total external bank funding/GDP (%) | 104.7 | 206.3 | 6.5 | 1,132.8 | 998 |
| Intragroup funding/total funding (%) | 45.6 | 25.2 | 0.1 | 97.4 | 998 |
| Intragroup funding of parents/intragroup funding (%) | 57.4 | 30.4 | 0.0 | 100.0 | 861 |
| *Emerging Market Economies* | | | | | |
| Total external bank funding/GDP (%) | 7.0 | 5.7 | 1.1 | 24.6 | 188 |
| Intragroup funding/total funding (%) | 24.3 | 16.9 | 0.1 | 66.0 | 188 |
| Intragroup funding of parents/intragroup funding (%) | 52.9 | 28.6 | 0.0 | 93.8 | 143 |

**Table 2.2:** ***Descriptive Statistics: Disaggregated Cross-Border Funding.***

over 80 percent of all cross-border bank-to-bank funding. In contrast, others have funded themselves almost entirely using the wholesale interbank market. Of the countries in the sample, around half receive the majority of funding in the form of intragroup flows, when borrowing internationally from other banks.

In addition, I explore the structure of intragroup funding in greater detail in Figure 2.1 by also displaying the average share of intragroup funding held by domestically-owned parent banks between 1998 and 2011. Again, a large disparity emerges across countries. For the countries with a high share of intragroup funding, I find this could be held primarily by parents (e.g. country 3) or by foreign affiliates (e.g. country 1). Overall, the figure provides an early indication of the importance of both interbank and intragroup funding across banking system business models, and suggests a need to understand if the intragroup funding of parent and foreign affiliate banks behaves differently in the face of fluctuating global risk.

### 2.4.3 A First Look at the Data

Before commencing the formal empirical analysis, I begin with a preliminary examination of the data on cross-border bank-to-bank funding. First, I examine the economic importance of these flows at the *aggregate* level.

**The economic importance of cross-border banking.** In Figure 2.2 I present cross-country changes in global bank-to-bank funding following the collapse of Lehman Brothers. In Figure 2.2a the change is shown as a percentage of the country's stock of cross-border bank funding at 2008Q3, while in Figure 2.2b it is shown

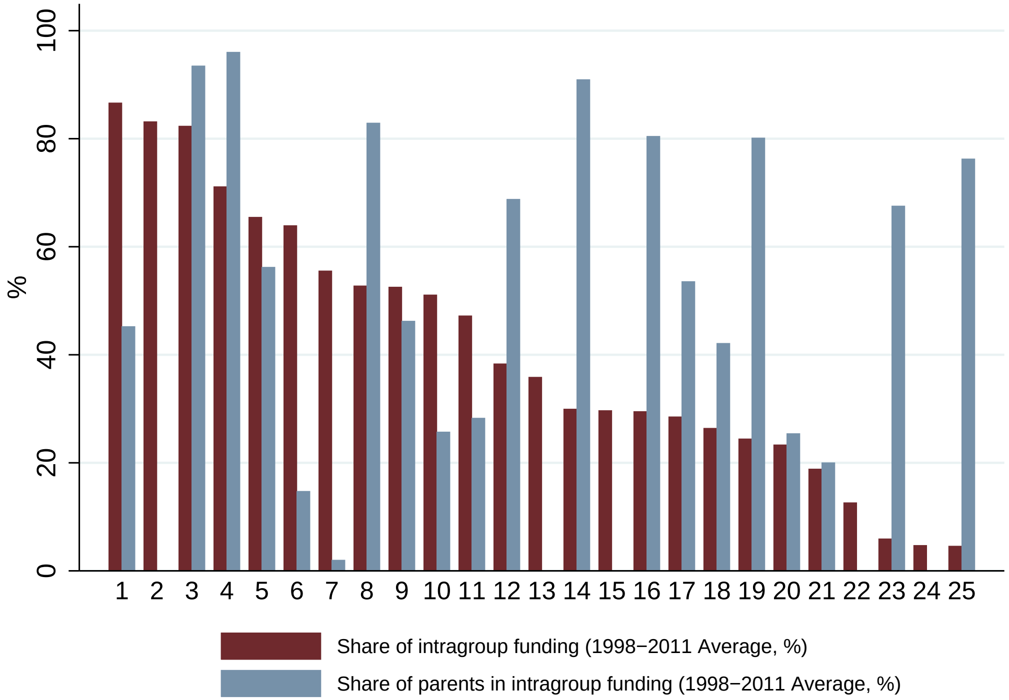
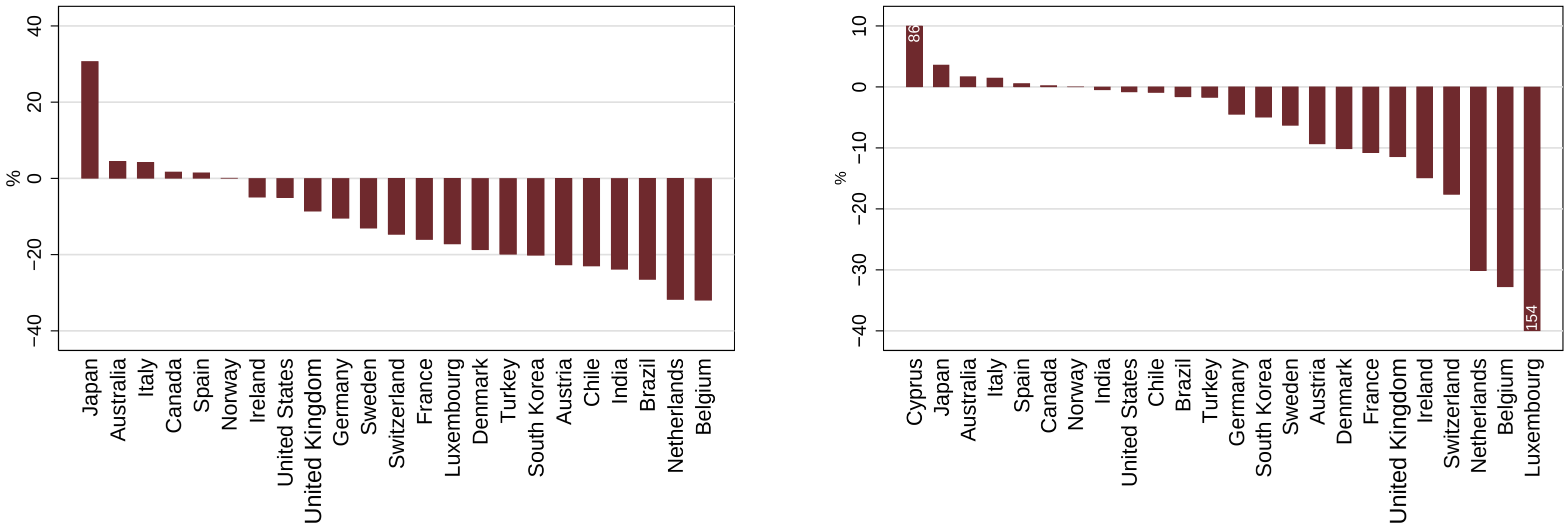



**Figure 2.1:** ***Intragroup Funding Across Countries.*** *The figure presents the average share of intragroup funding as a percentage of total cross-border bank-to-bank funding, between 1998 and 2011, for the 25 banking systems within the sample. Also included is the average share of intragroup funding held by domestically-owned parent banks, also averaged between 1998 and 2011. Country specific data are confidential and hence anonymized. Data on banking flows are collected from the Bank for International Settlements's International Banking Statistics database. The sample period is from 1998Q1 to 2011Q4.*




**(a)** % Aggregate Cross-Border Bank-to-Bank Funding

**(b)** % GDP

**Figure 2.2:** ***Cross-Border Funding Following the Collapse of Lehman Brothers.*** *Figure (a) presents the cumulative change in cross-border interbank and intragroup funding following the collapse of Lehman Brothers in 2008Q3. The change is measured as the sum of exchange-rate-adjusted flows between 2008Q4 and 2009Q2 relative to the stock of cross-border funding in 2008Q3. In Figure (b) the change is measured relative to GDP at 2008Q3. Data on banking flows are collected from the Bank for International Settlements's International Financial Statistics database. The sample period is from 1998Q1 to 2011Q4.*

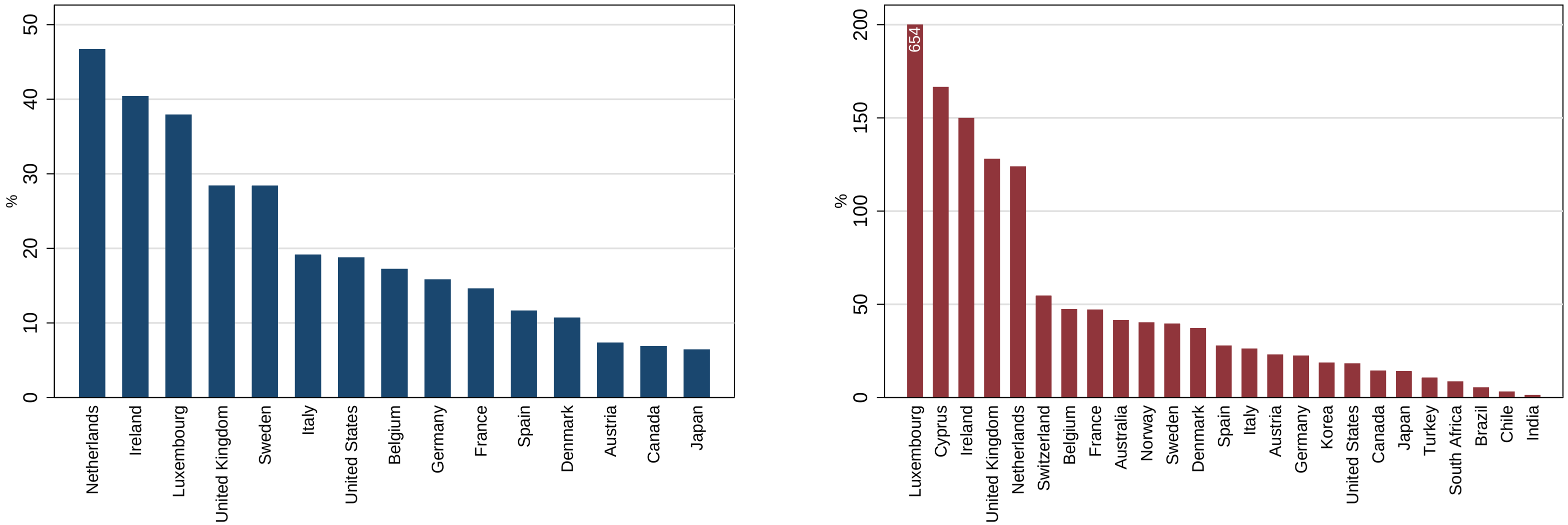
relative to the country's size (GDP). Only a handful of countries experienced an inflow of bank-to-bank funding in the immediate aftermath of Lehman's collapse (Japan, Australia, Italy, Canada, Spain and Norway). Most countries witnessed a large fall in their aggregate cross-border bank funding. Even if the fall was mild relative to total cross-border bank-to-bank funding, it could still generate an economy-wide shock due to the size of a banking system relative to the underlying economy. Ireland, for example, witnessed a comparatively small drop in funding from banks abroad, relative to its stock of cross-border bank funding. But the drop translated into a much larger, 15 percent fall, relative to GDP.

The Irish case provides an illustration of the economic importance of international banking flows, which I document further in Figure 2.3. In 2011Q4, cross-border bank-to-bank funding accounted for over 40 percent of total resident banking system assets in the Netherlands and Ireland, and over 20 percent in the United Kingdom, Luxembourg, and Sweden (see Figure 2.3a).[16] As a share of GDP the numbers are even more pronounced (see Figure 2.3b), accounting for over 100 percent of GDP in five banking systems: Luxembourg (654 percent), Cyprus (167 percent), Ireland (150 percent), United Kingdom (128 percent) and the Netherlands (124 percent). Even in emerging market economies, where proportions were lower, contractions in funding could still impact the expansion of domestic credit due to relatively smaller banking systems, and a heavy reliance on foreign bank affiliates to expand domestic credit, as demonstrated by Schnabl (2012) in the case of Peru.

**Interbank and intragroup funding.** In Figure 2.4a I disaggregate cross-border funding between banks into two baskets - arms-length interbank flows, and related intragroup flows - and find that interbank funding fell on average across the sample of BIS reporters by almost 30 percent between September 2008 and the end of 2009. Yet, in contrast, intragroup funding *increased* in the immediate aftermath of Lehman Brothers collapse and was stable for the remainder of the crisis period.[17] Contrasting behavior in interbank and intragroup flows is not limited, however, to the recent global financial crisis. To see this, in Figure 2.4b I present the distributional relationship across time between cross-border bank-to-bank funding and the VIX index. I find that on average, between 1998 and 2011, interbank funding *contracted* by two percent during quarters when the VIX index was at an elevated level (upper-$25^{th}$ percentile), while during the same quarters intragroup funding *ex-*

[16]The data for total banking system assets are collected from the IMF's *Global Financial Stability Report* and are available for 15 countries in the sample.

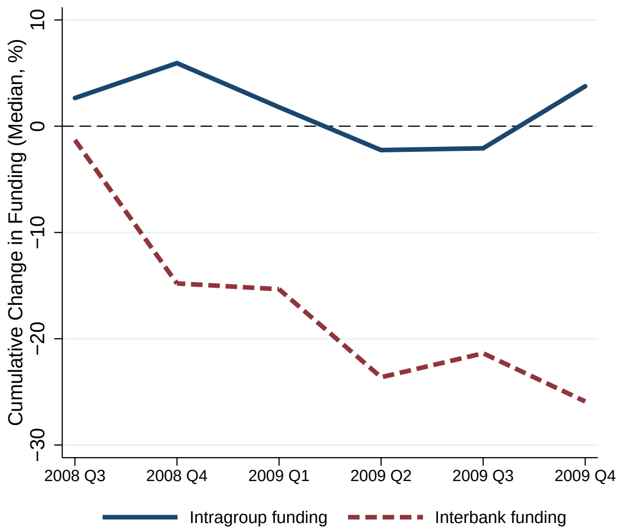
[17]The numbers reflect the median change in interbank and intragroup funding across all 25 banking systems in the study. To calculate the change, I sum over *flows* (adjusted for exchange rate fluctuations) and divide by the stock at the start of the crisis.



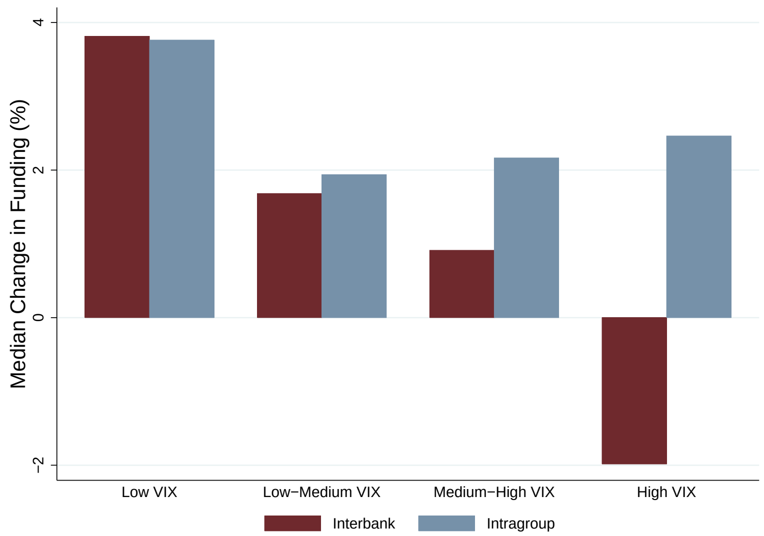

**(a)** Ratio of Cross-Border Funding to Total Bank Assets (%)

**(b)** Ratio of Cross-Border Funding to GDP (%)

**Figure 2.3:** ***The Economic Importance of Cross-Border Bank-to-Bank Funding.*** *Panel (a) presents the ratio of cross-border bank-to-bank funding to the total assets of resident commercial banks (including foreign subsidiaries) in 2011Q4. Data on total resident bank assets are taken from the IMF's Global Financial Stability Report. Panel (b) shows the ratio of cross-border bank-to-bank funding relative to GDP in 2011Q4. Data on banking flows are collected from the Bank for International Settlements's International Financial Statistics database. The sample period is from 1998Q1 to 2011Q4.*




**(a)** Cross-border flows after Lehman Brothers Collapse




**(b)** The relationship between cross-border flows and the VIX index

**Figure 2.4:** ***A First Look at Interbank and Intragroup Funding.*** *Figure (a) presents the cumulative median change in aggregate cross-border interbank and intragroup funding, across 25 advanced and emerging market banking systems, following the collapse of Lehman Brothers in September 2008. The change is measured relative to the stock of cross-border funding in 2008Q2. In Figure (b) quarterly funding is split into four groups, conditional on the average level of the VIX index in each quarter between 1998 and 2011. Each bar represents the median quarterly percentage change in interbank or intragroup funding if the VIX index is low (below the* $20^{th}$ *percentile), at a medium level (between the* $20^{th}$ *and* $50^{th}$ *percentiles), at an elevated level (between the* $50^{th}$ *and* $80^{th}$ *percentiles) or at a high level (above the* $80^{th}$ *percentile). Data on banking flows are collected from the Bank for International Settlements's International Financial Statistics database. The sample period is from 1998Q1 to 2011Q4.*

*panded* by over two percent. In the quarters when the VIX index was particularly low (lower-$25^{th}$ percentile), both intragroup *and* interbank funding expanded by approximately four percent.

**Intragroup funding to parents and foreign affiliates.** In Figure 2.5 I plot median cumulative changes in aggregate (interbank plus intragroup) cross-border bank-to-bank funding following the collapse of Lehman Brothers, conditional on (i) the banking system's share of intragroup funding and (ii) the proportion of intragroup funding held by resident parent banks.

First, I split countries into two baskets based on their share of intragroup funding at 2008Q2. I find countries with a high share of intragroup funding experienced a much smaller loss of cross-border bank financing following the collapse of Lehman Brothers. By the end of 2009, banking systems funded with a relatively high share of arms-length interbank funding had experienced, on average, a 20 percent drop in funding, while the fall in funding was less than eight percent for banking systems with a high share of intragroup funding.

Next, I split the basket of high intragroup funded countries based on the mix of intragroup funding held by parents and foreign affiliates. Banking systems with a high share of intragroup funding held predominately by parent banks, experienced almost no loss in cross-border bank-to-bank funding during the global financial crisis – amplifying the contrasting behavior in interbank and intragroup funding in relation to fluctuations in global risk. Next, I explore these relationships in greater depth in the formal empirical investigation.

## 2.5 Empirical Methods and Results

In this section, I outline the empirical methodology used in this study and present the findings. I first describe results for the disaggregation of cross-border bank-to-bank funding between interbank and intragroup flows, and explore whether the findings are mirrored across advanced *and* emerging market economies. Next, I turn the attention exclusively to intragroup flows, examining the split in funding between parent and foreign affiliate banks.

### 2.5.1 Empirical Methods

I begin by examining the relationship between interbank and intragroup funding and fluctuations in global risk, which I proxy using the VIX index. To do so, I estimate a fixed-effects panel regression, based on equation 2.3, which takes the form

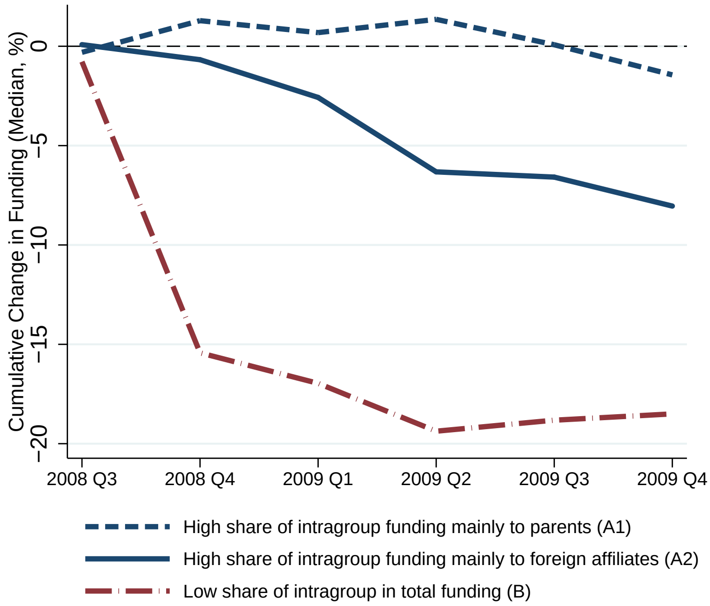



**Figure 2.5:** ***Intragroup Funding and Parent Banks.*** *The figure presents the cross-country median, exchange rate adjusted change of total (interbank plus intragroup) cross-border bank funding between 2008Q3 and 2009Q4. The values are scaled by the stock of funding at 2008Q2. Countries are classified as having a high share of intragroup funding if their 2008Q2 share of intragroup funding, as a proportion of total cross-border bank-to-bank funding, exceeds the cross-country median. Within the group of countries with a high share of intragroup funding, I further classify them as having intragroup funding 'mainly held by parents', if the share of intragroup funding held by parents, as a proportion of total intragroup funding, exceeds the cross-country median. Data on banking flows are collected from the Bank for International Settlements's International Financial Statistics database. The sample period is from 1998Q1 to 2011Q4.*

$$\begin{aligned} \Delta L^j_{i,t} = \beta_{i,0} + \beta_{i,1} \cdot VIX_{t-1} + \beta_{i,2} \cdot \Delta VIX_t \\ + \left( \sum_{l=1}^{3} \beta_{i,l+2} \cdot TCV_{j,t-1} \right) + \alpha_j + Controls + \epsilon_{i,t} \end{aligned} \tag{2.6}$$

where $\Delta L^j_{i,t}$ is the quarterly percent change in either interbank or intragroup funding (see equation 2.4 for details).[18] $VIX$ is the average level of the VIX index (in logs) during the quarter and proxies for the *level* of global risk, while $\Delta VIX$ is the quarterly change in the average level of the VIX index (in logs) and proxies for the *change* in global risk. The three theoretically-motivated control variables (return on domestic bank book equity, foreign exchange returns and interest rate differentials) are denoted $TCV$. Control variables sampled at a quarterly frequency

[18]The framework for the empirical analysis is outlined fully in Section 2.3. I estimate a Hausman test and find the null hypothesis (the random-effects estimator is consistent) is strongly rejected, indicating the need to estimate a fixed-effects rather than random-effects model.

are lagged by one quarter, while those sampled at yearly frequency are lagged by four quarters. Both theoretically determined and other macroeconomic and financial control variables are discussed in Section 2.4. I include country level fixed effects $\alpha_j$, in an attempt to capture any other time invariant country level effects not picked-up by the set of control variables. I calculate robust standard errors, clustered at country level.

### 2.5.2 Baseline Regression

In Table 2.3, I present the baseline results. In columns one and two I consider changes in interbank funding while in columns three and four, I investigate intragroup funding. In the first and third columns I only include theoretically motivated control variables. The coefficients on interbank funding support the theoretical hypotheses outlined in Section 2.3. Interbank funding contracts when the VIX is high or rising during a quarter. In contrast, and *counter* to theoretical prediction, intragroup funding shows no relationship with the level of the VIX and *expands* in quarters when the VIX rises. I also find the return on domestic bank book equity displays, as predicted, a statistically significant and positive relationship with subsequent interbank *and* intragroup funding. Currency market movements are also shown to drive both interbank and intragroup funding. The FX return variable enters the model with the correct sign. A lower return (appreciation of the local currency) generates an inflow of funding to the local economy banking system. Finally, in this baseline regression, I find no evidence of a relationship between bank-to-bank funding and interest rate differentials.

The results from the full specification, including all control variables, are shown in the second and fourth columns. Two of the controls variables, domestic GDP growth and the change in public debt (as a proportion of GDP), are found to be statistically significant drivers of arms-length interbank funding. However, I find none of the control variables are significant in determining intragroup funding, suggesting that interbank flows are more responsive to local economic and financial factors. One potential reason why intragroup funding is less affected by the control variables is offered by Cetorelli and Goldberg (2012b). Examining internal capital markets, the authors find that the funding of foreign affiliates by U.S. parent banks is, in part, determined by factors detached from short-term macroeconomic fluctuations. For example, the location of the affiliate bank as a source of funding or destination for foreign investment, and its distance from the headquarters of the parent bank, could both be more important determinants of funding than local economic or financial conditions.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Interbank | | Intragroup | |
| VIX | -5.22*** | -5.20*** | 0.32 | 0.97 |
| | (1.18) | (1.09) | (1.29) | (1.47) |
| Δ VIX | -3.94* | -4.04* | 5.32** | 4.09* |
| | (1.97) | (2.03) | (2.21) | (2.39) |
| ROE | 0.13*** | 0.08** | 0.18*** | 0.14** |
| | (0.03) | (0.03) | (0.04) | (0.05) |
| FX Return | -12.15** | -12.98*** | -24.02** | -24.70** |
| | (5.16) | (3.98) | (8.71) | (9.37) |
| Δ IR Spread | 1.09 | 0.93 | -0.26 | -0.98 |
| | (0.66) | (0.70) | (1.18) | (1.25) |
| Inflation | | -0.10 | | -0.74 |
| | | (0.32) | | (0.58) |
| GDP Growth | | 0.15*** | | -0.08 |
| | | (0.05) | | (0.09) |
| Δ Public Debt | | -0.73** | | -0.13 |
| | | (0.32) | | (0.51) |
| Stock Volatility | | 0.02 | | -0.08 |
| | | (0.04) | | (0.08) |
| Constant | 16.53*** | 15.86*** | 1.84 | 4.25 |
| | (3.72) | (3.65) | (4.03) | (4.64) |
| Observations | 1,142 | 1,088 | 1,142 | 1,088 |
| R-squared | 0.07 | 0.08 | 0.04 | 0.05 |
| Countries | 25 | 25 | 25 | 25 |

**Table 2.3:** ***Baseline Results.*** *The table presents the estimated parameter values from fixed-effects panel regressions. The dependent variable is the quarterly percentage change in either interbank or intragroup funding. In columns (1) and (2) I report results for interbank funding, while in columns (3) and (4) I do the same for intragroup funding. VIX is the quarterly average of the log VIX index, while $\Delta$VIX is the quarterly change in the average level of the log VIX index. All control variables are discussed in Section 2.4.1 with summary statistics provided in Table 2.1. Standard errors, clustered at country level, are reported in brackets. *** is significant at the 1% level, ** at the 5% level and * at the 10% level. Data on banking flows are collected from the Bank for International Settlements's International Financial Statistics database. The sample period is from 1998Q1 to 2011Q4.*

### Economic Significance

In this subsection, I examine the relative economic significance of the estimated coefficients in the baseline regression. I do so by studying a stylized scenario analysis that reflects events following the collapse of Lehman Brothers. I consider three hypothetical banking systems (A, B, and C). The banking systems have different business models in terms of their mix of arms-length and related funding. Banking System A is financed 20 percent with intragroup funding and 80 percent in the interbank market (the Netherlands has similar proportions). Banking System B is equally funded with intragroup and interbank funding (similar to the German banking system), while Banking System C obtains 80 percent of overseas bank-to-bank funding in internal capital markets (similar to the United States). I consider a scenario in which the VIX index rises from an average of 25 during the first quarter to an average of 45 in the subsequent quarter. The VIX then remains at an average of 45 for two quarters.[19]

First, the statistically significant coefficients on the VIX and ΔVIX, estimated in the baseline regression (Table 2.3), are used to estimate the change in cross-border bank-to-bank funding when the VIX rises by 20 points.[20] Banking System A, with the lowest share of intragroup funding, experiences a 17 percent drop in funding. Funding to Banking System B falls by ten percent, while Banking System C maintains a roughly stable level of funding. The stability of funding to Banking System C is a consequence of intragroup inflows offsetting interbank outflows. Since intragroup flows remain stable during periods of high global risk, flows over the following two quarters – when the VIX remains at 45 – are *only* due to outflows in interbank funding. Accounting for these flows results in Banking System A losing almost 40 percent of cross-border bank funding over the entire three quarter period. However, Banking System C, with the largest share of intragroup funding, experiences a relatively modest eight percent drop in funding. Banking System B, as expected, falls in between, with a 23 percent drop in funding.

Comparing the scenario with the actual outcomes for the countries listed above (Netherlands, Germany and the United States) results in a similarly large and economically important difference across countries. The Dutch banking system experienced over a *30 percent* drop in cross-border bank-to-bank funding following the collapse of Lehman Brothers. The German banking system faced a smaller drop in funding, of approximately ten percent, while the United States, at the epicenter of the financial crisis, but holding the largest relative share of intragroup funding, experienced only a five percent withdrawal of total cross-border bank-to-bank funding.

**Advanced and Emerging Market Economies**

I augment the baseline regression to include an emerging-market dummy variable, which is equal to **1** when the funding is to an emerging economy (as classified by the BIS, see Section 2.4 for sample information), and zero otherwise. The dummy variable is interacted with the VIX and the other theoretically motivated control variables. In Table 2.4, I report parameter estimates for interbank funding in column one and for intragroup funding in column two. Once again, I find the coefficient on

[19]The average level of the VIX in 2008Q3 was 25 and increased to an average of 45 between 2008Q4 and 2009Q2.

[20]The coefficients are: $VIX$ (interbank: $-5.20$) and $\Delta VIX$ (interbank: $-4.04$; intragroup: 4.09). I provide details of these calculations in Appendix Table A.6.

| | (1) | (2) |
|---|---|---|
| | Interbank | Intragroup |
| VIX | -4.14*** | 1.18 |
| | (1.22) | (1.31) |
| VIX*EME | -7.40** | -1.31 |
| | (2.77) | (5.97) |
| *VIX+VIX*EME* | *-11.54**** | *-0.14* |
| *p-value* | *0.0001* | *0.9823* |
| ΔVIX | -3.37 | 5.23*** |
| | (2.26) | (1.78) |
| ΔVIX*EME | -4.66 | -9.06 |
| | (4.22) | (8.87) |
| *ΔVIX+ΔVIX*EME* | *-8.03*** | *-3.83* |
| *p-value* | *0.0346* | *0.6648* |
| ROE | 0.10*** | 0.18*** |
| | (0.03) | (0.04) |
| ROE*EME | -0.16 | -0.90*** |
| | (0.15) | (0.31) |
| *ROE+ROE*EME* | *-0.06* | *-0.72*** |
| *p-value* | *0.6975* | *0.0275* |
| FX Return | -8.62** | -13.17 |
| | (3.85) | (8.32) |
| FX Return*EME | -11.74 | -63.19** |
| | (10.25) | (24.16) |
| *FX Return+FX Return*EME* | *-20.36*** | *-76.36**** |
| *p-value* | *0.0389* | *0.0020* |
| ΔIR Spread | 1.96** | -2.40* |
| | (0.91) | (1.16) |
| ΔIR Spread*EME | -1.50 | 3.27* |
| | (1.16) | (1.70) |
| *ΔIR Spread+ΔIR Spread*EME* | *0.46* | *0.87* |
| *p-value* | *0.5631* | *0.5040* |
| **Controls** | Y | Y |
| Observations | 1,088 | 1,088 |
| R-squared | 0.09 | 0.07 |
| Countries | 25 | 25 |

**Table 2.4:** ***Advanced and Emerging Economy Banking Systems.*** *The table presents the estimated parameter values from fixed-effects panel regressions. The dependent variable is the quarterly percentage change in either interbank or intragroup funding. In column (1) I report results for interbank funding, while in column (2) I do the same for intragroup funding. EME is a dummy variable which equals* **1** *if the banking system is in an emerging market economy and zero otherwise. VIX is the quarterly average of the log VIX index, while ΔVIX is the quarterly change in the average level of the log VIX index. The control variables are discussed in Section 2.4.1 with summary statistics provided in Table 2.1. Standard errors, clustered at country level, are reported in brackets. *** is significant at the 1% level, ** at the 5% level and * at the 10% level. I include F-tests to determine if the effect of a variable on emerging economies is significant. Data on banking flows are collected from the Bank for International Settlements's International Financial Statistics database. The sample period is from 1998Q1 to 2011Q4.*

the VIX is negative and statistically significant for interbank funding. However, the effect is almost *three times larger* for banks resident in emerging market economies.

In the third row, I run an *F-test* to investigate if the sum of coefficients on the VIX index is statistically significant, with the *p-value* reported below. The equivalent *F-test* is also run and reported for ΔVIX and all other theoretically motivated control variables. The *F-test* for both the VIX and ΔVIX yields a negative and statistically significant coefficient, indicating that banks resident in emerging economies observe an outflow of interbank funding when the VIX index is high or rising during a quarter. The coefficient on the ΔVIX alone, is not, however, statistically different from zero. This finding provides evidence that an increase in global risk over one quarter does indeed impact interbank funding, but *only* to those banks resident in emerging economies.

The split between advanced and emerging economies also impacts intragroup funding. The ΔVIX coefficient is positive and highly significant, in keeping with the earlier baseline regression. However, the *F-test* for ΔVIX implies *only* advanced economy resident banks experience an inflow of intragroup funding when global risk rises. Moreover, I find contrasting implications for the return on equity. Mirroring the earlier result and prediction from theory, the ROE coefficient is positive across both interbank and intragroup funding – better domestic conditions increase the capacity to borrow. Yet the *F-test* on ROE for intragroup funding, yields a negative and statistically significant value. This finding implies that emerging market banking systems *receive* funding when their average profitability is low. I find a similar asymmetric result on the FX return variable. Currency market activity is particularly relevant for emerging economies, which lose both interbank *and* intragroup funding following a depreciation of the local currency.

### Funding During the Financial Crisis

I examine the extent to which information on a country's mix of interbank and intragroup funding could explain cross-border bank-to-bank flows following the collapse of Lehman Brothers. To do so, I estimate a cross-sectional regression which takes the form

$$\Delta L_j = \beta_0 + \beta_1 \cdot IntraShare_j + \epsilon_j, \tag{2.7}$$

where $IntraShare_j$ is the amount of intragroup funding held by country $j$ as a percentage of its total (interbank *plus* intragroup) cross-border funding from banks, measured at 2008Q3. $\Delta L$ is the percent change in total funding (interbank plus

| | (1) | (2) | (3) |
|---|---|---|---|
| | All countries | AEs with systemic banking crisis | AEs without systemic banking crisis |
| Share of intragroup funding | 0.21** | 0.34** | 0.04 |
| | (0.09) | (0.12) | (0.14) |
| Constant | -20.10*** | -31.61*** | -2.00 |
| | (4.64) | (6.99) | (6.23) |
| Observations | 23 | 10 | 8 |
| R-squared | 0.12 | 0.45 | 0.00 |

**Table 2.5:** ***Explaining Funding During the Global Financial Crisis.*** *The table presents the estimated parameter values from cross-sectional regressions. The dependent variable is the change in total (interbank plus intragroup) cross-border bank-to-bank funding to countries between 2008Q4 and 2009Q2. The right-hand-side variable is the share of intragroup funding as a percentage of total (interbank plus intragroup) cross-border bank-to-bank funding, measured at 2008Q3. In column (1) all 25 countries are included in the regression. In column (2) only the ten countries having experienced a systemic banking crisis as classified by Laeven and Valencia (2013) are included. Finally, in column (3) I only include advanced market economies not classified as having experienced a systemic banking crisis. *** is significant at the 1% level, ** at the 5% level and * at the 10% level. Data on banking flows are collected from the Bank for International Settlements's International Financial Statistics database.*

intragroup) between 2008Q4 and 2009Q2, relative to the stock at 2008Q3.

In Table 2.5, I present the results from the bivariate regression. In column one, I show the result for all banking systems in the sample. The fit across the 25 countries can explain around 12 percent of the total variation in funding loss during the crisis. The coefficient on intragroup funding is positive and statistically significant. I then investigate if the share of intragroup funding was particularly important for countries having suffered from a systemic banking crisis following the collapse of Lehman Brothers. To do so, I classify countries as having suffered a systemic banking crisis or not, using the database compiled by Laeven and Valencia (2013).[21] None of the emerging economies in the sample were classified as having experienced a systemic banking crisis during 2008-09, while ten advanced economies banking systems were found to have experienced such a crisis.

When I limit the regression to the ten banking systems having experienced a systemic banking crisis (column two), the simple bivariate regression explains 45 percent of the variation in funding loss across countries. The coefficient on intragroup funding is now larger than in the first specification and remains highly significant. A country which experienced a systemic banking crisis and held no intragroup funding could expect to witness a loss of funding exceeding 30 percent. If, however, the banking system relied fully on intragroup funding when borrowing

[21] Laeven and Valencia (2013) define a borderline set of countries, not found to have experienced a systemic banking crisis, but whose banking systems were affected by the crisis. These countries include Sweden, Italy, France and Switzerland. I choose to classify these countries as not having experienced a systemic banking crisis.

from banks overseas, the country would be expected to see a small inflow of funding. To contrast with this finding, I run a third specification (column three) including advanced economy countries which did not experience a systemic crisis. This time I do not find any clear relationship between the use of intragroup funding and the amount of funding withdrawn. In addition, the constant in the regression becomes insignificantly different from zero, indicating that these countries did not, on average, lose any cross-border bank-to-bank funding during the crisis.

The results from the bivariate regression point to a selective withdrawal of bank-to-bank funding. Banking systems not directly connected with the 2008-09 global financial crisis, including Norway, Australia, Japan, Italy and Canada, experienced limited cross-border bank-to-bank outflows. Furthermore, as suggested by the scenario analysis, countries with high shares of intragroup funding – even if suffering a systemic banking crisis – were less likely to experience a large outflow of funding, while emerging market economies (with relatively low shares of intragroup funding) faced some of the largest outflows, despite not having experienced systemic banking crises.

As a follow-up exercise, I investigate how much of the loss in total (interbank plus intragroup) funding could have been predicted from the prior regression on advanced and emerging economies. Specifically, I focus on advanced economies, split between those having experienced a systemic banking crisis and those which did not, and use the regression coefficients estimated on the VIX and $\Delta$VIX *only*. In Figure 2.6, I plot the actual and predicted loss in total funding based on each country's mix of interbank and intragroup funding between 2008Q3 and 2009Q2 (as a percentage of the 2008Q3 stock), combined with the coefficients on the VIX and $\Delta$VIX reported in Table 2.4. I find that over 20 percent of the total fall in funding could be explained for banking systems which experienced a systemic banking crisis. To put the result in context, had the split between interbank and intragroup funding not been made, then none of the cross-sectional spread could have been explained.[22]

### 2.5.3 Parent and Foreign Affiliate Banks

The second part of the sequential disaggregation of cross-border banking flows involves splitting intragroup funding between parent and foreign affiliate banks. In doing so, I tease out more detail on the behavior of intragroup funding than could

[22] Using aggregate information, in which interbank and intragroup flows are predicted to behave symmetrically, results in a predicted loss of around 15 percent in funding for *every* banking system (see Figure 2.6). The results from the regression on aggregate flows are provided in Appendix Table A.1.

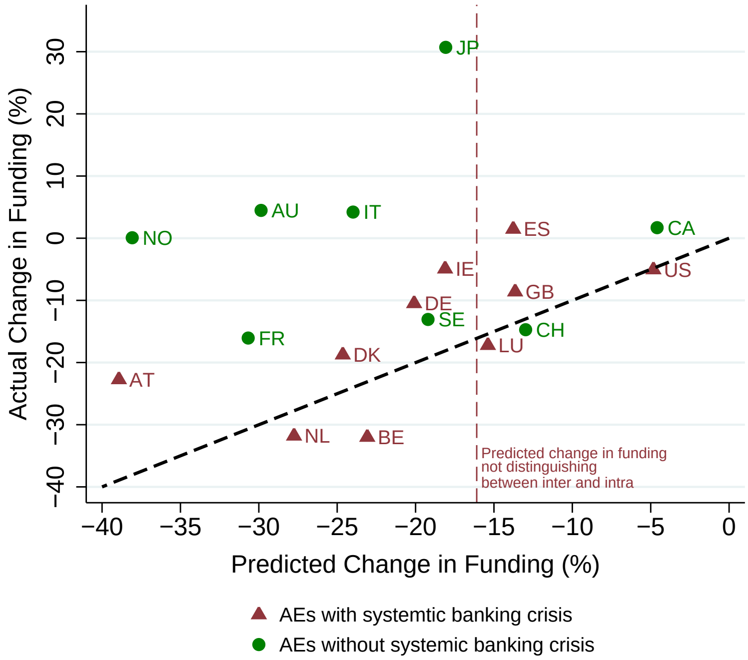



**Figure 2.6:** ***Funding Loss During the Global Financial Crisis.*** *The figure presents the predicted loss or gain in total cross-border bank-to-bank funding between 2008Q4 and 2009Q2 using the actual data on the VIX between 2008Q4 and 2009Q2, in combination with the statistically significant coefficients estimated for the $VIX$ and $\Delta VIX$, reported in Table 2.4. I also split the advanced market economies between those which experienced a systemic banking crisis during the global financial crisis and those which did not. The classification as to whether a country experienced a systemic banking crisis or not is based on the database of Laeven and Valencia (2013). Following the BIS country classification system: AT=Austria, AU=Australia, BE=Belgium, BR=Brazil, CA=Canada, CH=Switzerland, CL=Chile, DE=Germany, DK=Denmark, ES=Spain, FR=France, GB=United Kingdom, IE=Ireland, IN=India, IT=Italy, JP=Japan, KR=South Korea, LU=Luxembourg, NL=Netherlands, NO=Norway, SE=Sweden, TR=Turkey, US=United States. Data on banking flows are collected from the Bank for International Settlements's International Banking Statistics database. The sample period is from 1998Q1 to 2011Q4.*

be achieved at the first level of disaggregation.[23]

I run the augmented baseline regression, including an emerging market dummy variable in which the left-hand-side variables are the quarterly percentage change in intragroup flows to parent and foreign affiliate banks (see equation 2.5 for details). Results are reported in Table 2.6. In columns one and two, I present results for domestically headquartered parent banks, and do the same for foreign affiliates in columns three and four. Parent banks resident in advanced economies are found to have a robust positive relationship with the VIX and ΔVIX, while foreign affiliates do not. The finding indicates that advanced economy parent banks receive funding from their foreign affiliates during periods of heightened global risk. The result supports a recent finding by Hoggarth, Hooley, and Korniyenko (2013), who show that

[23]In Appendix Table A.2, I report the analogous results for interbank flows.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Parents | | Foreign Affiliates | |
| VIX | 3.90* | 4.69** | -1.81 | -0.76 |
| | (2.25) | (2.20) | (1.36) | (1.48) |
| VIX*EME | | -8.86* | | -6.84 |
| | | (4.99) | | (5.47) |
| *VIX+VIX*EME* | | *-4.17* | | *-7.60* |
| *p-value* | | *0.3808* | | *0.1545* |
| ΔVIX | 4.66 | 7.97* | 2.52 | 1.92 |
| | (4.17) | (4.05) | (2.83) | (3.08) |
| ΔVIX*EME | | -27.12*** | | 1.18 |
| | | (8.12) | | (3.79) |
| *ΔVIX+ΔVIX*EME* | | *-19.15**** | | *3.10* |
| *p-value* | | *0.0092* | | *0.2346* |
| ROE | 0.23*** | 0.26*** | 0.09 | 0.12 |
| | (0.06) | (0.06) | (0.10) | (0.10) |
| ROE*EME | | -0.15 | | -1.06*** |
| | | (0.49) | | (0.31) |
| *ROE+ROE*EME* | | *0.11* | | *-0.94**** |
| *p-value* | | *0.8265* | | *0.0065* |
| FX Return | -35.09** | -38.36** | -8.44 | -2.46 |
| | (15.58) | (16.21) | (13.97) | (6.50) |
| FX Return*EME | | 24.96 | | -32.41 |
| | | (50.45) | | (67.72) |
| *FX Return+FX Return*EME* | | *-13.40* | | *-34.87* |
| *p-value* | | *0.7848* | | *0.6067* |
| ΔIR Spread | -1.40 | 0.23 | 0.84 | -2.34 |
| | (1.89) | (1.50) | (1.21) | (1.83) |
| ΔIR Spread*EME | | -2.22 | | 5.67** |
| | | (3.36) | | (1.99) |
| *ΔIR Spread+ΔIR Spread*EME* | | *-1.99* | | *3.33**** |
| *p-value* | | *0.5255* | | *0.0000* |
| **Controls** | Y | Y | Y | Y |
| Observations | 919 | 919 | 922 | 922 |
| R-squared | 0.05 | 0.05 | 0.04 | 0.06 |
| Countries | 20 | 20 | 20 | 20 |

**Table 2.6:** ***Intragroup Funding: Flows to Parent and Foreign Affiliate Banks.*** *The table presents the estimated parameter values from fixed-effects panel regressions. The dependent variable is the quarterly percentage change in intragroup funding of either parent or foreign affiliate banks. In columns (1) and (2) I report results for parents banks, while in columns (3) and (4) I do the same for foreign affiliates. $EME$ is a dummy variable which equals* **1** *if the banking system is in an emerging market economy and zero otherwise. VIX is the quarterly average of the log VIX index, while $\Delta VIX$ is the quarterly change in the average level of the log VIX index. The control variables are discussed in Section 2.4.1 with summary statistics presented in Table 2.1. Standard errors, clustered at country level, are reported in brackets. *** is significant at the 1% level, ** at the 5% level and * at the 10% level. I include F-tests to determine if the effect of a variable on emerging economies is significant. Data on banking flows are collected from the Bank for International Settlements's International Financial Statistics database. The sample period is from 1998Q1 to 2011Q4.*

gross intragroup lending by foreign affiliates resident in the U.K. increased strongly following the run on the British bank, Northern Rock.[24]

Parent banks in emerging economies are more exposed to global shocks, echoing the earlier finding. Possibly due to limited banking presence overseas, these parent banks observe a large fall in intragroup funding when global risk rises. The evidence is mixed, however, on their ability to withstand periods when the VIX is elevated, with the *F-test* showing a negative, albeit insignificant, point estimate. I find a similar result for foreign affiliates resident in emerging economies, although overall I find no robust evidence that foreign affiliates, in either advanced or emerging economies, lose funding when global risk is high.

Earlier, I noted that intragroup funding to emerging economies appears to increase when the average return on equity in those banking systems is low. Comparing columns two and four, I see that the result was driven by increased funding to foreign affiliate banks rather than to parent banks. The finding provides support to the view that negative local economic shocks in emerging economies, give rise to an increase in parent funding to their foreign affiliates resident in those economies. In an additional test, I find that including a three-way interaction between the return on equity, the emerging market dummy variable and a time dummy variable for the post-Lehman episode, yields a negative and statistically significant coefficient, indicating that parent banks increased support to their weakest subsidiaries in emerging economies *even* during the financial crisis.

Furthermore, I find that higher interest rates in emerging economies lead to an increase in intragroup funding, as parent banks fund foreign affiliates resident in those economies. But this finding also implies that emerging economies can expect resident foreign banks to *lose* intragroup funding whenever expansionary monetary policy is implemented.

## 2.6 Robustness Analysis

In this section, I examine the robustness of the results under alternative specifications. First, I investigate if any one country materially drives the results. Next, I use alternative measures of global risk in place of the VIX index, and finally I test if the results are robust to the exclusion of the global financial crisis and the European sovereign-debt crisis.

[24]Notably, the result is driven by the intragroup lending of foreign *branches*. The gross lending by foreign subsidiaries remained unchanged.

### 2.6.1 Excluding Individual Countries

I examine the impact individual countries have on the results, by augmenting the baseline model with a country-specific dummy variable $C$,

$$\Delta L^{j}_{i,t} = \beta_{i,0} + \beta_{i,1} \cdot VIX_{t-1} + \beta_{i,2} \cdot (VIX_{t-1} \cdot C_j) \\ + \beta_{i,3} \cdot \Delta VIX_t + \left( \sum_{l=1}^{3} \beta_{i,l+3} \cdot TCV_{j,t-1} \right) + \alpha_j + Controls + \epsilon_{i,t}. \tag{2.8}$$

In Panel A of Table 2.7, I report the range of coefficient estimates for $\beta_{i,1}$, which I estimate by sequentially adding and removing each country from the analysis by setting $C_j = 1, \; \forall \; j = 1, 2, ...25$. The interbank coefficient on the VIX is always statistically different from zero at the one percent level. The coefficient is never greater than $-4.75$ and reaches a low of $-5.48$. Consistent with the earlier baseline results, the intragroup coefficient on the VIX is always positive, ranging between 0.61 and 1.52.

In Panel B, I report individual country estimates of the $\beta_{i,2}$ coefficient – the interaction term between the $VIX$ and country dummy variable. I also run an *F-test* to determine if the sum of coefficients $\beta_{i,1} + \beta_{i,2}$, is statistically different from zero. I find the sum on interbank flows is negative and statistically significant for 17 of the 25 countries in the study. In fact, all emerging economy banking systems in the sample witness an outflow of interbank funding when global risk is high. The finding confirms the earlier result that emerging market banking systems are particularly vulnerable to fluctuations in global risk. In Brazil and India, the loss of interbank funding is particularly pronounced, and highly significant at the one percent level. Only two countries (Cyprus and Denmark) experience an increase in interbank inflows when global risk is high. The sum of coefficients on intragroup flows is either statistically insignificant (consistent with the earlier result) or *positive*, for 21 out of 25 countries.

### 2.6.2 Alternative Measures of Global Risk

I replace the VIX as the measure of global risk with five alternative measures: (i) the VXO provided by the CBOE, the predecessor to the VIX index and an alternative measure of global risk used in a related study by Forbes and Warnock (2012), (ii) the Credit Suisse Global Risk Appetite Index, a measure of risk calculated using asset

| Panel A: Range of coefficients $\beta_{i,j,1}$ | | | | |
|---|---|---|---|---|
| VIX | Interbank: | -5.48***/ -4.75*** | Intragroup: | 0.61/ 1.52 |

| Panel B: Individual country interaction coefficients ($\beta_{i,j,2}$) | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | Interbank | | Intragroup | | | Interbank | | Intragroup | |
| | | $\beta_{i,j,1} + \beta_{i,j,2} = 0$ | | $\beta_{i,j,1} + \beta_{i,j,2} = 0$ | | | $\beta_{i,j,1} + \beta_{i,j,2} = 0$ | | $\beta_{i,j,1} + \beta_{i,j,2} = 0$ |
| VIX*Austria | 2.21* | -3.08*** | -12.77*** | -11.25*** | VIX*Switzerland | -2.95*** | -8.00*** | -3.32*** | -2.18* |
| | (1.12) | | (1.14) | | | (0.94) | | (1.09) | |
| VIX*Belgium | 0.48 | -4.74*** | -2.08* | -1.01 | VIX*UK | 0.37 | -4.85*** | -1.60 | -0.56 |
| | (0.92) | | (1.17) | | | (0.91) | | (1.11) | |
| VIX*Cyprus | 10.78*** | 5.39*** | 15.58*** | 16.27*** | VIX*Australia | 4.60*** | -0.74 | 4.54*** | 5.37*** |
| | (1.75) | | (2.48) | | | (0.94) | | (1.40) | |
| VIX*France | -4.75*** | -9.69*** | 3.70*** | 4.46*** | VIX*Canada | -1.24 | -6.37*** | -1.65 | -0.59 |
| | (0.86) | | (1.01) | | | (0.96) | | (1.07) | |
| VIX*Germany | 3.46*** | -1.91*** | 2.07* | 2.94** | VIX*Japan | 2.30* | -3.01*** | 7.18*** | 7.79*** |
| | (0.90) | | (1.02) | | | (1.14) | | (1.43) | |
| VIX*Ireland | 5.19*** | -0.15 | -0.63 | 0.36 | VIX*US | -7.67*** | -12.42*** | -2.12* | -1.03 |
| | (1.12) | | (2.06) | | | (0.77) | | (1.15) | |
| VIX*Italy | 2.78*** | -2.55*** | -4.24*** | -3.07** | VIX*Brazil | -7.79*** | -12.71*** | 0.66 | 1.61 |
| | (0.93) | | (1.10) | | | (1.08) | | (2.03) | |
| VIX*Luxemburg | -2.40** | -7.49*** | -2.07* | -1.00 | VIX*Chile | -3.04 | -8.18*** | 20.51*** | 21.1*** |
| | (0.92) | | (1.16) | | | (2.02) | | (2.53) | |
| VIX*Netherlands | 4.85*** | -0.56 | 3.58** | 4.39*** | VIX*India | -12.36*** | -17.24*** | -5.03*** | -3.93*** |
| | (1.01) | | (1.41) | | | (0.95) | | (1.39) | |
| VIX*Spain | 4.69*** | -0.76 | -2.58** | -1.47 | VIX*Turkey | -3.24** | -8.29*** | 4.04** | 4.83*** |
| | (0.84) | | (1.08) | | | (1.23) | | (1.80) | |
| VIX*Denmark | 9.15*** | 3.67*** | 3.77** | 4.62*** | VIX*South Africa | -1.69 | -6.89*** | 18.82*** | 19.78*** |
| | (0.94) | | (1.50) | | | (2.17) | | (3.32) | |
| VIX*Norway | -1.83 | -6.96*** | -1.35 | -0.33 | VIX*Korea | -3.30*** | -8.39*** | -3.92*** | -2.83 |
| | (1.21) | | (1.51) | | | (1.09) | | (1.32) | |
| VIX*Sweden | 0.76 | -4.47*** | -3.03** | -1.93 | | | | | |
| | (1.10) | | (1.35) | | | | | | |
| Constant | Y | | Y | | | Y | | Y | |
| Controls | Y | | Y | | | Y | | Y | |
| Observations | 1088 | | 1088 | | | 1088 | | 1088 | |
| Countries | 25 | | 25 | | | 25 | | 25 | |

**Table 2.7:** ***Excluding Individual Countries.*** *The table presents the estimated parameter values from fixed-effects panel regressions. The dependent variable is the quarterly percentage change in either interbank or intragroup funding. In columns (1) and (2) I report results for interbank funding, while in columns (3) and (4) I do the same for intragroup funding.* $VIX$ *is the quarterly average of the log VIX index. In Panel A I report the range of coefficient estimates on* $\beta_{i,1}$ *from equation (8). In Panel B I report individual country estimates of the coefficient* $\beta_{i,2}$ *from equation (8). The control variables are discussed in Section 2.4.1 with summary statistics presented in Table 2.1. Standard errors, clustered at country level, are reported in brackets. *** is significant at the 1% level, ** at the 5% level and * at the 10% level. I include F-tests to determine if the effect of the VIX is significant for a country. Data on banking flows are collected from the Bank for International Settlements's International Financial Statistics database. The sample period is from 1998Q1 to 2011Q4.*

price data from advanced and emerging markets,[25] (iii) the spread between AAA and BAA rated securities, a measure of corporate bond credit quality provided by Moody's Corporation, (iv) the global risk factor from Chapter 3 (Della Corte, Riddiough, and Sarno, 2014) which reflects a measure of global risk extracted from fluctuations in the foreign exchange market and (v) the TED spread, a measure of funding liquidity equal to the difference between the rates on a three-month U.S. euro deposit contract and the three-month T-bill.

I run the full baseline specification, accounting for heterogeneity across advanced and emerging market economies, replacing the VIX index with each of the alternative risk metrics:

$$\begin{aligned}\Delta L_{i,t}^{j} = \beta_{i,0} + \beta_{i,1} \cdot RISK_{t-1} + \beta_{i,2} \cdot (RISK_{t-1} \cdot EME) + \beta_{i,3} \cdot \Delta RISK_{t} \\ + \beta_{i,4} \cdot (\Delta RISK_{t} \cdot EME) + \left( \sum_{l=1}^{3} \beta_{i,l+4} \cdot TCV_{j,t-1} \right) + \alpha_{j} + Controls + \epsilon_{i,t}.\end{aligned} \tag{2.9}$$

The results are reported in Table 2.8. In columns one to five, I report results for interbank funding and do the same for intragroup funding in columns six to ten.[26] The alternative measures of global risk lead to noticeably similar results. Interbank funding has a negative and statistically significant relationship with each alternative measure of global risk except for the TED spread. An increase in the TED spread leads, however, to a fall in interbank funding. In fact, a reduction in funding to emerging economies when global risk is high, is evident across all alternative measure of risk.

Intragroup funding is not found to have a clear relationship with any measure of global risk (echoing the earlier baseline estimation) except for the Credit Suisse risk appetite index, whereby the relationship is, in fact, *positive.* Intragroup funding also shows a positive relationship with the change in global risk across all alternative measures except for the global currency risk factor, although the point estimate on the factor is positive. Furthermore, the ROE and FX Return variables are shown to have robust links with global risk, which align correctly with the hypotheses stated in Section 2.3. In fact, the coefficient estimates for both variables are statistically

[25] The index is calculated as the coefficient on a cross-sectional linear regression of excess returns on risk (past price volatility). It is based on 64 indices of bonds and equities in advanced and emerging markets and is updated daily. Advanced market indexes are denominated in local currency while U.S. dollar indicies are used for emerging economies.

[26] In Appendix Tables A.4 and A.5, I provide summary statistics and correlations across the alternative measure of risk.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
|---|---|---|---|---|---|---|---|---|---|---|
| | Interbank | | | | | Intragroup | | | | |
| | VXO | CS | Moody's | Glob. Imb. | TED | VXO | CS | Moody's | Glob. Imb. | TED |
| Risk | -3.50*** | -0.45*** | -2.61** | -0.77** | -0.40 | 0.85 | 0.35* | -0.76 | 0.95 | 0.15 |
| | (1.14) | (0.15) | (1.15) | (0.35) | (0.36) | (1.23) | (0.17) | (1.66) | (0.56) | (0.55) |
| Risk*EME | -7.05*** | -0.66* | -9.35*** | -2.08** | -2.70** | 0.94 | 0.53 | 3.11 | -0.98 | 2.54 |
| | (1.96) | (0.32) | (1.62) | (0.96) | (0.97) | (4.44) | (0.65) | (7.32) | (1.38) | (3.57) |
| *Risk+Risk*EME* | *-10.55**** | *-1.11**** | *-11.95**** | *-2.85**** | *-3.10**** | *1.78* | *0.88* | *2.35* | *-0.04* | *2.70* |
| *p-value* | *0.0000* | *0.0023* | *0.0000* | *0.0051* | *0.0029* | *0.6865* | *0.1871* | *0.7364* | *0.9794* | *0.4731* |
| ΔRisk | -2.70 | -0.26 | -5.42* | -0.12 | -3.34** | 5.45*** | 0.38* | 6.11** | 0.57 | 4.58** |
| | (2.23) | (0.19) | (2.78) | (0.38) | (1.30) | (1.77) | (0.21) | (2.64) | (0.53) | (1.83) |
| ΔRisk*EME | -4.12 | -0.02 | -5.06 | -0.98 | 4.13 | -6.41 | 0.47 | -6.01 | 0.58 | -10.18* |
| | (3.39) | (0.41) | (3.83) | (0.67) | (2.85) | (8.28) | (0.83) | (14.87) | (1.44) | (5.14) |
| *ΔRisk+Risk*ΔRisk*EME* | *-6.83*** | *-0.28* | *-10.48**** | *-1.09** | *0.79* | *-0.96* | *0.85* | *0.10* | *1.15* | *1.21* |
| *p-value* | *0.0232* | *0.4499* | *0.0077* | *0.0656* | *0.7848* | *0.9092* | *0.3253* | *0.9948* | *0.4166* | *0.2823* |
| ROE | 0.09*** | 0.10*** | 0.09*** | 0.12*** | 0.12*** | 0.15** | 0.15*** | 0.13** | 0.14*** | 0.13** |
| | (0.03) | (0.03) | (0.03) | (0.03) | (0.03) | (0.05) | (0.05) | (0.05) | (0.05) | (0.05) |
| ER Depreciation | -11.72*** | -13.44*** | -9.34* | -13.58*** | -13.63*** | -25.12** | -27.03** | -28.09*** | -21.22** | -26.72*** |
| | (3.91) | (4.25) | (4.86) | (4.58) | (4.46) | (9.63) | (11.24) | (9.53) | (9.19) | (8.90) |
| IR Spread Change | 1.09 | 1.30* | 1.05 | 0.96 | 0.30 | -0.95 | -1.60 | -0.85 | -0.74 | -0.51 |
| | (0.67) | (0.73) | (0.70) | (0.76) | (0.65) | (1.30) | (1.26) | (1.39) | (1.29) | (1.25) |
| **Controls** | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y |
| Observations | 1,088 | 1,088 | 1,088 | 1,088 | 1,088 | 1,088 | 1,088 | 1,088 | 1,088 | 1,088 |
| R-squared | 0.09 | 0.08 | 0.08 | 0.08 | 0.08 | 0.05 | 0.05 | 0.05 | 0.05 | 0.06 |
| Countries | 25 | 25 | 25 | 25 | 25 | 25 | 25 | 25 | 25 | 25 |

**Table 2.8:** ***Alternative Measures of Global Risk.*** *The table presents the estimated parameter values from fixed-effects panel regressions. The dependent variable is the quarterly percentage change in either interbank or intragroup funding. In columns (1) to (5) I report results for interbank funding, while in columns (6) to (10) I do the same for intragroup funding. EME is a dummy variable which equals* **1** *if the banking system is in an emerging market economy and zero otherwise. I describe the alternative risk measures in Section 7.2. The control variables are discussed in Section 2.4.1 with summary statistics provided in Table 2.1. Standard errors, clustered at country level, are reported in brackets. *** is significant at the 1% level, ** at the 5% level and * at the 10% level. I include F-tests to determine if the effect of a variable on emerging economies is significant. Data on banking flows are collected from the Bank for International Settlements's International Financial Statistics database. The sample period is from 1998Q1 to 2011Q4.*

significant across *all* alternative measures of global risk for both interbank and intragroup funding.

### 2.6.3 Global Financial Crisis

I test if the earlier parameter estimates remain robust to the exclusion of the global financial and European sovereign-debt crises. To do so, I estimate the augmented baseline regression with an emerging market dummy variable, but exclude crisis periods. First, I exclude the period 2008Q4-2009Q2 and re-estimate the model to account for the immediate aftermath of the Lehman Brothers collapse. The results are reported in columns one and two of Table 2.9. Once again, interbank funding is shown to have a strong negative relationship with global risk, with the effect amplified for emerging market economies.

The main difference is that the $\Delta$VIX coefficient shows a less robust relationship with interbank funding. The large spike in the VIX during 2008Q4 is responsible for the negative relationship I documented earlier for emerging economies. Nonetheless, I still find a robust positive relationship for intragroup funding with the $\Delta$VIX coefficient. Moreover, the increase in intragroup funding to emerging economies, when their host banking system is experiencing low profitability, continues to be observed.

In the third and fourth columns, I exclude the entire period following 2008Q3 and, in doing so, exclude both the global financial crisis and European sovereign debt crisis. The results across global risk remain almost unchanged and qualitatively identical. The main change to the results is before the crisis, emerging economies are found to have received inflows of intragroup funding when global risk increased. The finding provides evidence for the European sovereign debt crisis, similar to the results of De Haas and Van Lelyveld (2014) for the global financial crisis – that European global banks, affected by the crisis, were unable to maintain lending to their foreign affiliates abroad and hence, when assessing the international transmission of funding shocks, one needs to first ascertain the extent to which the underlying global bank is affected.

## 2.7 Conclusions

The collapse of Lehman Brothers in September 2008, and the subsequent reduction in cross-border lending between banks, focussed policy-maker and academic attention on the behavior and determinants of this economically important form of cross-border finance. In fact, the Committee on International Economic Policy

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Exclude Crisis | | Exclude Crisis and Aftermath | |
| | Interbank | Intragroup | Interbank | Intragroup |
| VIX | -4.38*** | 1.65 | -4.90*** | 0.53 |
| | (1.52) | (1.38) | (1.51) | (1.19) |
| VIX*EME | -4.31 | 3.21 | -1.67 | -0.01 |
| | (2.79) | (8.37) | (2.55) | (10.62) |
| *VIX+VIX*EME* | *-8.69**** | *4.86* | *-6.57**** | *0.53* |
| *p-value* | *0.0006* | *0.5770* | *0.0028* | *0.9609* |
| Δ VIX | 0.36 | 6.43*** | -1.12 | 4.92** |
| | (2.40) | (1.82) | (2.94) | (2.34) |
| Δ VIX*EME | 0.58 | -4.75 | -4.15 | 12.97 |
| | (5.96) | (5.26) | (9.06) | (9.65) |
| *ΔVIX+ΔVIX*EME* | *0.94* | *1.68* | *-5.27* | *17.89** |
| *p-value* | *0.8654* | *0.7346* | *0.5514* | *0.0653* |
| ROE | 0.06* | 0.14*** | 0.02 | 0.11 |
| | (0.04) | (0.05) | (0.04) | (0.07) |
| ROE*EME | -0.13 | -0.73** | -0.08 | -0.70** |
| | (0.14) | (0.33) | (0.18) | (0.28) |
| *ROE+ROE*EME* | *-0.06* | *-0.59** | *-0.05* | *-0.59*** |
| *p-value* | *0.6519* | *0.0757* | *0.7638* | *0.0369* |
| FX Return | -3.77 | -11.49 | -8.32 | -23.09* |
| | (5.35) | (9.34) | (6.06) | (12.00) |
| FX Return*EME | -8.43 | -63.85** | -21.71 | -52.72** |
| | (19.04) | (25.07) | (16.89) | (22.80) |
| *FX Return+FX Return*EME* | *-12.19* | *-75.34**** | *-30.03** | *-75.80**** |
| *p-value* | *0.5048* | *0.0033* | *0.0616* | *0.0011* |
| Δ IR Spread | 1.00 | -2.80* | 0.91 | -2.68* |
| | (0.84) | (1.46) | (0.86) | (1.39) |
| Δ IR Spread*EME | -0.22 | 3.88** | -0.89 | 4.38** |
| | (1.29) | (1.71) | (1.58) | (1.63) |
| *ΔIR Spread+ΔIR Spread*EME* | *0.78* | *1.08* | *0.02* | *1.70* |
| *p-value* | *0.4363* | *0.3163* | *0.9870* | *0.1307* |
| **Controls** | Y | Y | Y | Y |
| Observations | 1,017 | 1,017 | 784 | 784 |
| R-squared | 0.07 | 0.07 | 0.07 | 0.06 |
| Countries | 25 | 25 | 23 | 23 |

**Table 2.9:** ***The Global Financial and European Sovereign-Debt Crises.*** *The table presents the estimated parameter values from fixed-effects panel regressions. The dependent variable is the quarterly percentage change in either interbank or intragroup funding. In columns (1) and (2) I exclude the period 2008Q4-2009Q2 from the sample, while in columns (3) and (4) I exclude the entire post-2008Q3 period. $EME$ is a dummy variable which equals* **1** *if the banking system is in an emerging market economy and zero otherwise. $VIX$ is the quarterly average of the log VIX index, while $\Delta VIX$ is the quarterly change in the average level of the log VIX index. The control variables are discussed in Section 2.4.1 with summary statistics presented in Table 2.1. Standard errors, clustered at country level, are reported in brackets. *** is significant at the 1% level, ** at the 5% level and * at the 10% level. I include F-tests to determine if the effect of a variable on emerging economies is significant. Data on banking flows are collected from the Bank for International Settlements's International Financial Statistics database. The sample period is from 1998Q1 to 2011Q4.*

and Reform (2012) concluded that "effective regulation of cross-border banking is essential for domestic and global financial stability."

In this essay, I ask the question: do interbank and intragroup flows react differently to fluctuations in global risk and, if so, is the disaggregation of cross-border bank-to-bank funding of economic importance to academic and policy makers working in the area of international capital flows? To answer the question, I disaggregate cross-border bank-to-bank funding at two levels, first between arms-length *interbank* funding and related *intragroup* funding and then, by splitting intragroup funding between flows to parent and foreign affiliate banks.

This essay, to my knowledge, is the first to provide systematic cross-country evidence on the behavior of interbank and intragroup funding in relation to fluctuations in global risk. In the empirical analysis, I adopt the framework of Bruno and Shin (2014) and find the disaggregation of funding has statistical, theoretical *and* economic implications. A period of high and rising global risk results in markedly different behavior in subsequent interbank and intragroup funding, offering evidence, contrary to the theoretical predictions made by Bruno and Shin (2014), that both forms of funding should react symmetrically to movements in global risk. Intragroup funding is shown to remain stable during periods of heightened risk and *increase* when global risk rises. In contrast, interbank funding is withdrawn from all economies – but especially emerging markets – when global risk is high. I also reveal additional granularity in the results. For example, the decision to withdraw interbank funding during the financial crisis is found to have been closely related to whether a country was experiencing a systemic banking crisis.

Further disaggregation reveals that parent banks in advanced economies receive funding from their foreign affiliates to smooth liquidity shocks at home. This behavior explains the *increase* in intragroup funding when global risk rises. However, I do not find evidence of significantly reduced intragroup funding *to* foreign affiliates during these periods. In fact, I find that foreign affiliates resident in emerging economies experience an increase in intragroup funding, when the average profitability of banks in the local economy is low. This result is found to hold even during the financial crisis, and is indicative of the beneficial role financial globalization can play for emerging economies with resident foreign banks.

Overall, the results call for policy makers and academics to focus attention on the disaggregation of cross-border bank-to-bank flows, as the contrasting behavior of interbank and intragroup funding in response to fluctuations in global risk has implications for a banking system's underlying financial stability.

# Chapter 3

# Currency Premia and Global Imbalances

## 3.1 Introduction

Imbalances in trade and capital flows have been the centerpiece of much debate surrounding the causes and consequences of the global financial crisis. It would seem natural therefore, that given the financial crisis consisted of collapsing asset prices worldwide, global imbalances may help shed light on our fundamental understanding of asset price dynamics. The foreign exchange (FX) market provides a logical starting point for testing this hypothesis as exchange rate fluctuations are theoretically linked to external imbalances (Gourinchas and Rey, 2007; Gabaix and Maggiori, 2014), and recent events in the FX market provide a reminder of the potential importance of such a link. Following the U.S. Federal Reserve's announcement on 22 May 2013 that they would taper the size of their bond-buying programme, emerging market currencies including the Indian rupee, Brazilian real, South African rand and Turkish lira all sold-off sharply. A common characteristic among these four countries is that they are some of the world's largest debtor nations. In fact, in a *Financial Times* article on 26 June 2013, Alice Ross attributed the large depreciation of the Indian rupee (which fell by 22 percent against the U.S. dollar between May and August 2013) to investors' concerns over India being "one of the most vulnerable emerging market currencies due to its current account deficit".

In this essay, I provide empirical evidence that exposure to countries' external imbalances is key to understanding currency risk premia – the average excess return between baskets of high and low interest rate currencies. I thus support a risk-based interpretation of the carry trade, a popular strategy that involves an investor borrowing in currencies with low interest rates (funding currencies) and simultaneously lending in currencies with high interest rates (investment currencies).[1] The exercise is theoretically motivated by the recent contributions of Gourinchas and Rey (2007), Gourinchas (2008) and Gabaix and Maggiori (2014). Gourinchas and Rey (2007) show that a deterioration in the external account of a country is unsustainable over time unless counterbalanced by future trade surpluses and positive returns on the net foreign asset position. Currency fluctuations are key to this process of external adjustment - as a domestic currency depreciation affects the country's international competitiveness in goods and services, as well as the value of its foreign-currency denominated assets relative to the value of its domestic-currency-denominated liabilities. The latter effect, known as the valuation adjustment, relies on a currency mismatch between foreign assets and liabilities, which is largely true for developed countries but less so for emerging economies. Gourinchas (2008) demonstrates that a domestic currency depreciation will be initially destabilizing if a country has predominately foreign-currency-denominated liabilities. The immediate loss of wealth resulting from the increased stock of liabilities weakens the net foreign asset position and necessitates a large currency depreciation, or 'crash', to restore the external account via future trade balance surpluses. Taken together, these papers suggest that in bad times international net debtor countries suffer currency depreciations whereas net creditor economies experience currency appreciations.

Recently, Gabaix and Maggiori (2014) propose a two-country model in which exchange rates are jointly determined by global imbalances and financiers' risk-bearing capacity. In their model, countries run trade imbalances and financiers absorb the resultant currency risk, i.e., financiers are long the debtor country and short the creditor country. Financiers, however, are financially constrained and this affects their ability to take positions. Intuitively, those with little risk-bearing capacity are unwilling to intermediate currency mismatches regardless of the excess return on offer, and thus international trade must balance in each period. In contrast, when financiers have unlimited risk-bearing capacity they are willing to take positions in currencies whenever an excess return is available, and hence UIP holds. An important implication of this model is that a negative shock on the risk-bearing capacity of financiers causes a currency depreciation for net debtor countries while the opposite is true for net creditor countries. This happens because financiers demand compensation for the increased level of currency risk, and the magnitude of the effect depends on the financiers' risk-bearing capacity.

[1] The carry strategy builds on the violation of uncovered interest rate parity (UIP). See Hansen and Hodrick (1980); Bilson (1981); Fama (1984); Engel (1996); Lustig and Verdelhan (2007); Della Corte, Sarno, and Tsiakas (2009); Lustig, Roussanov, and Verdelhan (2011); Burnside, Eichenbaum, Kleshchelski, and Rebelo (2011a); Koijen, Moskowitz, Pedersen, and Vrugt (2013); Menkhoff, Sarno, Schmeling, and Schrimpf (2012) and Lettau, Maggiori, and Weber (2013).

Motivated by the insights of these papers, I empirically test whether a risk factor that captures the combination of spread in external imbalances and a country's propensity to issue external liabilities in foreign currency can explain the excess returns of currency portfolios in a standard asset pricing framework. The central result of this essay is that the proposed global imbalance risk factor explains over 90 percent of currency excess returns, thus supporting a risk-based view of exchange rate determination that is based on macroeconomic fundamentals.[2] The results hold both for a broad sample of 55 currencies and for a subsample of the 15 most liquid currencies over the period from 1983 to 2011.

This essay builds on the growing literature that searches for a risk-based explanation to currency premia. In one strand of this literature, Lustig, Roussanov, and Verdelhan (2011) and Menkhoff, Sarno, Schmeling, and Schrimpf (2012) have both found a global risk factor in currency excess returns. However, while these global risk factors provide valuable information on the properties of currency returns, the question as to what fundamental economic forces drive the factors and, hence, currency risk premia, remains unanswered. In a second strand of literature, a 'crash' premium has been proposed to explain currency excess returns. This 'crash' or disaster risk has been shown to explain, at least in part, the excess return to the carry trade.[3] While this is a compelling theory, it does not directly connect crash risk (or the probability of a crash) to underlying economic fundamentals that may generate the crash. The argument is as follows: (i) High interest rate currencies require a high expected return. (ii) The higher return is compensation for the risk of a large and sudden drawdown. (iii) High interest rate currencies experience this 'crash' and thus require a higher return because they are the riskiest. The question as to *why* high yielding currencies are the riskiest is not resolved. Both strands of literature, therefore, leave us tantalizingly close to a more complete understanding of currency premia. This essay tackles exactly this issue by shedding empirical light on the *macroeconomic* forces driving currency premia.

In the empirical analysis, I sort currencies into five portfolios according to their forward premia, as pioneered by Lustig and Verdelhan (2007). This is equivalent to using the interest rate differential relative to the U.S. dollar to rank foreign

[2]Despite the existence of theoretical models that link exchange rates to external imbalances, there have hardly been any attempts to relate currency risk premia *cross-sectionally* to currencies' sensitivity to external imbalances. When the FX literature has investigated the empirical link between exchange rates and external imbalances, the analysis was carried out in a time series setting (e.g. Alquist and Chinn, 2008; Della Corte, Sarno, and Sestieri, 2012). It thus seems quite natural to employ a cross-sectional perspective on the role of global imbalances to help understand currency risk premia in general, and carry trades in particular.

[3]See, for example, Brunnermeier, Nagel, and Pedersen (2008), Farhi and Gabaix (2013), Farhi, Fraiberger, Gabaix, Ranciere, and Verdelhan (2013) and Jurek (2013).

currencies because no-arbitrage requires that forward premia are equal to interest rate differentials. The first portfolio contains the funding currencies of a carry trade strategy (lowest forward premia or interest rate differential), while the last portfolio contains the investment currencies in a carry trade strategy (highest forward premia or interest rate differential). I then show that carry trade returns can be understood as compensation for risk, by relating their cross-section to the global imbalance factor. This factor is an easily constructed variable. I first split currencies into two baskets using the ratio of net foreign assets to GDP, and then sort currencies within each basket based on countries' percentage share of external liabilities denominated in domestic currency. The reordered currencies, beginning with creditors whose external liabilities are primarily denominated in domestic currency (the safest currencies) and moving to debtors whose external liabilities are primarily denominated in foreign currency (the riskiest currencies), are grouped into quintiles. These quintiles form the five Net Foreign Asset ($NA$) portfolios. The global imbalance factor is simply constructed as the difference between the excess returns on the extreme portfolios. It is equivalent to a high-minus-low strategy that buys the currencies of debtor nations with mainly foreign currency denominated external liabilities and sells the currencies of creditor nations with mainly domestic currency denominated external liabilities. I refer to the global imbalance risk factor as $HML_{NA}$.

The empirical evidence suggests that the global imbalance factor accounts for most of the cross-sectional dispersion in currency excess returns. This equates to global imbalances being a plausible macroeconomic candidate for explaining carry trade returns. The economic intuition of this factor is simple: investors demand a risk premium to hold the currency of debtor countries funded principally in foreign currency as a reward for the higher probability of an exchange rate depreciation following an external shock. High interest rate currencies load positively on the global imbalance factor, and thus deliver low returns following an external shock, when the process of international financial adjustment requires their depreciation. Low interest rate currencies are negatively related to the global imbalance factor, and thus provide a hedge by yielding positive returns after an external shock. This result suggests that returns to carry trades are compensation for time-varying fundamental risk, and thus carry traders can be viewed as taking on global imbalance risk.

It is important to note at the outset that this finding is not mechanical in the sense that it cannot be attributed simply to feedback effects from interest rates to net foreign assets. Although feedback effects may exist between interest rates and net foreign assets whereby higher interest rates attract more capital flows, the global imbalance risk factor captures fundamental information relevant to currency risk premia that is not embedded in interest rates. This argument is supported by recent theoretical and empirical developments. Gabaix and Maggiori (2014) show theoretically that currency premia will be required even if both countries have the same interest rate as long as one is a debtor relative to the other, while in empirical work Habib and Stracca (2012) show that net foreign assets are more important for predicting exchange rate returns than interest rate differentials, and I demonstrate similar evidence in the robustness analysis in Section 3.6.[4]

I also examine the robustness of the main result in the following specifications: (i) I run cross-sectional asset pricing tests on yearly rebalanced portfolios, and find that $HML_{NA}$ is still priced in the cross-section. (ii) I show that sorting currencies on their beta with $HML_{NA}$ yields portfolios with a significant difference in returns. These portfolios are related, but not identical, to the base test assets of currency portfolios sorted on forward premia. (iii) I test the pricing power of the global imbalance risk factor for currency excess returns sorted by real (as opposed to nominal) interest rate differentials, and find that $HML_{NA}$ also prices these portfolios. (iv) I depart from the base scenario of a U.S.-based investor and run calculations using alternative base currencies, taking the viewpoint of a British, Japanese, Euro-based and Swiss investor. The results indicate that $HML_{NA}$ is priced in each case. (v) I test the $HML_{NA}$ risk factor on portfolios formed using only the 20 most liquid currencies, showing that there are no qualitative changes in the results. (vi) I run a series of panel regressions and determine that net foreign assets are more important than interest rate differentials for predicting exchange rate returns. (vii) I calculate the average risk-reversal of net-foreign-asset-sorted portfolios and find that debtor nations have the highest probability of experiencing a large depreciation. (viii) I also run cross-sectional asset pricing tests on individual currencies' excess returns, and again record that $HML_{NA}$ is priced. Overall, I find that the further analysis corroborates the core finding that global imbalance risk is a key fundamental driver of risk premia in the FX market.

The remainder of the chapter is organized as follows: Section 3.2 briefly describes the theoretical background of the analysis. In Section 3.3, I describe

[4] In fact, recent anecdotal evidence emphasizes the fundamental importance of net foreign assets over and above interest rates in determining currency premia: the U.S. Federal Reserve's announcement in May 2013 that it would scale-back its bond buying programme caused a spike in risk aversion – the VIX index rose from below 14 to over 20 during the subsequent month. In currency markets, at the point of the Federal Reserve announcement, Australia, New Zealand, and South Korea – three of the most volatile currencies in the Asia Pacific region – had almost identical interest rates (2.50 percent in New Zealand and Korea, 2.75 percent in Australia). Yet, over the May to September period, the Australian dollar depreciated by 16 percent against the U.S. dollar, the New Zealand dollar depreciated by 10 percent, while the Korean won fell by only 1 percent. The contrasting sizes of depreciation reflect the contrast in deficit positions at the end of the first quarter of 2013, when Australia and New Zealand both had external deficit positions relative to GDP of over 60 percent, while South Korea had a far more modest 6 percent deficit.

the data and provide details of how portfolios are constructed. I present a set of preliminary results in Section 3.4 and cross-sectional asset pricing results in Section 3.5. In Section 3.6, I present a number of robustness exercises before concluding in Section 3.7. In Appendix B, I provide further robustness tests and additional supporting analyses.

## 3.2 Global Imbalances and FX Markets

### 3.2.1 Theoretical Background

This section summarizes the recent literature theoretically linking exchange rates and global or external imbalances. Gourinchas and Rey (2007) study the process of international financial adjustment and show that external deficits imply future trade surpluses (the trade channel) or excess returns on the foreign asset portfolio (the valuation channel). Since the future exchange rate determines both future net exports and future returns on external assets and liabilities, it follows that today's imbalances contain valuable information regarding future exchange rate movements. This mechanism can be understood by defining the budget constraint of an economy as

$$NA_t = R_t NA_{t-1} + NX_t \tag{3.1}$$

where $NA_t$ is the net foreign asset position at the end of period $t$, $NX_t$ is the balance on goods and services between times $t-1$ and $t$, and $R_t$ is the gross return on the net foreign asset portfolio between times $t-1$ and $t$.[5] Solving this equation forward under the usual no-Ponzi condition produces the following intertemporal budget constraint

$$NA_t = -E_t\left(\sum_{i=j}^{\infty} \Lambda_{t+j}^{-1} NX_{t+j}\right) \tag{3.2}$$

where $\Lambda_{t+j} = \prod_{s=1}^{j} R_{t+s}$ and $E_t$ is the conditional expectation operator.[6] This equation states, for instance, that a future currency depreciation will help rebalance the external account of a debtor country via future net exports and positive returns on the net foreign asset position. From a risk perspective, when expected future current account surpluses become insufficient to cover external debt, an exchange

[5] I can also rewrite the budget constraint as $NA_t = NA_{t-1} + VA_t + CA_t$, where $CA_t = NX_t + NI_t$ is the current account, $VA_t = [(R_t - 1)NA_{t-1} - NI_t]$ is the valuation adjustment (capital gains on the net foreign assets), and $NI_t$ is the net investment income (income, dividends, and earnings distributed).

[6] The budget constraint is an identity and, hence, the intertemporal relationship must hold both ex-post and ex-ante.

rate depreciation works to rebalance the present value equation that satisfies the sustainability of the external position.

The valuation channel in Gourinchas and Rey (2007) operates through a currency mismatch between foreign assets denominated in foreign currency and foreign liabilities issued in domestic currency. Foreign liabilities, however, can be issued primarily in foreign currency as is the case for a number of emerging market economies. In this case, an exchange rate depreciation results in a foreign portfolio loss. Gourinchas (2008) studies this scenario and highlights the dominant role the trade channel must play over the valuation channel in rebalancing the external account. The readjustment is achieved via a sharp depreciation of the domestic currency such that it overshoots its equilibrium value. This prediction can explain the fact that countries with a high share of foreign-currency-denominated liabilities tend to display a higher propensity to experience sharp currency depreciations or 'crashes'.

In a recent paper, Gabaix and Maggiori (2014) consider the interaction between capital flows and financial intermediaries' risk-bearing capacity as the key determinants of exchange rates in a model with imperfect financial markets. In their model, each country borrows or lends in its own currency and global financial intermediaries absorb the exchange rate risk arising from imbalanced capital flows. Since the financial intermediaries demand compensation for holding currency risk in the form of an expected currency appreciation, exchange rates are jointly determined by global capital flows and by the intermediaries' risk-bearing capacity. When risk-bearing capacity is low, financial intermediaries are unwilling to absorb any imbalances, regardless of the excess return available, and hence no financial flows are necessary as trade inflows and outflows will be equal in each period. As capacity to bear risk increases, excess returns fall but do not entirely disappear - except when risk-bearing capacity is extremely high, and financial intermediaries are prepared to absorb any currency imbalance. Gabaix and Maggiori (2014) also show that during periods of financial distress, risk-bearing capacity declines and debtor countries suffer a currency depreciation, whereas creditor countries experience a currency appreciation. The currencies of debtor countries must depreciate when risk-bearing capacity falls in order to compensate global intermediaries for the increase in risk.[7]

These theoretical papers give us reason to consider external imbalances as a suitable state variable: carry traders require a premium to hold the currency of debtor nations relative to creditor nations, while debtor countries with a reliance

[7]A parallel literature has examined the determinants of exchange rates while maintaining the assumption of complete markets. In particular, Colacito and Croce (2013) show that a country's exposure to global risk is a function of its relative consumption of world output.

on foreign-currency-denominated liabilities have a propensity to offer higher risk premia in order to attract foreign savings to fund domestic investment.

### 3.2.2 Related Literature

This essay is closely related to the recent literature seeking to explain currency risk premia in a cross-sectional asset pricing setting. Lustig et al. (2011) rationalize returns to the carry trade using two risk factors, following the Arbitrage Pricing Theory framework of Ross (1976). The authors find that the first two principal components of currency portfolio returns can explain most of the variation in the data. The first principal component is proxied using the average excess return on all currency portfolios, and is denoted as the dollar factor ($DOL$). The second principal component is proxied with a long position in the last portfolio funded by a short position in the first portfolio – essentially the carry trade return. This factor is constructed in a similar vein to the Fama and French (1993) high-minus-low factor, and is named the *Slope* factor ($HML_{FX}$). High interest rate currencies are positively exposed to this risk, while low interest rate currencies are negatively exposed. Since average excess returns increase monotonically across portfolios and $DOL$ has no pricing power, $HML_{FX}$ is the only risk factor that explains the cross-section of portfolio returns. Empirically $HML_{FX}$ is shown to correlate almost perfectly with the second principal component – which can itself be viewed as the statistically 'true' underlying risk factor (see Lewellen, Nagel, and Shanken (2010) for a discussion of the Fama-French factors being good proxies for the 'true' underlying source of equity market risk). Therefore, while building on the work of Lustig et al. (2011), the main goal is to identify the macroeconomic determinants underlying $HML_{FX}$ rather than to construct an alternative or competing risk factor. I show that $HML_{NA}$ and $HML_{FX}$ are driven by a common component and that sorting currencies into portfolios on the basis of their exposure to $HML_{NA}$ is very similar to sorting on forward premia. I also find evidence that there is no additional pricing information in $HML_{FX}$ beyond $HML_{NA}$.

Furthermore, Menkhoff et al. (2012) find that average carry trade returns act as compensation for exposure to global FX volatility risk. In times of high unexpected volatility, high-interest rate currencies deliver low returns, whereas low-interest rate currencies perform well. I also show that $HML_{NA}$ replicates the information in global FX volatility risk reasonably well, and that FX volatility risk has no additional information beyond the global imbalance risk factor for pricing carry trade returns.[8]

[8]Related to this literature, Christiansen, Ranaldo, and Söderlind (2011) further show that the

## 3.3 Data and Currency Portfolios

This section describes the data on exchange rates, external assets and liabilities as well as the total share of external liabilities denominated in domestic currency, which is employed in the empirical analysis. I then describe the construction of currency portfolios and the global imbalance risk factor.

### 3.3.1 Data Sources and Currency Excess Returns

**Data on Spot and Forward Exchange Rates.** I collect daily spot and 1-month forward exchange rates vis-à-vis the U.S. dollar (USD) from Barclays and Reuters via Datastream. The empirical analysis uses monthly data obtained by sampling end-of-month rates from October 1983 to December 2011. The sample comprises 55 countries: Argentina, Australia, Austria, Belgium, Brazil, Canada, Chile, China, Colombia, Croatia, Czech Republic, Denmark, Egypt, Estonia, Euro Area, Finland, France, Germany, Greece, Hong Kong, Hungary, Iceland, India, Indonesia, Ireland, Israel, Italy, Japan, Kazakhstan, Latvia, Lithuania, Malaysia, Mexico, Morocco, Netherlands, New Zealand, Norway, Philippines, Poland, Portugal, Russia, Singapore, Slovakia, Slovenia, South Africa, South Korea, Spain, Sweden, Switzerland, Thailand, Tunisia, Turkey, Ukraine, United Kingdom, and Venezuela. I call this sample *All Countries*.

A number of currencies in this sample are pegged or subject to capital restrictions. In reality, investors may not easily trade some of these currencies in large amounts even though quotes on forward contracts (deliverable or non-deliverable) are available.[9] Hence, I also consider a subset of 15 countries which I refer to as *Developed Countries*. This sample includes: Australia, Belgium, Canada, Denmark, Euro Area, France, Germany, Italy, Japan, Netherlands, New Zealand, Norway, Sweden, Switzerland, and the United Kingdom. After the introduction of the euro in January 1999, I remove the Eurozone countries and replace them with the euro.[10] As in Lustig et al. (2011), I remove data when I observe large deviations from the

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risk exposure of carry trade returns to stock and bond markets depends on the level of FX volatility. Burnside, Eichenbaum, Kleshchelski, and Rebelo (2011a) investigate whether carry trade returns reflect a peso problem, which is a low probability of large negative returns. Although the authors do not find evidence of peso events in their sample, they argue that investors still attach great importance to these events and require compensation for them.

[9] According to the Triennial Survey of the Bank for International Settlements (2013), the top 10 currencies account for 90 percent of the average daily turnover in FX markets.

[10] The sample of *Developed Countries* matches both Lustig et al. (2011) and Menkhoff et al. (2012). The full sample of *All Countries*, instead, comprises a wider set of countries than previous studies. I also consider a set of 35 countries as in Lustig et al. (2011), and 48 countries as in Menkhoff et al. (2012). Qualitatively, the results remain the same.

covered interest rate parity (CIP) condition.[11]

**Data on External Assets and Liabilities.** Turning to macroeconomic data, I obtain end-of-year series on foreign assets and liabilities, and gross domestic product (GDP) from Lane and Milesi-Ferretti (2001, 2007), kindly provided by Gian Maria Milesi-Ferretti. Foreign (or external) assets are measured as the dollar value of assets a country owns abroad, while foreign (or external) liabilities refer to the dollar value of domestic assets owned by foreigners. The data for all countries included in the study are collected until the end of 2011. For each country I measure external imbalances – the indebtedness of a country to foreigners – using the net foreign asset position (the difference between foreign assets and foreign liabilities) relative to the size of the economy (GDP). I retrieve monthly observations by keeping end-of-period data constant until a new observation becomes available.[12]

I also collect end of year series on the proportion of external liabilities denominated in domestic currency from Lane and Shambaugh (2010), available on Philip Lane's website. The data is available from 1990 to 2004. I construct monthly observations by keeping end-of-period data constant until a new observation becomes available. Note that I maintain the 1990 proportions back until 1983 and the 2004 proportions through until the end of 2011.[13]

**Currency Excess Returns.** I denote time-$t$ spot and forward exchange rates as $S_t$ and $F_t$, respectively. Exchange rates are defined in units of foreign currency per U.S. dollar such that an increase in $S_t$ is an appreciation of the dollar. The excess return on buying a foreign currency in the forward market at time $t$ and then selling

[11] Specifically, I eliminate the following observations from the sample: Argentina from August 2008 to April 2009; Malaysia from April 1998 to July 1999 and from June 2005 to December 2010; Indonesia from June 1997 to March 1998, from January 2001 to September 2002, and from November 2008 to February 2009; Italy from August 1992 to September 1992; Japan from May 1998 to July 1998; Kazakhstan from October 2008 to February 2009; Norway from July 1998 to August 1998; Russia from November 2008 to April 2009; South Africa from July 1985 to August 1985 and from December 2001 to May 2004; Sweden from July 1998 to August 1998; Thailand from April 1997 to June 1997; and Turkey from January 2001 to November 2001.

[12] I provide a simple graphical analysis of external imbalances by presenting, in Appendix Figure B.1, the distribution of the net foreign asset positions relative to GDP as of December 2011. This illustrates some of the large external imbalances of the current time. *Prima facie*, I observe that countries with large external imbalances are associated with some of the classic carry trade currencies, which I document more rigorously below.

[13] In Appendix Figure B.2, I present the average share of foreign liabilities issued in domestic currency for both developed and non-developed countries. I also report 90th and 10th percentile bands. Since the early 1990s there has been a trend, in both developed and emerging countries, to issue external liabilities in domestic currency.

it in the spot market at time $t+1$ is computed as

$$RX_{t+1} = (F_t - S_{t+1})/S_t$$

which is equivalent to the forward premium minus the spot exchange rate return $RX_{t+1} = (F_t - S_t)/S_t - (S_{t+1} - S_t)/S_t$. According to the CIP condition, the forward premium approximately equals the interest rate differential $(F_t - S_t)/S_t \simeq i_t^* - i_t$, where $i_t$ and $i_t^*$ represent the domestic and foreign riskless rates over the maturity of the forward contract. Since CIP holds closely in the data at daily and lower frequency (e.g. Akram, Rime, and Sarno, 2008), the currency excess return is approximately equal to the interest rate differential minus the exchange rate return

$$RX_{t+1} \simeq i_t^* - i_t - (S_{t+1} - S_t)/S_t.$$

I compute currency excess returns adjusted for transaction costs using bid-ask quotes on spot and forward rates. The net excess return for holding foreign currency for a month is computed as $RX_{t+1}^l \simeq (F_t^b - S_{t+1}^a)/S_t^b$, where $a$ indicates the ask price, $b$ the bid price, and $l$ a long position in the foreign currency. This is equivalent to selling the dollar at the bid price $F_t^b$ at time $t$ in the forward market and buying dollars at the ask price $S_{t+1}^a$ in the spot market at time $t+1$. This net excess return reflects the full round-trip transaction cost occurring when the foreign currency is purchased at time $t$ and sold at time $t+1$. If the investor buys foreign currency at time $t$ but decides to maintain the position at time $t+1$, the net excess return is computed as $RX_{t+1}^l \simeq (F_t^b - S_{t+1})/S_t^b$. Similarly, if the investor closes a position in foreign currency at time $t+1$ already existing at time $t$, the net excess return is defined as $RX_{t+1}^l \simeq (F_t - S_{t+1}^a)/S_t$.

The net excess return for holding domestic currency for a month is computed as $RX_{t+1}^s \simeq -\left(F_t^a - S_{t+1}^b\right) S_t^a$, where $s$ denotes a short position on the foreign currency. This is equivalent to buying dollars at the ask price $F_t^a$ at time $t$ in the forward market and selling dollars at the bid price $S_{t+1}^b$ in the spot market at time $t+1$. If the domestic currency enters the strategy at time $t$ and the position is rolled over at time $t+1$, the net excess return is computed as $RX_{t+1}^s \simeq -(F_t^a - S_{t+1})/S_t^a$. Similarly, if the domestic currency leaves the strategy at time $t+1$ but the position was already opened at time $t$, the net excess return is computed as $RX_{t+1}^s \simeq -\left(F_t - S_{t+1}^b\right)/S_t$. In short, excess returns are adjusted for the full round-trip transaction cost in the first and last month of the sample period.

### 3.3.2 Forming Currency Portfolios

**Carry Trade Portfolios.** I construct five currency portfolios and rebalance them at the end of each month. I will refer to these portfolios as $FX$ portfolios. At the end of each period $t$, I allocate currencies to five portfolios on the basis of their forward premia $(F_t - S_t)/S_t$. Sorting on forward premia is equivalent to sorting currencies on the basis of the interest rate differential $i_t^* - i_t$ via the CIP condition. This exercise implies that currencies with the lowest forward premia (or lowest interest rate differential relative to the U.S.) are assigned to Portfolio 1, whereas currencies with the highest forward premia (or highest interest rate differential relative to the U.S.) are assigned to Portfolio 5. I then compute the excess return for each portfolio as an equally weighted average of the currency excess returns within that portfolio. For the purpose of computing portfolio returns net of transaction costs, I assume that investors go short on foreign currencies in Portfolio 1 and long on foreign currencies in the remaining portfolios. The total number of currencies in the portfolios changes over time. I only include currencies for which I have bid and ask quotes on forward and spot exchange rates in the current and subsequent period. The group of all countries starts with 8 countries at the beginning of the sample in 1983, and ends with 45 countries at the end of the sample in 2011. The set of developed countries starts with 6 countries in 1983, and ends with 10 countries in 2011. The maximum number of currencies managed during the sample is 50 in the All sample and 14 in the Developed sample.

Lustig et al. (2011) study these currency portfolio returns using the first two principal components. The first principal component is proxied using an equally weighted strategy across all portfolios. This average return is simply the outcome of a strategy that borrows in the U.S. money market and invests in foreign money markets. This zero-cost portfolio is called the dollar risk factor, abbreviated to $DOL$. The second principal component is proxied with a long position in Portfolio 5 and a short position in Portfolio 1. This is equivalent to a carry trade strategy that borrows in the money markets of low yielding currencies and invests in the money markets of high yielding currencies. This high-minus-low portfolio is called the slope factor, and is denoted as $HML_{FX}$. I construct $DOL$ and $HML_{FX}$ as in Lustig et al. (2011).

**External Imbalances Portfolios.** Motivated by the model of international financial adjustment by Gourinchas and Rey (2007) and Gourinchas (2008), I construct the global imbalance risk factor as follows. At the end of each period $t$, I first group currencies into two baskets using the net foreign asset position relative to GDP, then reorder currencies within each basket using the percentage share of external liabilities denominated in foreign currency. Hence, I allocate this set of currencies to five portfolios. Portfolio 1 corresponds to creditor countries whose external liabilities are primarily denominated in domestic currency (safest currencies) whereas Portfolio 5 comprises debtor countries whose external liabilities are primarily denominated in foreign currency (riskiest currencies). I refer to these five portfolios as the external imbalances portfolios, abbreviated to $NA$. I then compute the excess return for each portfolio as an equally weighted average of individual currency excess returns within the portfolio. For the purpose of computing portfolio returns net of transaction costs, I assume that investors go short foreign currencies in Portfolio 1 and long foreign currencies in the remaining portfolios. I construct the global imbalance risk factor as the difference between Portfolio 5 and Portfolio 1. This is equivalent to a high-minus-low strategy that buys the currencies of debtor countries with mainly foreign currency denominated external liabilities and sells the currencies of creditor nations with mainly domestic currency denominated external liabilities. I refer to the global imbalance risk factor as $HML_{NA}$.

## 3.4 Preliminary Analysis

This section presents a preliminary analysis of the relationship between currency excess returns and the global imbalance risk factor, before I turn to the more formal cross-sectional asset pricing tests in the next section.

### 3.4.1 Descriptive Statistics

Table 3.1 presents descriptive statistics for the five $FX$ portfolios, the $DOL$ and $HML_{FX}$ portfolios. Monthly rebalanced portfolios are displayed in Panel A whereas yearly rebalanced portfolios are presented in Panel B. I report results for the full sample of countries and the subset of developed countries. $DOL$ denotes the average return on the five currency portfolios while $HML$ denotes a long-short strategy that is long in Portfolio 5 (the investment currencies in the carry trade) and short in Portfolio 1 (the funding currencies in the carry trade). In the final two columns, I report $DOL$ and $HML$ adjusted for transaction costs ($\tau$). For $HML$, excess returns to Portfolio 1 are adjusted for transactions costs occurring in a short position and excess returns to Portfolio 5 are adjusted for transaction costs occurring in a long position. All excess returns are expressed in percentage per annum.

Average excess returns to monthly rebalanced portfolios display an increasing pattern when moving from Portfolio 1 to Portfolio 5 for both samples. The

| | Panel A: Monthly Rebalancing | | | | | | | | | Panel B: Yearly Rebalancing | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $P_1$ | $P_2$ | $P_3$ | $P_4$ | $P_5$ | $DOL$ | $HML$ | $DOL^{\tau}$ | $HML^{\tau}$ | $P_1$ | $P_2$ | $P_3$ | $P_4$ | $P_5$ | $DOL$ | $HML$ | $DOL^{\tau}$ | $HML^{\tau}$ |
| | *All Countries* | | | | | | | | | *All Countries* | | | | | | | | |
| *Mean* | −1.79 | −0.69 | 2.66 | 2.37 | 6.53 | 1.82 | 8.32 | 0.61 | 5.44 | −1.26 | 0.69 | 0.56 | 2.76 | 3.83 | 1.32 | 5.09 | 0.99 | 4.22 |
| *Med* | −1.02 | 1.99 | 3.27 | 4.02 | 9.30 | 3.46 | 11.51 | 2.28 | 8.42 | 1.57 | 1.71 | 2.10 | 1.91 | 9.51 | 2.68 | 8.86 | 2.45 | 8.00 |
| *Sdev* | 7.86 | 7.93 | 8.19 | 8.92 | 9.76 | 7.41 | 8.88 | 7.41 | 8.86 | 9.98 | 8.60 | 11.39 | 10.19 | 19.23 | 10.12 | 17.20 | 10.10 | 16.96 |
| *Skew* | −0.07 | −0.62 | −0.44 | −0.90 | −0.79 | −0.57 | −1.02 | −0.58 | −1.06 | −0.35 | −0.42 | −0.89 | 0.01 | −1.52 | −0.74 | −0.55 | −0.74 | −0.59 |
| *Kurt* | 4.17 | 5.26 | 4.44 | 6.30 | 5.66 | 4.45 | 5.25 | 4.45 | 5.20 | 2.57 | 2.45 | 3.44 | 1.80 | 5.30 | 3.17 | 2.71 | 3.16 | 2.73 |
| $AC_1$ | 0.03 | 0.05 | 0.09 | 0.08 | 0.19 | 0.10 | 0.14 | 0.10 | 0.14 | 0.00 | 0.05 | −0.04 | 0.07 | 0.20 | −0.04 | 0.37 | −0.04 | 0.36 |
| $SR$ | −0.23 | −0.09 | 0.32 | 0.27 | 0.67 | 0.24 | 0.94 | 0.08 | 0.61 | −0.13 | 0.08 | 0.05 | 0.27 | 0.20 | 0.13 | 0.30 | 0.10 | 0.25 |
| $MDD$ | −38.9 | −38.0 | −32.9 | −33.1 | −33.1 | −25.3 | −27.1 | −30.2 | −31.4 | −37.1 | −32.5 | −50.4 | −33.4 | −61.7 | −27.9 | −50.8 | −29.4 | −51.7 |
| *Freq* | 18.9 | 28.6 | 31.6 | 32.6 | 16.7 | 25.7 | 35.6 | 25.7 | 35.6 | 27.5 | 52.8 | 54.8 | 51.5 | 28.0 | 42.9 | 55.5 | 42.9 | 55.5 |
| | *Developed Countries* | | | | | | | | | *Developed Countries* | | | | | | | | |
| *Mean* | −1.46 | 0.76 | 1.66 | 2.33 | 5.61 | 1.78 | 7.08 | 0.97 | 5.25 | 0.24 | 0.80 | 2.07 | 1.60 | 3.04 | 1.55 | 2.80 | 1.39 | 2.42 |
| *Med* | −2.18 | 2.96 | 4.25 | 3.89 | 6.94 | 3.20 | 11.12 | 2.61 | 8.62 | 2.17 | 3.52 | 1.90 | 2.72 | 2.37 | 1.24 | 3.23 | 1.09 | 2.99 |
| *Sdev* | 10.10 | 9.82 | 9.42 | 9.78 | 11.41 | 8.82 | 11.04 | 8.82 | 11.04 | 12.27 | 11.67 | 9.80 | 12.96 | 13.01 | 10.42 | 13.81 | 10.41 | 13.87 |
| *Skew* | 0.16 | −0.21 | −0.35 | −0.75 | −0.51 | −0.33 | −1.13 | −0.34 | −1.14 | −0.41 | −0.21 | −0.02 | −0.79 | −0.06 | −0.15 | −0.72 | −0.16 | −0.71 |
| *Kurt* | 3.52 | 3.70 | 4.41 | 5.74 | 4.82 | 3.79 | 6.07 | 3.78 | 6.09 | 2.14 | 1.82 | 2.19 | 3.41 | 2.79 | 2.11 | 4.09 | 2.11 | 4.05 |
| $AC_1$ | 0.02 | 0.08 | 0.10 | 0.07 | 0.14 | 0.09 | 0.09 | 0.09 | 0.10 | 0.07 | 0.05 | 0.06 | −0.02 | 0.03 | 0.06 | −0.05 | 0.06 | −0.05 |
| $SR$ | −0.15 | 0.08 | 0.18 | 0.24 | 0.49 | 0.20 | 0.64 | 0.11 | 0.48 | 0.02 | 0.07 | 0.21 | 0.12 | 0.23 | 0.15 | 0.20 | 0.13 | 0.17 |
| $MDD$ | −46.8 | −45.9 | −38.0 | −32.4 | −35.7 | −36.9 | −38.9 | −39.9 | −40.2 | −44.9 | −46.0 | −30.3 | −33.1 | −34.1 | −33.9 | −37.0 | −34.5 | −37.3 |
| *Freq* | 11.7 | 26.0 | 31.1 | 25.0 | 13.9 | 21.6 | 25.6 | 21.6 | 25.6 | 11.1 | 52.6 | 66.9 | 50.6 | 34.0 | 43.0 | 45.1 | 43.0 | 45.1 |

**Table 3.1:** ***Descriptive Statistics: Carry Trade (FX) Portfolios.*** *The table presents descriptive statistics of currency portfolios sorted on time $t-1$ forward premia (or interest rate differential relative to the U.S. dollar). Portfolio 1 ($P_1$) contains the top 20% of all currencies with the lowest forward premia whereas Portfolio 5 ($P_5$) contains the top 20% of all currencies with the highest forward premia. DOL denotes the average return of the five currency portfolios. $HML$ denotes the slope factor and is equivalent to a long-short strategy that buys $P_5$ and sells $P_1$. Excess returns are expressed in percentage per annum, and $\tau$ denotes excess returns adjusted for transaction costs. The table also reports the first order autocorrelation coefficient ($AC_1$), the annualized Sharpe ratio (SR), the maximum drawdown in percent (MDD), and the frequency of portfolio switches (Freq) in percent. Panel A (Panel B) presents portfolios rebalanced at the end of each month (year) using one-month (one-year) forward premia. The sample runs from October* 1983 *to December* 2011, *and comprises* 338 *(*28*) observations for the monthly (yearly) exercise. Exchange rates are from Datastream.*

annualized average excess return on Portfolio 1 is about $-1.79$ percent per annum for all countries and $-1.46$ percent per annum for developed countries. Portfolio 5 exhibits an annualized average excess return of 6.53 percent per annum for all countries and 5.61 percent per annum for developed countries. The average excess return from holding an equally weighted portfolio of foreign currencies (i.e., the $DOL$ portfolio) is 1.82 (0.61) percent per annum before (after) transaction costs for all countries, and 1.78 (0.97) percent per annum before (after) transaction costs for developed countries. These figures, taken together, suggest that a U.S. investor would demand a small but positive risk premium for holding foreign currency while borrowing in the U.S. money market. The average excess return from a long-short strategy that borrows in low-interest rate currencies and invests in high-interest rate currencies (essentially the $HML_{FX}$ portfolio) is 8.32 (5.44) percent per annum before (after) transaction costs for all countries, and 7.08 (5.25) percent per annum before (after) transaction costs for developed countries. A similar pattern emerges for the yearly rebalanced average returns. Likewise, both the median and kurtosis display a spread across the five portfolios, while standard deviations fail to show any systematic pattern. At a monthly rebalancing frequency I find almost no skewness in Portfolio 1 but this becomes increasingly negative as I move towards Portfolio 5, consistent with the findings of Brunnermeier, Nagel, and Pedersen (2008) who suggest that investment currencies (or high yielding currencies) may be subject to 'crash' risk.

I also report the realized Sharpe ratio ($SR$), the maximum drawdown ($MDD$), and the frequency of currency portfolio switches ($Freq$). The $SR$, computed as the average excess return of a portfolio divided by its standard deviation, increases systematically when moving from Portfolio 1 to Portfolio 5 in the monthly rebalancing setting. For instance, the annualized $SR$ ranges from $-0.23$ (Portfolio 1) to 0.67 (Portfolio 5) for all countries, and from $-0.15$ (Portfolio 1) to 0.49 (Portfolio 5) for developed countries. The $MDD$, defined as the maximum cumulative loss from the strategy's peak to the following trough, is large in both samples, reflecting the large-scale unwinding of carry trade positions following the bankruptcy of Lehman Brothers in September 2008. $Freq$ is computed as the ratio between the number of portfolio switches and the total number of currencies at each date. Overall, there is little variation in the composition of these portfolios, which is not surprising given that interest rates are very persistent. For yearly rebalanced portfolios, I find largely comparable results.

In Table 3.2 I present the same summary statistics for the five $NA$ portfolios, as well as the $DOL$ and $HML_{NA}$ strategies. When rebalancing monthly, the average excess return is monotonically increasing from Portfolio 1 ($-0.03$ percent per annum)

| | Panel A: Monthly Rebalancing | | | | | | | | | Panel B: Yearly Rebalancing | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $P_1$ | $P_2$ | $P_3$ | $P_4$ | $P_5$ | $DOL$ | $HML$ | $DOL^{\tau}$ | $HML^{\tau}$ | $P_1$ | $P_2$ | $P_3$ | $P_4$ | $P_5$ | $DOL$ | $HML$ | $DOL^{\tau}$ | $HML^{\tau}$ |
| | *All Countries* | | | | | | | | | *All Countries* | | | | | | | | |
| *Mean* | −0.16 | 1.79 | 0.76 | 2.23 | 4.54 | 1.83 | 4.70 | 0.70 | 2.31 | −0.51 | 1.18 | 2.07 | 0.84 | 3.87 | 1.49 | 4.38 | 1.15 | 3.64 |
| *Med* | 0.76 | 1.35 | 2.59 | 4.88 | 6.09 | 3.45 | 6.02 | 2.54 | 4.24 | 0.67 | 0.97 | 1.75 | 1.86 | 6.63 | 3.03 | 3.81 | 2.68 | 3.15 |
| *Sdev.* | 7.81 | 9.19 | 6.82 | 8.62 | 9.70 | 7.39 | 6.25 | 7.39 | 6.25 | 10.11 | 10.32 | 8.42 | 11.92 | 13.87 | 9.73 | 7.97 | 9.69 | 7.81 |
| *Skew* | −0.32 | −0.43 | −1.23 | −1.16 | −0.55 | −0.58 | −0.23 | −0.59 | −0.37 | −0.75 | 0.03 | −0.69 | −1.19 | −0.50 | −0.59 | −0.46 | −0.58 | −0.53 |
| *Kurt* | 3.74 | 4.54 | 9.07 | 8.15 | 4.86 | 4.44 | 6.59 | 4.44 | 6.59 | 2.86 | 2.51 | 3.76 | 4.54 | 2.46 | 2.65 | 3.26 | 2.64 | 3.26 |
| $AC_1$ | 0.09 | 0.08 | 0.12 | 0.05 | 0.14 | 0.10 | 0.21 | 0.10 | 0.21 | 0.02 | −0.01 | −0.14 | 0.08 | −0.05 | −0.04 | 0.19 | −0.04 | 0.20 |
| $SR$ | −0.02 | 0.19 | 0.11 | 0.26 | 0.47 | 0.25 | 0.75 | 0.09 | 0.37 | −0.05 | 0.11 | 0.25 | 0.07 | 0.28 | 0.15 | 0.55 | 0.12 | 0.47 |
| $MDD$ | −49.4 | −31.8 | −35.0 | −31.4 | −29.3 | −24.7 | −19.0 | −29.5 | −23.4 | −40.9 | −32.4 | −21.7 | −39.1 | −34.5 | −28.4 | −16.4 | −29.9 | −17.1 |
| *Freq* | 2.2 | 3.5 | 3.2 | 2.8 | 2.3 | 2.8 | 4.5 | 2.8 | 4.5 | 13.9 | 27.4 | 22.2 | 20.8 | 20.8 | 21.0 | 34.6 | 21.0 | 34.6 |
| | *Developed Countries* | | | | | | | | | *Developed Countries* | | | | | | | | |
| *Mean* | −0.03 | 0.89 | 2.05 | 2.38 | 4.02 | 1.86 | 4.05 | 1.10 | 2.61 | −0.34 | 0.86 | 1.54 | 2.08 | 3.67 | 1.56 | 4.01 | 1.40 | 3.71 |
| *Med* | 1.20 | 1.34 | 3.06 | 4.26 | 5.87 | 3.33 | 5.99 | 2.75 | 4.53 | 0.51 | 0.98 | 2.44 | 3.88 | 2.86 | 1.21 | 3.30 | 1.07 | 3.04 |
| *Sdev.* | 10.08 | 10.76 | 9.14 | 9.49 | 10.03 | 8.92 | 6.51 | 8.92 | 6.51 | 12.62 | 11.07 | 10.77 | 11.22 | 11.41 | 10.50 | 8.02 | 10.49 | 8.02 |
| *Skew* | −0.15 | −0.33 | −0.44 | −0.63 | −0.49 | −0.35 | −0.82 | −0.35 | −0.81 | −0.31 | −0.10 | −0.13 | −0.52 | −0.19 | −0.15 | −0.24 | −0.15 | −0.25 |
| *Kurt* | 3.40 | 3.90 | 4.56 | 7.14 | 4.21 | 3.74 | 5.88 | 3.74 | 5.90 | 1.93 | 2.43 | 2.13 | 3.01 | 2.12 | 2.00 | 3.39 | 1.99 | 3.38 |
| $AC_1$ | 0.05 | 0.05 | 0.10 | 0.11 | 0.08 | 0.09 | 0.01 | 0.09 | 0.02 | 0.09 | −0.03 | 0.16 | 0.04 | 0.01 | 0.07 | −0.03 | 0.07 | −0.02 |
| $SR$ | 0.00 | 0.08 | 0.22 | 0.25 | 0.40 | 0.21 | 0.62 | 0.12 | 0.40 | −0.03 | 0.08 | 0.14 | 0.19 | 0.32 | 0.15 | 0.50 | 0.13 | 0.46 |
| $MDD$ | −58.2 | −39.9 | −36.9 | −38.1 | −27.1 | −37.2 | −26.0 | −39.9 | −27.4 | −49.2 | −31.9 | −39.3 | −35.9 | −23.0 | −36.2 | −17.4 | −36.7 | −17.9 |
| *Freq* | 1.5 | 2.6 | 2.6 | 3.2 | 2.6 | 2.5 | 4.1 | 2.5 | 4.1 | 17.3 | 27.5 | 20.6 | 29.4 | 24.7 | 23.9 | 42.0 | 23.9 | 42.0 |

**Table 3.2:** ***Descriptive Statistics: External Imbalances (NA) Portfolios.*** *The table presents descriptive statistics of currency portfolios sorted on time* $t-1$ *external imbalances (net foreign assets to GDP ratio) and the share of foreign liabilities in domestic currency. Portfolio 1 (*$P_1$*) contains the top 20% of all currencies with positive external imbalances (creditor nations) and the highest share of foreign liabilities in domestic currency whereas Portfolio 5 (*$P_5$*) contains the top 20% of all currencies with negative external imbalances (debtor nations) and the lowest share of foreign liabilities in domestic currency.* $DOL$ *denotes the average return of the five currency portfolios.* $HML$ *denotes the global imbalance factor and is equivalent to a long-short strategy that buys* $P_5$ *and sells* $P_1$*. Excess returns are expressed in percentage per annum, and* $\tau$ *denotes excess returns adjusted for transaction costs. The table also reports the first order autocorrelation coefficient (*$AC_1$*), the annualized Sharpe ratio (SR), the maximum drawdown in percent (*$MDD$*), and the frequency of portfolio switches (Freq) in percent. Panel A (Panel B) presents portfolios rebalanced at the end of each month (year). The sample runs from October* 1983 *to December* 2011*, and comprises* 338 *(28) observations for the monthly (yearly) exercise. Exchange rates are from Datastream. Yearly data on GDP, foreign assets and liabilities are from Lane and Milesi-Ferretti (2007) whereas yearly data on the share of foreign liabilities in domestic currency are from Lane and Shambaugh (2010). Monthly observations are retrieved by keeping end-of-period data constant until a new observation becomes available.*

to Portfolio 5 (4.02 percent per annum) in developed countries, and upward sloping (albeit non-monotonically) for all countries. The patterns in skewness and kurtosis are similar to $FX$ portfolios, albeit with higher absolute statistics on Portfolio 4 rather than Portfolio 5. When I compare $SR$s, I observe that $HML_{FX}$ has a higher risk-adjusted return than $HML_{NA}$ for all countries: 0.94 compared to 0.75 before transaction costs, and 0.61 compared to 0.37 after transaction costs. For developed countries, the difference is virtually eliminated with the $SR$ equal to 0.64 (0.48) for $HML_{FX}$, and 0.62(0.48) for $HML_{NA}$ before (after) transaction costs.

Strategies based on forward premia, however, are not immediately comparable to strategies based on external imbalances when monthly rebalanced portfolios are taken into consideration. This is because forward premia are observed every month, whereas new information on countries' external imbalances only arrives at the end of each year. This is confirmed by the frequency of currency portfolio switches ($Freq$), which displays far less variation in the portfolio compositions of the $NA$ portfolios compared to the $FX$ portfolios. The comparison between $FX$ and $NA$ portfolios becomes, to some extent, unfair for excess returns net of transaction costs. Monthly rebalanced $NA$ portfolios are subject to monthly transaction costs even though there is no turnover in the portfolio composition as the investor has to roll-over the one-month forward contract. Therefore, I also consider yearly rebalanced strategies.

When I rebalance currencies at the end of each year, the difference between $HML_{FX}$ and $HML_{NA}$ is flipped around. $HML_{NA}$ now displays a Sharpe ratio of 0.55 (0.47) compared to 0.30 (0.25) for $HML_{FX}$ before (after) transaction costs for all countries. Similarly for developed countries, the Sharpe ratio for $HML_{NA}$ is 0.50 (0.46) but only 0.20 (0.17) for $HML_{FX}$ before (after) transaction costs. In sum, the two sets of summary statistics line up well with one another. There are some differences but this is not overly surprising given the two-speed nature of the variables. Given $NA$ information arrives with annual frequency, it is perhaps surprising that the risk-adjusted $NA$ strategy performs almost as well as the carry strategy when rebalancing at a monthly frequency.

### 3.4.2 Carry Trade Returns and Global Imbalance Risk

In Figure 3.1 I present preliminary evidence on the relation between carry trade returns and global imbalance risk by grouping carry trade returns into four baskets conditional on the distribution of $HML_{NA}$. The first group comprises the 25 percent of months with the lowest realizations of the global imbalance risk factor whereas the last group contains the 25 percent of months with the highest realizations of the

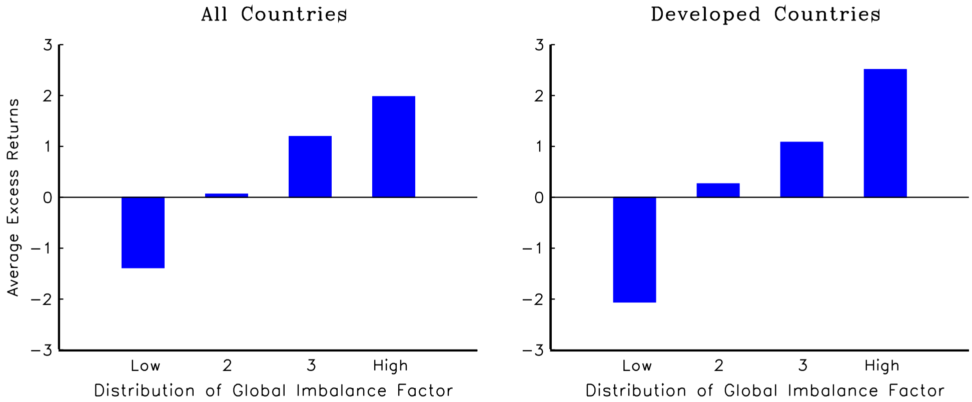


**Figure 3.1:** ***Currency Excess Returns and External Imbalances.*** *The figure presents average excess returns for carry trade portfolios conditional on the global imbalance risk factor being within the lowest to highest quartile of its sample distribution. The bars show average excess returns for being long in Portfolio 5 (largest forward premia) and short in Portfolio 1 (lowest forward premia). Excess returns are expressed in percentage per month. The sample runs from October 1983 to December 2011.*

global imbalance risk factor. I then compute for each group the average carry trade return. Figure 3.1 shows that average excess returns for the carry trade strategy increase monotonically when moving from low to high global imbalance risk. The carry trade has its best overall performance when global imbalance risk is high and vice versa, suggesting a relation between currency excess returns and global imbalance risk.

In Figure 3.2 I present further graphical evidence on the relationship between $HML$ risk factors by showing the one-year rolling Sharpe ratios for $HML_{FX}$ and $HML_{NA}$. This is a simple exercise to visualize the similarity between a long/short strategy on forward premia and a long/short strategy on external imbalances. The top panel refers to all countries, while the bottom panel to developed countries. The two series show a high degree of correlation, and since the mid 1990s the general pattern of peaks and troughs in $HML_{FX}$ has been exactly replicated by $HML_{NA}$. This result is particularly promising if one considers that forward premia are observed at monthly intervals while net foreign assets are only recorded at the end of each calendar year.[14] This preliminary evidence suggests that $HML_{NA}$ and $HML_{FX}$ move closely together and reflect very similar portfolios. I now turn to a more rigorous investigation of this similarity using formal asset pricing tests.

[14]Throughout the sample I observe a few deviations between $HML_{FX}$ and $HML_{NA}$, which are easily identifiable as they generally tend to be episodes of major central bank interventions or other global shocks, such as the coordinated intervention operations of 1985 and 1987, the currency crises of the early 1990s that led Italy and the U.K. to defend their currencies in the European Exchange Rate Mechanism via higher interest rates, the Mexican crisis in 1994, the collapse of Lehman Brothers in September 2008, and more recently the European sovereign crisis.

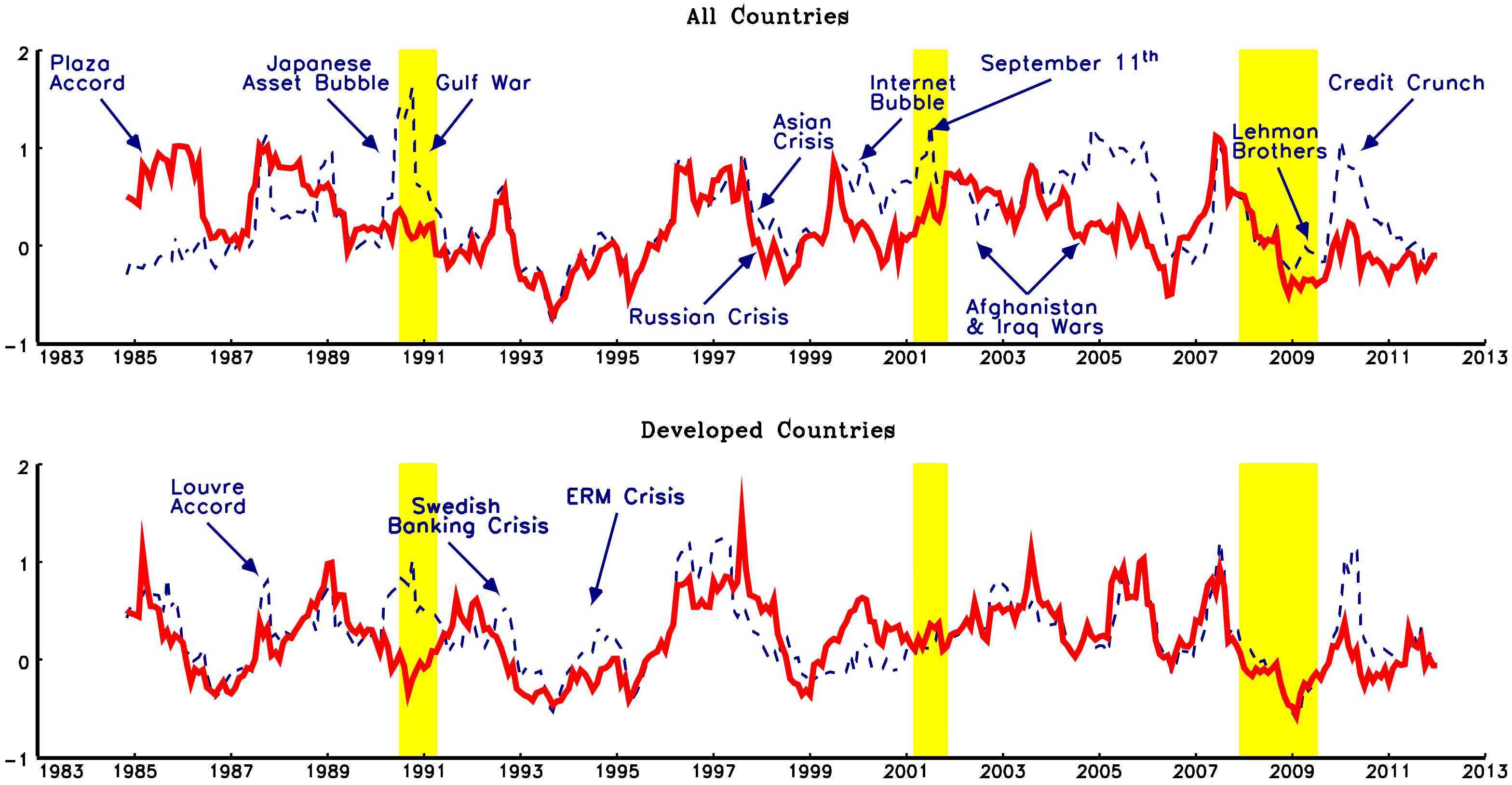


**Figure 3.2:** ***Rolling Sharpe Ratios.*** *The figure presents the one-year rolling Sharpe ratios for the global imbalance risk factor* $HML_{NA}$ *(solid line) and the slope factor* $HML_{FX}$ *(dashed line). The Shaded areas are the NBER recession periods for the United States. The strategies are rebalanced monthly from October 1983 to December 2011.*

## 3.5 Asset Pricing Tests

This section presents cross-sectional asset pricing tests for the five $FX$ portfolios and the global imbalance factor, and empirically documents that carry trade returns can be thought of as compensation for time-varying global imbalance risk.

### 3.5.1 Empirical Methods

I closely follow the cross-sectional asset pricing methodology described in Cochrane (2005) and used, among others, by Lustig et al. (2011) and Menkhoff et al. (2012). I denote the discrete excess returns on portfolio $j$ in period $t$ as $RX_t^j$. To avoid the assumption of joint log-normality of returns and the pricing kernel, I run all asset pricing tests on discrete excess returns, not log excess returns.[15] In the absence of arbitrage opportunities, risk-adjusted excess returns have a price of zero and satisfy the following Euler equation:

$$E_t[M_{t+1} RX_{t+1}^j] = 0 \tag{3.3}$$

with a Stochastic Discount Factor (SDF), $M_{t+1}$ linear in the pricing factors $f_{t+1}$, given by

$$M_{t+1} = 1 - b' \left( f_{t+1} - \mu \right) \tag{3.4}$$

where $b$ is the vector of factor loadings, and $\mu$ denotes the factor means. This specification implies a beta pricing model where the expected excess return on portfolio $j$ is equal to the factor risk price $\lambda$ times the risk quantities $\beta^j$. The beta pricing model is defined as

$$E[RX^j] = \lambda' \beta^j \tag{3.5}$$

where the market price of risk $\lambda = \Sigma_f b$ can be obtained via the factor loadings $b$. $\Sigma_f = E\left[ \left( f_t - \mu \right) \left( f_t - \mu \right)' \right]$ , is the variance-covariance matrix of the risk factors, and $\beta^j$ are the regression coefficients of each portfolio's excess return $RX_{t+1}^j$ on the risk factors $f_{t+1}$.

The factor loadings $b$ entering equation (4.1) are estimated via the Generalized Method of Moments ($GMM$) of Hansen (1982). To implement $GMM$, I use the pricing errors as a set of moments and a prespecified weighting matrix. Since the objective is to test whether the model can explain the cross-section of expected currency excess returns, I only rely on unconditional moments and do not employ

[15]Note that Lustig et al. (2011) and Menkhoff et al. (2012) also use discrete returns for asset pricing tests, although they take logs in the main text for expositional simplicity. Here, I use discrete returns throughout the chapter.

instruments other than a constant and a vector of ones. The first-stage estimation ($GMM_1$) employs an identity weighting matrix. The weighting matrix tells us how much attention to pay to each moment condition. With an identity matrix, $GMM$ attempts to price all currency portfolios equally well. The second-stage estimation ($GMM_2$) uses an optimal weighting matrix based on a heteroskedasticity and autocorrelation consistent (HAC) estimate of the long-run covariance matrix of the moment conditions. In this case, since currency portfolio returns have different variances and may be correlated, the optimal weighting matrix will attach more weight to linear combinations of moments about which the data are more informative (Cochrane, 2005). The tables report estimates of $b$ and implied $\lambda$, and standard errors based on Newey and West (1987) with optimal lag length selection according to Andrews (1991).[16] The model's performance is then evaluated using the cross-sectional $R^2$, the square-root of mean-squared errors $RMSE$, the $\chi^2$ test statistics, and the $HJ$ distance measure of Hansen and Jagannathan (1997). The $\chi^2$ test statistic evaluates the null hypothesis that all cross-sectional pricing errors (i.e., the difference between actual and predicted excess returns) are jointly equal to zero. I report asymptotic $p$-values for the $\chi^2$ test statistics. The $HJ$ distance quantifies the mean-squared distance between the SDF of a proposed model and the set of admissible SDFs. To test whether the $HJ$ distance is equal to zero, I simulate $p$-values using a weighted sum of $\chi^2_1$-distributed random variables as in Jagannathan and Wang (1996).

The estimation of the portfolio betas $\beta^j$ and factor risk price $\lambda$ in equation (4.3) is also undertaken using a two-pass ordinary least squares regression following Fama and MacBeth (FMB, 1973). In the first step, I run time-series regressions of portfolio excess returns against a constant and the risk factors, and estimate the betas $\beta^j$. In the second step, I run cross-sectional regressions of portfolio returns on the betas, and estimate the factor risk prices $\lambda$ as averages of all these slope coefficients. Note that in the second stage of FMB regressions I do not add any constant to capture the common over- or under-pricing in the cross section of returns. The results, however, remain virtually identical when I replace the $DOL$ factor with a constant in the second stage regression. This is because the $DOL$ factor has no cross-sectional relation with currency returns, and it works as a constant that allows for a common mispricing.[17] I report Newey and West (1987) and Shanken (1992)

[16] I estimate $\mu$ and $\Sigma_f$ using the sample average and the sample covariance matrix of the risk factors, respectively (e.g. Lustig et al., 2011). I also implement a first-stage GMM where $\mu$ and $\Sigma_f$ are jointly estimated with the factor loadings $b$. In doing so, I account for estimation uncertainty associated with the fact that factor means and the factor covariance matrix have to be estimated (Burnside, 2011; Menkhoff et al., 2012). The results remain qualitatively the same.

[17] See Burnside (2011) and Lustig and Verdelhan (2007) for a detailed discussion of this issue.

standard errors with optimal lag length selection according to Andrews (1991).

**Risk Factors.** The most recent literature on cross-sectional asset pricing in currency markets has considered a two-factor pricing kernel. The first risk factor is typically the expected market excess return, approximated by the average excess return on a portfolio strategy that is long in all foreign currencies with equal weights and short in the domestic currency – essentially the $DOL$ factor. For the second risk factor, the literature has employed several return-based factors such as the slope factor $HML_{FX}$ of Lustig et al. (2011) or the global volatility factor $VOL_{FX}$ of Menkhoff et al. (2012). Regardless of its parsimony and the likely omission of other potential factors, this simple empirical model has delivered important insights on the relation between global risk and expected currency returns. However, the risk factors used by the literature to date are built on financial variables that are themselves endogenously determined, which begs the question of what the fundamental economic forces that drive global risk factors are. Following this literature, I employ a two-factor SDF with $DOL$ as the first factor. For the second risk factor, I use global imbalance risk in an attempt to assess the validity of the theoretical prediction that exchange rates are linked to external imbalances, and that currencies more exposed to global imbalance risk offer a risk premium related to interest rate differentials.

### 3.5.2 Results

**Cross-Sectional Regressions.** Panel A of Table 3.3 presents the cross-sectional asset pricing results with monthly rebalanced portfolios. The excess returns to currency portfolios $RX^j_{FX}$, for $j = 1, \ldots, 5$, serve as test assets whereas the dollar factor $DOL$ and the global imbalance factor $HML_{NA}$ enter as risk factors. Both test assets and risk factors are adjusted for transactions costs. The SDF is defined as

$$M_{t+1} = 1 - b_{DOL}\left(DOL_{t+1} - \mu_{DOL}\right) - b_{NA}\left(HML_{NA,t+1} - \mu_{NA}\right)$$

where $\mu_{DOL}$ and $\mu_{NA}$ denote the factor means. Panel A reports estimates of factor loadings $b$, the market prices of risk $\lambda$, the cross-sectional $R^2$, the square-root of mean-squared errors $RMSE$, the $\chi^2$ test statistics, and the $HJ$ distance. Newey and West (1987) corrected standard errors with lag length determined according to Andrews (1991) are reported in parentheses, while Shanken corrected standard errors are in brackets. The $p$-values of the $\chi^2$ test statistics and $HJ$ distance measure are also reported in brackets. The results are reported for all countries (left panel) and developed countries (right panel) using $GMM_1$, $GMM_2$, and the $FMB$ approach.

| Panel A: Factor Prices | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $b_{DOL}$ | $b_{NA}$ | $\lambda_{DOL}$ | $\lambda_{NA}$ | $R^2$ | $RMSE$ | $\chi^2$ | $HJ$ | $b_{DOL}$ | $b_{NA}$ | $\lambda_{DOL}$ | $\lambda_{NA}$ | $R^2$ | $RMSE$ | $\chi^2$ | $HJ$ |
| | *All Countries* | | | | | | | | *Developed Countries* | | | | | | | |
| $GMM_1$ | −0.22 | 1.61 | 0.01 | 0.07 | 0.84 | 1.87 | 4.46 | 0.15 | 0.07 | 0.95 | 0.01 | 0.05 | 0.93 | 1.02 | 0.84 | 0.06 |
| | (0.31) | (0.61) | (0.02) | (0.02) | | | [0.22] | [0.21] | (0.23) | (0.52) | (0.02) | (0.02) | | | [0.84] | [0.86] |
| $GMM_2$ | −0.17 | 1.63 | 0.01 | 0.06 | 0.83 | 1.97 | 4.43 | | 0.09 | 1.04 | 0.01 | 0.05 | 0.93 | 1.02 | 0.80 | |
| | (0.30) | (0.61) | (0.02) | (0.02) | | | [0.22] | | (0.22) | (0.50) | (0.02) | (0.02) | | | [0.85] | |
| $FMB$ | −0.22 | 1.60 | 0.01 | 0.07 | 0.84 | 1.87 | 4.47 | | 0.07 | 0.95 | 0.01 | 0.05 | 0.93 | 1.02 | 0.84 | |
| | (0.26) | (0.50) | (0.02) | (0.02) | | | [0.22] | | (0.20) | (0.41) | (0.02) | (0.02) | | | [0.84] | |
| | [0.24] | [0.49] | [0.01] | [0.02] | | | | | [0.18] | [0.39] | [0.02] | [0.02] | | | | |

| Panel B: Factor Betas | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | $\alpha$ | $\beta_{DOL}$ | $\beta_{NA}$ | $R^2$ | $\alpha$ | $\beta_{DOL}$ | $\beta_{NA}$ | $R^2$ |
| $P_1$ | −0.01 | 0.98 | −0.32 | 0.78 | −0.01 | 0.95 | −0.51 | 0.75 |
| | (0.01) | (0.05) | (0.04) | | (0.01) | (0.05) | (0.07) | |
| $P_2$ | −0.02 | 0.99 | −0.21 | 0.79 | −0.01 | 1.01 | −0.18 | 0.82 |
| | (0.01) | (0.04) | (0.04) | | (0.01) | (0.04) | (0.04) | |
| $P_3$ | 0.01 | 1.03 | −0.07 | 0.84 | 0.01 | 0.99 | 0.01 | 0.86 |
| | (0.01) | (0.04) | (0.04) | | (0.01) | (0.03) | (0.04) | |
| $P_4$ | 0.01 | 1.07 | 0.15 | 0.84 | 0.01 | 1.00 | 0.16 | 0.83 |
| | (0.01) | (0.04) | (0.06) | | (0.01) | (0.03) | (0.05) | |
| $P_5$ | 0.03 | 0.94 | 0.45 | 0.71 | 0.02 | 1.05 | 0.53 | 0.79 |
| | (0.01) | (0.07) | (0.08) | | (0.01) | (0.04) | (0.06) | |

**Table 3.3:** ***Asset Pricing: Global Imbalance Risk.*** *The table presents cross-sectional asset pricing results for the linear factor model based on the dollar ($DOL$) and the global imbalance ($HML_{NA}$) risk factor. The test assets are excess returns to five currency ($FX$) portfolios sorted on the one-month forward premia. Panel A reports GMM (first and second-stage) and Fama-MacBeth (FMB) estimates of the factor loadings b, the market price of risk $\lambda$, and the cross-sectional $R^2$. Newey and West (1987) standard errors with Andrews (1991) optimal lag selection are reported in parentheses whereas Shanken (1992) standard errors are reported in brackets. $\chi^2$ denotes the test statistics (with p-value in parentheses) for the null hypothesis that all pricing errors are jointly zero. $HJ$ refers to the Hansen and Jagannathan (1997) distance (with simulated p-value in parentheses) for the null hypothesis that the $HJ$ distance is equal to zero. Panel B reports least-squares estimates of time series regressions with Newey and West (1987) standard errors in parentheses. Excess returns are expressed in percentage per annum and adjusted for transaction costs. The portfolios are rebalanced monthly from October* 1983 *to December* 2011.

I focus attention on the sign and the statistical significance of $\lambda_{NA}$, the market price of risk attached to the global imbalance risk factor. I find a positive and significant estimate of $\lambda_{NA}$. The global imbalance risk premium is 7 percent per annum for all countries, and 5 percent per annum for developed countries when I use the first-stage $GMM$ and the $FMB$ procedure. The results remain largely unaffected when using the second-stage GMM, with only a small shift downwards in the point estimate of the factor risk price for all countries (6 percent per annum). For this set of currencies, however, the $RMSE$ increases from 187 to 197 basis points when moving from $GMM_1$ to $GMM_2$. A positive estimate of the factor price of risk implies higher risk premia for currency portfolios whose returns comove positively with the global imbalance factor, and lower risk premia for currency portfolios exhibiting a negative covariance with the global imbalance factor. The standard errors of the risk prices are approximately equal to 2 percent for all estimation methods. Overall, the risk price is more than two standard deviations from zero, and thus highly statistically significant. I also uncover strong cross-sectional fit with $R^2$s of more than 80 percent for the full sample of countries, and 90 percent for the subset of developed countries. Further support in favor of these results comes from the fact that I are unable to reject the null hypotheses that the cross-sectional pricing errors are jointly equal to zero and that the $HJ$ distance is equal to zero. The $p$-values of the $\chi^2$ test statistics and $HJ$ distance are large for both samples of countries.

The $DOL$ factor has a risk price of 1 percent per annum, in line with the findings of Lustig et al. (2011). Since all currency portfolios have a time-series $\beta_{DOL}$ close to one, this factor does not have power in explaining the cross-sectional variation in currency excess returns. Indeed, I record a standard error approximately twice as large as the estimated price of risk. Although the $DOL$ factor does not explain any of the cross-sectional dispersion in expected returns, it is important for the level of average returns: there is no need to add a constant in the cross-sectional regression as the $DOL$ factor serves as the constant. Therefore, the strong explanatory power is delivered entirely by $HML_{NA}$.[18]

**Time-Series Regressions.** In Panel B of Table 3.3, I report the least squares estimates obtained from running time-series regressions of currency excess returns on a constant and risk factors for each of the five currency portfolios (for $j = 1, \ldots, 5$)

$$RX^j_{FX,t+1} = \alpha^j + \beta^j_{DOL} DOL_{t+1} + \beta^j_{NA} HML_{NA,t+1} + \varepsilon^j_{t+1}.$$

[18] Appendix Figure B.3 shows graphically the fit of the model. I plot the actual average excess returns along the vertical axis and the fitted average excess returns implied by the model along the horizontal axis. The model-predicted excess returns lie very close to the 45 degree line, suggesting that global imbalance risk explains the spread in average carry trade returns reasonably well, both for all countries (left panel) and developed countries (right panel).

This exercise allows me to clearly identify which of the currency portfolios provide a hedge against global imbalance risk. The estimate of the betas for the $DOL$ factor are essentially all equal to one as this factor does not capture any of the dispersion in average excess returns across currency portfolios. The estimates of the betas for the global imbalance risk factor $\beta_{NA}$, are positive for currencies with a high forward premium (high interest rate differential), and negative for currencies with a low forward premium (low interest rate differential). These betas increase monotonically for all countries from $-0.32$ for the first portfolio to 0.45 for the last portfolio. Results for developed countries are largely comparable. Finally, the last column reports the time-series $R^2$s, which range from 71 to 84 percent for all countries, and from 75 to 86 percent for developed countries.

I also investigate whether the unconditional betas in Panel B are determined by the covariance between spot exchange rate returns and risk factors, or between interest rate differentials and risk factors. This is important because the conditional covariance between the currency excess returns and the global imbalance risk factor is only driven by the exchange rate return as $Cov_t[RX^j_{FX,t+1}, HML_{NA,t+1}] = -Cov_t[(S_{t+1} - S_t)/S_t, HML_{NA,t+1}]$. Hence, I also regress discrete exchange rate returns on $DOL$ and $HML_{NA}$ for each portfolio, and find that the estimates of these betas are largely comparable to the betas (when multiplied by minus one) reported in Panel B. These estimates of betas (times minus one) move from $-0.31$ (Portfolio 1) to 0.43 (Portfolio 5) for the full sample of countries, and from $-0.50$ (Portfolio 1) to 0.55 (Portfolio 5) for the subsample of developed countries.

Overall, investors demand a premium for holding high-yielding currencies (high forward premia) because these currencies are associated with large global imbalance risk, whereas they accept a low return for holding low-yielding currencies as these currencies provide a hedge against global imbalance risk.[19]

**Carry Trade versus External Imbalances Portfolios.** I now present further evidence on the relationship between carry trade and external imbalances portfolios by running the following time-series regressions

$$RX^j_{FX,t+1} = \alpha^j + \beta RX^j_{NA,t+1} + \varepsilon^j_{t+1}$$

where $RX^j_{FX}$ denotes the excess return of the $j$-th carry trade portfolio (i.e., $FX$ portfolios), and $RX^j_{NA}$ is the excess return of the $j$-th external imbalances portfolio (i.e., $NA$ portfolios). Table 3.4 reports the least squares estimates of these regres-

[19] In Appendix Table B.1, I present the analogous results when the excess returns to the test assets exclude transaction costs. While in Appendix Table B.2, I replace the test assets with the five external imbalance portfolios.

| | $P_1$ | $P_2$ | $P_3$ | $P_4$ | $P_5$ | $HML$ | $P_1$ | $P_2$ | $P_3$ | $P_4$ | $P_5$ | $HML$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | *All Countries* | | | | | | *Developed Countries* | | | |
| $\alpha$ | −1.51 | −2.10 | 1.76 | 0.41 | 2.20 | 3.68 | −1.27 | −0.09 | −0.15 | 0.25 | 1.53 | 2.50 |
| | (0.80) | (0.80) | (1.06) | (1.18) | (1.19) | (1.42) | (1.06) | (0.98) | (1.06) | (1.06) | (1.21) | (1.68) |
| $\beta$ | 0.89 | 0.75 | 0.93 | 0.77 | 0.78 | 0.76 | 0.84 | 0.77 | 0.86 | 0.85 | 0.92 | 1.05 |
| | (0.05) | (0.04) | (0.06) | (0.07) | (0.05) | (0.10) | (0.05) | (0.05) | (0.04) | (0.03) | (0.06) | (0.10) |
| $R^2$ | 0.77 | 0.74 | 0.60 | 0.54 | 0.60 | 0.29 | 0.70 | 0.72 | 0.69 | 0.68 | 0.66 | 0.38 |
| $LM_3$ | 5.39 | 3.30 | 6.10 | 2.17 | 3.51 | 2.62 | 1.23 | 3.20 | 13.49 | 1.93 | 3.78 | 2.98 |
| | [0.15] | [0.35] | [0.11] | [0.54] | [0.32] | [0.45] | [0.75] | [0.36] | [0.00] | [0.59] | [0.29] | [0.40] |
| $\rho_{83-11}$ | 0.88 | 0.86 | 0.77 | 0.74 | 0.78 | 0.54 | 0.84 | 0.85 | 0.83 | 0.82 | 0.81 | 0.62 |
| $\rho_{83-97}$ | 0.89 | 0.87 | 0.65 | 0.59 | 0.70 | 0.44 | 0.87 | 0.89 | 0.76 | 0.77 | 0.72 | 0.54 |
| $\rho_{98-11}$ | 0.86 | 0.89 | 0.90 | 0.89 | 0.87 | 0.66 | 0.80 | 0.80 | 0.89 | 0.88 | 0.92 | 0.71 |

**Table 3.4:** ***Carry Trade versus External Imbalances Portfolios.*** *The table presents least squares estimates of regressing $FX$ portfolios' excess returns on $NA$ portfolios' excess returns. The $FX$ portfolios are obtained by grouping currencies into five portfolios using the one-month forward premia at time $t-1$. The $NA$ portfolios are obtained by sorting currencies into five groups using countries' external imbalances (net foreign assets to GDP ratio) and the share of foreign liabilities in domestic currency at time $t-1$. $LM_p$, indicates the Breusch-Godfrey Lagrange Multiplier test for the null hypothesis of no serial correlation up to p lags. $\rho$ denotes the sample correlation. Newey and West (1987) standard errors with Andrews (1991) optimal lag selection are reported in parentheses, and p-values in brackets. Excess returns are expressed in percentage per annum, and adjusted for transaction costs. The portfolios are rebalanced monthly from October 1983 to December 2011.*

sions for $j = 1, 2, \ldots, 5$, and suggests that carry trade returns are systematically related to the external imbalances portfolios. Carry trade funding currencies are associated with net creditor nations whereas carry trade investment currencies are linked to net debtor nations. Estimates of $\beta$ are all statistically different from zero and are in the range between 0.75 and 0.93 for all countries, and 0.77 and 1.05 for developed countries. I also report estimates of $\alpha$ in percent per annum. For developed countries, estimates of $\alpha$ are always statistically insignificant, suggesting that risk exposure to external imbalances fully explains the time-series variation in currency portfolio returns. For all countries, I find that 4 out of 5 estimates of $\alpha$ are statistically insignificant. These results are corroborated by the $R^2$, which ranges from 54 to 77 percent for all countries, and from 66 to 72 percent for developed countries. In addition to the $R^2$, I also report the correlation for the full sample and two subsamples. I find that the relationship between carry trade portfolios and the external imbalances portfolios has improved, especially for all countries, over time. This higher degree of comovement between the two sets of portfolios in the second half of the sample is not surprising as it reflects less stringent capital controls as well as an increase in trading activity for some of the emerging market currencies. In short, all five $FX$ and $NA$ portfolio returns tend to move together.[20] From the perspective of $HML$ factors, I find a strong positive correlation between $HML_{NA}$ and $HML_{FX}$ ranging from 54 percent for all countries to 62 percent for developed countries, suggesting that the strength of the asset pricing results is not artificially driven by the underlying factor structure of currency returns. Lewellen et al. (2010) show that a strong factor structure in test asset returns can give rise to misleading results in empirical work. If the risk factor has a small (but non-zero) correlation with the 'true' factor, the cross-sectional $R^2$ could still be high suggesting an impressive model fit. Here, I show that the correlation between the factor and $HML_{FX}$ is indeed reasonably high and has improved over the last decade.

**Portfolios based on $HML_{NA}$ Betas.** I provide evidence of the explanatory power of the global imbalance risk factor for currency excess returns from a different viewpoint. I form portfolios based on an individual currency's exposure to global imbalance risk, and investigate whether these portfolios have similar return distributions to portfolios sorted on forward premia. If global imbalance risk is a priced factor, then currencies sorted according to their exposure to global imbalance

[20]Appendix Table B.4 reports the portfolio composition of $FX$ and $NA$, portfolios. Panel A (Panel B) reports the top six currencies for each of the $FX$ ($NA$) portfolios. Panel C reports the probability that a given currency enters simultaneously in the same $FX$ and $NA$ portfolio. For corner portfolios, this probability ranges from 45 to 36 percent for all countries and from 44 to 35 percent for developed countries.

risk should yield a cross section of portfolios with a significant spread in average currency returns. Currencies that hedge global imbalance risk should trade at a forward discount, whereas currencies that provide exposure to global imbalance risk should trade at a forward premium.

I regress individual currency excess returns at time $t$ on a constant and the global imbalance risk factor using a 36-month rolling window that ends in period $t-1$, and denote this slope coefficient as $\beta^i_{NA,t}$. This exercise provides currency $i$ exposure to $HML_{NA}$ only using information available at time $t$. I then rank currencies according to $\beta^i_{NA,t}$ and allocate them to five portfolios at time $t$. Portfolio 1 contains the currencies with the largest negative exposure to the global imbalance factor (lowest betas), while Portfolio 5 contains the most positively exposed currencies (highest betas). Table 3.5 summarizes the descriptive statistics for these portfolios. I find that buying currencies with a low beta (i.e., insurance against global imbalance risk) yields a significantly lower return than currencies with a high beta (i.e., high exposure to global imbalance risk). The spread between the last portfolio and the first portfolio is around 3 percent per annum for all countries and 5 percent per annum for developed countries. Average excess returns generally increase, albeit not always monotonically, when moving from the first to the last portfolio. I also find that beta-sorted portfolios have a skewness pattern similar to the currency portfolios in Table 3.2. High beta currencies show a greater propensity to experience large return drawdowns than low beta currencies. Moreover, I also find a clear monotonic increase in both average *pre*-formation and *post*-formation betas when moving from Portfolio 1 to Portfolio 5: they line up perfectly well with the cross-section of average excess returns in Table 3.2. Average *pre*-formation betas vary from $-0.32$ to 1.19 for all countries, and from $-1.04$ to 0.62 for developed countries. *Post*-formation betas are calculated by regressing realized excess returns of beta-sorted portfolio $j$ on $DOL$ and $HML_{NA}$. These figures range from $-0.36$ to 0.26 for all countries, and from $-0.58$ to 0.57 for developed countries. Overall, these results confirm that global imbalance risk is important for understanding the cross-section of currency excess returns.

**The Relation between $HML_{NA}$, $HML_{FX}$ and $VOL_{FX}$.** Lustig et al. (2011) contribute to the literature in two respects. First, they show that currency excess returns are not a free lunch but can be understood as compensation for time-varying risk. Second, they find that the cross-sectional dispersion in currency excess returns can be explained by one global risk factor. In a similar vein, Menkhoff et al. (2012) use volatility innovations and construct a volatility factor $VOL_{FX}$ to price the cross-section of currency excess returns. In a horse race analysis, they conclude that

| | $P_1$ | $P_2$ | $P_3$ | $P_4$ | $P_5$ | $DOL$ | $HML$ | $P_1$ | $P_2$ | $P_3$ | $P_4$ | $P_5$ | $DOL$ | $HML$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | *All Countries* | | | | | | | *Developed Countries* | | | | | | |
| $Mean$ | −0.56 | 2.07 | 2.17 | 1.92 | 2.27 | 1.57 | 2.84 | −0.21 | 2.37 | 1.00 | 1.69 | 4.52 | 1.87 | 4.73 |
| $Med$ | 0.07 | 2.34 | 3.81 | 2.39 | 3.94 | 3.09 | 4.78 | −0.10 | 3.55 | 3.36 | 3.51 | 6.25 | 3.42 | 5.32 |
| $Sdev$ | 7.29 | 7.99 | 8.63 | 9.46 | 9.46 | 7.15 | 9.76 | 9.89 | 10.25 | 10.02 | 9.15 | 10.04 | 8.51 | 10.94 |
| $Skew$ | −0.88 | −0.26 | −0.84 | −0.59 | −0.99 | −0.61 | −0.43 | −0.20 | −0.39 | −0.31 | −0.82 | −0.83 | −0.40 | −0.23 |
| $Kurt$ | 8.73 | 4.91 | 5.38 | 4.82 | 6.79 | 4.76 | 5.66 | 3.77 | 3.92 | 3.93 | 5.08 | 7.75 | 4.04 | 4.25 |
| $AC_1$ | 0.15 | 0.08 | 0.14 | 0.11 | 0.17 | 0.15 | 0.11 | 0.11 | 0.10 | 0.12 | 0.13 | 0.11 | 0.13 | 0.11 |
| $SR$ | −0.08 | 0.26 | 0.25 | 0.20 | 0.24 | 0.22 | 0.29 | −0.02 | 0.23 | 0.10 | 0.18 | 0.45 | 0.22 | 0.43 |
| $MDD$ | −52.8 | −28.7 | −22.9 | −33.8 | −36.7 | −31.3 | −27.7 | −55.4 | −42.8 | −42.3 | −36.2 | −36.0 | −36.2 | −37.5 |
| *pre-$fp$* | −0.74 | 0.90 | 2.01 | 2.34 | 4.08 | | | −1.40 | 0.08 | 1.17 | 1.52 | 2.83 | | |
| *post-$fp$* | −0.73 | 0.89 | 1.99 | 2.37 | 3.99 | | | −1.37 | 0.06 | 1.19 | 1.50 | 2.76 | | |
| *pre-$\beta$* | −0.32 | 0.03 | 0.45 | 0.72 | 1.19 | | | −1.04 | −0.62 | −0.36 | 0.00 | 0.62 | | |
| | [0.44] | [0.55] | [0.72] | [0.79] | [0.79] | | | [0.98] | [0.94] | [0.86] | [0.67] | [0.59] | | |
| *post-$\beta$* | −0.36 | −0.31 | −0.03 | 0.03 | 0.26 | | | −0.58 | −0.14 | 0.04 | 0.17 | 0.57 | | |
| | (0.06) | (0.04) | (0.06) | (0.05) | (0.07) | | | (0.05) | (0.04) | (0.05) | (0.06) | (0.06) | | |
| $Freq$ | 8.0 | 11.3 | 16.0 | 18.9 | 9.0 | | | 8.1 | 14.6 | 15.8 | 11.5 | 4.3 | | |

**Table 3.5:** ***Portfolios Sorted on Betas.*** *The table presents descriptive statistics of $\beta$-sorted currency portfolios. Each $\beta$ is obtained by regressing individual currency excess returns on the global imbalance risk factor ($HML_{NA}$) using a 36-month moving window that ends in period $t-1$. Portfolio 1 ($P_1$) contains the top 20% of all currencies with the lowest betas whereas Portfolio 5 ($P_5$) contains the top 20% of all currencies with the highest betas. $DOL$ denotes the average return of the five currency portfolios. $HML$ denotes a long-short strategy that buys $P_5$ and sells $P_1$. Excess returns are expressed in percentage per annum. The table also reports the first order autocorrelation coefficient ($AC_1$), the annualized Sharpe ratio ($SR$), the maximum drawdown ($MDD$) in percent, the pre- and post-formation $\beta$s, and the pre- and post-formation forward premia ($fp$), and the frequency of portfolio switches ($Freq$). Standard errors are reported in parentheses and standard deviations in brackets. The sample runs from October 1983 to December 2011, and comprises 338 observations.*

$HML_{FX}$ and $VOL_{FX}$ are equally powerful at pricing the cross-section of currency portfolios, confirming that carry trade returns are compensation for time-varying risk and there exists only one global risk factor. In this section I compare the global imbalance risk factor to $HML_{FX}$ and $VOL_{FX}$, ultimately to show that the global imbalance risk is able to replicate their information content for the purpose of pricing carry trade returns.

I first consider horse races between the global imbalance risk factor and the $HML_{FX}$ of Lustig et al. (2011) using three different specifications: i) I include $DOL$, $HML_{NA}$, and $HML_{FX}$ jointly in the pricing kernel, ii) I include all three factors but orthogonalize $HML_{FX}$ with respect to $HML_{NA}$ (i.e., $HML_{FX}^{\perp}$), and iii) I include all three factors but orthogonalize $HML_{NA}$ with respect to $HML_{FX}$ (i.e., $HML_{NA}^{\perp}$). In the first specification, the global imbalance factor and the slope factor are correlated. In this case, I examine, as suggested by Cochrane (2005), the statistical significance of the factor loadings $b$s rather than the statistical significance of the factor risk premia $\lambda$s, to test whether a factor is marginally useful in pricing assets given the presence of another factor. However, as shown in Panel A of Table 3.6, I find that the SDF slopes ($b_{NA}$ and $b_{FX}$) of both factors turn insignificant, and neither factor is able to drive out the other. This result is confirmed for both sets of countries. In the second and third specifications I acknowledge that $HML_{FX}$ and $HML_{NA}$ are correlated and attempt to mitigate the effect of multicollinearity by simply orthogonalizing one factor against the other. The goal of these exercises is to test whether the orthogonal components of either factor is priced, while avoiding the statistical inference problem that multicollinearity may cause. Moving along Panel A, it can be seen that neither $HML_{FX}^{\perp}$ nor $HML_{NA}^{\perp}$ is priced in the cross-section of carry trade returns, thus suggesting that $HML_{NA}$ replicates $HML_{FX}$ reasonably well and there is no additional information in $HML_{FX}$ that is not captured by $HML_{NA}$. In Panel B of Table 3.6, I present comparisons between the global imbalance risk factor $HML_{NA}$, and the $VOL_{FX}$ factor of Menkhoff et al. (2012). I find that $HML_{NA}$ is largely comparable to $VOL_{FX}$ as $HML_{NA}$ reproduces the pricing information content of $VOL_{FX}$. In essence, the discussion of the results in Panel A applies also to the results in Panel B.

**Yearly Rebalanced Portfolios.** In Table 3.7 I present cross-sectional asset pricing tests for the full sample of countries when portfolio returns and risk factors are rebalanced at the end of each year. In Panel A, the test assets are five currency portfolios sorted on the one-year forward premia while $DOL$ and $HML_{NA}$ act as risk factors. I replace $HML_{NA}$ with $HML_{FX}$ in Panel B, and $HML_{NA}$ with $VOL_{FX}$ in Panel C. The market price of global imbalance risk $\lambda_{NA}$ is equal to 5 percent

| Panel A: $HML_{NA}$ vs. $HML_{FX}$ | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $DOL$ | $HML_{NA}$ | $HML_{FX}$ | $R^2$ | $HJ$ | $DOL$ | $HML_{NA}$ | $HML^{\perp}_{FX}$ | $R^2$ | $HJ$ | $DOL$ | $HML^{\perp}_{NA}$ | $HML_{FX}$ | $R^2$ | $HJ$ |
| | | | | | | | | *All Countries* | | | | | | | |
| $b$ | −0.04 | 0.54 | 0.42 | 0.87 | 0.14 | −0.04 | 1.33 | 1.89 | 0.87 | 0.14 | −0.04 | 0.70 | 0.71 | 0.87 | 0.14 |
| | (0.39) | (1.40) | (0.54) | | [0.08] | (0.39) | (0.64) | (2.44) | | [0.08] | (0.39) | (1.80) | (0.34) | | [0.08] |
| $\lambda$ | 0.01 | 0.04 | 0.06 | | | 0.01 | 0.04 | 0.01 | | | 0.01 | 0.01 | 0.06 | | |
| | (0.02) | (0.04) | (0.02) | | | (0.02) | (0.04) | (0.02) | | | (0.02) | (0.03) | (0.02) | | |
| | | | | | | | | *Developed Countries* | | | | | | | |
| $b$ | 0.07 | 0.18 | 0.29 | 0.94 | 0.06 | 0.07 | 0.83 | 1.73 | 0.94 | 0.06 | 0.07 | 0.22 | 0.37 | 0.94 | 0.06 |
| | (0.23) | (2.35) | (0.89) | | [0.70] | (0.23) | (0.60) | (5.27) | | [0.70] | (0.23) | (2.83) | (0.27) | | [0.70] |
| $\lambda$ | 0.01 | 0.03 | 0.05 | | | 0.01 | 0.03 | 0.01 | | | 0.01 | 0.01 | 0.05 | | |
| | (0.02) | (0.07) | (0.02) | | | (0.02) | (0.07) | (0.03) | | | (0.02) | (0.06) | (0.02) | | |

| Panel B: $HML_{NA}$ vs. $VOL_{FX}$ | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $DOL$ | $HML_{NA}$ | $VOL_{FX}$ | $R^2$ | $HJ$ | $DOL$ | $HML_{NA}$ | $VOL^{\perp}_{FX}$ | $R^2$ | $HJ$ | $DOL$ | $HML^{\perp}_{NA}$ | $VOL_{FX}$ | $R^2$ | $HJ$ |
| | | | | | | | | *All Countries* | | | | | | | |
| $b$ | −0.09 | 2.54 | 1.14 | 0.87 | 0.14 | −0.09 | 1.99 | 1.40 | 0.87 | 0.14 | −0.09 | 1.12 | −1.19 | 0.87 | 0.14 |
| | (0.35) | (1.70) | (1.71) | | [0.23] | (0.35) | (0.99) | (2.11) | | [0.23] | (0.35) | (0.75) | (0.59) | | [0.23] |
| $\lambda$ | 0.01 | 0.10 | −0.02 | | | 0.01 | 0.10 | 0.02 | | | 0.01 | 0.12 | −0.07 | | |
| | (0.02) | (0.04) | (0.01) | | | (0.02) | (0.04) | (0.02) | | | (0.02) | (0.09) | (0.03) | | |
| | | | | | | | | *Developed Countries* | | | | | | | |
| $b$ | 0.16 | 1.68 | 0.87 | 0.99 | 0.03 | 0.16 | 1.28 | 1.05 | 0.99 | 0.03 | 0.16 | 0.79 | −0.80 | 0.99 | 0.03 |
| | (0.25) | (0.95) | (1.04) | | [0.93] | (0.25) | (0.61) | (1.27) | | [0.93] | (0.25) | (0.45) | (0.38) | | [0.93] |
| $\lambda$ | 0.01 | 0.07 | −0.01 | | | 0.01 | 0.07 | 0.02 | | | 0.01 | 0.08 | −0.05 | | |
| | (0.02) | (0.03) | (0.01) | | | (0.02) | (0.03) | (0.01) | | | (0.02) | (0.07) | (0.03) | | |

**Table 3.6:** ***Asset Pricing:*** $HML_{NA}$***,*** $HML_{FX}$***, and*** $VOL_{FX}$***.*** *Panel A presents cross-sectional asset pricing results for the linear factor model based on the dollar (DOL), the global imbalance (*$HML_{NA}$*), and the slope (*$HML_{FX}$*) risk factor.* $HML^{\perp}_{NA}$ *(*$HML^{\perp}_{FX}$*) denotes a factor orthogonalized with the respect to* $HML_{FX}$ *(*$HML_{NA}$*). In Panel B, I replace* $HML_{FX}$ *with the global volatility (*$VOL_{FX}$*) risk factor. The test assets are excess returns to five currency (FX) portfolios sorted on the one-month forward premia. The table reports first-stage estimates of the factor loadings b, the market price of risk* $\lambda$*, and the cross-sectional* $R^2$*. Newey and West (1987) standard errors with Andrews (1991) optimal lag selection are reported in parentheses.* $\chi^2$ *denotes the test statistics (with p-value in parentheses) for the null hypothesis that all pricing errors are jointly zero.* $HJ$ *refers to the Hansen and Jagannathan (1997) distance (with simulated p-value in parentheses) for the null hypothesis that the* $HJ$ *distance is equal to zero. Excess returns are expressed in percentage per annum and adjusted for transaction costs. The portfolios are rebalanced monthly from October* 1983 *to December* 2011*.*

| Panel A: Global Imbalance Factor ($HML_{NA}$) | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | $b_{DOL}$ | $b_{NA}$ | $\lambda_{DOL}$ | $\lambda_{NA}$ | $R^2$ | $RMSE$ | $\chi^2$ | $HJ$ |
| $GMM_1$ | $-1.83$ | 9.10 | 0.01 | 0.05 | 0.71 | 1.85 | 1.04 | 0.28 |
| | (2.04) | (4.77) | (0.02) | (0.02) | | | [0.79] | [0.82] |
| $GMM_2$ | $-2.05$ | 9.94 | 0.01 | 0.05 | 0.69 | 1.90 | 0.99 | |
| | (2.01) | (4.28) | (0.02) | (0.02) | | | [0.80] | |
| $FMB$ | $-1.76$ | 8.78 | 0.01 | 0.05 | 0.71 | 1.85 | 1.10 | |
| | (2.19) | (3.88) | (0.02) | (0.02) | | | [0.78] | |
| | [2.38] | [4.48] | [0.02] | [0.02] | | | | |
| Panel B: Slope Factor ($HML_{FX}$) | | | | | | | | |
| | $b_{DOL}$ | $b_{FX}$ | $\lambda_{DOL}$ | $\lambda_{FX}$ | $R^2$ | $RMSE$ | $\chi^2$ | $HJ$ |
| $GMM_1$ | 0.37 | 1.04 | 0.01 | 0.03 | 0.55 | 2.29 | 3.86 | 0.47 |
| | (2.13) | (1.56) | (0.02) | (0.04) | | | [0.28] | [0.43] |
| $GMM_2$ | 0.37 | 1.96 | 0.02 | 0.07 | $-0.22$ | 3.96 | 3.43 | |
| | (2.09) | (1.45) | (0.02) | (0.04) | | | [0.33] | |
| $FMB$ | 0.36 | 1.01 | 0.01 | 0.03 | 0.55 | 2.29 | 3.91 | |
| | (1.98) | (1.40) | (0.02) | (0.04) | | | [0.27] | |
| | [2.05] | [1.26] | [0.02] | [0.03] | | | | |
| Panel C: Global Volatility Factor ($VOL_{FX}$) | | | | | | | | |
| | $b_{DOL}$ | $b_{VOL}$ | $\lambda_{DOL}$ | $\lambda_{VOL}$ | $R^2$ | $RMSE$ | $\chi^2$ | $HJ$ |
| $GMM_1$ | $-0.91$ | $-6.12$ | 0.01 | $-0.04$ | 0.71 | 1.85 | 3.62 | 0.45 |
| | (2.83) | (7.41) | (0.02) | (0.03) | | | [0.31] | [0.54] |
| $GMM_2$ | $-1.59$ | $-7.64$ | 0.01 | $-0.04$ | 0.70 | 1.86 | 3.48 | |
| | (2.29) | (4.48) | (0.02) | (0.03) | | | [0.32] | |
| $FMB$ | $-0.88$ | $-5.90$ | 0.01 | $-0.04$ | 0.71 | 1.85 | 3.66 | |
| | (2.22) | (4.02) | (0.02) | (0.03) | | | [0.30] | |
| | [2.55] | [5.58] | [0.02] | [0.04] | | | | |

**Table 3.7:** ***Asset Pricing: Yearly Rebalanced Portfolios.*** *The table presents cross-sectional asset pricing results when currency portfolios are rebalanced yearly. The test assets are excess returns to five currency (FX) portfolios sorted on the one-year forward premia. In Panel A, the linear factor model comprises the dollar (DOL) and the global imbalance ($HML_{NA}$) risk factor. $HML_{NA}$ is replaced by the slope ($HML_{FX}$) risk factor in Panel B, and by the global volatility ($VOL_{FX}$) risk factor in Panel C. The table reports GMM (first and second-stage) and Fama-MacBeth (FMB) estimates of the factor loadings b, the market price of risk $\lambda$, and the cross-sectional $R^2$. Newey and West (1987) standard errors with Andrews (1991) optimal lag selection are reported in parentheses whereas Shanken (1992) standard errors are reported in brackets. $\chi^2$ denotes the test statistics (with p-value in parentheses) for the null hypothesis that all pricing errors are jointly zero. $HJ$ refers to the Hansen and Jagannathan (1997) distance (with simulated p-value in parentheses) for the null hypothesis that the $HJ$ distance is equal to zero. Excess returns are expressed in percentage per annum and adjusted for transaction costs. The portfolios are rebalanced yearly from December* 1983 *to December* 2011*, and are based on currencies from all countries.*

per annum and is statistically significant. The result is invariant to the estimation technique, and is further confirmed by a cross-sectional $R^2$ revolving around 70 percent. In contrast, the market price of risk attached to the slope factor $\lambda_{FX}$ and the global volatility factor $\lambda_{VOL}$ are both statistically insignificant. In terms of economic significance, I find that $HJ$ distances – the maximum mispricing possible per unit of standard deviation – of $HML_{FX}$ (47%) and $VOL_{FX}$ (45%) are larger than the $HJ$ distance of $HML_{NA}$ (28%). Thus, global imbalance risk seems to outperform both the slope factor and the global volatility factor in terms of smaller pricing errors.[21] Overall, these results suggest that $HML_{NA}$ has a strong ability to price carry trade portfolios across rebalancing frequencies. This is more than a trivial mechanical statement, as manifested by the weak pricing performance of $HML_{FX}$ and $VOL_{FX}$ at this lower frequency.

## 3.6 Further Analysis

In this section, I present a battery of additional exercises that support the risk-based interpretation of currency excess returns proposed in the previous section.

**Removing Illiquid Currencies.** Table 3.8 displays the cross-sectional asset pricing results when currencies with limited liquidity are removed from the pool of available currencies. Using the latest *Bank for International Settlements*, I select the top 20 most liquid currencies and name this sample 'developed and emerging countries'.[22] I hypothesize that while forward rates may be available for a large number of currencies, there would have been low liquidity in many of them. Additionally, the imposition of capital controls in a number of the emerging market nations would have made it almost impossible to engage in a carry trade strategy in the FX market. If this is the case, I would anticipate that the asset pricing results for a limited subset of the most liquid currencies would show an improvement over and above the full sample. In addition I would expect the link between $HML_{NA}$ and $HML_{FX}$ to grow stronger once I exclude the most illiquid currencies. The economic intuition is that while on paper higher interest rates are exploitable, the market reality may be very different and could result in a situation of observed high interest rates but no significant movement in net foreign assets. In Panel A I report cross-sectional asset pricing results. I find a market price of risk for $HML_{NA}$ equal to approximately 6 percent per annum, in line with the earlier results for all countries and developed countries. Moreover, the standard error remains around 2 percent per annum, resulting in $\lambda_{NA}$ being highly statistically significant. Again I find a $DOL$ price of risk of around 1 percent per annum but, as before, this risk

[21] Note that the $HJ$ distance - the least-square distance between a given pricing kernel and the closest point in the set of the pricing kernels that can price the base assets correctly - is estimated using the standard $GMM$ procedure where the weighting matrix is simply the inverse of the covariance matrix of the asset returns. I cannot use the optimal weighting matrix for model comparisons as the weights are specific to each model. In contrast, the inverse of the covariance matrix of asset returns is invariant across models, so that the $HJ$ distance offers a uniform measure across different models.

[22] This is the set of currencies employed by Deutsche Bank for its global carry trade (Global Currency Harvest) strategy. Appendix Table B.5 reports the descriptive statistics for this set of

| Panel A: Factor Prices | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | $b_{DOL}$ | $b_{NA}$ | $\lambda_{DOL}$ | $\lambda_{NA}$ | $R^2$ | $RMSE$ | $\chi^2$ | $HJ$ |
| $GMM_1$ | $-0.03$ | 0.91 | 0.01 | 0.06 | 0.80 | 1.94 | 3.33 | 0.12 |
| | (0.25) | (0.47) | (0.02) | (0.02) | | | [0.34] | [0.48] |
| $GMM_2$ | 0.07 | 1.15 | 0.01 | 0.06 | 0.79 | 1.98 | 2.83 | |
| | (0.23) | (0.44) | (0.02) | (0.02) | | | [0.42] | |
| $FMB$ | $-0.03$ | 0.91 | 0.01 | 0.06 | 0.80 | 1.94 | 3.33 | |
| | (0.21) | (0.38) | (0.02) | (0.02) | | | [0.34] | |
| | [0.20] | [0.37] | [0.02] | [0.02] | | | | |

| Panel B: Factor Betas | | | | |
|---|---|---|---|---|
| | $\alpha$ | $\beta_{DOL}$ | $\beta_{NA}$ | $R^2$ |
| $P_1$ | 0.01 | 0.95 | $-0.41$ | 0.78 |
| | (0.01) | (0.05) | (0.06) | |
| $P_2$ | $-0.01$ | 1.00 | $-0.15$ | 0.83 |
| | (0.01) | (0.04) | (0.04) | |
| $P_3$ | 0.01 | 0.98 | 0.00 | 0.87 |
| | (0.01) | (0.03) | (0.03) | |
| $P_4$ | $-0.01$ | 1.11 | 0.10 | 0.85 |
| | (0.01) | (0.04) | (0.05) | |
| $P_5$ | 0.02 | 0.96 | 0.45 | 0.70 |
| | (0.01) | (0.09) | (0.06) | |

**Table 3.8:** ***Asset Pricing: Liquid Currencies.*** *The table presents cross-sectional asset pricing results for the top 20 most liquid currencies - Developed and Emerging Countries. The linear factor model is based on the dollar (DOL) and the global imbalance ($HML_{NA}$) risk factor. The test assets are excess returns to five currency (FX) portfolios sorted on the one-month forward premia. Panel A reports GMM (first and second-stage) and Fama-MacBeth (FMB) estimates of the factor loadings b, the market price of risk $\lambda$, and the cross-sectional $R^2$. Newey and West (1987) standard errors with Andrews (1991) optimal lag selection are reported in parentheses whereas Shanken (1992) standard errors are reported in brackets. $\chi^2$ denotes the test statistics (with p-value in parentheses) for the null hypothesis that all pricing errors are jointly zero. $HJ$ refers to the Hansen and Jagannathan (1997) distance (with simulated p-value in parentheses) for the null hypothesis that the $HJ$ distance is equal to zero. Panel B reports least-squares estimates of time series regressions with Newey and West (1987) standard errors in parentheses. Excess returns are expressed in percentage per annum and adjusted for transaction costs. The portfolios are rebalanced monthly from October* 1983 *to December* 2011.

factor is not priced in the cross section. I find high $p$-values for the $\chi^2$ test statistic suggesting that I cannot reject the null of zero pricing errors. In addition, I also fail to reject the null that the $HJ$ distance is equal to zero. In Panel B I find similar results to the core results of Table 3.3: $\beta_{DOL}$ is approximately equal to one for all portfolios and I see a monotonic increase in $\beta_{NA}$ from $-0.41$ in Portfolio 1 to 0.45 in Portfolio 5. The $R^2$ statistics are all high, ranging from 70 percent to 87 percent. In Figure 3.3 I present the rolling one-year Sharpe ratio for $HML_{FX}$ and $HML_{NA}$ based on developed and emerging countries. Strikingly, the two series almost perfectly overlap.[23]

currencies.

[23]In a similar vein, I systematically remove from the full sample of currencies both pegged and

**Risk Reversal and Global Imbalance Risk.** I also examine whether global imbalance risk is manifested in the currency options market, i.e., debtor countries with liabilities primarily in foreign currency are perceived to be riskier than creditor countries with liabilities primarily in domestic currencies. Essentially, I take currencies ranked by global imbalances (at time $t$) and document their risk-reversal (at time $t$) rather than their excess returns (at time $t+1$). I compute the risk reversal as the implied volatility of an out-of-the-money call option minus the implied volatility of an equally out-of-the-money put option, scaled by the at-the-money implied volatility in order to allow for a meaningful cross-currency comparison. The risk reversal reflects the cost of a long position in a call with a short position in a put, and it is widely used to quantify whether exchange rate returns are positively or negatively skewed. A negative risk reversal typically suggests that the cost of buying protection against foreign currency depreciation is more expensive than the cost of providing insurance against foreign currency appreciation.

I use over-the-counter quotes from JP Morgan on 1-month at-the-money, 25-delta call options and 25-delta put options from January 1996 to August 2011.[24] The OTC currency option market is characterized by specific trading conventions, and I refer to Della Corte, Sarno, and Tsiakas (2011) for a detailed description.

The results of this exercise are reported in Figure 3.4. The top panels display the average risk-reversal of the five $NA$ portfolios whereas the bottom panels present the cumulative risk-reversals in the extreme $NA$ portfolios. I find that risk reversals follow exactly the pattern implied by global imbalances as the riskiest currency in terms of global imbalance risk have a negative risk reversal whereas the safest currencies in term of global imbalance risk present a positive risk reversal, thus suggesting that the cost of insuring against foreign currency depreciation is more expensive for the former relative to the latter.[25]

**Real Returns.** In Table 3.9, I show that the results are robust to inflation-adjusted returns. At time $t$, I allocate currencies to five portfolios according to their inflation-adjusted forward premia $\left(F_t - S_t\right)/S_t - E_t(\pi^*_{t+1} - \pi_{t+1})$, where $\pi^*_{t+1}$ and $\pi_{t+1}$ denote the one-month foreign and domestic inflation rates at time t+1,

crawling pegged currencies using the classification of Ilzetzki et al. (2009). The asset pricing results remain qualitatively similar.

[24] The sample comprises 35 countries: Argentina, Australia, Brazil, Canada, Chile, China, Colombia, Czech Republic, Denmark, Euro Area, Hong Kong, Hungary, Iceland, India, Indonesia, Israel, Japan, Malaysia, Mexico, New Zealand, Norway, Peru, Philippines, Poland, Russia, Singapore, Slovak Republic, South Africa, South Korea, Sweden, Switzerland, Taiwan, Thailand, Turkey, and United Kingdom.

[25] Appendix Figure B.4 reports a similar figure based on 10-delta options.

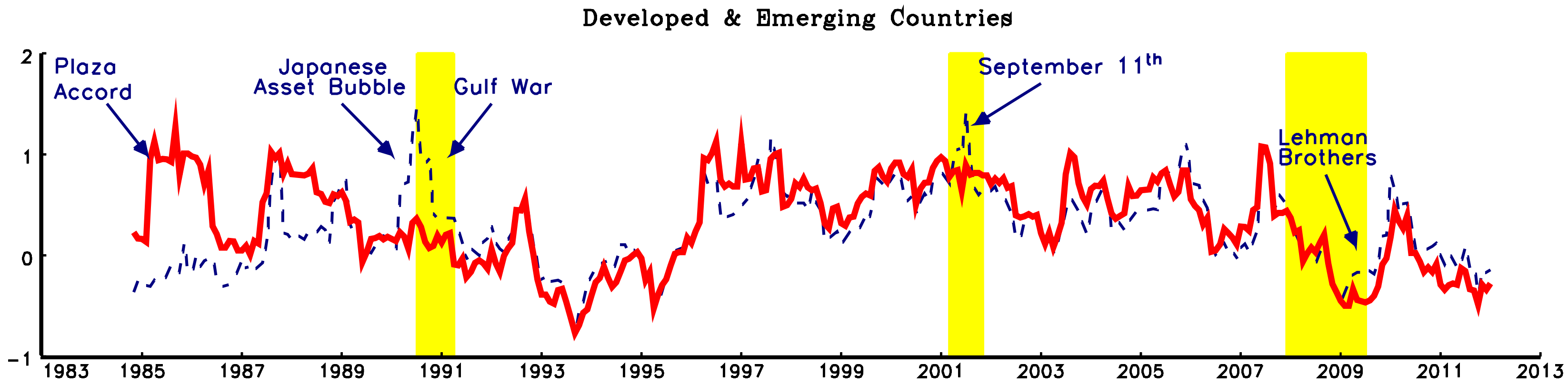


**Figure 3.3:** ***Rolling Sharpe Ratios of Liquid Currencies.*** *The figure presents the one-year rolling Sharpe ratios for the global imbalance risk factor* $HML_{NA}$ *(solid line) and the slope factor* $HML_{FX}$ *(dashed line) when the top 20 most liquid currencies are selected (Developed and Emerging Countries). Shaded areas are the NBER recession periods for the United States. The strategies are rebalanced monthly from October 1983 to December 2011.*

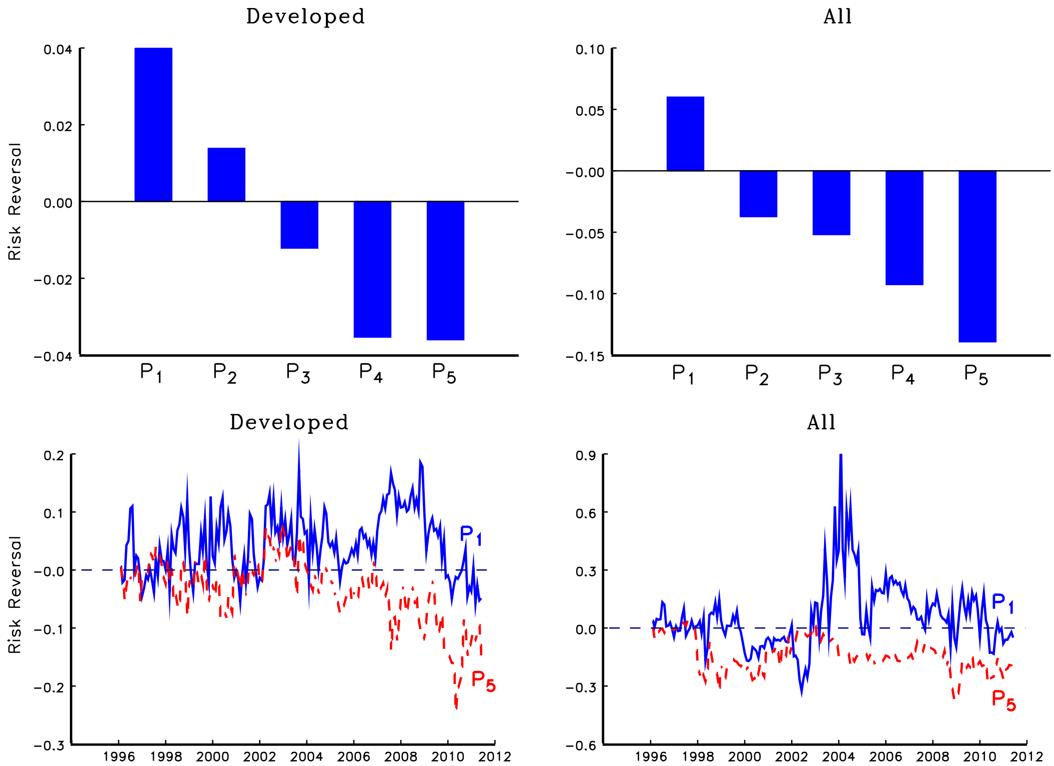


**Figure 3.4: *Risk Reversal and Global Imbalance Risk.*** *The figure presents the one-month risk reversal of the external imbalance portfolios. The risk reversal is computed as the implied volatility of a 25-delta call minus the implied volatility of 25-delta put, scaled by the at-the-money implied volatility. Implied volatility data are from JP Morgan and range from January 1996 to August 2011.*

respectively, and $E_t$ is the conditional expectations operator given information at time $t$. This is equivalent to sorting currencies according to their real, rather than nominal, interest rate differential. Since $\pi^*_{t+1}$ and $\pi_{t+1}$ are not observed at time $t$, I construct inflation forecasts by simply using current inflation, that is I set $E_t(\pi^*_{t+1} - \pi_{t+1}) = \pi^*_t - \pi_t$.[26] Currencies with the lowest real interest rate differential are assigned to Portfolio 1, whereas currencies with the highest real interest rate differential are assigned to Portfolio 5. At time $t+1$, for each currency portfolio I compute either nominal excess returns (left panels) or inflation-adjusted excess returns (right panels) using the inflation rate at time $t+1$ from the perspective of the domestic investor. Note that I use the same $DOL$ and $HML_{NA}$ as in Table 3.3 as risk factors. Panel A reports cross-sectional results whereas Panel B displays

[26]While this assumption is obviously strong, it is empirically motivated since inflation is a very persistent process and current inflation is highly correlated with future inflation at the monthly frequency.

| Panel A: Factor Prices | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $b_{DOL}$ | $b_{NA}$ | $\lambda_{DOL}$ | $\lambda_{NA}$ | $R^2$ | $RMSE$ | $\chi^2$ | $HJ$ | $b_{DOL}$ | $b_{NA}$ | $\lambda_{DOL}$ | $\lambda_{NA}$ | $R^2$ | $RMSE$ | $\chi^2$ | $HJ$ |
| | *Nominal Excess Returns* | | | | | | | | *Real Excess Returns* | | | | | | | |
| $GMM_1$ | −0.27 | 1.86 | 0.01 | 0.08 | 0.95 | 0.69 | 0.80 | 0.04 | −0.76 | 2.03 | −0.02 | 0.08 | 0.95 | 0.68 | 0.88 | 0.05 |
| | (0.35) | (0.90) | (0.02) | (0.03) | | | [0.85] | [0.93] | (0.33) | (0.91) | (0.02) | (0.03) | | | [0.83] | [0.90] |
| $GMM_2$ | −0.29 | 1.92 | 0.01 | 0.08 | 0.95 | 0.70 | 0.79 | | −0.82 | 2.05 | −0.02 | 0.08 | 0.95 | 0.69 | 0.83 | |
| | (0.34) | (0.78) | (0.02) | (0.03) | | | [0.85] | | (0.32) | (0.77) | (0.02) | (0.03) | | | [0.84] | |
| $FMB$ | −0.26 | 1.85 | 0.01 | 0.08 | 0.95 | 0.69 | 0.80 | | −0.75 | 2.03 | −0.02 | 0.08 | 0.95 | 0.68 | 0.88 | |
| | (0.27) | (0.6) | (0.02) | (0.03) | | | [0.85] | | (0.28) | (0.60) | (0.02) | (0.03) | | | [0.84] | |
| | [0.26] | [0.64] | [0.01] | [0.03] | | | | | [0.26] | [0.65] | [0.01] | [0.03] | | | | |

| Panel B: Factor Betas | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | $\alpha$ | $\beta_{DOL}$ | $\beta_{NA}$ | $R^2$ | $\alpha$ | $\beta_{DOL}$ | $\beta_{NA}$ | $R^2$ |
| $P_1$ | 0.01 | 0.85 | 0.02 | 0.64 | −0.02 | 0.86 | 0.02 | 0.64 |
| | (0.01) | (0.05) | (0.07) | | (0.01) | (0.05) | (0.07) | |
| $P_2$ | −0.01 | 1.01 | −0.22 | 0.86 | −0.04 | 1.01 | −0.22 | 0.85 |
| | (0.01) | (0.03) | (0.03) | | (0.01) | (0.03) | (0.03) | |
| $P_3$ | 0.01 | 1.06 | −0.09 | 0.85 | −0.03 | 1.07 | −0.09 | 0.85 |
| | (0.01) | (0.04) | (0.04) | | (0.01) | (0.04) | (0.04) | |
| $P_4$ | 0.01 | 1.00 | 0.05 | 0.79 | −0.03 | 1.01 | 0.06 | 0.79 |
| | (0.01) | (0.04) | (0.04) | | (0.01) | (0.04) | (0.04) | |
| $P_5$ | 0.02 | 1.05 | 0.28 | 0.77 | −0.01 | 1.05 | 0.28 | 0.77 |
| | (0.01) | (0.05) | (0.08) | | (0.01) | (0.05) | (0.08) | |

**Table 3.9:** ***Asset Pricing: Test Assets Sorted by Real Interest Rates.*** *The table presents cross-sectional asset pricing results for the linear factor model based on the dollar (DOL) and the global imbalance ($HML_{NA}$) risk factors. The test assets are nominal excess returns (left-hand side) and real excess returns (right-hand side) to five currency (FX) portfolios sorted on the one-month inflation-adjusted forward premia (real interest rate differentials). Panel A reports GMM (first and second-stage) and Fama-MacBeth (FMB) estimates of the factor loadings b, the market price of risk $\lambda$, and the cross-sectional $R^2$. Newey and West (1987) standard errors with Andrews (1991) optimal lag selection are reported in parentheses whereas Shanken (1992) standard errors are reported in brackets. $\chi^2$ denotes the test statistics (with p-value in parentheses) for the null hypothesis that all pricing errors are jointly zero. $HJ$ refers to the Hansen and Jagannathan (1997) distance (with simulated p-value in parentheses) for the null hypothesis that the $HJ$ distance is equal to zero. Panel B reports least-squares estimates of time series regressions with Newey and West (1987) standard errors in parentheses. Excess returns are expressed in percentage per annum and adjusted for transaction costs. The portfolios are rebalanced monthly from October* 1983 *to December* 2011.

time-series estimates. The global imbalance risk premium remains positive and statistically different from zero: the estimate of $\lambda_{NA}$ is about 8 percent per annum for both nominal and real returns, and strongly statistically significant. The cross-sectional $R^2$ remains high, at around 95 percent for both sets of test assets, and I cannot reject the null hypothesis that the pricing errors are zero as well as the null hypothesis that the $HJ$ distance is zero. The $DOL$ risk factor is still not priced in the cross section but turns negative when pricing the real excess returns, possibly indicating the existence of a small inflation premium within $DOL$. Overall, these results are largely comparable to the core findings in Table 3.3. I confirm higher risk premia for currency portfolios whose returns comove positively with the global imbalance factor, and lower risk premia for currency portfolios exhibiting a negative covariance with the global imbalance factor.

**Individual Currencies.** Ang, Liu, and Schwarz (2010) argue that forming portfolios may potentially destroy information by shrinking the dispersion of betas. In Table 3.10 I deal with this concern and present cross-sectional asset pricing tests with individual currency excess returns as test assets. As risk factors, I continue to use the same factors employed in the core analysis. Since the set of currencies is now unbalanced, I only report estimates of time-series betas, market prices of risk, and factor loadings obtained via FMB regressions. Also, since country-level excess returns, especially for currencies with limited trading activity, may be contaminated by outliers, least square estimates can be severely distorted and fail to deliver unbiased estimates. I deal with this problem by using the least absolute deviation (LAD) estimator which is robust to thick-tailed errors and is not sensitive to atypical data points (Bassett and Koenker, 1978; Koenker and Bassett, Jr., 1982). In short, I use the FMB procedure with robust regressions in the first and second step to account for outliers in individual currency excess returns. I report bootstrapped standard errors in parentheses.[27]

In Panel A the test assets are excess returns constructed as long positions in foreign currencies irrespective of the level of interest rates. Note that these individual currency excess returns are not adjusted for transaction costs as ex-ante I ignore whether an investor should buy or sell the foreign currency. I refer to

[27] To calculate bootstrapped standard errors, I simulate $y_{i,t} = \alpha_i + \beta_i f_t + \varepsilon_{i,t}$ and $f_t = \mu + \sum_{i=1}^{p} A_i f_{t-i} + u_t$, where $y_{i,t}$ is the excess return on the $i$-th currency, $\alpha_i$ is the constant, $\beta_i$ is the vector of factor loadings, $f_t$ denotes the risk factors following a $p$-order VAR process, $\varepsilon_{i,t}$ are idiosyncratic residuals, and $u_t \sim N(0, \Sigma)$. I estimate this system, and use the parameter estimates to generate $1,000$ time-series by jointly resampling $\varepsilon_{i,t}$ and $u_t$. Since the panel is unbalanced, I carefully resample the same dates across all individual currencies, and then remove the missing values before running FMB regressions.

these excess returns as unconditional excess returns. On the *left-hand side,* the pricing kernel includes the $DOL$ and $HML_{NA}$ as risk factors. The market price of global imbalance risk is positive and statistically significant: $\lambda_{NA}$ ranges from 5 percent per annum for the set of developed countries to 8 percent per annum for the full set of countries, and these figures are largely comparable to the estimates reported in Table 3.3. The cross-sectional $R^2$ is reasonably high, ranging from 72 percent for developed countries to 40 percent for all countries, but lower than the $R^2$ for portfolio returns. This is expected as individual excess returns are far more noisy than portfolio returns. Moving along Panel A, I present results for $DOL$ and $HML_{FX}$ as risk factors. The market price of slope risk is positive but not always statistically significant. The point estimate of $\lambda_{FX}$ ranges from 5 percent per annum for developed countries to 9 percent per annum for developed and emerging countries, and is statistically significant only in the latter case when I consider the bootstrapped standard errors. On the *right-hand side*, the pricing kernel includes the $DOL$ and $VOL_{FX}$ as risk factors. Here, I uncover statistically significant estimates of $\lambda_{VOL}$ in two out of the three sets of countries.

In Panel B I use as test assets excess returns managed on the basis of interest rate differentials: the U.S. investor buys the foreign currency and sells the U.S. dollar when the forward premium is positive and vice versa (i.e., $RX_{t+1} = \gamma\left(F_t - S_{t+1}\right)/S_t$, where $\gamma = 1$ when $F_t > S_t$, and $\gamma = -1$ when $F_t < S_t$). Results remain largely comparable to the previous panel. In Figure 3.5, I present the fit of the asset pricing model for country-level excess returns for the full set of currencies. I plot the actual average excess returns along the vertical axis, and the average excess returns predicted by $DOL$ and $HML_{NA}$ along the horizontal axis. On the vertical axis, I use unconditional excess returns on the left-hand side chart, and conditional excess returns on the right-hand side chart. The symbols refer to developed countries (solid circle), emerging countries (solid plus), and other countries (diamond). The model-predicted excess returns lie very close to the 45 degree line, suggesting that global imbalance risk explains the spread in average excess returns reasonably well for most of the countries.[28]

**Determinants of Exchange Rate Returns.** Gourinchas and Rey (2007) point out that global imbalances are a key driver of exchange rates. In Gabaix and Maggiori (2013), exchange rates are jointly determined by global imbalances and financiers' risk-bearing capacity. I empirically test these predictions in Table 3.11 where I present results of a panel regression exercise with fixed-effects. The left-

[28]There are of course some exceptions, such as Brazil (BRL), Slovakia (SKK), Turkey (TRY), and Venezuela (VEF).

| | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Panel A: Unconditional Excess Returns | | | | | | | | | | | |
| $\lambda_{DOL}$ | $\lambda_{NA}$ | $R^2$ | $RMSE$ | $\lambda_{DOL}$ | $\lambda_{FX}$ | $R^2$ | $RMSE$ | $\lambda_{DOL}$ | $\lambda_{VOL}$ | $R^2$ | $RMSE$ |
| *All Countries* | | | | | | | | | | | |
| 0.03 | 0.08 | 0.40 | 25.2 | 0.03 | 0.06 | 0.51 | 22.9 | 0.02 | −0.12 | 0.46 | 24.0 |
| (0.02) | (0.03) | | | (0.02) | (0.03) | | | (0.02) | (0.05) | | |
| *Developed & Emerging Countries* | | | | | | | | | | | |
| 0.03 | 0.08 | 0.64 | 11.8 | 0.03 | 0.09 | 0.54 | 13.5 | 0.02 | −0.16 | 0.36 | 15.9 |
| (0.02) | (0.03) | | | (0.02) | (0.03) | | | (0.02) | (0.07) | | |
| *Developed Countries* | | | | | | | | | | | |
| 0.02 | 0.05 | 0.72 | 4.8 | 0.02 | 0.05 | 0.32 | 6.7 | 0.02 | −0.14 | 0.54 | 5.5 |
| (0.02) | (0.02) | | | (0.02) | (0.03) | | | (0.02) | (0.08) | | |
| Panel B: Conditional Excess Returns | | | | | | | | | | | |
| $\lambda_{DOL}$ | $\lambda_{NA}$ | $R^2$ | $RMSE$ | $\lambda_{DOL}$ | $\lambda_{FX}$ | $R^2$ | $RMSE$ | $\lambda_{DOL}$ | $\lambda_{VOL}$ | $R^2$ | $RMSE$ |
| *All Countries* | | | | | | | | | | | |
| 0.04 | 0.08 | 0.24 | 28.9 | 0.04 | 0.12 | 0.29 | 27.8 | 0.04 | −0.14 | 0.23 | 29.3 |
| (0.02) | (0.03) | | | (0.02) | (0.03) | | | (0.02) | (0.07) | | |
| *Developed & Emerging Countries* | | | | | | | | | | | |
| 0.04 | 0.10 | 0.37 | 15.3 | 0.04 | 0.13 | 0.18 | 17.6 | 0.04 | −0.22 | 0.17 | 18.7 |
| (0.02) | (0.03) | | | (0.02) | (0.03) | | | (0.02) | (0.10) | | |
| *Developed Countries* | | | | | | | | | | | |
| 0.03 | 0.06 | 0.46 | 8.0 | 0.04 | 0.13 | −0.28 | 11.0 | 0.03 | −0.22 | 0.30 | 11.9 |
| (0.02) | (0.02) | | | (0.02) | (0.03) | | | (0.02) | (0.13) | | |

**Table 3.10:** ***Asset Pricing: Individual Currencies.*** *The table presents cross-sectional asset pricing results for individual currencies. The linear factor model includes the dollar (DOL), the global imbalance ($HML_{NA}$), the slope ($HML_{FX}$), and the global volatility ($VOL_{FX}$) risk factor. Panel A (Panel B) employs unconditional (conditional) excess returns as test assets. The unconditional excess return for a given currency pair is computed as $RX_{t+1} = (F_t - S_{t+1})/S_t$, where $S_t$ denotes the spot exchange rate and $F_t$ is the one-month forward rate. The conditional excess return is calculated as $RX_{t+1} = \gamma \times (F_t - S_{t+1})/S_t$, where $\gamma = 1$ when $F_t > S_t$ (foreign interest rate is higher than U.S. interest rate) and $\gamma = -1$ when $F_t < S_t$ (foreign interest rate is lower than U.S. interest rate). The table reports estimates of the market price of risk $\lambda$, the cross-sectional $R^2$ and the root mean squared error ($RMSE$) obtained via Fama-MacBeth procedure with robust regressions in the first and second step to account for outliers in individual currency excess returns. Bootstrapped standard errors obtained via 1,000 repetitions are reported in parentheses. The currencies are rebalanced monthly from October* 1983 *to December* 2011.

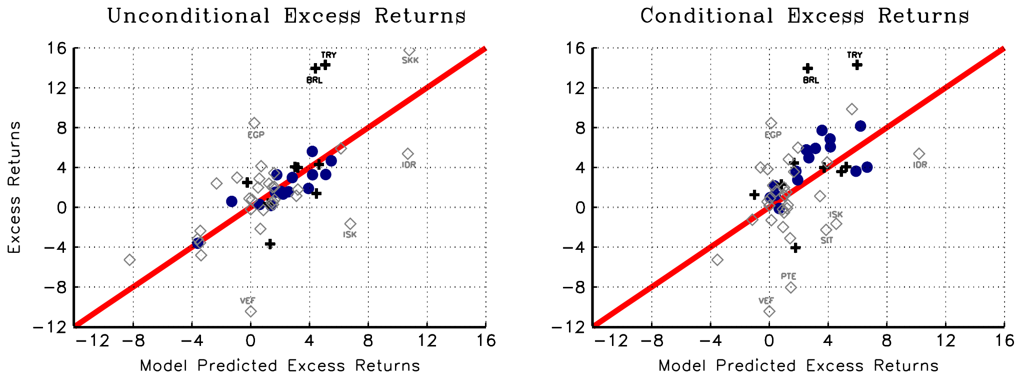


**Figure 3.5:** ***Pricing Errors of Individual Currencies.*** *The figure presents cross-sectional pricing errors for the linear factor model based on the dollar (DOL) and the global imbalance risk ($HML_{NA}$) factor. The test assets are country-level unconditional (left-hand side) and conditional (right-hand side) excess returns. The symbols denote the pricing errors of developed countries (solid circle), emerging countries (solid plus), and other countries (diamond). Excess returns are expressed in percentage per annum. The strategies are rebalanced monthly from October 1983 to December 2011.*

hand-side variable is the monthly exchange rate return. Remember that exchange rates are defined as units of foreign currency per unit of U.S. dollar and a positive return indicates foreign currency depreciation. As right-hand-side variables, I employ the net foreign assets to GDP ratio lagged by 12 months and the interest rate spread lagged by 1 month. In addition, I also allow for an interaction term between the former variables and the change in the VIX index (column 1), and the TED spread (column 2).[29] The VIX index is often used as a proxy for global risk appetite whereas the TED spread is frequently used to proxy funding illiquidity. In the exercise, these measures proxy the willingness and the ability of financiers to absorb exchange rate risk.

For *All* countries, the interaction term between net foreign assets and the change in VIX (as well as the change in TED spread) is significant at the 1 percent significance level with the correct sign. Consistent with the theoretical predictions of Gourinchas and Rey (2007) and Gabaix and Maggiori (2014), currencies depreciate for net debtor countries especially when risk-bearing capacity is low, i.e., global risk appetite is high and funding liquidity constraints are binding. For *Developed* countries, I find that foreign assets and the change in VIX are both significant at the 1 percent significance level with the correct sign, although the interaction term is not significant. Overall, this exercise provides further supportive evidence that global imbalances and risk-bearing capacity are important factors driving exchange rate fluctuations.

[29] I also add a constant and the lagged exchange rate return as a control variable.

| | *All Countries* | | *Developed Countries* | |
|---|---|---|---|---|
| | (1) | (2) | (1) | (2) |
| NFA/GDP (lagged 12 months) | $-0.014$ | 0.021 | $-0.861^{c}$ | $-0.609^{c}$ |
| | [$-0.15$] | [0.22] | [$-4.66$] | [$-3.86$] |
| Interest Rate Spread (lagged 1 month) | $0.408^{c}$ | 0.257 | $-0.055$ | $-0.403^{a}$ |
| | [4.02] | [1.53] | [$-0.21$] | [$-2.11$] |
| Change in VIX | $0.172^{c}$ | | $0.112^{c}$ | |
| | [8.23] | | [3.71] | |
| NFA/GDP (lagged 12 months) × Change in VIX | $-0.069^{c}$ | | $-0.074$ | |
| | [$-3.26$] | | [$-1.13$] | |
| Interest Rate Spread (lagged 1 month) × Change in VIX | 0.036 | | 0.131 | |
| | [1.11] | | [1.09] | |
| Change in TED Spread | | $0.770^{c}$ | | 0.014 |
| | | [2.89] | | [0.04] |
| NFA/GDP (lagged 12 months) × Change in TED Spread | | $-0.907^{c}$ | | $-0.818$ |
| | | [$-2.73$] | | [$-0.87$] |
| Interest Rate Spread (lagged 1 month) × Change in TED Spread | | 0.007 | | 2.098 |
| | | [0.01] | | [1.17] |
| Additional Variables: Constant and lagged exchange rate returns | *YES* | *YES* | *YES* | *YES* |
| Observations | 7045 | 7860 | 2933 | 3557 |

**Table 3.11:** ***Determinants of Exchange Rate Returns.*** *The table presents a fixed-effects panel regression results. We regress monthly exchange rate returns on macroeconomic and financial variables in addition to a constant and the lagged exchange rate returns. Exchange rates are from Datastream, and defined as units of foreign currency per U.S. dollar such that a positive return denotes foreign currency depreciation. Yearly data on GDP and net foreign assets (NFA) are from Lane and Milesi-Ferretti (2007). Interest rate spreads are computed via covered interest rate parity using spot and forward exchange rates. The VIX index is collected from the Chicago Board of Options Exchange whereas the TED Spread is collected from the FRED database of the Federal Reserve Bank of St. Louis. Data on the VIX is available from 1990 onwards, while data on the TED Spread is available from 1986 onwards. Robust standard errors are clustered at country level. We report t-statistics in brackets. The superscripts a, b and c denote statistical significance at 10, 5 and 1 percent level, respectively.*

## 3.7 Conclusions

The large and sudden depreciation of high-interest currencies in the aftermath of the Lehman Brothers' collapse has revived interest in the risk-return profile of the carry trade, a popular strategy that exploits interest rate differentials across countries. If high-interest rate currencies deliver low returns when consumption is low, then currency excess returns simply compensate investors for higher risk exposure and carry trade returns reflect time-varying risk premia (Fama, 1984; Engel, 1996). In a recent attempt to validate this risk-based explanation, Lustig et al. (2011) propose a return-based factor that helps explain the difference in the average returns between baskets of high and low interest rate currencies. While this approach establishes that there is systematic risk in carry trades, it is silent about the economic determinants underlying currency premia. Related work has posited the existence of a 'crash' premium to compensate investors for large and sudden drawdowns in carry trades. But again, this explanation provides limited intuition surrounding the economic rationale for why a currency depreciation is required.

This essay tackles exactly this issue by shedding empirical light on the *macroeconomic* forces driving currency premia and crashes in the currency market. Motivated by the models of Gourinchas and Rey (2007), Gourinchas (2008), and Gabaix and Maggiori (2014), I construct a risk factor that captures exposure to global imbalances and the currency denomination of external liabilities, and show that it explains the bulk of excess returns in a standard asset pricing model. The economic intuition for the factor is as follows: debtor countries offer a currency risk premium to compensate investors willing to finance negative external imbalances. Following an external shock, debtor nations experience a sharp currency depreciation to restore balance in their net foreign asset position - a depreciation that is amplified in countries with predominantly foreign currency denominated liabilities. This finding suggests that carry trade investors can be viewed as taking on global imbalance risk.

Overall, I provide empirical support for the existence of a meaningful link between exchange rate returns and macroeconomic fluctuations. The global risk factors previously identified in the currency market can be viewed as global imbalance risk: a fundamental and theoretically motivated source of risk driving currency returns.

# Chapter 4

# The Mystery of Currency Betas

## 4.1 Introduction

An investor who simultaneously lends in high-interest-rate currencies and borrows in low-interest-rate currencies will, on average, make a profit. This is perhaps the most widely cited puzzle in international finance and a result often attributed as compensation for bearing risk (Hansen and Hodrick, 1980; Fama, 1984; Lustig and Verdelhan, 2007; Lustig, Roussanov, and Verdelhan, 2011).[1] Yet the finding raises a fundamental question: *why* are high-interest-rate currencies more likely to depreciate during 'bad times', and thus expected to earn a higher rate of return than low-interest-rate currencies?

Understanding the source of heterogeneous exposure to currency risk is important. It is well known to currency and risk managers that high-yielding currencies have the highest expected return (the highest beta).[2] Yet the underpinning macroeconomic explanation for *why* this is the case goes unresolved. If the fundamental source of exposure to risk is relatively stable compared to interest rates, then a strategy which loads positively on the exposure could generate higher returns, lower volatility and reduced transaction costs relative to a standard 'carry-trade'.

[1] Other early work in this area includes Tryon (1979) and Bilson (1981). Useful surveys of the literature include Froot and Thaler (1990), Lewis (1995) and Engel (1996), while Koijen, Moskowitz, Pedersen, and Vrugt (2013) provide recent empirical evidence across assets. Other explanations exist in the literature for why high-interest-rate currencies earn a high expected return – the so called "forward-premium puzzle." These include, among others, 'peso' problems (Burnside, Eichenbaum, Kleshchelski, and Rebelo, 2011a), funding liquidity spirals (Brunnermeier, Nagel, and Pedersen, 2008; Gabaix and Maggiori, 2014), overconfidence (Burnside, Han, Hirshleifer, and Wang, 2011b) and adverse selection problems within the foreign exchange market (Burnside, Eichenbaum, and Rebelo, 2009).

[2] In fact, the carry-trade – investing in high-yielding currencies while funding the position by borrowing in low-yielding currencies – is the most popular quantitative strategy in the foreign exchange market (Galati, Heath, and McGuire, 2007; Rime and Schrimpf, 2013).

Furthermore, changes in exposure to risk may be relatively easier to forecast than interest rates, alerting currency managers to changes in the underlying riskiness of a portfolio in a more timely and efficient manner. Moreover, if we can develop a firm understanding of *why* some currencies are more (or less) exposed to risk – why betas differ across currencies – it could feedback to provide richer insights into the fundamental source of macroeconomic risk itself.

Most empirical attempts to understand currency premia largely ignore beta and, instead, approach the topic by investigating the nature of risk. Usually this involves the construction of a risk factor, to which currencies are shown to exhibit heterogeneous exposure. In particular, following the path breaking work of Lustig, Roussanov, and Verdelhan (2011), who demonstrate that a single 'global' risk factor (*Slope* risk) can explain the cross section of currency excess returns, a number of alternative factors have been proposed– replacing *Slope* risk – which are shown to perform equally well in explaining currency portfolio returns. These alternative risks include: innovations in currency volatility (Menkhoff, Sarno, Schmeling, and Schrimpf, 2012), skewness Rafferty (2012) and correlation (Mueller, Stathopoulos, and Vedolin, 2013), as well as 'downside' market risk (Dobrynskaya, 2013; Galsband and Nitschka, 2013; Lettau, Maggiori, and Weber, 2013).

Three concerns arise from this approach. First, the factors tell us nothing about *why* currencies exhibit heterogeneous exposure to risk – beta remains a mystery. Next, the factors tend to be at arms-length from fundamental macroeconomic considerations. That a high-interest-rate currency, for example, depreciates in months when currency volatility, skewness or correlations rise, or when the U.S. stock market falls, tells us little about whether consumption growth shocks (traditionalist), animal spirits (behaviorist), or some other fundamental explanation for asset price movements, is at play. Finally, the surge in newly proposed currency factors echoes developments in the maturer equity market literature that is characterized by an ever expanding set of new 'risk factors' (Harvey, Liu, and Zhu, 2013). In fact, this phenomenon has generated a growing literature critiquing empirical asset pricing, by showing that many equity factors may only have a spurious relationship with equity portfolio returns (Lewellen, Nagel, and Shanken, 2010; Kan, Robotti, and Shanken, 2013) and indeed, have little correlation with other proposed factors (Daniel and Titman, 2012).

It seems therefore, that the possibility of witnessing a factor proliferation in the currency literature, similar to that already observed for the equity market, should perhaps be met with lukewarm enthusiasm. This is particularly the case if factors are not supported by a strong theoretical basis, leading to concerns over potential 'fishing' within the data for new factors, which then provide limited economic insight for why currencies exhibit heterogeneous betas. These factors may have no intrinsic relationship with the 'true' risk factor but, due to statistical biases, are supported in standard empirical asset pricing tests.

In this chapter, I investigate currency betas. In doing so, I attempt to alleviate the three concerns raised above by (i) exploring *why* certain currencies have higher betas than others, (ii) linking the source of beta with fundamental macroeconomic explanations, underpinned by leading theoretical models of currency premia, and (iii) showing that by investigating currency beta, standard empirical asset pricing techniques *can* filter out spurious currency risk factors.

A natural starting point in investigating currency betas and to avoid 'data snooping' criticisms, is the theoretical literature on currency premia. Theoretical models of currency premia provide a precise link between a currency's beta and an underlying macroeconomic state variable or 'characteristic'. In this regard, we have been fortunate to have witnessed a recent surge in new theoretical developments in currency research. In particular, recent consumption-based models in international finance, which have made considerable progress in explaining various currency market puzzles,[3] provide a rich variety of explanations for the fundamental source of heterogenous risk exposure.[4] But these theoretical predictions are rarely discussed and have not been empirically scrutinized in the literature.

I begin by investigating the predictions made by these leading consumption-based models. To do so, I construct 'characteristic' factors from currency portfolios, which are sorted on the basis of the 'characteristic' predicted to explain currency betas. If the predictions are accurate, then the factors should perform well in explaining the cross-section of currency portfolio returns. High-interest-rate (high-beta) currencies should load positively on the factor, while low-interest-rate (low-beta) currencies should load negatively. I focus on the external-habit model of Verdelhan (2010), the long-run risks model of Colacito and Croce (2013) and the variable rare disasters models of Farhi and Gabaix (2013). The test group of models reflect the main three branches, or variations, of the consumption-based model in use today and represent the analogous group of models to those investigated in an equity market setting by Van Binsbergen, Brandt, and Koijen (2012).[5]

[3]Including, for example, the Backus and Smith (1993) puzzle as to why the correlation between consumption and real exchange rates is approximately zero.

[4]Lustig et al. (2011) find that the 'unconditional' carry-trade accounts for almost half of total carry-trade returns. That is, investing in currencies which, on average, have high interest rates generates a sizeable spread in currency returns. Ready, Roussanov, and Ward (2013) show, in a model of currency premia, that a country's exports of primary commodities can help explain unconditional carry-trade returns. The models examined in this chapter, however, seek to explain *conditional* currency betas.

[5]In their paper, the authors focus on the habit preferences model of Campbell and Cochrane

I find that the theoretically grounded factors cannot price any of the cross-section of currency portfolio returns. In fact, within a standard two-pass asset pricing test, I find that each theoretically motivated model generates a *negative* cross-sectional $R^2$, large pricing errors and a large root-mean-squared error. Additionally, I find the factor itself has a zero or negative correlation with the *Slope* risk factor of Lustig et al. (2011) and, in only one instance, does the factor have a positive t-statistic exceeding 2.0. In fact, for the case of the long-run risks model of Colacito and Croce (2013), the factor price of risk is significant but negative, indicating that the model's prediction regarding currency betas are diametrically opposed to the empirical reality. These findings overall are particularly surprising, given that the test assets are characterized by a strong factor structure, which has been shown by Lewellen et al. (2010) to make empirical asset pricing a less burdensome task.

Given the inability of leading theoretical models to explain currency betas, I ask the question: can *any* fundamentally based factor explain why currencies exhibit heterogenous exposure to risk? To answer the question I perform a 'fishing' exercise, by investigating alternative characteristic factors which lack a theoretical basis. Specifically, using data from the Political Risk Services (PRS) Group, I construct 25 alternative characteristic factors based on country-level macroeconomic, financial and political risks. In contrast to the theoretically grounded factors, these alternative characteristic based factors are found to be overwhelmingly successful in explaining currency portfolio returns and thus in offering explanations for heterogenous betas across currencies. In fact, I find that 20 of the 25 factors have a t-statistic exceeding 2.0, while all macroeconomic-based factors are 'priced', with a t-statistic in excess of 3.0 and a cross-sectional $R^2$ of between 60 and 80 percent. Some of the alternative factors even exhibit comparable pricing performance to the benchmark *Slope* factor of Lustig et al. (2011).

In light of this finding, a question arises as to whether assessing a model's ability to predict currency betas by constructing a factor to explain currency portfolio returns is, in fact, a sufficiently high benchmark. Despite the fact that none of the leading theoretical models assessed in this chapter were able to pass the test, it is possible to imagine a future scenario where competing theories meet this baseline threshold. To address this concern, I perform a simple secondary test, to determine if the non-theoretical characteristic factors can *also* explain the returns to a natural alternative set of currency portfolios.

The alternative set of test assets are currency portfolios, formed by sorting currencies on the same characteristic as the factor itself. As an example, if currency

(1999), the long-run risks model of Bansal and Yaron (2004) and the variable rare disaster model of Gabaix (2012) which is based on the earlier work of Rietz (1988) and Barro (2006).

betas are determined by a country's size (GDP), then the factor reflecting GDP should explain returns to (i) currency portfolios sorted by interest rates (the standard set of currency test assets), and (ii) currency portfolios sorted by GDP, since these portfolios should also generate a sizeable cross-sectional spread in returns. When I subject the 25 alternative factors to this second test, I find that *none* of the factors generate a t-statistic exceeding 2.0, while this time, 20 of the 25 models generate a negative cross-sectional $R^2$ in a standard empirical asset pricing test.

To explore the issue further, I randomly generate 20,000 sets of test asset portfolios by arbitrarily sorting currencies and, from these test portfolios, construct 20,000 'useless' factors. That is, each randomly generated set of test assets is associated with a randomly generated factor. I use these 'useless' factors, which contain no economic content, in standard asset pricing tests to explain (i) currency portfolios sorted by interest rates and (ii) currency portfolios sorted by the same criteria (the random 'characteristic') as the factor.

When pricing interest-rate-sorted portfolios, these 'useless' factors perform well, supporting the critique of Lewellen et al. (2010). In fact, I find that 36 percent have a t-statistic over 2.0, while 20 percent of factors help generate a cross-sectional $R^2$ over 70 percent.[6] However, when the 'useless' factors price the portfolios from which they were created – an exercise equivalent to pricing currency portfolios sorted by the same characteristic as the factor – less than 5 percent are significant, while only 3 percent of models generate a cross-sectional $R^2$ over 70 percent. In fact, less than 1.5 percent of all 'useless' factors can explain *both* interest-rate-sorted portfolios *and* randomly sorted portfolios from which the factor was constructed.

Overall, this essay calls for a stricter empirical benchmark for judging all new theories of currency risk premia. A theoretical model of currency premia should provide a precise and fundamental explanation for variation in currency betas. These predictions should naturally lead to the construction of a characteristic factor that is capable of pricing currency portfolios sorted by (i) interest rates and (ii) the proposed characteristic. Any theoretical model found to pass both tests could be considered a strong candidate explanation for understanding the fundamental source of heterogeneous risk exposure in the currency market and hence a credible theoretical explanation of currency premia. Moreover, the essay offers support that, in spite of the recent criticism, when investigating currency betas, standard empirical asset pricing techniques can filter out around 99 percent of spurious currency risk

[6] I find that a t-statistic of around 2.7 is required for significance at the 95% confidence level. Harvey, Liu, and Zhu (2013) also find that a high t-statistic – much larger than 2.0 and probably greater than 3.0 – is required to deem a candidate factor as exhibiting pricing power within the equity market.

factors.

The remainder of the chapter is organized as follows: in Section 4.2, I describe the empirical methodology. I provide details of the data and portfolio construction in Section 4.3. I present results in Section 4.4 and investigate the impact of changing the test asset portfolios in Section 4.5. In Section 4.6, I run a simulation exercise to investigate 'useless' factors. Finally, I offer concluding remarks in Section 4.7. In Appendix C, I provide further robustness tests and additional supporting analyses.

## 4.2 Empirical Methods

In this section, I outline the background to investigating the leading theoretical models of currency premia, provide details of each model's predictions regarding heterogenous exposure to currency risk and describe the theoretical framework for the empirical analysis. Finally, I describe the observations we would expect to witness if the predictions of the models regarding currency betas are consistent with the data.

### 4.2.1 Background

Lustig et al. (2011) construct a set of currency portfolios, sorted by interest rates and find that a single 'global' risk factor can explain the portfolio returns.[7] The portfolios themselves are found to exhibit a strong factor structure, with two principal components explaining around 90 percent of variation in returns. The authors use this finding to construct two risk factors which correlate highly with the first two principal components, in an application of the Arbitrage Pricing Theory of Ross (1976).

The first risk factor is constructed as an equally weighted average of currency portfolio returns and is denoted *Dollar* risk (*DOL*).[8] The second risk factor, constructed as the difference between returns on the highest- and lowest-interest-rate-sorted portfolios, is denoted *Slope* risk. *Slope* risk explains all of the heterogeneity in currency risk exposure, with high-interest-rate currencies found to be the most exposed to this risk. In fact, *Slope* risk correlates almost perfectly with the second

[7]Strictly, the authors sort by forward premia but, under no-arbitrage conditions, sorting on forward premia is equivalent to sorting on interest rates, and hence the portfolios range from the lowest to the highest-interest-rate currencies. The construction of currency portfolios sorted by forward premia was pioneered by Lustig and Verdelhan (2007). The portfolios are rebalanced monthly and all currencies are quoted relative to the U.S. dollar.

[8]The factor works as a constant in the model and has no pricing power of its own although some recent papers, including Verdelhan (1979) and Maggiori (2013), have given more weight to *DOL* risk being an economically important, and priced, risk factor.

principal component, and thus could be viewed as a proxy for the 'true' underlying risk factor.[9]

The methodology adopted by Lustig et al. (2011) provides an ideal tool for testing theoretical models which provide a fundamental explanation for why high-interest-rate currencies are the riskiest. That is, why they exhibit heterogeneous exposure to the 'global' risk factor. Therefore, if currencies are sorted into portfolios on the basis of the predicted source of exposure, these new portfolios should take on the appearance of currency portfolios sorted by interest rates, since the models themselves attempt to capture the fundamental rationale for why beta varies across currencies.

To test these theoretical predictions, I sort currencies into five portfolios on the basis of the characteristic which captures each model's rationale for exposure to risk. The safest currencies according to the model are assigned to Portfolio 1, while the riskiest are assigned to Portfolio 5. 'Characteristic' factors with a theoretical foundation can then be formed, by taking the difference in returns between the 'riskiest' and 'safest' portfolios, forming a 'high-minus-low' factor, which can be introduced into a standard linear asset pricing model to replace *Slope* risk and yet theoretically, perform equally well within empirical asset pricing tests.

### 4.2.2 Theoretical Predictions

In this section, I describe the leading theoretical models of currency premia which I investigate in this essay. I explain each model's predictions for the source of heterogeneous currency betas and provide details of how I capture this exposure to risk, within an empirical context.

**Verdelhan (2010).** The author constructs a model centered around habit-based preferences. Countries with low interest rates are shown to be experiencing 'bad times', in that the representative investor's *aggregate level of consumption is near the subsistence, or 'habit', level.* Investors in low-interest rate economies are shown to be the most risk averse, and hence require the highest expected return from investing in foreign currency bonds. One method widely used for measuring whether a country is currently experiencing an economic downturn, or 'bad time', is its output gap. In this context, the output gap, measured as the 'difference between the actual output of an economy and its potential output' (IMF, 2013), can be viewed as a proxy

[9] Similarly, Lewellen et al. (2010) suggest the *HML* and *SMB* risk factors proposed by Fama and French (1993) are good proxies for the 'true' risk factors for Book-to-Market-and-Size-sorted portfolios, because of their high correlation with the underlying principal components.

for the difference between the representative agent's level of consumption (actual output) and the 'habit' level (potential output).[10]

To reflect the model, I sort currencies into portfolios on the basis of a country's output gap. The currencies of countries with the lowest (most negative) output gap are placed in Portfolio 1 (the safest). Countries with the largest output gap have their currencies placed into Portfolio 5 (the riskiest).

**Colacito and Croce (2013).** The authors construct a recursive preferences model of currency premia, considering situations with and without long-run risks. A country's *share of world consumption* explains a currency's exposure to risk. In a mean-variance trade-off, investors prefer higher consumption but dislike volatility in their future consumption stream. Countries with the highest share of world consumption are most exposed to aggregate consumption shocks since they are more constrained in sharing risk internationally. In fact, the authors demonstrate that a positive relationship exists between a country's share of world consumption and the variance of its representative investor's continuation utility.

To reflect the model, I sort currencies into portfolios on the basis of a country's aggregate household consumption. The currencies of countries with low relative consumption are placed in Portfolio 1 (the safest). Countries with high consumption have their currencies placed into Portfolio 5 (the riskiest).

**Farhi and Gabaix (2013).** The authors construct a variable rare disasters model in which the 'resilience' of a country explains its exposure to common shocks. Resilience is measured by how well *productivity is insulated from world disasters.* In the model, less resilient countries have the highest interest rates and most depreciated exchange rate and hence, issue currencies with the highest expected excess return. The extent to which a country is insulated from a global disaster can be empirically proxied by its economic openness. In fact, a recent United Nations (2011) report notes that "[i]t is widely acknowledged that an economy's vulnerability to exogenous economic shocks is largely determined by its degree of exposure to the global economy."[11] The report goes on to state that economies which are highly dependent on exports are extremely vulnerable and that "a country's exposure to external eco-

[10]In the habit model, the difference between actual consumption and habit consumption is never less than zero. But the same principal applies here. Over time the habit level changes (potential output changes) and utility of consumption is always measured relative to the habit level (actual output is measured relative to an economy's potential output).

[11]In the popular press, Singapore "is often seen as a barometer of world demand because its economy...is one of the most export-reliant in Asia" (Alex Kennedy, 'Singapore Sees Economy Growing 15 percent in 2010', Bloomberg Businessweek, July 14, 2010).

nomic shocks *generally depends on its reliance on exports* because export earnings finance imports and also contribute directly to investment and growth."[12]

To reflect the model, I sort currencies into portfolios on the basis of a country's ratio of total exports to GDP. The currencies of countries with low ratios are placed in Portfolio 1 (the safest). Countries with high export ratios have their currencies placed into Portfolio 5 (the riskiest).

### 4.2.3 Two-Stage Empirical Asset Pricing

In this section, I briefly outline the theoretical framework and empirical methodology used to test these theoretically motivated factors.

**Methods.** I follow standard notation and denote the discrete excess return on currency portfolio $j$ in period $t$ as $RX_t^j$. In the absence of arbitrage opportunities, risk-adjusted excess returns have a price of zero and satisfy the following Euler equation:

$$E_t[M_{t+1}RX_{t+1}^j] = 0 \tag{4.1}$$

with a Stochastic Discount Factor (SDF) $M_{t+1}$, linear in the pricing factors $f_{t+1}$, given by

$$M_{t+1} = 1 - b'\left(f_{t+1} - \mu\right) \tag{4.2}$$

where $b$ is the vector of factor loadings, and $\mu$ denotes the factor means. This specification implies a beta pricing model where the expected excess return on portfolio $j$ is equal to the factor price or risk $\lambda$, times the quantity of risk $\beta^j$, such that

$$E[RX^j] = \lambda'\beta^j \tag{4.3}$$

where the market price of risk $\lambda = \Sigma_f b$ can be obtained via the factor loadings $b$.[13] $\Sigma_f = E\left[\left(f_t - \mu\right)\left(f_t - \mu\right)'\right]$ is the variance-covariance matrix of the risk factors, and $\beta^j$ are the regression coefficients of each portfolio's excess return $RX_{t+1}^j$ on the risk factors $f_{t+1}$.

**Testing theoretically motivated factors.** To test the theoretically motivated factors, the excess returns to interest-rate-sorted currency portfolios $RX_{FX}^j$, for $j = 1, \ldots, 5$, are used as test assets, while the dollar factor $DOL$ and the theoretically motivated factor $HML_{TM}$ enter as risk factors. The SDF is thus defined as

[12]Emphasis added. Further evidence on the importance of economic openness and, in particular, the role of exports can be found in Briguglio, Cordina, Farrugia, and Vella (2009); Foxley (2009); World Bank (2010).

[13]See Cochrane (2005) pp. 100-101, for full details.

$$M_{t+1} = 1 - b_{DOL}\left(DOL_{t+1} - \mu_{DOL}\right) - b_{TM}\left(HML_{TM,t+1} - \mu_{TM}\right)$$

where $\mu_{DOL}$ and $\mu_{TM}$ denote the factor means.

The estimation of the currency betas $\beta^j$ and factor prices of risk $\lambda$ in equation (4.3) is undertaken using a two-step ordinary least squares regression, following Fama and MacBeth (FMB, 1973).[14] In the first step, portfolio excess returns are regressed against a constant, $DOL$ risk, and the characteristic-based risk factor for each of the five interest-rate-sorted portfolios (for $j = 1, \ldots, 5$)

$$RX^j_{FX,t+1} = \alpha^j + \beta^j_{DOL} DOL_{t+1} + \beta^j_{TM} HML_{TM,t+1} + \varepsilon^j_{t+1}.$$

In the second step, a series of cross-sectional regressions are estimated in which portfolio returns, at each point in time, are regressed on the currency betas estimated in the first-stage time series regressions. The factor prices of risk $\lambda$, are then calculated by taking the average across all the estimated slope coefficients.[15] Standard errors are corrected according to Shanken (1992) with optimal lag length set according to Newey and West (1987).

### 4.2.4 Hypotheses

If a theoretical model of currency premia can accurately explain currency betas, we would expect to make two observations in the empirical results:

1. The excess return to Portfolio 5 should be greater than to Portfolio 1. In fact, returns should increase monotonically between Portfolio 1 and Portfolio 5.

2. A return-based risk factor, constructed as the difference in returns between Portfolio 5 and Portfolio 1, should price interest-rate-sorted currency portfolios.

The first observation simply means that riskier assets should command higher returns. The second observation relates to the empirical finding by Lustig et al.

[14]It is possible to estimate $b$ via Hansen's (1982) generalized methods of moments technique. Previous work in the literature has demonstrated, however, that both methods result in almost identical parameter point estimates and standard errors (Lustig et al., 2011; Menkhoff et al., 2012; Della Corte et al., 2014).

[15]Note that no constant is included in the second stage of the FMB regressions. The results would remain virtually identical however, if the $DOL$ factor was replaced with a constant, since the $DOL$ factor has no cross-sectional relationship with currency returns, and therefore effectively substitutes into the model as a common mispricing term.

(2011), that *Slope* risk can price interest-rate-sorted currency portfolios. High-interest-rate currencies are shown to be positively exposed to *Slope* risk, while low-interest-rate currencies are negatively exposed. If a theoretical model of currency premia is able to capture a currency's fundamental *exposure* to risk, then it follows that the difference in returns between Portfolio 5 and Portfolio 1 should be highly correlated with *Slope* risk and, therefore, also perform well in explaining currency portfolio returns.[16]

## 4.3 Data and Portfolio Construction

### 4.3.1 Foreign Exchange Rates and Currency Portfolios

To test the theoretically motivated factors, I use foreign exchange rate data and currency-sorted portfolios from Chapter 3 (Della Corte, Riddiough, and Sarno, 2014).

**Foreign exchange data.** The dataset includes monthly forward and spot exchange rates for 55 currencies collected from Barclays and Reuters via Datastream. All exchange rates are quoted against the U.S. dollar (USD) and the sample period is from October 1983 to December 2011. The countries include: Argentina, Australia, Austria, Belgium, Brazil, Canada, Chile, China, Colombia, Croatia, Czech Republic, Denmark, Egypt, Estonia, Euro Area, Finland, France, Germany, Greece, Hong Kong, Hungary, Iceland, India, Indonesia, Ireland, Israel, Italy, Japan, Kazakhstan, Latvia, Lithuania, Malaysia, Mexico, Morocco, Netherlands, New Zealand, Norway, Philippines, Poland, Portugal, Russia, Singapore, Slovakia, Slovenia, South Africa, South Korea, Spain, Sweden, Switzerland, Thailand, Tunisia, Turkey, Ukraine, United Kingdom, and Venezuela. I refer to this sample as *All Countries.*

As a robustness check, I also examine a smaller *Developed Countries* sample within the dataset. The sample comprises the most liquidly traded currencies in the market, including: Australia, Belgium, Canada, Denmark, Euro Area, France, Germany, Italy, Japan, Netherlands, New Zealand, Norway, Sweden, Switzerland, and the United Kingdom. After the introduction of the euro in January 1999, the Eurozone countries are replaced with the euro.

[16] In Chapter 3, I show that sorting currencies on the basis of a country's net foreign assets can generate a currency sort similar to one based on interest rates. Their proposed factor – global imbalance risk – also constructed as a high-minus-low factor, is then able to price the cross-section of currency portfolio returns sorted on the basis of forward premia, providing supporting evidence for alternative (non-consumption based) theories of currency premia (Gourinchas and Rey, 2007; Gourinchas, 2008; Gabaix and Maggiori, 2014).

**Computing Currency Excess Returns.** I denote time-$t$, spot and forward exchange rates as $S_t$ and $F_t$, respectively. Exchange rates are defined in units of foreign currency per U.S. dollar such that an increase in $S_t$ is an appreciation of the dollar. The excess return on buying a foreign currency in the forward market at time $t$ and then selling it in the spot market at time $t+1$ is computed as

$$RX_{t+1} = (F_t - S_{t+1})/S_t,$$

which is equivalent to the forward premium minus the spot exchange rate return $RX_{t+1} = (F_t - S_t)/S_t - (S_{t+1} - S_t)/S_t$. According to the CIP condition, the forward premium approximately equals the interest rate differential $(F_t - S_t)/S_t \simeq i_t^* - i_t$, where $i_t$ and $i_t^*$ represent the domestic and foreign riskless rates over the maturity of the forward contract. Since CIP holds closely in the data at daily and lower frequencies (Akram, Rime, and Sarno, 2008), the currency excess return is approximately equal to the interest rate differential minus the exchange rate return

$$RX_{t+1} \simeq i_t^* - i_t - (S_{t+1} - S_t)/S_t.$$

**Currency portfolios.** The dataset contains two sets of currency portfolios. The first set includes five currency portfolios sorted by interest rates, in which the underlying currencies are the 55 currencies from the *All Countries* sample. The highest interest rate currencies are sorted into portfolio 5, while the lowest interest rate currencies are sorted into Portfolio 1. The second set, again, includes five currency portfolios, but this time the underlying currencies are from the smaller subset of *Developed Countries*. The returns to the portfolios are adjusted for transaction costs. Full details on the formation of currency portfolios can be found in Chapter 3 (Della Corte et al., 2014).

### 4.3.2 Theoretical Factors

#### Factor Construction

In this section, I describe how I empirically capture the 'beta predictions' of the theoretical models of currency premia, by sorting currencies into portfolios and forming 'characteristic' factors to be used in empirical asset pricing tests. I then provide details of the data employed for sorting currencies.

**Verdelhan (2010).** I use quarterly data on real GDP across the 55 countries in the sample to calculate the output gap of countries. To do so, I estimate the trend in output for each country, using a standard Hodrick and Prescott (1997) filter and measure the output gap as deviations from trend. Countries with the most positive output gap are placed into Portfolio 5 (the riskiest portfolio), while countries experiencing 'bad times', with current output well below trend, are placed into Portfolio 1 (the safest portfolio).

The factor is constructed by taking the difference in returns on the fifth and first portfolios. To enable asset pricing tests to be implemented at a monthly frequency, I hold constant a country's output gap for an entire quarter and therefore avoid any 'look ahead' bias. The construction of a *Developed Countries* factor is then implemented in exactly the same manner.

**Colacito and Croce (2013).** I use yearly data on household final consumption across the 55 countries in the sample in order to sort currencies, such that countries with the highest household consumption expenditure are placed into Portfolio 5 (the riskiest portfolio), while countries with the lowest household consumption expenditure are placed into Portfolio 1 (the safest portfolio).

Once again, the factor is constructed by taking the difference in returns on the fifth and first portfolios. To enable asset pricing tests to be implemented at a monthly frequency, I hold constant a country's total household consumption for an entire year.

**Farhi and Gabaix (2013).** I use quarterly data on exports and GDP across 52 countries in the sample to calculate each country's ratio of exports to GDP. Countries most exposed to global shocks and hence, exhibiting the highest ratio of exports to GDP, are placed into Portfolio 5 (the riskiest portfolio), while countries with less exposure to the global economy are placed into Portfolio 1 (the safest portfolio).

As before, the factor is constructed by taking the difference in returns on the fifth and first portfolios while, in order to enable asset pricing tests to be implemented at a monthly frequency, I hold constant a country's ratio of exports to GDP for an entire quarter.

### Macroeconomic Data

I collect data on 'household final consumption expenditure' (denominated in U.S. dollars), between 1982 and 2010 from the World Bank's *World Development Indicators* (WDI) database. Data on exports, GDP and real GDP are collected from the IMF *International Financial Statistics* (IFS) database at a quarterly interval between 1983 and the end of 2011. All data are seasonally adjusted and denominated in U.S. dollars or, when not available, are converted using the end of period exchange rate and seasonally adjusted using the U.S. Census Bureau's seasonal adjustment methodology (X-12-ARIMA).[17]

### 4.3.3 Alternative Non-Theoretical Characteristic Factors

I construct alternative characteristic factors using the Political Risk Services (PRS) Group's *International Country Risk Guide* (ICRG) database. The data is comprised of three composite indices as well as 22 sub-indices for each of the 55 countries in the sample, and spans macroeconomic, financial and political risks. The sub-indices are split across the three risk categories: 12 for political risk including: (i) government stability, (ii) socioeconomic conditions, (iii) investment profile, (iv) internal conflict, (v) external conflict, (vi) corruption, (vii) military in politics, (viii) religious tensions, (ix) law and order, (x) ethnic tensions, (xi) democratic accountability and (xii) bureaucracy quality; 5 for macroeconomic risk including: (i) GDP per capita, (ii) real GDP growth rate, (iii) annual inflation rate, (iv) budget balance as a percentage of GDP and (v) current account as a percentage of GDP; and finally 5 for financial risk including: (i) foreign debt as a percentage of GDP, (ii) foreign debt service as a percentage of exports of goods and services, (iii) current account as a percentage of exports of goods and services, (iv) net international liquidity as months of import cover and (v) exchange rate stability.

Each country is assigned a score for each risk category, whereby lower scores represent higher overall risk. In the composite indices, political risk is scored out of 100, while economic and financial risk are both scored out of 50, due to being comprised of less sub-indices. The data are collected monthly between January 1984 and July 2011.[18]

To construct the alternative non-theoretical characteristic factors, I again begin by sorting currencies into one of five portfolios, based on each underlying risk metric or 'characteristic'. The riskiest countries for each category have their currencies sorted into Portfolio 5, while the safest countries' currencies are sorted into Portfolio 1. I take the difference in returns between Portfolio 5 and Portfolio 1 each month to form the non-theoretical factor (denoted $HML_{alt}$) and hence, in total, construct 25 alternative candidate factors.

[17] Data on exports are unavailable for Kuwait, Tunisia and Taiwan.

[18] A complete series of definitions of how each risk category is measured can be found at `http://www.prsgroup.com`

## 4.4 Results

In this section, I describe summary statistics for the five interest-rate-sorted test portfolios, and for the characteristic-sorted portfolios reflecting the theoretical models of currency premia. I then present the asset-pricing results.

### 4.4.1 Test Portfolios and Characteristic-Based Risk Factors

Expected excess returns of the five test portfolios, as well as portfolios sorted to reflect the predictions of the theoretical models, are presented in Table 4.1. Currencies with a high interest rate earn, on average, a higher return than low interest rate currencies (4.56% compared to $-0.93\%$). This same pattern is found among *Developed Countries*. We would anticipate that the portfolios sorted to reflect the theoretical models of currency premia would generate a similar (and preferably monotonic) pattern in average excess returns. But the results are far less clear.

First, the portfolios sorted by the output gap, reflecting the habit-based model of Verdelhan (2010, V), do display the predicted pattern in average excess returns. In fact, in both samples a clear monotonic pattern emerges. Countries with a higher output gap (Portfolio 5) offer higher currency premia relative to countries experiencing 'bad times' in their domestic economy (Portfolio 1). Specifically, Portfolio 5 yields an excess return of 4.14% per annum compared to 0.70% for Portfolio 1 in the *All Countries* sample, and 3.73% compared to -0.91% in the *Developed Countries* subsample.

Next, however, I find that sorting currencies on the basis of total household consumption generates a set of approximately equal portfolio returns (CC, Panel A), while in the *Developed Countries* sample, the ordering goes in the *opposite* direction to that predicted. The 'riskiest' portfolio generates a return of 0.93%, on average each year, compared to 3.44% for the 'safest' (lowest household consumption) portfolio.

Finally, the portfolios sorted by the ratio of exports to GDP (FG) also display little obvious pattern in average excess returns. This finding applies across the *All Countries* sample (Panel A) and the *Developed Countries* subsample (Panel B). In both cases, the difference in returns between Portfolio 5 and Portfolio 1 are not statistically different from zero. In fact, the return on Portfolio 2 (the second lowest risk portfolio) is as high, *or higher*, than the average return on Portfolio 5 (the 'riskiest' portfolio).

| | **Panel A** | | | | | | |
|---|---|---|---|---|---|---|---|
| | | *All Countries* | | | | | |
| | Portfolio | **1** | **2** | **3** | **4** | **5** | ***HML*** |
| **FP** | *mean* | -0.93 | -1.40 | 1.67 | 1.16 | 4.56 | 5.49 |
| | *std* | 7.85 | 7.94 | 8.19 | 8.94 | 9.73 | 8.85 |
| **CC** | *mean* | 2.29 | 1.32 | 1.61 | 2.46 | 2.04 | -0.24 |
| | *std* | 7.53 | 8.38 | 8.62 | 8.40 | 8.55 | 7.34 |
| **FG** | *mean* | 1.96 | 2.73 | 1.75 | 1.77 | 2.82 | 0.86 |
| | *std* | 8.78 | 8.84 | 8.87 | 9.43 | 10.1 | 8.74 |
| **V** | *mean* | 0.70 | 1.13 | 1.93 | 3.10 | 4.14 | 3.44 |
| | *std* | 8.98 | 8.87 | 8.79 | 9.08 | 8.42 | 7.92 |

| | **Panel B** | | | | | | |
|---|---|---|---|---|---|---|---|
| | | *Developed Countries* | | | | | |
| | Portfolio | **1** | **2** | **3** | **4** | **5** | ***HML*** |
| **FP** | *mean* | -0.82 | 0.13 | 0.95 | 1.50 | 4.47 | 5.29 |
| | *std* | 10.1 | 9.82 | 9.42 | 9.79 | 11.4 | 11.0 |
| **CC** | *mean* | 3.44 | 1.78 | 0.96 | 2.15 | 0.93 | -2.51 |
| | *std* | 10.1 | 11.2 | 8.97 | 9.44 | 9.63 | 8.04 |
| **FG** | *mean* | 0.76 | 2.71 | 2.25 | 1.31 | 2.26 | 1.50 |
| | *std* | 8.83 | 10.3 | 9.03 | 10.3 | 10.9 | 8.67 |
| **V** | *mean* | -0.91 | 1.48 | 1.77 | 2.55 | 3.73 | 4.64 |
| | *std* | 10.9 | 9.57 | 9.84 | 9.41 | 9.81 | 8.26 |

**Table 4.1:** ***Currency Portfolio Returns.*** *The table presents average excess returns to five currency portfolios for All Countries in the sample (Panel A) and a Developed Countries subsample (Panel B). Currencies are sorted into portfolios on the basis of forward premia (FP), aggregate household consumption expenditure (CC), the ratio of exports to GDP (FG), and the output gap (V). HML represents a portfolio constructed by taking the difference in returns between Portfolio 5 and Portfolio 1. The units for all values are percent per annum. Data on test portfolios and currencies are taken from Chapter 3 (Della Corte et al., 2014). The sample period is from October 1983 to December 2011. Details of all other data are provided in Section 4.3.*

**Cross-sectional asset pricing results.** In Table 4.2, I present the cross-sectional asset pricing results from the FMB procedure. Results are presented for *All Countries* in Panel A and for *Developed Countries* in Panel B. To provide a benchmark, I also include results for the *Slope* factor of Lustig et al. (2011). The results for the factors based on the theoretical models, are far from successful. In the *All Countries* sample, *none* of the factors can explain *any* of the cross-section of currency portfolio returns. In fact, each model has a *negative* $R^2$, pricing errors significantly different from zero and root-mean-squared error (*RMSE*) over twice that observed for *Slope* risk. Surprisingly, all the risk factors also have a low correlation with the second principal component of the test assets.

On the surface, the factor constructed to reflect the long-run risks model of Colacito and Croce (CC, 2013) shows the most promising evidence of pricing capabilities, with the factor generating comparable pricing performance to *Slope* risk in the *Developed Countries* sample. But on closer inspection it is found that the pricing goes in the *opposite* direction to that predicted by the model, and hence a *negative* factor price of risk is generated. This finding implies that currencies with the largest share of world consumption are in fact the safest, offering the lowest average returns, not the highest.[19]

In fact, only the factor reflecting the external habit model of Verdelhan (2010) offers any support in favor of the underlying model. The factor price of risk $\lambda$, is high and statistically significant for *All Countries*, however the price of risk (12.99%) is considerably higher than the average excess return on the factor itself (3.44%) when, in fact, they should be equal. Moreover, the factor price of risk is *not* statistically different from zero in the *Developed Countries* sample, while the $R^2$ is $-46\%$ and $-63\%$ in the *All Countries* and *Developed Countries* samples, respectively. Moreover, the factor has almost zero correlation with the second principal component across the two samples (5% and 7%). Finally, the risk factor based on the ratio of exports-to-GDP, reflecting the variable rare disasters model of Farhi and Gabaix (FG, 2013), is never statistically different from zero, while the model generates the largest $RMSE$ and lowest $R^2$ statistics.

Pricing error plots are presented in Figure 4.1. The average returns to the five interest-rate-sorted test assets are plotted on the vertical axis, while the model

[19]It should be noted that while the factor cannot explain the currency portfolio returns for the *All Countries* sample, the strength of the results for *Developed Countries* is, however, favorable for theoretical work, which implies that a country's size is important. Hassan (2013) and Martin (2013) both find that larger countries should offer lower currency premia. In an additional exercise, I examine this proposition by sorting currencies on the basis of nominal GDP, and find almost identical results (quantitatively and qualitatively) to those for aggregate household consumption (once the factor is multiplied by $-1$). However, in Section 4.5, I show that even this promising development can be dismissed once the factor is exposed to a simple second test.

| **Panel A** | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | *All Countries* | | | | | | | |
| | **LRV (2011)** | | **CC (2013)** | | **FG (2013)** | | **V (2010)** | |
| | *DOL* | *RISK* | *DOL* | *RISK* | *DOL* | *RISK* | *DOL* | *RISK* |
| *Parameter* | 1.02 | 5.93 | 1.12 | -10.37 | 1.23 | -5.35 | 1.13 | 12.99 |
| *t-stat* | (0.73) | (3.37) | (0.81) | (-2.45) | (0.80) | (-0.60) | (0.77) | (2.36) |
| | *Cross-sectional regression statistics* | | | | | | | |
| $R^2$ | 73.6% | | -22.2% | | -88.2% | | -45.9% | |
| $\chi^2$ | 0.10 | | 0.00 | | 0.00 | | 0.01 | |
| *RMSE* | 1.73 | | 3.72 | | 4.62 | | 4.07 | |
| $\rho$ | 95.2% | | -20.9% | | -5.3% | | 5.1% | |

| **Panel B** | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | *Developed Countries* | | | | | | | |
| | **LRV (2011)** | | **CC (2013)** | | **FG (2013)** | | **V (2010)** | |
| | *DOL* | *RISK* | *DOL* | *RISK* | *DOL* | *RISK* | *DOL* | *RISK* |
| *Parameter* | 1.22 | 5.38 | 1.22 | -5.15 | 1.34 | -4.05 | 1.30 | 8.00 |
| *t-stat* | (0.75) | (2.53) | (0.73) | (-2.53) | (0.82) | (-1.05) | (0.78) | (1.46) |
| | *Cross-sectional regression statistics* | | | | | | | |
| $R^2$ | 88.9% | | 88.1% | | -73.8% | | -63.2% | |
| $\chi^2$ | 0.80 | | 0.78 | | 0.08 | | 0.04 | |
| *RMSE* | 0.94 | | 0.98 | | 3.74 | | 3.62 | |
| $\rho$ | 97.1% | | -73.2% | | -3.7% | | 7.6% | |

**Table 4.2:** ***Asset Pricing Tests: Theoretical Factors (Cross Section).*** *The table presents second stage cross-sectional results from the Fama and MacBeth (1973) procedure. The test assets are five portfolios sorted on the basis of forward premia. Each regression contains two risk factors (i) DOL risk and (ii) a characteristic based risk factor constructed on the basis of (a) forward premia (LRV, 2011), (b) aggregate household consumption (CC, 2013), (c) the ratio of exports to GDP (FG, 2013) and (d) the output gap (V, 2010). Standard errors are corrected according to Shanken (1992) with optimal lag length according to Newey and West (1987). Panel A contains results for All Countries in the sample, while Panel B contains results for Developed Countries. Additional regression statistics are reported, including the adjusted $R^2$, a chi-squared test that all pricing errors are jointly equal to zero ($\chi^2$, a value less than 0.05 indicates large pricing errors), the square root of the average mispricing (*RMSE*) and the correlation of the second risk factor with the second principal component of the test assets ($\rho$). Data on test portfolios and currencies are taken from Chapter 3 (Della Corte et al., 2014). The sample period is from October 1983 to December 2011. Details of all other data are provided in Section 4.3.*

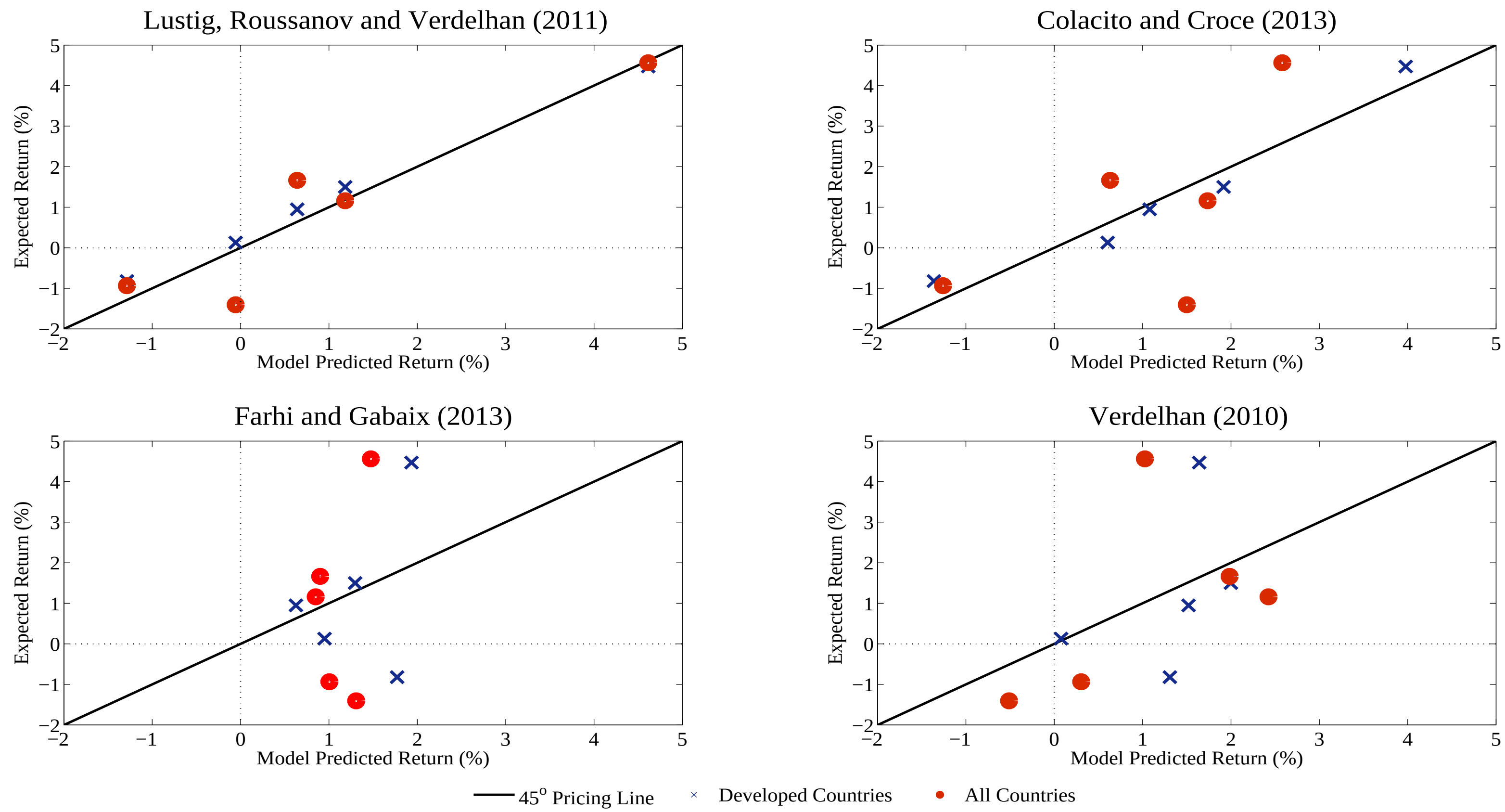


**Figure 4.1:** ***Pricing Errors.*** *The figure presents pricing errors associated with the alternative, characteristic-based, linear factor pricing models. The pricing errors are calculated by comparing predicted average returns from Fama-MacBeth asset pricing regressions (x-axes) with the actual average returns to the five forward-premia-sorted currency portfolios (y-axes). In the top-left corner are the benchmark pricing errors for the Slope risk factor of Lustig et al. (2011). The other three plots relate to the three consumption-based models: recursive preferences and long-run risks (Colacito and Croce, 2013), rare-disasters (Farhi and Gabaix, 2013) and the external habits model (Verdelhan, 2010). Pricing errors are plotted for All countries (solid circles) and the Developed countries subsample (crosses). Data on test portfolios and currencies are taken from Chapter 3 (Della Corte et al., 2014). The sample period is from October 1983 to December 2011. Details of all other data are provided in Section 4.3.*

predicted excess returns are plotted on the horizontal axis. The plot provides a visual confirmation that only the factor constructed based on the long-run risks models of Colacito and Croce (2013) performs well when pricing the cross-section of forward-premia-sorted portfolios (albeit counter to the theoretical prediction). All other plots show large pricing errors for at least one portfolio across both the *All Countries* and *Developed Countries* samples.

**Time-series results.** In Table 4.3, I present results from the first-stage time-series regressions of the FMB procedure. Within the table, I report the estimated beta coefficients and t-statistics for the five test portfolios when regressed on each characteristic factor. High-interest-rate currencies (Portfolio 5) should load positively on the risk factor and vice-versa for low-interest-rate currencies (Portfolio 1). As expected, the *Slope* risk factor (LRV) exhibits this characteristic for both samples; however, none of the characteristic-based factors demonstrate this relationship with the test assets and, in general, the factors exhibit no clear relationship with forward-premia-sorted portfolios. In fact, the factor loadings on the highest- and lowest-interest-rate-sorted portfolios are not significant in either the *All Countries* or *Developed Countries* samples, for either the factor reflecting the external habit model of Verdelhan (2010) or for the factor reflecting the variable rare disasters model of Farhi and Gabaix (2013).

### 4.4.2 Alternative Non-Theoretical Characteristic Factors

In this subsection, I perform a 'fishing' exercise to determine if *any* arbitrarily chosen, and fundamental, 'characteristic' factor, can explain the cross-section of currency portfolio returns and, hence, offer a candidate explanation for why high-interest-rate currencies earn the highest expected return (i.e. exhibit the highest currency betas).

The results of the second-stage cross-sectional regressions are presented in Table 4.4 (composite indices) and Table 4.5 (sub-indices). The composite macroeconomic and financial indices both perform well. The factor prices of risk are both highly significant (t-statistics over 3.0), while the correlations with *Slope* risk are also high (66.2% and 53.4% respectively). Unlike the factors reflecting the leading theoretical models of currency premia, which all generate negative $R^2$ statistics, the composite factors generate positive $R^2$s of up to 60% for *All Countries* and up to 95% for *Developed Countries*.

In Table 4.5, I present the *All Countries* cross-sectional asset-pricing results for each of the sub-indices which make up the macroeconomic (Panel A) and financial

| | Panel A | | | | | Panel B | | | |
|---|---|---|---|---|---|---|---|---|---|
| | *All Countries* | | | | | *Developed Countries* | | | |
| Portfolio | **LRV** | **CC** | **FG** | **V** | Portfolio | **LRV** | **CC** | **FG** | **V** |
| 1 (*Low IR*) | -0.38 | 0.22 | 0.00 | -0.05 | 1 (*Low IR*) | -0.49 | 0.49 | -0.12 | -0.01 |
| | *(-17.7)* | *(4.26)* | *(0.08)* | *(-0.88)* | | *(-15.62)* | *(9.12)* | *(-1.90)* | *(0.19)* |
| 2 | -0.18 | -0.04 | -0.04 | -0.11 | 2 | -0.13 | 0.12 | 0.09 | -0.15 |
| | *(-6.78)* | *(-0.80)* | *(-0.61)* | *(-2.97)* | | *(-3.48)* | *(3.19)* | *(2.16)* | *(-3.06)* |
| 3 | -0.07 | 0.05 | 0.04 | 0.07 | 3 | -0.00 | 0.02 | 0.16 | 0.03 |
| | *(-2.66)* | *(1.39)* | *(1.11)* | *(1.83)* | | *(-0.17)* | *(0.90)* | *(4.60)* | *(0.83)* |
| 4 | 0.01 | -0.05 | 0.07 | -0.09 | 4 | 0.10 | -0.14 | 0.02 | 0.08 |
| | *(0.29)* | *(-0.98)* | *(1.51)* | *(2.24)* | | *(2.63)* | *(-3.46)* | *(0.36)* | *(2.49)* |
| 5 (*High IR*) | 0.61 | -0.13 | -0.05 | 0.01 | 5 (*High IR*) | 0.51 | -0.53 | -0.11 | 0.03 |
| | *(28.5)* | *(-1.60)* | *(-0.63)* | *(-0.09)* | | *(16.46)* | *(-9.36)* | *(-1.22)* | *(0.49)* |

**Table 4.3:** ***Asset Pricing Tests: Theoretical Factors (Time Series).*** *The table presents estimated time-series regression coefficients and t-statistics from the first stage of the Fama and MacBeth (1973) procedure. The returns to the five test-asset portfolios, sorted on the basis of interest rates are regressed on a constant and two risk factors: (i) DOL risk and (ii) a characteristic based risk factor constructed on the basis of (a) interest rates (LRV), (b) aggregate household consumption (CC), (c) the ratio of exports to GDP (FG) and (d) the output gap (V). The $\beta$ coefficient on the second risk factor is presented for each portfolio. Standard errors are corrected according to Newey and West (1987). Data on test portfolios and currencies are taken from Chapter 3 (Della Corte et al., 2014). The sample period is from October 1983 to December 2011. Details of all other data are provided in Section 4.3.*

| **Panel A** | | | | | | |
|---|---|---|---|---|---|---|
| | *All Countries* | | | | | |
| | **Political Risk** | | **Economic Risk** | | **Financial Risk** | |
| | *DOL* | *RISK* | *DOL* | *RISK* | *DOL* | *RISK* |
| *Parameter* | 1.97 | 9.47 | 1.85 | 7.49 | 1.91 | 11.24 |
| *t-stat* | [1.41] | [2.53] | [1.31] | [3.07] | [1.36] | [3.14] |
| *Cross-sectional regression statistics* | | | | | | |
| $R^2$ | 24.4% | | 42.5% | | 58.6% | |
| $\chi^2$ | 0.00 | | 0.01 | | 0.01 | |
| *RMSE* | 3.03 | | 2.64 | | 2.24 | |
| $\rho$ | 42.3% | | 66.2% | | 53.4% | |

| **Panel B** | | | | | | |
|---|---|---|---|---|---|---|
| | *Developed Countries* | | | | | |
| | **Political Risk** | | **Economic Risk** | | **Financial Risk** | |
| | *DOL* | *RISK* | *DOL* | *RISK* | *DOL* | *RISK* |
| *Parameter* | 1.85 | -15.55 | 1.91 | 6.95 | 1.87 | 6.74 |
| *t-stat* | [1.10] | [-1.75] | [1.15] | [2.41] | [1.12] | [2.50] |
| *Cross-sectional regression statistics* | | | | | | |
| $R^2$ | -1.8% | | 94.7% | | 90.2% | |
| $\chi^2$ | 0.02 | | 0.88 | | 0.82 | |
| *RMSE* | 2.95 | | 0.67 | | 0.92 | |
| $\rho$ | -9.8% | | 53.5% | | 69.4% | |

Table 4.4: ***Asset Pricing Tests: Non-Theoretical Factors (Composite).*** *The table presents second stage cross-sectional results from the Fama and MacBeth (1973) procedure. The test assets are five portfolios sorted on the basis of forward premia. Each regression contains two risk factors (i) DOL risk and (ii) a characteristic based risk factor constructed on the basis of data from the PRS Group on country-level macroeconomic, financial and political risks. Standard errors are corrected according to Shanken (1992) with optimal lag length according to Newey and West (1987). Panel A contains results for All Countries in the sample, while Panel B contains results for Developed Countries. Additional regression statistics are reported, including the adjusted* $R^2$*, a chi-squared test that all pricing errors are jointly equal to zero (*$\chi^2$*, a value less than 0.05 indicates large pricing errors), the square root of the average mispricing (*RMSE*) and the correlation of the second risk factor with the second principal component of the test assets (*$\rho$*). Data on test portfolios and currencies are taken from Chapter 3 (Della Corte et al., 2014). The sample period is from October 1983 to December 2011. Details of all other data are provided in Section 4.3.*

| Panel A | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | **GDP per Capita** | | **GDP Growth Rate** | | **Inflation Yearly Rate** | | **Budget Balance** | | **Current Account** | |
| | *DOL* | *RISK* | *DOL* | *RISK* | *DOL* | *RISK* | *DOL* | *RISK* | *DOL* | *RISK* |
| *Parameter* | 1.68 | 10.22 | 1.70 | 13.64 | 1.80 | 9.53 | 1.65 | 13.40 | 1.68 | 10.28 |
| *t-stat* | [1.23] | [3.05] | [1.22] | [3.00] | [1.28] | [3.17] | [1.19] | [3.09] | [1.22] | [3.13] |
| *Cross-sectional regression statistics* | | | | | | | | | | |
| $R^2$ | 78.4% | | 63.5% | | 61.4% | | 73.9% | | 63.2% | |
| $\chi^2$ | 0.12 | | 0.02 | | 0.04 | | 0.09 | | 0.02 | |
| *RMSE* | 1.62 | | 2.10 | | 2.16 | | 1.78 | | 2.11 | |
| $\rho$ | 40.4% | | 32.6% | | 58.0% | | 31.1% | | 44.5% | |

| Panel B | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | **Exchange Rate Stability** | | **International Liquidity** | | **Current Account** | | **Debt Service (% Exports)** | | **Foreign Debt (% GDP)** | |
| | *DOL* | *RISK* | *DOL* | *RISK* | *DOL* | *RISK* | *DOL* | *RISK* | *DOL* | *RISK* |
| *Parameter* | 2.02 | 19.24 | 1.80 | 28.18 | 1.62 | 9.74 | 1.88 | 19.44 | 1.72 | 10.40 |
| *t-stat* | [1.43] | [2.58] | [1.30] | [2.15] | [1.18] | [2.72] | [1.37] | [2.72] | [1.23] | [2.46] |
| *Cross-sectional regression statistics* | | | | | | | | | | |
| $R^2$ | 51.3% | | 27.9% | | 18.0% | | 79.0% | | -6.5% | |
| $\chi^2$ | 0.01 | | 0.01 | | 0.00 | | 0.15 | | 0.00 | |
| *RMSE* | 2.43 | | 2.96 | | 3.15 | | 1.60 | | 3.59 | |
| $\rho$ | 21.7% | | 9.5% | | 41.4% | | 20.2% | | 24.1% | |

**Table 4.5:** ***Asset Pricing Tests: Non-Theoretical Factors (Sub-Indices).*** *The table presents second stage cross-sectional results from the Fama and MacBeth (1973) procedure. The test assets are five portfolios sorted on the basis of forward premia. Each regression contains two risk factors (i) DOL risk and (ii) a characteristic based risk factor constructed on the basis of data from the PRS Group on country-level macroeconomic and financial risks. Standard errors are corrected according to Shanken (1992) with optimal lag length according to Newey and West (1987). Panel A contains results for All Countries in the sample, while Panel B contains results for Developed Countries. Additional regression statistics are reported, including the adjusted $R^2$, a chi-squared test that all pricing errors are jointly equal to zero ($\chi^2$, a value less than 0.05 indicates large pricing errors), the square root of the average mispricing (*RMSE*) and the correlation of the second risk factor with the second principal component of the test assets ($\rho$). Data on test portfolios and currencies are taken from Chapter 3 (Della Corte et al., 2014). The sample period is from October 1983 to December 2011. Details of all other data are provided in Section 4.3.*

(Panel B) composite indices.[20] The pricing performance is especially strong for the macroeconomic characteristic factors. Each factor has a significant factor price of risk, with associated t-statistics of 3.0 or higher, while the cross-sectional $R^2$ statistic never falls below 60%. The financial characteristic factors also perform well, with each factor exhibiting a t-statistics in excess of 2.0. In fact, the factor constructed on the basis of a country's ratio of debt-service-payments to exports, shows a particularly strong pricing performance, with a higher $R^2$, lower $RMSE$ and smaller pricing errors than *Slope* risk.

## 4.5 Pricing Characteristic-Sorted Portfolios

In light of the finding that arbitrarily chosen macroeconomic and financial characteristic factors perform overwhelming well in pricing currency portfolio returns, I turn to a second test of their pricing performance.

One additional test for assessing a candidate factor's pricing capabilities is to test if the factor can price an alternative set of currency portfolios. Those sorted by the characteristic of interest are natural candidates for the alternative portfolios. For example, if a country's debt-service ratio really *is* important for explaining currency premia, then a factor which captures a country's debt-service ratio should price interest-rate-sorted portfolios *and* currency portfolios sorted by the debt-service ratio itself. To capture this approach, I construct sets of five currency portfolios sorted on the characteristics of interest. Specifically, this involves the creation of six sets of 'theoretical' test portfolios – three each for *All Countries* and *Developed Countries* – which are sorted by consumption, output gaps and export ratios. I then construct 50 sets of 'non-theoretical' test portfolios – 25 each for *All Countries* and *Developed Countries* – sorted based on the composite and sub-indices of the PRS data.

In Table 4.6, I record the t-statistic and associated $R^2$ statistic from the second-step of the FMB procedure. I do this for each theoretical characteristic factor and the 25 non-theoretical characteristic factors when the test assets are the currency portfolios sorted by the same characteristic as the factor itself. I find that *none* of the 25 $HML_{alt}$ factors are statistically significant when tested, with many of the models now generating negative $R^2$ statistics. I find comparable results across *Developed Countries*, where all 25 factors are found to be insignificant.[21] Of the

[20] In Appendix Table C.2, I document the performance of factors constructed based on the sub-indices of political risk. The equivalent results for *Developed Countries* are provided in Appendix Table C.3.

[21] The results for the *Developed Countries* sample are reported in Appendix Table C.4.

| *Variable* | *t-stat* | $R^2$ | *Variable* | *t-stat* | $R^2$ |
|---|---|---|---|---|---|
| 'Slope' Risk (LRV) | 4.73 | 85.1% | 'Global Imbalances' (DCRS) | 3.65 | 84.8% |

***Theoretically Motivated* Characteristic Factors**

| *Variable* | *t-stat* | $R^2$ | *Variable* | *t-stat* | $R^2$ |
|---|---|---|---|---|---|
| Colacito and Croce | 0.38 | -84.1% | Verdelhan | 2.32 | 50.0% |
| Farhi and Gabaix | 0.53 | -54.9% | | | |

***Financial* Characteristic Factors**

| *Variable* | *t-stat* | $R^2$ | *Variable* | *t-stat* | $R^2$ |
|---|---|---|---|---|---|
| Aggregate Financial | 0.64 | -127% | Current Account | 0.06 | -96.0% |
| Exchange Rate Stability | 0.90 | -61.8% | Debt Service | 0.55 | -24.6% |
| International Liquidity | 0.04 | -78.1% | Foreign Debt | 0.52 | -123% |

***Macroeconomic* Characteristic Factors**

| *Variable* | *t-stat* | $R^2$ | *Variable* | *t-stat* | $R^2$ |
|---|---|---|---|---|---|
| Aggregate Economic | 1.37 | 56.7% | Inflation | 0.44 | -115% |
| GDP per Capita | 0.47 | -110% | Budget Balance | 0.69 | -15.8% |
| GDP Growth Rate | 0.03 | -116% | Current Account | 0.37 | -50.0% |

***Political* Characteristic Factors**

| *Variable* | *t-stat* | $R^2$ | *Variable* | *t-stat* | $R^2$ |
|---|---|---|---|---|---|
| Aggregate Political Risk | 1.35 | -19.6% | Military in Politics | 0.52 | -70.6% |
| Government Stability | 0.78 | -99.4% | Religious Tensions | 1.44 | -0.24% |
| Socioeconomic Conditions | 0.44 | -50.5% | Law and Order | 1.68 | 51.0% |
| Investment Profile | 1.27 | 26.5% | Ethnic Tensions | 0.32 | -26.7% |
| Internal Conflict | 1.18 | 1.23% | Democratic Accountability | 0.67 | 9.18% |
| External Conflict | 0.74 | -60.4% | Bureaucracy Quality | 1.51 | -29.7% |
| Corruption | 0.38 | -51.0% | | | |

**Table 4.6:** ***Asset Pricing Tests: Characteristic-Sorted Portfolios.*** *The table presents second stage cross-sectional adjusted* $R^2$ *and t-statistics from the Fama and MacBeth (1973) procedure. The test assets are five currency portfolios sorted on the same basis as the factor itself. Each regression contains two risk factors (i) DOL risk and (ii) a characteristic based risk factor. Standard errors are corrected according to Shanken (1992) with optimal lag length according to Newey and West (1987). The sample period is from October 1983 to December 2011. Details of all other data are provided in Section 4.3.*

theoretical factors, only the factor reflecting the external habit model of Verdelhan (2010) is significant. Both the factors reflecting the long-run risks model of Colacito and Croce (2013) and the variable rare disasters model of Farhi and Gabaix (2013) are associated with insignificant factor prices of risk and negative $R^2$ statistics. In contrast, I also provide the results for an alternative characteristic factor suggested by Chapter 3 (Della Corte et al., 2014). This fundamental factor, sorted based on the mixture of a country's net foreign asset position and currency denomination of foreign debt, is termed the 'Global Imbalance Factor'. Chapter 3 (Della Corte et al., 2014) demonstrate that the factor can explain the returns of interest-rate-sorted currency portfolios. In Table 4.6, we find this is the only fundamental factor which also prices the set of test-asset portfolios sorted by its own characteristic.

I provide a visual comparison of each factors' performance, when pricing interest-rate-sorted and characteristic-sorted portfolios in Figure 4.2.[22] As previously documented, all but 5 of the non-theoretical factors (all sub-indices of political risk) are significant when the test assets are sorted by interest rates. In contrast, when pricing portfolios sorted by the same characteristic as the risk factor, all the t-statistics fall below 2.0, while 20 of the 25 models generate a negative cross-sectional $R^2$ statistic. The same information is plotted in the right-hand panel of Figure 4.2 for the theoretical characteristic factors.

A reason for the drop in pricing performance of the $HML_{alt}$ factors is provided in Figures 3 and 4. In Figure 4.3, I plot the average returns to the 25 $HML_{alt}$ factors, conditional on the distribution of returns to *Slope* risk (horizontal axes). For a significant number of factors, a monotonic pattern emerges. High *Slope* risk (carry trade) returns are often associated with high returns to the $HML_{alt}$ factor. Yet, in Figure 4.4, we find that almost none of the characteristics provide a monotonic pattern in currency excess returns when currencies are sorted into one of five portfolios based on macroeconomic, financial or political risks.[23] This finding suggests that many of the characteristics, while associated with variation in currency betas are all, in fact, by-products of some other underlying driving force.

## 4.6 Simulation of 'Useless' Factors

In this section, I explore the issue of pricing interest-rate-sorted and characteristic-sorted portfolios more deeply, by constructing randomly generated 'useless' factors which lack any economic content.

[22]The equivalent figure for *Developed Countries* is presented in Appendix Figure C.1.

[23]The equivalent figures for *Developed Countries* are presented in Appendix Figures C.2 and C.3.

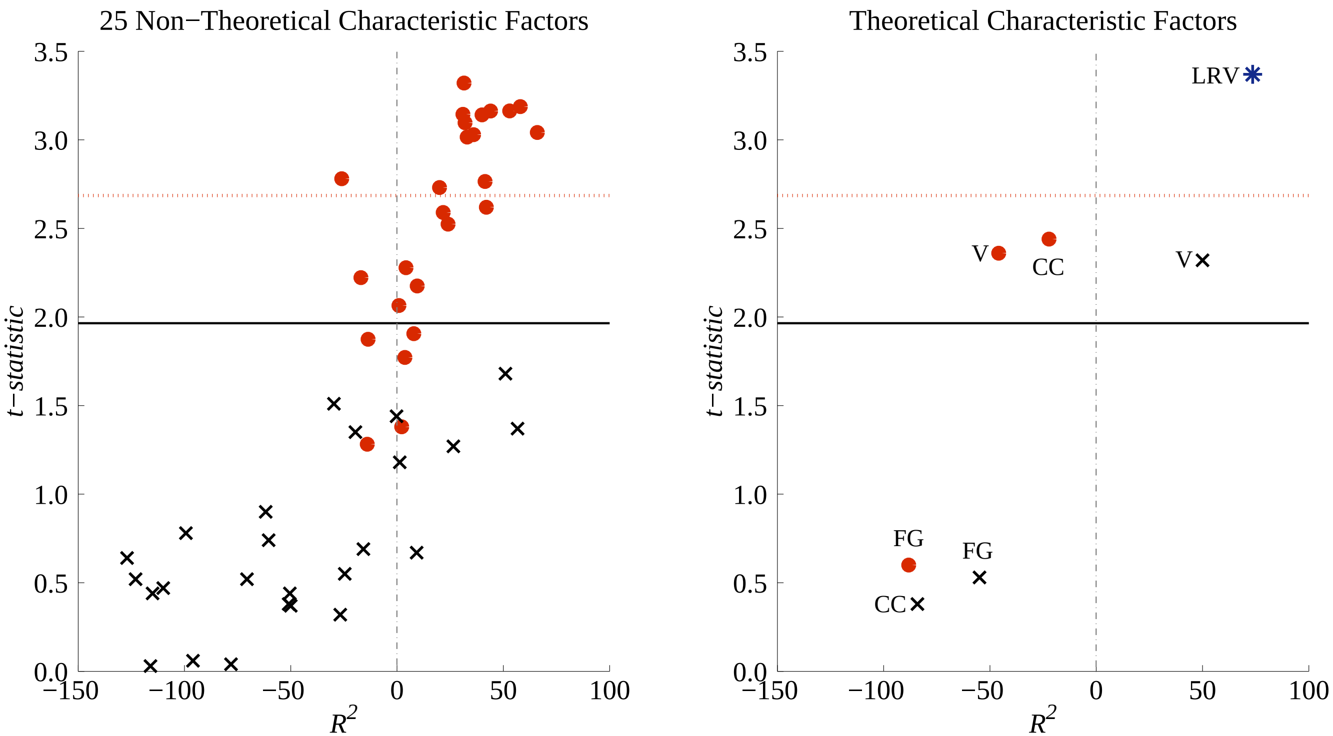


**Figure 4.2:** ***Pricing Alternative Test Assets.*** *The figure presents adjusted-$R^2$ and t-statistics from Fama-MacBeth asset pricing regressions. In the left-hand chart are the cross-sectional asset pricing statistics for the 25 characteristic-based risk factors constructed using data from the Political Risk Services (PRS) Group on underlying economic, financial and political risks. The t-statistics are calculated using Shanken (1992) corrected standard errors with optimal lag length chosen according to Newey and West (1987). The adjusted-$R^2$ is taken from the second stage cross-sectional regression of the Fama-MacBeth procedure. Results are reported for two sets of test assets: (i) the forward-premia-sorted currency portfolios (solid circles), and (ii) the randomly sorted portfolios from which the risk factors are constructed (crosses). In the right-hand chart the results are reported for the characteristic-based risk factors designed to capture consumption-based models of currency premia as well as for the Slope risk factor of Lustig et al. (2011). Horizontal lines are included at 1.96 (the standard 5% critical threshold) and 2.69 (the simulated 5% critical threshold when the test assets are forward-premia-sorted currency portfolios). The abbreviations are: LRV: Lustig et al. (2011); CC: Colacito and Croce (2013); FG: Farhi and Gabaix (2013); V: Verdelhan (2010). Data on test portfolios and currencies are taken from Chapter 3 (Della Corte et al., 2014). The sample period is from October 1983 to December 2011. Details of all other data are provided in Section 4.3.*

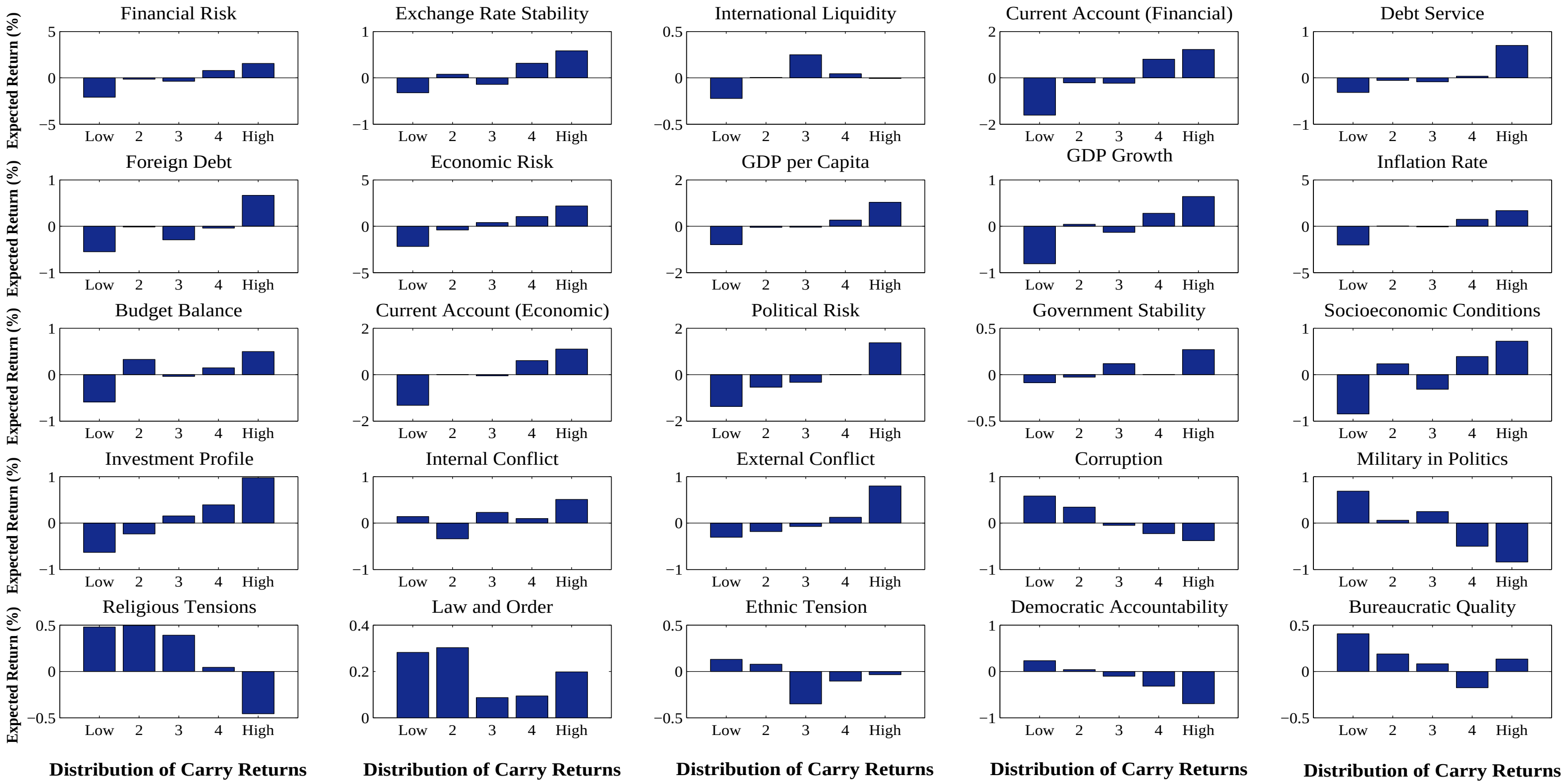


**Figure 4.3:** ***Conditional Excess Currency Returns of Non-Theoretical Factors.*** *The figure presents the average excess return to each of the 25 characteristic-sorted currency factors generated using data on underlying economic, financial and political risks from the Political Risk Services (PRS) Group, conditional on the distribution of the Slope risk factor of Lustig et al. (2011). The Slope risk factor is constructed using data from Chapter 3 (Della Corte et al., 2014). Data on test portfolios and currencies are taken from Chapter 3 (Della Corte et al., 2014). The sample period is from October 1983 to December 2011. Details of all other data are provided in Section 4.3.*

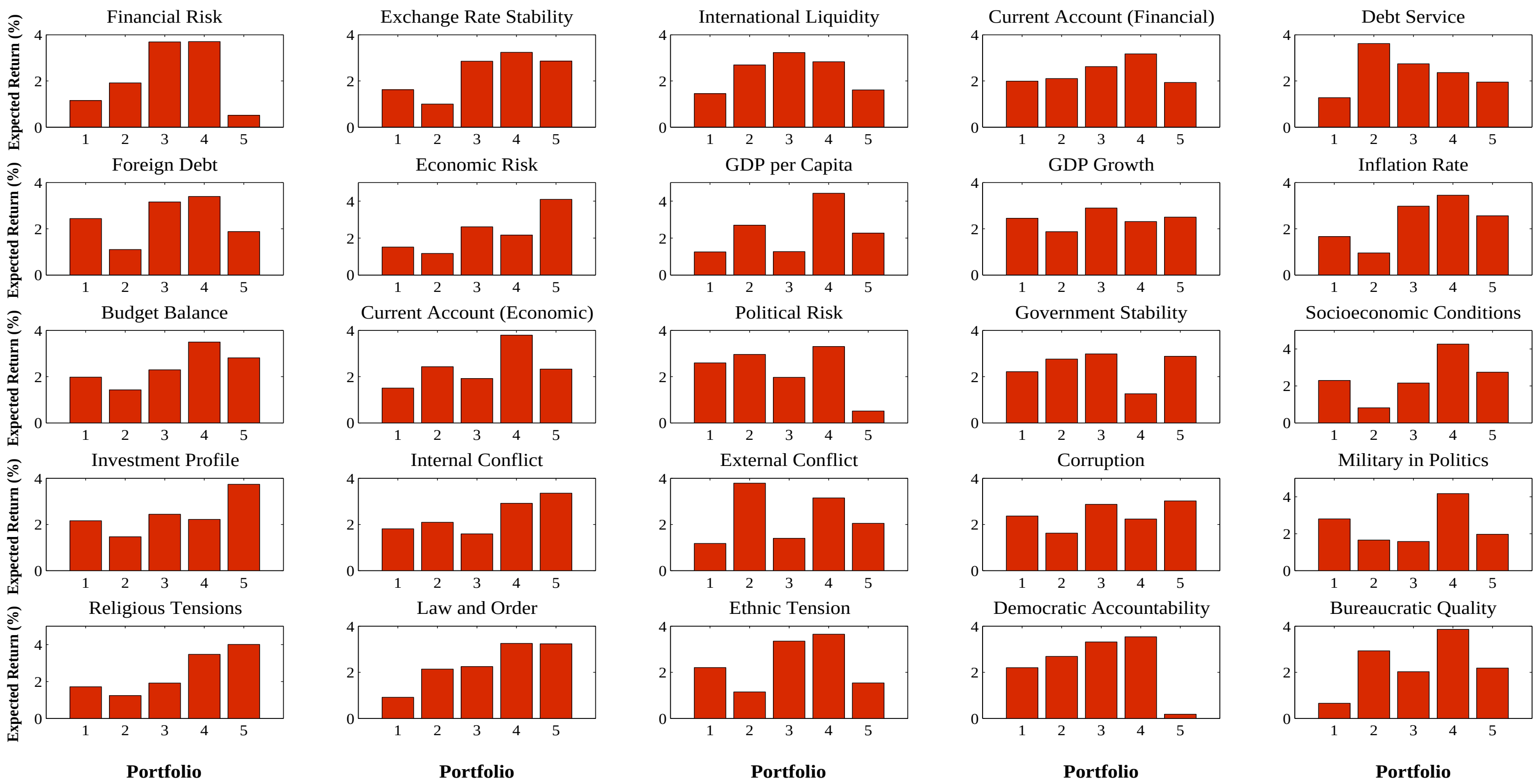


**Figure 4.4:** ***Expected Excess Returns to Characteristic-Sorted Portfolios.*** *The figure presents the expected excess returns to each of the five currency portfolios, sorted according to the 25 country characteristics which span data on economic, financial and political risks from the Political Risk Services (PRS) Group. Data on test portfolios and currencies are taken from Chapter 3 (Della Corte et al., 2014). The sample period is from October 1983 to December 2011. Details of all other data are provided in Section 4.3.*

**Constructing 'useless' factors.** To construct the randomly generated 'useless' factors, I arbitrarily allocate currencies to one of five currency portfolios each month. In total, I simulate 20,000 sets of five currency portfolios. From these currency portfolios, I construct the 'useless' factor by taking the difference in returns between Portfolio 5 and Portfolio 1. Hence, I generate 20,000 factors, with the construction of the factors mimicking the construction of the theoretical and non-theoretical 'characteristic' factors. I denote the randomly-generated factors $HML_{rnd}$.

**Tests.** I assess the pricing performance of the factors, once combined with *Dollar* risk, using the FMB procedure, to explain two sets of currency portfolio returns. The first set of portfolios are the standard set of interest-rate-sorted test assets used throughout this chapter. Each of the 20,000 'useless' factors is, therefore, tested based on the same set of test assets. I then test if each of the 20,000 factors can price their associated, randomly generated, test portfolios. In this case, each factor prices its own unique set of test assets. The two tests replicate the testing of the theoretical and non-theoretical factors, whereby each factor is asked to also price currency portfolios sorted by the same characteristic as the factor itself.

**Results.** In Table 4.7, I present statistics from the second-step cross-sectional regression of the FMB procedure for interest-rate-sorted test portfolios (Panel A) and randomly generated test portfolios (Panel B). When pricing interest-rate-sorted portfolios, the $HML_{rnd}$ factors have, on average, low correlations $\rho$ with *Slope* risk. Over 40% of the factors have a correlation of less than 0.05, while only 1.8% have a correlation over 0.2. The proportions are almost identical for the *Developed Countries* sample.[24] Asymptotically, we would expect 5% of the randomly-generated $HML_{rnd}$ factors to exhibit a t-statistic over 1.96. I find, however, that 38% of the randomly-generated 'useless' factors exceed this threshold. A t-statistic of around 2.7 is required before significance is achieved at the 95% confidence level. The cross-sectional goodness of fit is also strong for the randomly-generated factors. In the all countries sample, over 35% of models generate a cross-sectional $R^2$ over 50%. One-in-five models has an $R^2$ exceeding 70%. The values are similar, albeit even higher for the *Developed* Countries sample. Nearly half of the models generate an $R^2$ of 50% or more, while over one-in-four exceeds 70%.

When I rerun the exercise by changing the test assets to the five randomly generated test portfolios, a noticeable distinction arises. This time only 4.7% of $HML_{rnd}$ factors have a t-statistic exceeding 1.96, while only 3.1% of all models have a cross-sectional $R^2$ exceeding 70%. In Figure 4.5, I plot histograms of the simulated

[24] The results for *Developed Countries* are reported in Appendix Table C.5.

| Panel A | | | | | | | |
|---|---|---|---|---|---|---|---|
| *Interest-Rate-Sorted Test Assets* | | | | | | | |
| *Relationship between 'useless' factors and the 'true' factor* | | | | | | | |
| Correlation ($\rho$) | **0.05** | **0.10** | **0.20** | **0.50** | **0.80** | **0.90** | **1.0** |
| *Proportion* $>\rho$ | 57.3% | 24.9% | 1.79% | 0.0% | 0.0% | 0.0% | 0.0% |
| *Factor price of risk* | | | | | | | |
| t-stat (absolute value) | **0.67** | **1.65** | **1.96** | **2.33** | **2.58** | **2.81** | **3.29** |
| *Proportion >t-stat (theory)* | 50.0% | 10.0% | 5.0% | 2.0% | 1.0% | 0.5% | 0.1% |
| *Proportion >t-stat (actual)* | 90.1% | 56.0% | 38.0% | 18.1% | 8.0% | 2.5% | 0.0% |
| *Model fit* | | | | | | | |
| $R^2$ | **50%** | **60%** | **70%** | **80%** | **90%** | **95%** | **99%** |
| *Proportion* $>R^2$ | 37.5% | 28.6% | 19.9% | 11.3% | 4.1% | 1.4% | 0.1% |
| *Pricing errors* | | | | | | | |
| $\chi^2$ p-value | **0.05** | **0.10** | **0.30** | **0.50** | **0.70** | **0.90** | **0.95** |
| *Proportion <p-value* | 88.2% | 91.8% | 96.6% | 98.4% | 99.3% | 99.8% | 99.9% |

| Panel B | | | | | | | |
|---|---|---|---|---|---|---|---|
| *Randomly-Sorted Test Assets* | | | | | | | |
| *Relationship between 'useless' factors and the 'true' factor* | | | | | | | |
| Correlation ($\rho$) | **0.05** | **0.10** | **0.20** | **0.50** | **0.80** | **0.90** | **1.0** |
| *Proportion* $>\rho$ | 57.3% | 24.9% | 1.79% | 0.0% | 0.0% | 0.0% | 0.0% |
| *Factor price of risk* | | | | | | | |
| t-stat (absolute value) | **0.67** | **1.65** | **1.96** | **2.33** | **2.58** | **2.81** | **3.29** |
| *Proportion >t-stat (theory)* | 50.0% | 10.0% | 5.0% | 2.0% | 1.0% | 0.5% | 0.1% |
| *Proportion >t-stat (actual)* | 50.1% | 9.7% | 4.7% | 1.7% | 0.7% | 0.3% | 0.0% |
| *Model fit* | | | | | | | |
| $R^2$ | **50%** | **60%** | **70%** | **80%** | **90%** | **95%** | **99%** |
| *Proportion* $>R^2$ | 6.8% | 4.9% | 3.1% | 1.7% | 0.6% | 1.4% | 0.1% |
| *Pricing errors* | | | | | | | |
| $\chi^2$ p-value | **0.05** | **0.10** | **0.30** | **0.50** | **0.70** | **0.90** | **0.95** |
| *Proportion <p-value* | 6.7% | 12.6% | 34.0% | 54.1% | 73.5% | 91.4% | 95.6% |

**Table 4.7:** ***Asset Pricing Tests: 'Useless' Factors.*** *The table presents the estimated distributions of statistics collected from Fama and MacBeth (1973) asset pricing tests using simulated risk factors. Two currency 'risk factors' are randomly generated by arbitrarily reassigning currencies to one of five portfolios each month. The test assets are interest-rate-sorted portfolios (Panel A) and randomly sorted currency portfolios (Panel B). The first risk factor is calculated as an equally weighted average of all five portfolio returns. The second risk factor is calculated as the difference between the returns on the* $1^{st}$ *and* $5^{th}$ *portfolios. The correlation is between the second simulated risk factor and the Slope factor from Lustig et al. (2011). The t-statistics are reported for the second risk factor. Standard errors are adjusted according to Shanken (1992) with optimal lag length according to Newey and West (1987). The adjusted* $R^2$ *is from the second-stage cross-sectional regression in the Fama-MacBeth approach. The* $\chi^2$ *p-value is greater than 0.05 if pricing errors are small. In total 20,000 pairs of risk factors are simulated. Data on currencies are taken from Chapter 3 (Della Corte et al., 2014). The sample period is from October 1983 to December 2011.*

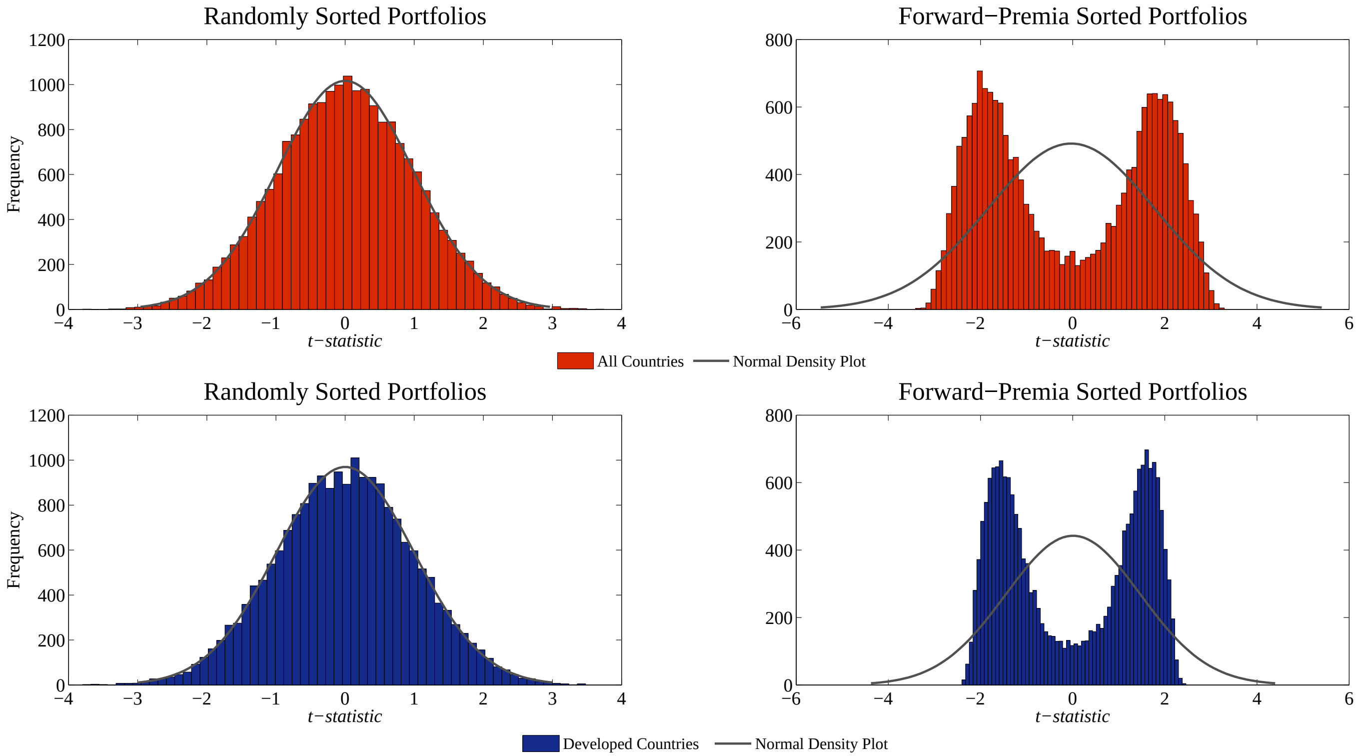


**Figure 4.5:** ***Histograms of Simulated t-statistics.*** *This figure presents the histograms of t-statistics estimated from Fama-MacBeth asset pricing regressions. Risk-factors are artificially generated by randomly sorting currencies into one of five portfolios each month. In total 20,000 pairs of 'risk factors' are created. The first risk factor is calculated as an equally weighted average of all five portfolio returns. The second risk factor is calculated as the difference between the returns on portfolios 5 and 1. I plot the t-statistic for the second risk factor. The t-statistics are calculated using Shanken (1992) corrected standard errors with optimal lag length chosen according to Newey and West (1987). In the left-hand panel the t-statistics are calculated for when pricing the five randomly sorted currency portfolios. In the right-hand panel the t-statistics are calculated for when pricing five forward-premia-sorted portfolios. The exercise is run for All countries (top panel) and the Developed countries subsample (bottom panel). Data on test portfolios and currencies are taken from Chapter 3 (Della Corte et al., 2014). The sample period is from October 1983 to December 2011.*

t-statistics for each of the $HML_{rnd}$ factors when pricing randomly-sorted test portfolios (left-hand panel) and interest-rate-sorted portfolios (right-hand panel). A normal density plot is overlaid. Histograms associated with the randomly-generated test portfolios are approximately normally distributed, but the histograms associated with interest-rate-sorted test portfolios display a highly non-normal, bi-modal distribution. The finding supports the conclusions of Lewellen et al. (2010), that an arbitrary factor could, by chance, explain currency portfolios sorted by interest rates. However, I find the factor would have a more challenging task in pricing portfolios sorted by the characteristic itself, which corroborates the earlier finding that none of the 25 non-theoretical characteristic factors could beat this benchmark. In fact, I find that less than 1.5% of all randomly-generated 'useless' factors are statistically significant when pricing interest-rate-sorted portfolios *and* when pricing the portfolios from which the 'useless' factors are generated. Hence, any characteristic factor shown to pass both tests *is* overcoming a non-trivial empirical exercise and, therefore, is indicative of strong pricing performance.

## 4.7 Conclusions

The recent literature on currency premia – both empirical and theoretical – has made great strides. A new wave of 'risk factors' have been shown empirically to explain the returns to currency portfolios sorted by interest rates, while the expanding suite of theoretical currency models provide compelling explanations for various puzzles in international finance. Both developments are encouraging signs of the progress researchers are making in understanding this important, and often overlooked, asset class.

But a nagging doubt clouds the research. If we want to understand currency premia – or, in fact, the returns to any asset class – it is important to have an explanation for *why* certain currencies (assets) are riskier than others. It is widely acknowledged that high-interest-rate currencies earn a higher rate of return, but the fundamental source of this additional exposure to risk – the currency beta – remains a mystery. Empirical work overwhelmingly focusses on currency risk by demonstrating that high-interest-rate currencies are more exposed to some 'risk factor'. Yet, the reasons for why this is the case are rarely discussed. Moreover, recent criticism by Lewellen et al. (2010) suggests that finding new risk factors should be relatively straight forward, given the strong factor structure of currency portfolio returns (sorted by interest rates).

In this essay, therefore, I propose taking a side-step. Rather than focus on currency 'risk', instead I choose to investigate the fundamental source of exposure to risk, and hence learn about currency betas themselves. Using the techniques of empirical asset pricing, I turn to recent leading theoretical contributions in international finance, which all provide precise predictions on the fundamental nature of currency betas. If the models' predictions are accurate, then sorting on the basis of the 'characteristic', argued to drive currency betas, should result in a set of portfolios equivalent to the standard set of interest-rate-sorted currency portfolios. A factor constructed from these portfolios should then exhibit similar pricing performance to the *Slope* factor of Lustig et al. (2011) and, pertinently, also provide a fundamental and theoretically rooted explanation for *why* high interest rate currencies are the riskiest.

Unfortunately, none of the theoretically grounded factors prove successful in this endeavor. All give rise to negative cross-sectional $R^2$ statistics and large pricing errors while, in general, the factors are either not priced or the pricing goes in the *opposite* direction to that predicted by the model. Beta continues to remain a mystery. Despite this performance, I find that alternative, non-theoretical, macroeconomic and financial characteristics are almost overwhelmingly good at explaining the returns to currency portfolios. In fact, t-statistics over 3.0 and $R^2$ statistics over 60 percent are the norm, not the exception. Suddenly we are overwhelmed by an embarrassment of riches for explaining currency betas. The critique of Lewellen et al. (2010) rears up again, while a future scenario in which all theoretical models beat this benchmark seems a distinct possibility.

Focussing on currency betas, however, allows researchers to overcome this concern by providing a natural alternative set of test assets. By sorting currencies on the basis of the 'beta characteristic' of interest, I find that all non-theoretical factors, which had initially exhibited strong pricing performance, are no longer significant. Moreover, when exploring the issue in more depth with a simulation exercise, I find that only around 1.5% of return-based currency risk factors can pass both tests, making it a significant benchmark and helping to mitigate the recent criticism of empirical asset pricing techniques, which emphasize the relative ease of pricing test assets that exhibit a strong factor structure.

Overall, this essay calls for a stricter empirical benchmark for assessing all new theoretical models of currency premia. These models should provide precise predictions for why betas (risk exposures) vary across currencies. The predictions should naturally give rise to characteristic factors which can price the economically important interest-rate-sorted currency portfolios and, pertinently, also explain the returns of own-characteristic-sorted portfolios. Any theoretical model which passes both tests could be considered consistent with the data and hence a candidate explanation for why we witness heterogeneous exposure to risk in the currency market.

# Appendix A

# Supporting Documentation: Chapter 2

## Summary of Additional Material

**Table A.1** presents a fixed-effects panel regression equivalent to the baseline specification originally presented in Table 2.3. This time, the dependent variable is the aggregate cross-border bank flow (summation of quarterly interbank and intragroup flows) as a proportion of the previous quarter stock of total cross-border bank-to-bank funding. The results confirm the main findings of Bruno and Shin (2014). One discrepancy is the $\Delta$VIX coefficient, which I find to be consistently insignificant for aggregate flows. This finding is likely due to sample differences, as I am confined to investigating 25 banking systems which report both interbank and intragroup flows to the BIS. The additional banking systems analyzed by Bruno and Shin (2014) are primarily emerging market economies and, as I demonstrate in the main results, emerging economy banking systems have a higher propensity to lose funding given an increase in the VIX index.

**Table A.2** presents a fixed-effects panel regression equivalent to the augmented specification presented in Table 2.6. This time, the dependent variables are the cross-border interbank flows to parent and foreign affiliate banks as a proportion of the previous quarter stock of total interbank cross-border bank-to-bank funding of either parent or foreign affiliates (see equation 2.5 for full details). Interbank funding to both parent and foreign affiliate banks is found to be vulnerable to periods of heightened global risk.

**Table A.3** presents correlations across the main dependent and independent variables. The correlation between interbank and intragroup funding is negative and statistically different from zero. The correlations across independent variables are low, mitigating any concerns over multicollinearity.

**Table A.4** presents descriptive statistics for the five alternative measures of global risk: the VXO index, Credit Suisse Global Risk Appetite Index, the corporate bond spread between AAA and BAA rated securities provided by Moody's, the TED spread, and the global imbalance risk factor from Chapter 3 (Della Corte et al., 2014).

**Table A.5** presents the correlations between the five alternative measures of global risk: the VXO index, Credit Suisse Global Risk Appetite Index, the corporate bond spread between AAA and BAA rated securities provided by Moody's, the TED spread, and the global imbalance risk factor from Chapter 3 (Della Corte et al., 2014). The correlations are not, on average, particularly high. This finding indicates that a 'common' source of global risk is driving cross-border bank-to-bank funding.

**Table A.6** presents an example calculation from the scenario analysis described in section 2.5.2. The significant coefficients on the VIX and $\Delta$VIX from Table 2.3 are used in a scenario in which the VIX rises from a value of 20 in one quarter to an average of 45 in the subsequent quarter. The VIX then remains at 45 for two quarters. The scenario replicates the actual movements in the VIX betweeen 2008Q4 and 2009Q2, following the collapse of Lehman Brothers.

| | (1) | (2) | (3) |
|---|---|---|---|
| | Interbank and Intragroup | | |
| VIX | -2.62*** | -2.39*** | -1.50* |
| | (0.77) | (0.85) | (0.83) |
| VIX*EME | | | -6.37*** |
| | | | (1.89) |
| *VIX+VIX*EME* | | | *-7.87**** |
| *p-value* | | | *0.0001* |
| Δ VIX | -0.25 | -0.53 | 0.24 |
| | (1.40) | (1.43) | (1.59) |
| Δ VIX*EME | | | -5.68** |
| | | | (2.60) |
| *ΔVIX+ΔVIX*EME* | | | *-5.44*** |
| *p-value* | | | *0.0139* |
| ROE | 0.15*** | 0.11*** | 0.13*** |
| | (0.02) | (0.03) | (0.03) |
| ROE*EME | | | -0.33* |
| | | | (0.16) |
| *ROE+ROE*EME* | | | *-0.19* |
| *p-value* | | | *0.2357* |
| FX Return | -12.32*** | -11.94*** | -6.89* |
| | (4.32) | (3.73) | (3.57) |
| FX Return*EME | | | -18.73* |
| | | | (9.81) |
| *FX Return+FX Return*EME* | | | *-25.62**** |
| *p-value* | | | *0.0069* |
| Δ IR Spread | 0.51 | 0.24 | 0.70 |
| | (0.40) | (0.42) | (0.50) |
| Δ IR Spread*EME | | | -0.43 |
| | | | (0.59) |
| *ΔIR Spread+ΔIR Spread*EME* | | | *0.27* |
| *p-value* | | | *0.4424* |
| **Controls** | N | Y | Y |
| Observations | 1,142 | 1,088 | 1,088 |
| R-squared | 0.09 | 0.10 | 0.12 |
| Countries | 25 | 25 | 25 |

**Table A.1:** ***Aggregate Cross-Border Bank-to-Bank Funding.*** *The table presents the estimated parameter values from fixed-effects panel regressions. The dependent variable is the quarterly percentage change in aggregate cross-border bank-to-bank funding. $EME$ is a dummy variable which equals* **1** *if the banking system is in an emerging market economy and zero otherwise. $VIX$ is the quarterly average of the log VIX index, while $\Delta VIX$ is the quarterly change in the average of the log VIX index. The control variables are discussed in 2.4.1 with summary statistics provided in Table 2.1. Standard errors, clustered at country level, are reported in brackets. *** is significant at the 1% level, ** at the 5% level and * at the 10% level. I include F-tests to determine if the effect of a variable on emerging economies is significant. Data on banking flows are collected from the Bank for International Settlements's International Financial Statistics database. The sample period is from 1998Q1 to 2011Q4.*

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Parents | | Foreign Affiliates | |
| VIX | -3.96*** | -3.24** | -7.32*** | -6.45*** |
| | (1.33) | (1.34) | (1.75) | (1.73) |
| VIX*EME | | -5.20 | | -9.96 |
| | | (3.68) | | (6.36) |
| *VIX+VIX*EME* | | *-8.44*** | | *-16.40*** |
| *p-value* | | *0.0243* | | *0.0190* |
| $\Delta$ VIX | -5.08* | -5.03* | -1.56 | -0.04 |
| | (2.44) | (2.73) | (3.14) | (3.30) |
| $\Delta$ VIX*EME | | -0.88 | | -13.85 |
| | | (3.64) | | (9.95) |
| *$\Delta$VIX+$\Delta$VIX*EME* | | *-5.91*** | | *-13.89* |
| *p-value* | | *0.0298* | | *0.1530* |
| ROE | 0.12*** | 0.14*** | 0.02 | 0.06 |
| | (0.03) | (0.03) | (0.05) | (0.04) |
| ROE*EME | | -0.15 | | -0.26 |
| | | (0.18) | | (0.33) |
| *ROE+ROE*EME* | | *-0.01* | | *-0.20* |
| *p-value* | | *0.9559* | | *0.5483* |
| FX Return | -13.55** | -8.25 | -1.86 | 3.60 |
| | (5.35) | (5.27) | (7.54) | (8.61) |
| FX Return*EME | | -22.20* | | -15.03 |
| | | (11.78) | | (13.87) |
| *FX Return+FX Return*EME* | | *-30.45**** | | *-11.43* |
| *p-value* | | *0.0067* | | *0.2737* |
| $\Delta$ IR Spread | 0.78 | 1.26 | -0.55 | 3.42** |
| | (0.85) | (1.49) | (1.34) | (1.47) |
| $\Delta$ IR Spread*EME | | -0.50 | | -6.01*** |
| | | (1.75) | | (1.56) |
| *$\Delta$IR Spread+$\Delta$IR Spread*EME* | | *0.76* | | *-2.59**** |
| *p-value* | | *0.4191* | | *0.0006* |
| **Controls** | Y | Y | Y | Y |
| Observations | 919 | 919 | 922 | 922 |
| R-squared | 0.07 | 0.08 | 0.06 | 0.07 |
| Countries | 20 | 20 | 20 | 20 |

**Table A.2:** ***Interbank Funding: Flows to Parent and Foreign Affiliate Banks.*** *The table presents the estimated parameter values from fixed-effects panel regressions. The dependent variable is the quarterly percentage change in interbank funding to either parent or foreign affiliate banks. In columns (1) and (2), I report results for parents banks, while in columns (3) and (4), I do the same for foreign affiliates. EME is a dummy variable which equals* **1** *if the banking system is in an emerging market economy and zero otherwise. VIX is the quarterly average of the log VIX index, while $\Delta$VIX is the quarterly change in the average level of the log VIX index. The control variables are discussed in 2.4.1, with summary statistics presented in Table 2.1. Standard errors, clustered at country level, are reported in brackets. *** is significant at the 1% level, ** at the 5% level and * at the 10% level. I include F-tests to determine if the effect of a variable on emerging economies is significant. Data on banking flows are collected from the Bank for International Settlements's International Financial Statistics database. The sample period is from 1998Q1 to 2011Q4.*

| *Variables* | *Inter* Fund | *Intra* Fund. | VIX | VIX Change | ROE | ER Dep. | ΔIR Spread | Inflation | Growth | Public Debt | Stock Vol. |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Interbank Funding | 1.000 | | | | | | | | | | |
| Intragroup Funding | -0.071 | 1.000 | | | | | | | | | |
| | (0.015) | | | | | | | | | | |
| VIX | -0.172 | -0.059 | 1.000 | | | | | | | | |
| ΔVIX | -0.020 | 0.044 | -0.320 | 1.000 | | | | | | | |
| Return on Equity | 0.166 | 0.135 | -0.313 | -0.037 | 1.000 | | | | | | |
| FX Return | -0.090 | -0.084 | 0.143 | 0.068 | -0.098 | 1.000 | | | | | |
| ΔIR Spread | -0.001 | -0.032 | 0.122 | 0.022 | -0.065 | 0.060 | 1.000 | | | | |
| Inflation | 0.010 | 0.020 | 0.109 | -0.053 | 0.027 | 0.100 | -0.235 | 1.000 | | | |
| GDP Growth | 0.162 | 0.009 | -0.243 | 0.029 | 0.175 | -0.078 | -0.067 | 0.072 | 1.000 | | |
| ΔPublic Debt | -0.096 | -0.056 | 0.138 | -0.137 | -0.272 | 0.007 | -0.039 | -0.202 | -0.125 | 1.000 | |
| Stock Volatility | -0.049 | -0.028 | 0.265 | -0.112 | -0.164 | 0.091 | -0.179 | 0.359 | 0.044 | 0.349 | 1.000 |

**Table A.3:** ***Correlations: Dependent and Independent Variables.*** *The table presents correlations across dependent and independent variables used in the panel regression analysis. The p-value on the correlation between interbank and intragroup funding is reported in parentheses.*

| Variable | Mean | Std.dev. | Min | Max | Obs. |
|---|---|---|---|---|---|
| VXO | 3.09 | 0.37 | 2.36 | 4.12 | 1,400 |
| CS Global Risk Appetite Index | -0.33 | 2.70 | -6.31 | 4.69 | 1,400 |
| Moody's Spread | -0.01 | 0.34 | -0.53 | 1.11 | 1,400 |
| global imbalance risk factor | -0.26 | 1.32 | -3.06 | 3.84 | 1,400 |
| TED Spread | 3.74 | 0.71 | 2.52 | 5.57 | 1,400 |

**Table A.4:** ***Descriptive Statistics: Alternative Measures of Global Risk.*** *The table presents descriptive statistics for the alternative measures of global risk. Moody's Spread refers to the spread between AAA and BAA rated securities. The global imbalance risk factor is taken from Chapter 3 (Della Corte et al., 2014). Data on the TED Spread is collected from Bloomberg. See Section 2.6.2 for further details.*

| Variable | VIX | VXO | CS | Moody's | GI Risk | TED |
|---|---|---|---|---|---|---|
| VIX | 1.000 | | | | | |
| VXO | 0.989 | 1.000 | | | | |
| CS Global Risk Appetite Index | 0.692 | 0.701 | 1.000 | | | |
| Moody's Spread | 0.562 | 0.522 | 0.376 | 1.000 | | |
| global imbalance risk factor | 0.264 | 0.239 | 0.083 | 0.115 | 1.000 | |
| TED Spread | 0.292 | 0.258 | 0.171 | 0.201 | 0.267 | 1.000 |

**Table A.5:** ***Correlations: Alternative Measures of Global Risk.*** *The table presents correlations across the alternative measures of global risk. Moody's Spread refers to the spread between AAA and BAA rated securities. The global imbalance risk factor is taken from Chapter 3 (Della Corte et al., 2014). Data on the TED Spread is collected from Bloomberg. See Section 2.6.2 for further details.*

| | Banking System A | | | Banking System C | | |
|---|---|---|---|---|---|---|
| Quarter | Interbank | Intragroup | Total | Interbank | Intragroup | Total |
| 2008 Q3 | 80 | 20 | 100 | 20 | 80 | 100 |
| 2008 Q4 | 62.3 | 20.5 | 82.7 | 15.6 | 81.9 | 97.5 |
| 2009 Q1 | 49.9 | 20.5 | 70.4 | 12.5 | 81.9 | 94.4 |
| 2009 Q2 | 40.1 | 20.5 | 60.5 | 10 | 81.9 | 91.9 |

**Table A.6:** ***Example Calculation (Section 2.5.2).*** *The table presents an example calculation from the scenario analysis in Section 2.5.2 in which the VIX rises from 25 to 45 and remains at that level for two quarters. Based on the significant coefficients in Table 2.4, the change in total bank-to-bank funding in 2008Q4 for an advanced economy that has a pre-crisis stock of interbank funding of 80 is calculated as:* $80 \times [1 + (-0.0520 \times log(45) + -0.0404 \times log(45/25)] + 20 \times [1 + (0.0409 \times log(45/25))] = 82.7$. Then for 2009Q1: $62.3 \times [1 + (-0.0520 \times log(45))] + 20.5 = 70.4$.

# Appendix B

# Supporting Documentation: Chapter 3

## Summary of Additional Material

**Table B.1** presents cross-sectional asset pricing results as in Table 3.3. The difference here is that excess returns to the test assets exclude bid-ask spread transaction costs. I find global imbalance risk is still priced in the cross-section for *All Countries* and *Developed Countries*, albeit with slightly higher factor risk prices.

**Table B.2** presents cross-sectional asset pricing results for the linear factor model based on the dollar ($DOL$) and the global imbalance ($HML_{NA}$) risk factor. In contrast to Table B.1, the test assets employed here are the external imbalances ($NA$) portfolios sorted on the basis of the net foreign assets to GDP ratio and the share of foreign liabilities in domestic currency. I find the global imbalance risk factor ($HML_{NA}$) is able to price the $NA$ portfolios, reemphasizing its claim to be a currency risk factor.

**Table B.3** shows the probability of a currency moving from one portfolio to another in a transition matrix. The $FX$ portfolios in the top panels are the monthly carry trade portfolios formed using the forward premia at time $t-1$. The $NA$ portfolios in the bottom panels are the monthly external imbalances portfolios sorted on the net foreign assets to GDP ratio and the share of foreign liabilities in domestic currency at time $t-1$. The $NA$ portfolios show a slightly higher level of persistence due to the lower frequency of the net foreign asset data compared to interest rate data. The steady-state transition probabilities in the last row of each panel, however, are very similar. This implies that the performance of the strategies cannot simply be attributed to long-lived positions in particular currencies, but rather to a similar currency rotation across quintile portfolios.

**Table B.4** presents the currency composition of both $FX$ and $NA$ portfolios. I report the breakdown of the currencies most frequently found in each of the five $FX$ portfolios in Panel A, and in each of the five $NA$ portfolios in Panel B. In Panel C, I compute the joint probability that the same currency will simultaneously enter the same $FX$ and $NA$ portfolio. The figures reveal that approximately 45 (44) percent of the time, a currency in the first $FX$ portfolio will also be in the first $NA$ portfolio for *All Countries* (*Developed Countries*). I also calculate the joint probability for Portfolio 1 combined with Portfolio 2, and Portfolio 4 combined with Portfolio 5. The joint probabilities suggest that approximately 60 percent of the time a currency in the first (last) two $FX$ portfolios will also be in the first (last) two $NA$ portfolios, thus suggesting a very similar pattern for both $FX$ and $NA$ portfolios.

**Table B.5** presents descriptive statistics for the 20 most liquidly traded currencies for both $FX$ portfolios (top panels) and $NA$ Portfolios (bottom panels). As with the *All Countries* sample, I find a monotonic pattern in average excess returns, portfolio skewness and portfolio Sharpe Ratios. I find the Sharpe ratio attached to the $HML_{NA}$ risk factor is higher than for $HML_{FX}$ no matter whether rebalancing takes place at monthly or yearly frequency.

**Table B.6** employs alternative base currencies as an additional robustness check, taking the perspective of a Swiss, Euro-based, British and Japanese investor. Panel A presents cross-sectional regressions while Panel B reports time-series regressions for *All Countries*. The estimates of $\lambda$ and $b$ remain statistically different from zero and largely comparable to the core results. The cross-sectional fit remains high as the $R^2$ goes from 60 percent to 74 percent, and I cannot reject the null hypotheses of zero pricing errors and zero $HJ$ distance. Overall, the results appear to be robust to this additional check.

**Table B.7** presents descriptive statistics for the external imbalances portfolios sorted only on the basis of the net foreign assets to GDP ratio, i.e. I do not re-sort currencies on the countries' share of foreign liabilities in domestic currency. Here, the monotonic pattern for average excess returns, portfolio skewness and portfolio Sharpe ratios is not observed. More importantly, the average excess return on the $HML_{NA}$ risk factor is indistinguishable from zero for *All Countries*, compared to nearly 5 percent in the sequentially sorted case. The Sharpe ratio for $HML_{NA}$ is also much lower in the single-sort exercise. These results suggest the importance of conditioning on the share of foreign liabilities in domestic currency as suggested by Gourinchas (2008).

**Figure B.1** presents a visual depiction of countries' external accounts around the world. Traditional carry trade investment currencies, such as the Australian and New Zealand dollars, are found to be issued by countries with large external deficits. In contrast, traditional funding currencies, such as the Japanese yen and Swiss franc, are shown to be issued by large creditor nations. The same is true in emerging markets, where carry-trade investment currencies, including the Brazilian real, Turkish lira, South African rand and Indian rupee, are all issued by countries with large external deficit positions.

**Figure B.2** presents the average share of foreign liabilities held in domestic currency across *Developed Countries* and *Non-Developed Countries*. The data is collected from Lane and Shambaugh (2010). Between 1990 and 2004 the average share of debt issued in domestic currency has been on the rise, reaching a level above 50 percent, on average, in both samples.

**Figure B.3** presents pricing errors of the test asset portfolios sorted by the one-month forward premia (nominal interest rate differentials). The model fit for both samples is found to be strong, with all points lying either on or close to the $45^o$ line. The figure supports the findings in Table 3.3, that pricing errors are not jointly different from zero for either the *All Countries* or *Developed Countries* samples.

**Figure B.4** presents the equivalent information to that displayed in Figure 3.4 but for 10-delta risk reversals (the implied volatility of a 10-delta call minus the implied volatility of a 10-delta put). On average, Portfolio 5 is found to have the most negatively skewed distribution, implying it has the largest expected future depreciation. In the time series, Portfolio 5 is found to have a consistently negative risk reversal, while the opposite is true for Portfolio 1.

Panel A: Factor Prices

| | $b_{DOL}$ | $b_{NA}$ | $\lambda_{DOL}$ | $\lambda_{NA}$ | $R^2$ | $RMSE$ | $\chi^2$ | $HJ$ | $b_{DOL}$ | $b_{NA}$ | $\lambda_{DOL}$ | $\lambda_{NA}$ | $R^2$ | $RMSE$ | $\chi^2$ | $HJ$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | *All Countries* | | | | | | | | *Developed Countries* | | | | | | | |
| $GMM_1$ | −0.23 | 2.24 | 0.02 | 0.10 | 0.92 | 1.90 | 5.53 | 0.26 | 0.11 | 1.26 | 0.02 | 0.06 | 0.99 | 0.61 | 0.36 | 0.04 |
| | (0.34) | (0.67) | (0.02) | (0.02) | | | [0.14] | [0.16] | (0.25) | (0.56) | (0.02) | (0.02) | | | [0.95] | [0.96] |
| $GMM_2$ | −0.17 | 2.37 | 0.02 | 0.08 | 0.89 | 2.20 | 5.45 | | 0.10 | 1.27 | 0.02 | 0.06 | 0.97 | 1.01 | 0.36 | |
| | (0.34) | (0.66) | (0.02) | (0.02) | | | [0.14] | | (0.23) | (0.53) | (0.02) | (0.02) | | | [0.95] | |
| $FMB$ | −0.23 | 2.24 | 0.02 | 0.10 | 0.92 | 1.90 | 5.53 | | 0.11 | 1.26 | 0.02 | 0.06 | 0.99 | 0.61 | 0.36 | |
| | (0.26) | (0.50) | (0.02) | (0.02) | | | [0.14] | | (0.20) | (0.41) | (0.02) | (0.02) | | | [0.95] | |
| | [0.24] | [0.50] | [0.01] | [0.02] | | | | | [0.18] | [0.40] | [0.02] | [0.02] | | | | |

Panel B: Factor Betas

| | $\alpha$ | $\beta_{DOL}$ | $\beta_{NA}$ | $R^2$ | $\alpha$ | $\beta_{DOL}$ | $\beta_{NA}$ | $R^2$ |
|---|---|---|---|---|---|---|---|---|
| $P_1$ | −0.02 | 0.98 | −0.32 | 0.79 | −0.01 | 0.95 | −0.51 | 0.75 |
| | (0.01) | (0.05) | (0.04) | | (0.01) | (0.05) | (0.07) | |
| $P_2$ | −0.02 | 0.99 | −0.21 | 0.79 | 0.01 | 1.01 | −0.18 | 0.82 |
| | (0.01) | (0.04) | (0.04) | | (0.01) | (0.04) | (0.04) | |
| $P_3$ | 0.01 | 1.03 | −0.07 | 0.84 | 0.01 | 0.99 | 0.00 | 0.86 |
| | (0.01) | (0.04) | (0.04) | | (0.01) | (0.03) | (0.04) | |
| $P_4$ | 0.01 | 1.07 | 0.14 | 0.84 | 0.00 | 0.99 | 0.16 | 0.83 |
| | (0.01) | (0.04) | (0.06) | | (0.01) | (0.03) | (0.05) | |
| $P_5$ | 0.03 | 0.94 | 0.46 | 0.71 | 0.02 | 1.05 | 0.53 | 0.79 |
| | (0.01) | (0.07) | (0.08) | | (0.01) | (0.04) | (0.06) | |

**Table B.1:** ***Asset Pricing: Global Imbalance Risk.*** *The table presents cross-sectional asset pricing results for the linear factor model based on the dollar (DOL) and the global imbalance ($HML_{NA}$) risk factor. The test assets are excess returns to five currency ($FX$) portfolios sorted on the one-month forward premia. Panel A reports GMM (first and second-stage) and Fama-MacBeth (FMB) estimates of the factor loadings b, the market price of risk $\lambda$, and the cross-sectional $R^2$. Newey and West (1987) standard errors with Andrews (1991) optimal lag selection are reported in parentheses whereas Shanken (1992) standard errors are reported in brackets. $\chi^2$ denotes the test statistics (with p-value in parentheses) for the null hypothesis that all pricing errors are jointly zero. $HJ$ refers to the Hansen and Jagannathan (1997) distance (with simulated p-value in parentheses) for the null hypothesis that the $HJ$ distance is equal to zero. Panel B reports least-squares estimates of time series regressions with Newey and West (1987) standard errors in parentheses. Excess returns are expressed in percentage per annum. The portfolios are rebalanced monthly from October* 1983 *to December* 2011.

Panel A: Factor Prices

| | $b_{DOL}$ | $b_{NA}$ | $\lambda_{DOL}$ | $\lambda_{NA}$ | $R^2$ | $RMSE$ | $\chi^2$ | $HJ$ | $b_{DOL}$ | $b_{NA}$ | $\lambda_{DOL}$ | $\lambda_{NA}$ | $R^2$ | $RMSE$ | $\chi^2$ | $HJ$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | *All Countries* | | | | | | | | *Developed Countries* | | | | | | | |
| $GMM_1$ | 0.07 | 0.93 | 0.02 | 0.04 | 0.92 | 0.98 | 1.71 | 0.08 | 0.15 | 0.74 | 0.02 | 0.04 | 0.86 | 1.14 | 1.82 | 0.08 |
| | (0.28) | (0.33) | (0.02) | (0.01) | | | [0.64] | [0.67] | (0.22) | (0.39) | (0.02) | (0.01) | | | [0.61] | [0.66] |
| $GMM_2$ | 0.09 | 1.05 | 0.02 | 0.05 | 0.90 | 1.15 | 1.55 | | 0.17 | 0.86 | 0.01 | 0.02 | 0.73 | 1.83 | 1.66 | |
| | (0.27) | (0.3) | (0.02) | (0.01) | | | [0.67] | | (0.22) | (0.32) | (0.02) | (0.01) | | | [0.65] | |
| $FMB$ | 0.07 | 0.93 | 0.02 | 0.04 | 0.92 | 0.98 | 1.71 | | 0.15 | 0.74 | 0.02 | 0.04 | 0.86 | 1.14 | 1.82 | |
| | (0.25) | (0.29) | (0.02) | (0.01) | | | [0.64] | | (0.2) | (0.26) | (0.02) | (0.01) | | | [0.61] | |
| | (0.22) | [0.27] | [0.01] | [0.01] | | | | | [0.18] | [0.27] | [0.02] | [0.01] | | | | |

Panel B: Factor Betas

| | $\alpha$ | $\beta_{DOL}$ | $\beta_{NA}$ | $R^2$ | $\alpha$ | $\beta_{DOL}$ | $\beta_{NA}$ | $R^2$ |
|---|---|---|---|---|---|---|---|---|
| $P_1$ | 0.01 | 1.03 | −0.41 | 0.88 | 0.01 | 1.02 | −0.62 | 0.91 |
| | (0.01) | (0.04) | (0.04) | | (0.01) | (0.04) | (0.05) | |
| $P_2$ | 0.01 | 1.19 | −0.20 | 0.86 | −0.01 | 1.14 | −0.12 | 0.89 |
| | (0.01) | (0.04) | (0.04) | | (0.01) | (0.03) | (0.04) | |
| $P_3$ | −0.01 | 0.78 | 0.01 | 0.71 | 0.01 | 0.92 | 0.11 | 0.82 |
| | (0.01) | (0.07) | (0.07) | | (0.01) | (0.03) | (0.04) | |
| $P_4$ | 0.00 | 0.98 | 0.00 | 0.70 | 0.00 | 0.90 | 0.25 | 0.77 |
| | (0.01) | (0.06) | (0.04) | | (0.01) | (0.05) | (0.06) | |
| $P_5$ | 0.01 | 1.03 | 0.59 | 0.92 | 0.01 | 1.02 | 0.38 | 0.91 |
| | (0.01) | (0.04) | (0.04) | | (0.01) | (0.04) | (0.05) | |

**Table B.2:** ***External Imbalances Portfolios as Test Assets.*** *The table presents cross-sectional asset pricing results when the test assets are excess returns to five currency (NA) portfolios sorted on time $t-1$ external imbalances (net foreign assets to GDP ratio) and the share of foreign liabilities in domestic currency. The linear factor model is based on the dollar (DOL) and the global imbalance ($HML_{NA}$) risk factor. Panel A reports GMM (first and second-stage) and Fama-MacBeth (FMB) estimates of the factor loadings b, the market price of risk $\lambda$, and the cross-sectional $R^2$. Newey and West (1987) standard errors with Andrews (1991) optimal lag selection are reported in parentheses whereas Shanken (1992) standard errors are reported in brackets. $\chi^2$ denotes the test statistics (with p-value in parentheses) for the null hypothesis that all pricing errors are jointly zero. $HJ$ refers to the Hansen and Jagannathan (1997) distance (with simulated p-value in parentheses) for the null hypothesis that the $HJ$ distance is equal to zero. Panel B reports least-squares estimates of time series regressions with Newey and West (1987) standard errors in parentheses. Excess returns are expressed in percentage per annum. The portfolios are rebalanced monthly from October* 1983 *to December* 2011.

| | | | Panel A: FX Portfolios | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| $\pi_{t\to t+1}$ | $P_1$ | $P_2$ | $P_3$ | $P_4$ | $P_5$ | $P_1$ | $P_2$ | $P_3$ | $P_4$ | $P_5$ |
| | *All Countries* | | | | | *Developed Countries* | | | | |
| $P_L$ | 0.81 | 0.16 | 0.02 | 0.01 | 0.00 | 0.88 | 0.09 | 0.02 | 0.01 | 0.00 |
| $P_2$ | 0.13 | 0.71 | 0.13 | 0.02 | 0.00 | 0.07 | 0.74 | 0.15 | 0.03 | 0.01 |
| $P_3$ | 0.02 | 0.14 | 0.68 | 0.14 | 0.02 | 0.01 | 0.16 | 0.69 | 0.13 | 0.01 |
| $P4$ | 0.01 | 0.02 | 0.17 | 0.67 | 0.13 | 0.00 | 0.03 | 0.13 | 0.75 | 0.08 |
| $P_S$ | 0.00 | 0.00 | 0.02 | 0.14 | 0.83 | 0.00 | 0.01 | 0.02 | 0.11 | 0.86 |
| $\overline{\pi}$ | **0.19** | **0.23** | **0.22** | **0.19** | **0.18** | **0.17** | **0.23** | **0.22** | **0.21** | **0.16** |

| | | | Panel A: NA Portfolios | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| $\pi_{t\to t+1}$ | $P_1$ | $P_2$ | $P_3$ | $P_4$ | $P_5$ | $P_1$ | $P_2$ | $P_3$ | $P_4$ | $P_5$ |
| | *All Countries* | | | | | *Developed Countries* | | | | |
| $P_L$ | 0.98 | 0.02 | 0.00 | 0.00 | 0.00 | 0.99 | 0.01 | 0.00 | 0.00 | 0.00 |
| $P_2$ | 0.02 | 0.96 | 0.01 | 0.00 | 0.00 | 0.01 | 0.97 | 0.01 | 0.01 | 0.00 |
| $P_3$ | 0.01 | 0.02 | 0.97 | 0.01 | 0.00 | 0.00 | 0.01 | 0.97 | 0.01 | 0.01 |
| $P4$ | 0.00 | 0.01 | 0.01 | 0.97 | 0.01 | 0.00 | 0.01 | 0.02 | 0.97 | 0.01 |
| $P_S$ | 0.00 | 0.00 | 0.01 | 0.01 | 0.98 | 0.00 | 0.01 | 0.01 | 0.01 | 0.97 |
| $\overline{\pi}$ | **0.26** | **0.26** | **0.21** | **0.16** | **0.12** | **0.22** | **0.24** | **0.21** | **0.17** | **0.15** |

**Table B.3:** ***Transition Matrix.*** *The table presents the transition matrix of currency portfolios formed using time $t-1$ information. $\pi_{t\to t+1}$ denotes the probability of moving from one portfolio to another between time $t$ and time $t+1$ (read by row). The $FX$ portfolios are sorted on time $t-1$ one-month forward premia. The $NA$ portfolios are sorted on time $t-1$ external imbalances (net foreign assets to GDP ratio) and the share of foreign liabilities in domestic currency. The portfolios are rebalanced monthly from October* 1983 *to December* 2011.

| | $P_1$ | $P_2$ | $P_3$ | $P_4$ | $P_5$ | $P_1$ | $P_2$ | $P_3$ | $P_4$ | $P_5$ |
|---|---|---|---|---|---|---|---|---|---|---|
| **Panel A: FX Portfolios** | | | | | | | | | | |
| | | | *All Countries* | | | | | *Developed Countries* | | |
| *Top* 1 | JPY [0.18] | DKK [0.08] | GBP [0.08] | AUD [0.09] | ZAR [0.14] | JPY [0.43] | NLG [0.15] | DKK [0.22] | GBP [0.18] | NZD [0.34] |
| *Top* 2 | CHF [0.17] | CAD [0.07] | NOK [0.06] | NZD [0.07] | TRY [0.10] | CHF [0.42] | EUR [0.11] | CAD [0.14] | AUD [0.15] | AUD [0.23] |
| *Top* 3 | SGD [0.13] | EUR [0.06] | DKK [0.06] | GBP [0.06] | MXN [0.06] | DEM [0.07] | CAD [0.11] | GBP [0.11] | SEK [0.14] | ITL [0.13] |
| *Top* 4 | HKD [0.08] | SGD [0.05] | CAD [0.06] | INR [0.05] | NZD [0.06] | CAD [0.03] | DEM [0.11] | NOK [0.11] | NOK [0.13] | NOK [0.11] |
| *Top* 5 | CNY [0.06] | HKD [0.05] | HKD [0.05] | PHP [0.05] | HUF [0.05] | NLG [0.02] | SEK [0.08] | SEK [0.10] | CAD [0.11] | GBP [0.09] |
| *Top* 6 | SEK [0.04] | NLG [0.05] | SEK [0.05] | NOK [0.05] | BRL [0.05] | SEK [0.01] | FRF [0.08] | FRF [0.08] | DKK [0.08] | SEK [0.06] |
| **Panel B: NA Portfolios** | | | | | | | | | | |
| *Top* 1 | SGD [0.15] | GBP [0.13] | AUD [0.15] | NZD [0.15] | DKK [0.11] | CHF [0.23] | CHF [0.22] | AUD [0.29] | CAD [0.25] | DKK [0.35] |
| *Top* 2 | CHF [0.11] | CHF [0.09] | NOK [0.11] | HUF [0.10] | TRY [0.10] | JPY [0.22] | GBP [0.20] | NOK [0.27] | NZD [0.24] | NZD [0.18] |
| *Top* 3 | JPY [0.10] | NLG [0.08] | MYR [0.09] | CAD [0.09] | PHP [0.09] | DEM [0.20] | NLG [0.17] | JPY [0.13] | SEK [0.22] | SEK [0.18] |
| *Top* 4 | EUR [0.09] | JPY [0.07] | HKD [0.08] | ZAR [0.08] | SEK [0.09] | EUR [0.13] | FRF [0.13] | ITL [0.11] | NOK [0.10] | GBP [0.17] |
| *Top* 5 | HKD [0.09] | CAD [0.06] | DKK [0.07] | PLN [0.07] | IDR [0.09] | CAD [0.11] | DKK [0.09] | EUR [0.09] | AUD [0.10] | ITL [0.07] |
| *Top* 6 | DEM [0.09] | FRF [0.06] | ITL [0.05] | MXN [0.06] | HRK [0.06] | FRF [0.09] | JPY [0.08] | GBP [0.04] | ITL [0.04] | CAD [0.05] |
| **Panel B: Joint Probability** | | | | | | | | | | |
| | [0.45] | [0.24] | [0.22] | [0.23] | [0.36] | [0.44] | [0.25] | [0.18] | [0.26] | [0.35] |
| | [0.62] | | | [0.60] | | [0.67] | | | [0.57] | |

**Table B.4:** ***Portfolio Composition.*** *The table presents a break-down of the FX and NA portfolios. Panel A (Panel B) reports the top six currencies (with probabilities in parentheses) entering each of the five FX (NA) portfolios. Panel C presents the probability that the same currency simultaneously enters the same FX and NA portfolio. The FX portfolios are sorted on time $t-1$ one-month forward premia. The NA portfolios are sorted on time $t-1$ external imbalances (net foreign assets to GDP ratio) and the share of foreign liabilities in domestic currency. The portfolios are rebalanced monthly from October* 1983 *to December* 2011*. Exchange rates are from Datastream. Yearly data on GDP, foreign assets and liabilities are from Lane and Milesi-Ferretti (2007). Yearly data on the share of foreign liabilities in domestic currency are from Lane and Shambaugh (2010). Monthly observations are retrieved by keeping end-of-period data constant until a new observation becomes available.*

| | Panel A: Monthly Rebalancing | | | | | | | | | Panel B: Yearly Rebalancing | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $P_1$ | $P_2$ | $P_3$ | $P_4$ | $P_5$ | $DOL$ | $HML$ | $DOL^{\tau}$ | $HML^{\tau}$ | $P_1$ | $P_2$ | $P_3$ | $P_4$ | $P_5$ | $DOL$ | $HML$ | $DOL^{\tau}$ | $HML^{\tau}$ |
| | *FX Portfolios* | | | | | | | | | *FX Portfolios* | | | | | | | | |
| *Mean* | −1.22 | 0.41 | 2.78 | 2.12 | 6.66 | 2.15 | 7.88 | 1.07 | 5.25 | −0.05 | 0.80 | 0.12 | 1.96 | 5.46 | 1.66 | 5.51 | 1.39 | 4.78 |
| *Med* | −2.08 | 3.39 | 4.34 | 6.19 | 11.10 | 4.23 | 11.15 | 3.08 | 9.24 | 2.93 | 1.47 | 2.72 | 3.45 | 8.38 | 2.48 | 5.84 | 2.03 | 5.21 |
| *Sdev.* | 9.13 | 9.31 | 9.05 | 10.58 | 11.54 | 8.64 | 11.03 | 8.64 | 11.01 | 10.43 | 11.19 | 12.90 | 12.54 | 17.98 | 10.81 | 17.34 | 10.77 | 17.18 |
| *Skew* | 0.10 | −0.45 | −0.31 | −1.18 | −1.62 | −0.67 | −1.44 | −0.68 | −1.46 | −0.54 | −0.17 | −1.53 | −0.03 | −1.59 | −0.58 | −0.62 | −0.58 | −0.65 |
| *Kurt* | 3.84 | 4.12 | 4.37 | 7.57 | 10.57 | 4.81 | 7.21 | 4.81 | 7.23 | 2.47 | 1.93 | 5.47 | 1.98 | 6.45 | 2.91 | 3.05 | 2.91 | 3.06 |
| $AC_1$ | −0.01 | 0.10 | 0.06 | 0.09 | 0.09 | 0.09 | 0.05 | 0.09 | 0.05 | 0.02 | 0.00 | 0.03 | 0.01 | 0.23 | −0.02 | 0.29 | −0.02 | 0.28 |
| *SR* | −0.13 | 0.04 | 0.31 | 0.20 | 0.58 | 0.25 | 0.71 | 0.12 | 0.48 | 0.00 | 0.07 | 0.01 | 0.16 | 0.30 | 0.15 | 0.32 | 0.13 | 0.28 |
| *MDD* | −0.53 | −0.44 | −0.35 | −0.38 | −0.44 | −0.29 | −0.32 | −0.30 | −0.38 | −0.44 | −0.37 | −0.60 | −0.47 | −0.62 | −0.30 | −0.51 | −0.32 | −0.52 |
| *Freq* | 14.0 | 26.8 | 29.0 | 25.7 | 13.1 | 21.7 | 27.1 | 21.7 | 27.1 | 25.0 | 52.7 | 56.3 | 52.7 | 32.7 | 43.9 | 57.7 | 43.9 | 57.7 |
| | *NA Portfolios* | | | | | | | | | *NA Portfolios* | | | | | | | | |
| *Mean* | 0.19 | 1.25 | 1.23 | 1.96 | 7.05 | 2.33 | 6.85 | 1.28 | 4.72 | −0.36 | 1.54 | 1.69 | 0.37 | 4.98 | 1.64 | 5.34 | 1.38 | 4.78 |
| *Med* | 1.48 | 0.99 | 3.06 | 3.99 | 9.68 | 4.09 | 8.67 | 3.27 | 7.22 | 2.03 | 0.97 | 3.02 | 1.19 | 6.70 | 2.46 | 6.46 | 2.01 | 6.16 |
| *Sdev.* | 8.99 | 9.95 | 8.81 | 9.63 | 10.63 | 8.57 | 7.56 | 8.57 | 7.53 | 10.96 | 11.12 | 11.02 | 14.41 | 15.48 | 10.81 | 11.23 | 10.76 | 11.03 |
| *Skew* | −0.09 | −0.31 | −0.63 | −1.16 | −1.05 | −0.63 | −0.94 | −0.64 | −0.97 | −0.77 | −0.28 | −0.47 | −2.21 | −0.43 | −0.53 | −0.50 | −0.53 | −0.58 |
| *Kurt* | 3.19 | 4.18 | 5.20 | 8.07 | 5.95 | 4.73 | 7.92 | 4.73 | 7.92 | 2.58 | 2.53 | 2.77 | 10.16 | 3.32 | 2.79 | 4.20 | 2.79 | 4.24 |
| $AC_1$ | 0.09 | 0.06 | 0.08 | 0.08 | 0.11 | 0.09 | 0.25 | 0.09 | 0.25 | 0.14 | −0.03 | −0.07 | 0.20 | −0.11 | −0.02 | 0.15 | −0.02 | 0.14 |
| *SR* | 0.02 | 0.13 | 0.14 | 0.20 | 0.66 | 0.27 | 0.91 | 0.15 | 0.63 | −0.03 | 0.14 | 0.15 | 0.03 | 0.32 | 0.15 | 0.48 | 0.13 | 0.43 |
| *MDD* | −0.54 | −0.42 | −0.31 | −0.35 | −0.36 | −0.27 | −0.32 | −0.30 | −0.36 | −0.56 | −0.33 | −0.25 | −0.61 | −0.35 | −0.31 | −0.30 | −0.32 | −0.31 |
| *Freq* | 2.6 | 3.1 | 3.0 | 3.1 | 2.7 | 2.9 | 5.3 | 2.9 | 5.3 | 25.6 | 34.2 | 30.4 | 26.2 | 26.8 | 28.6 | 52.4 | 28.6 | 52.4 |

**Table B.5:** ***Descriptive Statistics: Liquid Currencies.*** *The table presents descriptive statistics of currency portfolios sorted on time $t-1$ information for the top 20 most liquid currencies - Developed and Emerging Countries. The $FX$ portfolios are sorted on forward premia. Portfolio 1 ($P_1$) contains the top 20% of all currencies with the lowest forward premia whereas Portfolio 5 ($P_5$) contains the top 20% of all currencies with the highest forward premia. The $NA$ portfolios are sorted on external imbalances (net foreign assets to GDP ratio) and the share of foreign liabilities in domestic currency. Portfolio 1 ($P_1$) contains the top 20% of all currencies with positive external imbalances (creditor nations) and the highest share of foreign liabilities in domestic currency whereas Portfolio 5 ($P_5$) contains the top 20% of all currencies with negative external imbalances (debtor nations) and the lowest share of foreign liabilities in domestic currency. $DOL$ denotes the average return of the five currency portfolios. $HML$ denotes a long-short strategy that buys $P_5$ and sells $P_1$. Excess returns are expressed in percentage per annum, and $\tau$ denotes excess returns adjusted for transaction costs. The table also reports the first order autocorrelation coefficient ($AC_1$), the annualized Sharpe ratio ($SR$), the maximum drawdown in percent ($MDD$), and the frequency of portfolio switches ($Freq$) in percent. Panel A (Panel B) presents portfolios rebalanced at the end of each month (year) using one-month (one-year) forward premia. The sample runs from October* 1983 *to December* 2011, *and comprises* 338 *(28) observations for the monthly (yearly) exercise. Exchange rates are from Datastream. Yearly data on GDP, foreign assets and liabilities are from Lane and Milesi-Ferretti (2007) whereas yearly data on the share of foreign liabilities in domestic currency are from Lane and Shambaugh (2010). Monthly observations are retrieved by keeping end-of-period data constant until a new observation becomes available.*

Panel A: Factor Prices

| | $b_{DOL}$ | $b_{NA}$ | $\lambda_{DOL}$ | $\lambda_{NA}$ | $R^2$ | $RMSE$ | $\chi^2$ | $HJ$ | $b_{DOL}$ | $b_{NA}$ | $\lambda_{DOL}$ | $\lambda_{NA}$ | $R^2$ | $RMSE$ | $\chi^2$ | $HJ$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | *CHF* | | | | | | | | *DEM/EUR* | | | | | | | |
| $GMM_1$ | −0.32 | 1.59 | 0.01 | 0.07 | 0.68 | 2.11 | 5.33 | 0.15 | −0.29 | 1.59 | −0.01 | 0.07 | 0.67 | 2.43 | 5.98 | 0.16 |
| | (0.25) | (0.78) | (0.01) | (0.03) | | | [0.15] | [0.15] | (0.30) | (0.71) | (0.01) | (0.02) | | | [0.11] | [0.07] |
| $GMM_2$ | −0.29 | 1.30 | 0.01 | 0.05 | 0.60 | 2.36 | 5.18 | | −0.40 | 1.59 | −0.01 | 0.05 | 0.61 | 2.66 | 5.84 | |
| | (0.24) | (0.77) | (0.01) | (0.03) | | | [0.16] | | (0.30) | (0.71) | (0.01) | (0.02) | | | [0.12] | |
| $FMB$ | −0.32 | 1.59 | 0.01 | 0.07 | 0.68 | 2.11 | 5.33 | | −0.28 | 1.58 | −0.01 | 0.07 | 0.67 | 2.43 | 5.99 | |
| | (0.22) | (0.58) | (0.01) | (0.03) | | | [0.15] | | (0.29) | (0.54) | (0.01) | (0.02) | | | [0.11] | |
| | [0.23] | [0.61] | [0.01] | [0.03] | | | | | [0.28] | [0.53] | [0.01] | [0.02] | | | | |

Panel B: Factor Betas

| | $\alpha$ | $\beta_{DOL}$ | $\beta_{NA}$ | $R^2$ | $\alpha$ | $\beta_{DOL}$ | $\beta_{NA}$ | $R^2$ |
|---|---|---|---|---|---|---|---|---|
| $P_1$ | −0.01 | 0.93 | −0.29 | 0.76 | 0.01 | 0.91 | −0.35 | 0.69 |
| | (0.01) | (0.04) | (0.04) | | (0.01) | (0.06) | (0.05) | |
| $P_2$ | −0.01 | 0.97 | −0.16 | 0.77 | −0.02 | 0.95 | −0.18 | 0.66 |
| | (0.01) | (0.04) | (0.05) | | (0.01) | (0.07) | (0.05) | |
| $P_3$ | 0.01 | 0.88 | −0.04 | 0.78 | 0.01 | 0.79 | −0.03 | 0.66 |
| | (0.01) | (0.03) | (0.04) | | (0.01) | (0.05) | (0.03) | |
| $P_4$ | 0.01 | 0.96 | 0.16 | 0.78 | 0.01 | 0.88 | 0.20 | 0.64 |
| | (0.01) | (0.04) | (0.06) | | (0.01) | (0.05) | (0.06) | |
| $P_5$ | 0.04 | 1.29 | 0.29 | 0.75 | 0.04 | 1.51 | 0.31 | 0.72 |
| | (0.01) | (0.07) | (0.10) | | (0.01) | (0.10) | (0.10) | |

*Continued*

**Table B.6:** ***Asset Pricing: Other Base Currencies.*** *The table presents cross-sectional asset pricing results for other base currencies. The linear factor model is based on the dollar (DOL) and the global imbalance ($HML_{NA}$) risk factor. The test assets are excess returns to five currency (FX) portfolios sorted on the one-month forward premia. Panel A reports GMM (first and second-stage) and Fama-MacBeth (FMB) estimates of the factor loadings b, the market price of risk $\lambda$, and the cross-sectional $R^2$. Newey and West (1987) standard errors with Andrews (1991) optimal lag selection are reported in parentheses whereas Shanken (1992) standard errors are reported in brackets. $\chi^2$ denotes the test statistics (with p-value in parentheses) for the null hypothesis that all pricing errors are jointly zero. HJ refers to the Hansen and Jagannathan (1997) distance (with simulated p-value in parentheses) for the null hypothesis that the HJ distance is equal to zero. Panel B reports least-squares estimates of time series regressions with Newey and West (1987) standard errors in parentheses. Excess returns are expressed in percentage per annum and adjusted for transaction costs. The portfolios are rebalanced monthly from October* 1983 *to December* 2011.

**Asset Pricing: Other Base Currencies (cont.)**

Panel A: Factor Prices

| | $b_{DOL}$ | $b_{NA}$ | $\lambda_{DOL}$ | $\lambda_{NA}$ | $R^2$ | $RMSE$ | $\chi^2$ | $HJ$ | $b_{DOL}$ | $b_{NA}$ | $\lambda_{DOL}$ | $\lambda_{NA}$ | $R^2$ | $RMSE$ | $\chi^2$ | $HJ$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | *CHF* | | | | | | | | *DEM/EUR* | | | | | | | |
| $GMM_1$ | −0.32 | 1.59 | 0.01 | 0.07 | 0.68 | 2.11 | 5.33 | 0.15 | −0.29 | 1.59 | −0.01 | 0.07 | 0.67 | 2.43 | 5.98 | 0.16 |
| | (0.25) | (0.78) | (0.01) | (0.03) | | | [0.15] | [0.15] | (0.30) | (0.71) | (0.01) | (0.02) | | | [0.11] | [0.07] |
| $GMM_2$ | −0.29 | 1.30 | 0.01 | 0.05 | 0.60 | 2.36 | 5.18 | | −0.40 | 1.59 | −0.01 | 0.05 | 0.61 | 2.66 | 5.84 | |
| | (0.24) | (0.77) | (0.01) | (0.03) | | | [0.16] | | (0.30) | (0.71) | (0.01) | (0.02) | | | [0.12] | |
| $FMB$ | −0.32 | 1.59 | 0.01 | 0.07 | 0.68 | 2.11 | 5.33 | | −0.28 | 1.58 | −0.01 | 0.07 | 0.67 | 2.43 | 5.99 | |
| | (0.22) | (0.58) | (0.01) | (0.03) | | | [0.15] | | (0.29) | (0.54) | (0.01) | (0.02) | | | [0.11] | |
| | [0.23] | [0.61] | [0.01] | [0.03] | | | | | [0.28] | [0.53] | [0.01] | [0.02] | | | | |

Panel B: Factor Betas

| | $\alpha$ | $\beta_{DOL}$ | $\beta_{NA}$ | $R^2$ | $\alpha$ | $\beta_{DOL}$ | $\beta_{NA}$ | $R^2$ |
|---|---|---|---|---|---|---|---|---|
| $P1$ | −0.01 | 0.93 | −0.29 | 0.76 | 0.01 | 0.91 | −0.35 | 0.69 |
| | (0.01) | (0.04) | (0.04) | | (0.01) | (0.06) | (0.05) | |
| $P2$ | −0.01 | 0.97 | −0.16 | 0.77 | −0.02 | 0.95 | −0.18 | 0.66 |
| | (0.01) | (0.04) | (0.05) | | (0.01) | (0.07) | (0.05) | |
| $P3$ | 0.01 | 0.88 | −0.04 | 0.78 | 0.01 | 0.79 | −0.03 | 0.66 |
| | (0.01) | (0.03) | (0.04) | | (0.01) | (0.05) | (0.03) | |
| $P4$ | 0.01 | 0.96 | 0.16 | 0.78 | 0.01 | 0.88 | 0.20 | 0.64 |
| | (0.01) | (0.04) | (0.06) | | (0.01) | (0.05) | (0.06) | |
| $P5$ | 0.04 | 1.29 | 0.29 | 0.75 | 0.04 | 1.51 | 0.31 | 0.72 |
| | (0.01) | (0.07) | (0.10) | | (0.01) | (0.10) | (0.10) | |

*Continued*

| | Panel A: Monthly Rebalancing | | | | | | | | | Panel B: Yearly Rebalancing | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $P_1$ | $P_2$ | $P_3$ | $P_4$ | $P_5$ | $DOL$ | $HML$ | $DOL^\tau$ | $HML^\tau$ | $P_1$ | $P_2$ | $P_3$ | $P_4$ | $P_5$ | $DOL$ | $HML$ | $DOL^\tau$ | $HML^\tau$ |
| | *All Countries* | | | | | | | | | *All Countries* | | | | | | | | |
| $Mean$ | 1.23 | 0.85 | 2.66 | 2.57 | 1.95 | 1.85 | 0.72 | 0.72 | −1.67 | 0.69 | 0.67 | 3.06 | 2.07 | 0.18 | 1.34 | −0.52 | 1.02 | −1.20 |
| $Med$ | 1.17 | 1.26 | 4.66 | 4.96 | 4.52 | 3.46 | 4.97 | 2.59 | 2.44 | 0.26 | 2.45 | 3.81 | 4.01 | 4.33 | 2.57 | 2.42 | 2.21 | 1.52 |
| $Sdev$ | 6.35 | 9.00 | 8.73 | 7.63 | 9.86 | 7.22 | 8.34 | 7.22 | 8.35 | 6.06 | 9.82 | 10.49 | 10.39 | 16.99 | 9.32 | 15.12 | 9.31 | 15.16 |
| $Skew$ | −0.89 | −0.42 | −0.57 | −0.88 | −0.71 | −0.57 | −0.72 | −0.58 | −0.77 | 0.49 | −0.35 | −0.82 | −0.35 | −1.96 | −0.70 | −2.46 | −0.70 | −2.49 |
| $Kurt$ | 9.58 | 4.36 | 4.81 | 6.36 | 6.08 | 4.49 | 7.08 | 4.48 | 7.09 | 2.58 | 2.62 | 3.73 | 2.20 | 6.93 | 3.08 | 9.52 | 3.08 | 9.69 |
| $AC_1$ | 0.07 | 0.10 | 0.09 | 0.12 | 0.11 | 0.10 | 0.06 | 0.10 | 0.07 | 0.17 | −0.11 | −0.10 | 0.06 | −0.15 | −0.05 | −0.10 | −0.05 | −0.08 |
| $SR$ | 0.19 | 0.09 | 0.31 | 0.34 | 0.20 | 0.26 | 0.09 | 0.10 | −0.20 | 0.11 | 0.07 | 0.29 | 0.20 | 0.01 | 0.14 | −0.03 | 0.11 | −0.08 |
| $MDD$ | −0.30 | −0.44 | −0.27 | −0.28 | −0.33 | −0.24 | −0.31 | −0.29 | −0.48 | −0.22 | −0.36 | −0.24 | −0.25 | −0.61 | −0.25 | −0.66 | −0.26 | −0.69 |
| $Freq$ | 2.0 | 3.4 | 3.9 | 4.1 | 2.6 | 3.2 | 5.2 | 3.2 | 5.2 | 16.8 | 35.1 | 35.6 | 34.3 | 24.2 | 29.2 | 46.0 | 29.2 | 46.0 |
| | *Developed Countries* | | | | | | | | | *Developed Countries* | | | | | | | | |
| $Mean$ | 0.81 | 0.64 | 2.51 | 0.92 | 4.56 | 1.89 | 3.75 | 1.11 | 1.87 | 0.24 | 0.80 | 2.07 | 1.60 | 3.04 | 1.55 | 2.80 | 1.38 | 2.40 |
| $Med$ | 0.99 | 1.96 | 3.55 | 3.56 | 6.30 | 3.47 | 5.79 | 2.75 | 3.91 | 2.17 | 3.52 | 1.90 | 2.72 | 2.37 | 1.24 | 3.23 | 1.08 | 2.99 |
| $Sdev$ | 11.30 | 9.45 | 9.66 | 8.76 | 10.94 | 8.78 | 10.43 | 8.78 | 10.43 | 12.27 | 11.67 | 9.80 | 12.96 | 13.01 | 10.42 | 13.81 | 10.41 | 13.87 |
| $Skew$ | −0.22 | −0.11 | −0.41 | −0.57 | −0.59 | −0.33 | −0.31 | −0.34 | −0.31 | −0.41 | −0.21 | −0.02 | −0.79 | −0.06 | −0.15 | −0.72 | −0.15 | −0.72 |
| $Kurt$ | 3.33 | 3.31 | 4.44 | 4.46 | 5.86 | 3.79 | 3.84 | 3.78 | 3.84 | 2.14 | 1.82 | 2.19 | 3.41 | 2.79 | 2.11 | 4.09 | 2.11 | 4.04 |
| $AC_1$ | 0.09 | 0.04 | 0.09 | 0.08 | 0.07 | 0.09 | 0.06 | 0.09 | 0.06 | 0.07 | 0.05 | 0.06 | −0.02 | 0.03 | 0.06 | −0.05 | 0.05 | −0.05 |
| $SR$ | 0.07 | 0.07 | 0.26 | 0.11 | 0.42 | 0.21 | 0.36 | 0.13 | 0.18 | 0.02 | 0.07 | 0.21 | 0.12 | 0.23 | 0.15 | 0.20 | 0.13 | 0.17 |
| $MDD$ | −0.50 | −0.49 | −0.31 | −0.33 | −0.42 | −0.37 | −0.30 | −0.40 | −0.36 | −0.47 | −0.46 | −0.30 | −0.33 | −0.34 | −0.34 | −0.37 | −0.34 | −0.37 |
| $Freq$ | 2.2 | 3.1 | 3.6 | 3.2 | 1.6 | 2.7 | 4.9 | 2.7 | 4.9 | 25.0 | 30.4 | 35.1 | 29.8 | 13.7 | 26.8 | 51.8 | 26.8 | 51.8 |

**Table B.7:** ***Descriptive Statistics: Single-Sorted External Imbalances Portfolios.*** *The table presents descriptive statistics of currency portfolios sorted external imbalances (net foreign assets to GDP ratio) at time $t-1$. Portfolio 1 ($P_1$) contains the top 20% of all currencies with positive external imbalances (creditor nations) whereas Portfolio 5 ($P_5$) contains the top 20% of all currencies with negative external imbalances (debtor nations). DOL denotes the average return of the five currency portfolios. $HML$ denotes the global imbalance factor and is equivalent to a long-short strategy that buys $P_5$ and sells $P_1$. Excess returns are expressed in percentage per annum, and $\tau$ denotes excess returns adjusted for transaction costs. The table also reports the first order autocorrelation coefficient ($AC_1$), the annualized Sharpe ratio (SR), the maximum drawdown in percent ($MDD$), and the frequency of portfolio switches (Freq) in percent. Panel A (Panel B) presents portfolios rebalanced at the end of each month (year). The sample runs from October 1983 to December 2011, and comprises 338 (28) observations for the monthly (yearly) exercise. Exchange rates are from Datastream. Yearly data on GDP, foreign assets and liabilities are from Lane and Milesi-Ferretti (2007). Monthly observations are retrieved by keeping end-of-period data constant until a new observation becomes available.*

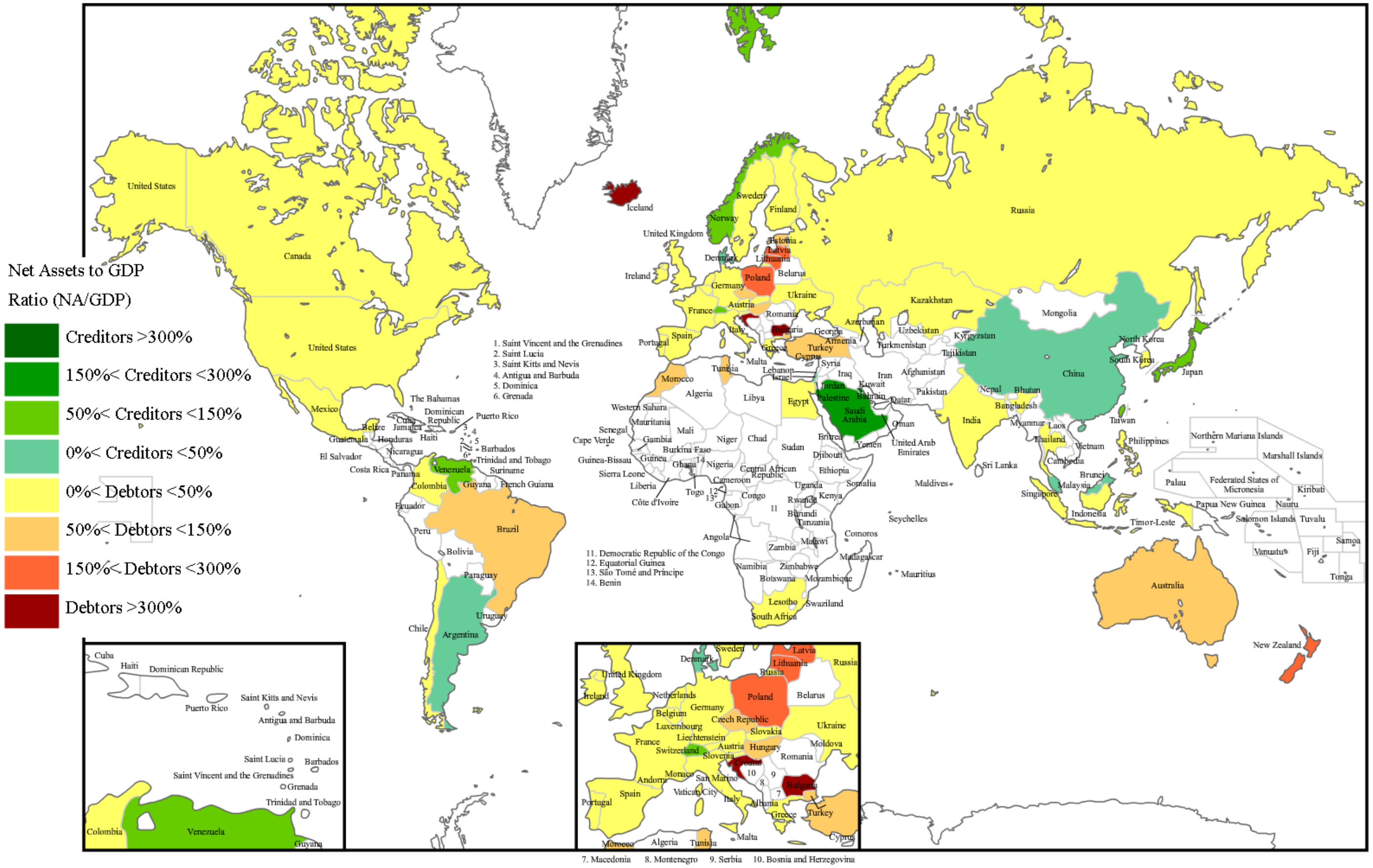


**Figure B.1:** ***The World Distribution of External Imbalances.*** *The figure presents the net foreign asset position relative to gross domestic product of All Countries included in the sample. I report the distribution of external imbalances as of December 2011 using data from the International Financial Statistics database. I build the map using P&P World Map (`http://edit.freemap.jp/en/`).*

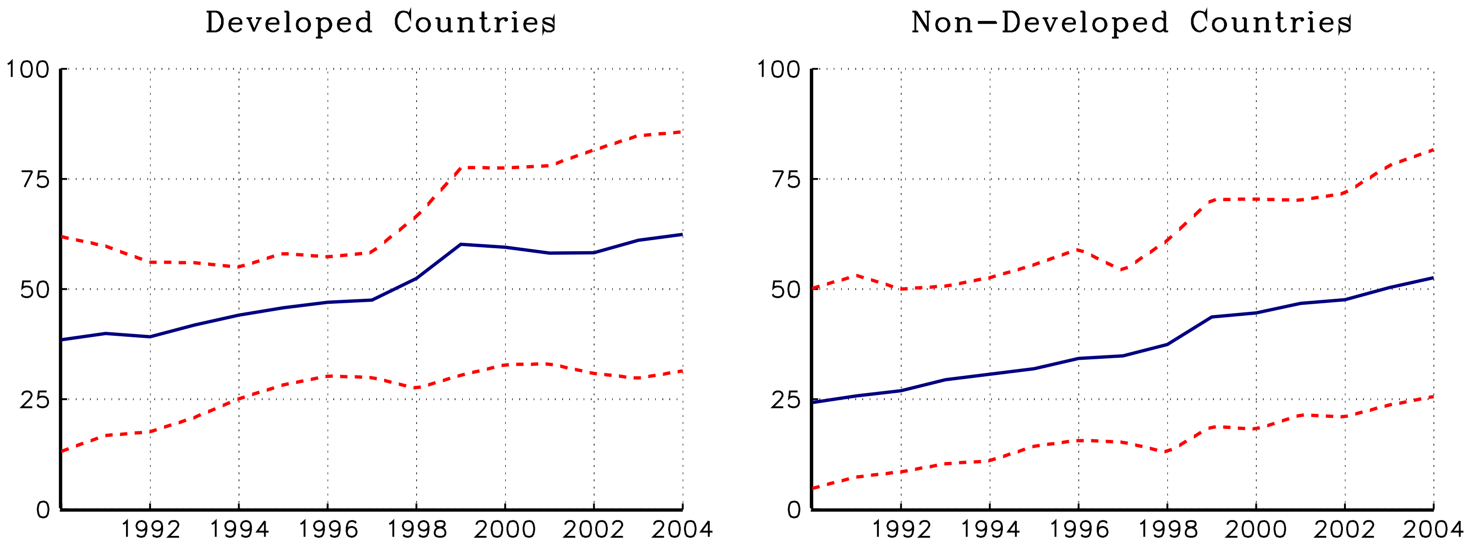


**Figure B.2:** ***Share of Foreign Liabilities in Domestic Currency.*** *The figure presents the average share of foreign liabilities issued in domestic currency (solid line) and the 90th and 10th percentile (dashed line). The dataset is from Lane and Shambaugh (2010) and comprises yearly estimates from 1990 through 2004.*

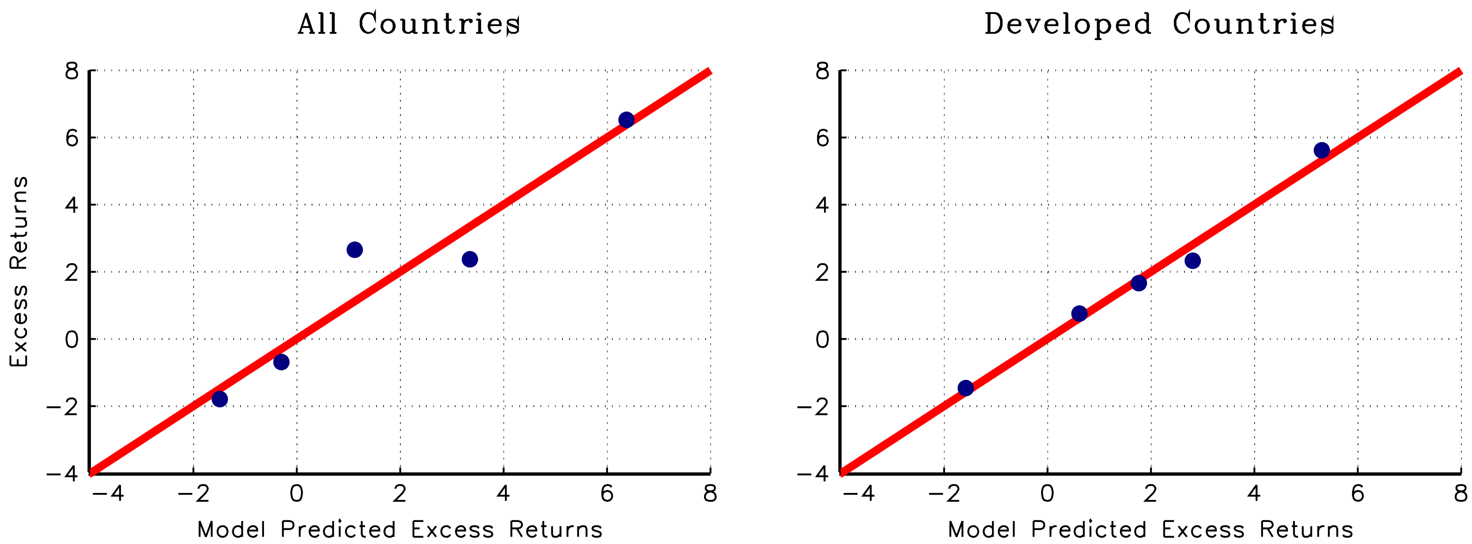


**Figure B.3:** ***Pricing Errors.*** *The figure presents cross-sectional pricing errors for the linear factor model based on the dollar (DOL) and the global imbalance risk ($HML_{NA}$) factor. The test assets are excess returns to currency (FX) portfolios obtained by sorting currencies into five groups using the one-month forward premia (nominal interest rate differentials). Portfolio 1 contains currencies with the lowest forward premia (funding currencies) whereas Portfolio 5 contains currencies with the highest forward premia (investment currencies). Excess returns are expressed in percentage per annum. The portfolios are rebalanced monthly from October 1983 to December 2011.*

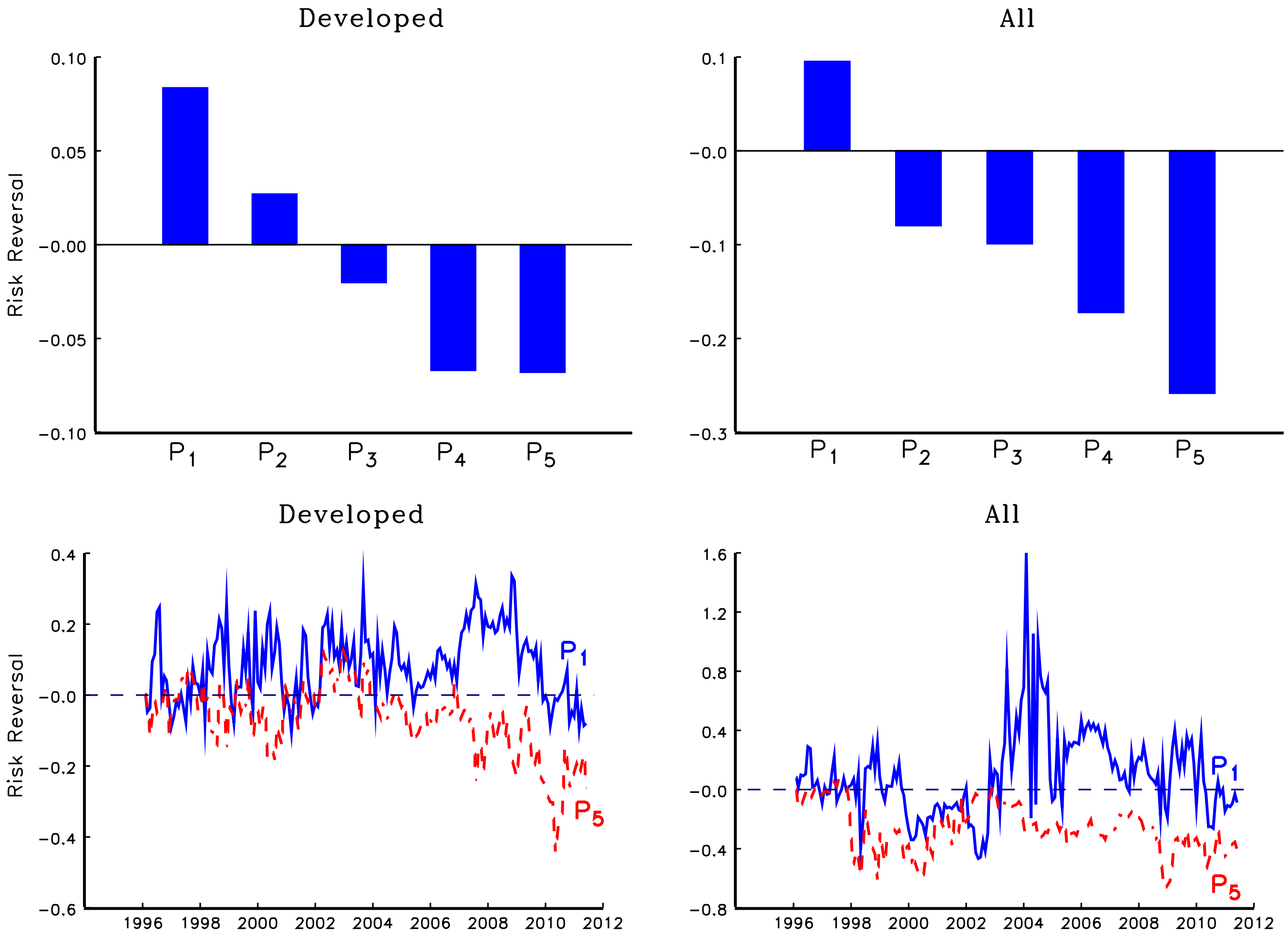


**Figure B.4:** ***Risk Reversal and Global Imbalance Risk.*** *The figure presents the one-month risk reversal of the external imbalance portfolios. The risk reversal is computed as the implied volatility of a 10-delta call minus the implied volatility of 10-delta put, scaled by the at-the-money implied volatility. Implied volatility data are from JP Morgan and range from January 1996 to August 2011.*

# Appendix C

# Supporting Documentation: Chapter 4

## Summary of Additional Material

**Table C.1** presents the loadings of the five currency portfolios, sorted by interest rates, on the five principal components which underlie the returns. The first two principal components explain around 90 percent of total variation in returns. The majority of the variation is accounted for by the first principal component, which acts a 'level' factor. The second principal component explains the heterogeneity in currency excess returns. High-interest-rate currencies (Portfolio 5) load positively on the principal component, while low-interest-rate currencies (Portfolio 1) load negatively.

**Table C.2** presents the cross-sectional Fama and MacBeth (1973) results for non-theoretical characteristic factors. The factors are sorted on the basis of the sub-indices of political risk, taken from the Political Risk Service Group's *International Country Risk Guide* database. The table augments the results presented in Table 4.5. Eight of the twelve factors are found to be statistically significant. The pricing, however, measured by other criteria including $R^2$ and $RMSE$ statistics is, overall, less supportive for the models than for the macroeconomic and financial factors.

**Table C.3** presents the cross-sectional Fama and MacBeth (1973) results for non-theoretical characteristic factors. The factors are sorted on the basis of the sub-indices of macroeconomic, financial and political risk, taken from the Political Risk Service Group's *International Country Risk Guide* database. The table provides the equivalent *Developed Countries* results to those presented for *All Countries* in Tables 4.5 and C.2. I find that 17 of the 22 characteristic factors are significant.

The results are found to be particular strong for the factors sorted on the basis of financial risks.

**Table C.4** presents the cross-sectional $R^2$ and t-statistic from the second-stage of the Fama and MacBeth (1973) procedure. The test assets are five portfolios sorted on the same basis as the factor itself. The table provides the equivalent *Developed Countries* results to those presented for *All Countries* in Table 4.6. The results largely overlap with the findings for *All Countries.* Again, I find that none of the 25 non-theoretical factors are statistically priced.

**Table C.5** presents simulation results from the second step of the Fama and MacBeth (1973) procedure. A set of 20,000 'useless' factors are generated to price currency portfolios sorted by interest rates (Panel A) and sorted randomly (Panel B). The table provides the equivalent *Developed Countries* results to those presented for *All Countries* in Table 4.7. The pricing of interest-rate-sorted portfolios is again found to generate biased results, supporting the findings of Lewellen, Nagel, and Shanken (2010). The bias, however, disappears once the 'useless' factors are asked to price the associated, and randomly-generated, currency portfolios.

**Figure C.1** presents a visual depiction of the results in Table C.4 for *Developed Countries.* The majority of non-theoretical factors are suggestive of strong pricing capabilities when pricing currency portfolios sorted by interest rates. When the test assets are changed to currency portfolios sorted by the characteristic of interest, none of the factors are significant.

**Figure C.2** presents the conditional excess returns to the 25 non-theoretical factors for the *Developed Countries* sample. Conditional on carry trade returns, the majority of characteristic factors display a monotonic pattern of returns. The finding suggests a common source of variation which drives macroeconomic, financial and political risks.

**Figure C.3** presents the average excess returns to the five currency portfolios sorted by each of the macroeconomic, financial and political characteristics for *Developed Countries.* If the characteristics could accurately explain currency exposure to risk, we would observe a monotonic pattern in excess currency returns. In the majority of instances, however, the factors are unable to generate monotonic patterns in returns, which helps to explain why the non-theoretical factors are unable to explain their respective set of currency portfolios.

| | **Panel A** | | | | | | **Panel B** | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | *All Countries* | | | | | | *Developed Countries* | | | | |
| Portfolio | 1 | 2 | 3 | 4 | 5 | Portfolio | 1 | 2 | 3 | 4 | 5 |
| $P_1$ | **0.39** | **-0.42** | -0.46 | -0.64 | -0.21 | $P_1$ | **0.40** | **-0.67** | 0.57 | -0.24 | -0.08 |
| $P_2$ | **0.42** | **-0.34** | -0.38 | 0.75 | -0.01 | $P_2$ | **0.45** | **-0.28** | -0.37 | 0.72 | -0.27 |
| $P_3$ | **0.45** | **-0.15** | 0.34 | -0.13 | 0.80 | $P_3$ | **0.44** | **-0.03** | -0.28 | -0.11 | 0.84 |
| $P_4$ | **0.49** | **-0.02** | 0.66 | 0.04 | -0.56 | $P_4$ | **0.45** | **0.17** | -0.43 | -0.61 | -0.46 |
| $P_5$ | **0.47** | **0.83** | -0.30 | -0.04 | 0.02 | $P_5$ | **0.49** | **0.67** | 0.52 | 0.21 | -0.03 |
| *Cum. % Var* | **75.3%** | **87.8%** | 93.4% | 96.9% | 100% | *Cum. % Var* | **76.0%** | **88.5%** | 93.5% | 97.1% | 100% |

**Table C.1:** ***PCA Analysis: Interest-Rate-Sorted Currency Portfolios.*** *The table presents the loadings of the five interest-rate-sorted test asset portfolios on the 5 principal components. I also report the cumulative proportion of return variation explained by the five principal components. The test-assets are collected from Chapter 3 (Della Corte et al., 2014). Panel A contains principal component loadings for All Countries, while Panel B contains principal component loadings for Developed Countries.*

| | Government Stability | | Socioeconomic Conditions | | Investment Profile | | Internal Conflict | | External Conflict | | Corruption | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | *DOL* | *RISK* | *DOL* | *RISK* | *DOL* | *RISK* | *DOL* | *RISK* | *DOL* | *RISK* | *DOL* | *RISK* |
| *Parameter* | 1.77 | 19.60 | 1.54 | 13.61 | 1.66 | 11.62 | 1.67 | 13.62 | 1.52 | 11.46 | 1.63 | -10.95 |
| *t-stat* | [1.28] | [1.91] | [1.11] | [3.04] | [1.20] | [2.98] | [1.20] | [2.07] | [1.10] | [3.28] | [1.18] | [-2.24] |
| *Cross-sectional regression statistics* | | | | | | | | | | | | |
| $R^2$ | -37.3% | | 71.3% | | 71.1% | | -62.0% | | 85.7% | | -25.2% | |
| $\chi^2$ | 0.00 | | 0.06 | | 0.06 | | 0.01 | | 0.30 | | 0.00 | |
| *RMSE* | 4.08 | | 1.86 | | 1.87 | | 4.43 | | 1.32 | | 3.90 | |
| $\rho$ | 7.9% | | 32.3% | | 36.5% | | 0.9% | | 31.5% | | -17.3% | |

| | Military in Politics | | Religious Tensions | | Law and Order | | Ethnic Tensions | | Democratic Accountability | | Bureaucracy Quality | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | *DOL* | *RISK* | *DOL* | *RISK* | *DOL* | *RISK* | *DOL* | *RISK* | *DOL* | *RISK* | *DOL* | *RISK* |
| *Parameter* | 1.62 | -17.70 | 1.67 | -5.08 | 1.54 | 13.05 | 1.27 | 33.85 | 1.81 | -8.81 | 1.60 | 4.25 |
| *t-stat* | [1.17] | [-2.75] | [1.20] | [-1.28] | [1.11] | [2.54] | [0.92] | [1.76] | [1.34] | [-1.87] | [1.18] | [1.31] |
| *Cross-sectional regression statistics* | | | | | | | | | | | | |
| $R^2$ | 50.0% | | -74.0% | | -49.6% | | -21.9% | | -60.7% | | -80.7% | |
| $\chi^2$ | 0.01 | | 0.00 | | 0.00 | | 0.01 | | 0.00 | | 0.00 | |
| *RMSE* | 2.46 | | 4.59 | | 4.26 | | 3.85 | | 4.42 | | 4.68 | |
| $\rho$ | -26.8% | | -14.3% | | 4.2% | | 3.7% | | -13.6% | | 2.2% | |

**Table C.2:** ***Asset Pricing Tests: Non-Theoretical Factors (Political Risk).*** *The table presents second stage cross-sectional results from the Fama and MacBeth (1973) procedure. The test assets are five portfolios sorted on the basis of forward premia. Each regression contains two risk factors (i) DOL risk and (ii) a characteristic based risk factor constructed on the basis of data from the PRS Group on country-level political risks. Standard errors are corrected according to Shanken (1992) with optimal lag length according to Newey and West (1987). Panel A contains results for All Countries in the sample, while Panel B contains results for Developed Countries. Additional regression statistics are reported, including the adjusted* $R^2$*, a chi-squared test that all pricing errors are jointly equal to zero (*$\chi^2$*, a value less than 0.05 indicates large pricing errors), the square root of the average mispricing (RMSE) and the correlation of the second risk factor with the second principal component of the test assets (*$\rho$*). Data on test portfolios and currencies are taken from Chapter 3 (Della Corte et al., 2014). The sample period is from October 1983 to December 2011. Details of all other data are provided in Section 4.3.*

**Panel A**

| | GDP per Capita | | GDP Growth Rate | | Inflation Yearly Rate | | Budget Balance | | Current Account | |
|---|---|---|---|---|---|---|---|---|---|---|
| | *DOL* | *RISK* | *DOL* | *RISK* | *DOL* | *RISK* | *DOL* | *RISK* | *DOL* | *RISK* |
| *Parameter* | 1.85 | 12.48 | 1.91 | -1.35 | 1.85 | 6.52 | 1.89 | 4.48 | 1.83 | 7.45 |
| *t-stat* | [1.12] | [2.42] | [1.15] | [-0.21] | [1.12] | [2.55] | [1.14] | [0.94] | [1.10] | [2.49] |
| | *Cross-sectional regression statistics* | | | | | | | | | |
| $R^2$ | 63.3% | | -85.4% | | 76.5% | | -73.9% | | 93.8% | |
| $\chi^2$ | 0.40 | | 0.05 | | 0.54 | | 0.09 | | 0.86 | |
| *RMSE* | 1.77 | | 3.99 | | 1.42 | | 3.86 | | 0.73 | |
| $\rho$ | 20.1% | | -3.6% | | 62.5% | | 1.6% | | 56.3% | |

**Panel B**

| | Exchange Rate Stability | | International Liquidity | | Current Account | | Debt Service (% Exports) | | Foreign Debt (% GDP) | |
|---|---|---|---|---|---|---|---|---|---|---|
| | *DOL* | *RISK* | *DOL* | *RISK* | *DOL* | *RISK* | *DOL* | *RISK* | *DOL* | *RISK* |
| *Parameter* | 1.80 | 9.40 | 1.89 | 8.69 | 1.86 | 8.02 | 1.84 | 10.66 | 1.85 | 8.10 |
| *t-stat* | [1.09] | [2.51] | [1.14] | [2.12] | [1.13] | [2.48] | [1.11] | [2.33] | [1.10] | [2.46] |
| | *Cross-sectional regression statistics* | | | | | | | | | |
| $R^2$ | 88.1% | | 34.2% | | 91.5% | | 67.7% | | 95.6% | |
| $\chi^2$ | 0.67 | | 0.10 | | 0.84 | | 0.28 | | 0.91 | |
| *RMSE* | 1.01 | | 2.37 | | 0.85 | | 1.66 | | 0.62 | |
| $\rho$ | 40.8% | | 29.0% | | 64.7% | | 29.1% | | 0.45% | |

See next page for caption...

**Panel C**

| | Government Stability | | Socioeconomic Conditions | | Investment Profile | | Internal Conflict | | External Conflict | | Corruption | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | *DOL* | *RISK* | *DOL* | *RISK* | *DOL* | *RISK* | *DOL* | *RISK* | *DOL* | *RISK* | *DOL* | *RISK* |
| *Parameter* | 1.98 | -19.2 | 1.64 | 18.19 | 1.83 | 15.70 | 2.01 | -12.94 | 1.44 | 42.80 | 1.81 | -14.30 |
| *t-stat* | [1.18] | [-1.59] | [0.99] | [2.05] | [1.11] | [1.77] | [1.23] | [-2.19] | [0.87] | [1.19] | [1.09] | [-2.24] |
| *Cross-sectional regression statistics* | | | | | | | | | | | | |
| $R^2$ | -16.4% | | 88.3% | | -27.3% | | 5.3% | | 1.2% | | 77.9% | |
| $\chi^2$ | 0.02 | | 0.79 | | 0.11 | | 0.19 | | 0.12 | | 0.48 | |
| *RMSE* | 3.16 | | 1.00 | | 3.30 | | 2.85 | | 2.91 | | 1.37 | |
| $\rho$ | -8.2% | | 14.7% | | 5.7% | | -11.0% | | 1.7% | | -21.2% | |

| | Military in Politics | | Religious Tensions | | Law and Order | | Ethnic Tensions | | Democratic Accountability | | Bureaucracy Quality | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | *DOL* | *RISK* | *DOL* | *RISK* | *DOL* | *RISK* | *DOL* | *RISK* | *DOL* | *RISK* | *DOL* | *RISK* |
| *Parameter* | 2.04 | -9.71 | 1.90 | -9.75 | 1.91 | -7.84 | 1.83 | 6.26 | 1.94 | -7.35 | 1.96 | -13.30 |
| *t-stat* | [1.26] | [-2.11] | [1.15] | [-2.27] | [1.18] | [-2.11] | [1.10] | [2.35] | [1.20] | [-2.25] | [1.21] | [-2.04] |
| *Cross-sectional regression statistics* | | | | | | | | | | | | |
| $R^2$ | 71.0% | | 69.4% | | 78.5% | | 79.8% | | 88.8% | | 71.5% | |
| $\chi^2$ | 0.38 | | 0.35 | | 0.55 | | 0.60 | | 0.78 | | 0.44 | |
| *RMSE* | 1.58 | | 1.62 | | 1.36 | | 1.32 | | 0.98 | | 1.56 | |
| $\rho$ | -30.0% | | -37.2% | | -43.0% | | 53.3% | | -52.3% | | -24.0% | |

**Table C.3:** ***Asset Pricing Tests: Non-Theoretical Factors (Developed Countries).*** *The table presents second stage cross-sectional results from the Fama and MacBeth (1973) procedure. The test assets are five portfolios sorted on the basis of forward premia. Each regression contains two risk factors (i) DOL risk and (ii) a characteristic based risk factor constructed on the basis of data from the PRS Group on country-level macroeconomic, financial and political risks. Standard errors are corrected according to Shanken (1992), with optimal lag length according to Newey and West (1987). Panel A contains results for All Countries in the sample, while Panel B contains results for Developed Countries. Additional regression statistics are reported, including the adjusted $R^2$, a chi-squared test that all pricing errors are jointly equal to zero ($\chi^2$, a value less than 0.05 indicates large pricing errors), the square root of the average mispricing (RMSE) and the correlation of the second risk factor with the second principal component of the test assets ($\rho$). Data on test portfolios and currencies are taken from Chapter 3 (Della Corte et al., 2014). The sample period is from October 1983 to December 2011. Details of all other data are provided in Section 4.3.*

| Panel A | | | | | |
|---|---|---|---|---|---|
| *Statistical* Risk | | | *Macroeconomic* Risk | | |
| *Variable* | *t-stat* | $R^2$ | *Variable* | *t-stat* | $R^2$ |
| 'Slope' Risk (LRV) | 3.34 | 98.9% | 'Global Imbalance' (DCRS) | 2.75 | 72.5% |
| | | | | | |
| *Theoretically Motivated* Risk Characteristic | | | | | |
| *Variable* | *t-stat* | $R^2$ | *Variable* | *t-stat* | $R^2$ |
| Colacito and Croce | 1.21 | -0.5% | Verdelhan | 2.97 | 92.8% |
| Farhi and Gabaix | 0.98 | -4.2% | | | |
| | | | | | |
| *Financial* Risk Characteristics | | | | | |
| *Variable* | *t-stat* | $R^2$ | *Variable* | *t-stat* | $R^2$ |
| Aggregate Financial | 1.28 | 80.7% | Current Account | 1.02 | -30.8% |
| Exchange Rate Stability | 1.37 | 31.0% | Debt Service | 0.42 | -101% |
| International Liquidity | 0.72 | -4.5% | Foreign Debt | 1.43 | 2.4% |
| | | | | | |
| *Economic* Risk Characteristics | | | | | |
| *Variable* | *t-stat* | $R^2$ | *Variable* | *t-stat* | $R^2$ |
| Aggregate Economic | 0.46 | -111% | Inflation | 0.81 | -91.3% |
| GDP per Capita | 1.05 | -20.5% | Budget Balance | 1.08 | 8.5% |
| GDP Growth Rate | 0.39 | -95.2% | Current Account | 1.14 | 5.6% |
| | | | | | |
| *Political* Risk Characteristics | | | | | |
| *Variable* | *t-stat* | $R^2$ | *Variable* | *t-stat* | $R^2$ |
| Aggregate Political Risk | 0.93 | -40.5% | Military in Politics | 0.17 | -154% |
| Government Stability | 0.22 | -81.8% | Religious Tensions | 0.54 | -117% |
| Socioeconomic Conditions | 0.00 | -102% | Law and Order | 0.88 | -2.3% |
| Investment Profile | 0.07 | -112% | Ethnic Tensions | 1.43 | 41.3% |
| Internal Conflict | 0.30 | -105% | Democratic Accountability | 0.13 | -78.1% |
| External Conflict | 0.06 | -46.2% | Bureaucracy Quality | 0.29 | -106% |
| Corruption | 0.73 | 1.1% | | | |

**Table C.4:** ***Asset Pricing Tests: Characteristic-Sorted Portfolios (Developed Countries).*** *The table presents second stage cross-sectional adjusted $R^2$ and t-statistics from the Fama and MacBeth (1973) procedure. The test assets are five currency portfolios sorted on the same basis as the factor itself. Each regression contains two risk factors (i) DOL risk and (ii) a characteristic based risk factor. Standard errors are corrected according to Shanken (1992) with optimal lag length according to Newey and West (1987). The sample period is from October 1983 to December 2011. Details of all other data are provided in Section 4.3.*

| Panel A | | | | | | | |
|---|---|---|---|---|---|---|---|
| | *Interest-Rate-Sorted Test Assets* | | | | | | |
| | *Relationship between 'useless' factors and the 'true' factor* | | | | | | |
| Correlation ($\rho$) | **0.05** | **0.10** | **0.20** | **0.50** | **0.80** | **0.90** | **1.0** |
| *Proportion* $>\rho$ | 59.5% | 28.7% | 2.7% | 0.0% | 0.0% | 0.0% | 0.0% |
| | *Factor price of risk* | | | | | | |
| t-stat (absolute value) | **0.67** | **1.65** | **1.96** | **2.33** | **2.58** | **2.81** | **3.29** |
| *Proportion >t-stat (theory)* | 50.0% | 10.0% | 5.0% | 2.0% | 1.0% | 0.5% | 0.1% |
| *Proportion >t-stat (actual)* | 88.3% | 34.2% | 10.7% | 0.1% | 0.0% | 0.0% | 0.0% |
| | *Model fit* | | | | | | |
| $R^2$ | **50%** | **60%** | **70%** | **80%** | **90%** | **95%** | **99%** |
| *Proportion* $>R^2$ | 45.7% | 36.7% | 27.4% | 17.4% | 7.4% | 2.8% | 0.2% |
| | *Pricing errors* | | | | | | |
| $\chi^2$ p-value | **0.05** | **0.10** | **0.30** | **0.50** | **0.70** | **0.90** | **0.95** |
| *Proportion <p-value* | 29.8% | 62.9% | 84.2% | 91.4% | 95.9% | 98.9% | 99.6% |

| Panel B | | | | | | | |
|---|---|---|---|---|---|---|---|
| | *Randomly-Sorted Test Assets* | | | | | | |
| | *Relationship between 'useless' factors and the 'true' factor* | | | | | | |
| Correlation ($\rho$) | **0.05** | **0.10** | **0.20** | **0.50** | **0.80** | **0.90** | **1.0** |
| *Proportion* $>\rho$ | 59.5% | 28.7% | 2.7% | 0.0% | 0.0% | 0.0% | 0.0% |
| | *Factor price of risk* | | | | | | |
| t-stat (absolute value) | **0.67** | **1.65** | **1.96** | **2.33** | **2.58** | **2.81** | **3.29** |
| *Proportion >t-stat (theory)* | 50.0% | 10.0% | 5.0% | 2.0% | 1.0% | 0.5% | 0.1% |
| *Proportion >t-stat (actual)* | 50.0% | 10.2% | 4.8% | 1.8% | 0.9% | 0.4% | 0.1% |
| | *Model fit* | | | | | | |
| $R^2$ | **50%** | **60%** | **70%** | **80%** | **90%** | **95%** | **99%** |
| *Proportion* $>R^2$ | 7.1% | 4.9% | 3.1% | 1.6% | 0.6% | 0.2% | 0.0% |
| | *Pricing errors* | | | | | | |
| $\chi^2$ p-value | **0.05** | **0.10** | **0.30** | **0.50** | **0.70** | **0.90** | **0.95** |
| *Proportion <p-value* | 5.9% | 11.6% | 32.5% | 52.3% | 72.1% | 90.7% | 95.6% |

**Table C.5:** ***Asset Pricing Tests: 'Useless' Factors (Developed Countries).*** *The table presents the estimated distributions of statistics collected from Fama and MacBeth (1973) asset pricing tests using simulated risk factors. Two currency 'risk factors' are randomly generated by arbitrarily reassigning currencies to one of five portfolios each month. The test assets are interest-rate-sorted portfolios (Panel A) and randomly sorted currency portfolios (Panel B). The first risk factor is calculated as an equally weighted average of all five portfolio returns. The second risk factor is calculated as the difference between the returns on the* $1^{st}$ *and* $5^{th}$ *portfolios. The correlation is between the second simulated risk factor and the Slope factor from Lustig et al. (2011). The t-statistics are reported for the second risk factor. Standard errors are adjusted according to Shanken (1992) with optimal lag length according to Newey and West (1987). The adjusted* $R^2$ *is from the second-stage cross-sectional regression in the Fama-MacBeth approach. The* $\chi^2$ *p-value is greater than 0.05 if pricing errors are small. In total 20,000 pairs of risk factors are simulated. Data on currencies are taken from Chapter 3 (Della Corte et al., 2014). The sample period is from October 1983 to December 2011.*

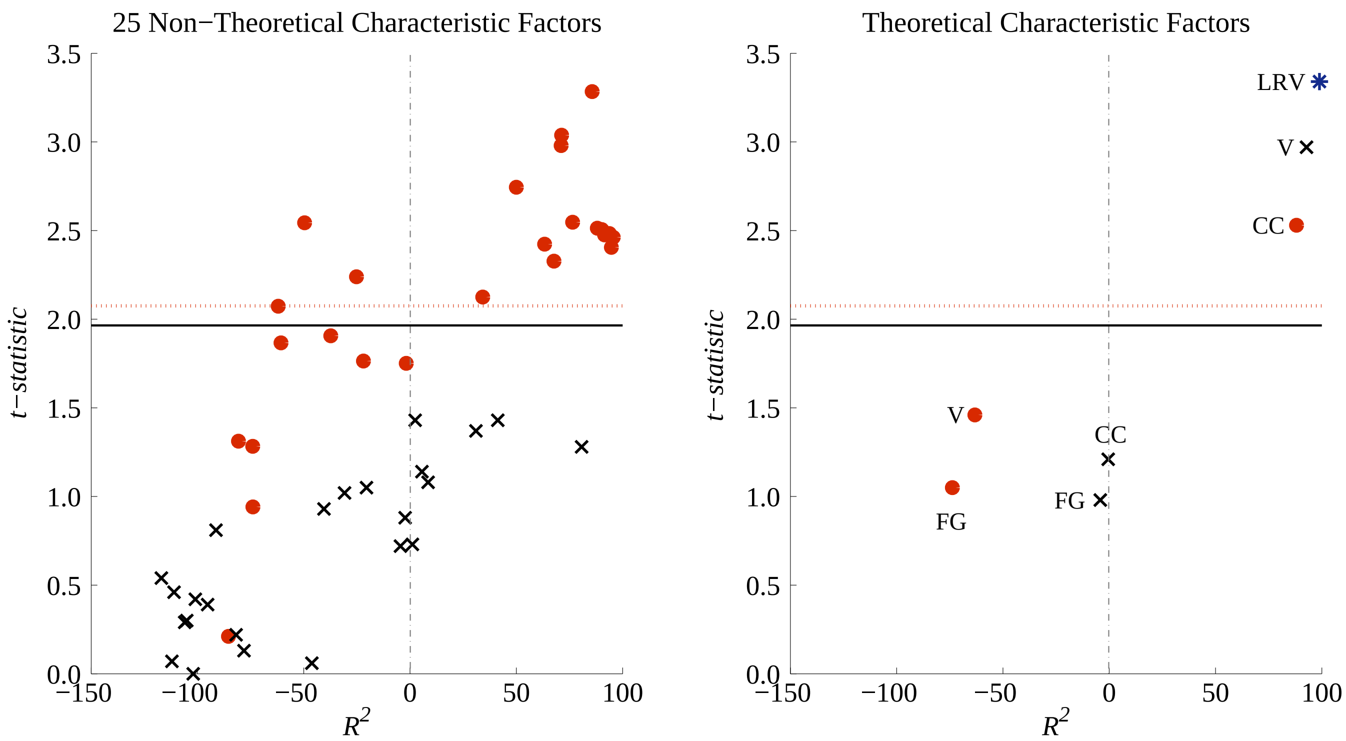


**Figure C.1:** ***Pricing Alternative Test Assets (Developed Countries).*** *The figure presents adjusted-$R^2$ and t-statistics from Fama-MacBeth asset pricing regressions. In the left-hand chart are the cross-sectional asset pricing statistics for the 25 characteristic-based risk factors constructed using data from the Political Risk Services (PRS) Group on underlying economic, financial and political risks. The t-statistics are calculated using Shanken (1992) corrected standard errors with optimal lag length chosen according to Newey and West (1987). The adjusted-$R^2$ is taken from the second stage cross-sectional regression of the Fama-MacBeth procedure. Results are reported for two sets of test assets: (i) the forward-premia-sorted currency portfolios (solid circles), and (ii) the randomly sorted portfolios from which the risk factors are constructed (crosses). In the right-hand chart the results are reported for the characteristic-based risk factors designed to capture consumption-based models of currency premia as well as for the Slope risk factor of Lustig et al. (2011). Horizontal lines are included at 1.96 (the standard 5% critical threshold) and 2.69 (the simulated 5% critical threshold when the test assets are forward-premia-sorted currency portfolios). The abbreviations are: LRV: Lustig et al. (2011); CC: Colacito and Croce (2013); FG: Farhi and Gabaix (2013); V: Verdelhan (2010). Data on test portfolios and currencies are taken from Chapter 3 (Della Corte et al., 2014). The sample period is from October 1983 to December 2011. Details of all other data are provided in Section 4.3.*

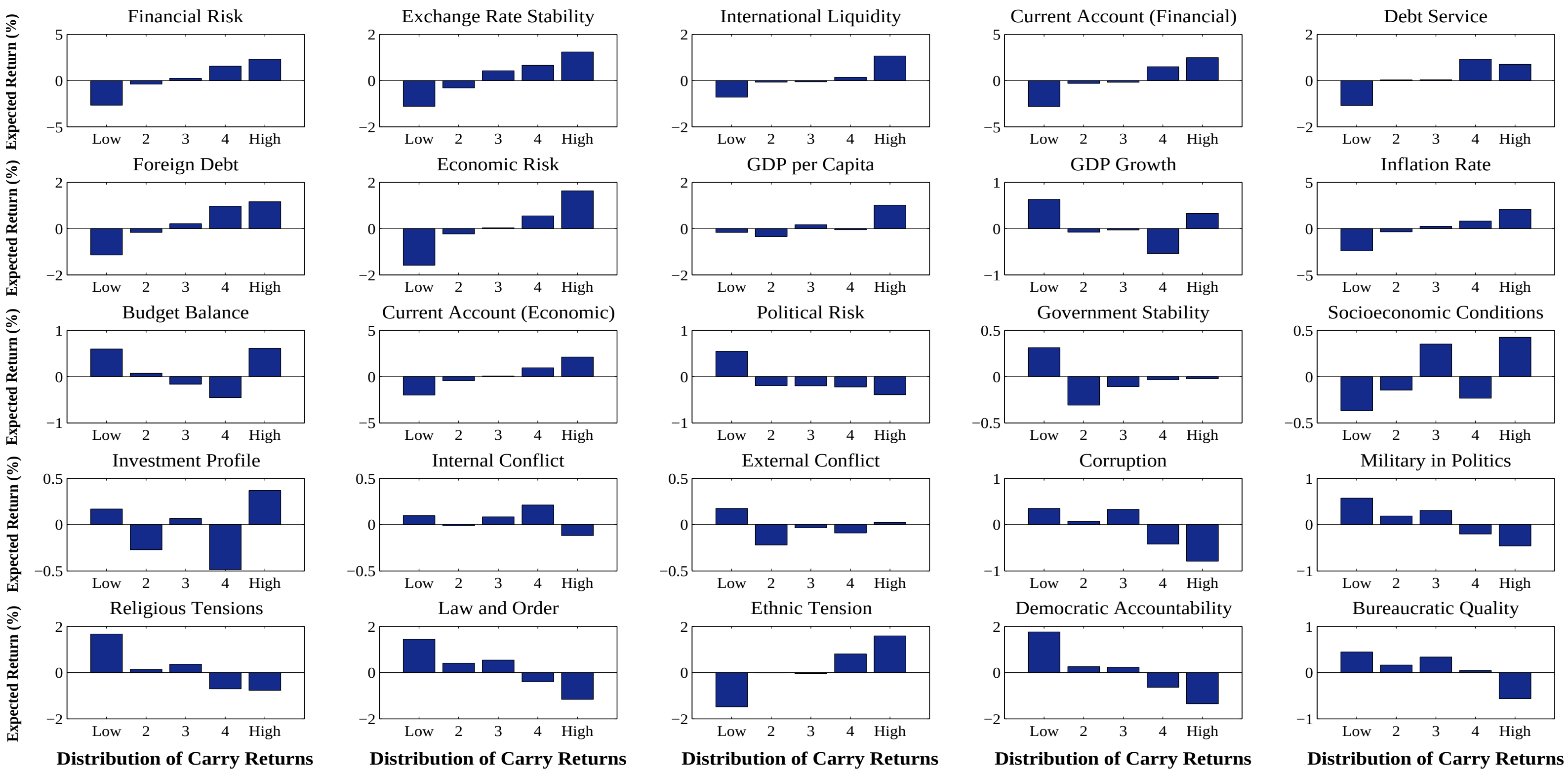


**Figure C.2:** ***Conditional Excess Currency Returns of Non-Theoretical Factors (Developed Countries).*** *The figure presents the average excess return to each of the 25 characteristic-sorted currency factors generated using data on underlying economic, financial and political risks from the Political Risk Services (PRS) Group, conditional on the distribution of the Slope risk factor of Lustig et al. (2011). The Slope risk factor is constructed using data from 3 (Della Corte et al., 2014). Data on test portfolios and currencies are taken from Chapter 3 (Della Corte et al., 2014). The sample period is from October 1983 to December 2011. Details of all other data are provided in Section 4.3.*

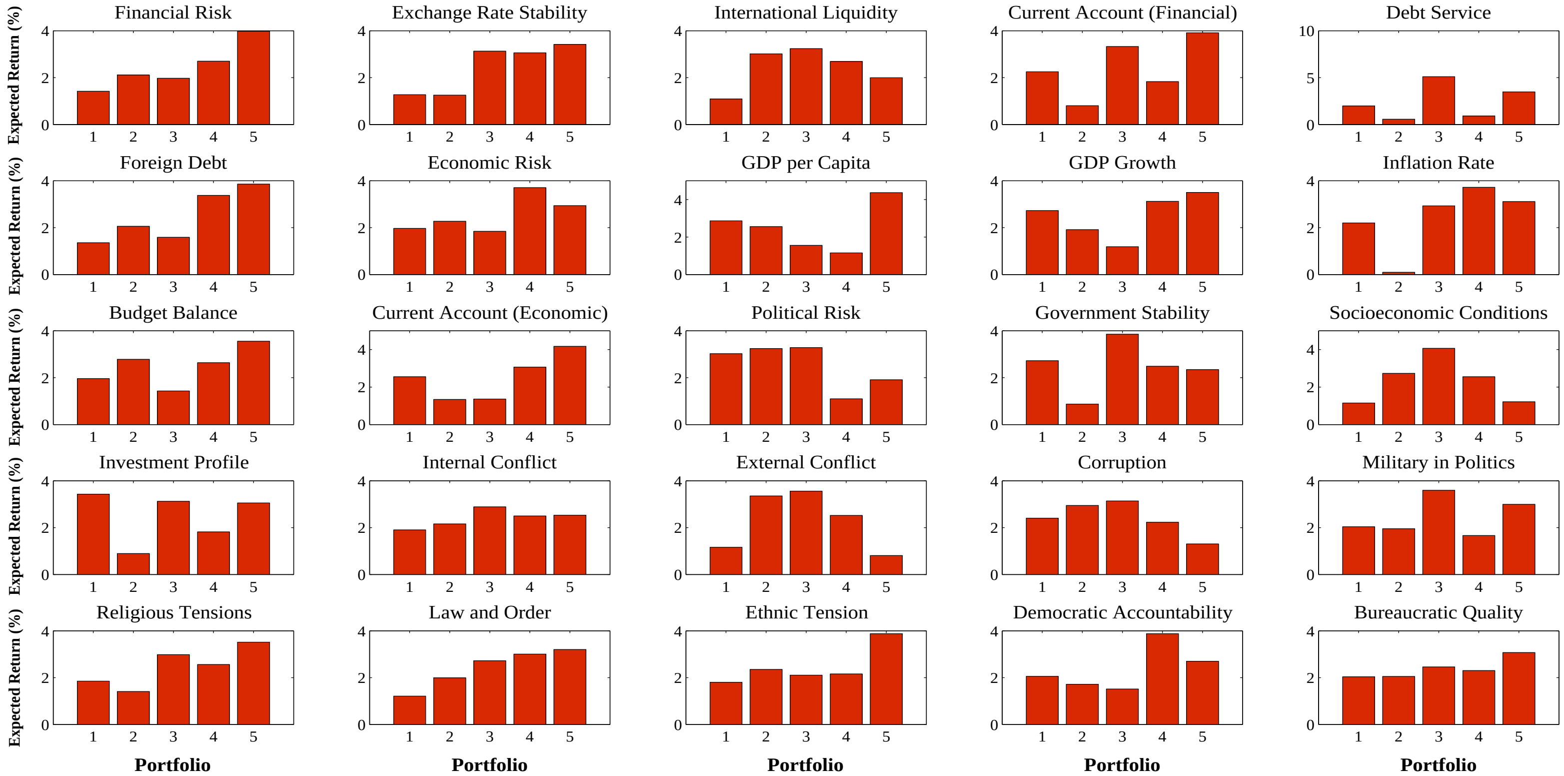


**Figure C.3:** ***Expected Excess Returns to Characteristic-Sorted Portfolios (Developed Countries).*** *The figure presents the expected excess returns to each of the five currency portfolios, sorted according to the 25 country characteristics which span data on economic, financial and political risks from the Political Risk Services (PRS) Group. Data on test portfolios and currencies are taken from Chapter 3 (Della Corte et al., 2014). The sample period is from October 1983 to December 2011. Details of all other data are provided in Section 4.3.*

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