Essays on Empirical Asset Pricing in the Foreign Exchange Market

by

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A thesis submitted in partial fulfilment of
the requirements for the degree of
Doctor of Philosophy in Finance

Warwick Business School
University of Warwick

September 2014

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Acknowledgements

I am grateful and indebted to my supervisors Mark P. Taylor and Söhnke M. Bartram for their continuous support and invaluable pieces of advice.

I am also grateful to Stephen Brown (editor of the *Journal of Financial and Quantitative Analysis*), an anonymous referee, Abhay Abhyankar, Peter Corvi, Philippe Dupuy, Arie Gozluklu, Mohammad R. Jahan-Parvar, Andrew Karolyi, Gi Kim, Eylem Ersal Kiziler, Leonid Kogan, Roman Kozhan, Rong Leng, Dong Lou, Michael Melvin, Michael Moore, Aline Muller, Vikram Nanda, Ingmar Nolte, Vikas Raman, Alessandro Palandri, Paolo Porchia, Jon Rushman, Gideon Saar, Alex Stremme, Avanidhar Subrahmanyam, John Thanassoulis, David Thesmar, Onur Tosun, Christian Wagner and Chishen Wei as well as seminar participants at the WBS Finance Workshops, the 2013 International Conference at the ESCP (Paris), the Georgetown Center of Economic Research Conference, the China International Conference in Finance, the XXIII Finance Forum, the FMA European conference and the International conference of the French Finance Association for useful conversations and constructive comments.

I would also like to thank my family and my best friends at Warwick: Spyros Angelopoulos, Pedro A. Garcia Ares, Ungkyu Han, Lucious Li, Simon Parker, Edouard Pignot and Spyros Terovitis.

Finally, I would like to thank the Economic and Social Research Council (ESRC) as well as the Warwick Business School for the financial support.

Declaration

I declare that any material included in this thesis has not been submitted for a degree to any other University. I also declare that one paper entitled: "Common Macro Factors and Currency Premia", drawn from Chapter One of this thesis, is co-authored with Mark P. Taylor and it is forthcoming in the *Journal of Financial and Quantitative Analysis.* In addition, the paper "Global Political Risk and Currency Momentum", drawn from Chapter Two of this thesis, is co-authored with Arie E. Gozluklu and Mark P. Taylor.

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September 2015

Abstract

This thesis focuses on the dynamics of currency premia. Specifically, we study the time-series and cross-sectional variation of currency carry trade and momentum strategies.

In the first chapter, we study the role of domestic and global factors on payoffs of portfolios built to mimic carry, dollar carry and momentum strategies. We construct domestic and global factors from a large dataset of macroeconomic and financial variables and find that global equity market factors render strong predictive power for carry trade returns, while U.S. inflation and consumption variables drive dollar carry trade payoffs and momentum returns are driven by U.S. inflation factors. In addition, global factors can capture the countercyclical nature of currency premia. We also find evidence of predictability in the exchange rate component of each strategy and demonstrate strong economic value to a risk-averse investor with mean-variance preferences.

In the second chapter, we propose a measure of global political risk relative to U.S. that captures unexpected political conditions. Global political risk is priced in the cross-section of currency momentum and it contains information beyond other risk factors. Our results are robust after controlling for transaction costs, reversals and alternative limits to arbitrage. The global political environment affects the profitability of the momentum strategy in the foreign exchange market; investors following such strategies are compensated for the exposure to

the global political risk of those currencies they hold, i.e., the past *winners*, and exploit the lower returns of *loser* portfolios.

In the third chapter, we identify a unique dimension of currency carry trades that it is related to the intensity of technology transition across countries. Particularly, we show that technology diffusion is a fundamental determinant of currency premia and it is priced in the cross-section of currency excess returns. We define a novel risk factor that captures the cross-country diffusion of technology. *Investment* currencies load *positively* on the global technology diffusion factor while *funding* currencies load *negatively*. Intuitively, we show that carry traders require a risk premium for financing risky innovation in countries with *low* technology diffusion.

Overview

This thesis aims to provide a deeper understanding of the forward premium puzzle and its implications for currency investment strategies that exploit deviations from the Uncovered Interest Rate parity condition (hereafter UIP). To this end, we study the time-series as well as cross-sectional variation of the most profitable strategies in the foreign exchange market, namely carry, dollar carry and momentum strategies. In the first chapter we identify the macroeconomic exposures of currency premia. To do that, three widely used currency investment strategies are examined, namely the carry trade strategy (i.e. going long in high-interest rate currencies and short in low-interest rate currencies), dollar carry trade (i.e. a carry trade strategy relative to the U.S. dollar) and momentum. All strategies exploit deviations from the well-known uncovered interest rate parity (UIP) condition according to which, under risk neutrality and rational expectations, the forward exchange rate should be an optimal predictor of the future spot exchange rate. However, many studies (e.g. Bilson, 1981; Fama, 1984; Froot and Thaler, 1990) document the empirical rejection of UIP, the so-called forward premium puzzle (Froot and Thaler, 1990; Taylor, 1995; Sarno and Taylor, 2002). Thus, the apparent profitability of the carry trade and momentum strategies has captured the attention of many academics and practitioners. A particularly noteworthy feature of these strategies is the presence of downside risk, as witnessed by the strong appreciation of the funding currencies under periods of stress.

As noted above, the currency carry trade involves a short position in low interest rate (funding) currencies and a long position in high interest rate (investment) currencies. In addition, Lustig et al. (2014) propose a different version of the carry trade - the dollar carry trade - where investors short the dollar when the average short-term interest rate of the foreign currencies is greater the U.S. short-term interest rate and go long in the dollar otherwise. This strategy is driven by the U.S. business cycle, since the investors sell the dollar just before the start of the NBER recessions and purchases the dollar after the trough (end of the NBER recessions).

A momentum strategy is based on the assumption that currencies that were appreciating well in the past will render higher excess returns in the future in comparison to currencies with poor past performances; in other words, investors buy forward foreign currency units that were worth buying forward in a previous time period.

Despite the fact that a lot of research has been carried out in recent years on carry and momentum strategies, it is still questionable whether the macroeconomic environment can explain the average time-series profitability of those strategies. If so what is the statistical and economic value of this finding for a U.S. investor and how can she protect herself from erratic macroeconomic conditions? Consequently, the fundamental questions that drive our analysis are: (i) whether the macroeconomic environment plays an economically significant role in determining currency excess returns and exchange rate changes, and (ii) which macroeconomic or financial variables are driving this phenomenon. Answers to both issues provide crucial implications for the forward premium puzzle.

The difficulty of finding a strong empirical link between macroeconomic fundamentals and currency premia has also been documented (see, e.g. Lustig et al., 2014), and may be explained in various ways. Firstly, it may be argued that many macroeconomic variables are imperfectly measured and that a small number of variables cannot capture the high variability of exchange rates (Flood and Rose, 1995). Thus, the first principal component of a panel of many different proxies of the same macro variable may be more informative in this respect than one official measure of the macro variable itself. Interestingly, Lustig et al. (2014) point out that macro variables exhibit low predictive power per se, but their common movements could contain important information for carry trades. Secondly, the carry trade and momentum strategies exploit disparities observed in global macroeconomic conditions and especially between debtor and creditor economies (Plantin and Shin, 2011; Della Corte et al., 2013). Therefore, dynamic factor analysis is a valid methodology as it gives us the opportunity to confine those disparities in a few unobserved variables.

Taking the U.S. investors viewpoint, we apply dynamic factor analysis in order to obtain U.S. (domestic) and global (mainly from G10 countries) factors that capture the variability of a large panel of macroeconomic and financial variables. This methodology has extensively been used in different strands of the literature. In particular, Stock and Watson (2002a,b, 2004, 2006) show that dynamic factor models applied to large datasets can enhance the forecasting power of many macroeconomic variables. Ludvigson and Ng (2009, 2011) find that U.S. static factors have strong predictive power for future U.S. excess government bond returns over and above the information contained in the Cochrane and Piazzessi (2005) predictor. They also show that static and dynamic factors exhibit similar predictive power. Bernanke and Boivin (2003) and Bernanke et al. (2005) came to the same conclusion regarding the forecastability of static and dynamic factors in their analysis of Federal Reserve policy in a data-rich environment. In the foreign exchange literature, Engel et al. (2012) develop static factors from a panel of exchange rates and employ the idiosyncratic diversions from the factors as a predictor of exchange rates. Their findings with regards to predictability are mixed.

Our domestic panel contains 127 monthly U.S. time series that capture a variety of categories: real output, employment, consumption, housing starts, orders, stock prices, exchange rates, interest rates, money and credit quality aggregates, price indices, earnings, international trade, capacity utilization, and others. Likewise, the global factors are obtained from a panel of 97 macro variables gathered from developed countries.

We construct times-series of the payoffs based on spot and forward exchange rates of 48 currencies vis-a-vis the U.S. dollar after taking into account bid and ask quotes. We also focus on a smaller sample of 15 developed countries in order to guard against capital constraints and pegged currencies. In addition, we consider only dynamically rebalanced strategies, because they seem to be more profitable and also mimic the behavior of foreign exchange investors (Bakshi and Panayotov, 2013).

A number of recent contributions in the research literature focus on the cross-sectional variation of carry trade and momentum strategies. In particular, Lustig et al. (2011) develop a factor model that resembles the Fama and French (1993) model for the foreign exchange market; they find that a carry trade factor that goes long a basket of high interest rate currencies and short a basket of low interest rate currencies, together with a dollar factor that is defined as the average return across portfolios each month, can price the cross-section of currency returns. In the same spirit, Menkhoff et al. (2012a) introduce a volatility risk factor and Mancini et al. (2013) a liquidity factor that explain most of the cross-sectional variation in monthly carry trade returns. We deviate from these studies, as we focus on the time-series variability of carry trades. Similarly, Menkhoff et al. (2012b) examine a momentum strategy in a cross-sectional framework.

Our in-sample empirical results indicate that carry trade returns are more exposed to the global economy rather than to U.S. economic conditions. In particular, we find strong evidence of predictability in global factors that capture the macroeconomy of the G7 countries as well as the global stock market. This finding might be related to the exit strategies in the G7 economies during the financial crisis and the tendency of the domestic currency to depreciate when the home equity return exceeds the foreign counterpart (Hau and Rey, 2006). Regarding the domestic economy, we find that real and inflation factors are highly significant. The dollar carry trade is mainly driven by domestic variables because, as mentioned previously, investors focus more on the U.S. economy when they form expectations with regard to the dollar carry trade. Thus, global factors do not seem to provide useful information, but U.S. inflation and consumption factors have strong predictive power. The momentum returns are mainly driven by U.S. inflation factors. We also find predictable components in the exchange rate returns gathered from the aforementioned strategies.

The forecasting ability of the factors is also verified by out-of-sample tests based on positive out-of-sample R^2 of Campbell and Thompson (2008) and one-sided *p-values* of the MSPE-*adj* statistic following Clark and West (2007). Moreover, combination forecasts emphasize the out-of-sample performance of the individual models and provide an overall improvement over the individual predictions.

We also consider a decision-rule that takes into account our forecasts in order to evaluate the economic significance of our results. We find an increase in the Sharpe ratios and an improvement in the skewness of the payoffs for all three strategies and a mixed strategy, which invests only on the strategies that are profitable according to the signals obtained from our forecasts. Then, we question whether a risk-averse investor with mean-variance preferences would acquire economic value from the use of the factors. To do that, we estimate the certainty equivalent return gain and find that a U.S. investor would be willing to pay a management fee in order to benefit from the predictive regression forecasts.

Our analysis takes into consideration other factors in the literature, such as the Bakshi and Panayotov (2013) predictors or average forward discounts in order to estimate conditional predictive regressions of the common factors. We find that our factors can forecast currency excess returns over and above commodity, volatility, and liquidity factors as well as average forward discounts. The only exception is the momentum strategy where only U.S. inflation factors seem to contain useful information.

In the second chapter, we try to understand better the reasons behind the disconnection between time-series momentum and fundamentals. Here, we follow a cross-sectional perspective and investigate the role of political risk in momentum strategies. In particular, we question whether global political risk can price the cross-section of currency momentum returns. Specifically, we develop a novel measure of political risk that captures the differences between the political environment of the U.S. economy and the rest of the world. A striking feature of this measure is that it is sensitive to *unexpected* global political changes, meaning that it captures political events that are less likely to be predicted by a naive investor. We thus examine whether global political shocks affect the momentum profitability, helping us to understand better the determinants of currency premia. To this end, we construct a two-factor asset pricing model that incorporates the information contained in the our global political risk measure. More precisely, the first factor is a *level* factor (i.e. DOL) as originally introduced by Lustig et al. (2011) which is measured as the average across portfolios on each occasion. This traded factor resembles a strategy that buys all foreign currencies and sells the dollar. As such it is highly correlated with first principal component of currency excess return portfolios. The second factor is our global political risk that it is replaced by innovations so as to account for its high persistence. We find that global political risk is priced in the cross-section of currency returns being that it is able to capture a significant bulk of currency excess returns. Our main intuition in regard this finding is linked to the fact that investors require a higher premium for taking on global political risk which is attached to the *winner* portfolios. On the other hand, investors accept a lower premium from investing in *loser* portfolios as they provide a hedge against adverse movements of currency returns in bad states of the world. We mainly focus on momentum strategies that rebalance their portfolios every month and use a formation period of one, three and six months. The main reason for focusing upon these particular strategies is related to their high profitability (Menkhoff et al., 2012b). However, we show later that our results are robust to longer formation periods.

Our results are robust both in economic as well as statistical terms. Firstly, we show that global political risk can explain the *time-series* variation of currency momentum returns even after controlling for other predictors in the literature such global FX volatility, FX liquidity, FX correlation and changes in CDS spreads. However, it captures only a small part of the time-series variability as it is suggested by the R-squares. Thus, we question whether political risk is able to capture the *cross-sectional* variation of currency premia that it is related to currency momentum. We employ both *unconditional* and *conditional* momentum returns and find that *conditional* momentum returns sorted into portfolios based on exposures with political risk provide a monotonic pattern which suggests that investors require a higher premium when currency exposure to political risk increases. This pattern is less pronounced for unconditional returns as we observe a nonlinear pattern that could be related to differences in beliefs in the currency market that is plausibly led by the global political environment (Bakshi et al., 2010). In any case the extreme portfolios render a positive spread that indicates the pricing ability of global political risk.

In regard to the asset pricing tests employed in the paper we show that our asset pricing model exhibits a strong cross-sectional performance both in statistical and economic terms. Firstly, we display results of Fama and MacBeth (1973) regressions as well as GMM procedures. Here we find highly significant risk factor prices that are related to global political risk with standard errors, corrected for autocorrelation and heteroskedasticity (HAC) following Newey and West (1987) methodology using the optimal number of lags as in Andrews (1991) along with Shanken (1992) that control for potential error-in-variable issues. In addition, our results demonstrate strong cross-sectional behaviour in term of goodness of fit. Specifically, we show that we cannot reject the null; that is, all the pricing errors are jointly equal to zero as it is depicted in terms of the very large *p-values* of the χ^2 test statistic. In addition, the cannot reject the null that the HJ distance is equal to zero and the cross-sectional R^2 range from 66% to 99% for formation period from one to six months. Our results are similar whether we employ a mimicking portfolio or the raw measure.

In the next stage, we examine whether global political risk is priced even after accounting for other determinants of currency premia. We start with idiosyncratic volatility and skewness so as to determine whether we can explain a different measures of limits to arbitrage. Thus, we double-sort conditional excess returns into two portfolios based on their idiosyncratic volatility (skewness). Then within each portfolio, we sort them according to their exposure to global political risk. We find that currency excess returns are larger in high political risk portfolios than in low political risk baskets under low or high idiosyncratic volatility portfolios implying a statistically significant and positive spread. We perform a similar exercise by replacing the idiosyncratic volatility with illiquidity, volatility and correlation variable to come to the same conclusions. Therefore, global political risk is priced in the cross-section of currency returns.

Finally, we perform a few robustness checks so as to verify our results. In order to make our analysis more realistic we apply a few filters to the data to check for currencies that do not belong in the exchange rate regime 3 or 4 of the IMF coarse classification, as well checking for the degree of capital account openness (Chinn and Ito, 2006) in the market following Della Corte et al. (2013). We find that the results have improved in most of the cases. In addition, we show that the implementation cost of the strategies does not affect the cross-sectional predictive ability of global political risk. We also ask whether currency reversals could potentially alter our findings. To this end, we estimate the conditional weights of the mimicking portfolio by using as conditional variable the previous month's momentum return. Here we find that the results are similar. Finally, we perform currency-level cross-sectional regressions for both unconditional and conditional returns and demonstrate the pricing ability of global political risk.

Overall, our empirical evidence suggests that global political risk is able to capture most of the dispersion of currency momentum returns. This finding suggests that political risk might be one of the fundamental determinants of the momentum strategy in the foreign exchange market.

In the third chapter, we provide a novel explanation for the carry trade profitability. Particularly, we study the impact of technology diffusion in currency carry trades. To do that, we employ the Cross-country Historical Adoption of Technology (CHAT) dataset as a proxy of technology diffusion in order to create a country-specific technology diffusion factor that is constructed as the average across technologies per country/time pair. Then we construct an asset pricing model, in the same spirit with Lustig et al. (2011). Specifically, we employ two factors, a dollar factor (i.e. DOL) and a technology diffusion factor (i.e. $LMH^{\mathcal{TD}}$). The dollar factor is defined as the average across portfolios each time and the technology diffusion is a zero-investment portfolio that goes long low technology diffusion baskets and sells high technology diffusion portfolios. We show that technology diffusion is priced in the cross-section of carry trade returns as it is able to capture most of the carry trade variability.

Our results are robust to different specification tests. Particularly, we show asset pricing tests for individual currencies and show that our model performs well in capturing the carry trade profitability. The pricing ability is also verified by beta-sorted portfolios, where a positive and statistically significant spread is obtained. The results are also robust after taking into account transaction costs. Finally, technology diffusion is able to price conditional excess returns.

Overall, we find that technology diffusion is a priced factor in the cross-section of currency returns. High interest rate currencies load positively on the technology diffusion factor and low interest rate currencies load negatively. Intuitively, carry trades require a risk premium for holding *low* technology diffusion currencies as a compensation for financing risky innovation. On the other hand, they invest on *high* technology diffusion currencies, despite the low profitability that they offer because it provides a hedge against downside movements of carry trade profitability.

Chapter 1

Common Macro Factors and Currency Premia

1.1 Introduction

In this chapter we investigate the domestic and global drivers of currency premia. To do that, three widely used currency investment strategies are examined, namely the carry trade strategy (i.e. going long in high-interest rate currencies and short in low-interest rate currencies), dollar carry trade (i.e. a carry trade strategy relative to the U.S. dollar) and momentum. All strategies exploit deviations from the well-known uncovered interest rate parity (UIP) condition according to which, under risk neutrality and rational expectations, the forward exchange rate should be an optimal predictor of the future spot exchange rate. However, many studies (e.g. Bilson, 1981; Fama, 1984; Froot and Thaler, 1990) document the empirical rejection of UIP, the so-called forward premium puzzle (Froot and Thaler, 1990; Taylor, 1995; Sarno and Taylor, 2002). Thus, the apparent profitability of the carry trade and momentum strategies has captured the attention of many academics and practitioners. A particularly noteworthy feature of these strategies is the presence of downside risk, as witnessed by the strong appreciation of the funding currencies under periods of stress.

As noted above, the currency carry trade involves a short position in low interest rate (funding) currencies and a long position in high interest rate (investment) currencies. In addition, Lustig et al. (2014) propose a different version of the carry trade - the dollar carry trade - where investors short the dollar when the average short-term interest rate of the foreign currencies is greater the U.S. short-term interest rate and go long in the dollar otherwise. This strategy is driven by the U.S. business cycle, since the investors sell the dollar just before the start of the NBER recessions and purchases the dollar after the trough (end of the NBER recessions).

A momentum strategy is based on the assumption that currencies that were appreciating well in the past will render higher excess returns in the future in comparison to currencies with poor past performances; in other words, investors buy forward foreign currency units that were worth buying forward in a previous time period.

Despite the fact that a lot of research has been carried out in recent years on carry and momentum strategies, it is still questionable whether the macroeconomic environment can explain the average time-series profitability of those strategies. If so what is the statistical and economic value of this finding for a U.S. investor and how can she protect herself from erratic macroeconomic conditions? Consequently, the fundamental questions that drive our analysis are: (i) whether the macroeconomic environment plays an economically significant role in determining currency excess returns and exchange rate changes, and (ii) which macroeconomic or financial variables are driving this phenomenon. Answers to both issues have crucial implications for the forward premium puzzle.

The difficulty of finding a strong empirical link between macroeconomic fundamentals and currency premia has also been documented (see, e.g. Lustig et al., 2014), and may be explained in various ways. Firstly, it may be argued that many macroeconomic variables are imperfectly measured and that a small number of variables cannot capture the high variability of exchange rates (Flood and Rose, 1995). Thus, the first principal component of a panel of many different proxies of the same macro variable may be more informative in this respect than one official measure of the macro variable itself. Interestingly, Lustig et al. (2014) point out that macro variables exhibit low predictive power per se, but their common movements could contain important information for carry trades. Secondly, the carry trade and momentum strategies exploit disparities observed in global macroeconomic conditions and especially between debtor and creditor economies (Plantin and Shin, 2011; Della Corte et al., 2013). Therefore, dynamic factor analysis is a valid methodology as it gives us the opportunity to confine those disparities in a few unobserved variables.

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came to the same conclusion regarding the forecastability of static and dynamic factors in their analysis of Federal Reserve policy in a data-rich environment. In the foreign exchange literature, Engel et al. (2012) develop static factors from a panel of exchange rates and employ the idiosyncratic diversions from the factors as a predictor of exchange rates. Their findings with regards to predictability are mixed.

Our domestic panel contains 127 monthly U.S. time series that capture a variety of categories: real output, employment, consumption, housing starts, orders, stock prices, exchange rates, interest rates, money and credit quality aggregates, price indices, earnings, international trade, capacity utilization, and others. Likewise, the global factors are obtained from a panel of 97 macro variables gathered from developed countries.

We construct times-series of the payoffs based on spot and forward exchange rates of 48 currencies vis-a-vis the U.S. dollar after taking into account bid and ask quotes. We also focus on a smaller sample of 15 developed countries in order to guard against capital constraints and pegged currencies. In addition, we consider only dynamically rebalanced strategies, because they seem to be more profitable and also mimic the behavior of foreign exchange investors (Bakshi and Panayotov, 2013).

A number of recent contributions in the research literature focus on the cross-sectional variation of carry trade and momentum strategies. In particular, Lustig et al. (2011) develop a factor model that resembles the Fama and French (1993) model for the foreign exchange market; they find that a carry trade factor that goes long a basket of high interest rate currencies and short a basket of low interest rate currencies, together with a dollar factor that is defined as the average return across portfolios each month, can price the cross-section of currency returns.

In the same spirit, Menkhoff et al. (2012a) introduce a volatility risk factor and Mancini et al. (2013) a liquidity factor that explain most of the cross-sectional variation in monthly carry trade returns. We deviate from these studies, as we focus on the time-series variability of carry trades. Similarly, Menkhoff et al. (2012b) examine a momentum strategy in a cross-sectional framework.

Our in-sample empirical results indicate that carry trade returns are more exposed to the global economy rather than to U.S. economic conditions. In particular, we find strong evidence of predictability in global factors that capture the macroeconomy of the G7 countries as well as the global stock market. This finding might be related to the exit strategies in the G7 economies during the financial crisis and the tendency of the domestic currency to depreciate when the home equity return exceeds the foreign counterpart (Hau and Rey, 2006). Regarding the domestic economy, we find that real and inflation factors are highly significant. The dollar carry trade is mainly driven by domestic variables because, as mentioned previously, investors focus more on the U.S. economy when they form expectations with regard to the dollar carry trade. Thus, global factors do not seem to provide useful information, but U.S. inflation and consumption factors have strong predictive power. The momentum returns are mainly driven by U.S. inflation factors. We also find predictable components in the exchange rate returns gathered from the aforementioned strategies.

The forecasting ability of the factors is also verified by out-of-sample tests based on positive out-of-sample R^2 of Campbell and Thompson (2008) and one-sided *p-values* of the MSPE-*adj* statistic following Clark and West (2007). Moreover, combination forecasts emphasize the out-of-sample performance of the individual models and provide an overall improvement over the individual predictions.

We also consider a decision-rule that takes into account our forecasts in order to evaluate the economic significance of our results. We find an increase in the Sharpe ratios and an improvement in the skewness of the payoffs for all three strategies and a mixed strategy, which invests only on the strategies that are profitable according to the signals obtained from our forecasts. Then, we question whether a risk-averse investor with mean-variance preferences would acquire economic value from the use of the factors. To do that, we estimate the certainty equivalent return gain and find that a U.S. investor would be willing to pay a management fee in order to benefit from the predictive regression forecasts.

Our analysis takes into consideration other factors in the literature, such as the Bakshi and Panayotov (2013) predictors or average forward discounts in order to estimate conditional predictive regressions of the common factors. We find that our factors can forecast currency excess returns over and above commodity, volatility, and liquidity factors as well as average forward discounts. The only exception is the momentum strategy where only inflation factors seem to contain useful information.

The remainder of this chapter is set out as follows. The carry trade, dollar carry trade and momentum strategies are presented in Section 2. In Section 3 we describe dynamic factor analysis while in Section 4 we provide a brief description of the data. In Section 5 we discuss the empirical results of the chapter. Section 6 provides an economic evaluation of the forecasts and Section 7 offers a number of robustness checks on our analysis. Finally, in Section 8 we offer some concluding remarks.

1.2 Multi-Currency Investment Strategies

In this section, we consider currency excess returns of the most profitable investment strategies in the foreign exchange market. In particular, we construct payoffs of currency portfolios built to mimic carry trade, dollar carry trade and momentum strategies. The carry trade strategy involves a long (short) position in a basket of high (low) interest rate currencies. The profitability of this strategy emerges from the violation of uncovered interest rate parity, as high interest rate currencies are assumed to appreciate on average, rather than depreciate, as UIP would predict. Thus, investors earn the difference between the risk-free interest rates of the domestic and foreign country while facing the risk of currency depreciation. In the dollar carry trade the investors buy the dollar when the U.S. short-term interest rate exceeds the average interest rate of the foreign countries and invest in the basket of all foreign currencies otherwise. In this strategy, investors short the dollar before the start of the U.S. recessions and take an opposite position at the end of the U.S. recession. A momentum strategy focuses on past performances of currency excess returns. That is, if a currency was worth buying in the past (formation period) it is assumed it will render higher excess returns in the future (holding period) in comparison to currencies with poor past performances. Thus, deviating from currency level approaches, we explore predictable components and potential commonalities in the variation of the payoffs across basket-level investment strategies.[1]

Currency Excess Returns. We employ end-of-month series of spot and one-month forward rates. S_t represents the level of the nominal exchange rate at time t and F_t denotes the one-month forward rate, known at time t. Taking the

[1] Among others, Burnside et al. (2011a); Lustig et al. (2011, 2014); Menkhoff et al. (2012a,b) provide a very clear description of these strategies.

U.S. investors perspective, all currencies are expressed in foreign currency units per U.S. dollar, meaning that a rise in S_t implies a depreciation of the foreign currency. The level of the currency excess return (RX_t) resulting from going long the foreign currency in the forward market at time t and then selling the same currency at time $t+1$ in the spot market can be expressed as:

$$RX_{t+1} = \frac{F_t - S_{t+1}}{S_t} = \frac{F_t - S_t}{S_t} - \frac{S_{t+1} - S_t}{S_t}. \tag{1.1}$$

As can be seen in equation 1.1, excess returns can be decomposed into two parts; the forward discount and the change in the spot exchange rate. In addition, under the covered interest rate parity condition, the forward discount must be equal to the interest rate differential: $FD_t = \frac{F_t - S_t}{S_t} \simeq \hat{i}_t - i_t$, where $\hat{i}_t$ is the risk-free interest rate of the foreign country and i_t is the home country counterpart.[2] Thus, under the assumption that the aforementioned arbitrage condition holds, excess returns are equal to the interest rate differential corrected for the rate of depreciation: $RX_{t+1} \simeq \hat{i}_t - i_t - (S_{t+1} - S_t/S_t)$.

Transaction Costs. Our analysis takes into account the implementation cost of the strategies in order to estimate the actual realized excess returns. In particular, bid and ask quotes are employed for the spot and forward contracts and the long and short position are modified as follows. The *net* position of buying the foreign currency forward at time t using the bid price (F_t^b) and selling it at time $t+1$ in the spot market at ask price (S_t^a) is given by: $RX_{t+1}^l = (F_t^b - S_{t+1}^a)/S_t^b$. Whereas the corresponding short position in the foreign currency

[2] Many studies in the past (e.g., Taylor, 1987, 1989; Burnside, Eichenbaum, and Rebelo, 2006; Akram, Rime, and Sarno, 2008; Baba, and Packer, 2009; Levich, 2013) have shown that deviations from CIP (at daily or lower frequencies) are very small and infrequent, when transaction costs are taken into consideration. Nevertheless, this condition was significantly violated during the crisis of 2008 for some currencies, mainly because of liquidity constraints and counterparty risk.

(or short in the dollar) will render a *net* excess return of the form: $RX^s_{t+1} = (F^a_t - S^b_{t+1})/S^a_{t+1}$. Throughout the chapter we consider only net currency excess returns and *net* exchange rate changes.

Carry Trade Portfolios. We build two baskets of currencies. The first basket contains a set of 48 currencies, which we label *All countries*, and the second basket consists of 15 currencies, which we label *Developed countries* (Section 4 provides a detailed description of the currency baskets). Then, we sort currency excess returns into six (five) portfolios using the sample of *All countries* (*Developed countries*) based on forward discounts.[3] Thus, the first portfolio contains the lowest yielding currencies and the last portfolio is associated with the highest interest rate currencies. Each portfolio is rebalanced on monthly basis. The payoff to a carry trade strategy (ψ^{HML}_{t+1}) represents a long position in the last portfolio while taking a short position in the first portfolio each month. A similar procedure is carried out for the exchange rate component of the excess return.

Dollar Carry Trade Portfolios. We also design a different version of the carry trade strategy that was first introduced by Lustig et al. (2014). Specifically, we consider an equally weighted portfolio that goes long all foreign currencies when the average foreign short-term interest rate of the Developed countries is greater that the home countrys (U.S.) analogue as inferred through the average forward discount (AFD). The AFD is defined as the mean of the forward discounts across portfolios each month. In other words, investors short the dollar when the AFD of the *developed countries* is positive and go long otherwise. Consequently, the payoff to a *dollar* carry trade (ψ^{USD}_{t+1}) is given by:

[3] Our results are largely the same when sorting currencies of All countries into five portfolios, instead of six. However, we follow this approach in order to be consistent with the literature.

$$\psi_{t+1}^{USD} = \begin{cases} \overline{(\frac{F_t^b - S_{t+1}^a}{S_t^b})} & \text{if } \overline{AFD}_t > 0, \\ \overline{(\frac{S_{t+1}^b - F_t^a}{S_t^a})} & \text{if } \overline{AFD}_t \leq 0. \end{cases} \tag{1.2}$$

where AFD_t denotes the average forward discount at time t. As before, we focus on two baskets of currencies and the positions are rebalanced on a monthly frequency. Results for the resulting exchange rate returns are reported.

Momentum Portfolios. We also construct portfolios of currencies based on the past performances. Particularly, currency excess returns of *All countries* (*Developed countries*) are allocated into six (five) portfolios each month according to the lagged excess return over the previous period. Thus, we consider a formation period of one month and the investors hold the portfolio until next month. The first portfolio corresponds to the *loser* portfolio and the last portfolio serves as the *winner* portfolio. We focus on a momentum portfolio (ψ_{t+1}^{WML}) that buys the last portfolio and sells the first portfolio each month. An important feature of this strategy (which also holds for the carry trade) is that it is dollar neutral as the dollar cancels out when subtracting one portfolio from another. We also report results for the spot exchange rate component because, consistent with Menkhoff et al. (2012b), we show that it captures a significant amount of the momentum portfolios variability.

1.3 Dynamic Factor Analysis

This section introduces the econometric framework. We consider two large panels of macroeconomic data[4] as well as financial variables and we apply dynamic factor analysis in order to extract common factors that can capture most of

[4]The data is winsorized so as to control against rare events.

the variability of each panel. The first panel consists of 127 variables from the U.S. economy and we label the corresponding factors as *domestic factors* (h_{it}).[5] The *global factors* (g_{jt}) are estimated from the second panel, which comprises 97 variables obtained mainly from G10 countries. The main reason for making the separation between the domestic and global factors is that the strategies of interest are exposed to different shocks. In particular, the carry trade strategy is mainly affected by the disparities observed among countries and so we expect the global factors to be stronger predictors. On the other hand, the dollar carry trade is mainly driven by U.S. economic conditions, as its risk premia will be negatively correlated with the U.S. business cycle and domestic factors should therefore be more informative for this strategy. Then, the profitability of the momentum strategy is subject to limits to arbitrage, such as transaction costs, liquidity levels, country risk, idiosyncratic volatility (Menkhoff et al., 2012b). To that end, we expect both domestic and global factors to have explanatory power on the momentum payoffs.

There are many methodologies proposed in the literature regarding the appropriate estimation method of the factors. We apply principal component analysis (PCA) as in Stock and Watson (2002a,b, 2006) for two reasons. Firstly, the factors obtained when other more computationally demanding methods are employed have not in general rendered stronger predictive power, because the precision of the factors remains the same;[6] for example, the Bayesian posterior means are very close to the corresponding PCA estimates. In addition, the estimation of dynamic factors, using methods such as the EM algorithm or Bayesian approaches has not improve the forecasting performance of the factors, as is also

[5]Recall that we take the U.S. investors perspective, which means that the U.S. dollar is the domestic currency.

[6]For more details see Ludvigson and Ng (2011).

verified in the literature.[7] Therefore, we follow a methodology that has extensively been used in many other studies (e.g. Ludvigson and Ng, 2009, 2010; Bernanke and Boivin, 2003; Bernanke et al., 2005; Kim and Taylor, 2011). However, we need to stress here that it is harder to interpret static factors, as they are unobserved. In contrast, it is easier to explain dynamic factors, since the data is organized into blocks, but they do not allow for cross-sectional correlation of the idiosyncratic errors and also the precision achieved from those factors is quite similar.

As discussed in in Section 2, we denote the payoff of a strategy at time $t+1$ as ψ^i_{t+1}, where $i = HML$ when we consider the payoffs to a carry trade strategy, $i = USD$ for the dollar carry trade and $i = WML$ when we examine the performance of the momentum strategy. Therefore, we can assess the in-sample predictive ability of a set of K predetermined predictors at time t, provided by a $K \times 1$ vector Z_t[8] , by estimating the following model:

$$\psi^i_{t+1} = \alpha + \gamma' Z_t + \varepsilon_{t+1} \quad \text{for } i = HML, USD, WML \tag{1.3}$$

For example, the consideration of the panel of the U.S. macro variables leads to a restrictive model as the cross-sectional dimension of the panel increases. In particular, assume that we have a $T \times N$ panel of macroeconomic variables, where T denotes the time dimension and N represents the cross-sectional dimension. As the cross-sectional dimension (N) increases a dimensionality issue arises. More precisely, when $N + K > T$ the model runs into degrees of freedom, which means that standard econometric techniques are not appropriate, as it is not apparent how to explore the information contained in such very large panels.

[7] Bai and Ng (2008) provide a very comprehensive survey on factor models.

[8] Z_t could contain the panel of domestic or global variables. We can also include other predictive variables.

Let us assume that each element in the macro panel is denoted by x_{it} and x_t is a vector of macro variables at time t. Therefore, we conjecture that x_{it} has a factor structure of the form:

$$x_{it} = \lambda_i^{'} h_t + u_{it}, \tag{1.4}$$

where h_t denotes a $k \times 1$ vector of latent common factors ($k \ll N$), $\lambda_i^{'}$ represents the corresponding $k \times 1$ vector of factor loadings and u_{it} is the vector of idiosyncratic errors.[9] Therefore, we consider the following regression:

$$\psi_{t+1}^{i} = \alpha + \beta' H_t + \gamma' Z_t + \varepsilon_{t+1} \quad \text{for } i = HML, USD, WML \tag{1.5}$$

where H_t is a subset of h_t and Z_t could be a benchmark.[10] As already mentioned the common factors (h_t), estimated by principal component analysis, are unobserved so we denote them by $\hat{h}_t$. The main feature of the PCA is that the factor space is estimated precisely as the time series and cross-sectional dimensions increase significantly (i.e. as $N, T \rightarrow \infty$). More specifically, the estimated factors are linear combinations obtained optimally by minimizing the sum of squared residuals ($x_t - \Lambda h_t$), where x_t denotes the vector of panel elements and Λ the corresponding $N \times K$ matrix of latent factor loadings.

The number of common factors ($\hat{k}$) is determined by the panel information criteria detailed in Bai and Ng (2002). More precisely, a random number k_{max} is selected in such a way that is not greater than the minimum of T and N. Then, we obtain the optimal number of common factors by solving the following optimization problem:

[9]A limited cross-sectional correlation among the idiosyncratic errors is allowed. Particularly, the idiosyncratic covariances are limited to the total variance of x as the cross-sectional dimension of the panel increases.

[10]We will consider different benchmark in a later section.

$$\hat{k} = \underset{0 \leq k \leq k_{max}}{\arg\min}\ h(k) = \ln\left(V(k)\right) + kg(N,T)), \tag{1.6}$$

where $g(N,T)$ denotes a penalty function[11] and the average sum of squared residuals with k factors ($V(k)$) could be expressed as:

$$V(k) = \frac{1}{NT} \sum_{i=1}^{N} \sum_{t=1}^{T} (z_{it} - \hat{\lambda}_i^k \hat{h}_t^k)^2, \tag{1.7}$$

where $\hat{h}_t^k$ is a matrix of k factors and $\hat{\lambda}_i^k$ is the vector of the corresponding factor loadings. Thereafter, we estimate the $\hat{k}$ common factors with principal component analysis, as described above. In addition, we employ different information criteria, so as to determine the most informative set of static factors for currency premia. We consider linear, non-linear and lagged values of the factors.[12] In particular, we form different subsets of the factors and for each candidate subset we project the ψ_{t+1} on $\widehat{H}_t = [\hat{h}_1, \hat{h}_2, \ldots, \hat{h}_{\hat{k}}]$, and we compute the Bayesian Information Criterion (BIC), Akaike Information Criterion (AIC), log-likelihood (LL) and adjusted coefficient of determination,($\bar{R}^2$). The log-likelihood function and the adjusted R-squared are used as decision tools in case of inconsistency between the BIC and the AIC criteria.[13] According to Stock and Watson (2002a,b, 2006), we can obtain the optimal set of factors $\hat{H}_t$, by getting the minimum BIC estimates. That is, we find the most informative factors for currency premia, as follows:

$$\psi_{t+1}^i = \alpha + \beta \widehat{H}_t + \varepsilon_{t+1} \quad \text{for } i = HML, USD, WML \tag{1.8}$$

where $\widehat{H}_t \subset \hat{h}_t$ and denotes all the possible subsets of the factors. Moreover, we

[11] i.e. $g(N,T) = \frac{N+T}{NT} \ln \frac{NT}{N+T}$.

[12] i.e. squared or cubed terms.

[13] We also try to identify the optimal set of factors in a forecasting context. However, we find that the two methodologies lead to the same subset of factors in most of the cases.

estimate the global factors in the same way and we denote them by $\hat{g}_t$. Therefore, we get the following regression:

$$\psi^i_{t+1} = \alpha + \beta' \widehat{G}_t + \epsilon_{t+1} \quad \text{for } i = HML, USD, WML \tag{1.9}$$

where $\widehat{G}_t \subset \hat{g}_t$.

Thus, our analysis focuses on two regression models. In the first model we examine the unconditional predictive power of the domestic and global factors. This version of the model tests whether the coefficients of the factors in the following model are statistically different from zero,

$$\psi^i_{t+1} = \alpha + \beta' \widehat{H}_t + \gamma' \widehat{G}_t + u_{t+1} \quad \text{for } i = HML, USD, WML \tag{1.10}$$

Later, we consider the performance of the static domestic and global factors conditional on the information provided by other predictors in the literature denoted by Z_t. That is,

$$\psi^i_{t+1} = \alpha + \beta' \widehat{H}_t + \gamma' \widehat{G}_t + \delta' \widehat{Z}_t + v_{t+1} \quad \text{for } i = HML, USD, WML \tag{1.11}$$

where $\widehat{H}_t$ represents the optimal subset of the U.S. static factors, and $\widehat{G}_t$ represents the optimal subset of global factors, all at time t.

It is apparent that the use of dynamic factor analysis for the estimation of the common factors as well as the use of information criteria that determine the relevant factors leads to a parsimonious model that may capture the variability of currency premia. In addition, the factors may be more informative than other variables used in the literature as they exploit the information content of a large number of macro variables and capture the common trends of the major economies that are involved in our sample.

1.4 Data

US data. The domestic data consist of a large balanced panel of 127 monthly macroeconomic and financial series of the U.S. economy spanning the time period 1985:07-2012:03; the data was downloaded from Datastream. Moreover, the panel covers a variety of categories of the U.S. economy: real output, employment, consumption, housing start, orders, stock prices, exchange rates, interest rates, money and credit quality aggregates, price indices, earning, international trade, capacity utilization and miscellaneous. In addition, the raw data have been standardized and transformed according to simple stationarity tests. Table B.1 in the Data Appendix offers a detailed description of the data.

Our data set spans almost three decades. However, the inclusion of observations before 1985 leads to an unbalanced panel, since many variables have missing values, which is common when dealing with macroeconomic data. There are many different ways of tackling this problem, such as interpolation, EM algorithm, or Kalman filter methods. However, we exclude the unbalanced panel and apply the methodology only on the balanced panel, since all of the above methodologies smooth the data.

Global Data. The global variables comprise a panel of 97 macroeconomic and financial variables collected (mainly) from G10 countries for the period 1985:07-2012:03. The reasoning behind the inclusion of G10 countries corresponds to the tradability of their currencies. In particular, the G10 currencies are the most actively traded currencies in the foreign exchange market, and thus we suspect that the macroeconomic and financial environment of those countries would affect the variability of our strategies and reveal potential commonalities.[14] The data cover a broad spectrum of the macroeconomic and financial environment of the economies in question, namely real output, employment, consumption, stock prices, price indices, interest rates, international trade, reserves and aggregate variables of the G7 countries.[15] All the series are transformed based on unit root tests and standardized prior to estimation of the global factors. Tables A.10 and A.11 in the Data Appendix provides a detailed description of the global data.

A very important characteristic of our domestic and global data is that we do not include only macro variables in the panel, but we also consider financial variables. This feature of our data gives us the opportunity to identify business cycle variations in currency premia as they are depicted in comovements in financial and real variables.

Spot and Forward Exchange Rates. We begin with daily spot and 1-month forward exchange rates *vis-à-vis* the U.S. dollar for the period 1985:07-2012:03. The data are available on Datastream from WM/Reuters and Barclays Bank International (BBI). Moreover, we create end-of-month series of spot and forward rates (i.e. we take the last business day of each month) as in Burnside et al. (2011). Afterwards, bid, middle and ask quotes are employed, so as to take into consideration transaction costs. The whole sample consists of the following 48 currencies: Australia, Austria, Belgium, Brazil, Bulgaria, Canada, Croatia, Cyprus, Czech Republic, Denmark, Egypt, Euro area, Finland, France, Germany, Greece, Hong Kong, Hungary, India, Indonesia, Ireland, Israel, Italy,

[14]According to BIS triennial Survey 2010 the top 10 currencies account for almost 90% of the average daily foreign- exchange turnover that reached $4 trillion.

[15]United States, Japan, Germany, UK, France, Canada, and Italy.

Iceland, Japan, Kuwait, Malaysia, Mexico, Netherlands, New Zealand, Norway, Philippines, Poland, Portugal, Russia, Saudi Arabia, Singapore, Slovakia, Slovenia, South Africa, South Korea, Spain, Sweden, Switzerland, Taiwan, Thailand, Ukraine and United Kingdom. We label this sample All countries.

The inclusion of some of the above currencies could be problematic because of capital constraints or the fact that some them are pegged to other currencies. That is, the investors may experience difficulties trading some of the currencies in significant volumes despite the availability of their forward contract. In order to tackle this problem and make our analysis more realistic, we also consider a smaller sample of 15 Developed countries, namely: Australia, Belgium, Canada, Denmark, Euro Area, France, Germany, Italy, Japan, Netherlands, New Zealand, Norway, Sweden, Switzerland, and the United Kingdom. The Euro Area currencies are excluded from the sample after the introduction of the Euro in January 1999 and thus the sample is narrowed down to G10 currencies. This sample is similar to the one employed by Lustig et al. (2011, 2014) and Menkhoff et al. (2012b). Consistently with other studies, we delete observations for which we observe significant deviations from the CIP condition.[16]

1.5 Empirical Results

In this section we offer descriptive statistics of the payoffs as well the common factors before turning to the in-sample and out-of-sample analysis. We also provide an economic interpretation of the factors that were selected to enter the optimal samples.

[16]In particular, we remove the following data: South Africa for the periods 1985:07-1985:08 and 2001:12-2004:05; Indonesia for the periods 1997:06-1998:03, 2001:01-2002:09 and 2008:11-2009:02; and Kuwait for the period 2001:03-2001:04.

1.5.1 Summary Statistics of the Currency Excess Returns

Carry Trades. Table 1 presents descriptive statistics of the payoffs to carry trade and dollar carry trade strategies. In particular, ψ^{HML} is the payoff to a carry trade strategy and ψ^{USD} denotes the return of a portfolio that mimics the dollar carry trade strategy. We report annualized estimates of the mean, standard deviation, Sharpe Ratio and Sortino Ratio. The annualized mean of the carry trade is 4.24% with a Sharpe ratio of 0.46 for the group of *All countries* and 2.79% with a Sharpe ratio of 0.27 for the *Developed countries*. The Sortino ratio is a measure of downside risk and is measured as the average excess return divided by the standard deviation of negative excess returns only. The currency excess returns exhibit left skewness and excess kurtosis, which is in line with other studies in the literature such as Brunnermeier et al. (2008) and Burnside et al. (2011b). $AR1$ represents the first order autocorrelation coefficient, and is 0.20 for the case of *All countries* and 0.11 for the *Developed countries*. Thus, we can infer that the carry trade payoffs exhibit positive autocorrelation with low persistence.

The annualized mean of the dollar carry trade strategy is 3.93% for the whole sample with a Sharpe ratio of 0.55 and 5.86% with a Sharpe ratio of 0.69 for the *Developed countries*. This finding is in line with that of Lustig et al. (2014), who show that the dollar carry is more profitable than the carry trade for the case of the developed countries. However, the reverse is observed when we take into account all the countries of our sample. As is pointed out in Lustig et al. (2014), the strategies under consideration are not highly correlated (not reported in the table) and deliver significantly different mean returns and thus Sharpe ratios. The main reason for this observation lies in the fact that the two strategies exploit the variation between different economies. That is, the dollar carry trade is more exposed to the U.S. economy, since the investors short the dollar before the NBER recessions and go long the dollar right after the end of the U.S. recessions. On the other hand, the carry trades are more affected by variations of the global economic environment rather that the home countrys condition. As in the case of the carry trade, the dollar carry trade displays negative skewness and excess kurtosis with negative and low autocorrelation. We also report the corresponding summary statistics for the exchange rate component of the strategies. As can be seen, a large bulk of the profitability comes from exchange rate returns, which implies potential exchange rate predictability.

Momentum. Table 1 also reports summary statistics for the momentum strategy (ψ^{WML}). The annualized mean is 5.17% (1.57%) and the annualized standard deviation is 9.57 (8.74) yielding a Sharpe ratio of 0.54 (0.18) for the full sample (Developed countries). The payoffs exhibit positive skewness and excess kurtosis with almost zero first-order autocorrelation for both samples. We also report descriptive statistics for the exchange rate changes. Figure 1 displays annualized payoffs of the strategies and the shaded areas represent the NBER recessions for the U.S. economy.

1.5.2 Summary Statistics of the Static Factors

Table 2 reports summary statistics for the domestic and global factors. The Bai and Ng (2002) criterion suggests the use of the maximum number of factors in the case of the domestic data and three factors for the global data. Therefore, we estimate nine static factors[17] for the U.S. economy and three global factors. The first factor in each case explains the largest proportion of the total variation in the panel and then each factor explains the largest fraction of the variation

[17]In-sample and out-of-sample examination of the factors suggests the use of nine factors.

conditional on the information provided by the previous factors. In other words, the R_i^2 is defined as the sum of the first i largest eigenvalues divided by the sum of the eigenvalues of the panel $x'x$, which determines the total variation of the panel. As can be seen from the table, the first three domestic factors capture more than 60% of the total variance of the U.S. data, while three global factors capture less than 25% of the variation of the global data.

Table 2 also reports the first-order and second-order autocorrelation coefficients of the common factors. The top factors exhibit high persistence, while the bottom factors have very low persistence. Thus, there is substantial heterogeneity across factors as depicted in the high dispersion of the coefficients. In particular, the first order autocorrelations coefficients ($AR1$) in the case of the domestic factors range from 0.03 to 0.97, whereas the corresponding range for the global factors goes from 0.11 to 0.95.

Optimal Subsets of Factors. As was mentioned in Section 3, the optimal set of factors is determined based on information criteria (i.e. BIC and AIC). The optimal subset of factors represents the candidate subset that has the minimum value of the corresponding BIC and AIC. The log likelihood function and the adjusted R-squares are used as decision tools if there is an inconsistency between the two information criteria. More specifically, we first estimate all the combinatorial subsets of the factors in sets of n, where $n = 2, \ldots, \hat{k} - 1$ and then make the final decision based on BIC and AIC. Table C in the Internet appendix presents information criteria and adjusted R-squares for each competing set of factors for each strategy. For example, in Panel A we report the competing subsets for the carry trade strategy, where $G1$ is the factor with the smallest BIC out of all the possible univariate regressions. $G3$ contains all the available factors and $G2$ is the set of factors with the smallest BIC when taking into consideration all possible pairs. A similar procedure is followed for the set of the domestic factors (i.e. H) and when we merge the domestic and global variables (i.e. HG).

Thus, the optimal subsets of global factors[18] ($\widehat{G}_t \subset \hat{g}_t$) are the following: $\widehat{G}_t^{HML} = (\hat{g}_{2t})'$, $\widehat{G}_t^{USD} = (\hat{g}_{3t})'$, $\widehat{G}_t^{WML} = (\hat{g}_{3t})'$. The sets of domestic factors for the three currency strategies ($\widehat{H}_t \subset \hat{h}_t$) are given by $\widehat{H}_t^{HML} = (\hat{h}_{2t}, \hat{h}_{3t}, \hat{h}_{4t}, \hat{h}_{6t})'$, $\widehat{H}_t^{USD} = (\hat{h}_{6t}, \hat{h}_{7t})'$, $\widehat{H}_t^{WML} = (\hat{h}_{1t}, \hat{h}_{4t})'$ and the corresponding subsets of all factors ($\widehat{HG}_t \subset \hat{hg}_t$) are $\widehat{HG}_t^{HML} = (\hat{h}_{6t}, \hat{g}_{2t}, \hat{g}_{3t})'$, $\widehat{HG}_t^{USD} = (\hat{h}_{6t}, \hat{h}_{7t}, \hat{g}_{3t})'$, $\widehat{HG}_t^{WML} = (\hat{h}_{1t}, \hat{h}_{4t}, \hat{g}_{3t})'$. Later, we also examine nonlinear and lagged forms of the factors.

1.5.3 In-sample Analysis

In this section we conduct the in-sample analysis. The main advantage of this approach has to do with the fact that all the available information in the sample can be used, whereas the out-of sample tests use only a part of the available information which lowers their power and increases the forecast error significantly. This phenomenon is amplified in smaller samples. However, both tests are useful for different reasons. That is, the in-sample test helps us understand the relationship between the optimal subset of common factors and the payoffs of the strategies employed in the chapter. On the other hand, the out-of sample analysis provides information regarding data mining, overfitting, structural changes or model instability as well, as it resembles the behavior of an investor in real time.

Tables 4, 5 and 6 report in-sample predicting regressions of the form of equation 6 for currency excess returns as well as exchange rate changes. We take into

[18] We report results for the full sample.

consideration transactions costs in all cases. First, we ask whether the global factors (domestic factors) have unconditional predictive power on each payoff.[19] To do that, the slope coefficients of the global factors (domestic factors) are restricted to zero. Thereupon, we further examine the predictive ability of the factors when the prediction is conditional on the information contained in domestic regressors. Thus, we present estimates of the slope coefficients of the regressions, the corresponding *t-statistics* and adjusted R^2 for each regression. NW denotes the *t-statistics*[20] with asymptotic standard errors that are corrected for heteroskedasticity and autocorrelation (HAC) based on the Newey and West (1987) correction with the optimal number of lags selected following Andrews (1991). B denotes two-sided *p-values* based on a wild bootstrap with $10,000$ bootstrap iterations in order to account for potential small-sample bias in the inference about the models in use. Our bootstrap procedure is similar to that used by Mark (1995), Kilian (1999), Kilian and Taylor (2003), Amihud et al. (2009) and Bakshi and Panayotov (2013). In particular, we estimate the bias-adjusted standard errors by simulating a data generating process (DGP) that generates 10,000 samples (with replacement) of the payoffs and factors from a vector autoregression (VAR) under the null of no predictability. The number of lags in the VAR is determined by information criteria (i.e. BIC). The use of bootstrapping is very important because of the persistence of the predictors, which can lead to biased slope coefficients with greater dispersion than the asymptotic distribution (Bekaert et al., 1997; Stambaugh, 1999). Below the R-squares we report the corresponding χ^2 and *p-values* for joint tests of parameter significance.

[19]The results for log returns are very close to those presenting here for raw returns.

[20]Our results are also verified by the estimation of Hansen and Hodrick (1980) standard errors.

Carry Trades. Table 4 reports in-sample predictions for the carry trade using the optimal subset of factors analyzed in the previous section. Panel A reports results for the excess returns and Panel B reports estimates for exchange rate changes. Firstly, we consider predictive regressions with global factors. As can be seen for the full sample and the group of Developed countries, the slope coefficients are highly statistically significant yielding an adjusted R-square of 0.05 (0.04) for *All countries* (*Developed countries*), which is comparable with the corresponding goodness-of-fit statistics of those found in previous studies. However, the domestic factors provide much smaller R-squares (i.e. 0.02-0.03), verifying our assumption concerning the exposure of carry trades in the global environment rather than the domestic. However, most of the slope coefficients of the domestic factors are highly significant both for excess returns and exchange rate returns, although when we examine the set of global and domestic factors only the slope coefficient of the sixth domestic factor remains statistically significant in contrast to the global factors, which yield highly significant coefficients.

Dollar Carry Trades. Table 5 displays results for the dollar carry trade strategy when considering the most informative set of factors. Here we observe results that are in many ways opposite to those reported above. In particular, the global factors are not statistically significant, yielding an adjusted R-square of 1%, whereas the set of domestic factors ($\hat{h}_6$, $\hat{h}_7$) provide high *t-statistics* and R-squares around 4% both for excess returns and exchange rate changes. The consideration of both global and domestic factors leads to highly significant estimates and an R-square around 5%. These results are verified from the bootstrapped *p-values* and results are in line with our conjecture regarding the exposure of the dollar carry trade to the U.S. economy and to lesser extent the global environment, consistent with Lustig et al. (2014). Once again, the factors provide strong exchange rate predictability as can be viewed in the second panel of the table.

Momentum. Table 6 provides estimates of the predictive regressions when considering momentum returns. Firstly, we examine the conditional predictive power of the global factors and we find very low R-squares (1%) and insignificant slope coefficients. The inclusion of domestic factors shows that the fourth domestic factor is highly significant for both samples when examining excess returns as well as exchange rate changes. However, the third global factor and fourth domestic factor contain valuable information for currency momentum profits at the 10% significance level, offering adjusted R-squares of $2-4\%$. Overall, we find that the optimal set of domestic factors as well as the second global factor provide evidence of in-sample predictability mainly for the sample of the developed countries.

1.5.4 Economic Interpretation of the Factors

In this section we attempt to provide an economic intuition behind the common factors. We need to be very careful when analyzing the factors because they are unobserved since they capture the variation of the whole panel and thus absorbing information from all the economic variables. Thus, labelling the predictors could be problematic, as we cannot link the factor directly with specific economic series, such as unemployment or consumption. However, some factors seem to load heavily on particular economic or financial variables that help us make inferences with regards to the identity of the factors.[21]

Figure 2 (Figure 3) provides a graphical illustration of the marginal R-squares from regressing each of the 127 (97) economic and financial series onto each

[21] Ludvigson and Ng (2009) follow a similar procedure.

domestic (global) factor. The individual series are grouped into more general categories, as in the Appendix (tables B.1. and B.2.) and follow the same numbered ordering. Table 3 displays the names of the economic series that exhibit the highest correlation with the common factors. Once again, we use this table as a verification tool of the marginal R-squares and we do not try to link particular series with the factors.

Domestic Factors. Figure 2 displays marginal R-squares of the domestic factors that were selected for the optimal subsets. The second factor ($\hat{h}_2$) is an *interest rate factor* as it exhibits higher marginal R-squares for interest rates. The third factor ($\hat{h}_3$) loads heavily on series that measure real output, employment and consumption, but also on measures of money and credit and price indices. A similar pattern is observed for the fifth factor ($\hat{h}_5$) with slightly lower correlations. The eighth factor ($\hat{h}_8$) exhibits low correlation with price indices and loads heavily on real output, employment and consumption. Thus, we label $\hat{h}_3$, $\hat{h}_5$ and $\hat{h}_8$ *real factors*. The fourth factor ($\hat{h}_4$) load heavily on price indices, money and credit variables and to a lesser extent on real variables (e.g. U.S. personal income); thus, we label it as *inflation factor*. The sixth and seventh factor ($\hat{h}_6$,$\hat{h}_7$) load heavily on measures of consumption and thus we call them *consumption factors*.

Global Factors. Figure 3 shows graphically the marginal R-squares from projecting each of the series in the global panel onto each global factor for the period 1985:07-2012:03. The first global factor ($\hat{g}_1$) loads heavily on variables that measure international trade and is highly correlated with variables that measure employment (i.e. 0.77), so we label $\hat{g}_1$ as *international trade factor*. The second and third global factors ($\hat{g}_2$, $\hat{g}_3$) contain information for the global stock market of the countries in the sample, since they are highly correlated with variables that capture the variation of the stock market. In addition they load heavily on interest rates and reserves. In the same vein, the marginal R-squares provide the same information as we obtain R-squares around 40% for stock market indices as well as interest rates. Therefore, we name them *money* & *credit factors*.

As we saw in the previous section, the second global factor seems to be a very strong predictor, especially for the carry trades. This is not surprising as the link between the global stock market and the foreign exchange market is quite strong. For example, Hau and Rey (2006) show empirically and theoretically that under circumstances of incomplete hedging in the foreign exchange market that the foreign currency appreciates when the return in the home equity market is greater than the foreign counterpart.

Longer horizons. We also look at the predictive power of the factor for longer horizons. We find in table A.6. that the slope coefficients of the factors are highly significant and the R-squares increase from $6-25\%$ for average exchange rates and dollar carry returns obtained from Lustig et al. (2014). These payoffs consider forward rates of longer horizons. However, table A.7. shows that the R-squares are quite high even when we ignore the information of longer horizon forward rates.

1.5.5 Out-of-sample Analysis

In this section we report the results of out-of-sample analysis in order to assess further the forecasting power of the common factors. A particularly noteworthy feature of this approach has to do with the implications for the scapegoat theory developed by Bacchetta and Wincoop (2004); Bacchetta and Van Wincoop (2013), and empirically tested (in a different context) by Fratzscher et al. (2013). More precisely, we employ recursive estimates of the factors and parameters using data up to time t in order to forecast at time $t+1$, accounting in this way for potential look-ahead bias. We question whether an economic agent can obtain better forecasts from the use of the factors than simply relying on the historical mean.

Table 7 reports out-of-sample R^2 as in Campbell and Thompson (2008): ($R^2_{OOS} = 1 - \sum_{t=1}^{T-1} \frac{\psi^i_{t+1} - \hat{\mu}_{t+1})^2}{(\psi^i_{t+1} - \mu_{t+1})^2}$), where $\hat{\mu}_{t+1}$ represents the one-step ahead conditional forecast from the model of interest and μ_{t+1} is the historical mean of the payoff. Thus, a positive R^2_{OOS} statistic means that the competing model outperforms the benchmark model because it has a lower mean square prediction error.

Then, we test the forecasting ability of the above models using the mean-squared prediction error statistic (MSPE-*adj*) following Clark and West (2007). Under the null hypothesis the mean square error of the competing model is expected to be greater than the mean square error of the benchmark model. Therefore, we construct $\hat{f}_t$ as:

$$\hat{f}_t = (\psi^i_t - \mu_t)^2 - [(\psi^i_t - \hat{\mu}_t)^2 - (\mu_t - \hat{\mu}_t)^2]. \tag{1.12}$$

and then $\hat{f}_t$ is regressed on a constant and rejecting the null of a zero estimated coefficient then implies that the competing model out-performs the benchmark model, so the factors forecast better that the historical mean.

The in-sample period spans the first 180 observations (out of 321) that correspond to the period 1985:07-2000:05.[22] The factors are fixed and we follow an expanding window approach. The recursively estimated factors provide positive R^2_{OOS} but not as high as those obtained from the fixed factors. Table 7 offers out-of-sample R^2_{OOS} as well as one-sided *p-values* of the MSPE-*adj* statistic for

[22]Many different in-sample periods have been employed and render similar results.

the competing models described in the passage against the benchmark model. All the sets of factors that are statistically significant in the in-sample test pass the out-of-sample test with R^2_{OOS} that range from $1\% - 10\%$, all statistically significant. Furthermore, most of the one sided *p-values* of the MSPE-*adj* statistics are not greater than 0.05, verifying further the forecasting ability of the factors. Very similar results are obtained for exchange rate changes.

Combined Forecasts. The out-of-sample results are reinforced by combination forecasts, following Stock and Watson (2004). This approach is based on the idea that the weighted averages of the individual predictions obtained from different models may exhibit a significantly better performance than the individual models. Therefore, we consider *mean* predictions as well as *weighted* predictions based on the performance of the predictions in the holdout period, p. In particular, as in Rapach et al. (2010), each prediction i at time t is associated with a weight ω_t^i, such that:

$$\omega_t^i = \frac{1/\phi_t^i}{\sum_{j=1}^N (1/\phi_t^j)}, \tag{1.13}$$

where $\phi_t^i = \theta^{t-1-k} \sum_{k=p}^{t-1} (\psi_{k+1}^i - \hat{\mu}_{k+1}^i)^2$ and $\hat{\mu}_{k+1}^i$ is the *i-th* individual prediction for the $k+1$ month and the discount factor θ is less than unity providing a higher weight to the latest prediction. Here, we consider a holding period of $p = 180$ months and a holdout period of 141 months. In addition, we set $\theta = 0.9$ as in previous studies, although other values of θ provide similar results.

Table 7 also reports R^2_{OOS} and one-sided *p-values* of the MSPE-*adj* based on combined forecasts. The superscript $Mean$ denotes mean forecasts and the superscript $Weighted$ the corresponding weighted forecasts. The subscripts denote the set of forecasts that we used. Overall, the results align with those obtained from individual forecasts. For instance, all the out-of-sample R-squares are positive and overall better than before and the associated one-sided *p-values* of the MSPE-*adj* statistic are largely significant. Once again the results confirm the existence of forecast ability in the carry and momentum returns.[23]

1.5.6 Data-Mining Concerns

One might raise concerns regarding the presence of data fishing in our methodology.[24] The main reasoning behind this claim might arise from the way that the factors are extracted from the large datasets. The main advantage of the dynamic factor analysis, however, is its robustness against data mining. For example, Ludvigson and Ng (2011) came to the same conclusion when they tried to guard against data snooping. More precisely, instead of following the procedure detailed in section 3, they consider all possible combinations of linear and nonlinear forms of the factors (i.e. 106762 models) and evaluate the best performing set of factors based on in-sample and out-of-sample information criteria (i.e. BIC). They find that the optimal set of factors that is proposed by this extensive search of the data is the same with the one suggested by the initial, less intense, method. This might suggest that data mining does not affect the findings of this method.

However, we demonstrate the robustness of our methodology against data snooping by utilizing a statistically more powerful approach. Specifically, we follow Clark and McCracken (2012) who extended the White (2000)'s reality check, using a wild fixed-regressor bootstrap so as to account for the fact that the competing models nest the benchmark model (i.e. the historical average).

[23] Table A.8 provides out-of-sample results for a different sample that employs information until 2007.12. The purpose of this exercise is to see whether the factors performed well during the recent financial crisis.

[24] We would like to thank the editor and the referee for pointing this out.

Particularly, we test the null hypothesis that the MSFE of the historical mean does not exceed the minimum MSFE of all the competing models (maxMSFE-F statistic). To that end, we simulate the innovation term (i.e. $\hat{\varepsilon}_t$), obtained from a kitchen sink model estimated using the whole sample so as to generate the pseudo payoffs (i.e. ψ_t^*) for each strategy, such that

$$\psi_t^* = \alpha_{0,T} + \eta_t \hat{\varepsilon}_t, \tag{1.14}$$

where $\alpha_{0,T}$ is the sample mean of each strategy and η_t is drawn from a standard normal distribution. Then the optimal factors are used to forecast the pseudo samples. We employ $1,000$ replications and the *p-value* is measured as the mean of a dummy variable that takes a value of 1 if maxMSFE-F statistic of all competing models from the simulation is greater than the sample counterpart and 0 otherwise. For carry trade excess returns we find a maxMSFE-F statistic of 8.22 for the whole sample and 4.98 for the developed countries with *p-values* of 0.01 and 0.03 respectively. The corresponding statistic for the dollar carry trade is 10.66 for all countries with a *p-value* of 0.01 and 7.56 for the group of the developed countries with a *p-value* of 0.01. Regarding the momentum strategy, we find significant results for the group of the developed countries, which is not surprising because our macro factors exhibit stronger predictive power when we consider the smaller group of currencies. Particularly, the maxMSFE-F statistic for the momentum returns of the developed countries is 6.07 with a *p-value* of 0.04. Overall, the Clark and McCracken (2012) statistic suggests that the out-of-sample predictive power of the factors for the currency strategies cannot be linked to data mining.

1.5.7 Countercyclical Currency Premia and Policy Implications

In this section we question whether the forecasts of the currency excess returns can reveal the countercyclical nature of currency premia. According to theory (i.e. Ludvigson and Ng, 2009; Lustig et al., 2014) the forecasts of excess returns should be countercyclical reflecting the decrease in the global risk aversion during *good* states of the world and *vice versa*. Lustig et al. (2014) show that currency premia exhibit countercyclical behavior that could be captured by forward discounts. In the term structure literature, Ludvigson and Ng (2009) find that the forecasts of bond risk premia demonstrate countercyclical movements only when they consider the macro factors. Thus, we attempt to see whether our domestic and global macro factors could help predict this behavior. To this end, figure A.1 (A.2) in the appendix show standardized 12-month moving average of carry and dollar carry trade excess returns - when considering the global (panel A) or domestic (panel B) factors - as well as the corresponding US (G7 countries) IP growth. We find that the inclusion of the global factors reveals the countercyclical nature of currency premia, while the domestic factors lead to acyclical or reverse results.[25] In line with Lustig et al. (2014), the dollar carry trades exhibit a stronger countercyclical component (-0.82 correlation with the US IP growth) in comparison to the carry trade analogue (-0.22). This finding might be of interest to policy makers as it could help them adjust currency premia with the appropriate monetary policy or examine the interaction among risk premia, monetary policy and the economic environment (e.g. Ireland, 2014).[26]

[25] We come to a similar conclusion when we employ other predictors. The results are similar for US and G7 IP growth because they are highly correlated. We also obtain similar results when, we exclude the US from the sample of the G7 countries.

[26] We would like to thank the referee for pointing this out.

1.6 Economic Evaluation of the Forecasts

In order to assess the economic value of the forecasts, we develop a strategy that resembles a decision rule. In particular, the investor is involved in one of the strategies at the end of month t if the forecast of the corresponding strategy is positive for the month $t+1$, otherwise she does not enter into a position. We use the forecasts of domestic and global factors as well as combination forecasts. Then, we examine the performance of the factors when investing in all strategies at the same time. In this case, identical weights are assigned to each strategy.

Table 8 displays Sharpe ratios (Panel A) and skewness (Panel B) of the conditional and unconditional payoffs. The unconditional payoff embodies the realized value of the payoff, while the conditional payoff is determined by a decision rule. As can be seen in the table, there is an overall significant increase in the Sharpe ratios and an improvement in the skewness profile of the payoffs both for whole sample and for the group of the *Developed countries*. In curly brackets we report p-values estimated based on $10,000$ stationary bootstrap samples (Politis and Romano, 1994), for the null hypothesis that the Sharpe ratios of the conditional strategy do not exceed (statistically) the unconditional counterparts, which take a position in the FX strategy regardless of the sign of the prediction. With the exception of the momentum strategy, where there is no big improvement, the forecasts provide strong out-of-sample economic value for an investor who applies the strategies of interest. In addition, the mixed strategy that combines all the three strategies provides exceptionally high annualized Sharpe ratios of around 1.06 with positive skewness.

Figure 4 illustrates rolling Sharpe ratios, using a 12-month window for carry, dollar carry and momentum strategies as well as the mixed strategy. The solid lines represent rolling Sharpe ratios of conditional payoffs obtained from the forecasts of the optimal subset of factors (black) and the combination forecasts (blue). The dashed line displays the realized value of the payoffs. There is clearly an improvement in the rolling Sharpe ratios, especially during the crisis. Our decision rule shows that an investor could gain very high Sharpe ratios during the recent financial turmoil (2008-2009) if she had taken into account the domestic and global macroeconomic environment.

Overall, the out-of-sample study revealed a strong economic value in the payoffs to carry, dollar carry and momentum strategy. In addition, the consideration of the factors improves not only the overall Sharpe ratio and the skewness profile of the payoffs, but also helps to mitigate the downside risk experienced during the recent global financial crisis.

Dynamic Asset Allocation. The decision rule does not amalgamate the investors risk preferences into the asset allocation decision. Thus, we ask whether our forecasts can benefit a risk-averse investor with mean-variance preferences who allocates her wealth on a monthly basis across risky assets (i.e. equities and currency strategies) and risk-free assets (i.e. U.S. Treasury bills). Particularly, we ask whether an investor could benefit from a currency investment strategy that it is appended by a traditional institutional investors 60/40 portfolio.[27] To this end, we estimate the certainty equivalent return (CER), following Campbell and Thompson (2008) and Ferreira and Santa-Clara (2011).

The investor rebalances her portfolio at the end of month t, forming the weights of the currency strategies (w_t^i) for investing at time $t+1$ as:

$$w_t^i = \left(\frac{1}{\gamma}\right)\left(\frac{\hat{\psi}_{t+1}^i}{\hat{\sigma}_{i,t+1}^2}\right) \quad \text{for } i = HML, USD, WML \tag{1.15}$$

[27] We would like to thank the referee for pointing this out.

where $\hat{\psi}^i_{t+1}$ is the forecast of the payoff for the *i-th* strategy, $\hat{\sigma}^2_{i,t+1}$ the corresponding forecast of the variance and γ denotes the investors absolute risk aversion. Therefore, the portfolio return at time $t+1$ is given by:

$$R^i_{p,t+1} = w^i_t \psi^i_{t+1} + R_{p60/40_{t+1}} \quad \text{for } i = HML, USD, WML \tag{1.16}$$

where $R_{p60/40_{t+1}}$ is the return of a traditional 60/40 portfolio that allocates 60% on equities (i.e. S&P 500) and 40% on risk free bonds at time $t+1$. As in Campbell and Thompson (2008) the variance of the payoffs is estimated on the basis of a five-year rolling window, the risk aversion coefficient equals five and the weights for the risky asset are confined in a particular interval (i.e. between 0 and 1). In this way, we do not allow for leverage. Thus, the average realized utility or CER is defined as:

$$CER^i_p = \hat{\mu}^i_p - \frac{\left(\gamma \hat{\sigma}^2_{i,p}\right)}{2} \quad \text{for } i = HML, USD, WML \tag{1.17}$$

where $\hat{\mu}^i_p$ is the mean and $\hat{\sigma}^2_{i,p}$ is the variance of the portfolio when investing in each of the three strategies over the out-of-sample period.

The certainty equivalent return is the risk-free return that a mean-variance investor would consider sufficient in order to avoid investing in the strategy. The CER gain represents the difference between the average realized utility of the forecasts and the corresponding value of the historical average. It can be interpreted as the fee that an investor is willing to pay in order to utilize the forecasts rather than relying on the historical mean. Thus, a positive value of the CER means that the investor prefers the forecasts over the estimate of the historical mean when forming expectations with regard to the strategies of interest.

Panel C of table 8 presents CER gains for the carry, dollar carry and momentum strategy. In agreement with the R^2_{OOS} and the one-sided *p-values* of the MSPE-*adj*, the CER gains are positive with the exception of the momentum strategy and the carry trade strategy only when we consider all the sample of all countries. Thus, there is a predictable component in the carry and dollar carry trade strategy that provides strong economic value to a risk-averse investor with mean-variance preferences.

1.7 Robustness and Other Specification Tests

In this section, we offer some additional tests in order to examine further the robustness of our results. In particular, we examine the performance of the factors in the presence of other predictors in the literature and question whether our factors have stronger explanatory power over other variables. Then, we explore potential predictable components in the short and long legs of the carry trade and momentum strategies.

1.7.1 Conditional Predictive Regressions

We assess the predictive ability of the factors conditional on the information provided by other predictors in the literature, such as the Bakshi and Panayotov (2013) predictors (hereafter BP). Bakshi and Panayotov (2013) employ three predictors that are traditionally strong indicators of currency premia. Focusing only on carry trades, they construct three measures that exhibit strong in-sample and out-of-sample predictability. That is, commodity, volatility and liquidity measures (ΔCRB ,$\Delta\sigma^{fx}$, ΔLIQ), all estimated on a monthly basis. According to their results commodity and volatility factors and to a lesser extend liquidity factors can capture the time-series behavior of carry trade payoffs. Here, we examine whether our factors maintain their predictability conditional on the information provided by the aforementioned factors. Appendix A.1.3 presents a brief description of the BP predictors.

Panel A of Table 9 provides in-sample estimates of the factors in the presence of the BP variables. In order to con serve space, we report results only for combined subsets of domestic and global factors. For the carry trade strategy the set of common factors are highly significant rendering an adjusted R-square of 5% for the full sample and 9% for the *Developed countries*. Regarding the dollar carry trade, the factors $\hat{h}_4$, $\hat{h}_6$, $\hat{h}_7$ are significant and among the BP predictors only the volatility factor explains the behavior of the dollar carry trade. However, only the fourth common factor is statistically significant when we consider the momentum strategy of whole sample and the factors $\hat{g}_2$, $\hat{h}_8$, $\hat{h}_9$ with the commodity factor of the BP variables are statistically significant at 10% significance level only for the case of the developed countries.

Lustig et al. (2014) show that average forward discounts (AFD) exhibit important information for dollar carry trade returns. Thus, we examine whether the predictability of our factors remains after including the AFD. Panel B of Table 9 displays results of the predictive regressions for all the payoffs. In all cases the AFD is not statistically significant and our factors remain highly significant.[28]

1.7.2 Predictability in the Long and Short Legs

Following Bakshi and Panayotov (2013), we examine potential predictable components in the short and long legs of the carry trade and momentum strategies. Panel A of table 10 presents results of the in-sample estimates when projecting the long or short components of the carry trade strategy on the optimal set of

[28] We obtain similar results with data obtained from Lustig et al. (2014).

factors. We find strong evidence of predictability in the long leg with highly significant estimates of the global factors and R-squares around 8%. However, we find weak evidence of predictability in the short leg of the strategy. Similar results are obtained for both samples (*All countries* and *Developed countries*). Panel B of table 10 reports the corresponding results when considering momentum returns. We find evidence of predictability both in the loser and the winner portfolios with the global money & credit factors ($\hat{g}_2$, $\hat{g}_3$) to be highly significant as well as the optimal set of domestic factors for both samples. Overall, we find that our factors provide useful information for currency premia over and above other predictors in the literature.

1.7.3 Other Tests

Different payoffs. We also look at more naive strategies, such as the Deutsche Banks (DB) global and G10 carry trade. Table 11 shows that our factors provide very strong in-sample predictive power for the excess returns of the aforementioned indices, as it can be seen from the highly significant slope coefficients and the high R-squares (i.e. 9-14%). In addition, we investigate the variation of two more strategies that deviate from the scope of this chapter, namely DB value and DB momentum (trend-based). We find that domestic factors exhibit strong predictive power. Moreover, we employ additional payoffs (table A.1) that are available from other studies in the literature, such as the carry trade excess returns of Lustig et al. (2011) and Bakshi and Panayotov (2013) (available on their website).

Alternative subsamples. In order to assess further the robustness of our analysis we examine the predictive power of the factors in different time periods (1985:07-1992:12 and 1992:12-2012:03). Tables A.2-A.4 of the Appendix show that the results are similar for all the strategies of interest. For the out-of-sample part we consider a different in-sample period until 2007:12 so as to see the performance of the factors during the crises. The results verify the out-of-sample Sharpe ratios, as they remain highly significant.

Different base currencies. We also consider the point of view of foreign investors. To that end, we examine the predictive power of our factors when considering different base currencies. Table A.5 shows that the results remain statistically and economically significant.

Alternative asset classes. Next we investigate the in-sample predictive power of the factors for similar strategies (i.e. value and momentum) that focus on different asset classes, such as equities, commodities and fixed income.[29] Table A.9 reports results for the short and long legs of the aforementioned strategies. We find that they are highly predictable which might indicate that an investor could benefit from the macro factors when investing in across asset classes. We leave this question for future research.

1.8 Conclusion

The chapter provides strong implications for the role of the domestic and global macroeconomy on carry trade, dollar carry trade and momentum strategies. We constructed domestic (i.e. U.S.) and global (i.e. G10) factors that are extracted from large panels of macroeconomic and financial variables. Thus, the main focus of the chapter is on the time-series predictability of the payoffs and the economic value that can be earned by a U.S. investor from the use of these domestic and global common factors.

[29]The data is obtained from Asness et al. (2013).

We find very strong evidence of in-sample predictability in the carry, dollar carry and momentum returns. In particular, the carry trade variability can be explained by global variables that are exposed to G7 economies and are highly correlated with the global stock market. This finding shows that carry trade activity depends more on the global environment rather than on the domestic (i.e. U.S.) economy. It is also shown in many studies that U.S. stock indices cannot capture the time-series or cross-sectional variation of the returns to carry trade. However, here we show that the movements of the global equity markets provide very useful information in this respect. In addition, U.S. real and inflation factors also provide useful information. On the other hand, the dollar carry trade is mainly driven by the U.S. economy and thus we find that only domestic inflation and consumption factors have strong predictive power for the dollar carry trade returns. U.S. inflation factors and to a lesser extend commodity measures gathered from G10 countries are also strong predictors of the momentum strategy. In addition, very strong evidence of profitability is found in the exchange rate component of the aforementioned strategies.

Moreover, we find that our results are reinforced by out-of-sample analysis and combination forecasts. We also find strong economic value to a U.S. investor from the use of the common factors. In particular, we observe a significant improvement in the Sharpe ratios and the skewness profile of the payoff when we employ a decision rule that gathers information from our forecasts. Another striking feature revealed from examination of rolling Sharpe ratios is associated with very high annualized Sharpe ratios during the recent financial crisis. The estimation of the certainty equivalent return shows that a risk-averse investor with mean-variance preferences would be willing to pay an annual management fee in order to have access to the forecasts in lieu of the historical mean.

We also showed that the common factors are able to forecast the carry and dollar carry trade returns over and above other factors in the literature, such as the Bakshi and Panayotov (2013) predictors or average forward discounts. Finally, there is evidence of predictability in the long leg of the carry trade and to a smaller magnitude in the short leg of the trade. However, the returns of the winner and loser portfolios of the momentum strategy are highly predictable from a global money and credit factors and a U.S. inflation factor.

Table 1.1. Summary Statistics of the Payoffs

This table reports descriptive statistics of payoffs to carry trade, dollar carry trade and momentum strategies. Panel A reports descriptive statistics for currency excess returns and Panel B for exchange rate changes. In particular, ψ^{HML} denotes the carry trade strategy that goes long (short) a basket of currencies with highest (lowest) forward discounts, ψ^{USD} is the dollar carry trade that shorts the dollar when the average interest rate is greater than the U.S. risk free rate and ψ^{WML} represents the payoff to a momentum strategy that invests (borrows) on a basket of currencies with the highest (lowest) last month return. All the payoffs are estimated in the presence of transaction costs and the portfolios are rebalanced on a monthly basis. Finally, the mean, standard deviation, Sharpe Ratio and Sortino Ratio are annualized (the means are multiplied by 12 and the standard deviation by $\sqrt{12}$) and expressed in percentage points. The data span the period 1985:07-2012:03.

Panel A: Currency Excess Returns						
	ψ^{HML}	ψ^{USD}	ψ^{WML}	ψ^{HML}	ψ^{DOL}	ψ^{WML}
	All Countries			*Developed Countries*		
Mean	4.24	3.93	5.17	2.79	5.86	1.57
Std.Dev.	9.19	7.18	9.57	10.47	8.48	8.74
SR	0.46	0.55	0.54	0.27	0.69	0.18
SOR	0.62	0.82	0.86	0.36	1.09	0.27
Skew	-1.17	-0.39	0.07	-0.96	-0.29	0.03
Kurt	5.23	4.71	5.00	5.66	4.17	4.34
*AC*1	0.20	-0.04	-0.04	0.11	-0.03	0.01
Panel B: Exchange Rate Returns						
Mean	7.85	4.18	2.81	1.63	5.56	-1.14
Std.Dev.	9.02	7.22	10.56	10.53	8.51	8.71
SR	0.87	0.58	0.27	0.15	0.65	-0.13
SOR	1.96	0.88	0.41	0.26	1.02	-0.18
Skew	1.23	-0.40	0.37	0.98	-0.28	-0.13
Kurt	5.43	4.80	5.74	0.13	-0.03	0.03
*AC*1	0.20	-0.04	-0.01	0.01	0.01	0.01

Table 1.2. Summary Statistics of the Common Factors ($\hat{h}_{it}$, $\hat{g}_{jt}$)

This table presents summary statistics for the common factors. *Panel A* reports correlations for the U.S. data and *Panel B* for the global data. Both datasets span the period of 1985:07-2012:03. The domestic panel includes 127 macroeconomic and financial variables from the U.S. economy and the global panel consists of 98 variables from all the countries that are involved in our portfolio. The data is transformed and standardized prior to estimation. We report the first-order and second-order autocorrelation coefficients (AR1 and AR2) for the U.S. and global factors as well as the relative importance of the factors as it is measured by the R_i^2. The R_i^2 is estimated as the sum of the eigenvalues of the ith first factors divided by the sum of the eigenvalues in the data. The data is available from Datastream.

Panel A: U.S. Data			
i	$AR1(\hat{h}_{it})$	$AR2(\hat{h}_{it})$	$\sum R_i^2$
1	0.98	0.96	0.39
2	0.97	0.95	0.52
3	0.75	0.62	0.63
4	0.64	0.46	0.70
5	0.65	0.54	0.75
6	0.49	0.57	0.79
7	0.05	0.11	0.82
8	0.12	-0.01	0.85
9	0.16	0.16	0.87
Panel B: Global Data			
j	$AR1(\hat{g}_{it})$	$AR2(\hat{g}_{it})$	$\sum R_i^2$
1	0.86	0.94	0.10
2	0.72	0.66	0.18
3	0.16	0.001	0.25

Table 1.3. Correlations with the Common Factors

This table reports the variables that exhibit the highest correlation with the domestic and global factors. We report the positions of each variable in the panel as well as a detailed description of the variables. *Panel A* reports correlations for the U.S. data and *Panel B* for the global data. The variables are transformed according to simple unit root tests and they are standardized prior to estimation. In addition, the data span the period 1985:07-2012:03.

			Panel A: U.S. Data	
$\hat{h}_1$	95	0.55	USOMA002B	US MONEY SUPPLY - BROAD MONEY (M2) CURA (bil, US $) $)
$\hat{h}_2$	32	0.88	USNEWCONB	US EXISTING HOME SALES: SINGLE-FAMILY & CONDO (AR) VOLA
$\hat{h}_3$	71	0.76	USNAPMNO	US ISM MANUFACTURERS SURVEY: NEW ORDERS INDEX SADJ
$\hat{h}_4$	7	0.40	60611444	US PERSONAL INCOME LESS TRANSFER PAYMENTS (BCI 51) CONA
$\hat{h}_5$	15	0.38	870004623	US UNEMPLOYED (16 YRS & OVER) VOLA
$\hat{h}_6$	20	0.44	62244022	US PERSONAL CONSUMPTION EXPENDITURES - LESS FOOD & ENERGY CURA
$\hat{h}_7$	20	0.69	62244022	US PERSONAL CONSUMPTION EXPENDITURES - LESS FOOD & ENERGY CURA
$\hat{h}_8$	122	0.33	870011929	US HOURLY EARN: PRIVATE SECTOR SADJ
$\hat{h}_9$	90	0.42	60200205	US 3-MONTH US $ DEPOSITS, LONDON OFFER
			Panel B: Global Data	
$\hat{g}_1$	7	0.77	100900842	DK UNEMPLOYMENT NET (METHDOLOGY BREAK APRIL 2000) VOLA
$\hat{g}_2$	83	0.60	870015830	US FOREIGN NET LONG TERM FLOWS IN SECURITIES CURN
$\hat{g}_3$	97	0.60	CNSHRPRCF	G7 MSCI (US$) PRICE INDEX

Table 1.4. In-sample analysis: *Carry Trades*

The table reports OLS estimates for the carry trade strategy. In *Panel A* the dependent variable is the currency excess return (ψ^{HML}), based on the carry trade strategy that goes long (short) a basket of currencies with highest (lowest) forward discounts. *Panel B* reports results for the exchange rate component of the strategy. NW represents Newey and West (1987) corrected for autocorrelation and heteroskedasticity *t-statistics* with the optimal number of lags following Andrews (1991). B denotes the bootstrap *p-values* based on $10,000$ bootstrap iterations. The data span the period 1985:07-2012:03.

	cons	$\hat{g}_2$	$\hat{g}_3$	$\hat{h}_2$	$\hat{h}_3$	$\hat{h}_4$	$\hat{h}_6$	$\bar{R}^2$	*cons*	$\hat{g}_1$	$\hat{g}_2$	$\hat{h}_3$	$\hat{h}_6$	$\bar{R}^2$
Panel A: Currency Excess Returns														
	All Countries								*Developed Countries*					
(a)	0.35	0.52						0.05	0.43	0.29	0.50		0.32	0.04
NW	2.16	2.84						8.08	1.34	1.17	3.34		2.18	4.60
B	0.02	0.01						0.00	0.17	0.23	0.03		0.02	0.00
(b)	0.35			0.23	0.30	-0.28	0.21	0.03	0.23			0.44	0.37	0.03
NW	2.16			1.72	1.22	-1.91	1.48	13.50	1.35			1.48	2.58	7.50
B	0.01			0.09	0.14	0.05	0.14	0.00	0.16			0.09	0.00	0.02
(c)	0.35	0.56	-0.21				0.36	0.06	0.23	0.27	0.54			0.05
NW	2.22	3.17	-1.31				2.02	15.16	1.41	1.23	2.61			11.15
B	0.01	0.00	0.20				0.03	0.00	0.10	0.24	0.02			0.01
Panel B: Exchange Rate Returns														
	All Countries								*Developed Countries*					
(a)	0.66	-0.48						0.03	0.14	-0.18	-0.60			0.04
NW	4.16	-2.75						9.78	0.77	-0.73	-2.81			6.88
B	0.00	0.00						0.00	0.43	0.44	0.01			0.03
(b)	0.66			-0.08	-0.33	0.25	-0.17	0.02	0.13			-0.47	-0.25	0.02
NW	4.16			-0.64	-1.61	1.70	-1.20	9.61	0.75			-1.61	-1.61	5.98
B	0.00			0.54	0.06	0.08	0.27	0.15	0.41			0.08	0.07	0.05
(c)	0.66	-0.52	0.16				-0.29	0.05	0.14	-0.16	-0.64		-0.33	0.06
NW	4.18	-2.97	1.00				-1.62	14.27	0.79	-0.74	-3.02		-2.17	12.53
B	0.00	0.00	0.31				0.09	0.00	0.41	0.48	0.01		0.03	0.01

Table 1.5. In-sample analysis: ***Dollar Carry Trades***

The table reports OLS estimates of the dollar carry trade strategy. In *Panel A* the dependent variable is the currency excess return (ψ^{USD}), based on the dollar carry trade strategy described in the paper. *Panel B* displays the exchange rates component of the strategy. Newey and West (1987) (NW) corrected for autocorrelation and heteroskedasticity *t-statistics* with the optimal number of lags following Andrews (1991) are in parenthesis. B denotes the bootstrap *p-values* based on 10,000 bootstrap iterations. The data span the period 1985:07-2012:03.

	cons	$\hat{g}_3$	$\hat{h}_6$	$\hat{h}_7$	$\bar{R}^2$	*cons*	$\hat{g}_3$	$\hat{h}_4$	$\hat{h}_6$	$\hat{h}_7$	$\bar{R}^2$
Panel A: Currency Excess Returns											
	All Countries					*Developed Countries*					
(a)	0.33	-0.12			0.01	0.49	-0.17				0.00
NW	2.90	-0.92			0.84	3.74	-1.07				1.14
B	0.00	0.45			0.45	0.00	0.37				0.37
(b)	0.32		0.28	-0.35	0.04	0.49			0.29	-0.38	0.03
NW	3.11		2.50	-3.12	15.93	3.87			2.20	-3.06	13.89
B	0.00		0.03	0.01	0.00	0.00			0.04	0.00	0.00
(c)	0.33	-0.24	0.36	-0.34	0.05	0.49	-0.29	0.17	0.39	-0.36	0.05
NW	3.13	-1.80	3.10	-3.11	19.47	3.90	-1.91	1.27	2.98	-3.05	18.71
B	0.00	0.15	0.00	0.00	0.00	0.00	0.12	0.19	0.00	0.00	0.00
Panel B: Exchange Rate Returns											
	All Countries					*Developed Countries*					
(a)	0.35	-0.17			0.01	0.46	-0.18				0.00
NW	3.08	-1.29			1.02	3.50	-1.08				1.18
B	0.00	0.31			0.31	0.00	0.36				0.36
(b)	0.35		0.24	-0.31	0.03	0.47			0.28	-0.38	0.03
NW	3.20		2.09	-2.77	11.63	3.62			2.12	-3.11	14.25
B	0.00		0.04	0.01	0.00	0.00			0.04	0.00	0.00
(c)	0.35	-0.28	0.34	-0.28	0.03	0.46	-0.30		0.39	-0.36	0.04
NW	3.21	-2.20	2.84	-2.72	16.37	3.65	-1.90		2.91	-3.11	19.41
B	0.00	0.05	0.00	0.01	0.00	0.00	0.12		0.00	0.01	0.00

Table 1.6. In-sample analysis: *Momentum*

The table reports OLS estimates of the momentum strategy. *Panel A* reports results of the predictive regressions for the momentum strategy (ψ^{WML}). *Panel B* displays the exchange rates component of the strategy. NW represents Newey and West (1987) corrected for autocorrelation and heteroskedasticity *t-statistics* with the optimal number of lags following Andrews (1991). B denotes the bootstrap *p-values* based on 10,000 bootstrap iterations. The data span the period 1985:07-2012:03.

	Panel A: Currency Excess Returns											
	cons	$\hat{g}_3$	$\hat{h}_1$	$\hat{h}_4$	$\bar{R}^2$	*cons*	$\hat{g}_2$	$\hat{h}_3$	$\hat{h}_4$	$\hat{h}_7$	$\hat{h}_8$	$\bar{R}^2$
	All Countries					*Developed Countries*						
(a)	0.43	-0.16			0.01	0.13	-0.38					0.02
NW	3.08	-0.63			0.39	1.05	-2.80					4.15
B	0.00	0.38			0.76	0.34	0.04					0.04
(b)	0.43		-0.17	0.28	0.01	0.13		-0.28	-0.28	-0.22	-0.24	0.03
NW	3.19		-1.23	1.60	3.95	1.05		-2.17	-2.02	-1.54	-1.48	9.56
B	0.00		0.24	0.09	0.10	0.34		0.05	0.06	0.12	0.14	0.05
(c)	0.43	-0.14	-0.16	-0.28	0.01	0.13	-0.43			-0.18	0.30	0.04
NW	3.18	-0.55	-1.00	-1.68	3.22	1.05	-3.04			-1.31	1.81	7.62
B	0.00	0.50	0.34	0.08	0.21	0.35	0.02			0.17	0.07	0.02
	Panel B: Exchange Rate Returns											
	All Countries					*Developed Countries*						
(a)	0.23	0.06			0.01	-0.1	0.41					0.02
NW	1.38	0.26			0.01	-0.77	2.89					4.47
B	0.3	0.75			0.75	0.48	0.03					0.03
(b)	0.23		0.12	0.45	0.02	-0.1		0.3	-0.3	0.2	-0.22	0.03
NW	1.42		0.74	2.3	5.55	-0.77		2.29	-2.14	1.46	-1.42	9.54
B	0.29		0.31	0.02	0.05	0.48		0.09	0.05	0.15	0.17	0.05
(c)	0.23	0.04	0.11	0.45	0.02	-0.1	0.45			0.17	-0.28	0.04
NW	1.41	0.19	0.69	2.26	6.87	-0.77	3.11			1.24	1.79	8.06
B	0.15	0.85	0.54	0.02	0.07	0.48	0.02			0.19	0.08	0.02

Table 1.7. Out-of-sample analysis: ***Against the Mean***

The table presents out-of sample R-squares (R^2_{OOS}) as described in Campbell and Thompson (2008) ($R^2_{OOS} = 1 - \sum_{t=1}^{T-1} \frac{\psi^i_{t+1} - \hat{\mu}_{t+1})^2}{(\psi^i_{t+1} - \mu_{t+1})^2}$), where $\hat{\mu}_{t+1}$ represents the one-step ahead conditional forecast from the model of interest and μ_{t+1} is the historical mean of the payoff. Thus, a positive R^2_{OOS} statistic means that the competing model outperforms the benchmark model because it has a lower mean square prediction error. *Panel A* reports results for currency excess returns and *Panel B* for exchange rate changes. The superscript mean represents the mean combined forecast and the superscript weighted the weighted counterpart. The in-sample period spans the first 180 observations (out of 321) that correspond to the period 1985.07-2000.05.

Panel A: Currency Excess Returns												
	ψ^{HML}		ψ^{USD}		ψ^{WML}		ψ^{HML}		ψ^{USD}		ψ^{WML}	
	R^2_{OOS}	$MSPEadj$	R^2_{OOS}	$MSPEadj$	R^2_{OOS}	$MSPEadj$	R^2_{OOS}	$MSPEadj$	R^2_{OOS}	$MSPEadj$	R^2_{OOS}	$MSPEadj$
			All Countries						*Developed Countries*			
$C_1 = [\hat{g}_2]$	0.07	0.00					0.01	0.10				
$C_2 = [\hat{h}_{2,3,4,6}]$	0.01	0.01										
$C_2' = [\hat{h}_{3,6}]$							0.04	0.07				
$C_3 = [\hat{g}_{2,3}\hat{h}_{5,6}]$	0.10	0.01					0.04	0.05				
$C_{2,3}^{Mean}$	0.08	0.00					0.04	0.05				
$C_{2,3}^{Weighted}$	0.08	0.00					0.04	0.05				
$D_2 = [\hat{h}_{6,7}]$			0.07	0.00					0.04	0.00		
$D_3 = [\hat{g}_3\hat{h}_{6,7}]$			0.07	0.00					0.05	0.00		
$D_{2,3}^{Mean}$			0.07	0.00					0.05	0.00		
$D_{2,3}^{Weighted}$			0.07	0.00					0.05	0.00		
$M_2 = [\hat{h}_{1,4}]$					0.01	0.14						
$M_2' = [\hat{h}_{3,4,7,8}]$											0.04	0.03
$M_3 = [[\hat{g}_3\hat{h}_4]$					0.01	0.12						
$M_3' = [[\hat{g}_2\hat{h}_8]$											0.04	0.04
$M_{2,3}^{Mean}$					0.01	0.12					0.05	0.03
$M_{2,3}^{Weighted}$					0.01	0.12					0.05	0.03

Table 1.7. Out-of-sample analysis: *Against the Mean* *(continued)*

Panel B: Exchange Rate Returns												
	ψ^{HML}		ψ^{USD}		ψ^{WML}		ψ^{HML}		ψ^{USD}		ψ^{WML}	
	R^2_{OOS}	$MSPEadj$	R^2_{OOS}	$MSPEadj$	R^2_{OOS}	$MSPEadj$	R^2_{OOS}	$MSPEadj$	R^2_{OOS}	$MSPEadj$	R^2_{OOS}	$MSPEadj$
	All Countries						*Developed Countries*					
$C_1 = [\hat{g}_2]$	0.08	0.00					0.02	0.07				
$C_2 = [\hat{h}_{2,3,4,6}]$	0.01	0.08										
$C_2^{'} = [\hat{h}_{3,6}]$							0.03	0.08				
$C_3 = [\hat{g}_{2,3}\hat{h}_{5,6}]$	0.09	0.01										
$C_3^{'} = [\hat{g}_{2,3}\hat{h}_6]$							0.03	0.04				
$C_{1,3}^{Mean}$	0.10	0.01					0.03	0.05				
$C_{1,3}^{Weighted}$	0.10	0.01					0.03	0.05				
$D_2 = [\hat{h}_{6,7}]$			0.05	0.00					0.05	0.00		
$D_3 = [\hat{g}_3\hat{h}_{6,7}]$			0.05	0.01					0.05	0.00		
$D_{2,3}^{Mean}$			0.06	0.00					0.05	0.00		
$D_{2,3}^{Weighted}$			0.06	0.00					0.05	0.00		
$M_1 = [\hat{g}_3]$					0.00	0.28						
$M_2 = [\hat{h}_{1,4}]$					0.00	0.21						
$M_1^{'} = [\hat{g}_2]$					0.09	0.12						
$M_2^{'} = [\hat{h}_{3,4,7,8}]$											0.04	0.03
$M_3 = [[\hat{g}_3\hat{h}_4]$											0.04	0.04
$M_3^{'} = [[\hat{g}_2\hat{h}_8]$											0.04	0.04
$M_{2,3}^{Mean}$					0.01	0.21						
$M_{2,3}^{Weighted}$					0.01	0.21						
$M_{2,3}^{'Mean}$											0.05	0.03
$M_{2,3}^{'Weighted}$											0.05	0.03

Table 1.8. Out-of-sample Sharpe Ratios and Skewness based on Decision-Rules

The table presents out-of sample (annualized) Sharpe Ratios (*Panel A*) based on conditional and unconditional payoffs of the strategies. The conditional strategies are based on the forecasts when considering the optimal set of factors or combined forecasts. ψ^{HML} denotes the carry trade strategy, ψ^{USD} represents the dollar carry trade, ψ^{WML} is the momentum strategy and ψ^{ALL} displays the combination of the previous three strategies with equal weights. *Panel B* displays the corresponding Skewness and *Panel C* the certainty equivalent return gain (ΔCER), expressed in annual percentage points. In curly brackets we report *p-values* estimated based on 10,000 stationary bootstrap samples (Politis and Romano, 1994), for the null hypothesis that the Sharpe ratios of the conditional strategy do not exceed (statistically) the unconditional counterparts, which take a position in the FX strategy regardless of the sign of the prediction. The in-sample period spans the first 180 observations (out of 321) that correspond to the period 1985.07-2000.05.

	Panel A: Sharpe Ratios			
	Multiple Predictors	Combined Forecasts	Multiple Predictors	Combined Forecasts
	All Countries		*Developed Countries*	
ψ^{HML}	1.55	1.74	1.12	1.04
B	{0.01}	{0.02}	{0.01}	{0.02}
ψ^{USD}	0.54	0.51	0.72	0.56
B	{0.40}	{0.45}	{0.38}	{0.22}
ψ^{WML}	0.54	0.54	0.44	0.42
B	{0.47}	{0.46}	{0.24}	{0.19}
ψ^{ALL}	1.06	1.12	1.06	1.12
B	{0.56}	{0.52}	{0.57}	{0.54}
	Panel B: Skewness			
	All Countries		*Developed Countries*	
ψ^{HML}	-0.52	-0.51	-0.61	-0.54
ψ^{USD}	-0.11	-0.79	0.09	-0.35
ψ^{WML}	0.34	0.34	0.02	-0.04
ψ^{ALL}	0.75	0.93	0.75	0.93
	Panel C: ΔCER			
	All Countries		*Developed Countries*	
ψ^{HML}	0.10	0.09	0.04	0.05
ψ^{USD}	0.12	0.12	0.06	0.06
ψ^{ALL}	-0.07	-0.07	-0.12	-0.06

Table 1.9. Conditional Predictive Regressions

The table reports OLS estimates of conditional predictive regressions. *Panel A* reports results of the predictive regressions for the carry, dollar carry and momentum strategies (ψ^{HML}, ψ^{USD}, ψ^{WML}) in the presence of the Bakshi and Panayotov (2013) predictors (ΔCRB , $\Delta\sigma^{fx}$, ΔLIQ). *Panel B* offers results of in-sample estimates of the common factors conditional on the information provided by the average forward discounts (AFD). NW represents Newey and West (1987) corrected for autocorrelation and heteroskedasticity t-statistics with the optimal number of lags following Andrews (1991). B denotes the bootstrap p-values based on 10,000 bootstrap iterations. The data span the period 1985:07-2012:03.

Panel A: Bakshi and Panayotov (2013)

All Countries

	$cons$	$\hat{g}_{2,t}$	$\hat{g}_{3,t}$	$\hat{h}_{3,t}$	$\hat{h}_{4,t}$	$\hat{h}_{6,t}$	$\hat{h}_{7,t}$	ΔCRB_t	$\Delta\sigma_t^{fx}$	ΔLIQ_t	$\bar{R}^2$
ψ^{HML}	0.37	0.60	-0.35			0.39		-7.93	-1.25	2.19	0.05
NW	2.28	3.08	-1.62			2.07		-1.06	1.76	1.41	19.02
B	0.01	0.00	0.05			0.04		0.42	0.08	0.04	0.00
ψ^{USD}	0.26		-0.29		0.21	0.23	-0.27	6.32	-2.75	0.52	0.06
NW	2.42		-1.75		1.87	1.79	-2.65	1.13	-1.82	0.47	28.35
B	0.03		0.09		0.08	0.06	0.01	0.45	0.05	0.69	0.00
ψ^{WML}	0.44			-0.19	0.28			0.87	-1.27	-1.99	0.01
NW	3.10			-1.06	1.92			0.09	-0.85	-1.12	6.38
B	0.00			0.42	0.06			0.93	0.39	0.14	0.27

Developed Countries

	$cons$	$\hat{g}_{2,t}$	$\hat{g}_{2,t-2}$	$\hat{g}_{3,t}$	$\hat{h}_4$	$\hat{h}_7$	$\hat{h}_8$	$\hat{h}_9$	ΔCRB_t	$\Delta\sigma_t^{fx}$	ΔLIQ_t	$\bar{R}^2$
ψ^{HML}	0.15	0.62	-0.65		0.06				21.48	-3.09	1.83	0.09
NW	1.48	2.45	-3.35		0.33				2.10	-1.90	1.48	21.06
B	0.39	0.02	0.00		0.76				0.06	0.06	0.34	0.00
ψ^{USD}	0.42			-0.29	0.28	-0.28			5.60	-3.52	0.93	0.05
NW	3.21			-1.38	1.97	-2.26			0.80	1.96	0.73	18.61
B	0.00			0.14	0.05	0.02			0.56	0.03	0.53	0.00
ψ^{WML}	0.08	-0.59			0.20		0.28	-0.30	14.35	-1.70	-2.27	0.05
NW	0.63	-3.08			1.52		1.82	-1.62	1.71	-1.19	-1.65	15.52
B	0.57	0.00			0.20		0.08	0.06	0.10	0.21	0.12	0.02

Panel B: Average Forward Discounts

All Countries

	$cons$	$\hat{g}_{2,t}$	$\hat{g}_{3,t}$	$\hat{g}_{3,t-3}$	$\hat{h}_{4,t}$	$\hat{h}_{6,t}$	$\hat{h}_{7,t}$	AFD_t	$\bar{R}^2$
ψ^{HML}	0.50	0.46		-0.37		0.43		-1.63	0.07
NW	2.31	2.09		-2.35		3.14		-1.19	24.62
B	0.00	0.01		0.00		0.00		0.14	0.00
ψ^{USD}	0.34		-0.23			0.37	-0.34	-0.18	0.05
NW	2.85		-1.80			2.95	-2.91	-0.22	18.71
B	0.00		0.10			0.00	0.01	0.80	0.00
ψ^{WML}	0.36		-0.18		0.28			0.85	0.01
NW	2.40		-0.79		1.74			0.20	4.16
B	0.03		0.34		0.08			0.36	0.24

Developed Countries

	$cons$	$\hat{g}_{1,t}$	$\hat{g}_{2,t}$	$\hat{g}_{3,t}$	$\hat{h}_3$	$\hat{h}_4$	$\hat{h}_6$	$\hat{h}_7$	$\hat{h}_8$	AFD_t	$\bar{R}^2$
ψ^{HML}	0.41	0.36	0.40				0.46			-2.00	0.05
NW	2.01	1.62	1.91				2.93			-1.56	14.08
B	0.28	0.12	0.10				0.00			0.10	0.01
ψ^{USD}	0.55			-0.28			0.43	-0.38		-0.76	0.04
NW	3.88			-1.91			3.06	-2.94		-0.80	16.34
B	0.00			0.14			0.00	0.01		0.38	0.00
ψ^{WML}	0.01				-0.25	0.28			0.30	1.38	0.03
NW	0.06				-1.92	2.01			1.73	1.75	8.94
B	0.95				0.24	0.07			0.08	0.08	0.07

Table 1.10. Predictability in the Long and Short Legs of the Strategies

The table displays in-sample estimates for the long and short positions of the carry trade and momentum strategies. *Panel A* reports results of the predictive regressions for the momentum strategy (ψ^{HML}). *Panel B* reports results of the predictive regressions for the momentum strategy (ψ^{WML}). NW represents Newey and West (1987) corrected for autocorrelation and heteroskedasticity t-statistics with the optimal number of lags following Andrews (1991). B denotes the bootstrap p-values based on 10,000 bootstrap iterations. The data span the period 1985:07-2012:03.

	cons	$\hat{g}_{2,t}$	$\hat{h}_{4,t}$	$\hat{h}_{6,t}$	$\hat{h}_{7,t}$	$\bar{R}^2$	*cons*	$\hat{g}_{2,t}$	$\hat{g}_{3,t-1}$	$\hat{h}_6$	$\hat{h}_7$			$\bar{R}^2$
***Panel A*: Carry Trade Portfolios**														
	All Countries						*Developed Countries*							
Long	0.40	0.47	-0.33	0.56	-0.33	0.08	0.31	0.35		0.65	-0.53			0.07
NW	2.47	2.64	-2.24	3.01	-2.35	24.85	1.81	1.64		4.05	-2.94			25.03
B	0.01	0.03	0.03	0.00	0.03	0.00	0.07	0.15		0.00	0.00			0.07
Short	-0.04	0.14	0.18	-0.28	0.28	0.03	-0.06	0.17	0.62	-0.36	0.41			0.07
NW	-0.34	1.07	1.43	-2.10	2.51	12.05	-0.41	1.34	4.37	-2.34	3.37			24.30
B	0.72	0.73	0.20	0.03	0.02	0.01	0.67	0.26	0.00	0.02	0.01			0.00
***Panel B*: Momentum Portfolios**														
Winners	0.47	-0.50	0.25		0.30	0.04	0.10	-0.60	-0.41		0.31	-0.36		0.06
NW	3.88	-3.08	1.72		2.20	17.75	0.71	-3.10	-1.87		2.48	-2.48		20.34
B	0.00	0.00	0.03		0.02	0.00	0.68	0.00	0.05		0.14	0.03		0.00
Losers	-0.04	0.27		0.28	-0.23	0.02	-0.11	0.64	0.38	-0.35	-0.33	0.29	-0.33	0.05
NW	-0.27	1.85		1.97	-1.41	7.56	-0.68	3.10	2.64	-2.24	-1.29	1.93	-1.83	17.16
B	0.78	0.11		0.10	0.18	0.00	0.49	0.00	0.05	0.04	0.18	0.06	0.08	0.01

Table 1.11. Robustness: In-sample analysis - *DB Indices*

The table reports OLS estimates for Deutsche Bank (DB) indices. In *Panel A* the dependent variable is the currency excess returns of the DB global and G10 currency carry trade strategies. *Panel B* reports results for the DB value and momentum strategies. NW represents Newey and West (1987) corrected for autocorrelation and heteroskedasticity t-statistics with the optimal number of lags following Andrews (1991). B denotes the bootstrap p-values based on 10,000 bootstrap iterations. The data span the period 2000:12-2012:03 for the Global and G10 Carry trade and the period 1989:09-2012:03 for value and momentum.

Panel A: Currency Harvest USD

	cons	$\hat{g}_{2,t}$	$\hat{g}_{2,t-3}$	$\hat{h}_{2,t}$	$\hat{h}_{3,t}$	$\hat{h}_{5,t}$	$\bar{R}^2$	*cons*	$\hat{g}_{1,t-1}$	$\hat{g}_{2,t}$	$\hat{g}_{2,t-3}$	$\hat{g}_{3,t-3}$	$\hat{h}_{3,t}$	$\hat{h}_{5,t}$	$\hat{h}_{6,t}$	$\bar{R}^2$
				Global								*G10*				
(a)	0.52	0.82	-0.76				0.09	1.32	0.84	0.37	-0.84	0.40				0.14
NW	1.77	2.64	-4.31				13.79	3.46	2.90	1.36	-3.98	2.04				14.49
B	0.11	0.01	0.00				0.00	0.02	0.01	0.26	0.00	19.00				0.00
(b)	0.34			0.40	0.53	0.64	0.07	0.43					0.50	0.42	0.39	0.09
NW	0.97			1.36	1.98	2.79	7.46	2.35					1.92	1.63	2.75	9.46
B	0.46			0.31	0.05	0.05	0.05	0.04					0.10	0.22	0.03	0.02
(c)	0.27	0.37	-0.74	0.61	0.55	0.41	0.12	0.79			-0.70	0.42	0.75	0.37		0.16
NW	0.94	1.24	-4.75	2.35	1.57	2.03	20.91	3.25			-3.89	2.02	3.31	1.68		12.46
B	0.57	0.31	0.00	0.07	0.16	0.06	0.00	0.00			0.01	0.21	0.01	0.26		0.01

Panel B: Value & Momentum

	cons	$\hat{g}_{1,t-3}$	$\hat{g}_{3,t}$	$\hat{h}_{2,t}$	$\hat{h}_{3,t}$	$\hat{h}_{4,t}$	$\bar{R}^2$	*cons*	$\hat{g}_{3,t-2}$	$\hat{g}_{3,t-3}$			$\hat{h}_{3,t}$	$\hat{h}_{4,t}$		$\bar{R}^2$
				FX PPP								*FX Momentum*				
(a)	0.20	-0.34	0.26				0.02	0.17	-0.41	-0.33						0.04
NW	1.22	-2.48	1.02				6.98	1.10	2.15	-2.21						3.90
B	0.21	0.04	0.17				0.03	0.44	0.03	0.04						0.03
(b)	0.21			0.26	-0.32	0.19	0.02	0.15					-0.25	0.38		0.03
NW	1.30			1.66	-2.33	1.46	9.30	0.94					-0.99	3.15		5.48
B	0.19			0.11	0.02	0.18	0.03	0.37					0.20	0.00		0.06
(c)	0.17	-0.40	0.26		-0.23	0.31	0.04	0.14	-0.42	-0.35			-0.13	0.44		0.07
NW	1.08	-2.77	1.14		-1.39	2.34	14.40	0.93	-2.42	-2.68			-0.58	3.33		16.98
B	0.28	0.02	0.17		0.23	0.05	0.01	0.36	0.00	0.06			0.58	0.00		0.00

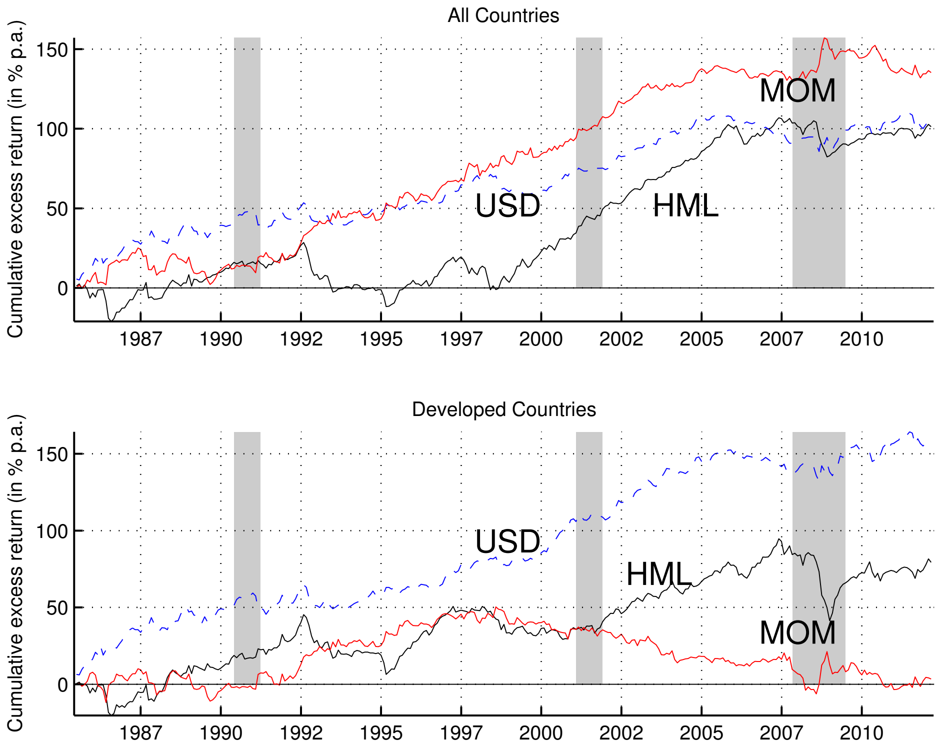


Figure 1.1. Cumulative payoffs

The figure presents cumulative payoffs for the carry trade, the dollar carry trade and the momentum strategy for the period 1985:07 to 2012:03.

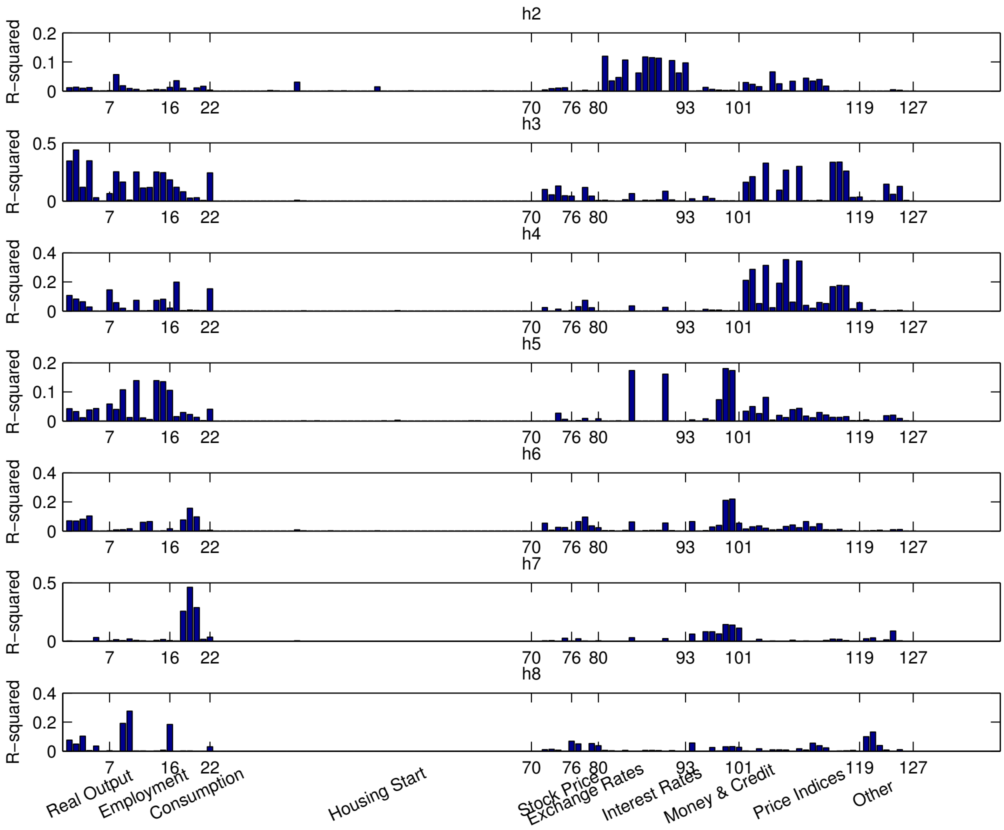


Figure 1.2. Marginal R-squares for each U.S. factor

The figure shows the R-square from regressing the series number given on the x-axis on each factor ($\hat{h}_2$,$\hat{h}_3$,$\hat{h}_4$,$\hat{h}_5$,$\hat{h}_6$,$\hat{h}_7$,$\hat{h}_8$). The factors are estimated using data from 1985:07 to 2012:03.

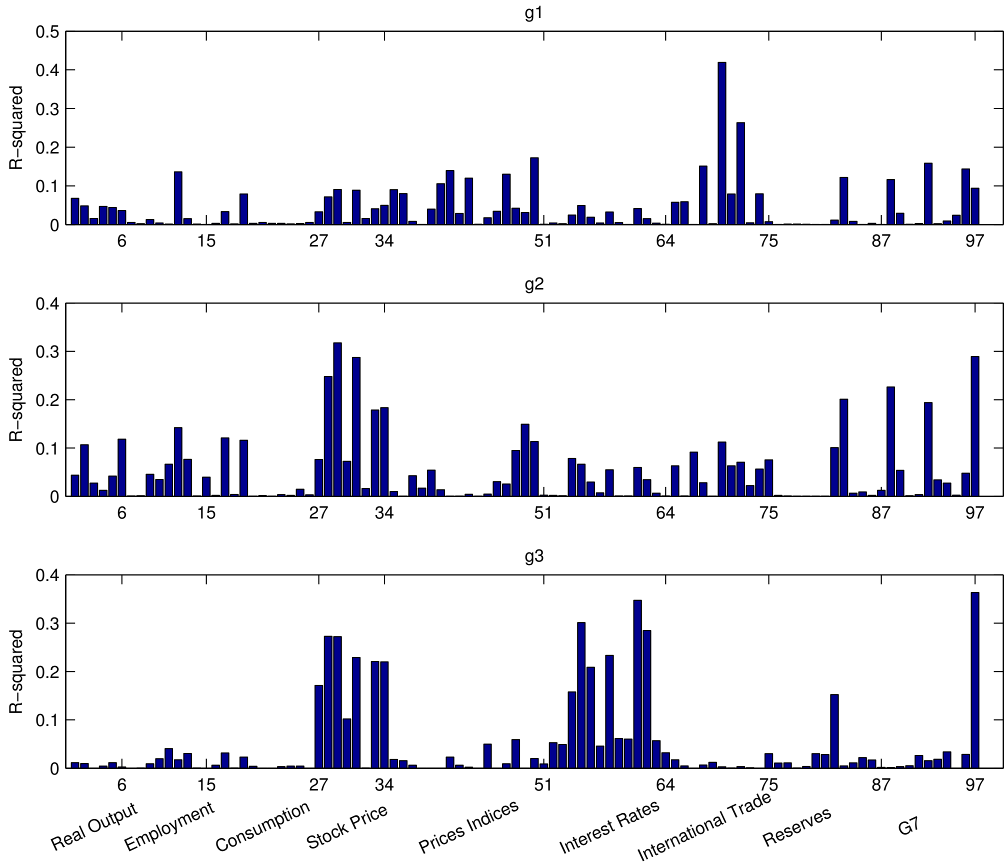


Figure 1.3. Marginal R-squares for each Global factor

The figure shows the R-square from regressing the series number given on the x-axis on each factor ($\hat{g}_1$,$\hat{g}_2$,$\hat{g}_3$). The factors are estimated using data from 1985:07 to 2012:03.

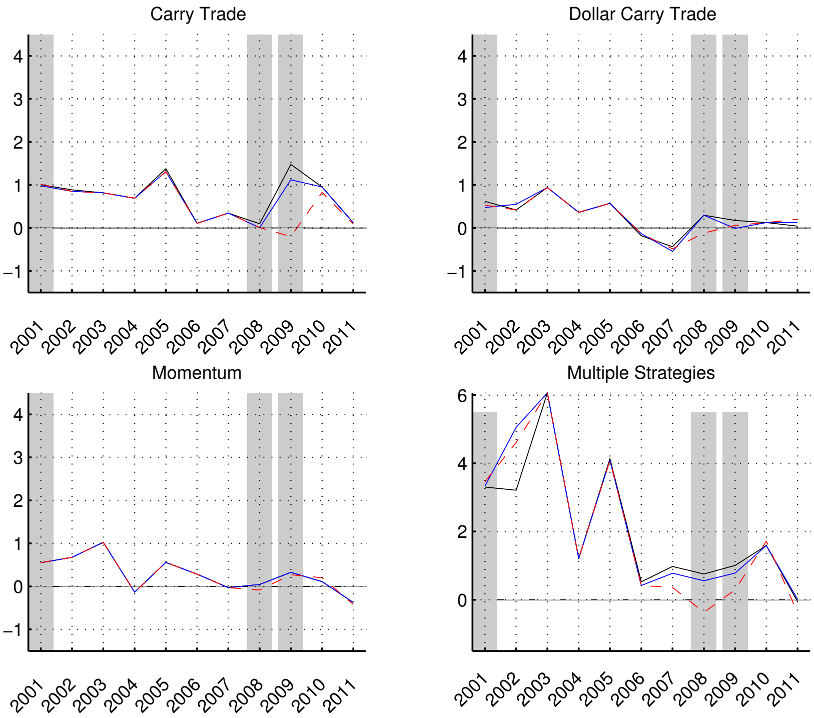


Figure 1.4. Rolling Sharpe Ratios of Conditional and Unconditional Strategies

The figure displays rolling Sharpe ratios (estimated over each year) of the conditional and unconditional strategies, when using the optimal set of domestic and global factors as well as combined forecasts. The dashed line represents the unconditional payoffs and the solid line shows the conditional payoffs when we use the optimal set of factors (black) or combined forecasts (blue). We consider the group of *All countries*. The shaded areas represent the NBER recessions of the U.S. economy. The in-sample period spans the first 180 observations (out of 321) that correspond to the period 1985.07-2000.05.

Chapter 2

Global Political Risk and Currency Momentum

2.1 Introduction

One of the main concerns of policy makers and academics is the role of the political environment on the investor's decisions and its effect on her perspective with regards to the current state of the economy. This situation could lead to irrational behaviours that could potentially drive asset prices away from their equilibrium state. In this chapter we focus on the role of political risk in the foreign exchange market. In particular, we investigate how unexpected global political factors enter into currency investment strategies and influence their profitability. To that end, we employ the two most profitable strategies in the foreign exchange market; namely currency carry trade and momentum. We give more weight to the latter strategy as the absence of a "tangible" fundamental anchor (e.g., Stein, 2009; Lou and Polk, 2013) leads to more unstable profitability and more pronounced vulnerability to the limits to arbitrage.

Currency carry trade is a currency strategy that exploits deviations from the Uncovered interest rate parity condition (UIP). The UIP states that under conditions of rational expectations and risk neutrality, the exchange rate depreciation must be offset by the corresponding interest rate differentials. In other words, the forward rate must be an optimal predictor of the future spot exchange rate. However, this condition is violated in the data (Bilson, 1981; Fama, 1984) which implies a *risk premium* for currency investors that *bet* against the UIP. One example of such a strategy is the carry trade strategy, which involves a long position in a group of *high* interest rate currencies (investment currencies) and a short position in a basket of *low* interest rate currencies (funding currencies). The profitability of this strategy stems from the tendency of the high interest rate currencies to appreciate rather than depreciate. However, it exhibits downside risk and thus leads to investors suffering huge losses during periods of stress (e.g., Brunnermeier et al., 2008; Melvin and Taylor, 2009).

Currency momentum is a foreign exchange (FX) strategy that it is driven by past performances of currency excess returns or exchange rate changes. In particular, an investor who follows a momentum strategy buys a basket of currencies that performed relatively well in the past (*winners*) while short-selling currencies with relatively poor past performances (*losers*). This naive strategy renders high annualized Sharpe ratios and it is uncorrelated with the payoffs of other strategies, such as the currency value or carry trade (Burnside et al., 2011a; Menkhoff et al., 2012b). Its profitability could partially be explained by transaction costs, limits to arbitrage or illiquidity. However, to the best of our knowledge there is no successful FX asset pricing model that explains the cross-sectional dispersion of currency momentum returns. Particularly, Menkhoff et al. (2012b) show that momentum exhibits a significant time-variation that it is mainly driven by limits to arbitrage. Thus, currency momentum is more profitable in less developed countries with high risk of capital controls, fragile political environment, and other country risk characteristics that could cause sudden moves in the exchange rate which increases volatility.

In this chapter, we question whether global political risk can price the cross-section of currency momentum returns. Specifically, we develop a novel measure of political risk that captures the differences between the political environment of the U.S. economy and the rest of the world. A striking feature of this measure is that it is sensitive to *unexpected* global political changes, meaning that it captures political events that are less likely to be predicted by a naive investor. We thus examine whether global political shocks affect the momentum profitability, helping us to understand better the determinants of currency premia. To this end, we construct a two-factor asset pricing model that incorporates the information contained in the our global political risk measure. More precisely, the first factor is a *level* factor (i.e. DOL) as originally introduced by Lustig et al. (2011) which is measured as the average across portfolios on each occasion. This traded factor resembles a strategy that buys all foreign currencies and sells the dollar. As such it is highly correlated with the first principal component of currency excess return portfolios. The second factor is our global political risk that it is replaced by innovations so as to account for its high persistence. We find that global political risk is priced in the cross-section of currency returns being that it is able to capture a significant part of currency excess returns. Our main intuition for this finding is linked to the fact that investors require a higher premium for taking on global political risk which is attached to the *winner* portfolios. On the other hand, investors accept a lower premium from investing in *loser* portfolios as they provide a hedge against adverse movements of currency returns in bad states of the world. We mainly focus on momentum strategies that rebalance the portfolios every month and use a formation period of one, three and six months. The main reason for focusing upon these particular strategies is related to their high profitability (Menkhoff et al., 2012b). However, we show later that our results are robust to longer formation periods.

Our results are robust both in economic as well as statistical terms. Firstly, we show that global political risk can explain the *time-series* variation of currency momentum returns even after controlling for other predictors in the literature such global FX volatility, FX liquidity, FX correlation and changes in CDS spreads. However, it captures only a small part of the time-series variability as it is suggested by the R-squares. Thus, we question whether political risk is able to capture the *cross-sectional* variation of currency premia that it is related to currency momentum. We employ both *unconditional* and *conditional* momentum returns and find that *conditional* momentum returns sorted into portfolios based on exposures to political risk provide a monotonic pattern which suggests that investors require a higher premium when currency exposure to political risk increases. This pattern is less pronounced for unconditional returns as we observe a nonlinear pattern that could be related to differences in beliefs in the currency market that plausibly led by the global political environment (Bakshi et al., 2010). In any case the extreme portfolios render a positive spread that indicates the pricing ability of global political risk.

In regard to the asset pricing tests employed in the chapter we show that our asset pricing model exhibits a strong cross-sectional performance both in statistical and economic terms. Firstly, we display results of Fama and MacBeth (1973) regressions as well as GMM procedures. Here we find highly significant risk factor prices that are related to global political risk with standard errors, corrected for autocorrelation and heteroskedasticity (HAC) following Newey and

West (1987) methodology using the optimal number of lags as in Andrews (1991) along with Shanken (1992) that control for potential error-in-variable issues. In addition, our results demonstrate strong cross-sectional behaviour in term of goodness of fit. Specifically, we show that we cannot reject the null; that is, all the pricing errors are jointly equal to zero as it is depicted in terms of the very large *p-values* of the χ^2 test statistic. In addition, we cannot reject the null that the HJ distance is equal to zero and the cross-sectional R^2 range from 66% to 99% for formation period from one to six months. Our results are similar whether we employ a mimicking portfolio or the raw measure.

In the next stage, we examine whether global political risk is priced even after accounting for other determinants of currency premia. We start with idiosyncratic volatility and skewness so as to determine whether we can explain a different measures of limits to arbitrage. Thus, we double-sort conditional excess returns into two portfolios based on their idiosyncratic volatility (skewness). Then within each portfolio, we sort them according to their exposure to global political risk. We find that currency excess returns are larger in high political risk portfolios than in low political risk baskets under low or high idiosyncratic volatility portfolios implying a statistically significant and positive spread. We perform a similar exercise by replacing the idiosyncratic volatility with illiquidity, volatility and correlation variable to come to the same conclusions. Therefore, global political risk is a priced factor in the cross-section of currency returns.

Finally, we perform a few robustness checks so as to verify our results. In order to make our analysis more realistic we apply a few filters to the data to check for currencies that do not belong in the exchange rate regime 3 or 4 of the IMF coarse classification, as well checking for the degree of capital account openness (Chinn and Ito, 2006) in the market following Della Corte et al. (2013).

We find that the results have improved in most of the cases. In addition, we show that the implementation cost of the strategies does not affect the cross-sectional predictive ability of global political risk. We also ask whether currency reversals could potentially alter our findings. To this end, we estimate the conditional weights of the mimicking portfolio by using as conditional variable the previous month's momentum return. Here we find that the results are similar. Finally, we perform currency-level cross-sectional regressions for both unconditional and conditional returns and demonstrate the pricing ability of global political risk.

Overall, our empirical evidence suggests that global political risk is able to capture most of the dispersion of currency momentum returns. This finding suggests that political risk is one of the fundamental determinants of the momentum strategy in the foreign exchange market. Finally, we show that political risk is present in other currency strategies, such as carry trades and currency value, but it does not have a first order effect as the existing risk factors that explain those strategies dominate.

In what follows, a literature review on political risk and currency momentum is presented in section 2.2. We also provide the motivation for our study in section 2.3. In section 2.4 we provide a brief description of the data as well as the construction of the currency portfolios. Section 2.5 will discuss the empirical results of the chapter. Section 2.6 provides a better understanding of the determinants of currency premia. Section 2.7 offers some robustness checks. Finally, section 2.8 gives our conclusion.

2.2 Related Literature

In this section we review the main studies on political risk and currency momentum so as to set the grounds for our findings. Firstly, we document the most relevant studies linking political risk to the foreign exchange market and then to currency momentum.

Political Risk. There is an established body of literature on the relation between exchange rates and political risk. Aliber (1973); Dooley and Isard (1980) consider two main channels of risk that could be linked to deviations from the uncovered interest rate parity condition; namely, exchange rate risk and political risk. This separation is further understood by Dooley and Isard (1980) who focus on the role of capital controls, associated with a political risk premium. In addition, Bailey and Chung (1995) study the role of political risk and movements in the exchange rates in the cross-section of stock returns in Mexico, finding evidence of risk premiums that are associated with these risks. In addition, Blomberg and Hess (1997) find that political risk variables can beat the random walk in an out-of-sample forecasting exercise for three currency pairs.

Political Events. One strand of the literature focuses on the political risk premia that it is associated with political news. For example, Boutchkova et al. (2012) investigate how industry volatility is influenced by both local and global political uncertainty. Pastor and Veronesi (2012) study the influence of government policies on stock prices and show that the political risk associated with announcements of policy changes should lead to a drop in the equity prices on average, with an analogous increase in the volatility and the correlation. In addition, Addoum and Kumar (2013) develop a trading strategy that exploits changes in political events, such as Presidential elections or the beginning and end of a Presidential term, demonstrating that investors require a premium under those periods because the political uncertainty is higher. Lugovskyy (2012) employs a political risk factor that it is a dummy variable of political risk regime changes. Here, the main finding is that there is a political regime change risk that varies depending on the government under control. Kelly et al. (2014) show that political uncertainty is priced in the options market and the option with maturity around political events seems to be more expensive.[1] We deviate somewhat from these studies as we do not focus on specific political events but we rather attempt instead to capture the *unexpected* changes in the political environment that drive currency premia.

Currency Momentum. Currency momentum was recently introduced in the foreign exchange rate market by Okunev and White (2003); Burnside et al. (2011a); Menkhoff et al. (2012b) who focus on the cross-sectional dimension of the momentum strategy. Most of the earlier studies focus on *time-series* momentum, often labeled as "technical analysis".[2] Our methodology is closely related to the one employed by Menkhoff et al. (2012b). In regard to the performance of the momentum strategy Cen and Marsh (2013) show that momentum was more profitable in the interwar period providing in this way out-of-sample evidence of profitability for a period that could characterized by rare events. Menkhoff et al. (2012b) also show the disconnection between equity and currency momentum as well as the low correlations between carry and momentum returns. Another striking feature of currency momentum that emerges from their study is that momentum exhibits low profitability among developed economies because it seems to be more attractive to countries that are less developed and demonstrate high country risk. Barroso and Santa-Clara (2013) show that in the equities market that an investor could avoid momentum crashes by hedging against momentum-

[1]For more example please see Gao and Qi (2012); Julio and Yook (2012); Baker et al. (2012); Belo et al. (2013); Cao et al. (2013).

[2]For more details please see Menkhoff and Taylor (2007) for an excellent survey on technical trading rules.

specific risks rather than market risk. This evidence has a direct link to the currency market.

2.3 Motivation

This section discusses the role of political risk in the foreign exchange market and attempts to provide a deeper understanding of the channel through which political risk enters into the currency market and affects investors' decisions. Later, we analyse our measure of political risk and its dynamics.

Political Risk. There are many different interpretations of political risk in the literature. Here we attempt to provide a more tangible definition. There are two main definitions of political risk. The first relates political risk to *"unwanted consequences of political activity"* and the second links it to political events (Kobrin, 1979). This chapter focuses more on the first definition to explore the role of *unexpected* political risk in the foreign exchange market.

Menkhoff et al. (2012b) show that currency momentum is mainly concentrated in countries that are less developed and exhibit a high risk of employing capital controls that could inflate the volatility of the exchange rate. On the other hand developed countries exhibit very low profitability verifying this finding. Thus, it is apparent that currency momentum is subject to limits to arbitrage while its profitability is heavily determined by country-specific characteristics. For example, they demonstrate that momentum exhibits a particular time-variation that stems from country-specific shocks and will thus be more pronounced in high idiosyncratic volatility portfolios.

In the same vein, political risk is the main determinant of country-specific shocks. For example, Pástor and Veronesi (2013) employ a general equilibrium model to show that in economies with weak economic profile, political risk uncertainty requires a risk premium that should increase as the economic conditions deteriorate. Boutchkova et al. (2012) also shows that local political risks are related to systemic volatility but global political risks are concentrated in periods characterised by a large idiosyncratic volatility. We should recall that currency momentum is more extreme in periods of high idiosyncratic volatility (Menkhoff et al., 2012b) which verifies our assumption regarding the role of political risk in the momentum strategies. Moreover, Lensink et al. (2000) show that political risk a strong determinant of capital flight.[3] Therefore, it is apparent that political risk could serve as a candidate risk factor for currency momentum being that it is a forward looking measure that dominates all the country-specific characteristics when the country risk is high.

Measure of Political Risk. We introduce a novel measure of political risk that it is relative to the U.S. political conditions. The main purpose of this measure is to capture the differences between the political uncertainty of the U.S. economy and the rest of the world.[4] We normalise it with average political risk on a month-to-month basis so as to check against global political conditions. This normalisation is very useful because it gives us the opportunity to capture the simultaneous deterioration of the political conditions between countries with similar characteristics and *vice versa*.[5] Specifically, we define the global political risk as:[6]

[3]For more examples please see Alesina and Tabellini (1989).

[4]Bekaert et al. (2014) construct a similar measure to proxy for political risk spreads.

[5]Our results are similar or improved in some cases if we do not apply this normalisation. However, it is very useful as it increases the informativeness of our measure.

[6]We also account for the differences in *globalisation* across countries by creating a value-weighted global political index where the weights are determined based on the KOF Index of Globalization and the two measures behave similarly.

$$\mathcal{PR}_t = \frac{1}{n_t}\sum_{i=1}^{n_t} \overbrace{\frac{\ln(1/pr_{i,t}) - \ln(1/pr_{US,t})}{\sigma_{i,t}^{\mathcal{PR}}}}^{\mathcal{PR}_{i,t}}, \tag{2.1}$$

where n_t is the total number of available currencies at time t and $pr_{i,t}$ ($pr_{US,t}$) represents the time t foreign (domestic) measure of political risk.[7] $\sigma_{i,t}^{\mathcal{PR}}$ is the cross-sectional average of the time t absolute deviation of the foreign (i) political risk from the U.S. counterpart (i.e. $\frac{1}{n_t}\sum^{n_t} |\ln(1/pr_{i,t}) - \ln(1/pr_{US,t})|$)). In order to guard against the high persistence of the global political risk measure we replace it with innovations (i.e. $\Delta\mathcal{PR}_t$) of an autoregressive model with one lag.[8] In addition, this measure serves our purpose as we aim to capture *unexpected* political activity. Figure 2.1 provides a graphical illustration of our global political risk innovations along with other risk factors in the literature such as, global FX volatility (as in Menkhoff et al. (2012a)), global FX correlation (similarly to Mueller et al. (2013)), global FX liquidity innovations (measured as global bid-ask spread (e.g. Menkhoff et al., 2012a, section 4)) and global CDS spreads (measured as differences of average CDS spreads across countries (Della Corte et al., 2013)).[9] It can be seen that other risk factors in the foreign exchange market are unrelated to our measure, indicating our attempt to capture different dynamics of currency premia.[10]

[7] According to ICRG an *increase* in political risk is associated with a *decrease* in their political risk variable (i.e. $pr_{i,t}$). Thus, we use the reciprocal of pr_{it} in order to have a measure that increases with political risk.

[8] Another way to account for stationarity would be to take first differences. Our results remain similar regardless of the method being used. In addition, we follow a similar procedure for country level political risk measures (i.e. $\mathcal{PR}_{i,t}$).

[9] We will analyse these variables in a latter section.

[10] Apart from the relation with the NBER recessions that we illustrate in figure 2.1 we also show that our measure is not related with any business cycle variation of any other country in our sample. Particularly, we follow Bauer et al. (2014) and proxy the business cycle variation of the countries in our sample with the leading indicators of OECD (OECD plus six NME). After projecting our global political risk measure on the changes of the OECD leading indicator, we find that there is no contemporaneous or lagged relation between the two measures, indicating the disconnection of our variable with the business cycle.

2.4 Data and Currency Portfolios

In this section, we provide a detailed description of the currency data used in the paper as well as the different impositions applied to the dataset. In addition, we describe our political risk data.

Exchange Rates Data. We begin with daily spot and one-month forward exchange rates against the U.S. dollar spanning the period of January 1985 to January 2014. The data are collected from Barclays and Reuters *via* Datastream. Transaction costs are taken into consideration through the use of bid, ask and mid quotes. We construct end-of-month series of daily spot and one-month forward rates as in Burnside et al. (2011). The main advantage of this approach is that the data is not averaged over each month but it represents the rates of the last trading day every month. The sample comprises the following 48 countries: Australia, Austria, Belgium, Brazil, Bulgaria, Canada, Croatia, Cyprus, Czech Republic, Denmark, Egypt, Euro area, Finland, France, Germany, Greece, Hong Kong, Hungary, India, Indonesia, Ireland, Israel, Italy, Iceland, Japan, Kuwait, Malaysia, Mexico, Netherlands, New Zealand, Norway, Philippines, Poland, Portugal, Russia, Saudi Arabia, Singapore, Slovakia, Slovenia, South Africa, South Korea, Spain, Sweden, Switzerland, Taiwan, Thailand, Ukraine, United Kingdom.[11]

We apply various filters in the data so as to make the analysis more realistic. Those currencies that were partly or completely pegged to the U.S. dollar are not excluded from the sample because their forward contracts were available to investors. The euro area countries are excluded after the introduction of the euro in January 1999. However, some countries entered the euro zone later than

[11] This sample is similar to the one employed by Menkhoff et al. (2012a,b).

January 1999. In this case their exchange rates are excluded from the sample at a later date. We also delete the observations that are associated with large deviations from the covered interest rate parity condition. In particular, South Africa from July 1985 to August 1985 as well as from December 2001 to May 2004; Malaysia from August 1998 to June 2005 and Indonesia from December 2000 to May 2007.

Currency Excess Returns. We denote with S_t and F_t the level of the time t spot and forward exchange rates. Each currency is quoted *against* the U.S. dollar such that an appreciation of the U.S. dollar reflects an increase in S_t. The excess return (RX_{t+1}) is defined as the payoff of a strategy that buys a foreign currency in the forward market at time t and then sells it in the spot market at maturity (i.e. at time $t+1$). The excess return can be computed as

$$RX_{t+1} = \frac{F_t - S_{t+1}}{S_t} = \frac{F_t - S_t}{S_t} - \frac{S_{t+1} - S_t}{S_t}. \tag{2.2}$$

Thus, the excess return can be decomposed into two components; the forward discount and the exchange rate return. Moreover, the covered interest-rate parity (hereafter CIP) condition implies that the forward discount is a good proxy for the interest rate differentials, i.e. $(F_t - S_t)/S_t \simeq \hat{i}_t - i_t$, where $\hat{i}_t$ and i_t denote the foreign and domestic riskless interest rates, respectively. Akram et al. (2008) provide a detailed examination of CIP condition over different frequencies and they find that it holds at daily and lower frequencies. Therefore, the excess return could also be written as $RX_{t+1} \simeq (\hat{i}_t - i_t) - (S_{t+1} - S_t)/S_t$. In the latter expression, the currency excess returns can be approximated by the exchange rate exposure subtracted by the difference in the foreign and domestic risk-free interest rates.

Transaction Costs. We report results with and without transaction costs because the inclusion of bid and ask quotes inflates the volatility of the excess returns giving more weight to less traded and illiquid currencies. The implementation cost of the currency strategy is taken into consideration though the use of bid and ask spreads. Particularly, buying the foreign currency forward at time t using the bid price (F_t^b) and selling it at time $t+1$ in the spot market at ask price (S_t^a) is given by: $RX_{t+1}^l = (F_t^b - S_{t+1}^a)/S_t^b$. Whereas the corresponding short position in the foreign currency (or short in the dollar) will render a *net* excess return of the form: $RX_{t+1}^s = -(F_t^a - S_{t+1}^b)/S_t^a$.

Political Risk Data. Our measure of country level political risk (i.e. $pr_{i,t}$) is obtained from the International Country Risk Guide (ICRG).[12] ICRG calculates political risk based on a variety of categories that capture country risk such as: government stability, socioeconomic conditions, investment profile, internal conflict, external conflict, corruption, military in politics, religious tensions, ethnic tensions, and democratic accountability. The original index measure ranges from 0-100 where a *higher* value of $ICRG_{i,t}$ reflects a *decrease* in political risk. As we showed in the previous section we compute the log inverse of $ICRG_{i,t}$ so as to obtain a measure that comoves with political risk.

Momentum Portfolios. At the end of each month t, we allocate currencies into sextiles on the basis of their past performance obtained at time $t-f$, where f represents the formation period and each portfolio is held for a month (h). To this end, the first Portfolio contains the worst performing currencies (i.e. *losers*) and the last basket consists of the *winner* currencies. The currency excess returns within each portfolio are equally weighted. The *cross-sectional* momentum

[12]This measure captures only the variability of political risk per country and thus it is not related to economic or financial risk. For more details please visit ICRG's website.

strategy (i.e. $\mathcal{WML}^{f,h}$) involves a long position in the best performing currencies (i.e. Portfolio 6) and a short position in the basket of currencies with the poorest performance over a particular past time period (i.e. Portfolio 1) (e.g., Menkhoff et al., 2012b). We define conditional excess returns as:

$$CRX_t^i = sign(RX_{t-1}^i)RX_t^i. \tag{2.3}$$

The above equation is very similar to the one introduced by Burnside et al. (2011b) and it resembles a currency momentum strategy as we go *long* the currency i when the previous month returns was *positive* and *short* otherwise. However, the dynamics of this strategy differ from the *cross-sectional* momentum.[13] Particularly, we construct an equally weighted portfolio of all the conditional returns and we label it as *time-series* momentum (i.e. $TSMOM_t^{1,1} = \overline{CRX}_t$).

2.5 Empirical Results

2.5.1 Preliminary Analysis

In this section we report summary statistics of our global political risk factor and compare them with corresponding measures proposed in the literature. We then evaluate the performance of the most profitable currency momentum portfolios. Furthermore, we report the results of univariate predictive regressions of momentum payoffs with global political risk innovations.

Descriptive Statistics. Table 2.1 reports descriptive statistics of global political risk innovations as well as other risk factors in the literature such as innovations to global FX volatility, global FX correlation, global FX illiquidity and

[13] For a discussion on this issue we refer the reader to Menkhoff et al. (2012b).

global CDS spreads changes. In line with figure 2.1 we find that global political risk is uncorrelated ($Corr$) with other factors even when we take into consideration the time-variation in the correlation structure by employing rolling correlations based on a 60-month rolling window. In particular, $MaxCorr$ ($MinCorr$) represents the most extreme positive (negative) correlation of global political risk innovations with each of the other variables. Moreover, our political risk measure demonstrates low persistence (first-order autocorrelation of 0.09), exhibiting negative skewness and excess kurtosis. Likewise, all the remaining measures exhibit low persistence as they are measured in a similar way.

[Table 2.1 about here.]

Figure 2.2 shows the correlation of country level political risk innovations with respect to U.S. over the sample period. We first note that the correlations are on average low and never exceed 25 percent. There are some exceptions in case of those countries which have significant political ties with the U.S. such as U.K., Canada, Kuwait, Saudi Arabia, Egypt and Russia. In order to understand the source of the correlations we also report in Figure B.2 correlations of innovations to each individual component of political risk index relative to U.S. components of political risk. We see that the *investment* profile component which covers aspects related to contract expropriation, profits repatriation[14] or payment delays dominates in terms of significant correlations. Nonetheless correlations remain low across different components.[15]

[Figure 2.2 about here.]

[14]For example, firms tend to consider the tax jurisdiction in order to allocate their earning abroad or repatriate them immediately (see e.g., Foley et al., 2007; Faulkender and Petersen, 2012; Bennedsen and Zeume, 2015). This practice, in principle, could affect currency flows between countries with different tax environments.

[15]In Figure B.3, we show the turnover of portfolios sorted based on global political risk. The majority of the countries appear in extreme portfolios.

Table 2.2 displays summary statistics of the most profitable cross-sectional momentum strategies in the foreign exchange market. More specifically, *Panels A*, *B* and *C* present descriptive statistics of momentum strategies with different formation periods (f) and a holding period (h) of one month (i.e. $\mathcal{WML}^{1,1}$, $\mathcal{WML}^{3,1}$, $\mathcal{WML}^{6,1}$). Consistently with Menkhoff et al. (2012b) we find that currency momentum returns exhibit statistically significant high annualized mean excess returns (before transaction costs) of 10.18 for the formation period of one month which is the most profitable and then the profitability decreases monotonically as the formation period increases.[16] Transaction costs (i.e. $\mathcal{WML}^{\tau}$) partially explain momentum return as the corresponding average *net* excess returns drops to 6.29. All mean returns are expressed in percentage points. In addition, currency momentum renders high annualized sharpe ratios while exhibiting negative skewness and excess kurtosis. We also report first order autocorrelations with the corresponding *p-values*.

[TABLE 2.2 ABOUT HERE.]

Panel A of Table 2.3 shows summary statistics of time-series momentum portfolios with and without transaction costs. As expected, the time-series momentum renders an annualized excess return before (after) transaction costs of 5.32 (3.25) that it is statistically significant and smaller than the one obtained from the cross-sectional strategy (i.e. $\mathcal{WML}^{1,1}$). *Panel B* reports results of regressions of the time-series momentum strategy on the cross-sectional momentum returns. We find that the two strategies are quite different as it is illustrated by the economically and statistically significant alphas as well as the fact that the adjusted R^2 *decrease* with the formation period. However, the two strategies

[16] In Figure B.4, we show the portfolio turnover of the winner and loser portfolios. Mostly tradable currencies appear in both portfolios.

exhibit a common variation that it is revealed from the relatively high adjusted R^2 (i.e. 0.52) when the formation period is one month.

[TABLE 2.3 ABOUT HERE.]

Predictive Regressions. As a first step we question the predictive power of global political risk for both cross-sectional and time-series momentum returns. The main reason for performing this exercise is to investigate the time-series variation of momentum returns in an attempt to understand its (dis)connection with the macroeconomy or the financial environment. To this end, we run predictive regressions of momentum returns on different factors considered in the literature along with global risk innovations such that:

$$\mathcal{WML}_{t+1}^{f,h} = \alpha^{f,h} + \gamma \mathcal{Z}_t + \varepsilon_{t+1}^{f,h}. \tag{2.4}$$

$$TSMOM_{t+1}^{1,h} = \alpha^{1,h} + \gamma \mathcal{Z}_t + \varepsilon_{t+1}^{1,h}. \tag{2.5}$$

where f represents the formation period and takes the values 1, 3 and 6[17] and h is the holding period of the currency momentum strategy that is always equal to one month. $\mathcal{Z}_t$ includes $\Delta\mathcal{PR}_t$ or a set of other predictors in the literature, summarized in Table 2.1.[18] Table B.1 reports the slope estimates of univariate regressions with the variables of interest. We note that only global political risk exhibits significant slope estimates indicating that it contains important information for both cross-sectional and time-series currency momentum. However, it performs purely in terms of goodness of fit as it exhibits very low R^2. In Panel B of Table B.1 we analyze seperately loser and winner portfolios of cross-sectional momentum strategies. We make an important observation; while the returns to

[17]To save space we report the results with longer formation periods, i.e. three and six months, in Table B.1.

[18]The results remain similar when we control for *reversals* and they are available on demand.

winner portfolios are mainly predicted by the changes in FX volatility, only the innovations to global political risk explain the subsequent returns to loser portfolios. This suggests that the main channel through which the global political risk rationalizes momentum profitability is the short leg of the cross-sectional momentum strategy. Next, we turn our scope to a cross-sectional perspective so as to see whether the cross-country differences of political risk can capture the cross-section of currency momentum portfolios.

[Table B.1 about here.]

2.5.2 Currency Momentum and Global Political Risk

This section demonstrates the role of political risk in currency investment strategies with a focus on currency momentum strategies. More precisely, we question whether political risk affects currency premia and to what extend a foreign investor could protect herself from adverse political conditions. Therefore, we examine the pricing ability of global political risk innovations for FX momentum portfolios.

Political Risk-Sorted Portfolios. One way to investigate the pricing ability of global political risk is to see whether currency portfolios that are sorted based on currency exposures to global political risk render a significantly positive spread.

Therefore, we sort currencies into five portfolios at time t based on their past betas (i.e. $t-1$) with global political risk innovations. Following Lustig et al. (2011); Menkhoff et al. (2012a); Mueller et al. (2013) the betas are estimated based on a 60-month rolling window and we rebalance our portfolios on a monthly basis. We exclude the first 60 months for the calculation of the portfolio returns so as to avoid relying on the in-sample period.[19]

$$CRX_t^i = \alpha^i + \beta^{i,PR} \Delta\mathcal{PR}_t + \varepsilon_t^i, \tag{2.6}$$

where CRX_t^i is the conditional excess return of country i at time t and $\Delta\mathcal{PR}_{i,t}$ represents global political risk innovations.

The purpose of this exercise is twofold. Firstly, we ask whether political risk is a priced factor in the currency market and then we assess the political risk exposures of currency premia that it is associated with currency momentum. Table 2.5 displays descriptive statistics of currency portfolios sorted on global political risk betas. Excess returns of portfolios sorted on political risk exposures increase as their exposure to political risk increases. We observe almost a monotonic pattern verifying the pricing ability of political risk innovations for currency momentum. Particularly, Table 2.5 shows that when sorting conditional excess returns on political risk betas it renders a statistically lower excess return for the low beta portfolios in comparison to the high beta counterparts. Thus, the corresponding spread portfolio (i.e. $\mathcal{H}/\mathcal{L}$) provides a statistically and economically significant excess return of 4.13% per annum. Most of the portfolios exhibit positive skewness and excess kurtosis while the persistence level is low. In addition, we report *pre* and *post* estimation betas to discover that they increase when moving from low to high beta portfolios verifying the connection between global political risk and momentum.[20]

[Table 2.5 about here.]

[19]Smaller window sizes provide slightly weaker results.
[20]In Figure B.5 we show how the rolling betas evolve over time.

2.5.3 Factor-Mimicking Portfolio

Our global political risk measure is not a tradable factor and thus we create a mimicking portfolio that helps us overcome this issue. Therefore, in order to assess the pricing ability of global political risk innovations we construct a mimicking portfolio following Ang et al. (2006).[21] The premise behind this method is that a traded factor should have an average return that it is similar to the one of the traded portfolio meaning that it can price itself. Particularly, we regress contemporaneously our global political risk measure on excess returns of currency portfolios that are sorted based on their past performance:

$$\Delta\mathcal{PR}_{t+1} = a + b'\mathbf{RX}_{t+1} + v_{t+1}, \tag{2.7}$$

where $\mathbf{RX}_{t+1}$ is vector of the six portfolio returns at time $t+1$. Thus, the mimicking portfolio[22] is the projection of political risk innovations on the six portfolios returns $\mathcal{FPR}_{t+1}$ and it is defined as $\mathcal{FPR}_{t+1} \equiv \hat{b}'\mathbf{RX}_{t+1}$. We perform the same exercise for different formation periods. The annualized mean excess return of the mimicking portfolio when considering a momentum strategy with formation and holding periods of one month is 2.81% with weights that are formed as follows:

$$\mathcal{FPR}_{t+1} = -0.19RX^1_{t+1} - 0.06RX^2_{t+1} - 0.01RX^3_{t+1} + 0.05RX^4_{t+1} - 0.14RX^5_{t+1} + 0.33RX^6_{t+1} \tag{2.8}$$

[21] Please see Breeden et al. (1989); Menkhoff et al. (2012a); Mueller et al. (2013) for more examples of this approach.

[22] We also control for other variables (i.e. $\mathbf{Z}$) when estimating the optimal weights of the mimicking portfolios (i.e. b') such as, past momentum returns (reversals, see section 6.4), volatility and liquidity. We find that the results remain unchanged (e.g. Lamont, 2001; Ferson et al., 2006). For example, we run a regression of the form: $\Delta\mathcal{PR}_{t+1} = a + b'\mathbf{RX}_{t+1} + c'\mathbf{Z}_t + u_{t+1}$.

where the factor-mimicking portfolio loads positively on the excess return of the last portfolio and negatively on the return of the first portfolio. This finding is in line with the previous section where we showed that momentum returns increase monotonically as their exposure to political risk increases. This monotonic pattern is also an indication that our factor-mimicking portfolio could potentially provide pricing information for momentum returns. Furthermore, we find that our factor exhibits a correlation of 85% with the second principal component (PC) of currencies that are sorted into portfolios based on their previous month return. Thus, similarly to Lustig et al. (2011) who find that their HML_{FX} factor is highly correlated with the second PC of interest-rate sorted portfolios and it is a priced factor, we show in the next section that our *slope* factor involves all the required cross-sectional information to corroborate pricing past performance-sorted currency portfolios.

2.5.4 FX Asset Pricing Tests

This section performs cross-sectional asset pricing tests between the six currency portfolios and the political risk model, and shows that political risk is priced in the cross-section of currency excess returns.

Methods. Following the asset pricing methodology analyzed in Cochrane (2005) and implemented in many studies in the FX asset pricing literature, such as Lustig et al. (2011) and Menkhoff et al. (2012a) we examine the pricing ability of global political risk. We denote the currency excess return of each portfolio j at time $t+1$ as RX^j_{t+1}. In this paper we use discrete excess returns instead of log forms so as to avoid the joint log-normality assumption between returns and the pricing kernel. Under no arbitrage conditions, the risk-adjusted currency excess returns should be zero and satisfy the Euler equation:

$$E[M_{t+1}RX^j_{t+1}] = 0 \tag{2.9}$$

where M_{t+1} denotes a linear SDF in the risk factors ϕ_{t+1}.[23] In particular, the main focus is on the SDF of the following form:

$$M_{t+1} = [1 - b'(\phi_{t+1} - \mu_\phi)] \tag{2.10}$$

where b denotes the vector of factor loadings and μ_ϕ is the vector of expected values of the pricing factors (i.e. $\mu_\phi = E(\phi_{t+1})$). The beta representation of the model is obtained from the combination of above equations rendering the beta pricing model below:

$$E[RX^j] = \lambda'\beta^j \tag{2.11}$$

where $\lambda = \Sigma_\phi b$ represents the factor risk prices with $\Sigma_\phi = E[(\phi_t - \mu_\phi)(\phi_t - \mu_\phi)']$ denoting the variance-covariance matrix of the risk factors and b the factor loading.[24] After projecting each currency excess return (RX^j_t) on the risk factors (ϕ_t) contemporaneously, we obtain the regression coefficients β^j.

The simultaneous estimation of the factor loadings (b), factor means (μ) as well as the individual elements of the factor covariance matrix (Σ_ϕ) is based on the Generalized Method of Moments (GMM) of Hansen (1982). Particularly, the estimation is based on the system of the moment conditions below:

[23] In the robustness section, we analyze the potential effects of non-linearity.

[24] In order to control for the fact that the means and the covariance of the risk factors are estimated we compute the standard errors for the factor risk prices by applying the Delta method.

$$E[g(z_t, \theta)] = E \begin{bmatrix} [1 - b'(\phi_t - \mu_\phi)]RX_t \\ \phi_t - \mu_\phi \\ \text{vec}((\phi_t - \mu_\phi)(\phi_t - \mu_\phi)') - \text{vec}(\Sigma_\phi) \end{bmatrix} = 0$$

where $g(z_t, \theta)$ is a function of the set of parameters (i.e. $\theta = [b'\mu'\text{vec}(\Sigma_\phi)']')$ and the data (i.e. $z_t = [RX_t, \phi_t]$).

The main purpose of this study is to examine the pricing ability of the model on the cross-section of currency returns and thus we restrict our attention on unconditional moments with no instruments apart from a constant. Thus, the pricing errors are used as the set of moments under a prespecified weighting matrix. In the first stage of the GMM (GMM_1) we start with an identity weighting matrix so as to see whether the factors can price the cross-section of the currency excess returns equally well. Then in the second stage (GMM_2) we choose the weighting matrix optimally by minimizing the difference between the objective functions under heteroskedasticity and autocorrelation (HAC) estimates of the long-run covariance matrix of the moment conditions. To do that, we follow the Newey and West (1987) methodology using the optimal number of lags as in Andrews (1991).

As a verification tool we also apply a Fama and MacBeth (1973) (hereafter FMB) two pass regression. In the first stage, we run contemporaneous time-series regressions of currency portfolio excess returns on the risk factors. In the second stage, we perform cross-sectional regressions of average portfolio returns on factor loadings, obtained from the previous step, in order to compute the factor risk prices. In addition, we allow for common misspricing in the currency returns by including a constant but the cross-sectional estimate of political risk remains highly significant if we exclude it. In addition, we report both Newey and West (1987) as well as Shanken (1992) so as to account for the potential error-in-variable issue that might arise due to the fact that the regressors are estimated in the second stage of the FMB procedure.

Cross-Sectional Analysis. The SDF of each model takes the following form:

$$M_{t+1} = 1 - b_{DOL}(DOL_{t+1} - \mu_{DOL}) - b_{\mathcal{FPR}}(\mathcal{FPR}_{t+1} - \mu_{\mathcal{FPR}}). \qquad (2.12)$$

Panel A of table 2.6 provides results for the second-pass regression based on GMM and FMB methods. The table displays estimates for b and the implied factor risk prices (λ) as well as standard errors that are corrected for autocorrelation and heteroskedasticity following Newey and West (1987) based on the optimal number of lags as in Andrews (1991). We also evaluate the cross-sectional performance of our asset pricing model with various measures of goodness of fit such as χ^2, cross-sectional R^2, HJ distance following Hansen and Jagannathan (1997) as well as a generalized version of the cross-sectional F-test statistic of Shanken (1985) under the null of zero pricing errors and a cross-sectional R^2 of one. The χ^2 test statistics - obtained from the FMB (with Newey and West (1987) and Shanken (1992) corrections) as well as GMM_1 and GMM_2 procedures - test the null hypothesis that all pricing errors in the cross-section are mutually equal to zero. The cross-sectional pricing errors are computed as the difference between the realized and predicted excess returns. The HJ distance is a model diagnostic that helps us compare asset pricing models. In our context it tests whether the distance of the SDF of our model in squared terms and a group of acceptable SDFs is equal to zero. We report *p-values* in curly brackets.[25] Table 2.6 displays three panels that correspond to the three momentum strategies

[25]For the estimation of the *p-values* for the HJ distance we follow Jagannathan and Wang (1996).

of interest. Particularly, the left panel shows results for a momentum strategy with one month formation (f) period and one month holding (h) period whereas the other two panels display cross-sectional estimates for formation periods of 3 and 6 months respectively and monthly rebalancing.

Firstly, we focus on the statistical significance and the sign of the estimates of the factor risk prices of our political risk (i.e. $\lambda_{\mathcal{FPR}}$) measure as well the market factor (i.e. λ_{DOL}). We find that the our political risk prices of political risk are always positive and significant based on Newey and West (1987) and Shanken (1992) standard errors across our momentum strategies and they increase with the formation period when we include a constant in the cross-section. In addition, λ_{DOL} is not equal to one as in the case of the carry trades (Lustig et al., 2011) but it remains insignificant. The results are also verified by GMM_1 and GMM_2 estimates. In terms of goodness of fit the *p-values* of the χ^2 test statistic indicates that we cannot reject the null that all the pricing errors are equal to zero. We perform the same test using Newey and West (1987) and Shanken (1992) corrections in the FMB as well as GMM_1 and GMM_2. We find very strong results for all formation periods with the exception of the formation period of three months. These findings are in line with the $CSRT_{SH}$ statistic of Shanken (1985) when we include a constant in the cross-sectional regression. Furthermore, the cross-sectional R^2 range from 66% for three month formation period to 99% for the one month formation period. The R^2 for the momentum (6,1) is 86%. Finally, regarding HJ distance we cannot reject the null that the HJ distance is equal to zero for all momentum strategies because they exhibit very large *p-values*. Overall, we find that global political risk is priced in the cross-section of currency momentum - both in terms of statistical significance as well as goodness of fit.

Time-Series Analysis. *Panel B* of table 2.6 also displays estimates of the coefficients when projecting contemporaneously the time-series of currency excess returns on a constant and the factors of interest (i.e. DOL and $\mathcal{FPR}$) for each of the six currency portfolios p (i.e. $p = 1, \ldots, 6$),

$$RX_{t+1}^{p} = \beta_0^p + \beta_{DOL}^p DOL_{t+1} + \beta_{\mathcal{FPR}}^p \mathcal{FPR}_{t+1} + u_{t+1}^p. \tag{2.13}$$

Here we examine whether the global political risk explains the differences across momentum portfolio excess returns once we control for the DOL factor. Starting from the estimates of the DOL factor (β_{DOL}) we find that it is always very close to one indicating that it is not able to capture any of the variation of mean excess returns across momentum portfolios. On the other hand we find that the betas of the mimicking portfolios ($\beta_{\mathcal{FPR}}$) are highly significant and they increase as we move from the loser to winner portfolios. Specifically, the betas of the $\mathcal{FPR}$ for the formation period of one month increase monotonically from -1.64 for the *loser* to 2.05 for the *winner* portfolios. This finding is consistent for other formation periods demonstrating that the global political risk betas load negatively in *loser* portfolios and positively in *winner* portfolios. In addition, the times-series R^2 range from 73% to 95% for momentum (1,1), from 58% to 85% for momentum (3,1) and from 79% to 92% for six months formation period.

[Table 2.6 about here.]

In Figure 2.3 we show results graphically on the fit of our model. Here, we plot realized average excess returns on the vertical axis and the corresponding average fitted excess returns as they are implied by our model along the horizontal axis. We find that, for every formation period, global political risk is priced being that it is able to replicate the spread in average momentum returns adequately.

[FIGURE 2.3 ABOUT HERE.]

Overall, our results reveal that a currency investor requires a premium for holding *winner* portfolios since they are exposed to global political risk. At the same time, investors accept lower returns for *loser* portfolios which invest in USD by shorting loser currencies exactly when the global political risk increases, i.e. either an increase in political risk of foreign currencies or a decrease in U.S. political risk.

Global Political Risk Innovations. We also perform the same analysis after replacing the mimicking portfolio with our global political risk innovations. To this end, table 2.7 reports results for asset pricing tests when the set of the two risk factors are the market factor (i.e. DOL) and global political risk innovations (i.e. $\Delta\mathcal{PR}$). Particularly, we report cross-sectional results from the FMB regression and find that the estimates of $\lambda_{\mathcal{PR}}$ are highly significant even with or without the inclusion of a constant in the cross-sectional regression. We report both HAC standard errors as well as standard errors that take into consideration the error-in-variable problem. Regarding the goodness of fit, the χ^2 test statistic indicates that we cannot reject the null that all pricing errors are statistically different than zero. This is also verified by the large *p-values*. These statistics are based on FMB and GMM_1 and GMM_2 methods. This is also in line with the $CSRT_{SH}$ statistic when we include a constant in the cross-sectional regression as we also find very large *p-values*. In addition, the cross-sectional R^2 vary from 66% for momentum (3,1) to 99% for momentum (1,1). The cross-sectional R^2 for six months formation period is 86%. Finally, the HJ distance is not statistically different from zero as it is shown from the very large *p-values*. Thus, we see that the results are similar if you use global political risk innovation instead of the mimicking portfolio.

[Table 2.7 about here.]

2.6 Other Determinants of Currency Premia

This section aims to provide a more comprehensive view of our results. Particularly we examine the link between global political risk and other risk factors so as to see whether political risk captures different dynamics of currency premia. Consequently, we perform double sort of currency excess returns in order to investigate the conditional pricing ability of our measure after controlling for other variables.

2.6.1 Limits to Arbitrage

Political risk is one of the major dimensions of limits to arbitrage in the foreign exchange market that affect the profitability of currency momentum (e.g., Menkhoff et al., 2012b). Therefore, we need to examine whether it contains information for currency premia beyond that embodied in other measures of limits to arbitrage. Along these lines, we follow Menkhoff et al. (2012b) who show that momentum returns are more pronounced under high idiosyncratic volatility states and thus it would be hard for an investor to find another set of currencies that could potentially serve as hedge factors. To this end, we employ the idiosyncratic volatility of an FX asset pricing model. Particularly, we compute the idiosyncratic volatility and skewness of the Lustig et al. (2011) model. Lustig et al. (2011) show that two risk factors are enough to price the cross-section of currency carry trade returns. The first factor is a *level factor* (i.e. *DOL*) that goes long all the available *foreign* currencies across portfolios each time while short-selling the dollar, whereas the second factor is a *slope* factor (i.e. HML_{FX}) that buys a basket of *investment* currencies (high interest rate) and sells an *funding* currency portfolio (low interest rate). The latter strategy resembles the carry trade strategy.

We construct daily DOL and HML_{FX} factors obtained from daily currency excess returns (RX_{t+1}) sorted on forward discounts of 48 currencies. Each currency should have at least 20 observations each month in order to be considered in the analysis. Daily currency excess returns are regressed each month on a constant, a DOL and a HML_{FX} factor in order to obtain monthly error terms:

$$RX^i_{t,d+1} = \alpha^i + \beta^i_{1,t} DOL_{t,d+1} + \beta^i_{2,t} HML_{FXt,d+1} + \varepsilon^i_{t,d+1}, \tag{2.14}$$

where d represents the *daily* observations each month, t is the number of *monthly* observations and i denotes the number of currencies. We define currency $i's$ idiosyncratic volatility in month t ($IV^{FX}_{i,t}$), as the standard deviation of the daily error terms each month and the corresponding idiosyncratic skewness ($IS^{FX}_{i,t}$) as the third moment of the error term divided by the cubed form of idiosyncratic volatility.[26] Thus, the two measures take the following form:

$$IV^{FX}_{i,t} = \sqrt{\frac{1}{T_{i,t}} \sum_{d=1}^{T_{i,t}} \varepsilon^2_{i,d}}, \quad IS^{FX}_{i,t} = \frac{1}{T_{i,t}} \frac{\sum_{d=1}^{T_{i,t}} \varepsilon^3_{i,d}}{(IV^{FX}_{i,t})^3}. \tag{2.15}$$

where $T_{i,t}$ denotes the number of daily observations each month t for each currency i subtracted by one for idiosyncratic volatility and by two for idiosyncratic skewness, so as to account for the appropriate degrees of freedom.

We also compute average *deviations* from the CIP condition after controlling for transaction costs as another proxy of limits to arbitrage in the currency market (Mancini-Griffoli and Ranaldo, 2011). Figure 2.4 shows average CIP

[26] For examples on the construction of the idiosyncratic volatility and skewness please see Goyal and Santa-Clara (2003); Fu (2009); Boyer et al. (2009); Chen and Petkova (2012).

deviations along with global political risk betas for conditional excess returns. We find that countries with high political risk exhibit more pronounced CIP deviations reflected in the upward slopping regression line in the figure supporting our hypothesis regarding the role of global political risk in currency momentum strategies. This visual evidence is also verified by the significant cross-sectional beta ($\beta = 1.34$, $tstat = 2.55$) and R^2 of 11%.

[Figure 2.4 about here.]

2.6.2 Global FX Volatility and Liquidity

Here we examine the behaviour of political risk in currency momentum when we control for volatility or liquidity in the foreign exchange market. We follow Menkhoff et al. (2012a) and measure FX volatility and liquidity based on the cross-sectional average of individual daily absolute exchange rate returns that are averages each month. Particularly, we measure global FX volatility (σ_t^{FX}) and FX liquidity (ξ_t^{FX}) as:

$$\sigma_t^{FX} = \frac{1}{T_t} \sum_{d \in T_t} \left[\sum_{k \in K_d} \left(\frac{|\Delta s_d|}{K_d} \right) \right], \quad \xi_t^{FX} = \frac{1}{T_t} \sum_{d \in T_t} \left[\sum_{k \in K_d} \left(\frac{BAS_d^k}{K_d} \right) \right]. \qquad (2.16)$$

where $|\Delta s_d|$ represents the absolute change in the log spot exchange rate of currency k on day d. In the same vein, BAS_d^k is the bid-ask spread in percentage points of currency k on day d. T_t is the total number of days in month t and K_d is the total number of currencies on day d. Thus, an increase of this measure is associated with higher levels of illiquidity. In order to control for the high persistence of these measures we replace them with innovations of an $AR(1)$ models as we did for the political risk measure and we denote them as $\Delta\mathcal{RV}_t^{FX}$

and $\Delta\mathcal{L}_t^{FX}$ respectively.

2.6.3 Global FX Correlation

We also examine the pricing ability of global political risk for currency momentum in the presence of global correlation risk. Mueller et al. (2013) show that global FX correlation is priced in the cross-section of carry trade portfolios and it is a good proxy for global *risk aversion*. Therefore, it is very important to see the performance of political risk under different states of correlation risk. To this end, we use a similar measure with the one introduced by Mueller et al. (2013) and compute global FX correlation risk as:

$$\gamma_t^{FX} = \frac{1}{N_t^{comb}} \sum_{i=1}^{n_t} \left[\sum_{j>i} \left(RC_t^{ij} \right) \right], \tag{2.17}$$

where RC_t^{ij} is the realised correlation between currencies i and j at time t. N_t^{comb} is the total number of combinations of currencies (i, j) at time t and n_t is the total number of currencies in our sample at time t. As before, we replace the correlation variable with its innovations from an autoregressive model with one lag and denote it as $\Delta\mathcal{RC}_t^{FX}$.

2.6.4 Double Sorts

Now that we have defined our variables of interest, we turn out attention to the cross-sectional predictive ability of political risk conditional on the information encompassed in these variables. We compute the exposure of *conditional* excess returns to political risk based on a 60-month rolling window and then we sort *conditional* currency excess returns (i.e. momentum returns) firstly into two portfolios based on the variable of interest and then within each portfolio we sort them in three bins based on global political risk exposures. Each portfolio is rebalanced on a monthly basis. Note that we sort currencies into portfolios based on the currency exposures to our variables with the exception of idiosyncratic volatility where we use the raw measure instead of its betas.[27]

Starting with idiosyncratic volatility and skewness *Panels A* and *B* of Table 2.8 show double sorts on IV and IS respectively along with global political risk exposures. Consistently with Menkhoff et al. (2012b) we find that momentum returns increase as we move from low to high IV portfolios and also that the momentum returns are more extreme in the high idiosyncratic volatility basket making it more difficult for an investor to hedge this risk away. A reverse pattern is observed for IS portfolios. We thus attempt to determine whether this pattern influences our results. We find that in both in low and high IV portfolios, currencies with high political risk exhibit higher mean excess returns than the low political risk counterpart, but the diffrence is more pronounced in high IV portfolios. The results are similar for idiosyncratic skewness, except that the difference across political risk portfolios is greater in low IS portfolios.

Another determinant of currency momentum is illiquidity. Menkhoff et al. (2012b) show that currency momentum is more concentrated among countries with less liquid currencies and a fragile political environment. We would therefore question the pricing ability of political risk after controlling for illiquidity. *Panel C* of Table 2.8 shows that momentum returns increase as we move from low to high political risk portfolios both in high and low illiquidity states.

Another feature of exchange rates that are mainly involved in momentum portfolios is the high levels of volatility. Thus, in *Panel D* we ask whether political risk is priced even after controlling for global FX volatility. We find that

[27]We do not provide double sorts for CDS spreads because of data availability, i.e. short time-series and limited cross-section.

momentum profitability is larger in high political risk portfolios in comparison to low political risk baskets. This pattern is more striking in high volatility states.

Finally, we control for global FX correlation in *Panel D* of Table 2.8 so as to examine the momentum profitability under high and low levels of global *risk aversion*. Here, we show that the increasing pattern remains unchanged even after controlling for global FX correlation. However, the difference across global political risk portfolios is particularly significant in low correlation portfolios. Overall, we find that global political risk is priced in the cross-section of currency momentum returns even after controlling for other determinants of currency premia.[28]

[Table 2.8 about here.]

2.7 Robustness and other Specification Tests

In this section we apply several robustness checks to examine further the role of political risk. Particularly, we impose various filters in the data so as to focus on more tradable currencies. We check the implications of transaction costs, reversals and non-linearity in our asset pricing model. We consider different currency portfolio strategies such as carry and value. Finally, we explore the link with other uncertainty, macro and financial variables and we examine the robustness of our asset pricing results to alternative specifications of global and country-level political risk.

[28]It is also indicative that the differences between the high and low spread portfolios (i.e., $HML^{High} - HML^{low}$) of the different determinants of currency premia are not statistically significant.

2.7.1 Tradability

One of the main concerns regarding the validity of our results is related to potential impediments in the foreign exchange market that could refrain an investor from trading particular currencies. For example, some currencies cannot be traded in large volumes and they exhibit high illiquidity. To alleviate this issue, we follow Della Corte et al. (2013) and allow for currency-time combinations that meet particular conditions. More precisely, we include country-time pairs for countries that exhibit a non-negative value on the Chinn and Ito (2006) capital account openness index and their currencies belong in the exchange rate regime 3 or 4 of the IMF coarse classification. The latter filter eliminates currencies that are inside a pre-announced crawling band of $+/-2\%$, outside a de facto crawling band of $+/-5\%$, outside a moving band of $+/-2\%$, or those that are not in a free float. The filtered data comprise the following 33 countries: Australia, Bulgaria, Canada, Cyprus, Denmark, Egypt, France, Germany, Greece, Hungary, Iceland, India, Ireland, Israel, Japan, Korea, South, Kuwait, Malaysia, Mexico, New Zealand, Norway, Philippines, Poland, Russia, Saudi Arabia, Slovakia, Slovenia, South Africa, Sweden, Switzerland, Taiwan, Thailand, United Kingdom. We name this group of currencies *Filtered Data*.

In order to increase the robustness of our analysis we consider a larger sample of currencies. Particularly, we add 12 more currencies (60 countries in total) that we excluded from the initial sample as they exhibit very small tradability and thus high illiquidity. Those countries are Argentina, Chile, China, Colombia, Estonia, Kazakhstan, Latvia, Lithuania, Morocco, Tunisia, Turkey, Venezuala. Then we apply the filters that we described above and end up with 39 currencies.[29]

[29]Specifically, the new sample contains the following countries: Argentina, Australia, Bulgaria, Canada, China, Cyprus, Denmark, Egypt, Estonia, France, Germany, Greece, Hungary,

Table 2.9 reports results of asset pricing tests after accounting for the filters. Particularly, we employ a dollar factor along with the mimicking portfolio as we did in section 2.5.4. The results remain unchanged or they are improved in some cases. Overall, we find that our asset pricing model performs well in terms of statistical and economic significance as we find statistically significant slope risk factor prices and we cannot reject the null that all pricing errors are equal to zero based on χ^2 test statistics obtained from FMB and GMM_1 and GMM_2 procedures. In addition, we cannot reject the null that HJ distance is equal to zero for any formation period as it is indicated by the large *p-values*. Finally, the cross-sectional R^2 range from 0.89% for the momentum of one month formation period to 92% for the currency momentum with three months formation period. *Panel A* (*Panel B*) reports results for the *Filtered Data* that contain 33 countries (39 countries).

[Table 2.9 about here.]

2.7.2 Currency-level Asset Pricing Tests

The use of portfolios in our analysis could raise concerns because the inclusion of currencies into portfolios might destroy information by shrinking the dispersion of betas (e.g., Ang et al., 2010). We therefore perform cross-sectional tests on individual currencies using conditional excess returns. Figure 2.5 depicts realized average excess returns in the vertical axis and the corresponding average fitted excess returns as they are implied by our model along the horizontal axis of individual currencies. We find that most of the currencies line up or they are quite close to the 45 degree line indicating that political risk is priced even after

Iceland, India, Ireland, Israel, Japan, Korea South, Kuwait, Latvia, Lithuania, Malaysia, Mexico, New Zealand, Norway, Philippines, Poland, Russia, Saudi Arabia, Slovakia, Slovenia, South Africa, Sweden, Switzerland, Taiwan, Thailand, Venezuala, United Kingdom.

considering each currency in isolation.

[Figure 2.5 about here.]

Next, we ask what is the contribution of country-level political risk in our results. In Figure 2.6 we show cross-sectional t-statistics when considering only country-level political risk factors and a constant. In particular, we estimate a similar asset pricing model as in section 4.4 using the six momentum portfolios as test assets, but excluding the *DOL* factor and replacing the global political risk measure with *country-level* political risk *vis-à-vis* United States. As the figure shows while only few countries are the source of mispricing (i.e., not statistically significant zero-beta rates in most of the cases), many countries contribute significantly to the risk pricing of momentum returns. Our t-statistics take into consideration the error-in-variable problem following Jagannathan and Wang (1998). The blue horizontal line corresponds to the 1.96 significance bound.

[Figure 2.6 about here.]

2.7.3 Transaction Costs

We also examine the pricing ability of political risk for currency momentum when considering *net* excess returns. The inclusion of transaction costs is very important as they partially explain the profitability of this strategy (Menkhoff et al., 2012b). Table 2.10 displays results for FMB regressions after considering the implementation cost of the strategy. Specifically, the $\lambda_{\mathcal{FPR}}$ is highly significant across formation periods based on HAC standard errors as well as Shanken (1992) standard errors and t-statistics that account for the error-in-variable problem. In addition, we were unable to reject the null of zero pricing errors for any formation period (with the exception of the nine months formation period), something that it is verified by the $CSRT_{SH}$ statistic when we include a constant in the cross-sectional regression. Moreover, we cannot reject the null that HJ distance is equal to zero and the cross-sectional R^2 are slightly lower ranging from 45% for the 6-month formation period to 90% when we evaluate the previous month performance. Figure B.6 shows the corresponding pricing error plots. *Panel A* of Table B.2 offers results for longer formation periods. Overall, the global political risk is priced in cross-section of momentum returns even after controlling for transaction costs.

[TABLE 2.10 ABOUT HERE.]

2.7.4 Reversals

Here we consider a mimicking portfolio that incorporates conditional information on past returns. Particularly, we control for past month excess returns to see whether our results are driven by short-run reversals. This is important as in the equities literature the short-run reversals affect the momentum profitability and they are also related to idiosyncratic volatility which is one of the determinants of momentum profitability.[30] Thus, we run a regression of the form: $\Delta\mathcal{PR}_{t+1} = a + b'\mathbf{RX}_{t+1} + c'\mathbf{Z}_t + u_{t+1}$, where $\mathbf{Z}_t$ is the previous month momentum excess return and b' are the weights of the *conditional* mimicking portfolio (i.e. $\mathcal{CFPR}$).

Table 2.11 shows results for FMB regressions after replacing our political risk factor with the *conditional* mimicking portfolio. A visual illustration of the pricing errors is offered in Figure B.7. We also consider longer horizons of 9 and 12 months in *Panel B* of Table B.2. We find that the results are similar in terms of statistical significance of the $\lambda_{\mathcal{CFPR}}$ but for some formation period we reject the null that all the pricing errors are jointly equal to zero based on the χ^2

[30]See for example Huang et al. (2009); Chen and Petkova (2012).

test statistic. However, for the cases of momentum (1,1) and (12,1) the results remain unchanged. In addition, we cannot reject the null of zero HJ distance for any formation period and the cross-sectional R^2s vary from 55% for momentum (9,1) to 98% when considering the previous month's performance. Therefore, we find that short-run reversals might affect medium horizon momentum strategies but they do not have any effects on the short or long-run formation periods.

[Table 2.11 about here.]

2.7.5 Non-linearity

In the asset pricing model, we proposed a linear SDF to price the momentum returns. However, based on the double-sort evidence we provided before, one can argue that there might be a non-linear relation between momentum returns and global political risk innovations. Following this conjecture, we test whether the price of political risk depends on the sign of global political risk innovations. In Table 2.12 we report the results of cross-sectional asset pricing tests including positive and negative political risk innovations seperately. We note that the price of political risk is very significant in case of positive innovations regardless of the methods used to compute the standard errors, while in case of negative shocks the Shanken correction of the Fama and MacBeth procedure suggests that the risk price is not significant. In other words, the pricing implication is stronger when there is an unexpected increase in global political risk either through an increase of political risk in foreign countries or a decrease in U.S. political risk. However, we think that the linear model is still a good approximation to the true risk pricing relation.

[Table 2.12 about here.]

2.7.6 Long-short Strategies

The mechanism we proposed in the asset pricing model may also be relevant for other long-short currency strategies. In order to understand better the role of political risk for currency long-short strategies, we display the relationship between currency portfolio returns and global political risk. Particularly, we sort our global political risk measure into four bins (i.e. quartiles) so that we get 25% months with the *lowest* political risk in the *first* quartile and 25% of months with the *highest* political risk in the *last* basket. Then we compute the average excess currency returns of going long the winner portfolio and short the loser portfolio for the each bin. In this way, we assess the role of global political risk in the profitability of currency portfolio strategies. Figure A8 provides a visual illustration of annualized mean momentum returns conditional on global political risk innovations for different formation periods (i.e. $f = 1, 3, 6$) and a holding period (h) of one month. The figure shows specifically that average momentum returns increase when we move from low to high political states. This pattern is less pronounced as we increase the months of the formation period. In any case, currency momentum returns are higher in periods of extreme political conditions and perform poorly under low political states indicating the significant role played by political risk in the currency market. This finding will be tested more carefully in the next section. On top of the momentum strategy, we also consider value and carry trade strategies.[31] Figure B.9 provides a visual illustration of the corresponding annualized mean returns of the value and carry trade strategy, conditional on global political risk innovations. As we can see, the increasing pattern of the average value and carry trade profitability is consistent the our intuition regarding the presence of political risk in any long-

[31] Our currency value strategy is in the same vein with other studies such as Barroso and Santa-Clara (2012); Asness et al. (2013); Menkhoff et al. (2014).

short FX strategy. However, other risk factors that price FX value/carry returns dominate the pricing ability of global political risk in case of value and carry trade strategies.[32]

2.7.7 Other Measures

We explore how the global political risk measure relates to other measures. Table B.3 presents summary statistics of uncertainty measures as well as macroeconomic and financial variables. Global political risk exhibits low correlations with the aforementioned measures with the exception of the Consumer Sentiment Index and the return on the US MSCI index where we observe an overall correlation of about 20%.

Our analysis also incorporates an alternative data of political risk. Particularly, we employ political risk data based on the IFO World Economic Survey where the participants are asked to assess how the political stability of a particular country influences foreign investors' decisions to invest in that country. The IFO is only available on a quarterly frequency starting from 1992:Q1 until the end of our sample. Figure B.10 shows that global political risk is present in currency momentum strategies with the IFO data.

Before we conclude, we finally consider alternative definitions of global political risk measure. First we include the political risk measure for all the 145 countries available in ICRG data regardless of the tradability of the currencies. Next we omit the normalization factor $\sigma_{i,t}^{\mathcal{PR}}$ in the original definition in equation 2.1. Finally we construct a measure which takes into account only the innovations to U.S. political risk ignoring the global political risk originating from foreign countries.

[32]Figure B.8 provides the corresponding results for currency momentum.

We repeat the cross-section asset pricing tests using these alternative measures and report in Figure B.4 the t-statistics of the risk price and the constant (omitting the *DOL* factor) and the cross-sectional R^2. As a benchmark, we compare the results with the original measure and see that the original model performs better in terms of significance of pricing errors, risk price and the cross-sectional explanatory power.

[FIGURE B.4 ABOUT HERE.]

2.8 Conclusions

This paper examines the role of global political risk in the currency market. We find that a novel factor capturing *unexpected* global political conditions is priced in the cross-section of currency momentum strategies. This factor demonstrates strong cross-sectional predictability beyond other factors in the literature or existing measures of limits to arbitrage.

Currency momentum is a strategy where an investor forms expectations with regards to future excess returns based on the performance of currency premia in previous periods. Specifically, the investor buys currencies that performed well over a particular past period while short-selling currencies that exhibited poor past profitability. Current asset pricing models perform poorly in explaining the cross-section of momentum returns and sheding light on economic forces that drive the currency premia that is associated with the currency momentum. This paper provides an asset pricing model that incorporates information on unanticipated movements of political risk relative to the U.S. economy, showing that it is capable of capturing a significant part of currency momentum excess returns. Intuitively, investors will demand a premium for investing on high political risk currencies, while our empirical analysis suggests that currency trader tend to take on global political risk when investing in such strategies.

Currency momentum is likely to be driven by limits to arbitrage and it is more attractive to currencies that exhibit high illiquidity, volatility, correlation and idiosyncratic volatility. We show that political risk is a natural limit to arbitrage in the FX market, and thus determines the momentum profitability even after accounting for the aforementioned variables. Therefore, it captures a unique dimension of currency premia. The results are robust after controlling for transaction costs, short-run reversals and alternative specifications.

Finally, our findings suggest that global political risk is a main driver of momentum profitability, while future research is necessary to understand how political risk affects long-short strategies in other markets.

Table 2.1. Summary Statistics of Global Political Risk

This table presents descriptive statistics of global political risk innovations ($\Delta\mathcal{PR}_t$) along with other risk factors such as innovations of global FX volatility ($\Delta\mathcal{RV}_t^{FX}$), global FX correlation ($\Delta\mathcal{RC}_t^{FX}$), global FX illiquidity ($\Delta\mathcal{L}_t^{FX}$) and changes in global CDS spreads ($\Delta\mathcal{CDS}_t$). Moreover, the table shows mean, median, standard deviation, skewness, kurtosis, minimum and maximum values. We also report first order autocorrelations (i.e. $AC(1)$), $Corr$ is the overall correlation of global political risk with all the other variables and $MaxCorr$ ($MaxCorr$) represent the corresponding maximum (minimum) correlation based on a 60-month rolling window. Figures in parenthesis display *p-values*. Currency data is collected from Datastream *via* Barclays and Reuters. We also obtain CDS spreads from Datastream and Bloomberg. The data contain monthly series from January 1985 to January 2014 with the exception of the CDS data that spans the period October 2000 to January 2014.

Panel A: All Countries					
	$\Delta\mathcal{PR}_t$	$\Delta\mathcal{RV}_t^{FX}$	$\Delta\mathcal{RC}_t^{FX}$	$\Delta\mathcal{L}_t^{FX}$	$\Delta\mathcal{CDS}_t$
$Mean$	0.00	0.00	0.00	0.00	-0.01
$Median$	0.00	-0.02	0.00	0.00	-0.01
Std	0.07	0.10	0.10	0.02	0.37
$Skew$	-0.43	2.24	0.11	1.57	0.19
$Kurt$	10.32	14.20	3.05	11.97	8.28
Min	-0.46	-0.31	-0.27	-0.07	-1.74
Max	0.35	0.75	0.33	0.10	1.73
$AC(1)$	0.09	-0.11	-0.13	-0.03	-0.01
	(0.10)	(0.04)	(0.01)	(0.56)	(0.14)
$Corr$	1.00	-0.04	-0.07	0.03	-0.01
	–	(0.49)	(0.21)	(0.52)	(0.87)
$MaxCorr$	–	0.31	0.12	0.30	0.42
$MinCorr$	–	-0.38	-0.26	-0.35	-0.22

Table 2.2. Descriptive Statistics of Cross-Sectional Momentum Portfolios

This table presents descriptive statistics of currency portfolios sorted based on cumulative excess returns over a particular formation period (f). The first (last) portfolio P_L (P_H) comprise the basket of all currencies with the lowest (highest) expected return. $\mathcal{WML}$ is a long-short strategy that buys P_H and sells P_L. Moreover, the table presents annualized mean, standard deviation and Sharpe ratios, all in percentage points. We also report skewness and kurtosis. Figures in squared brackets represent Newey and West (1987) t-statistics corrected for heteroskedasticity and autocorrelation (HAC) using the optimal number of lags as in Andrews (1991) and numbers in parenthesis are *p-values*. More specifically, *Panels A*, *B* and *C* presents descriptive statistics of momentum strategies with different formation periods (f) and a holding period (h) of one month (i.e. $\mathcal{WML}^{1,1}$, $\mathcal{WML}^{3,1}$, $\mathcal{WML}^{6,1}$). The superscript τ represents the consideration of transaction costs. The data is collected from Datastream *via* Barclays and Reuters. The data contain monthly series from January 1985 to January 2014.

	P_L	$P2$	$P3$	$P4$	$P5$	P_H	DOL	$\mathcal{WML}$	$\mathcal{WML}^\tau$
Panel A: Currency Momentum ($f = 1$, $h = 1$)									
	Currency Excess Returns								
Mean	-1.78	0.32	2.90	4.08	3.44	8.40	2.89	10.18	6.29
	[-1.00]	[0.18]	[1.57]	[2.39]	[2.14]	[3.93]	[1.85]	[5.30]	[3.37]
Std	9.35	8.96	8.39	8.30	8.58	8.83	7.35	9.63	9.58
SR	-0.19	0.04	0.35	0.49	0.40	0.95	0.39	1.06	0.66
Skew	-0.66	-1.22	-0.59	-0.50	-0.47	0.03	-0.63	0.08	0.05
Kurt	5.97	7.85	6.03	4.06	5.53	3.50	4.52	4.89	4.95
$AC(1)$	0.00	0.06	0.08	0.08	0.02	0.15	0.08	0.02	0.03
	(0.99)	(0.30)	(0.15)	(0.12)	(0.67)	(0.01)	(0.13)	(0.68)	(0.64)
Panel B: Currency Momentum ($f = 3$, $h = 1$)									
Mean	-0.79	0.85	2.09	2.97	4.51	8.05	2.94	8.84	5.20
	[-0.42]	[0.45]	[1.31]	[1.74]	[2.83]	[3.54]	[1.87]	[4.60]	[2.73]
Std	9.19	8.74	8.17	8.46	8.47	9.08	7.25	9.75	9.76
SR	-0.09	0.10	0.26	0.35	0.53	0.89	0.41	0.91	0.53
Skew	-0.51	-1.20	-0.66	-0.33	-0.52	-0.14	-0.65	-0.08	-0.11
Kurt	5.96	8.10	6.01	4.31	4.77	4.46	4.65	3.93	3.91
$AC(1)$	0.10	0.08	0.00	0.08	0.10	0.19	0.12	0.04	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Panel C: Currency Momentum ($f = 6$, $h = 1$)									
Mean	0.10	0.76	1.77	2.21	3.21	5.77	2.30	5.67	2.39
	[0.06]	[0.47]	[1.06]	[1.33]	[1.85]	[2.91]	[1.55]	[3.09]	[1.29]
Std	9.04	8.02	8.28	8.35	8.69	8.84	7.16	9.90	9.94
SR	0.01	0.09	0.21	0.26	0.37	0.65	0.32	0.57	0.24
Skew	-0.17	-0.63	-0.45	-0.45	-0.64	-0.96	-0.69	-0.43	-0.44
Kurt	5.91	6.00	4.56	4.65	5.50	7.41	4.60	3.98	3.99
$AC(1)$	0.09	0.06	0.02	0.04	0.12	0.19	0.10	0.02	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

Table 2.3. Descriptive Statistics of Time-Series Momentum Portfolios
This table presents descriptive statistics of equally-weighted time-series momentum portfolios (i.e. $TSMOM^{1,1} = \overline{CRX}$) of one month formation and holding period. *Panel A* presents annualized mean, standard deviation and Sharpe ratios, all in percentage points. We also report skewness and kurtosis of time-series momentum portfolios where τ represents payoffs that incorporate transactions costs. *Panel B* reports results of contemporaneous regressions of time-series momentum portfolio (i.e. $TSMOM^{1,1}$) on cross-sectional momentum portfolios with different formation periods (f) from one month to twelve months. Figures in squared brackets represent Newey and West (1987) t-statistics corrected for heteroskedasticity and autocorrelation (HAC) using the optimal number of lags as in Andrews (1991) and numbers in parenthesis are *p-values*. The data is collected from Datastream *via* Barclays and Reuters. The data contain monthly series from January 1985 to January 2014.

Panel A: Time-Series Momentum ($f = 1$, $h = 1$)		
	$TSMOM^{1,1}$	$TSMOM^{1,1}_{\tau}$
$Mean$	5.32	3.25
	[5.25]	[3.26]
Std	5.66	5.70
SR	0.94	0.57
$Skew$	0.25	0.27
$Kurt$	5.37	5.53
Min	-0.05	-0.06
Max	0.08	0.08
$AC(1)$	0.04	0.03
	(0.50)	(0.59)

Panel B: $TSMOM^{1,1}_t = \alpha + \beta \mathcal{WML}^{f,h}_t + \varepsilon_t$ for $f = 1, 3, 6, 9, 12$ and $h = 1$					
	$\mathcal{WML}^{1,1}$	$\mathcal{WML}^{3,1}$	$\mathcal{WML}^{6,1}$	$\mathcal{WML}^{9,1}$	$\mathcal{WML}^{12,1}$
			Without TC		
α	0.30	0.33	0.33	0.50	0.34
	[2.27]	[2.45]	[2.44]	[3.74]	[2.63]
β	1.22	0.90	0.62	0.44	0.30
	[14.96]	[10.68]	[5.19]	[3.68]	[2.42]
$\bar{R}^2$	0.52	0.26	0.11	0.05	0.02
			With TC		
α	0.20	0.19	0.14	0.30	0.12
	[1.57]	[1.39]	[1.06]	[2.12]	[0.92]
β	1.21	0.90	0.59	0.42	0.29
	[15.08]	[10.45]	[4.79]	[3.52]	[2.20]
$\bar{R}^2$	0.52	0.26	0.10	0.05	0.02

Table 2.4. Univariate Predictive Regressions

This table reports univariate predictive regressions of currency momentum returns with global political risk ($\Delta\mathcal{PR}_t$), volatility ($\Delta\mathcal{RV}_t^{FX}$), correlation ($\Delta\mathcal{RC}_t^{FX}$) and liquidity ($\Delta\mathcal{L}_t^{FX}$) innovations as well as CDS spreads ($\Delta\mathcal{CDS}_t$). NW represents Newey and West (1987) t-statistics corrected for heteroskedasticity and autocorrelation (HAC) using the optimal number of lags as in Andrews (1991). We also present R^2 for each regression and below the R^2 we present χ^2 in squared brackets. *Panel A* shows results for $\mathcal{WML}_t^{1,1}$, *Panel B* for $\mathcal{WML}_t^{3,1}$ and *Panel C* for $\mathcal{WML}_t^{6,1}$. The data is collected from Datastream *via* Barclays and Reuters. The data contain monthly series from January 1985 to January 2014 with the exception of the CDS data that spans the period October 2000 to January 2014.

	Panel A: Currency Momentum													
	cons	$\Delta\mathcal{PR}_t$	$\Delta\mathcal{RV}_t^{FX}$	$\Delta\mathcal{RC}_t^{FX}$	$\Delta\mathcal{L}_t^{FX}$	$\Delta\mathcal{CDS}_t$	R^2	*cons*	$\Delta\mathcal{PR}_t$	$\Delta\mathcal{RV}_t^{FX}$	$\Delta\mathcal{RC}_t^{FX}$	$\Delta\mathcal{L}_t^{FX}$	$\Delta\mathcal{CDS}_t$	R^2
	Cross-sectional Momentum							*Time-series Momentum*						
(a)	0.84	-4.63					0.01	0.43	-2.97					0.02
NW	[5.21]	[-2.26]					[5.13]	[5.12]	[-2.50]					[6.26]
(b)	0.84		1.56				0.00	0.43		0.20				0.00
NW	[5.30]		[0.66]				[0.44]	[5.04]		[0.13]				[0.02]
(c)	0.84			0.98			0.00	0.43			-0.01			0.00
NW	[5.27]			[0.59]			[0.35]	[5.04]			[-0.01]			[0.00]
(d)	0.84				5.97		0.00	0.43				0.14		0.00
NW	[5.28]				[0.55]		[0.31]	[5.04]				[0.02]		[0.00]
(e)	0.92					-0.33	0.00	0.51					-0.15	0.00
NW	[3.62]					[-0.40]	[0.16]	[3.87]					[-0.43]	[0.19]
	Panel B: Loser and Winner Portfolios													
	Losers							*Winners*						
(a)	-0.14	4.98					0.02	0.71	0.35					0.00
NW	[-0.91]	[2.52]					[6.34]	[3.95]	[0.21]					0.04
(b)	-0.14		-2.49				0.01	0.71		-0.93				0.00
NW	[-0.93]		[-0.84]				[0.70]	[3.96]		[-0.56]				[0.31]
(c)	-0.14			2.06			0.00	0.71			3.04			0.01
NW	[-0.94]			[1.69]			[2.85]	[4.04]			[2.06]			[4.26]
(d)	-0.14				-9.53		0.00	0.71				-3.56		0.00
NW	[-0.92]				[-1.05]		[1.09]	[3.95]				[-0.33]		[0.11]
(e)	0.02					-0.31	0.00	0.94					-0.64	0.00
NW	[0.08]					[-0.38]	[0.15]	[3.31]					[-0.99]	[0.97]

Table 2.5. Portfolios sorted on Political Risk-Betas

This table presents descriptive statistics of currency portfolios sorted on betas with global political risk innovations. The first (last) portfolio P_L (P_H) comprise the basket of all currencies with the lowest (highest) political-risk betas. $\mathcal{H}/\mathcal{L}$ is the a long-short strategy that buys P_H and sells P_L and *Avg* is the average across portfolios each time. Moreover, the table presents annualized mean, standard deviation and Sharpe ratios, all in percentage points. We also report skewness and kurtosis. Figures in squared brackets represent Newey and West (1987) t-statistics corrected for heteroskedasticity and autocorrelation (HAC) using the optimal number of lags as in Andrews (1991) and numbers in brackets are *p-values*. All currency excess returns incorporate transaction costs by taking a short position in the first portfolio and long positions in the remaining baskets of currencies. The data is collected from Datastream *via* Barclays and Reuters. The data contain monthly series from January 1985 to January 2014.

Panel A: Conditional Excess Returns								
Portfolios	P_L	$P2$	$P3$	$P4$	$P5$	P_H	Avg	$\mathcal{H}/\mathcal{L}$
	Global Political Risk Innovations							
$Mean$	2.75	2.36	4.02	4.16	4.82	6.88	4.17	4.13
	[2.20]	[1.82]	[3.57]	[3.66]	[3.11]	[3.87]	[4.29]	[2.33]
Std	6.68	6.23	5.55	6.74	7.19	8.07	4.97	8.00
SR	0.41	0.38	0.72	0.62	0.67	0.85	0.84	0.52
$Skew$	0.64	0.95	1.24	0.56	1.37	0.33	0.78	0.71
$Kurt$	5.79	8.01	9.78	7.05	10.08	4.38	6.48	7.17
$AC(1)$	-0.06	0.18	0.03	0.03	0.01	0.08	0.10	-0.06
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
pre-β	-0.05	-0.01	0.01	0.03	0.04	0.11		
$post$-β	-0.05	-0.01	0.01	0.03	0.05	0.11		

Table 2.6. FX Asset Pricing Tests: *Factor-Mimicking Portfolio*

This table reports asset pricing results for the two-factor model that comprises the DOL and $\mathcal{FPR}$ risk factors. We use as test assets six currency portfolios sorted based on past performances of currency returns. Particularly, we employ formation periods of 1, 3 and 6 months. We rebalance our portfolios on a monthly basis. *Panel A* reports GMM_1, GMM_2 as well as Fama and MacBeth (1973) estimates of the factor loadings (b) and factor prices of risk (λ). We also display Newey and West (1987) standard errors (in parenthesis) or t-statistics (in squared brackets) corrected for autocorrelation and heteroskedasticity with Andrews (1991) optimal lag selection and Sh are the corresponding values of Shanken (1992). The table also shows χ^2, cross-sectional R^2, HJ distance following Hansen and Jagannathan (1997) as well as a generalized version of the cross-sectional F-test statistic of Shanken (1985) ($CSRT_{SH}$). We report *p-values* in curly brackets. *Panel B* reports OLS estimates of contemporaneous time-series regression with HAC standard errors in parenthesis. We do not control for transaction costs and excess returns are expressed in percentage points. The data are collected from Datastream *via* Barclays and Reuters. The data contain monthly series from January 1985 to January 2014.

Panel A: Factor Prices

Momentum ($f=1, h=1$)

	b_{DOL}	$b_{\mathcal{FPR}}$	λ_{DOL}	$\lambda_{\mathcal{FPR}}$	R^2	χ^2	HJ dist
GMM_1	0.07	0.44	0.24	0.22	0.99	2.91	0.03
s.e.	(0.09)	(0.17)	(0.13)	(0.05)		{0.57}	{0.94}
GMM_2	0.07	0.45	0.26	0.23		3.25	
s.e.	(0.11)	(0.19)	(0.13)	(0.05)		{0.52}	
	cons	λ_{DOL}	$\lambda_{\mathcal{FPR}}$	χ^2_{NW}	χ^2_{SH}		
FMB		0.24	0.22	3.17	2.85		
(Sh)		(0.11)	(0.04)	(0.67)	{0.72}		
(NW)		(0.11)	(0.04)				
$FMBc$	0.02	2.11	0.18	$CSRT_{SH}$	0.18		
$[Sh]$	[-0.68]	[0.76]	[2.35]		[0.89]		
$[NW]$	[-0.99]	[1.11]	[3.01]				

Momentum ($f=3, h=1$)

	b_{DOL}	$b_{\mathcal{FPR}}$	λ_{DOL}	$\lambda_{\mathcal{FPR}}$	R^2	χ^2	HJ dist
GMM_1	0.07	0.20	0.25	0.35	0.66	10.12	0.05
s.e.	(0.10)	(0.13)	(0.13)	(0.09)		{0.04}	{0.73}
GMM_2	0.07	0.15	0.24	0.26		11.09	
s.e.	(0.03)	(0.03)	(0.12)	(0.08)		{0.03}	
	cons	λ_{DOL}	$\lambda_{\mathcal{FPR}}$	χ^2_{NW}	χ^2_{SH}		
FMB		0.25	0.35	18.69	17.26		
(Sh)		(0.11)	(0.08)	(0.00)	{0.00}		
(NW)		(0.11)	(0.08)				
$FMBc$	-0.01	1.47	0.27	$CSRT_{SH}$	2.54		
$[Sh]$	[-0.76]	[0.91]	[2.66]		[0.04]		
$[NW]$	[-0.95]	[1.13]	[2.94]				

Momentum ($f=6, h=1$)

	b_{DOL}	$b_{\mathcal{FPR}}$	λ_{DOL}	$\lambda_{\mathcal{FPR}}$	R^2	χ^2	HJ dist
GMM_1	0.06	0.25	0.23	0.09	0.86	7.61	0.04
s.e.	(0.10)	(0.21)	(0.13)	(0.03)		{0.11}	{0.77}
GMM_2	0.06	0.25	0.23	0.09		7.85	
s.e.	(0.16)	(0.14)	(0.13)	(0.03)		{0.10}	
	cons	λ_{DOL}	$\lambda_{\mathcal{FPR}}$	χ^2_{NW}	χ^2_{SH}		
FMB		0.23	0.09	14.48	13.97		
(Sh)		(0.11)	(0.03)	(0.01)	{0.02}		
(NW)		(0.11)	(0.03)				
$FMBc$	0.04	-3.48	0.29	$CSRT_{SH}$	0.20		
$[Sh]$	[1.70]	[-1.59]	[2.37]		[0.87]		
$[NW]$	[1.50]	[-1.40]	[2.02]				

Panel B: Factor Betas

	α	β_{DOL}	$\beta_{\mathcal{FPR}}$	R^2
P_L	-0.15	0.94	-1.64	0.81
	(0.07)	(0.04)	(0.14)	
P_2	0.03	0.99	-0.97	0.78
	(0.06)	(0.05)	(0.14)	
P_3	0.24	1.01	-0.33	0.82
	(0.06)	(0.04)	(0.09)	
P_4	0.34	1.02	0.28	0.80
	(0.06)	(0.04)	(0.10)	
P_5	0.29	1.00	0.54	0.73
	(0.07)	(0.04)	(0.14)	
P_H	0.70	1.03	2.05	0.95
	(0.04)	(0.02)	(0.06)	

	α	β_{DOL}	$\beta_{\mathcal{FPR}}$	R^2
P_L	-0.07	0.96	-0.16	0.58
	(0.09)	(0.08)	(0.11)	
P_2	0.07	0.96	-0.79	0.85
	(0.05)	(0.03)	(0.05)	
P_3	0.17	0.98	-0.46	0.85
	(0.04)	(0.03)	(0.05)	
P_4	0.25	1.06	0.10	0.81
	(0.07)	(0.04)	(0.05)	
P_5	0.38	1.03	0.60	0.83
	(0.06)	(0.04)	(0.05)	
P_H	0.67	1.03	0.72	0.75
	(0.09)	(0.04)	(0.07)	

	α	β_{DOL}	$\beta_{\mathcal{FPR}}$	R^2
P_L	0.02	0.88	-2.45	0.92
	(0.05)	(0.03)	(0.12)	
P_2	0.12	0.91	-1.08	0.81
	(0.06)	(0.03)	(0.14)	
P_3	0.19	0.97	-0.29	0.79
	(0.05)	(0.03)	(0.11)	
P_4	0.20	1.06	0.77	0.82
	(0.06)	(0.04)	(0.10)	
P_5	0.21	1.09	1.21	0.85
	(0.06)	(0.03)	(0.10)	
P_H	0.63	1.06	1.87	0.81
	(0.08)	(0.04)	(0.14)	

Table 2.7. FX Asset Pricing Tests: *Global Political Risk Innovations*
This table reports asset pricing results for the two-factor model that comprises the DOL and $\Delta\mathcal{PR}$ risk factors. We use as test assets six currency portfolios sorted based on past performances of currency returns. Particularly, we employ formation periods of 1, 3 and 6 months. We rebalance our portfolios on a monthly basis. *Panel A* reports Fama and MacBeth (1973) estimates of the factor loadings (b) and factor prices of risk (λ). We also display Newey and West (1987) standard errors (in parenthesis) or t-statistics (in squared brackets) corrected for autocorrelation and heteroskedasticity with Andrews (1991) optimal lag selection and Sh are the corresponding values of Shanken (1992). The table also shows χ^2, cross-sectional R^2, HJ distance following Hansen and Jagannathan (1997) as well as a generalized version of the cross-sectional F-test statistic of Shanken (1985) ($CSRT_{SH}$). We report *p-values* in curly brackets. We do not control for transaction costs and excess returns are expressed in percentage points.The data are collected from Datastream *via* Barclays and Reuters. The data contain monthly series from January 1985 to January 2014.

Panel A: Factor Prices									
	$cons$	λ_{DOL}	$\lambda_{\Delta\mathcal{PR}}$	χ^2_{NW}	χ^2_{SH}	χ^2_{GMM1}	χ^2_{GMM2}	R^2	HJ dist
				$Momentum$ $(f=1, h=1)$					
FMB		0.23	0.25	3.17	0.27	0.33	0.35	0.99	0.03
(NW)		(0.11)	(0.05)	{0.67}	{0.99}	{0.98}	{0.99}		{0.94}
(Sh)		(0.11)	(0.14)						
$FMBc$	-0.02	2.10	0.29	$CSRT_{SH}$	0.06	0.97			
$[NW]$	[−0.99]	[1.11]	[4.67]						
				$Momentum$ $(f=3, h=1)$					
FMB		0.24	0.11	8.69	5.69	5.04	5.38	0.66	0.05
(NW)		(0.11)	(0.05)	{0.28}	{0.34}	{0.28}	{0.25}		{0.74}
(Sh)		(0.11)	(0.04)						
$FMBc$	-0.01	1.47	0.11	$CSRT_{SH}$	0.14	{0.20}			
$[NW]$	[−0.95]	[1.13]	[4.30]						
				$Momentum$ $(f=6, h=1)$					
FMB		0.21	0.14	4.48	3.27	1.59	1.80	0.86	0.04
(NW)		(0.11)	(0.05)	{0.63}	{0.66}	{0.81}	{0.77}		{0.91}
(Sh)		(0.11)	(0.10)						
$FMBc$	0.04	-3.52	0.26	$CSRT_{SH}$	0.12	{0.94}			
$[NW]$	[3.33]	[−3.13]	[4.27]						

Table 2.8. Double Sorts

This table reports annualized average conditional excess returns for double-sorted portfolios. All currencies are first sorted on lagged idiosyncratic volatility (*Panel A*) or idiosyncratic skewness (*Panel B*) or exposures to global FX illiquidity (*Panel C*) or global FX volatility (*Panel D*) or global FX correlation (*Panel E*) into two portfolios based on their median. Then, currencies within each of the two portfolios are sorted into three portfolios based on their previous month exposure to global political risk. Thus, *Low* and *High* denote the 33% (50%) of all the currencies with lowest and highest lagged returns (lagged *IV*, or *IS*, or *Illiq*, or *Vol*, or *Corr*) and *Med* represents the 33% of all the currencies with intermediate lagged returns. HML is a spread portfolio that is equal to the return difference between *High* and *Low* portfolios. We also display Newey and West (1987) t-statistics (in squared brackets) corrected for autocorrelation and heteroskedasticity with Andrews (1991) optimal lag selection. The data are collected from Datastream *via* Barclays and Reuters and contain monthly series from January 1985 to January 2014.

Panel A: Idiosyncratic Volatility (LRV model)				
	Low PR	*Med PR*	*High PR*	HML
Low IV	0.84	3.18	3.89	3.05
	[0.85]	[4.87]	[2.18]	[2.17]
High IV	2.81	7.06	7.00	4.19
	[1.20]	[3.58]	[3.73]	[1.22]
HML	1.97	3.88	3.11	1.14
	[0.36]	[2.45]	[0.53]	[0.45]
Panel B: Idiosyncratic Skewness (LRV model)				
	Low PR	*Med PR*	*High PR*	HML
Low IS	0.56	5.38	5.89	5.33
	[0.36]	[4.32]	[3.44]	[2.63]
High IS	2.99	4.52	5.03	2.03
	[2.51]	[3.88]	[2.69]	[1.53]
HML	2.43	-0.86	-0.86	-3.29
	[1.71]	[-0.72]	[-0.04]	[-1.23]
Panel C: FX Illiquidity Innovations				
	Low PR	*Med PR*	*High PR*	HML
Low Illiq	1.05	4.65	5.79	4.74
	[0.84]	[4.38]	[3.85]	[2.59]
High Illiq	1.70	4.97	4.57	2.87
	[1.11]	[3.14]	[2.34]	[1.45]
HML	0.64	0.32	-1.22	-1.86
	[0.63]	[0.24]	[-0.85]	[-0.90]
Panel D: FX Volatility Innovations				
	Low PR	*Med PR*	*High PR*	HML
Low Vol	0.15	4.24	3.94	3.79
	[0.15]	[3.48]	[2.87]	[2.11]
High Vol	3.46	5.84	8.15	4.69
	[2.16]	[3.31]	[3.05]	[1.78]
HML	3.30	1.61	4.20	0.90
	[1.82]	[0.96]	[1.64]	[0.80]
Panel E: FX Correlation Innovations				
	Low PR	*Med PR*	*High PR*	HML
Low Corr	2.65	5.40	4.64	1.99
	[1.31]	[3.28]	[2.70]	[0.60]
High Corr	0.05	4.23	6.52	6.48
	[0.04]	[3.80]	[2.90]	[2.05]
HML	-2.60	-1.17	1.89	4.49
	[0.49]	[0.29]	[0.85]	[0.33]

Table 2.9. Robustness: *Asset Pricing Tests - Filtered Data*

This table reports asset pricing results for the two-factor model that comprises the DOL and $\mathcal{FPR}$ risk factors. We use as test assets six currency portfolios sorted based on past performances of currency returns. We rebalance our portfolios on a monthly basis. *Panel A* reports Fama and MacBeth (1973) estimates of the factor loadings (b) and factor prices of risk (λ). We also display Newey and West (1987) standard errors (in parenthesis) or t-statistics (in squared brackets) corrected for autocorrelation and heteroskedasticity with Andrews (1991) optimal lag selection and Sh are the corresponding values of Shanken (1992). The table also shows χ^2, cross-sectional R^2, HJ distance following Hansen and Jagannathan (1997) as well as a generalized version of the cross-sectional F-test statistic of Shanken (1985) ($CSRT_{SH}$). We report *p-values* in curly brackets. We do not control for transaction costs and excess returns are expressed in percentage points. The data are collected from Datastream *via* Barclays and Reuters. The data contain monthly series from January 1985 to January 2014.

	Panel A: Factor Prices (33 countries)								
	$cons$	λ_{DOL}	$\lambda_{\mathcal{FPR}}$	χ^2_{NW}	χ^2_{SH}	χ^2_{GMM1}	χ^2_{GMM2}	R^2	HJ dist
				$Momentum$ $(f=1, h=1)$					
FMB		0.15	0.23	7.59	7.23	6.52	6.61	0.89	0.06
(NW)		(0.11)	(0.07)	{0.18}	{0.20}	{0.16}	{0.16}		{0.60}
(Sh)		(0.11)	(0.07)						
$FMBc$	-0.01	0.93	0.19	$CSRT_{SH}$	1.32	{0.20}			
$[NW]$	[−0.87]	[1.03]	[2.28]						
				$Momentum$ $(f=3, h=1)$					
FMB		0.12	0.16	14.46	14.03	10.11	10.06	0.92	0.10
(NW)		(0.11)	(0.07)	{0.01}	{0.02}	{0.04}	{0.04}		{0.14}
(Sh)		(0.11)	(0.07)						
$FMBc$	0.02	-1.50	0.36	$CSRT_{SH}$	0.59	{0.57}			
$[NW]$	[3.10]	[−2.77]	[3.32]						
	Panel B: Factor Prices (39 countries)								
	$cons$	λ_{DOL}	$\lambda_{\mathcal{FPR}}$	χ^2_{NW}	χ^2_{SH}	χ^2_{GMM1}	χ^2_{GMM2}	R^2	HJ dist
				$Momentum$ $(f=1, h=1)$					
FMB		0.12	0.23	7.98	7.62	4.96	5.01	0.79	0.10
(NW)		(0.11)	(0.07)	{0.16}	{0.18}	{0.29}	{0.24}		{0.28}
(Sh)		(0.11)	(0.07)						
$FMBc$	0.00	-0.02	0.24	$CSRT_{SH}$	1.57	{0.15}			
$[NW]$	[0.26]	[−0.03]	[3.24]						
				$Momentum$ $(f=3, h=1)$					
FMB		0.11	0.15	9.32	9.00	7.52	7.75	0.92	0.06
(NW)		(0.11)	(0.05)	{0.10}	{0.11}	{0.11}	{0.10}		{0.66}
(Sh)		(0.11)	(0.05)						
$FMBc$	0.02	-2.18	0.33	$CSRT_{SH}$	0.34	{0.76}			
$[NW]$	[2.43]	[−2.28]	[3.53]						

Table 2.10. Robustness: *Asset Pricing Tests - Transaction Costs*
This table reports asset pricing results for the two-factor model that comprises the DOL and $\mathcal{FPR}$ risk factors. We use as test assets six currency portfolios sorted based on past performances of currency returns. Particularly, we employ formation periods of 1, 3, 9 and 12 months. We rebalance our portfolios on a monthly basis. *Panel A* reports Fama and MacBeth (1973) estimates of the factor loadings (b) and factor prices of risk (λ). We also display Newey and West (1987) standard errors (in parenthesis) or t-statistics (in squared brackets) corrected for autocorrelation and heteroskedasticity with Andrews (1991) optimal lag selection and Sh are the corresponding values of Shanken (1992). The table also shows χ^2, cross-sectional R^2, HJ distance following Hansen and Jagannathan (1997) as well as a generalized version of the cross-sectional F-test statistic of Shanken (1985) ($CSRT_{SH}$). We control for transaction costs and excess returns are expressed in percentage points. We report *p-values* in curly brackets. The data are collected from Datastream *via* Barclays and Reuters. The data contain monthly series from January 1985 to January 2014.

	Panel A: Factor Prices								
	$cons$	λ_{DOL}	$\lambda_{\mathcal{FPR}}$	χ^2_{NW}	χ^2_{SH}	χ^2_{GMM1}	χ^2_{GMM2}	R^2	HJ dist
				$Momentum$ $(f=1, h=1)$					
FMB		0.15	0.14	6.31	5.97	5.59	6.03	0.90	0.03
(NW)		(0.11)	(0.04)	{0.28}	{0.31}	{0.23}	{0.20}		{0.96}
(Sh)		(0.11)	(0.04)						
$FMBc$	0.02	-1.53	0.18	$CSRT_{SH}$	0.87	{0.39}			
$[NW]$	[0.93]	[−0.84]	[2.87]						
				$Momentum$ $(f=3, h=1)$					
FMB		0.15	0.28	7.34	6.95	4.16	4.28	0.81	0.05
(NW)		(0.11)	(0.08)	{0.20}	{0.22}	{0.38}	{0.37}		{0.80}
(Sh)		(0.11)	(0.08)						
$FMBc$	0.01	-0.76	0.34	$CSRT_{SH}$	0.82	{0.42}			
$[NW]$	[0.71]	[−0.58]	[3.34]						
				$Momentum$ $(f=6, h=1)$					
FMB		0.14	0.04	14.60	14.46	7.11	7.37	0.45	0.04
(NW)		(0.11)	(0.03)	{0.01}	{0.01}	{0.13}	{0.12}		{0.80}
(Sh)		(0.11)	(0.03)						
$FMBc$	0.03	-2.68	0.18	$CSRT_{SH}$	0.61	{0.55}			
$[NW]$	[2.28]	[−2.16]	[2.45]						

Table 2.11. Robustness: *Asset Pricing Tests - Reversals*

This table reports asset pricing results for the two-factor model that comprises the DOL and $\mathcal{CFPR}$ risk factors. We use as test assets six currency portfolios sorted based on past performances of currency returns. Particularly, we employ formation periods of 1, 3, 6, 9 and 12 months. We rebalance our portfolios on a monthly basis. *Panel A* reports Fama and MacBeth (1973) estimates of the factor loadings (b) and factor prices of risk (λ). We also display Newey and West (1987) standard errors (in parenthesis) or t-statistics (in squared brackets) corrected for autocorrelation and heteroskedasticity with Andrews (1991) optimal lag selection and Sh are the corresponding values of Shanken (1992). The table also shows χ^2, cross-sectional R^2, HJ distance following Hansen and Jagannathan (1997) as well as a generalized version of the cross-sectional F-test statistic of Shanken (1985) ($CSRT_{SH}$). We report *p-values* in curly brackets. We do not control for transaction costs and excess returns are expressed in percentage points. The data are collected from Datastream *via* Barclays and Reuters. The data contain monthly series from January 1985 to January 2014.

Panel A: Factor Prices									
	cons	λ_{DOL}	$\lambda_{\mathcal{CFPR}}$	χ^2_{NW}	χ^2_{SH}	χ^2_{GMM1}	χ^2_{GMM2}	R^2	HJ dist
				$Momentum$ $(f=1, h=1)$					
FMB		0.24	0.21	3.40	3.05	3.08	3.58	0.98	0.03
(NW)		(0.11)	(0.04)	{0.64}	{0.69}	{0.54}	{0.47}		{0.94}
(Sh)		(0.11)	(0.04)						
$FMBc$	-0.02	2.01	0.18	$CSRT_{SH}$	0.22	{0.86}			
$[NW]$	[-0.94]	[1.06]	[3.27]						
				$Momentum$ $(f=3, h=1)$					
FMB		0.25	0.34	19.00	17.55	10.24	11.58	0.65	0.05
(NW)		(0.11)	(0.08)	{0.00}	{0.00}	{0.04}	{0.02}		{0.74}
(Sh)		(0.11)	(0.08)						
$FMBc$	-0.01	1.52	0.27	$CSRT_{SH}$	2.53	{0.04}			
$[NW]$	[-0.98]	[1.16]	[2.94]						
				$Momentum$ $(f=6, h=1)$					
FMB		0.23	0.10	14.64	14.13	7.57	7.77	0.86	0.04
(NW)		(0.11)	(0.04)	{0.01}	{0.01}	{0.11}	{0.10}		{0.79}
(Sh)		(0.11)	(0.04)						
$FMBc$	0.04	-3.64	0.25	$CSRT_{SH}$	0.18	{0.89}			
$[NW]$	[3.42]	[-3.20]	[4.33]						

Table 2.12. Robustness: *Asset Pricing Tests - Non-linearity*

This table reports asset pricing results for the two-factor model that comprises the DOL and positive or negative values of global political risk (i.e. $\Delta\mathcal{PR}^{+}$, $\Delta\mathcal{PR}^{-}$) as risk factors. We use as test assets six currency portfolios sorted based on past month's performances of currency returns (i.e. $f = 1$). *Panel A* reports Fama and MacBeth (1973) estimates of the factor loadings (b) and factor prices of risk (λ). We also display Newey and West (1987) standard errors (in parenthesis) or t-statistics (in squared brackets) corrected for autocorrelation and heteroskedasticity with Andrews (1991) optimal lag selection and Sh are the corresponding values of Shanken (1992). The table also shows χ^2, cross-sectional R^2, HJ distance following Hansen and Jagannathan (1997) as well as a generalized version of the cross-sectional F-test statistic of Shanken (1985) ($CSRT_{SH}$). We report *p-values* in curly brackets. We also report results without the DOL factor. We do not control for transaction costs and excess returns are expressed in percentage points.The data are collected from Datastream *via* Barclays and Reuters. The data contain monthly series from January 1985 to January 2014.

Panel A: Factor Prices - $\Delta\mathcal{PR}^{+}$									
	cons	λ_{DOL}	$\lambda_{\mathcal{CFPR}}$	χ^2_{NW}	χ^2_{SH}	χ^2_{GMM1}	χ^2_{GMM2}	R^2	HJ dist
				Momentum ($f = 1, h = 1$)					
FMB		0.25	9.87	20.96	3.62	3.01	2.43	0.79	0.03
(NW)		(0.11)	(1.98)	{0.00}	{0.61}	{0.56}	{0.66}		{0.94}
(Sh)		(0.11)	(4.74)						
$FMBc$	0.35		9.46	$CSRT_{SH}$	1.36	{0.33}			
$[Sh]$	[1.34]		[2.10]						
Panel B: Factor Prices - $\Delta\mathcal{PR}^{-}$									
	cons	λ_{DOL}	$\lambda_{\mathcal{CFPR}}$	χ^2_{NW}	χ^2_{SH}	χ^2_{GMM1}	χ^2_{GMM2}	R^2	HJ dist
				Momentum ($f = 1, h = 1$)					
FMB		0.21	24.61	19.56	0.75	1.55	1.96	0.54	0.03
(NW)		(0.11)	(4.37)	{0.00}	{0.98}	{0.82}	{0.74}		{0.95}
(Sh)		(0.12)	(22.28)						
$FMBc$	0.19		24.34	$CSRT_{SH}$	0.41	{0.84}			
$[Sh]$	[0.33]		[1.11]						

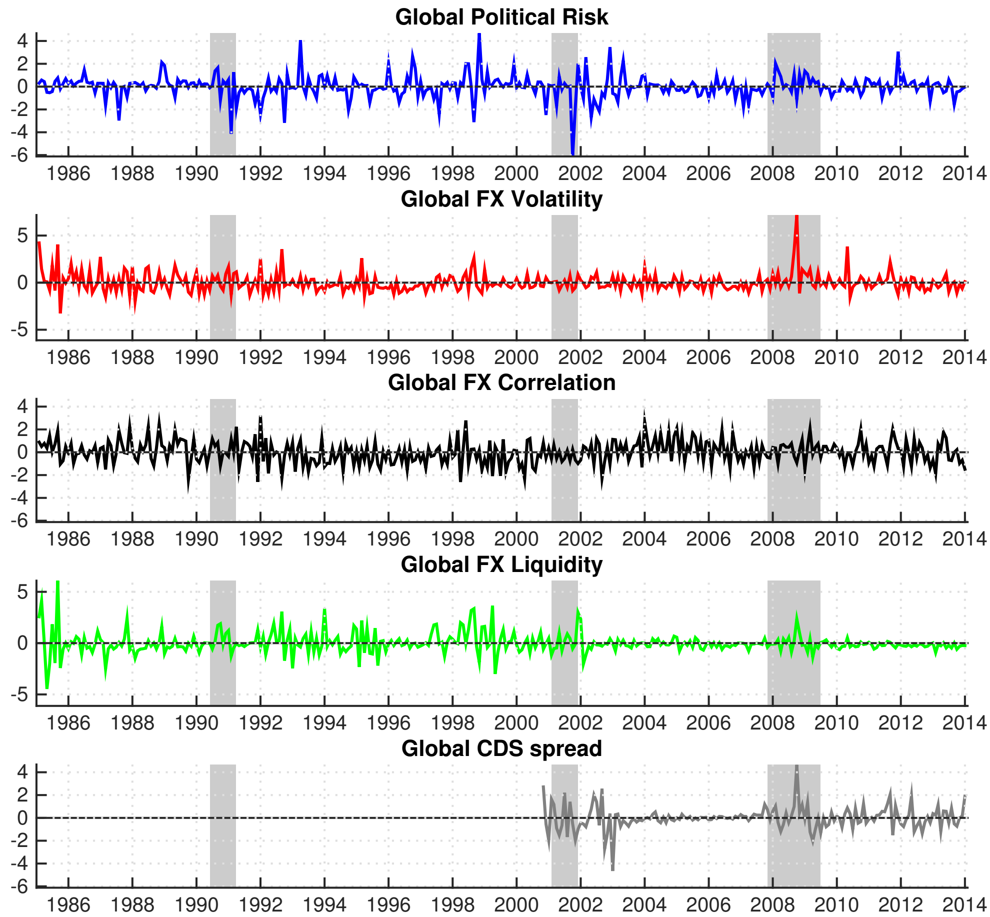


Figure 2.1. Global Political Risk

The figure presents global political risk, global FX volatility, global FX liquidity, global FX liquidity innovations as well as global CDS spreads. All measures are estimated in a similar fashion for consistency and they are standardised. The political risk data is collected from International Country Risk Guide (ICRG), the CDS spreads are obtained from Datastream and Bloomberg and exchange rates are collected from Datastream *via* Barclays and Reuters. The data contain monthly series from January 1985 to January 2014.

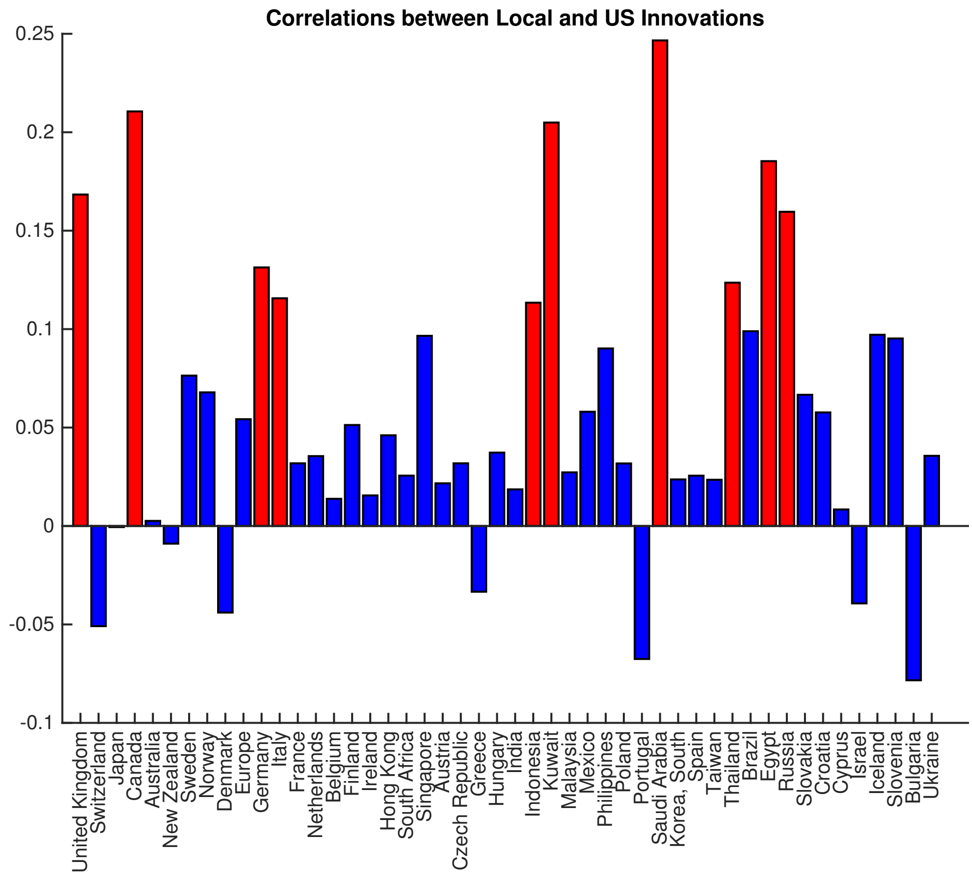


Figure 2.2. Correlations of US and Foreign Political Risk Innovations

The figure shows correlations between US and foreign country political risk innovations ($\Delta pr_{i,t}$). Bars in red represent statistically significant correlations at 0.05 significance level. The data contain monthly series from January 1985 to January 2014.

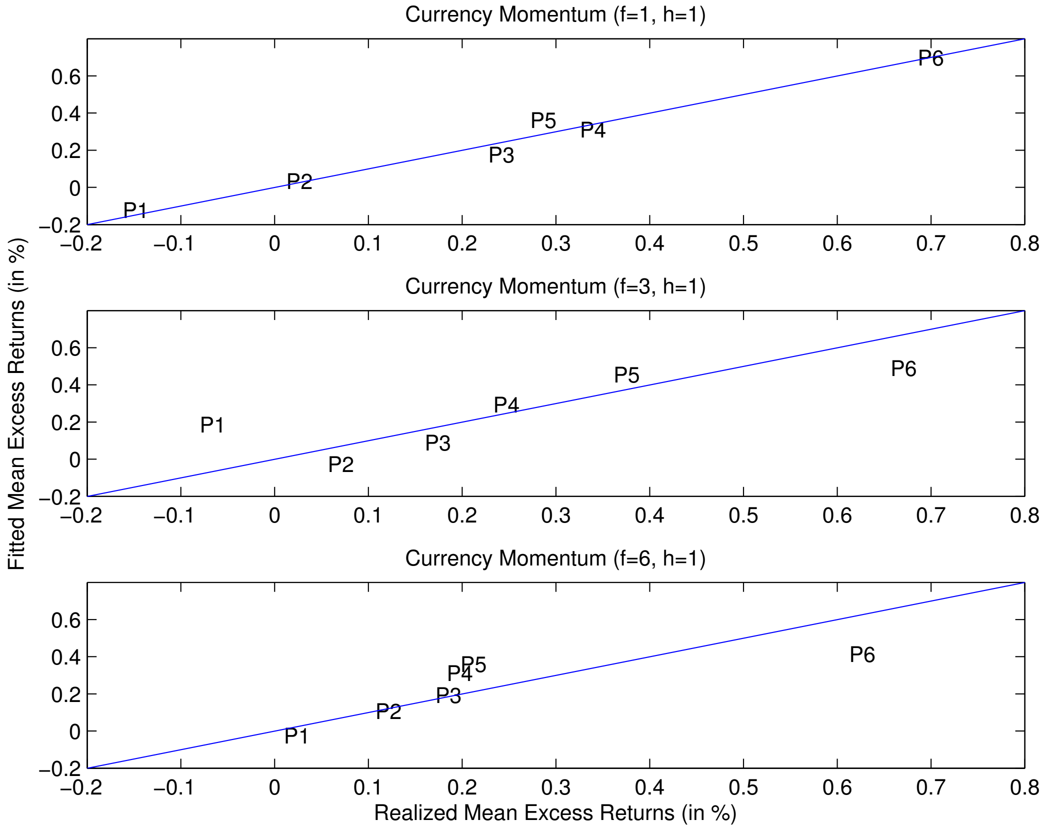


Figure 2.3. Pricing Error Plots - *Portfolio Level*

The figure displays pricing error plots for the asset pricing models with the DOL as well as the mimicking portfolio of global political risk innovations as the risk factor. We report result for thee currency momentum strategy (i.e. $f = 1, 3, 6$). The data contain monthly series from January 1985 to January 2014.

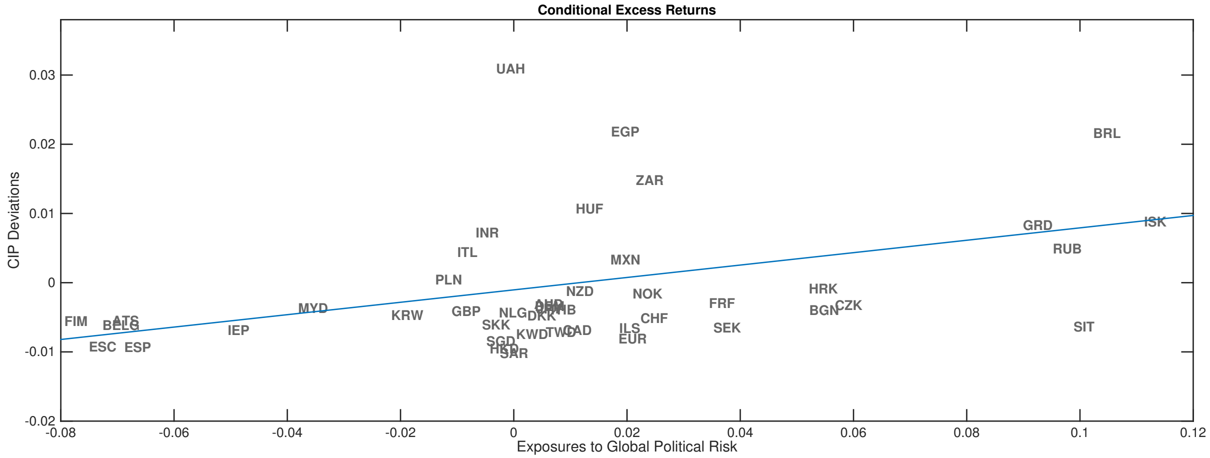


Figure 2.4. CIP deviations and Global Political Risk Betas

The figure displays CIP deviations along with global political risk exposures for each country in the sample. The data contain monthly series from January 1985 to January 2014.

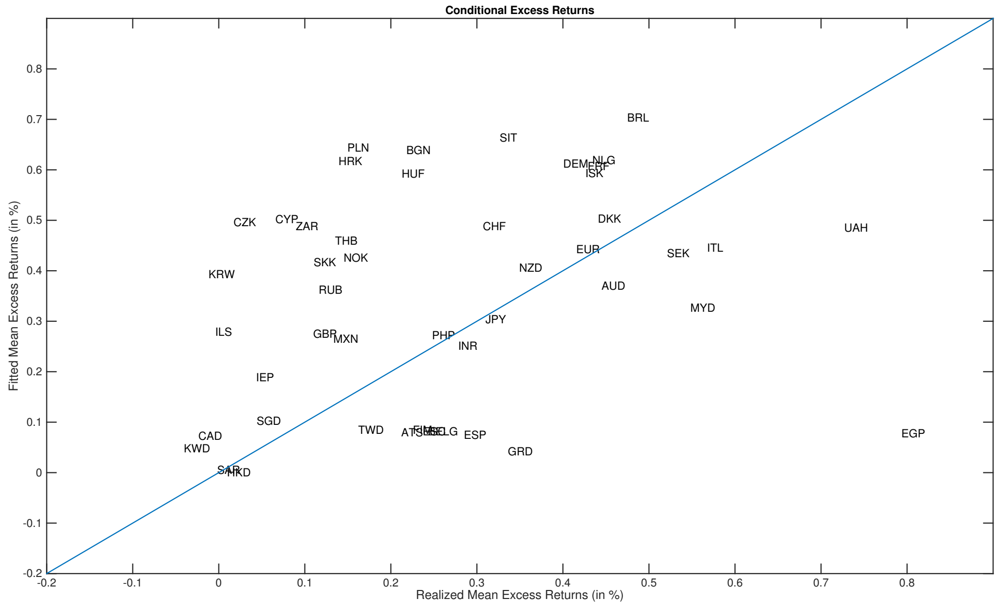


Figure 2.5. Pricing Error Plots - *Currency Level*

The figure displays pricing error plots for the asset pricing models with the DOL as well as the mimicking portfolio of global political risk innovations as the risk factor. We report result for tfor individual unconditional and conditional currency excess returns. The data contain monthly series from January 1985 to January 2014.

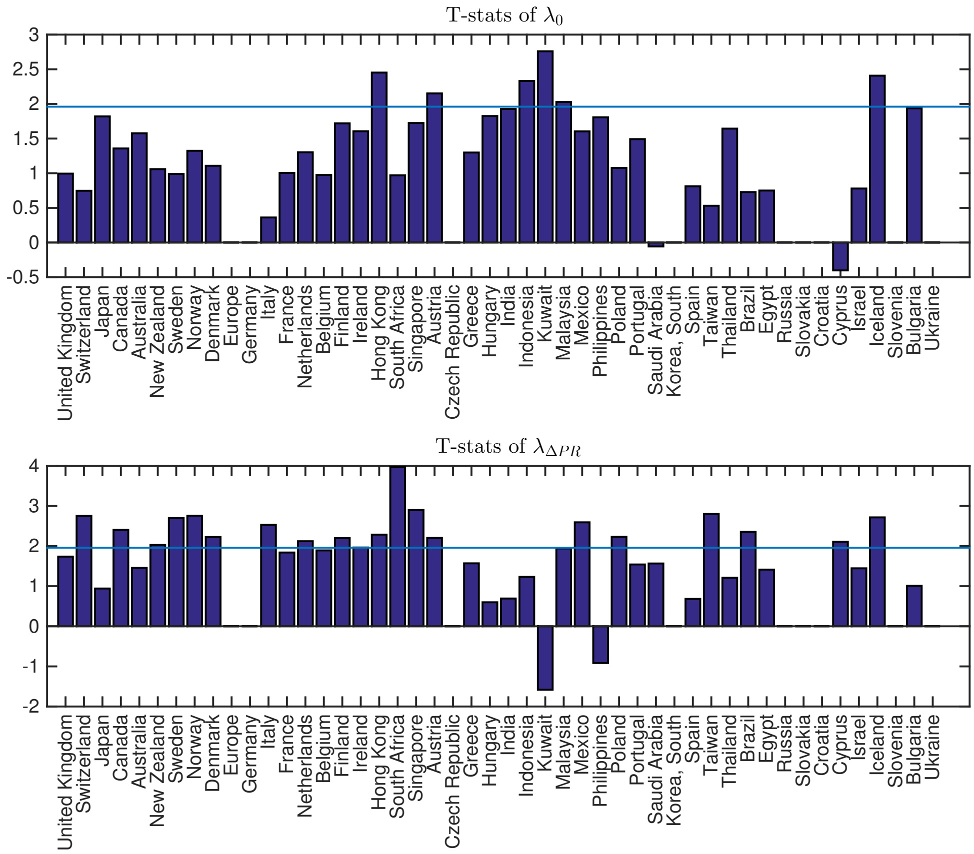


Figure 2.6. Cross-sectional t-statistics - *Country Level*

The figure displays t-statistics of zero-beta rates and risk premia. The test assets are currency portfolios sorted on previous months performance (i.e. momentum ($f = 1$, $h = 1$)) and the risk factors is innovations of country-level political risk against the US. All t-stats take into consideration the error-in-variable problem following Jagannathan and Wang (1998). The blue horizontal line corresponds to the 1.96 significance bound. The data contain monthly series from January 1985 to January 2014.

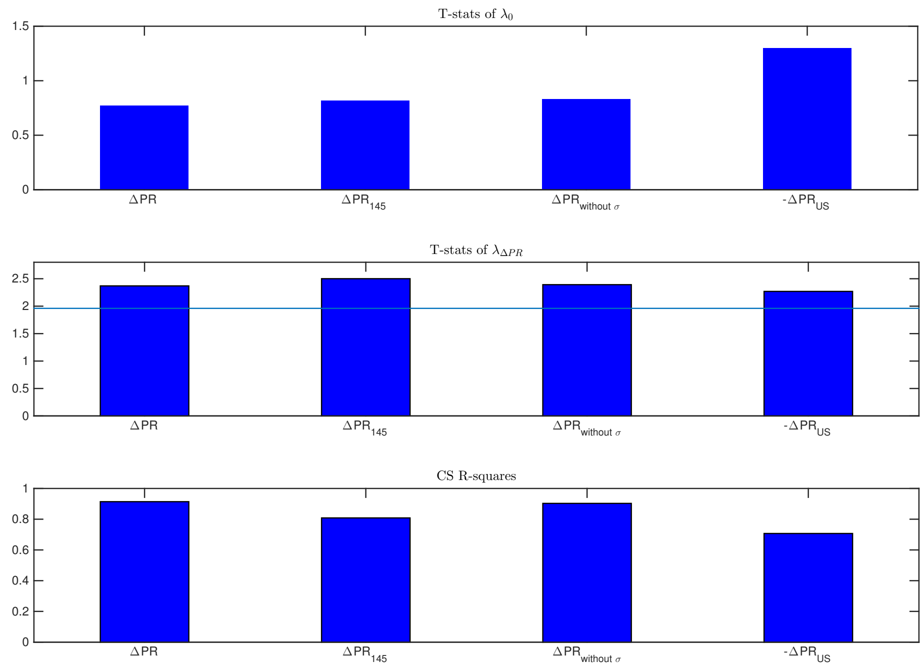


Figure 2.7. Cross-sectional t-statistics - *Alternative Definitions of Political Risk*

The figure reports t-stats of zero-beta rates, risk premia and the corresponding R^2. Test assets are currency portfolios sorted on previous months performance. As risk factors we employ different definitions of political risk. Particularly, ΔPR is the main measure used in the paper, ΔPR_{145} considers all the 145 countries of the ICRG dataset, $\Delta PR_{without\sigma}$ excludes the denominator of the original measure and ΔPR_{US} reports US political risk innovations. All t-stats take into consideration the error-in-variable problem following Jagannathan and Wang (1998). The blue horizontal line corresponds to 1.96 significance bound. The data contain monthly series from January 1985 to January 2014.

Chapter 3

Technology Diffusion and Currency Carry Trades

3.1 Introduction

We study the role of technology diffusion in carry trade strategies. Carry trade is a foreign exchange strategy that exploits deviations from the Uncovered interest rate parity (UIP). According to the UIP under conditions of risk neutrality and rational expectations the differences in the yields of foreign and domestic risk-free securities (i.e. government bonds) must be offset by an analogous depreciation of the high interest rate currency so that the aforementioned equilibrium condition is not violated. However, many studies have documented the empirical rejection of the UIP (see e.g. Bilson, 1981; Fama, 1984). Deviations from the UIP are associated with a *time-varying* risk premium that can be exploited in *real-time* by investors in the foreign exchange rate market via a naive strategy that exploits the persistent differences of the interest rates across countries the so-called currency carry trade. The currency carry trade strategy involves a long position in a basket of *high* interest rate currencies (i.e. funding currencies) while short-selling *low* interest rate currency portfolios (i.e. investment currencies).

Recent advances in the literature, along these lines, suggest that the carry trade profitability is related to a risk premium acquired by foreign exchange investors who seek to compensate themselves for adverse movements of the exchange rate under bad states of the world. Therefore, Lustig and Verdelhan (2007) as well as Lustig et al. (2011) are the first who follow this approach and develop the first asset-pricing model in the foreign exchange literature. Particularly, they show that two tradable risk factors that are highly correlated with the first two principal components of currency portfolios, sorted on interest rate differentials, are enough to price the cross-section of currency returns. The first risk factor resembles a strategy that invests in a basket of all available currencies each time and liquidates its position by borrowing the dollar. This strategy is mainly driven by the U.S. business cycle (Lustig et al., 2014) thus it is labeled as a dollar factor (i.e. DOL). This factor is highly correlated with the first principal component of the currency portfolios of interest and it represents a level factor. The second risk factor mirrors the traditional version of the carry trade strategy and thus it invests in a basket of high interest rate currencies and borrows from the bottom portfolio. This factor is highly correlated with the second principal component (i.e. slope factor) and it is named as carry factor (i.e. HML_{FX}).

A concern that one might raise regarding this asset-pricing model is related to the unobserved dynamics of the carry factor (i.e. financial or macroeconomic exposures). More precisely, how is the HML factor related to volatility, liquidity, political risk, foreign exchange risk, external imbalances, business cycle, output, degree of risk aversion, sentiment etc.? What other country- level or global features of this factor should be linked to its cross-sectional success in pricing currency returns? Many researchers have attempted to answer some of these questions and provide more insights about the carry trade strategy. For example, Menkhoff et al. (2012a) show that a global *volatility* factor along with a dollar factor demonstrates strong pricing ability for interest rate sorted portfolios. To this end, they show that high interest rate currencies load positively on the global volatility factor and the reverse holds for the investment currencies, meaning that they provide a hedge (insurance) against downside movements of the strategy. Along these lines other studies provide an economic intuition behind the HML_{FX} factor and thus the carry trade profitability. More specifically, Mueller et al. (2013) find that global FX *correlation* risk is priced in the cross-section of carry trade returns and they show that it is a good proxy for global risk aversion. Other studies provide different explanations of the carry trade activity that are related to *skewness* (Rafferty, 2012), *illiquidity* (Mancini et al., 2013), *external imbalances* (Della Corte et al., 2013), *commodity trading* (Ready et al., 2013) and *country size* (Hassan, 2013).

Thus, it is apparent that the carry trade profitability emerges from differences among countries with particular characteristics. In this chapter we attempt to identify a different dimension of carry trade profitability. Particularly, we examine the role of technology diffusion in the foreign exchange market. Technology diffusion is the *'dynamic consequence of adoption'*. In other words how long does it take for a particular country to adopt to a new technology and how *intensively* is this technology used per capita? Recent studies have show that the technology diffusion heavily depends on the characteristics of the country that adopts the new technology. Particularly, technology adoption *leaders* (i.e. high technology diffusion) tend to be *rich* and *large* economies (Comin and Hobijn, 2010), *high* income countries (Parente and Prescott, 1994), *low* country risk (Comin and Hobijn, 2004; Comin and Mestieri, 2014). Thus, we question whether technology diffusion is linked to carry trade profitability. There are two main channels of technology diffusion; the International Trade and the Foreign direct investment (Keller, 2004). Ready et al. (2013) show that commodity trading can explain the carry trade profitability. Particularly, we show that we capture a different dynamic of International trade that enters into the carry trade activity. That is, technology diffusion *followers* tend to have high interest rates on average and provide a risk premium to carry trades who might be willing to finance risky innovation. Our work is more related to Gavazzoni and Santacreu (2014) who show theoretically that technology diffusion through trade in varieties is a significant determinant of asset prices. Specifically, countries with more pronounced R&D spillovers exhibit stock return comovement and less volatile exchange rates. We deviate from this study as we examine empirically the role of technology diffusion for currency carry trades.

To this end, we employ the Cross-country Historical Adoption of Technology (CHAT) dataset as a proxy of technology diffusion and create a country-specific technology diffusion factor that is constructed as the average across technologies each per country/time pair. Then we construct an asset pricing model, in the same spirit with Lustig et al. (2011). Specifically, we employ two factors, a dollar factor (i.e. DOL) and a technology diffusion factor (i.e. $LMH^{\mathcal{TD}}$). The dollar factor is defined as the average across portfolios each time and the technology diffusion is a zero-investment portfolio that goes long low technology diffusion baskets and sells high technology diffusion portfolios. We show that technology diffusion is priced in the cross-section of carry trade returns as it is able to capture most of the carry trade variability.

Our results are robust to different specification tests. Particularly, we show asset pricing tests for individual currencies and show that our model performs well in capturing the carry trade profitability. The pricing ability is also verified by beta-sorted portfolios, where a positive and statistically significant spread is obtained. The results are also robust after taking into account transaction costs. Finally, technology diffusion is able to price conditional excess returns.

Overall, we find that technology diffusion is a priced factor in the cross-section of currency returns. High interest rate currencies load positively on the technology diffusion factor and low interest rate currencies load negatively. Intuitively, carry trades require a risk premium for holding *low* technology diffusion currencies as a compensation for financing risky innovation. On the other hand, they invest on *high* technology diffusion currencies, despite the low profitability that they offer because it provides a hedge against downside movements of carry trade profitability.

In what follows, we provide the motivation for our study in section 3.2. In section 3.3 we provide a brief description of the data as well as the construction of the currency portfolios. Section 3.4 will discuss the empirical results of the chapter. Section 3.5 offers some robustness checks. Finally, section 3.6 gives our conclusion.

3.2 Technology Diffusion and Carry Trades

Firstly, we need to test our hypothesis that technology *leaders* (i.e. countries with *high* levels of technology diffusion) tend to have *low* interest rates on average and *vise versa*. As a first attempt to answer this question, we plot annualized mean forward discounts in percentage points against mean values of technology diffusion for each currency in our sample. Figure 3.1 visualizes this relationship. The top panel contains 48 countries and the bottom panel reports results for 15 developed countries. As we can see currencies with *high* forward discounts (i.e.

JPY, CHF and DEM/EUR) exhibit *low* technology diffusion while *low* forward discounts (i.e. NZD, AUD and DKK) tend to have *high* technology diffusion on average. This finding suggests that technology diffusion might capture the dynamics of carry trades and thus provide a partial explanation of the carry trade profitability. In addition, Hassan (2013) shows that country size might be a potential explanation for the carry trade profitability. However, figure 3.1 suggests that it is not the case here as we control for countries with similar size.

3.3 Data and Currency Portfolios

In this section, we provide a detailed description of the currency data used in the chapter as well as the different impositions applied to the dataset. In addition, we describe our technology diffusion data.

Exchange Rates Data. We begin with daily spot and one-month forward exchange rates against the U.S. dollar spanning the period of November 1983 to December 2013. The data are collected from Barclays and Reuters *via* Datastream. Transaction costs are taken into consideration through the use of bid, ask and mid quotes[1]. We also collect the corresponding spot and forward rates of 16 currencies quoted against the British pound from Reuters.[2] Following Burnside et al. (2011), we merge the two datasets by multiplying the latter series by mid USD/GBP quotes. After merging the data, we construct end- of-month series of daily spot and one-month forward rates as in Burnside et al. (2011). The main advantage of this approach is that the data is not averaged over each month but it represents the rates of the last trading day every month. Thus, the empirical analysis focuses on monthly data from January 1976 to Decem-

[1] The mid quotes are defined as the mean of the bid and ask quotes for each currency.

[2] These additional *"dead"* series are available from January 1976.

ber 2013. The sample comprises the following 48 countries: Australia, Austria, Belgium, Brazil, Bulgaria, Canada, Croatia, Cyprus, Czech Republic, Denmark, Egypt, Euro area, Finland, France, Germany, Greece, Hong Kong, Hungary, India, Indonesia, Ireland, Israel, Italy, Iceland, Japan, Kuwait, Malaysia, Mexico, Netherlands, New Zealand, Norway, Philippines, Poland, Portugal, Russia, Saudi Arabia, Singapore, Slovakia, Slovenia, South Africa, South Korea, Spain, Sweden, Switzerland, Taiwan, Thailand, Ukraine, United Kingdom.

We apply various filters in the data so as to make the analysis more realistic. Those currencies that were partly or completely pegged to the U.S. dollar are not excluded from the samples because their forward contracts were available to investors. The euro area countries are excluded after the introduction of the euro in January 1999. However, some countries entered the euro zone later than January 1999. In this case their exchange rates are excluded from the samples at a later date. We also delete the observations that are associated with large deviations from the covered interest rate parity condition. In particular, South Africa from July 1985 to August 1985; Malaysia from August 1998 to June 2005 and Indonesia from December 2000 to May 2007.

Currency Excess Returns. We denote with S_t and F_t the level of the time t spot and forward exchange rates. Each currency is quoted *against* the U.S. dollar such that an appreciation of the U.S. dollar reflects an increase in S_t. The excess return (RX_{t+1}) is defined as the payoff of a strategy that buys a foreign currency in the forward market at time t and then sells it in the spot market at maturity (i.e. at time $t+1$). The excess return can be computed as

$$rx_{t+1} = f_t - s_{t+1} = (f_t - s_t) - (s_{t+1} - s_t). \tag{3.1}$$

where lower case variables are in logs. Thus, the excess return can be decomposed into two components; the forward discount and the exchange rate return. Moreover, the covered interest-rate parity (hereafter CIP) condition implies that the forward discount is a good proxy for the interest rate differentials, i.e. $(f_t - s_t \simeq \hat{i}_t - i_t$, where $\hat{i}_t$ and i_t denote the foreign and domestic riskless interest rates, respectively. Akram et al. (2008) provide a detailed examination of CIP condition over different frequencies and they find that it holds at daily and lower frequencies. Therefore, the excess return could also be written as $rx_{t+1} \simeq (\hat{i}_t - i_t) - (s_{t+1} - s_t)$. In the latter expression, the currency excess returns can be approximated by the exchange rate exposure subtracted by the change in the foreign and domestic risk-free interest rates.

Transaction Costs. We report results with and without transaction costs because the inclusion of bid and ask quotes inflates the volatility of the excess returns giving more weight to less traded and illiquid currencies. The implementation cost of the currency strategy is taken into consideration though the use of bid and ask spreads. Particularly, buying the foreign currency forward at time t using the bid price (f_t^b) and selling it at time $t+1$ in the spot market at ask price (s_t^a) is given by: $rx_{t+1}^l = (f_t^b - s_{t+1}^a)/s_t^b$. Whereas the corresponding short position in the foreign currency (or short in the dollar) will render a *net* excess return of the form: $rx_{t+1}^s = -(f_t^a - s_{t+1}^b)/s_t^a$.

Technology Diffusion Data. We employ the Cross-country Historical Adoption of Technology (CHAT) dataset as a proxy for technology diffusion.[3] This dataset is an unbalanced panel of 111 technologies for 150 countries that spans the period 1750 to 2008. The data is annual and we focus on 48 countries over

[3]The data is available from NBER's website.

a period that start from January 1976 until the end of the sample, so as to be consistent with the currency data. The CHAT dataset covers a broad set of technologies that are related to: transportation, telecommunication, information technology, health care, steel production, and electricity. Thus, we measure technology diffusion as the average across technologies per year/country. We construct monthly observations by keeping the previous year's value constant until a new observation is realized. In addition, we keep the observations constant until the end of the currency data period.[4]

The main advantage of this dataset is its ability to capture the *intensity* of technology adoption. According to the traditional approach, technology diffusion is defined as the number of producers that decide to adopt the new technology and thus incur the additional cost over the total number (constant) of potential adopters. In addition, this measure of diffusion can adequately be approximated by a logistic regression as it exhibits an S-shape behaviour. Comin and Hobijn (2010) provide a more sensitive measure to technology adoption. Firstly, they collect three datasets on technology adoption for a large number of countries and construct the CHAT dataset based on three criteria. Particularly, a technology enters in the CHAT dataset if it is a *"state of the art technology"*, it contributes to the GDP of the country and it is present in a broad set of countries. Then, technology diffusion ($\mathcal{TD}$) is defined as:

$$\mathcal{TD}_t = \frac{\textit{Intensity} \text{ of the technology usage}_t}{\text{Size of the economy}_t}, \tag{3.2}$$

where the size of the economy is approximated by the GDP or the population of the country. Therefore, this measure captures the number of people that use a

[4]A similar approach has been followed in other studies such as Della Corte et al. (2013). In addition, the extension of the data until the end of the currency sample does not affect the results and increases the robustness of our analysis.

particular technology (extent of diffusion) as well as the points of services that a particular technology offers per capita (intensity).

Carry Trade Portfolios. At the end of each month t, we allocate currencies into quintiles on the basis of their forward discounts $(f_t - s_t)$ obtained at time $t-1$, given that the CIP holds. To this end, the first Portfolio contains the lowest yielding or funding currencies and the last basket consists of the highest yielding or investment currencies. The currency excess returns within each portfolio are equally weighted. The carry trade strategy involves a long position in high yielding currencies (i.e. Portfolio 6) and a short position in low yielding currencies (i.e. Portfolio 1). Lustig et al. (2011) (hereafter *LRV*) construct a two-factor model with a HML_{FX} factor and a DOL factor. The former factor is a slope factor which goes long to Portfolio 6 and short to Portfolio 1. The DOL factor denotes the average across portfolios each month.

3.4 Empirical Results

3.4.1 Preliminary Analysis

This section presents the empirical results of our analysis. Firstly, we provide descriptive statistics of currency portfolios that are sorted on previous month's forward discounts (i.e. carry trade portfolios) and then we analyses the behaviour of currency portfolios that are sorted based on technology diffusion.

Descriptive Statistics. Table 3.1 reports summary statistics for carry trade portfolios. Particularly, currency excess returns are sorted into quintiles every month on the basis of their forward discount. *Panel A* reports results for the sample of All countries and *Panel B* displays summary statistics for the Developed countries. Consistently with other studies (e.g., Burnside et al., 2011a; Lustig et al., 2011; Menkhoff et al., 2012a) we find that the profitability of interest rate sorted portfolios increases *monotonically* when we move from low to high interest rate baskets. This behaviour renders a positive and statistically significant spread (i.e. HML^{FX}) of 10.71 per annum when we consider the whole sample and 6.50 per annum for the Developed countries. This spread resembles a carry trade strategy as it goes long high interest rate currencies (i.e. P_H) and short low interest rate currencies (i.e. P_L). The carry trade profitability remains high even after controlling for transaction costs (i.e. HML^{FX_τ}) providing an annualized mean return of 5.03 (4.11) for the sample of All countries (Developed countries). In addition, carry trades exhibit negative skewness and excess kurtosis with significantly high sharpe ratios. They also display low persistence as it can be seen from the very small first order autocorrelation.

Table 3.2 provides summary statistics of currency portfolios that are sorted based on technology diffusion of the previous period. We observe an almost monotonic pattern from high to low technology diffusion portfolios that renders a statistically significant spread of 3.27 per annum for the whole sample and 2.29 for the Developed countries. This strategy buys each month the currency portfolios of technology diffusion *followers* (low $\mathcal{TD}$) while short-selling currency baskets of technology diffusion *leaders* (high $\mathcal{TD}$). We find that technology diffusion portfolios exhibit similar characteristics with carry trade portfolios such as left negative skewness, excess kurtosis and low persistence. In addition, it renders a highly significant sharpe ratio of 0.66 (0.39) per annum for the sample of All countries (Developed countries).

Currency Carry Trades and Technology Diffusion. As a first attempt to understand better the relationship between currency carry trades and technology diffusion we provide a visual illustration of the carry trade profitability conditional on technology diffusion. To this end figure 3.2 visualizes such payoffs. In particular, we divide the time-series of technology diffusion factor (i.e. $LMH^{\mathcal{TD}}$) into quartiles so that the first quartile represents the basket with the lowest realizations of our factor and the the last basket 25% of months with the highest realisations of its sample distribution. Then we calculate annualized mean excess returns of the return difference between extreme quintiles of interest rate sorted portfolios. Particularly, each bar in figure 3.2 shows annualized mean carry trade returns under specific states of technology diffusion. The top panel presents results for all countries and the bottom panel for Developed countries. We observe a monotonic pattern which suggests that carry trade portfolio increase monotonically, on average, as the technology diffusion from technology leaders to technology followers increases.

3.4.2 FX Asset Pricing Tests

This section performs cross-sectional asset pricing tests between the five currency portfolios and the global technology diffusion, and shows that technology diffusion is priced in the cross-section of currency excess returns.

Methods. Following the asset pricing methodology analyzed in Cochrane (2005) and implemented in many studies in the FX asset pricing literature, such as Lustig et al. (2011) and Menkhoff et al. (2012a) we examine the pricing ability of global technology diffusion. We denote the currency excess return of each portfolio j at time $t+1$ as RX^{j}_{t+1}. In this section we use discrete excess returns instead of log forms so as to avoid the joint log-normality assumption between returns and the pricing kernel.[5] Under no arbitrage conditions, the risk-adjusted currency excess returns should be zero and satisfy the Euler equation:

$$E[M_{t+1}RX^j_{t+1}] = 0 \tag{3.3}$$

where M_{t+1} denotes a linear SDF in the risk factors f_{t+1}. In particular, the main focus is on the SDF of the following form:

$$M_{t+1} = [1 - b'(f_{t+1} - \mu_f)] \tag{3.4}$$

where b denotes the vector of factor loadings and μ_f is the vector of expected values of the pricing factors (i.e. $\mu_f = E(f_{t+1})$). The beta representation of the model is obtained from the combination of above equations rendering the beta pricing model below:

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

where $\lambda = \Sigma_f b$ represents the factor risk prices with $\Sigma_f = E[(f_t - \mu_f)(f_t - \mu_f)']$ denoting the variance-covariance matrix of the risk factors and b the factor loading.[6] After projecting each currency excess return (RX^j_t) on the risk factors (f_t) contemporaneously, we obtain the regression coefficients β^j.

The simultaneous estimation of the factor loadings (b), factor means (μ) as well as the individual elements of the factor covariance matrix (Σ_f) is based on the Generalized Method of Moments (GMM) of Hansen (1982). Particularly, the

[5] We follow Lustig et al. (2011); Menkhoff et al. (2012a) and replace log returns with their discrete counterparts so as to satisfy the Euler equation that requires levels instead of log returns. Particularly, discrete returns are expresses as $RX_{t+1} = \frac{F_t - S_{t+1}}{S_t} = \frac{F_t - S_t}{S_t} - \frac{S_{t+1} - S_t}{S_t}$, where the forward ($F$) and spot ($S$) rates are in levels.

[6] In order to control for the fact that the means and the covariance of the risk factors are estimated we compute the standard errors for the factor risk prices by applying the Delta method.

estimation is based on the system of the moment conditions below:

$$E[g(z_t,\theta)] = E\begin{bmatrix} [1-b'(f_t-\mu_f)]RX_t \\ f_t-\mu_f \\ \mathrm{vec}((f_t-\mu_f)(f_t-\mu_f)')-\mathrm{vec}(\Sigma_f) \end{bmatrix} = 0$$

where $g(z_t,\theta)$ is a function of the set of parameters (i.e. $\theta = [b'\mu'\mathrm{vec}(\Sigma_f)']'$) and the data (i.e. $z_t = [RX_t, f_t]$).

The main purpose of this study is to examine the pricing ability of the model on the cross-section of currency returns and thus we restrict my attention on unconditional moments with no instruments apart from a constant. Thus, the pricing errors are used as the set of moments under a prespecified weighting matrix. In the first stage of the GMM (GMM_1) we start with an identity weighting matrix so as to see whether the factors can price the cross-section of the currency excess returns equally well. Then in the second stage (GMM_2) we choose the weighting matrix optimally by minimizing the difference between the objective functions under heteroskedasticity and autocorrelation (HAC) estimates of the long-run covariance matrix of the moment conditions. To do that, we follow the Newey and West (1987) methodology using the optimal number of lags as in Andrews (1991).

In order to increase the robustness of our analysis, we also apply a Fama and MacBeth (1973) (hereafter FMB) two pass regression. In the first stage, we run contemporaneous time-series regressions of currency portfolio excess returns on the risk factors. In the second stage, we perform cross-sectional regressions of average portfolio returns on factor loadings, obtained from the previous step, in order to compute the factor risk prices. In addition, we do not allow for common miss-pricing in the currency returns by excluding the intercept in the cross-sectional regressions but the results are similar if we replace the DOL factor with a constant. In addition, we report both Newey and West (1987) as well as Shanken (1992) so as to account for the potential error-in-variable issue that might arise due to the fact that the regressors are estimated in the second stage of the FMB procedure.

Cross-Sectional Analysis. The SDF of each model takes the following form:

$$M_{t+1} = 1 - b_{DOL}(DOL_{t+1} - \mu_{DOL}) - b_{LMH^{\mathcal{TD}}}(LMH^{\mathcal{TD}}_{t+1} - \mu_{LMH^{\mathcal{TD}}}). \tag{3.6}$$

Panel A of table 3.3 shows results for second-pass cross-sectional regressions following GMM and FMB approaches. We report the factor risk prices (i.e. λ) as well as estimates for b. Standard errors that are corrected for autocorrelation and heteroskedasticity following Newey and West (1987) based on the optimal number of lags as in Andrews (1991) are in parenthesis. We also control for the fact the the betas are estimated in the second-pass regression (error-in-variable problem) by computing Shanken (1992) standard errors. Regarding the economic significance of the model we also employ a variety of goodness of fit so as to obtain a better understanding of the cross-sectional performance of our risk factors. In particular we present χ^2, cross-sectional R^2 and the HJ distance following Hansen and Jagannathan (1997). The χ^2 test statistics - obtained from the FMB (with Newey and West (1987) and Shanken (1992) corrections) as well as GMM_1 and GMM_2 procedures - test the null hypothesis that all pricing errors in the cross-section are mutually equal to zero. The cross-sectional pricing errors are computed as the difference between the realized and predicted excess returns. The HJ distance is a model diagnostic that helps us compare asset pricing models. In our context it test whether the distance of the SDF of our model in squared terms and a group of acceptable SDFs is equal to zero. We report *p-values* in curly brackets.[7]

Table 3.3 displays two panels that correspond to the two samples of interest. Particularly, the left panel shows results for the whole sample and the right panel results for the Developed countries. Starting from the statistical significance of our model we focus on the sign and the degree of statistical significance of $\lambda_{LMH^{\mathcal{TD}}}$. We find that the estimates of the factor risk prices of technology diffusion is always positive and highly significant based on HAC and Shanken (1992) standard errors. In addition, the factor risk price of the DOL factor is not economically or statistically significant consistently with Lustig et al. (2011) who find that the DOL factor does provide any cross-sectional information for carry portfolios. We verify our results by implementing GMM_1 and GMM_2 procedures. Regarding the goodness of fit of the model we find a cross-sectional R^2 of 93% and 90% for All countries and Developed countries respectively. In addition, the χ^2 obtained from FMB, GMM_1 and GMM_1 methods suggest that we cannot reject the null that all pricing errors are jointly equal to zero indicating the cross-sectional success of the model for currency excess returns. In addition, the large *p-value* of the HJ distance means that we cannot reject the null that the HJ distance is equal to zero. These findings are robust for both samples.

Time-Series Analysis. *Panel B* of table 3.3 also displays estimates of time-series regressions of currency excess returns on a constant and the factors of interest (i.e. DOL and $LMH^{\mathcal{TD}}$) for each of the five currency portfolios p (i.e. $p = 1, \ldots, 5$),

[7] For the estimation of the *p-values* for the HJ distance we follow Jagannathan and Wang (1996).

$$RX_{t+1}^{p} = \beta_0^p + \beta_{DOL}^p DOL_{t+1} + \beta_{LMH^{\mathcal{TD}}}^p LMH_{t+1}^{\mathcal{TD}} + u_{t+1}^p. \quad (3.7)$$

Panel B of table 3.3 shows first-pass time series regressions of currency excess returns on DOL and $LMH^{\mathcal{TD}}$. We find that the betas of the DOL factor (i.e. β_{DOL}) are very close to one and the betas of the technology diffusion factor (i.e. $\beta_{LMH^{\mathcal{TD}}}$) increase monotonically from -0.13 to 0.32 as moving from low to high interest rate currency portfolios. In addition, the slope coefficients are highly significant as indicated by the HAC standard errors. Moreover, the time-series R^2 range from $76-88\%$ for All countries and from $73\%-86\%$ for Developed countries.

Figure 3.4 demonstrates graphically the fit of our model. Particularly, in the vertical (horizontal) axis we illustrate the actual (fitted) mean excess returns. The fitted excess returns are implied by the model. We find that implied-returns that are based on our model lies closely to the 45 degree line, indicating that technology diffusion risk is priced as it is able to reproduce the spread of carry trade returns reasonably well. This finding is for the sample of All countries (top panel) as well as the sample of the Developed countries (bottom panel).

3.4.3 Portfolios Based on Technology Diffusion Betas

Here, we examine the predictive power of technology diffusion in the cross-section of currency excess returns. The fact that technology diffusion is priced might indicate that portfolios that are sorted based on exposures to technology diffusion will render a positive and statistically significant spread. To this end, we sort currency excess returns into portfolios based on 36-month rolling betas up to $t-1$.[8] Summary statistics of such portfolios are reported in table 3.4, where

[8] A similar procedure has been followed by Lustig et al. (2011); Menkhoff et al. (2012a).

Panel A shows results for the whole sample and *Panel B* display descriptive statistics for the Developed countries.

As we can see the exposure to technology diffusion generate a monotonic pattern from low to high technology diffusion betas, verifying our previous results. This patterns renders a positive and statistically significant spread (i.e. $\mathcal{H}/\mathcal{L}$) of 3.88 in percentage points. In addition, the portfolios exhibit negative skewness and excess kurtosis with high annualized sharpe ratios. We also report pre and post formation betas and forward discounts and find that both behave in a similar way being that they increase monotonically. This finding suggests that sorting on technology diffusion betas creates portfolios related to carry trade portfolios. Of course they are not identical as we observe a few differences in the summary statistics of the beta sorted portfolios such as the inflated skewness.

3.5 Robustness

This section provides some additional tests so as to examine further the robustness of our finding. In particular, we examine the case of conditional excess returns, we perform asset pricing tests for individual currencies and control for transaction costs.

Conditional Returns. We also investigate the role of technology diffusion when employing conditional returns. Particularly we define conditional carry returns as:

$$RX_{t+1}^{c} = \begin{cases} \frac{F_t - S_{t+1}}{S_t} & \text{if } F_t - S_t > 0, \\ \frac{S_{t+1} - F_t}{S_t} & \text{if } F_t - S_t \leq 0. \end{cases} \tag{3.8}$$

Table 3.5 reports descriptive statistics of portfolios of conditional excess returns that are sorted on technology diffusion betas, based on a 36-month rolling window and up to time $t-1$. *Panel A* (*Panel B*) reports results for All countries (Developed countries). We find that the annualized mean excess returns increase in an almost monotonic fashion and thus offering a positive and statistically significant spread (i.e. $\mathcal{H}/\mathcal{L}$) of 5.95 for All countries and 0.33 for Developed countries. We also find that the pre- and post- formation betas increase monotonically as we move from the low to high beta portfolios. This strategy offers very high sharpe ration with higher skewness and kurtosis than the traditional carry trade portfolios.

Individual Currencies. Many studies argue that portfolio-level approaches might cancel out important information embedded in asset prices (e.g., Ang et al., 2010). Therefore, we question the pricing ability of our factors for individual currencies when employing the same set of risk factors. Particularly, we run FMB regressions in order to estimate the first-pass and second-pass estimates that we analyzed in the previous section. One concern that arises from this methodology, however, is associated with the role of outliers in this study (for example less tradable currencies) that might cause biased estimators. To guard against this issue we follow Della Corte et al. (2013) and employ the least absolute deviation (LAD) estimator which controls for heavy-tailed errors (Bassett Jr and Koenker, 1978; Koenker and Bassett Jr, 1982). Figure 3.4 reports pricing error plot for unconditional excess returns and figure 3.5 displays results for conditional excess returns. The top panel shows results for All countries and the bottom panel for Developed countries. Particularly, in the vertical (horizontal) axis we illustrate the actual (fitted) mean excess returns. The fitted excess returns are implied by the model. In any case we find that most of the currencies lie closely to the 45 degree line indicating the pricing ability of the model for currency excess returns.

Transaction Costs. Here we ask whether the model is able to capture the cross-sectional variability of currency excess returns even after controlling for the implementation cost of the strategy. Table 3.6 displays asset pricing test when test assets are *net* excess returns of portfolios that are sorted on forward discounts. We find that the results are overall improved as it can be seen from the highly significant estimates of the factor risk price of technology diffusion. In addition, the χ^2 obtain via FMB, GMM_1 and GMM_2 approaches suggest that we cannot reject the null of zero pricing errors at any significance level. In the same vein, we cannot reject the null that the HJ distance is equal to zero. Finally, we obtain cross-sectional R^2s of 98% and 99% for All countries and Developed country respectively.

3.6 Conclusions

In this chapter we study the role of technology diffusion in the foreign exchange market. Particularly, we link technology diffusion with the carry trade activity. Carry trade is a foreign exchange strategy that goes long high interest rate currencies and short low interest rate currencies. Its profitability is driven by the persistent differences in interest rate differentials. On the other hand the technology diffusion is heavily determined by the income inequality across countries. In this chapter, we show that technology diffusion can partially explain the carry trade profitability.

Particularly, we develop a linear two-factor asset pricing model that incorporates information of global technology diffusion. The first factor is a dollar factor that is measured as the average across portfolios each time. The second factor is the technology diffusion factor that goes long low technology diffusion baskets while short-selling high technology diffusion portfolios. We show that technology diffusion is priced as it is able to capture the cross-section of currency premia.

The pricing ability of the model is also verified by rolling betas as well as currency level asset pricing tests. We also show that technology diffusion contains important information for conditional returns. Finally, our results are similar even after controlling for transaction costs.

Table 3.1. Summary Statistics of Carry Trade Portfolios

This table presents descriptive statistics of quintile currency portfolios sorted on monthly *forward discounts* at time $t-1$. The first (last) portfolio P_L (P_H) comprise the top 20% of all currencies with the lowest (highest) expected return. HML is the a long-short strategy that buys P_H and sells P_L. Moreover, the table presents annualized mean, standard deviation and Sharpe ratios, all in percentage points. We also report skewness and kurtosis. Figures in squared brackets represent Newey and West (1987) t-statistics corrected for heteroskedasticity and autocorrelation (HAC) using the optimal number of lags as in Andrews (1991) and numbers in parenthesis are p-values. All currency excess returns incorporate transaction costs by taking a short position in the first portfolio and long positions in the remaining baskets of currencies. *Panel A* (*Panel B*) reports results for the All Countries (Developed Countries) and τ represents the inclusion of transaction costs. The data is collected from Datastream *via* Barclays and Reuters. The data contain monthly series from January 1976 to December 2013.

	P_L	$P2$	$P3$	$P4$	P_H	DOL	HML^{FX}	$DOL^{FX\tau}$	$HML^{FX\tau}$
Panel A: All Countries									
$Mean$	-2.86	0.25	1.80	2.74	7.85	1.96	10.71	0.46	5.03
	[-1.74]	[0.16]	[1.14]	[1.75]	[3.71]	[1.28]	[5.72]	[0.30]	[2.52]
$Sdev$	8.70	8.23	8.33	8.74	9.51	7.87	8.12	7.88	8.33
SR	-0.33	0.03	0.22	0.31	0.83	0.25	1.32	0.06	0.60
$Skew$	-0.26	-0.54	-0.30	-0.52	-0.67	-0.44	-0.43	-0.45	-0.55
$Kurt$	4.67	4.68	4.88	4.44	4.69	4.25	4.39	4.26	4.36
$AC(1)$	0.05	0.03	0.07	0.04	0.22	0.07	0.28	0.07	0.31
	(0.25)	(0.51)	(0.11)	(0.45)	(0.00)	(0.14)	(0.00)	(0.15)	(0.00)
Panel B: Developed Countries									
$Mean$	-1.87	0.38	0.92	2.42	4.63	1.30	6.50	0.61	4.11
	[-1.00]	[0.21]	[0.52]	[1.46]	[2.31]	[0.79]	[3.79]	[0.37]	[2.41]
$Sdev$	10.14	9.59	9.31	9.47	10.77	8.77	9.73	8.77	9.72
SR	-0.18	0.04	0.10	0.26	0.43	0.15	0.67	0.07	0.42
$Skew$	-0.16	-0.21	-0.15	-0.51	-0.34	-0.27	-0.82	-0.27	-0.81
$Kurt$	4.32	3.70	4.26	5.23	4.48	3.81	5.43	3.81	5.41
$AC(1)$	0.02	0.06	0.09	0.02	0.10	0.05	0.11	0.05	0.11
	(0.73)	(0.19)	(0.07)	(0.74)	(0.03)	(0.26)	(0.02)	(0.26)	(0.02)

Table 3.2. Summary Statistics of Technology Diffusion ($\mathcal{TD}$)

This table presents descriptive statistics of quintile currency portfolios sorted on *technology diffusion* at time $t-1$. The first (last) portfolio P_L (P_H) comprise the top 20% of all currencies with the lowest (highest) expected return. $LMH^{\mathcal{TD}}$ is the a long-short strategy that buys P_L and sells P_H. Moreover, the table presents annualized mean, standard deviation and Sharpe ratios, all in percentage points. We also report skewness and kurtosis. Figures in squared brackets represent Newey and West (1987) t-statistics corrected for heteroskedasticity and autocorrelation (HAC) using the optimal number of lags as in Andrews (1991) and numbers in parenthesis are p-values. All currency excess returns incorporate transaction costs by taking a short position in the first portfolio and long positions in the remaining baskets of currencies. *Panel A* (*Panel B*) reports results for the All Countries (Developed Countries) and τ represents the inclusion of transaction costs. The data is collected from Datastream *via* Barclays and Reuters. The data contain monthly series from January 1976 to December 2013.

	P_H	$P2$	$P3$	$P4$	P_L	DOL	$LMH^{\mathcal{TD}}$
Panel A: All Countries							
$Mean$	0.31	3.54	1.18	1.21	3.58	1.97	3.27
	0.24	1.86	0.69	0.69	2.29	1.29	3.29
$Sdev$	7.61	8.84	9.26	9.26	7.61	7.87	4.93
SR	0.04	0.40	0.13	0.13	0.47	0.25	0.66
$Skew$	-0.39	-0.43	-0.28	-0.54	-0.36	-0.42	-0.05
$Kurt$	4.18	4.52	4.01	4.38	4.35	4.21	3.45
$AC(1)$	0.04	0.12	0.08	0.05	0.12	0.07	0.07
	(0.41)	(0.01)	(0.08)	(0.32)	(0.01)	(0.13)	(0.13)
Panel B: Developed Countries							
$Mean$	0.11	1.54	1.51	1.38	2.39	1.39	2.29
	0.07	0.98	0.80	0.67	1.30	0.84	2.21
$Sdev$	9.16	8.15	10.10	10.89	9.84	8.74	5.91
SR	0.01	0.19	0.15	0.13	0.24	0.16	0.39
$Skew$	-0.34	0.09	-0.26	-0.43	-0.22	-0.27	-0.09
$Kurt$	4.22	3.79	3.75	4.47	4.38	3.82	3.77
$AC(1)$	0.02	0.04	0.05	0.07	0.04	0.05	-0.01
	(0.73)	(0.36)	(0.29)	(0.17)	(0.42)	(0.30)	(0.78)

Table 3.3. FX Asset Pricing Tests: *Technology Diffusion*

This table reports asset pricing results for the two-factor model that comprises that DOL and $LMH^{\mathcal{TD}}$ risk factors. We use as test assets five currency portfolios sorted based on past forward discounts. We rebalance our portfolios on a monthly basis. *Panel A* reports GMM_1, GMM_2 as well as Fama and MacBeth (1973) estimates of the factor loadings (b) and factor prices of risk (λ). We also display Newey and West (1987) standard errors (in parenthesis) or t-statistics (in squared brackets) corrected for autocorrelation and heteroskedasticity with Andrews (1991) optimal lag selection and Sh are the corresponding values of Shanken (1992). The table also shows χ^2, cross-sectional R^2 and the HJ distance following Hansen and Jagannathan (1997). *Panel B* reports OLS estimates of contemporaneous time-series regression with HAC standard errors in parenthesis. We do not control for transaction costs and excess returns are expressed in percentage points.The data are collected from Datastream *via* Barclays and Reuters. The data contain monthly series from January 1985 to January 2014.

Panel A: Factor Prices

	λ_{DOL}	$\lambda_{LMH^{\mathcal{TD}}}$	b_{DOL}	$b_{LMH^{\mathcal{TD}}}$	R^2	HJ dist	λ_{DOL}	$\lambda_{LMH^{\mathcal{TD}}}$	b_{DOL}	$b_{LMH^{\mathcal{TD}}}$	R^2	HJ dist
			All Countries						*Developed Countries*			
GMM_1	0.12	1.55	0.00	0.74	0.93	0.04	0.06	0.60	0.09	0.20	0.90	0.03
s.e.	(0.13)	(0.45)	(0.08)	(0.37)		{0.74}	(0.14)	(0.19)	(0.40)	(0.03)		{0.78}
GMM_2	0.17	2.01	0.00	0.75			0.05	0.56	0.09	0.21		
s.e.	(0.13)	(0.55)	(0.09)	(0.37)			(0.14)	(0.18)	(0.40)	(0.04)		
	λ_{DOL}	$\lambda_{LMH^{\mathcal{TD}}}$	χ^2_{NW}	χ^2_{Sh}	χ^2_{GMM1}	χ^2_{GMM2}	λ_{DOL}	$\lambda_{LMH^{\mathcal{TD}}}$	χ^2_{NW}	χ^2_{Sh}	χ^2_{GMM1}	χ^2_{GMM2}
FMB	0.12	1.55	4.26	8.59	4.22	4.31	0.06	0.60	3.83	3.41	3.08	2.64
(NW)	(0.11)	(0.22)	{0.21}	{0.07}	{0.24}	{0.23}	(0.12)	(0.15)	{0.43}	{0.49}	{0.38}	{0.45}
(Sh)	(0.11)	(0.31)					(0.12)	(0.16)				

Panel B: Factor Betas

	α	β_{DOL}	$\beta_{LMH^{\mathcal{TD}}}$	R^2	α	β_{DOL}	$\beta_{LMH^{\mathcal{TD}}}$	R^2
P_L	-0.27	0.95	-0.13	0.77	-0.21	1.00	-0.27	0.73
	(0.07)	(0.06)	(0.06)		(0.08)	(0.07)	(0.06)	
P_2	-0.02	0.97	-0.12	0.87	-0.01	1.02	-0.23	0.86
	(0.07)	(0.03)	(0.04)		(0.05)	(0.03)	(0.05)	
P_3	0.11	0.99	-0.07	0.88	0.03	0.99	-0.10	0.86
	(0.07)	(0.03)	(0.05)		(0.05)	(0.03)	(0.04)	
P_4	0.18	1.04	-0.01	0.87	0.16	0.98	0.13	0.84
	(0.07)	(0.03)	(0.04)		(0.05)	(0.03)	(0.04)	
P_H	0.60	1.05	0.32	0.76	0.33	1.01	0.49	0.80
	(0.07)	(0.04)	(0.06)		(0.07)	(0.04)	(0.06)	

Table 3.4. Portofolios sorted on Technology Diffusion-Betas

This table presents descriptive statistics of currency portfolios sorted on betas with global technology diffusion ($LMH^{\mathcal{TD}}$). The first (last) portfolio P_L (P_H) comprise the basket of all currencies with the lowest (highest) technology diffusion betas. $\mathcal{H}/\mathcal{L}$ is the a long-short strategy that buys P_H and sells P_L and Avg is the average across portfolios each time. Moreover, the table presents annualized mean, standard deviation and Sharpe ratios, all in percentage points. We also report skewness and kurtosis. Figures in squared brackets represent Newey and West (1987) t-statistics corrected for heteroskedasticity and autocorrelation (HAC) using the optimal number of lags as in Andrews (1991) and numbers in brackets are *p-values*. pre-$f-s$ (post-$f-s$) is the pre-(post-) formation forward discount pre-β (post-β) is the pre-(post-) formation beta. *Panel A* (*Panel B*) reports results for the sample of All countries (Developed countries) without transaction costs. The data contain monthly series from January 1976 to December 2013.

	P_L	$P2$	$P3$	$P4$	P_H	Avg	$\mathcal{H}/\mathcal{L}$
			Panel A: All Countries				
$Mean$	-0.43	-0.33	0.54	1.38	3.44	0.92	3.88
	[-0.28]	[-0.19]	[0.32]	[0.81]	[1.44]	[0.56]	[2.20]
$Sdev$	7.74	8.40	8.92	9.22	9.79	7.91	7.81
SR	-0.06	-0.04	0.06	0.15	0.35	0.12	0.50
$Skew$	-0.73	-0.67	-0.35	-0.45	-0.46	-0.53	-0.18
$Kurt$	4.79	4.91	3.69	4.74	4.32	4.02	3.84
$AC(1)$	0.13	0.12	0.06	0.04	0.20	0.12	0.16
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
pre-$f-s$	-0.26	-0.02	0.13	0.32	0.96		
post-$f-s$	-0.28	-0.02	0.13	0.32	0.99		
pre-β	-0.27	-0.01	0.12	0.22	0.47		
post-β	-0.32	-0.01	0.11	0.23	0.48		
			Panel B: Developed Countries				
$Mean$	0.01	-0.60	-0.39	0.59	1.36	0.19	1.35
	[0.01]	[-0.31]	[-0.19]	[0.31]	[0.68]	[0.11]	[0.83]
$Sdev$	8.65	10.06	10.40	10.20	10.30	8.86	9.09
SR	0.00	-0.06	-0.04	0.06	0.13	0.02	0.15
$Skew$	-0.50	-0.31	-0.33	-0.33	-0.32	-0.32	-0.04
$Kurt$	5.06	4.83	3.55	3.88	3.94	3.63	4.14
$AC(1)$	0.07	0.04	0.08	0.03	0.12	0.08	0.06
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
pre-$f-s$	-0.23	-0.04	0.07	0.19	0.40		
post-$f-s$	-0.24	-0.04	0.07	0.19	0.41		
pre-β	-0.12	0.06	0.13	0.21	0.33		
post-β	-0.13	0.05	0.13	0.21	0.34		

Table 3.5. *Conditional* Returns sorted on Technology Diffusion-Betas
This table presents descriptive statistics of *conditional* excess returns sorted on betas with global technology diffusion ($LMH^{\mathcal{TD}}$). The first (last) portfolio P_L (P_H) comprise the basket of all currencies with the lowest (highest) technology diffusion betas. $\mathcal{H}/\mathcal{L}$ is the a long-short strategy that buys P_H and sells P_L and Avg is the average across portfolios each time. Moreover, the table presents annualized mean, standard deviation and Sharpe ratios, all in percentage points. We also report skewness and kurtosis. Figures in squared brackets represent Newey and West (1987) t-statistics corrected for heteroskedasticity and autocorrelation (HAC) using the optimal number of lags as in Andrews (1991) and numbers in brackets are *p-values*. pre-$f-s$ (post-$f-s$) is the pre-(post-) formation forward discount pre-β (post-β) is the pre-(post-) formation beta. *Panel A* (*Panel B*) reports results for the sample of All countries (Developed countries) without transaction costs. The data contain monthly series from January 1976 to December 2013.

	P_L	$P2$	$P3$	$P4$	P_H	Avg	$\mathcal{H}/\mathcal{L}$
Panel A: All Countries							
$Mean$	2.55	3.40	3.50	3.53	8.50	4.30	5.95
	[2.07]	[3.27]	[3.45]	[2.72]	[4.22]	[4.75]	[2.67]
$Sdev$	7.26	6.17	5.48	7.29	8.41	4.53	10.67
SR	0.35	0.55	0.64	0.48	1.01	0.95	0.56
$Skew$	-0.29	0.05	-0.79	-0.44	-0.34	-0.79	-0.35
$Kurt$	4.45	7.56	7.03	5.08	5.27	7.47	5.63
$AC(1)$	0.17	0.03	0.16	0.07	0.23	0.24	0.16
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
pre-$f-s$	-0.26	-0.02	0.13	0.32	0.96		
post-$f-s$	-0.28	-0.02	0.13	0.32	0.99		
pre-β	-0.38	-0.11	0.05	0.23	0.56		
post-β	-0.39	-0.11	0.06	0.24	0.61		
Panel B: Developed Countries							
$Mean$	4.72	4.42	3.45	5.16	5.05	4.56	0.33
	[4.10]	[3.41]	[2.27]	[3.84]	[3.33]	[4.73]	[0.20]
$Sdev$	6.71	7.96	8.47	8.15	8.52	5.16	10.18
SR	0.70	0.56	0.41	0.63	0.59	0.88	0.03
$Skew$	-0.62	-0.33	-0.19	0.02	-0.31	-0.57	-0.24
$Kurt$	5.17	4.97	4.24	6.20	4.92	5.53	3.72
$AC(1)$	0.05	0.08	0.09	0.03	0.08	0.17	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
pre-$f-s$	-0.23	-0.04	0.07	0.19	0.40		
post-$f-s$	-0.24	-0.04	0.07	0.19	0.41		
pre-β	-0.12	0.06	0.13	0.21	0.33		
post-β	-0.13	0.05	0.13	0.21	0.34		

Table 3.6. Robustness: *FX Asset Pricing Tests: Transaction Costs*

This table reports asset pricing results for the two-factor model that comprises that DOL and $LMH^{\mathcal{TD}}$ risk factors. We use as test assets five currency portfolios sorted based on past forward discounts. We rebalance our portfolios on a monthly basis. *Panel A* reports Fama and MacBeth (1973) estimates of the factor loadings (b) and factor prices of risk (λ). We also display Newey and West (1987) standard errors (in parenthesis) or t-statistics (in squared brackets) corrected for autocorrelation and heteroskedasticity with Andrews (1991) optimal lag selection and Sh are the corresponding values of Shanken (1992). The table also shows χ^2, cross-sectional R^2 and the HJ distance following Hansen and Jagannathan (1997). *Panel B* reports OLS estimates of contemporaneous time-series regression with HAC standard errors in parenthesis. We not control for transaction costs and excess returns are expressed in percentage points.The data are collected from Datastream *via* Barclays and Reuters. The data contain monthly series from January 1985 to January 2014.

Panel A: Factor Prices

	λ_{DOL}	$\lambda_{LMH^{\mathcal{TD}}}$	χ^2_{NW}	χ^2_{Sh}	χ^2_{GMM1}	χ^2_{GMM2}	λ_{DOL}	$\lambda_{LMH^{\mathcal{TD}}}$	χ^2_{NW}	χ^2_{Sh}	χ^2_{GMM1}	χ^2_{GMM2}
	All Countries						*Developed Countries*					
FMB	-0.01	0.80	2.20	1.68	0.81	1.29	0.00	0.45	0.04	0.04	0.03	0.04
(NW)	(0.10)	(0.22)	{0.70}	{0.79}	{0.85}	{0.73}	(0.12)	(0.15)	{0.99}	{0.99}	{0.99}	{0.99}
(Sh)	(0.11)	(0.25)					(0.12)	(0.15)				
R^2	0.98						0.99					
HJ dist	0.04	{0.72}					0.03	{0.79}				

Panel B: Factor Betas

	α	β_{DOL}	$\beta_{LMH^{\mathcal{TD}}}$	R^2	α	β_{DOL}	$\beta_{LMH^{\mathcal{TD}}}$	R^2
P_L	-0.16	0.95	-0.13	0.77	-0.12	1.00	-0.27	0.73
	(0.07)	(0.06)	(0.06)		(0.08)	(0.07)	(0.06)	
P_2	-0.12	0.97	-0.12	0.87	-0.11	1.02	-0.23	0.86
	(0.05)	(0.03)	(0.04)		(0.05)	(0.03)	(0.05)	
P_3	-0.02	0.99	-0.06	0.86	-0.05	0.99	-0.10	0.86
	(0.05)	(0.03)	(0.05)		(0.05)	(0.03)	(0.04)	
P_4	0.04	1.04	0.00	0.86	0.06	0.98	0.13	0.84
	(0.05)	(0.03)	(0.04)		(0.06)	(0.03)	(0.04)	
P_H	0.23	1.05	0.32	0.74	0.22	1.01	0.49	0.80
	(0.10)	(0.04)	(0.06)		(0.07)	(0.04)	(0.06)	

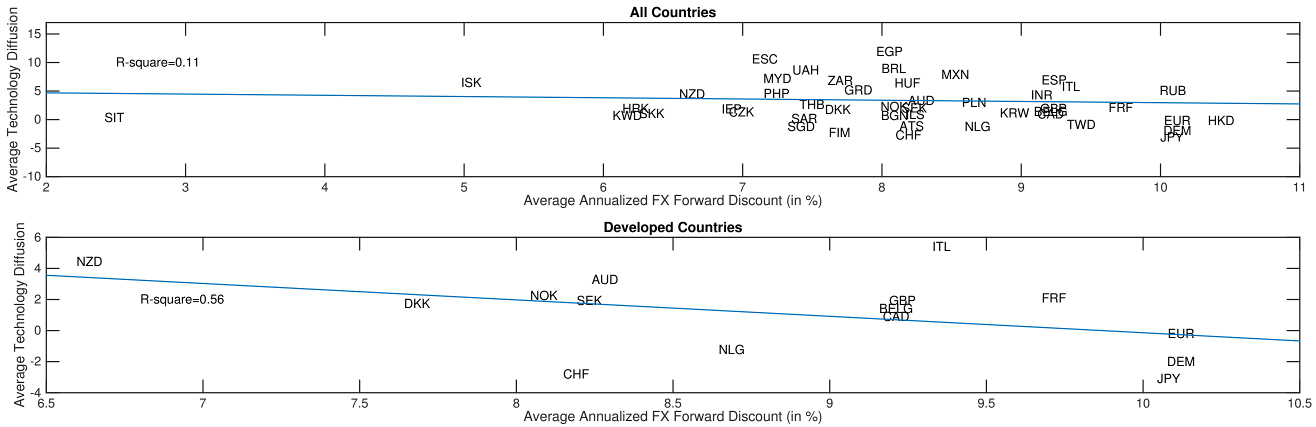


Figure 3.1. Average Forward Discounts and Technology Diffusion

The figure displays annualized mean forward discounts from 1976 to 2013 against the corresponding average of technology diffusion. The top panel report results for the sample of All countries and the bottom panel shows results for Developed countries. The data contain monthly series from January 1976 to December 2013.

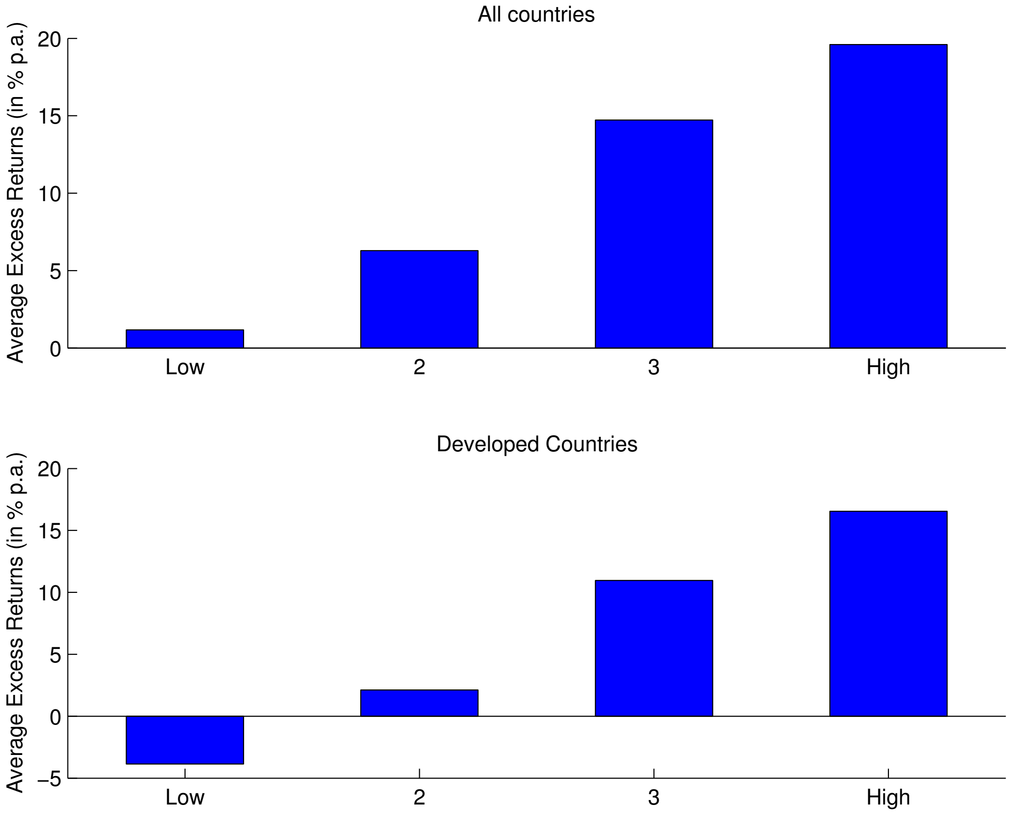


Figure 3.2. Currency Trades and Technology Diffusion

The figure visualizes the relationship between technology diffusion and currency carry trades. Particularly, we show annualized average excess returns for currency carry trade portfolios conditional on technology diffusion in the top and bottom quartiles of each sample distribution. Each bar represents annualized mean returns of going long the high interest rate portfolio and short the low interest rate portfolio. The top panel report results for the sample of All countries and the bottom panel shows results for Developed countries. The data contain monthly series from December 1976 to December 2013.

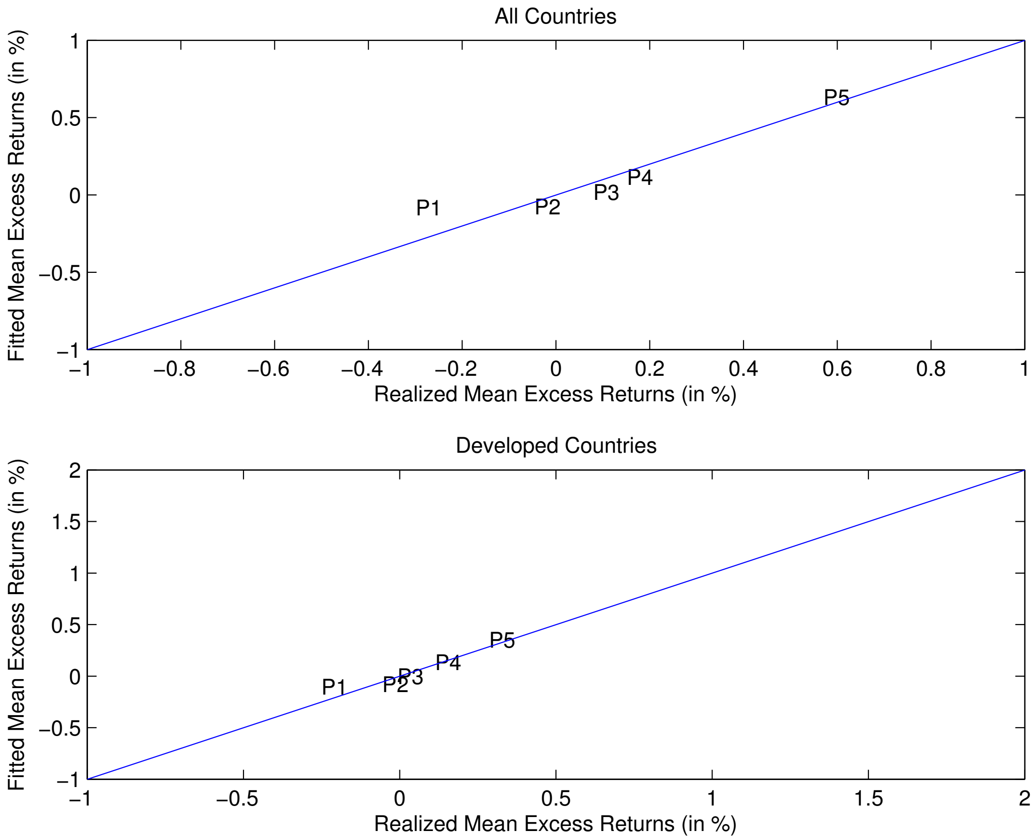


Figure 3.3. Pricing Error Plots - *Portfolio-Level*

The figure displays pricing error plots for the asset pricing models with the DOL as well as $LMH^{\mathcal{TD}}$ as risk factor. The top panel report results for the sample of All countries and the bottom panel shows results for Developed countries. The data contain monthly series from January 1976 to December 2013.

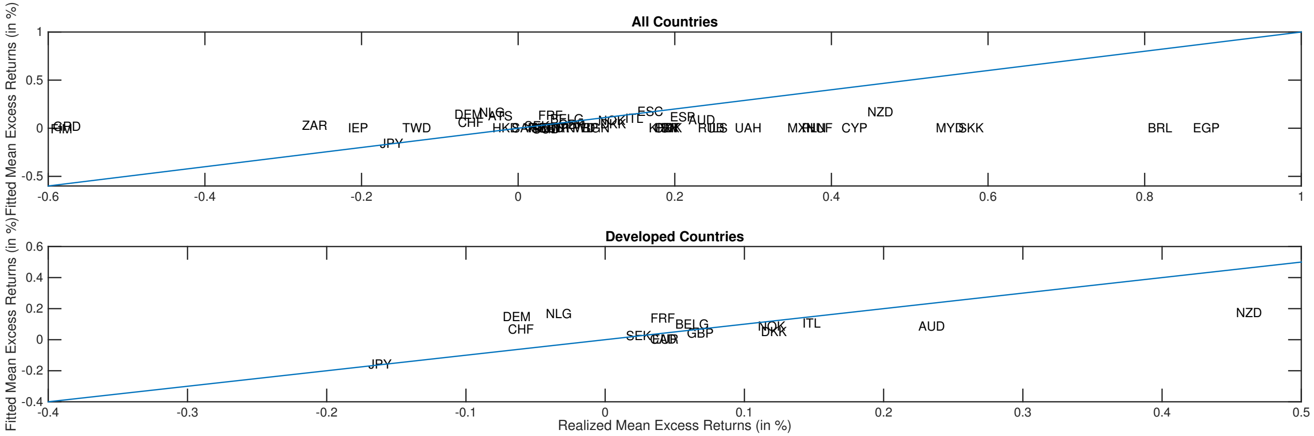


Figure 3.4. Pricing Error Plots - *Currency-Level*

The figure displays pricing error plots for the asset pricing models with the DOL as well as $LMH^{\mathcal{TD}}$ as risk factor for individual *unconditional* currency excess returns. The top panel report results for the sample of All countries and the bottom panel shows results for Developed countries. The data contain monthly series from January 1976 to December 2013.

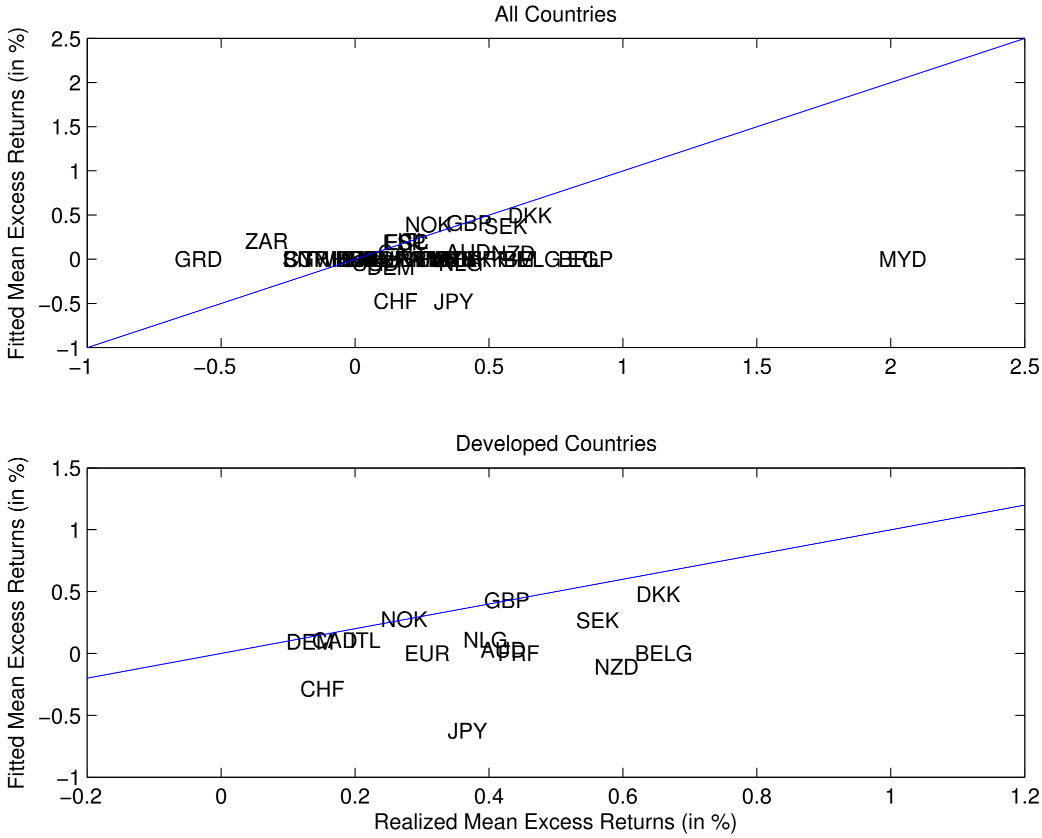


Figure 3.5. Pricing Error Plots - *Conditional Returns*

The figure displays pricing error plots for the asset pricing models with the DOL as well as $LMH^{\mathcal{TD}}$ as risk factor for individual *conditional* currency excess returns. The top panel report results for the sample of All countries and the bottom panel shows results for Developed countries. The data contain monthly series from January 1976 to December 2013.

Chapter 4

Concluding Remarks

In the first chapter we demonstrate strong implications for the role of the domestic and global macroeconomy on carry trade, dollar carry trade and momentum strategies. We constructed domestic (i.e. U.S.) and global (i.e. G10) factors that are extracted from large panels of macroeconomic and financial variables. Thus, the main focus of the chapter is on the time-series predictability of the payoffs and the economic value that can be earned by a U.S. investor from the use of these domestic and global common factors.

We find very strong evidence of in-sample predictability in the carry, dollar carry and momentum returns. In particular, the carry trade variability can be explained by global variables that are exposed to G7 economies and are highly correlated with the global stock market. This finding shows that carry trade activity depends more on the global environment rather than on the domestic (i.e. U.S.) economy. It is also shown in many studies that U.S. stock indices cannot capture the time-series or cross-sectional variation of the returns to carry trade. However, here we show that the movements of the global equity markets provide very useful information in this respect. In addition, U.S. real and inflation factors also provide useful information. On the other hand, the dollar carry trade is mainly driven by the U.S. economy and thus we find that only domestic inflation and consumption factors have strong predictive power for the dollar carry trade returns. U.S. inflation factors and to a lesser extend commodity measures gathered from G10 countries are also strong predictors of the momentum strategy. In addition, very strong evidence of profitability is found in the exchange rate component of the aforementioned strategies.

In addition, we find that our results are reinforced by out-of-sample analysis and combination forecasts. We also find strong economic value to a U.S. investor from the use of the common factors. In particular, we observe a significant improvement in the Sharpe ratios and the skewness profile of the payoff when we employ a decision rule that gathers information from our forecasts. Another striking feature revealed from examination of rolling Sharpe ratios is associated with very high annualized Sharpe ratios during the recent financial crisis. The estimation of the certainty equivalent return shows that a risk-averse investor with mean-variance preferences would be willing to pay an annual management fee in order to have access to the forecasts in lieu of the historical mean.

We also showed that the common factors are able to forecast the carry and dollar carry trade returns over and above other factors in the literature, such as the Bakshi and Panayotov (2013) predictors or average forward discounts. Finally, there is evidence of predictability in the long leg of the carry trade and to a smaller magnitude in the short leg of the trade. However, the returns of the winner and loser portfolios of the momentum strategy are highly predictable from a global money and credit factors and a U.S. inflation factor.

The second chapter examines the role of global political risk in the currency market. We find that a novel factor capturing *unexpected* political events is priced in the cross-section of currency momentum strategies. This factor demonstrates strong cross-sectional predictability beyond other factors mentioned in the literature or existing measures of limits to arbitrage. Therefore, it could "serve" as a fundamental anchor that partially drives its profitability.

Currency momentum is a strategy where an investor forms expectations with regards to future excess returns based on the performance of currency premia in previous periods. Specifically, the investor buys currencies that performed well over a particular past period while short-selling currencies that exhibited poor past profitability. Current asset pricing models perform poorly in explaining the cross-section of momentum returns and shed light on economic forces that drive the currency premia that is associated with the currency momentum. This chapter provides an asset pricing model that incorporates information on *unexpected* movements of political risk relative to the U.S. economy, showing that it is capable of capturing a significant bulk of currency excess returns. Intuitively, investors will demand a premium for investing on high political risk currencies, while our empirical analysis suggests that currency trader tend to take on global political risk when investing in currency momentum strategies.

In addition, currency momentum is driven by limits to arbitrage and it is more attractive to currencies that exhibit high illiquidity, volatility, correlation and idiosyncratic volatility. We show that political risk is a natural limit to arbitrage in the FX market, so determining the momentum profitability even after checking for the aforementioned variables. Therefore, it captures a unique dimension of currency premia. The results are less pronounced for currency carry trades because the interest rate differentials which are less affected by political risk are, in turn, quite persistent and dominate the carry trade portfolio movements. The results are robust after controlling for transaction costs or on the occasions when we employed short-run reversals as a conditional variable in the mimicking portfolio. When we apply filter that make our analysis more realistic, the results prove to be similar or improved in some cases.

In the final chapter, we study the role of technology diffusion in the foreign exchange market. Particularly, we link technology diffusion with the carry trade activity. Carry trade is a foreign exchange strategy that goes long high interest rate currencies and short low interest rate currencies. Its profitability is driven by the persistent differences in interest rate differentials. On the other hand the technology diffusion is heavily determined by the income inequality across countries. In this chapter, we show that technology diffusion can partially explain the carry trade profitability.

Particularly, we develop a linear two-factor asset pricing model that incorporates information of global technology diffusion. The first factor is a dollar factor that is measured as the average across portfolios each time. The second factor is the technology diffusion factor that goes long low technology diffusion baskets while short-selling high technology diffusion portfolios. We show that technology diffusion is priced as it is able to capture the cross-section of currency premia.

The pricing ability of the model is also verified by rolling betas as well as currency level asset pricing tests. We also show that technology diffusion contains important information for conditional returns. Finally, our results are similar even after controlling for transaction costs.

Appendices

Appendix A

Supporting Documentation: Chapter 1

A.1 Tables

A.1.1 Robustness Checks

In this section we provide addition robustness checks for our domestic and common factors. Particularly, Table A1 shows that our factors are performing well even when we consider payoffs from other studies in the literature such as the Lustig et al. (2011) payoffs or Bakshi and Panayotov (2013) carry positions.

Table A.1. Robustness: In-sample analysis - *Other payoffs*

The table reports OLS estimates for carry and momentum excess returns obtained from other studies. In Panel A the dependent variable is the currency excess returns of the carry trade strategy (net excess returns) from Lustig et al. (2011). Panel B reports results for currency excess returns of the carry trade strategy (equation 2 for K=1,2) of Bakshi and Panayotov (2013). NW represents Newey and West (1987) corrected for autocorrelation and heteroskedasticity t-statistics with the optimal number of lags following Andrews (1991). B denotes the bootstrap p-values based on 10,000 bootstrap iterations. The data span the period 1985:07-2012:03.

	cons	$\hat{g}_{2,t}$	$\hat{g}_{2,t-3}$	$\hat{h}_{3,t}$	$\hat{h}_{7,t}$	$\bar{R}^2$	*cons*	$\hat{g}_{2,t}$	$\hat{g}_{2,t-3}$	$\hat{h}_{4,t}$	$\hat{h}_{5,t}$	$\hat{h}_{6,t}$	$\hat{h}_{7,t}$	$\bar{R}^2$
	Panel A: Carry Trades (Lustig et al., 2011)													
	All Countries						*Developed Countries*							
(a)	0.38	0.67	-0.53			0.04	0.26	0.93	-0.79					0.07
NW	2.70	3.84	-3.74			15.84	1.69	3.24	-2.94					15.94
B	0.01	0.00	0.00			0.00	0.09	0.00	0.00					0.00
(b)	0.37			0.33		0.01	0.27			0.42	0.12	0.28	-0.16	0.02
NW	2.41			1.88		3.72	1.60			1.53	0.72	1.96	-1.07	7.66
B	0.01			0.05		0.05	0.10			0.10	0.51	0.05	0.29	0.10
(c)	0.38	0.62	-0.52	0.09	-0.01	0.04	0.27	0.86	-0.72	0.10	0.06	0.22	-0.19	0.07
NW	2.70	3.19	-3.90	0.47	-0.10	15.42	1.74	3.61	-2.56	0.40	0.43	1.45	-1.24	22.51
B	0.01	0.00	0.00	0.64	0.92	0.00	0.09	0.00	0.00	0.67	0.72	0.13	0.22	0.00
	Panel B: Carry Trades (Bakshi and Panayotov, 2013)													
	Carry 1						*Carry 2*							
(a)	0.18	0.64	-0.45			0.04	0.15	0.53	-0.40					0.08
NW	1.26	2.69	-3.28			12.48	1.48	3.47	-2.77					16.23
B	0.21	0.00	0.00			0.00	0.14	0.00	0.00					0.00
(b)	0.18			0.40	-0.25	0.03	0.14			-0.20	0.06	0.12		0.01
NW	1.27			1.81	-1.93	7.31	1.28			-1.76	0.60	1.38		4.39
B	0.21			0.02	0.07	0.03	0.16			0.10	0.60	0.13		0.22
(c)	0.16	0.51	-0.44	0.22	-0.27	0.05	0.15	0.49	-0.35	-0.08	0.04	0.10		0.08
NW	1.21	1.96	-3.62	0.86	-2.06	15.45	1.43	3.25	-2.33	-0.75	0.35	1.06		20.06
B	0.25	0.05	0.01	0.33	0.05	0.00	0.14	0.00	0.02	0.50	0.78	0.25		0.00

Table A.2. Robustness: *Different subsamples - Carry Trades*

The table reports OLS estimates for the carry trade strategy of different subsamples. The dependent variable is the currency excess return (ψ^{HML}), based on the carry trade strategy that goes long (short) a basket of currencies with highest (lowest) forward discounts or the exchange rate component (Δs^{HML}) of the strategy. NW represents Newey and West (1987) corrected for autocorrelation and heteroskedasticity t-statistics with the optimal number of lags following Andrews (1991). B denotes the bootstrap p-values based on 10,000 bootstrap iterations. The data span the period 1985:07-2012:03.

	cons	$\hat{g}_{2,t}$	$\hat{h}_{5,t}$	$\hat{h}_{6,t}$	$\bar{R}^2$	*cons*	$\hat{g}_{2,t}$	$\hat{h}_{5,t}$	$\hat{h}_{6,t}$	$\bar{R}^2$
Panel A: 1987:07-1992:12										
	All Countries					*Developed Countries*				
ψ^{HML}	1.3	1.67			0.05	1.31	1.46			0.03
NW	3.43	2.63			5.86	3.06	1.97			3.69
B	0.02	0.02			0.02	0.03	0.06			0.05
ψ^{HML}	1.33	1.82	0.06	0.24	0.04	1.45	1.75	0.22	0.33	0.02
NW	4.03	2.95	0.25	1.05	5.86	3.64	2.51	0.79	1.33	5.67
B	0.02	0.01	0.86	0.31	0.02	0.02	0.03	0.58	0.25	0.06
Δs^{HML}	-0.42	-1.64			0.05	-0.74	-1.54		-0.27	0.04
NW	-1.15	-2.44			5.37	-1.72	-1.97		-1.12	3.91
B	0.44	0.02			0.02	0.18	0.05		0.34	0.05
Δs^{HML}	-0.52	-1.85	-0.17	-0.2	0.04	-0.92	-1.84	-0.28		0.03
NW	-1.62	-2.87	-0.65	-0.87	6.76	-2.31	-2.53	-1.02		5.35
B	0.38	0.02	0.66	0.48	0.08	0.13	0.03	0.47		0.14
Panel B: 1992:12-2012:03										
	All Countries					*Developed Countries*				
	0.31	0.48			0.04	0.04	0.58			0.04
NW	1.4	2.08			5.29	0.17	1.89		0.38	3.28
B	0.1	0.02			0.02	0.85	0.07		2.66	0.07
	0.33	0.51	0.25	0.33	0.06	0.07	0.61	0.3	0.03	0.06
NW	1.82	3.2	1.45	2.01	12.59	0.29	2.05	1.14		9.49
B	0.07	0.02	0.12	0.03	0.01	0.78	0.06	0.31		0.02
	0.75	-0.48			0.04	0.23	-0.62		-0.38	0.04
NW	3.72	-2.4			7.42	0.86	-2.04		-2.61	4.14
B	0	0.01			0.01	0.32	0.04		0.03	0.04
	0.72	-0.49	-0.12	-0.26	0.04	0.2	-0.65	-0.28		0.06
NW	4.09	-2.63	-0.77	-1.93	9.46	0.8	-2.19	-1.07		10.17
B	0	0.01	0.43	0.1	0.02	0.41	0.05	0.35		0.02

Table A.3. Robustness: *Different subsamples - Dollar Carry Trades*

The table reports OLS estimates for the dollar carry trade strategy of different subsamples. The dependent variable is the currency excess return (ψ^{USD}), based on the carry trade strategy that goes long (short) a basket of currencies with highest (lowest) forward discounts or the exchange rate component (Δs^{HML}) of the strategy. NW represents Newey and West (1987) corrected for autocorrelation and heteroskedasticity t-statistics with the optimal number of lags following Andrews (1991). B denotes the bootstrap p-values based on 10,000 bootstrap iterations. The data span the period 1985:07-2012:03.

	All Countries					*Developed Countries*					
Panel A: 1987:07-1992:12											
	cons	$\hat{g}_{3,t}$	$\hat{h}_{6,t}$	$\hat{h}_{7,t}$	$\bar{R}^2$	*cons*	$\hat{g}_{3,t}$	$\hat{h}_{4,t}$	$\hat{h}_{6,t}$	$\hat{h}_{7,t}$	$\bar{R}^2$
ψ^{USD}	0.07	-0.53	0.75	-0.50	0.04	-0.05	-0.48	-0.41	0.96	-0.69	0.04
NW	0.22	-1.49	2.15	-1.92	5.31	-0.12	-1.27	-0.87	2.15	-2.06	5.38
B	0.83	0.11	0.05	0.09	0.15	0.90	0.20	0.35	0.04	0.05	0.25
Δs^{HML}	0.07	-0.55	0.74	-0.48	0.04	-0.11	-0.50	-0.47	0.94	-0.68	0.05
NW	0.21	-1.46	2.10	-1.84	4.98	-0.25	-1.29	-1.01	2.12	-2.02	5.35
B	0.21	0.12	0.06	0.09	0.17	0.81	0.18	0.30	0.04	0.06	0.25
Panel B: 1992:12-2012:03											
ψ^{USD}	0.34	-0.16	0.31	-0.32	0.05	0.50	-0.22	0.25	0.34	-0.34	0.05
NW	3.10	-1.30	2.13	-2.32	15.47	3.58	-1.37	1.73	2.13	-2.28	14.69
B	0.01	0.37	0.02	0.03	0.00	0.01	0.29	0.12	0.03	0.04	0.01
Δs^{HML}	0.36	-0.22	0.29	-0.26	0.04	0.49	-0.21	0.23	0.34	-0.35	0.06
NW	3.29	-1.94	1.94	-1.97	11.25	3.45	-1.34	1.61	2.11	-2.34	15.24
B	0.00	0.25	0.04	0.06	0.01	0.00	0.32	0.15	0.04	0.03	0.00

Table A.4. Robustness: ***Different subsamples - Momentum***

The table reports OLS estimates for the dollar carry trade strategy of different subsamples. The dependent variable is the currency excess return (ψ^{WML}),), based on the momentum strategy that goes long (short) a basket of currencies with highest (lowest) past returns or the exchange rate component (Δs^{HML}) of the strategy. NW represents Newey and West (1987) corrected for autocorrelation and heteroskedasticity t-statistics with the optimal number of lags following Andrews (1991). B denotes the bootstrap p-values based on 10,000 bootstrap iterations. The data span the period 1985:07-2012:03.

	cons	$\hat{g}_{1,t}$	$\hat{h}_{1,t}$	$\hat{h}_{4,t}$	$\bar{R}^2$	*cons*	$\hat{g}_{2,t}$	$\hat{h}_{7,t}$	$\hat{h}_{8,t}$	$\bar{R}^2$
Panel A: 1987:07-1992:12										
	All Countries					*Developed Countries*				
ψ^{WML}	2.91	-2.70	-0.06	-0.64	0.04	-1.01	-1.63	-0.17	0.21	0.05
NW	2.61	-2.25	-0.13	-1.19	5.95	-2.12	-3.28	-0.88	0.61	6.17
B	0.01	0.01	0.92	0.29	0.11	0.08	0.03	0.41	0.53	0.10
Δs^{HML}	3.16	-2.44	-0.06	0.72	0.04	1.16	1.77	0.10	-0.21	0.06
NW	3.83	-2.81	-0.09	1.21	9.96	2.40	3.43	0.55	-0.66	7.61
B	0.00	0.03	0.93	0.22	0.02	0.03	0.01	0.64	0.52	0.05
Panel B: 1992:12-2012:03										
	All Countries					*Developed Countries*				
ψ^{WML}	0.44	-0.05	-0.25	0.26	0.01	0.23	-0.43	-0.19	0.32	0.04
NW	2.98	-0.22	-1.66	1.16	5.40	1.62	-2.40	-1.06	1.64	5.88
B	0.02	0.85	0.10	0.21	0.14	0.19	0.08	0.30	0.10	0.12
Δs^{HML}	0.38	0.44	0.12	-0.66	0.02	-0.22	0.45	0.20	-0.30	0.04
NW	1.67	1.52	0.88	-2.46	7.10	-1.53	2.52	1.16	-1.61	6.89
B	0.10	0.13	0.43	0.02	0.07	0.22	0.07	0.26	0.12	0.07

Table A.5. Robustness: *Foreign Investors - Carry Trades*

The table reports OLS estimates for the carry trade strategy of different subsamples. The dependent variable is the currency excess return (ψ^{HML}), based on the carry trade strategy that goes long (short) a basket of currencies with highest (lowest) forward discounts or the exchange rate component (Δs^{HML}) of the strategy. NW represents Newey and West (1987) corrected for autocorrelation and heteroskedasticity t-statistics with the optimal number of lags following Andrews (1991). B denotes the bootstrap p-values based on 10,000 bootstrap iterations. The data span the period 1985:07-2012:03.

Panel A: Excess Returns & Exchange Rate Changes

	cons	$\hat{g}_{2,t}$	$\hat{g}_{2,t-3}$	$\hat{g}_{3,t-3}$	$\hat{h}_{2,t}$	$\hat{h}_{6,t}$	$\bar{R}^2$	*cons*	$\hat{g}_{2,t}$	$\hat{g}_{2,t-3}$	$\hat{g}_{3,t-3}$	$\hat{h}_{2,t}$	$\hat{h}_{6,t}$	$\bar{R}^2$
	GBP							*CHF*						
ψ^{HML}	1.23	0.72	-0.49	-0.37	0.21	0.29	0.07	0.95	0.60	-0.37	-0.34	0.33	0.31	0.08
NW	7.85	2.87	-2.55	-2.54	1.48	2.08	27.53	6.10	2.48	-1.91	-2.22	2.27	2.22	32.80
B	0.00	0.00	0.02	0.00	0.16	0.05	0.00	0.00	0.00	0.10	0.01	0.03	0.02	0.00
Δs^{HML}	-0.01	-0.71	0.36	0.32	0.08	-0.24	0.06	0.22	-0.62	0.28	0.31	-0.03	-0.25	0.05
NW	-0.08	-3.30	2.10	2.22	0.65	-1.85	23.21	1.55	-2.95	1.56	2.15	-0.25	-1.81	19.91
B	0.93	0.00	0.09	0.01	0.65	0.09	0.00	0.11	0.00	0.24	0.01	0.75	0.07	0.00
	CAD							*SEK*						
ψ^{HML}	0.95	0.75	-0.50	-0.39	0.28	0.28	0.09	0.83	0.69	-0.49	-0.39	0.29	0.26	0.08
NW	6.02	2.93	-2.49	-2.67	1.91	1.91	32.87	5.43	2.59	-2.45	-2.59	1.91	1.81	32.76
B	0.00	0.00	0.02	0.00	0.06	0.06	0.00	0.00	0.00	0.02	0.00	0.06	0.07	0.00
Δs^{HML}	0.23	-0.73	0.37	0.33	0.00	-0.22	0.06	0.30	-0.67	0.36	0.34	0.00	-0.21	0.05
NW	1.57	-3.45	2.08	2.20	0.00	-1.61	23.15	2.16	-3.02	2.04	2.23	0.01	-1.53	21.03
B	0.11	0.00	0.08	0.01	0.92	0.10	0.00	0.03	0.00	0.10	0.01	0.92	0.13	0.00
	JPY							*AUD*						
ψ^{HML}	0.91	0.63	-0.39	-0.34	0.33	0.30	0.08	0.88	0.74	-0.51	-0.34	0.30	0.23	0.09
NW	5.65	3.04	-2.44	-2.45	2.56	2.36	36.46	5.97	2.92	-2.62	-2.67	2.11	1.73	38.82
B	0.00	0.00	0.04	0.00	0.02	0.02	0.00	0.00	0.00	0.01	0.00	0.04	0.09	0.00
Δs^{HML}	0.24	-0.66	0.29	0.32	-0.04	-0.23	0.05	0.28	-0.71	0.35	0.29	0.02	-0.20	0.06
NW	1.64	-3.57	1.93	2.33	-0.30	-1.80	21.95	2.06	-3.38	2.04	2.22	0.14	-1.53	24.44
B	0.09	0.00	0.17	0.01	0.72	0.09	0.00	0.04	0.00	0.08	0.02	0.98	0.13	0.00

Table A.6. Robustness: *Longer Horizons*

The table reports OLS estimates of long-horizon predictive regressions. In *Panel A* the dependent variable is the average log excess returns of different horizons (using forward contracts with maturities that are equal to the length of the horizon) obtained from Lustig et al. (2014). *Panel B* reports results for the cumulative payoffs of the corresponding dollar carry trade returns. NW represents Newey and West (1987) corrected for autocorrelation and heteroskedasticity t-statistics with the optimal number of lags following Andrews (1991). B denotes the bootstrap p-values based on 10,000 bootstrap iterations. The data span the period 1985:07-2012:03.

Panel A: Average log Excess Returns (Lustig et al., 2014)										
	cons	$\hat{h}_{1,t}$	$\hat{h}_{6,t}$	$\hat{h}_{7,t}$	$\bar{R}^2$	*cons*	$\hat{h}_{1,t}$	$\hat{h}_{6,t}$	$\hat{h}_{7,t}$	$\bar{R}^2$
	All Countries					*Developed Countries*				
$1-month$	0.17	-0.36	0.42	-0.36	0.06	0.14	-0.43	0.47	-0.46	0.06
NW	1.18	-2.01	3.57	-2.89	21.26	0.82	-2.09	3.46	-3.52	22.97
B	0.75	0.96	0.00	0.54	0.00	0.76	0.97	0.00	0.52	0.00
$2-month$	0.16	-0.35	0.36	-0.32	0.08	0.13	-0.42	0.42	-0.40	0.09
NW	1.39	-2.02	4.21	-2.97	26.53	1.11	-2.23	4.43	-3.61	27.28
B	0.88	0.98	0.00	0.52	0.00	0.92	0.99	0.00	0.54	0.00
$3-month$	0.16	-0.32	0.39	-0.29	0.12	0.14	-0.39	0.45	-0.35	0.13
NW	1.41	-2.15	4.54	-2.14	30.41	1.21	-2.29	4.82	-2.67	29.36
B	0.97	0.96	0.00	0.54	0.00	0.97	0.98	0.00	0.56	0.00
$6-month$	0.17	-0.24	0.37	-0.16	0.15	0.15	-0.28	0.40	-0.18	0.15
NW	1.30	-1.91	3.69	-2.38	21.12	1.30	-1.77	3.97	-2.71	18.99
B	0.94	0.87	0.00	0.58	0.01	0.95	0.80	0.00	0.98	0.01
$12-month$	0.19	-0.13	0.30	-0.16	0.18	0.17	-0.13	0.33	-0.20	0.19
NW	1.01	-3.25	1.72	-2.30	19.58	0.91	-2.81	2.06	-2.60	19.12
B	0.99	0.79	0.00	0.59	0.01	0.98	0.74	0.00	0.96	0.01
Panel A: Dollar Carry Trade (Lustig et al., 2014)										
	All Countries					*Developed Countries*				
$1-month$	0.23	-0.43	0.36	-0.41	0.06	0.47	-0.40	0.41	-0.41	0.05
NW	1.68	-2.32	3.39	-3.30	22.83	3.42	-2.09	3.47	-3.66	21.76
B	0.82	0.99	0.00	0.53	0.00	0.70	0.95	0.00	0.54	0.00
$2-month$	0.24	-0.42	0.34	-0.33	0.09	0.46	-0.40	0.34	-0.27	0.06
NW	2.16	-2.41	4.24	-3.46	30.58	4.10	-1.96	3.88	-2.64	17.56
B	0.93	0.97	0.00	0.54	0.00	0.87	0.98	0.01	0.52	0.00
$3-month$	0.22	-0.33	0.37	-0.28	0.11	0.37	-0.38	0.38	-0.23	0.09
NW	1.88	-1.97	4.17	-2.21	28.50	3.35	-2.57	4.53	-3.66	22.88
B	0.96	0.94	0.00	0.64	0.01	0.93	0.99	0.00	0.56	0.00
$6-month$	0.22	-0.24	0.35	-0.14	0.14	0.32	-0.30	0.35	-0.13	0.12
NW	1.81	-1.86	3.46	-2.57	19.69	2.69	-2.35	4.10	-2.98	16.75
B	0.96	0.89	0.00	0.96	0.00	0.94	0.92	0.00	0.95	0.01
$12-month$	0.22	-0.08	0.30	-0.16	0.17	0.35	-0.12	0.26	-0.14	0.14
NW	1.42	-2.65	1.87	-2.29	24.91	2.23	-3.23	2.30	-2.34	13.32
B	0.96	0.32	0.00	0.94	0.00	0.99	0.75	0.00	0.99	0.03

Table A.7. Robustness: *Longer Horizons*

The table reports OLS estimates of long-horizon predictive regressions. In Panel A the dependent variable is the cumulative payoff (ψ^{HML}) of a carry trade strategy over 3 to 36 months that goes long (short) a basket of currencies with highest (lowest) forward discounts. Panel B reports results for the cumulative returns of the momentum strategy for the corresponding horizons. NW represents Newey and West (1987) corrected for autocorrelation and heteroskedasticity t-statistics with the optimal number of lags following Andrews (1991). B denotes the bootstrap p-values based on 10,000 bootstrap iterations. The data span the period 1985:07-2012:03.

Panel A: Carry Trades

	cons	$\hat{g}_{2,t}$	$\hat{g}_{3,t}$	$\hat{h}_{1,t}$	$\hat{h}_{6,t}$	$\hat{h}_{7,t}$	$\bar{R}^2$
			All Countries				
$3-months$	1.06	1.22	-0.41		0.87	0.87	0.07
NW	2.30	2.97	-1.22		1.85	1.85	13.46
B	0.89	0.00	0.88		0.04	0.04	0.03
$12-months$	4.29	2.04	-0.41		14.80	1.82	0.04
NW	2.26	1.25	-1.22		2.39	1.87	10.99
B	0.88	0.14	0.88		1.00	0.05	0.11
$24-months$	4.29	2.04	-1.34		1.26	1.82	0.07
NW	2.26	1.25	-1.07		0.43	1.87	4.63
B	0.89	0.14	0.85		0.36	0.05	0.64
$36-months$	14.80	6.05	-3.16		0.86	5.03	0.08
NW	2.39	1.13	-1.65		0.19	1.99	9.19
B	0.95	0.18	0.93		0.43	0.03	0.39

Panel A: Momentum

	cons	$\hat{h}_{1,t}$	$\hat{h}_{4,t}$	$\bar{R}^2$
	All Countries			
$3-months$	1.29	-0.49	0.29	0.01
NW	3.42	-1.20	1.00	2.20
B	0.58	0.87	0.20	0.39
$12-months$	4.98	-2.23	1.06	0.06
NW	3.73	-1.34	1.08	4.63
B	1.00	0.90	0.15	0.19
$24-months$	9.98	-2.53	2.88	0.08
NW	3.98	-0.64	2.46	6.69
B	1.00	0.70	0.03	0.17
$36-months$	16.33	-0.11	-0.11	0.12
NW	4.88	-0.02	-0.02	24.24
B	1.00	0.51	0.51	0.00

Table A.8. Out-of-sample analysis: *Against the Mean*

The table presents out-of sample R-squares (R^2_{OOS}) as described in Campbell and Thompson (2008) ($R^2_{OOS} = 1 - \sum_{t=1}^{T-1} \frac{\psi^i_{t+1} - \hat{\mu}_{t+1})^2}{(\psi^i_{t+1} - \mu_{t+1})^2}$), where $\hat{\mu}_{t+1}$ represents the one-step ahead conditional forecast from the model of interest and μ_{t+1} is the historical mean of the payoff. Thus, a positive R^2_{OOS} statistic means that the competing model outperforms the benchmark model because it has a lower mean square prediction error. *Panel A* reports results for currency excess returns and *Panel B* for exchange rate changes. The superscript mean represents the mean combined forecast and the superscript weighted the weighted counterpart. The in-sample period spans the first 271 observations (out of 321) that correspond to the period 1985.07-2007.12.

Panel A: Currency Excess Returns

	ψ^{HML}		ψ^{USD}		ψ^{WML}		ψ^{HML}		ψ^{USD}		ψ^{WML}	
	R^2_{OOS}	$MSPEadj$	R^2_{OOS}	$MSPEadj$	R^2_{OOS}	$MSPEadj$	R^2_{OOS}	$MSPEadj$	R^2_{OOS}	$MSPEadj$	R^2_{OOS}	$MSPEadj$
			All Countries						*Developed Countries*			
$C_1 = [\hat{g}_2]$	0.12	0.08										
$C_1' = [\hat{g}_{1,2}]$							0.05	0.10				
$C_2 = [\hat{h}_{3,6}]$							0.06	0.07				
$C_3' = [\hat{g}_{2,3}\hat{h}_{5,6}]$	0.17	0.05					0.07	0.05				
$C_{2,3}^{Mean}$	0.16	0.06					0.08	0.06				
$C_{2,3}^{Weighted}$	0.16	0.06					0.08	0.06				
$D_2 = [\hat{h}_{6,7}]$							0.04	0.05				
$D_3 = [\hat{g}_3\hat{h}_{6,7}]$			0.06	0.02					0.05	0.02		
$D_{2,3}^{Mean}$			0.06	0.01					0.05	0.02		
$D_{2,3}^{Weighted}$			0.06	0.01					0.05	0.01		
$M_2 = [\hat{h}_{1,4}]$			0.06	0.01					0.06	0.01		
$M_2' = [\hat{h}_{3,4,7,8}]$					0.00	0.14						
$M_2' = [\hat{h}_{3,4,7,8}]$											0.06	0.07
$M_3 = [\hat{g}_3\hat{h}_4]$					0.00	0.22						
$M_{2,3}^{Mean}$											0.05	0.14
$M_{2,3}^{Weighted}$					0.00	0.22					0.06	0.10

Table A.8. Out-of-sample analysis: *Against the Mean* *(continued)*

Panel B: Exchange Rate Returns												
	ψ^{HML}		ψ^{USD}		ψ^{WML}		ψ^{HML}		ψ^{USD}		ψ^{WML}	
	R^2_{OOS}	$MSPEadj$	R^2_{OOS}	$MSPEadj$	R^2_{OOS}	$MSPEadj$	R^2_{OOS}	$MSPEadj$	R^2_{OOS}	$MSPEadj$	R^2_{OOS}	$MSPEadj$
			All Countries						*Developed Countries*			
$C_1 = [\hat{g}_2]$	0.14	0.03					0.04	0.09				
$C_1' = [\hat{g}_{1,2}]$												
$C_2 = [\hat{h}_{2,3,4,6}]$	0.03	0.17										
$C_2' = [\hat{h}_{3,6}]$							0.06	0.08				
$C_3 = [\hat{g}_{2,3}\hat{h}_{5,6}]$	0.18	0.03										
$C_3' = [\hat{g}_{2,3}\hat{h}_6]$							0.07	0.05				
$C_{1,3}^{Mean}$	0.17	0.03					0.08	0.06				
$C_{1,3}^{Weighted}$	0.17	0.03					0.08	0.06				
$D_2 = [\hat{h}_{6,7}]$			0.07	0.02					0.05	0.02		
$D_3 = [\hat{g}_3\hat{h}_{6,7}]$			0.05	0.03					0.05	0.02		
$D_{2,3}^{Mean}$			0.06	0.01					0.06	0.01		
$D_{2,3}^{Weighted}$			0.06	0.02					0.06	0.01		
$M_1 = [\hat{g}_3]$					0.00	0.28						
$M_2 = [\hat{h}_{1,4}]$					0.00	0.21						
$M_3 = [[\hat{g}_3\hat{h}_4]$					0.00	0.12						
$M_1' = [\hat{g}_2]$											0.04	0.12
$M_2' = [\hat{h}_{3,4,7,8}]$											0.07	0.06
$M_3' = [[\hat{g}_2\hat{h}_8]$											0.06	0.12
$M_{2,3}^{Mean}$					0.00	0.21						
$M_{2,3}^{Weighted}$					0.00	0.21						
$M_{2,3}^{'Mean}$											0.07	0.09
$M_{2,3}^{'Weighted}$											0.07	0.09

Table A.9. Robustness: *Alternative Asset Classes*

The table reports OLS estimates for value and momentum strategies of alternative asset classes. In *Panel A* the dependent variable is the long or short leg of a momentum strategy of equities (EQ), foreign exchange (FX), fixed income (FI) and commodities (CM). *Panel B* reports the corresponding results for the value strategy. NW represents Newey and West (1987) corrected for autocorrelation and heteroskedasticity t-statistics with the optimal number of lags following Andrews (1991). B denotes the bootstrap p-values based on 10,000 bootstrap iterations. The data span the period 1985:07-2012:03.

	cons	$\hat{g}_{1,t}$	$\hat{g}_{2,t}$	$\hat{g}_{3,t}$	$\hat{g}_{3,t-1}$	$\hat{h}_{4,t}$	$\hat{h}_{8,t}$	$\bar{R}^2$
Panel A: Value Portfolios								
					EQ			
Long	0.60	0.77	0.55	0.81				0.06
NW	2.24	2.21	2.28	3.32				11.84
B	0.02	0.03	0.07	0.00				0.01
Short	0.27	0.30	0.60	0.74				0.03
NW	0.96	0.93	2.26	3.71				11.70
B	0.32	0.34	0.02	0.00				0.01
					FI			
Long	0.33	-0.15	-0.21		-0.14	0.17	-0.14	0.07
NW	4.20	-2.01	-2.84		-2.04	1.87	-2.14	25.29
B	0.00	0.07	0.01		0.09	0.04	0.12	0.00
Short	0.22	-0.23	-0.38		-0.18			0.07
NW	1.93	-1.80	-4.14		-1.75			34.90
B	0.02	0.03	0.00		0.09			0.00
Panel B: Momentum Portfolios								
					EQ			
Long	0.81	0.65	0.46	0.82				0.05
NW	3.01	2.00	1.93	3.73				11.34
B	0.00	0.04	0.10	0.00				0.01
Short	0.18		0.49	0.80				0.03
NW	0.65		1.41	3.05				8.38
B	0.50		0.13	0.01				0.02
					FI			
Long	0.29	-0.20	-0.23		-0.16	0.19		0.05
NW	2.69	-1.70	-2.09		-1.99	1.49		16.07
B	0.00	0.05	0.03		0.08	0.06		0.00
Short	0.34	-0.21	-0.26		-0.16	-0.16		0.09
NW	3.67	-2.20	-3.24		-2.37	-2.37		36.07
B	0.00	0.02	0.00		0.06	0.01		0.00

	cons	$\hat{g}_{1,t}$	$\hat{g}_{2,t}$	$\hat{g}_{3,t-2}$	$\hat{h}_{3,t}$	$\hat{h}_{4,t}$	$\hat{h}_{6,t}$	$\hat{h}_{7,t}$	$\bar{R}^2$	
Panel A: Value Portfolios										
							FX			
Long	0.40				-0.28	0.13		0.39	-0.28	0.05
NW	3.45				-2.45	1.06		3.72	-2.06	18.78
B	0.00				0.05	0.39		0.00	0.03	0.00
Short	0.12				-0.56	0.33		0.49	-0.38	0.07
NW	0.77				-3.54	1.64		3.06	-3.15	23.16
B	0.43				0.00	0.12		0.00	0.01	0.00
							CM			
Long	0.49	0.30	0.55	0.44			0.09	0.23		0.02
NW	2.11	1.32	2.55	1.93			0.36	1.03		7.06
B	0.04	0.29	0.04	0.08			0.73	0.36		0.22
Short	0.37	0.58	1.46	0.50			-0.72	0.53		0.12
NW	1.41	1.79	4.79	1.95			-3.03	1.94		28.28
B	0.20	0.13	0.00	0.09			0.02	0.06		0.00
Panel B: Momentum Portfolios										
							FX			
Long	0.36				-0.43		-0.08	0.41	-0.36	0.05
NW	2.85				-2.92		-0.64	2.87	-2.46	17.95
B	0.02				0.01		0.54	0.01	0.03	0.00
Short	0.11				-0.31		-0.32	0.38		0.04
NW	0.79				-2.00		-2.72	3.09		17.59
B	0.41				0.08		0.05	0.00		0.00
							CM			
Long	0.97			0.16		1.07	-0.69	0.30		0.05
NW	3.55			0.66		2.94	-2.44	0.97		10.19
B	0.00			0.59		0.01	0.06	0.29		0.04
Short	0.06			0.64		0.53	-0.56	0.36		0.05
NW	0.28			2.51		2.10	-3.14	1.66		13.30
B	0.82			0.02		0.12	0.04	0.19		0.01

A.1.2 Data

This table provides a detailed description of the U.S. and Global monthly (start of month) data as well as the transformations applied to the series based on stationarity tests, detailed in Stock and Watson (2002a, b): lv = no transformation; lv = first difference; ln = logarithm; Δln = first difference of logarithm. The data is available from Datastream and span the period 1985:7-2012:03.

Table A.10. U.S. Data

Series Number	Mnemonics	Tranf	Description
			Real Output
1	870010061	$\Delta \ln$	US PROD OF TOTAL INDUSTRY VOLA
2	870010074	$\Delta \ln$	US PROD IN TOTAL MFG VOLA
3	870010065	$\Delta \ln$	US PROD OF TOTAL MFC CONSUMER GOODS VOLA
4	870010070	$\Delta \ln$	US PROD OF TOTAL MFC INTERMEDIATE GOODS VOLA
5	870010058	$\Delta \ln$	US PROD OF DWELLINGS CURN
6	60624012	ln	US PERSONAL INCOME (MONTHLY SERIES) (AR) CURA
7	60611444	$\Delta \ln$	US PERSONAL INCOME LESS TRANSFER PAYMENTS (BCI 51) CONA
			Employment
8	870012315	$\Delta \ln$	US EMPLOYEES: TOTAL (BUSINESS SURVEY)(DISC.) VOLA
9	870004508	$\Delta \ln$	US CIVILIAN EMPLOYMENT: ALL PERSONS(DISC.) VOLA
10	870011929	$\Delta \ln$	US CIVILIAN LABOUR FORCE: ALL PERSONS(DISC.) VOLA
11	870004623	$\Delta \ln$	US UNEMPLOYMENT RATE: SURVEY-BASED (ALL PERSONS)(DISC.) SADJ
12	870004581	Δlv	US WEEKLY HOURS WORKED: MFG VOLA
13	870004585	Δlv	US WEEKLY OVERTIME HOURS: MFG VOLA
14	60200425	$\Delta \ln$	US UNEMPLOYMENT RATE SADJ
15	64554480	$\Delta \ln$	US UNEMPLOYED (16 YRS & OVER) VOLA
16	60200205	Δlv	US TOTAL CIVILIAN EMPLOYMENT VOLA
			Consumption
17	64110309	$\Delta \ln$	US CHAIN-TYPE PRICE INDEX FOR PERSONAL CONSMPTN.EXPENDITURE SADJ
18	60624032	$\Delta \ln$	US PERSONAL CONSUMPTION EXPENDITURES (AR) CURA
19	62244012	$\Delta \ln$	US PERSONAL CONSUMPTION EXPENDITURES - DURABLES (AR) CURA
20	64110362	$\Delta \ln$	US PERSONAL CONSUMPTION EXPENDITURES - LESS FOOD & ENERGY CURA
21	62244032	$\Delta \ln$	US PERSONAL CONSUMPTION EXPENDITURES - SERVICES (AR) CURA
22	62244022	$\Delta \ln$	US PERSONAL CONSUMPTION EXPENDITURES - NONDURABLES (AR) CURA
			Housing Start
23	64101515	ln	US HOUSING STARTED VOLN
24	64101504	ln	US HOUSING STARTED - MIDWEST (AR) VOLA
25	64101503	ln	US HOUSING STARTED - NORTHEAST (AR) VOLA
26	64101505	ln	US HOUSING STARTED - SOUTH (AR) VOLA
27	64101506	ln	US HOUSING STARTED - WEST (AR) VOLA
28	64101525	ln	US HOUSING AUTHORIZED VOLN
29	61110105	ln	US NEW PRIVATE HOUSING UNITS STARTED (AR) VOLA
30	61110405	ln	US NEW PRIVATE HOUSING UNITS AUTHORIZED BY BLDG.PERMIT (AR) VOLA
31	61105002	ln	US CONSTRUCTION EXPENDITURES - TOTAL (AR) CURA
32	64121950	ln	US EXISTING HOME SALES: SINGLE-FAMILY & CONDO (AR) VOLA
33	64101560	ln	US HOUSING COMPLETED - 1 UNIT VOLN
34	64101544	ln	US HOUSING COMPLETED - 1 UNIT (AR) VOLA
35	64110960	ln	US HOUSING COMPLETED - 2 TO 4 UNITS VOLN
36	64101564	ln	US HOUSING COMPLETED - 5 UNITS OR MORE VOLN
37	64101546	ln	US HOUSING COMPLETED - 5 UNITS OR MORE (AR) VOLA
38	64101566	ln	US HOUSING COMPLETED - MIDWEST VOLN
39	64101548	ln	US HOUSING COMPLETED - MIDWEST (AR) VOLA
40	64101565	ln	US HOUSING COMPLETED - NORTHEAST VOLN
41	64101547	ln	US HOUSING COMPLETED - NORTHEAST (AR) VOLA
42	64101567	ln	US HOUSING COMPLETED - SOUTH VOLN
43	64101549	ln	US HOUSING COMPLETED - SOUTH (AR) VOLA
44	64101568	ln	US HOUSING COMPLETED - WEST VOLN
45	64101550	ln	US HOUSING COMPLETED - WEST (AR) VOLA
46	64101516	ln	US HOUSING STARTED - 1 UNIT VOLN
47	64112140	ln	US HOUSING STARTED - 2 TO 4 UNITS VOLN
48	64101520	ln	US HOUSING STARTED - 5 UNITS OR MORE VOLN
49	64101502	ln	US HOUSING STARTED - 5 UNITS OR MORE (AR) VOLA
50	64101522	ln	US HOUSING STARTED - MIDWEST VOLN
51	64101521	ln	US HOUSING STARTED - NORTHEAST VOLN
52	64101523	ln	US HOUSING STARTED - SOUTH VOLN
53	64101524	ln	US HOUSING STARTED - WEST VOLN
54	64101552	ln	US HOUSING UNDER CONSTRUCTION - 1 UNIT (AR) VOLA
55	64101570	ln	US HOUSING UNDER CONSTRUCTION - 1 UNIT (EP) VOLN
56	64110944	ln	US HOUSING UNDER CONSTRUCTION - 2 TO 4 UNITS (EP) VOLN
57	64101554	ln	US HOUSING UNDER CONSTRUCTION - 5 UNITS OR MORE (AR) VOLA
58	64101574	ln	US HOUSING UNDER CONSTRUCTION - 5 UNITS OR MORE (EP) VOLN
59	64101556	ln	US HOUSING UNDER CONSTRUCTION - MIDWEST (AR) VOLA
60	64101576	ln	US HOUSING UNDER CONSTRUCTION - MIDWEST (EP) VOLN
61	64101555	ln	US HOUSING UNDER CONSTRUCTION - NORTHEAST (AR) VOLA
62	64101575	ln	US HOUSING UNDER CONSTRUCTION - NORTHEAST (EP) VOLN
63	64101557	ln	US HOUSING UNDER CONSTRUCTION - SOUTH (AR) VOLA
64	64101577	ln	US HOUSING UNDER CONSTRUCTION - SOUTH (EP) VOLN
65	64101558	ln	US HOUSING UNDER CONSTRUCTION - WEST (AR) VOLA
66	64101578	ln	US HOUSING UNDER CONSTRUCTION - WEST (EP) VOLN
67	64101569	ln	US HOUSING UNDER CONSTRUCTION AT END OF PERIOD (EP) VOLN
68	68233445	ln	US NEW PRIVATE HOUSING UNITS STARTED - 1 UNIT(AR) VOLA

Table A.10. U.S. Data *(continued)*

Series Number	Mnemonics	Tranf	Description
69	61105225	ln	US NEW PRIVATELY OWNED HOUSING UNITS COMPLETED (AR) VOLA
70	61105235	ln	US NEW PRIVATELY OWNED HOUSING UNITS UNDER CONSTRUCTION (AR) VOLA
			Orders
71	60201252	ln	US ISM MANUFACTURERS SURVEY: NEW ORDERS INDEX SADJ
72	61518004	Δ ln	US NEW ORDERS OF CONSUMER GOODS & MATERIALS (BCI 8) CONA
			Stock Prices
73	DUS(PI)	Δ ln	DOW JONES INDUSTRIALS - PRICE INDEX
74	870004617	Δ ln	US SHARE PRICES: NYSE COMPOSITE NADJ
75	61401000	Δ ln	US DOW JONES INDUSTRIALS SHARE PRICE INDEX (EP) NADJ
76	DJUTILS(PI)	Δ ln	DOW JONES UTIILITIES - PRICE INDEX
			Exchange Rates
77	640023985	Δ ln	SW SWISS FRANCS TO USD REAL INDEX VOLN
78	77000129	Δ ln	CN CANADIAN DOLLARS TO 1 U.S. DOLLAR (MONTHLY AVERAGE)
79	741120006	Δ ln	UK NATIONAL CURRENCY UNIT TO US $ - MARKET RATE (EP)
80	741580006	Δ ln	JP NATIONAL CURRENCY UNIT TO US $ - MARKET RATE (EP)
			Interest Rates
81	870004511	lv	US FEDERAL FUNDS RATE NADJ
82	870004512	lv	US PRIME RATE NADJ
83	870009005	lv	US YIELD 10-YEAR FED GVT SECS (COMPOSITE) NADJ
84	870009003	lv	US RATE 3-MONTH CDS NADJ
85	870009004	Δlv	US RATE 3-MONTH EURO-DOLLAR DEPOSITS NADJ
86	870009006	lv	US YIELD 10-YEAR FED GVT SECS NADJ
87	741110441	lv	US DISCOUNT RATE (EP)
88	741110450	lv	US TREASURY BILL RATE
89	741110465	lv	US 1-MONTH US $ DEPOSITS, LONDON OFFER
90	741110468	Δlv	US 3-MONTH US $ DEPOSITS, LONDON OFFER
91	741110471	lv	US 6-MONTH US $ DEPOSITS, LONDON OFFER CURN
92	741110480	lv	US GOVT BOND YIELD - LONGTERM
93	741110483	lv	US GOVT BOND YIELD - MEDIUM TERM
			Money and Credit Quantity Aggregates
94	870004548	Δ ln	US MONETARY AGGREGATE M1 CURA
95	870004544	ln	US MONETARY AGGREGATE M2 CURA
96	870004546	Δ ln	US MONETARY AGGREGATE M3 - PROXY CURA
97	741110057	Δ ln	US INTERNATIONAL RESERVES CURN
98	64125508	Δ ln	US COMMERCIAL BANK ASSETS - LOANS & LEASES IN BANK CREDIT CURA
99	64104036	Δ ln	US COMMERCIAL BANK ASSETS - COMMERCIAL & INDUSTRIAL LOANS CURA
100	440337331	lv	US COML BANK ASSETS-COMMERCIAL & INDL LOANS(BREAK ADJ,SAAR) SADJ
101	741110066	Δ ln	US FUND POSITION: SDR'S CURN
			Price Indices
102	870004479	Δ ln	US CPI ALL ITEMS SADJ
103	870004480	Δ ln	US CPI ALL ITEMS WAGE EARNERS NADJ
104	870006150	Δ ln	US CPI FOOD EXCL. RESTAURANTS NADJ
105	870006151	Δ ln	US CPI ENERGY NADJ
106	870006152	Δ ln	US CPI ALL ITEMS NON-FOOD NON-ENERGY NADJ
107	870004477	Δ ln	US CPI ALL ITEMS NEW YORK NADJ
108	64110656	Δ ln	US PPI - FINISHED GOODS SADJ
109	60823485	Δ ln	US PPI - FINISHED GOODS LESS FOODS & ENERGY (CORE) SADJ
110	64582033	Δ ln	US PPI - CONSUMER NONDURABLE GOODS LESS FOOD SADJ
111	64636479	Δ ln	US PPI - OTHER HOUSEHOLD DURABLE GOODS NADJ
112	64636770	Δ ln	US PPI - SPORTING & ATHLETIC GOODS NADJ
113	64636762	Δ ln	US PPI - TOYS, SPORTING GOODS, SMALL ARMS, ETC. NADJ
114	60823515	Δ ln	US PPI - CONSUMER NONDURABLE GOODS LESS FOOD & ENERGY SADJ
115	60823535	Δ ln	US PPI - INTERMEDIATE MATERIALS LESS ENERGY SADJ
116	64583023	Δ ln	US PPI - INTERMEDIATE MATERIALS LESS ENERGY NADJ
117	64581996	Δ ln	US PPI - CRUDE NONFOOD MATERIALS EXCEPT FUEL SADJ
118	64633584	Δ ln	US PPI-PORK PRODS,FRESH,FROZEN,OR PROCESSED, EXCEPT SAUSAGE NADJ
119	64582021	Δ ln	US PPI - MANUFACTURED ANIMAL FEEDS SADJ
120	870009105	Δ ln	US HOURLY EARN: MFG SADJ
121	870004515	Δ ln	US HOURLY EARN: MFG NADJ
122	870010200	Δ ln	US HOURLY EARN: PRIVATE SECTOR SADJ
123	870004629	Δ ln	US ITS IMPORTS C.I.F. TOTAL CURA
124	870004626	Δ ln	US ITS EXPORTS F.A.S. TOTAL CURA
125	870004632	Δ ln	US ITS NET TRADE (F.A.S. - C.I.F.) CURA
126	870006320	lv	US MFG - CONFIDENCE INDICATOR SADJ
127	61070005	lv	US CAPACITY UTILIZATION RATE - ALL INDUSTRY SADJ

Table A.11. Global Data

Series Number	Mnemonics	Tranf	Description
			Real Output
1	CN2PTOTCD	$\Delta \ln$	CN GDP - INDUSTRIAL PRODUCTION CONN
2	JPPRODVTE	Δlv	JP LABOR PRODUCTIVITY INDEX - ALL INDUSTRIES SADJ
3	AUSTEELPP	$\Delta \ln$	AU AUSTRALIA - STEEL PRODUCTION VOLN
4	UKIPTOT.G	$\Delta \ln$	UK INDEX OF PRODUCTION - ALL PRODUCTION INDUSTRIES VOLA
5	SDIPTOT5G	$\Delta \ln$	SD INDUSTRIAL PRODUCTION - MINING & MANUFACTURING (CAL ADJ) VOLA
6	BDIP0093G	$\Delta \ln$	BD INDUSTRIAL PRODUCTION: MANUFACTURING VOLA
			Employment
7	DKUNPTOTP	$\Delta \ln$	DK UNEMPLOYMENT NET (METHDOLOGY BREAK APRIL 2000) VOLA
8	CNUN%TOTQ	$\Delta \ln$	CN UNEMPLOYMENT RATE - CANADA (15 YRS & OVER) NADJ
9	JPUN%TOTQ	Δlv	JP UNEMPLOYMENT RATE (METHO BREAK MAR 2011) SADJ
10	AUUN%TOTQ	Δlv	AU UNEMPLOYMENT RATE (LABOUR FORCE SURVEY ESTIMATE) SADJ
11	NZMLM005P	$\Delta \ln$	NZ REGISTERED UNEMPLOYMENT: LEVEL (ALL PERSONS) VOLN
12	UKUN%TOTQ	Δlv	UK UNEMPLOYMENT RATE SADJ
13	SWUN%TOTR	Δlv	SW UNEMPLOYMENT RATE NADJ
14	OEUN%TOTR	ln	OE UNEMPLOYMENT RATE % NADJ
15	NWUN%TOTQ	Δlv	NW UNEMPLOYMENT RATE (% OF LFS) SADJ
			Consumption
16	NWPERCGDG	$\Delta \ln$	NW PRIVATE CONSUMPTION - GOODS VOLA
17	BCPIEXC	$\Delta \ln$	BOC. WEEKLY EXCLUDING ENERGY - PRICE INDEX
18	AUIMPCSGB	ln	AU IMPORTS FOB - CONSUMPTION GOODS CURA
19	JPCCEPCSE	Δlv	JP ELECTRIC POWER CONSUMPTION - LARGE CORPORATIONS SADJ
20	CNPPOCOMP	ln	CN PETROLEUM PRODUCTS: ALL PRODUCTS - OWN CONSUMPTION VOLN
21	AUIMPCGDA	ln	AU IMPORTS FOB - CONSUMPTION GOODS CURN
22	UKHYELECG	$\Delta \ln$	UK CONSUMPTION OF HYDRO ELECTRICITY VOLA
23	SDECTOTLP	$\Delta \ln$	SD CONSUMPTION OF ELECTRICITY VOLN
24	NWPERCGDG	$\Delta \ln$	NW PRIVATE CONSUMPTION - GOODS VOLA
25	EUCNMCOIP	$\Delta \ln$	EU CONSUMPTION - CRUDE OIL VOLN
26	DKESEIWBP	Δlv	DK ENERGY - CONSUMPTION, NATURAL GAS VOLN
			Stock Price
27	JPSHRPRCF	$\Delta \ln$	JP TOKYO STOCK EXCHANGE - TOPIX NADJ
28	CNSHRPRCF	$\Delta \ln$	CN TORONTO STOCK EXCHANGE COMPOSITE SHARE PRICE INDEX NADJ
29	TOTXTER	Δlv	EU-DS DS-MARKET EX TMT - PRICE INDEX
30	HLTHCDK	$\Delta \ln$	DK-DS HEALTH CARE - PRICE INDEX
31	TOTMKAU	Δlv	AU-DS MARKET - PRICE INDEX
32	FINANUK	$\Delta \ln$	UK-DS FINANCIALS - SHARE HOLDERS EQUT
33	MSSWDNL	Δlv	MSCI SWEDEN PRICE INDEX
34	MSSWITL	Δlv	MSCI SWITZERLAND PRICE INDEX
			Price Indices
35	CNCONPRCF	$\Delta \ln$	CN CPI NADJ
36	JPCONPRCF	Δlv	JP CPI: NATIONAL MEASURE NADJ
37	AUCPANNL	Δlv	AU INFLATION RATE (DS CALCULATED QUARTERLY) NADJ
38	NZCPANNL	Δlv	NZ INFLATION RATE NADJ
39	UKOCP009R	ln	UK CPI ALL ITEMS NADJ
40	SWCONPRCF	Δlv	SW CPI NADJ
41	SDCONPRCF	$\Delta \ln$	SD CPI NADJ
42	NWCONPRCF	Δlv	NW CPI NADJ
43	EUOCP009F	$\Delta \ln$	EU CPI ALL ITEMS NADJ
44	DKCONPRCF	ln	DK CPI NADJ
45	CNMPIFG1F	$\Delta \ln$	CN TOTAL PPI FINISHED GOODS NADJ
46	JPOPIFG2F	$\Delta \ln$	JP DOMESTIC PPI FINISHED GOODS NADJ
47	UKPROPRCF	$\Delta \ln$	UK PPI - OUTPUT OF MANUFACTURED PRODUCTS (HOME SALES) NADJ
48	SWPROPRCE	Δlv	SW PPI SADJ
49	NWPROPRCF	$\Delta \ln$	NW PPI NADJ
50	EUOPIMP2F	$\Delta \ln$	EU DOMESTIC PPI MFG NADJ
51	DKESPPINF	$\Delta \ln$	DK PPI: NON-DURABLE CONSUMER GOODS NADJ
			Interest Rates
52	ECCAD1M	lv	CANADA EURO-$ 1 MTH (FT/ICAP/TR) - MIDDLE RATE
53	ECJAP1M	lv	JAPAN EURO-YEN 1 MTH (FT/ICAP/TR) - MIDDLE RATE
54	ECUKP1M	Δlv	UK EURO-1M (FT/ICAP/TR) - MIDDLE RATE
55	ECWGM1M	Δlv	GERMANY EU-MARK 1M (FT/ICAP/TR) - MIDDLE RATE
56	ECSWF1M	Δlv	SWTZRLAND EU-FRC-1M (FT/ICAP/TR) - MIDDLE RATE
57	ECDKN1M	Δlv	DENMARK EURO-KRONE 1M (FT/ICAP/TR) - MIDDLE RATE
58	ECUSD1M	Δlv	US EURO-$ 1 MTH (FT/ICAP/TR) - MIDDLE RATE
59	ECCAD3M	lv	CANADA EURO-$ 3 MTH (FT/ICAP/TR) - MIDDLE RATE
60	ECJAP3M	lv	JAPAN EURO-YEN 3 MTH (FT/ICAP/TR) - MIDDLE RATE
61	ECWGM3M	Δlv	GERMANY EU-MARK 3M (FT/ICAP/TR) - MIDDLE RATE
62	ECSWF3M	Δlv	SWTZRLAND EU-FRC-3M (FT/ICAP/TR) - MIDDLE RATE
63	ECDKN3M	Δlv	DENMARK EURO-KRONE 3M (FT/ICAP/TR) - MIDDLE RATE
64	ECUSD3M	lv	US EURO-$ 3 MTH (FT/ICAP/TR) - MIDDLE RATE

Table A.11. Global Data *(continued)*

Series Number	Mnemonics	Tranf	Description
			International Trade
65	CNVISBOPB	lv	CN VISIBLE TRADE BALANCE (BALANCE OF PAYMENTS BASIS) CURA
66	JPVISGDSA	lv	JP VISIBLE TRADE BALANCE CURN
67	AUBALGOSA	lv	AU BALANCE OF TRADE IN GOODS & SERVICES (BOP BASIS) CURN
68	NZVISGDSA	lv	NZ VISIBLE TRADE BALANCE CURN
69	UKVISBOPB	Δlv	UK VISIBLE TRADE BALANCE - BALANCE OF PAYMENTS BASIS CURA
70	SWTA2891E	lv	SW TRADE BALANCE TOTAL 1 CURA
71	SDVISGDSA	lv	SD VISIBLE TRADE BALANCE CURN
72	NWVISGDSA	lv	NW VISIBLE TRADE BALANCE CURN
73	BDVISGDSB	Δlv	BD VISIBLE TRADE BALANCE CURA
74	DKVISGDSA	lv	DK VISIBLE TRADE BALANCE CURN
75	USVISGDSB	Δlv	US VISIBLE TRADE BALANCE F.A.S.-F.A.S. CURA
			Reserves
76	870008751	lv	DK SDR RESERVE ASSETS CURN
77	498012588	lv	JP FOREIGN RESERVES - FOREIGN CURRENCY CURN
78	360790010	lv	SW OFFICIAL RESERVES MINUS GOLD (US$) CURN
97	60700010	Δln	US FOREIGN RESERVE ASSETS CURN
80	77001675	lv	CN OFFICIAL INTERNATIONAL RESERVES: CONVERTIBLE NON-U.S.$ CURRENCY
81	100700010	lv	AU OFFICIAL RESERVE ASSETS CURN
82	109998872	Δln	AU AUSTRALIAN $ EFFECTIVE EXCHANGE RATE INDEX
83	USNLTSECA	lv	US FOREIGN NET LONG TERM FLOWS IN SECURITIES CURN
84	116600110	Δln	NZ PRIVATE SECTOR CREDIT CURN
85	116600740	Δln	NZ TOTAL OFFICIAL RESERVES CURN
86	870008981	Δln	NW RESERVE ASSETS CURN
87	SDRESERVA	Δln	SD BANK OF SWEDEN: ASSETS - GOLD & FOREIGN EXCHANGE RESERVE CURN
			G7 Economies
88	G7MPI009R	Δln	G7 DOMESTIC PPI MFG NADJ
89	G7MPI009R	Δlv	G7 ITS EXPORTS F.O.B. TOTAL SADJ
90	G7MXT008Q	Δlv	G7 ITS IMPORTS C.I.F. TOTAL SADJ
91	505676793	Δlv	G7 NET TRADE CURA
92	502621288	lv	G7 PRODUCTION - TOTAL INDUSTRY EXCL. CONSTRUCTION SADJ
93	503351909	Δln	G7 CPI ALL ITEMS NON FOOD NON ENERGY NADJ
94	503547075	Δlv	G7 CPI FOOD NADJ
95	504352258	lv	G7 HOURLY EARN: MFG SADJ
96	502120123	lv	G7 TOTAL RETAIL TRADE (VOLUME) SADJ
97	MSCIG7$	Δln	G7 MSCI (US$) PRICE INDEX

A.1.3 Bakshi and Panayotov (2013) Predictors

Here, we provide a brief description of the predictive variables used in Bakshi and Panayotov (2013) and employed in this article. We try to keep the same notation with Bakshi and Panayotov (2013) for the convenience of the reader. Their sample begins in January 1985 and ends in August 2011, focusing on G10 countries.

- **Commodity Measure**

$$\Delta CRB_t = \frac{1}{3}\log(CRB_t/CRB_{t-3}), \tag{A.1}$$

  where CRB_t represents the Raw Industrials Subindex of the CRB Spot Commodity Index.

- **Volatility Measure**

$$\Delta\sigma_t^{fx} = \frac{1}{3}\log(\sigma_t^{avg}/\sigma_{t-3}^{avg}), \tag{A.2}$$

  where σ_t^{avg} represents the average volatility at time t across the currencies of our data.

- **Liquidity Measure**

$$\Delta LIQ_t = -(LIQ_t^{avg} - \frac{1}{3}\sum_{j=1}^{3} LIQ_{t-j}^{avg}), \tag{A.3}$$

  where LIQ_t^{avg} is the equivalent of the average TED spread, which is defined as the difference between the 3-month LIBOR and the 3-month Treasury Bills (or an equivalent measure) across the G10 countries. All the measures are normalized in order to represent monthly frequencies.

A.2 Figures

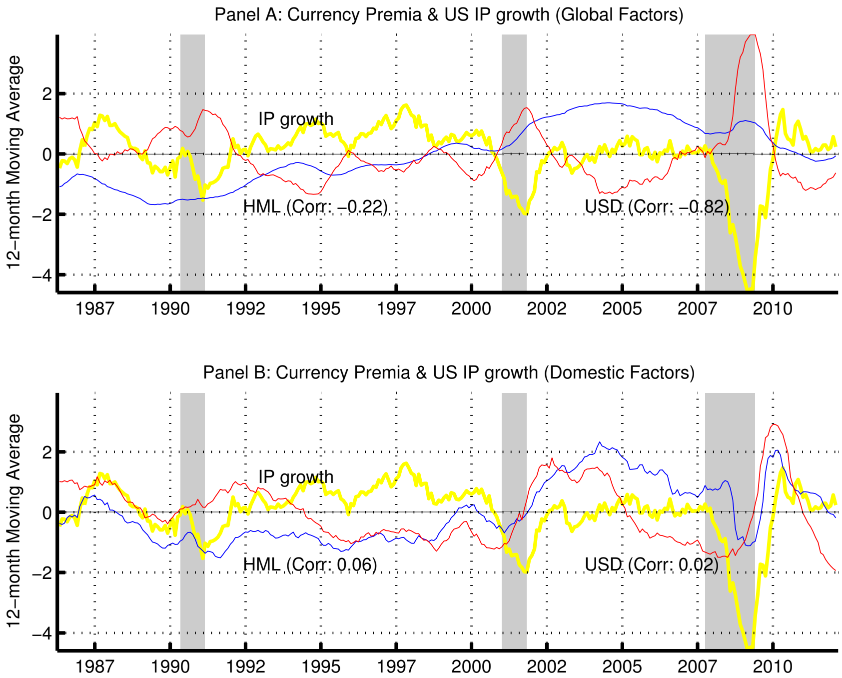


Figure A.1. Countercyclical Currency Premia (US)

The figure displays standardized 12-month moving average of carry trade and dollar carry trade excess returns, when considering the global (Panel A) or domestic (Panel B) factors as well as the 12-month moving average of the US IP growth. The blue line represents the carry trade strategy, the red line is the dollar carry trade and the yellow line depicts the IP growth. We consider the group of *All countries*. The shaded areas represent the NBER recessions of the U.S. economy.

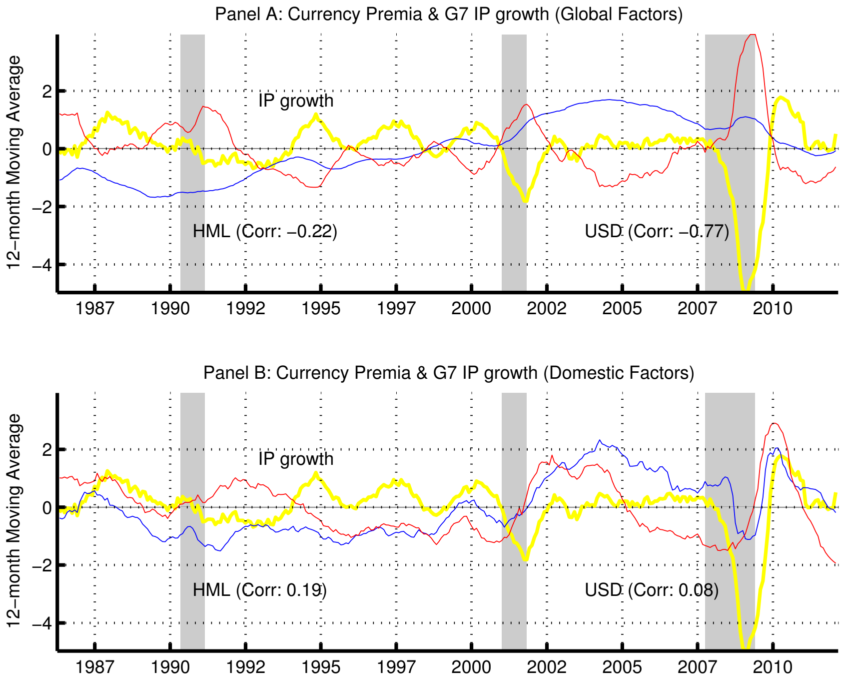


Figure A.2. Countercyclical Currency Premia (G7)

The figure displays standardized 12-month moving average of carry trade and dollar carry trade excess returns, when considering the global (Panel A) or domestic (Panel B) factors as well as the 12-month moving average of the G7 IP growth. The blue line represents the carry trade strategy, the red line is the dollar carry trade and the yellow line depicts the IP growth. We consider the group of *All countries*. The shaded areas represent the NBER recessions of the U.S. economy.

Appendix B

Supporting Documentation: Chapter 2

B.1 Tables

Table B.1. Univariate Predictive Regressions - *Alternative Formation Periods*

This table reports univariate predictive regressions of currency momentum returns with global political risk ($\Delta\mathcal{PR}_t$), volatility ($\Delta\mathcal{RV}_t^{FX}$), correlation ($\Delta\mathcal{RC}_t^{FX}$) and liquidity ($\Delta\mathcal{L}_t^{FX}$) innovations as well as CDS spreads ($\Delta\mathcal{CDS}_t$). NW represents Newey and West (1987) t-statistics corrected for heteroskedasticity and autocorrelation (HAC) using the optimal number of lags as in Andrews (1991). We also present R-squares (R^2) for each regression and below the R^2 we present χ^2 in squared brackets. *Panel A* shows results for $\mathcal{WML}_t^{3,1}$ and *Panel B* for $\mathcal{WML}_t^{6,1}$. The data is collected from Datastream *via* Barclays and Reuters. The data contain monthly series from January 1985 to January 2014 with the exception of the CDS data that spans the period October 2000 to January 2014.

	cons	$\Delta\mathcal{PR}_t$	$\Delta\mathcal{RV}_t^{FX}$	$\Delta\mathcal{RC}_t^{FX}$	$\Delta\mathcal{L}_t^{FX}$	$\Delta\mathcal{CDS}_t$	R^2	*cons*	$\Delta\mathcal{PR}_t$	$\Delta\mathcal{RV}_t^{FX}$	$\Delta\mathcal{RC}_t^{FX}$	$\Delta\mathcal{L}_t^{FX}$	$\Delta\mathcal{CDS}_t$	R^2
	Panel A: Currency Momentum ($f = 3$, $h = 1$)													
	Without Transaction Costs							*With Transaction Costs*						
(a)	0.73	-5.62					0.02	0.43	-5.97					0.02
NW	[4.62]	[-3.01]					[9.09]	[2.75]	[-3.17]					[10.03]
(b)	0.74		2.52				0.00	0.43		2.33				0.00
NW	[4.58]		[1.24]				[1.55]	[2.71]		[1.15]				[1.32]
(c)	0.73			1.31			0.00	0.43			1.24			0.00
NW	[4.61]			[0.79]			[0.62]	[2.72]			[0.74]			[0.55]
(d)	0.73				-8.49		0.00	0.43				-10.40		0.00
NW	[4.56]				[-0.94]		[0.89]	[2.70]				[-1.16]		[1.35]
(e)	0.95					-0.82	0.01	0.64					-0.82	0.01
NW	[4.09]					[-1.20]	[1.43]	[2.82]					[-1.21]	[1.46]
	Panel B: Currency Momentum ($f = 6$, $h = 1$)													
(a)	0.59	-3.23					0.00	0.30	-3.63					0.01
NW	[3.88]	[-1.43]					[2.06]	[1.95]	[-1.63]					[2.66]
(b)	0.60		0.45				0.00	0.30		0.16				0.00
NW	[3.85]		[0.17]				[0.03]	[1.94]		[0.06]				[0.00]
(c)	0.60			1.01			0.00	0.30			0.87			0.00
NW	[3.87]			[0.68]			[0.46]	[1.94]			[0.58]			[0.34]
(d)	0.59				-6.23		0.00	0.30				-7.82		0.00
NW	[3.86]				[-0.53]		[0.28]	[1.94]				[-0.66]		[0.44]
(e)	0.73					-0.70	0.00	0.43					-0.70	0.00
NW	[2.94]					[-0.82]	[0.67]	[1.74]					[-0.84]	[0.70]

Table B.2. Robustness: *Asset Pricing Tests - Longer Formation Periods*

This table reports asset pricing results for the two-factor model that comprises the DOL and $\mathcal{FPR}$ risk factors. We use as test assets six currency portfolios sorted based on past performances of currency returns. Particularly, we employ formation periods of 9 and 12 months. We rebalance our portfolios on a monthly basis. We reportFama and MacBeth (1973) estimates of the factor loadings (b) and factor prices of risk (λ). We also display Newey and West (1987) standard errors (in parenthesis) or t-statistics (in squared brackets) corrected for autocorrelation and heteroskedasticity with Andrews (1991) optimal lag selection and Sh are the corresponding values of Shanken (1992). The table also shows χ^2, cross-sectional R^2, HJ distance following Hansen and Jagannathan (1997) as well as a generalized version of the cross-sectional F-test statistic of Shanken (1985) ($CSRT_{SH}$). *Panel A* controls for transaction costs and *Panel B* for short-run reversals. The excess returns are expressed in percentage points. We report *p-values* in curly brackets. The data are collected from Datastream *via* Barclays and Reuters. The data contain monthly series from January 1985 to January 2014.

Panel A: Factor Prices - *Transaction Costs*									
	cons	λ_{DOL}	$\lambda_{\mathcal{FPR}}$	χ^2_{NW}	χ^2_{SH}	χ^2_{GMM1}	χ^2_{GMM2}	R^2	HJ dist
				Momentum $(f = 9, h = 1)$					
FMB		0.12	0.23	14.98	14.60	9.19	9.80	0.55	0.09
(NW)		(0.11)	(0.11)	{0.01}	{0.01}	{0.06}	{0.04}		{0.28}
(Sh)		(0.11)	(0.11)						
$FMBc$	0.01	-0.85	0.27	$CSRT_{SH}$	0.16	{0.12}			
$[NW]$	[1.63]	[−1.40]	[2.50]						
				Momentum $(f = 12, h = 1)$					
FMB		0.11	0.10	2.93	2.89	2.32	2.45	0.88	0.09
(NW)		(0.11)	(0.05)	{0.71}	{0.72}	{0.68}	{0.65}		{0.41}
(Sh)		(0.11)	(0.05)						
$FMBc$	0.01	-0.71	0.16	$CSRT_{SH}$	0.21	{0.19}			
$[NW]$	[1.27]	[−1.08]	[2.41]						

Panel B: Factor Prices - *Reversals*									
	cons	λ_{DOL}	$\lambda_{\mathcal{FPR}}$	χ^2_{NW}	χ^2_{SH}	χ^2_{GMM1}	χ^2_{GMM2}	R^2	HJ dist
				Momentum $(f = 9, h = 1)$					
FMB		0.20	0.35	26.36	24.90	12.87	13.80	0.55	0.09
(NW)		(0.11)	(0.11)	{0.00}	{0.00}	{0.01}	{0.01}		{0.30}
(Sh)		(0.11)	(0.11)						
$FMBc$	0.01	-0.53	0.38	$CSRT_{SH}$	3.62	{0.01}			
$[NW]$	[1.19]	[−0.85]	[3.46]						
				Momentum $(f = 12, h = 1)$					
FMB		0.20	0.15	2.73	2.62	3.06	3.14	0.96	0.08
(NW)		(0.11)	(0.06)	{0.74}	{0.76}	{0.55}	{0.53}		{0.43}
(Sh)		(0.11)	(0.06)						
$FMBc$	0.01	-0.45	0.20	$CSRT_{SH}$	0.30	{0.80}			
$[NW]$	[0.97]	[−0.66]	[2.96]						

Table B.3. Robustness: *Other Variables*

This table presents descriptive statistics of global political risk innovations ($\Delta\mathcal{PR}$) along with *Uncertainty*, *Macroeconomic* and *Financial* measures. The first group consists of changes in the $\Delta\mathcal{VIX}$, the University of Michigan Consumer Sentiment Index ($\Delta\mathcal{CONS}^{\mathcal{SENT}}$), the macroeconomic uncertainty of **?** ($\Delta\mathcal{MU}_1$) and the Economic Policy uncertainty of Baker et al. (2012) ($\Delta\mathcal{EPU}$). *Panel B* shows results for the growth rates of Industrial production ($\Delta\mathcal{IP}$), inflation ($\Delta\mathcal{CPI}$), consumption ($\Delta\mathcal{CONS}$) and employment ($\Delta\mathcal{EMP}$). *Panel C* displays summary statistics for financial variables such as the $\Delta\mathcal{TED}$ spread, the term spread ($\mathcal{TERM}$), the default spread ($\mathcal{DEF}$) and the return on the US MSCI index. Moreover, the table shows mean, median, standard deviation, skewness, kurtosis, minimum and maximum values. We also report first order autocorrelations ($AC(1)$), *Corr* is the overall correlation of global political risk with all the other variables. Figures in parenthesis display *p-values*. Currency data is collected from Datastream *via* Barclays and Reuters and contain monthly series from January 1985 to January 2014.

Panel A: Uncertainty Variables

	$\Delta\mathcal{PR}$	$\Delta\mathcal{VIX}$	$\Delta\mathcal{CONS}^{\mathcal{SENT}}$	$\Delta\mathcal{MU}_1$	$\Delta\mathcal{EPU}$
Mean	0.00	-0.02	-0.04	0.00	0.00
Median	0.00	0.00	-0.20	0.00	-0.02
Std	0.07	3.80	3.97	0.01	0.32
Skew	-0.43	0.90	0.05	0.91	0.29
Kurt	10.32	9.89	4.43	7.85	4.14
Min	-0.46	-15.28	-12.70	-0.05	-1.03
Max	0.35	20.50	17.30	0.08	1.14
$AC(1)$	0.09	-0.01	-0.03	0.67	-0.54
	(0.10)	(0.85)	(0.61)	(0.00)	(0.00)
Corr	1.00	-0.06	0.21	0.02	0.12
	–	(0.23)	(0.00)	(0.67)	(0.03)

Panel B: Macro Variables

	$\Delta\mathcal{PR}$	$\Delta\mathcal{IP}$	$\Delta\mathcal{CPI}$	$\Delta\mathcal{CONS}$	$\Delta\mathcal{EMP}$
Mean	0.00	0.18	0.23	0.43	0.10
Median	0.00	0.23	0.23	0.42	0.13
Std	0.07	0.01	0.00	0.01	0.00
Skew	-0.43	-1.66	-1.51	-0.12	-1.30
Kurt	10.32	11.88	15.40	8.13	5.93
Min	-0.46	-4.30	-1.79	-2.04	-0.62
Max	0.35	2.06	1.37	2.73	0.48
$AC(1)$	0.09	0.21	0.43	-0.21	0.76
	(0.10)	(0.00)	(0.00)	(0.00)	(0.00)
Corr	1.00	-0.07	0.04	-0.08	0.08
	–	(0.19)	(0.51)	(0.15)	(0.13)

Panel C: Financial Variables

	$\Delta\mathcal{PR}$	$\Delta\mathcal{TED}$	$\mathcal{TERM}$	$\mathcal{DEF}$	$\mathcal{MSCI}$
Mean	0.00	0.63	0.02	1.00	0.01
Median	0.00	0.50	0.03	0.92	0.01
Std	0.07	0.46	0.01	0.40	0.05
Skew	-0.43	1.87	-0.25	2.80	-0.74
Kurt	10.32	8.14	1.90	14.79	5.62
Min	-0.46	0.12	0.00	0.55	-0.22
Max	0.35	3.15	0.05	3.38	0.16
$AC(1)$	0.09	0.96	0.97	0.96	0.03
	(0.10)	(0.06)	(0.00)	(0.00)	(0.57)
Corr	1.00	0.10	-0.03	0.09	0.17
	–	(0.01)	(0.55)	(0.09)	(0.00)

B.2 Figures

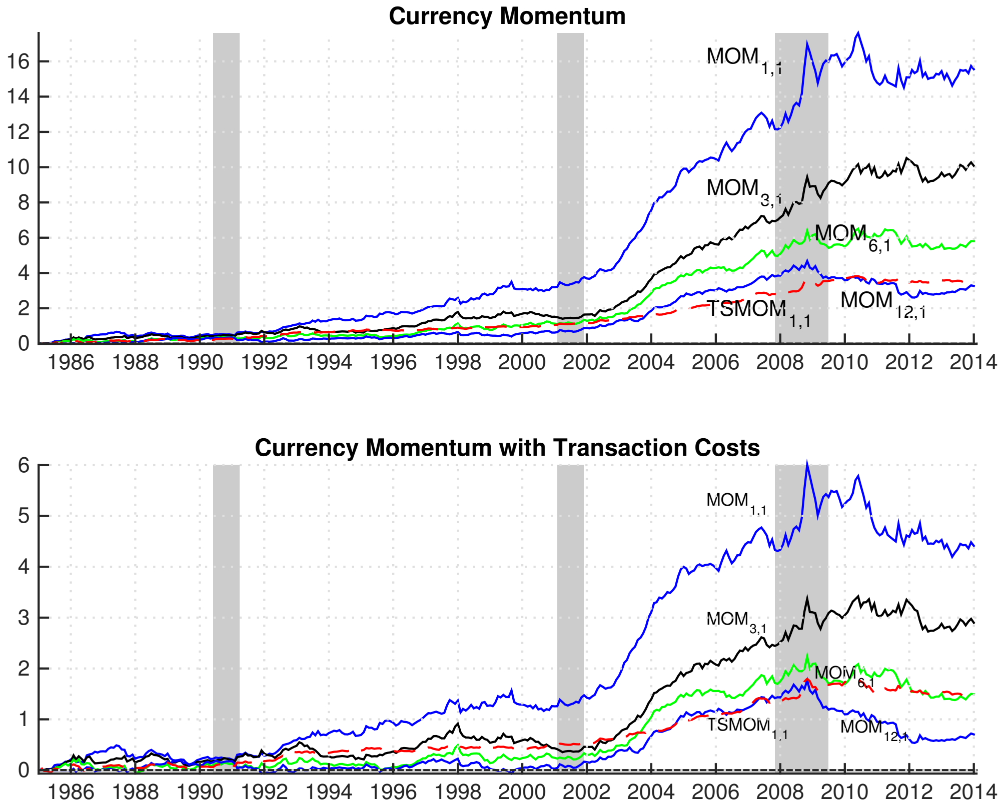


Figure B.1. Cumulative Returns of Momentum Portfolios

The figure presents cumulative momentum returns of cross-sectional and time-series momentum (red dashed line). The holding period is one month for both strategies but the formation period ranges from 1-12 months for the cross-sectional momentum and it is one month for the time-series counterpart. The data contain monthly series from January 1985 to January 2014.

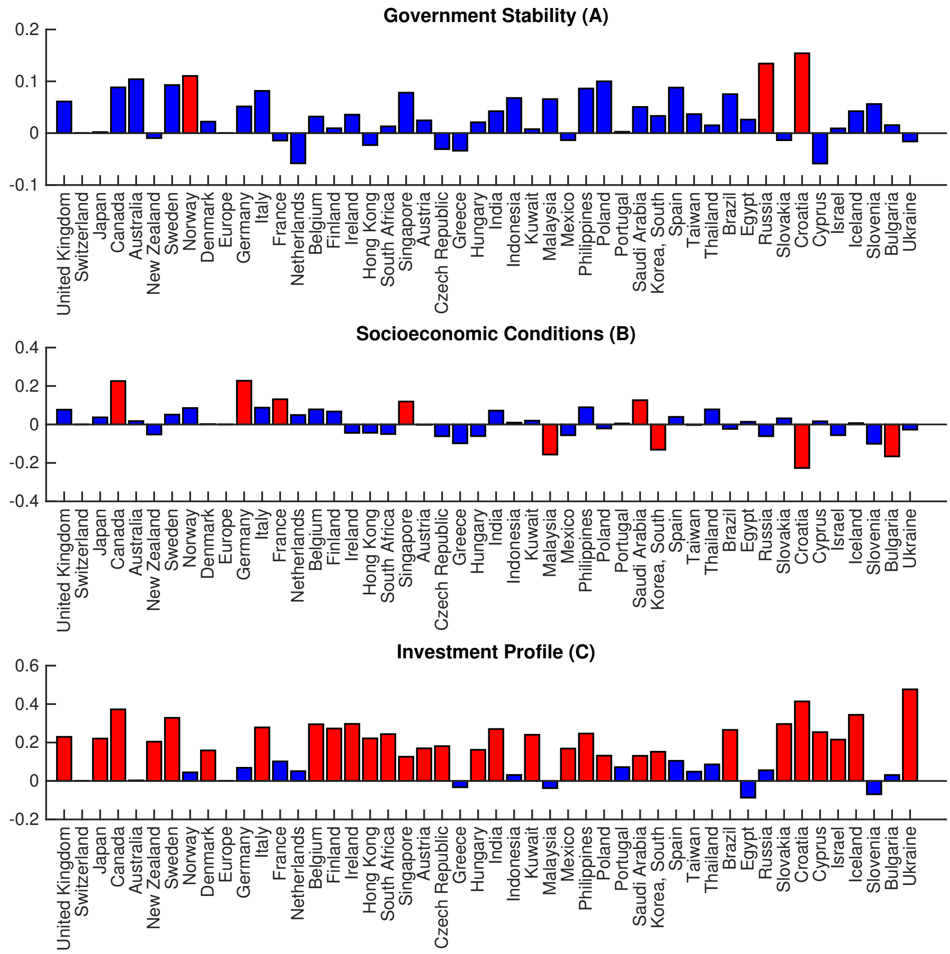


Figure B.2. Correlation of U.S. with Foreign Components of Political Risk

The figure shows correlations between foreign and US innovations of the different components of political risk. Bars in red represent statistically significant correlations (i.e. a p-value that is not greater than 0.05). Switzerland and Europe are missing from this dataset. The data contain monthly series from January 1985 to July 2013.

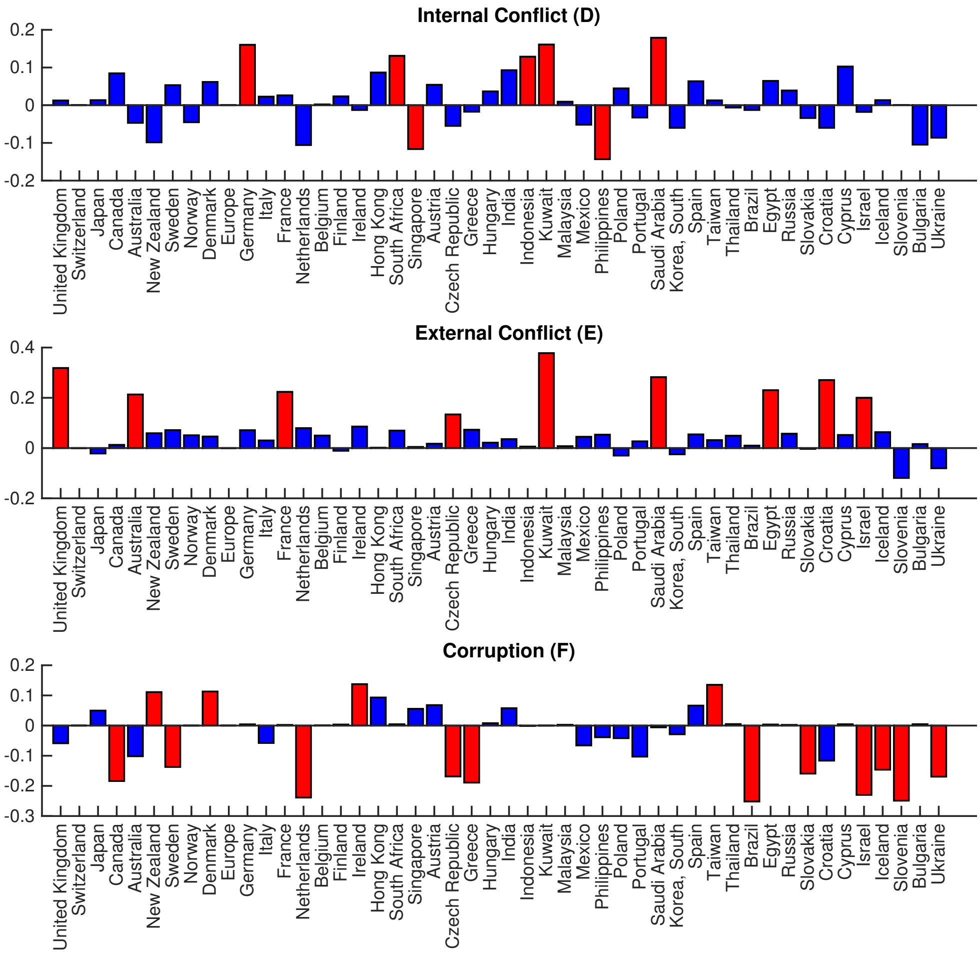


Figure B.2. Correlation of U.S. with Foreign Components of Political Risk *(Continued)*

The figure shows correlations between foreign and US innovations of the different components of political risk. Bars in red represent statistically significant correlations (i.e. a p-value that is not greater than 0.05). Switzerland and Europe are missing from this dataset. The data contain monthly series from January 1985 to July 2013.

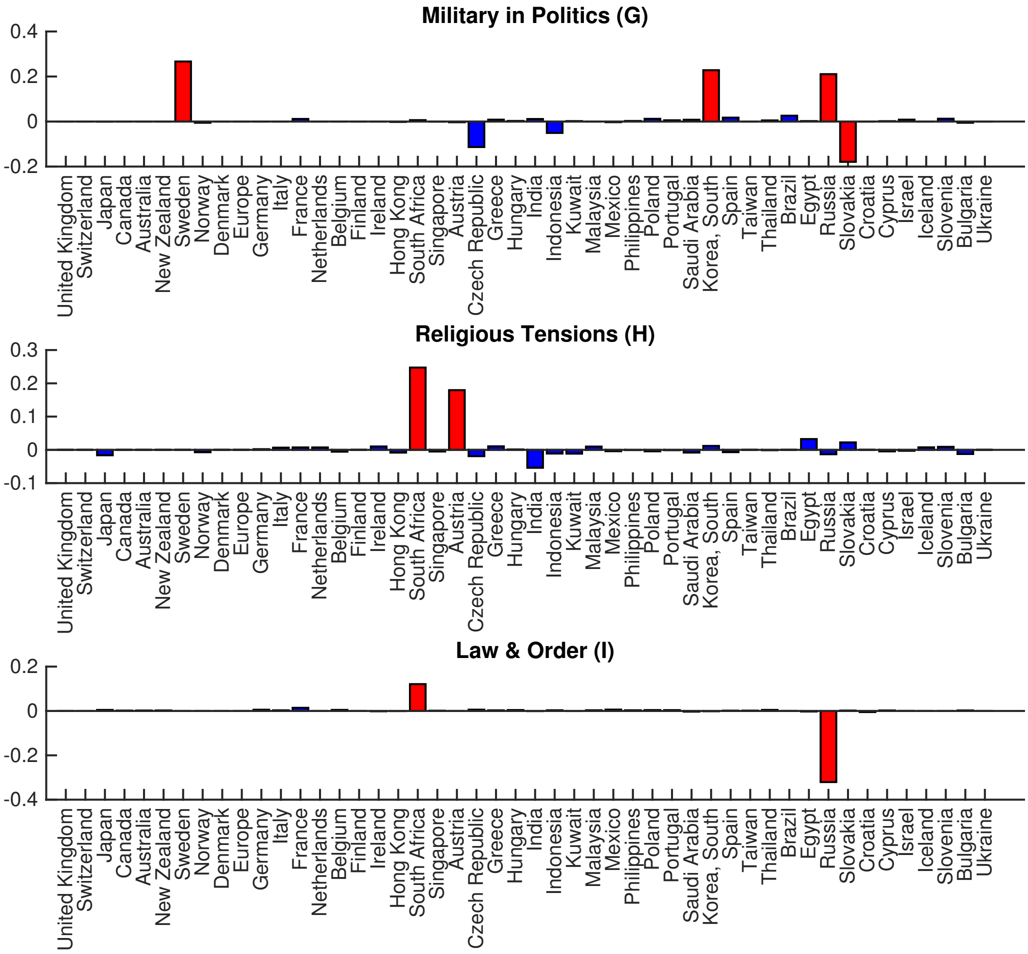


Figure B.2. Correlation of U.S. with Foreign Components of Political Risk *(Continued)*

The figure shows correlations between foreign and US innovations of the different components of political risk. Bars in red represent statistically significant correlations (i.e. a p-value that is not greater than 0.05). Switzerland and Europe are missing from this dataset. The data contain monthly series from January 1985 to July 2013.

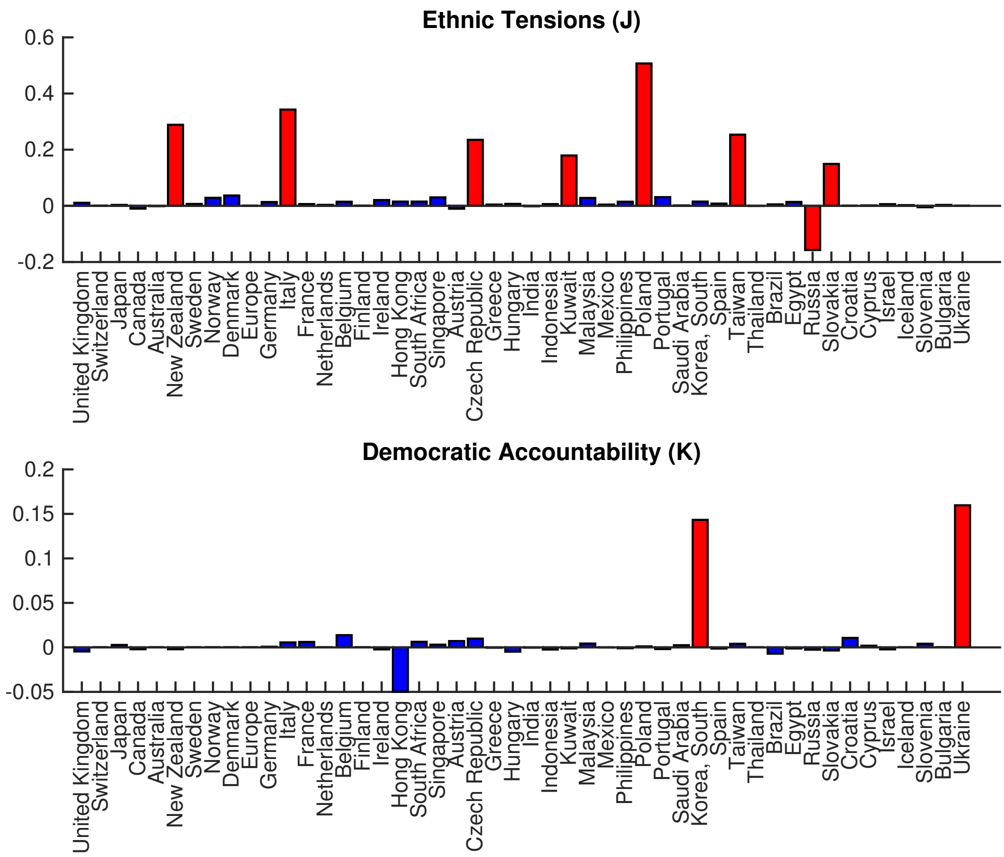


Figure B.2. Correlation of U.S. with Foreign Components of Political Risk *(Continued)*

The figure shows correlations between foreign and US innovations of the different components of political risk. Bars in red represent statistically significant correlations (i.e. a p-value that is not greater than 0.05). Switzerland and Europe are missing from this dataset. The data contain monthly series from January 1985 to July 2013.

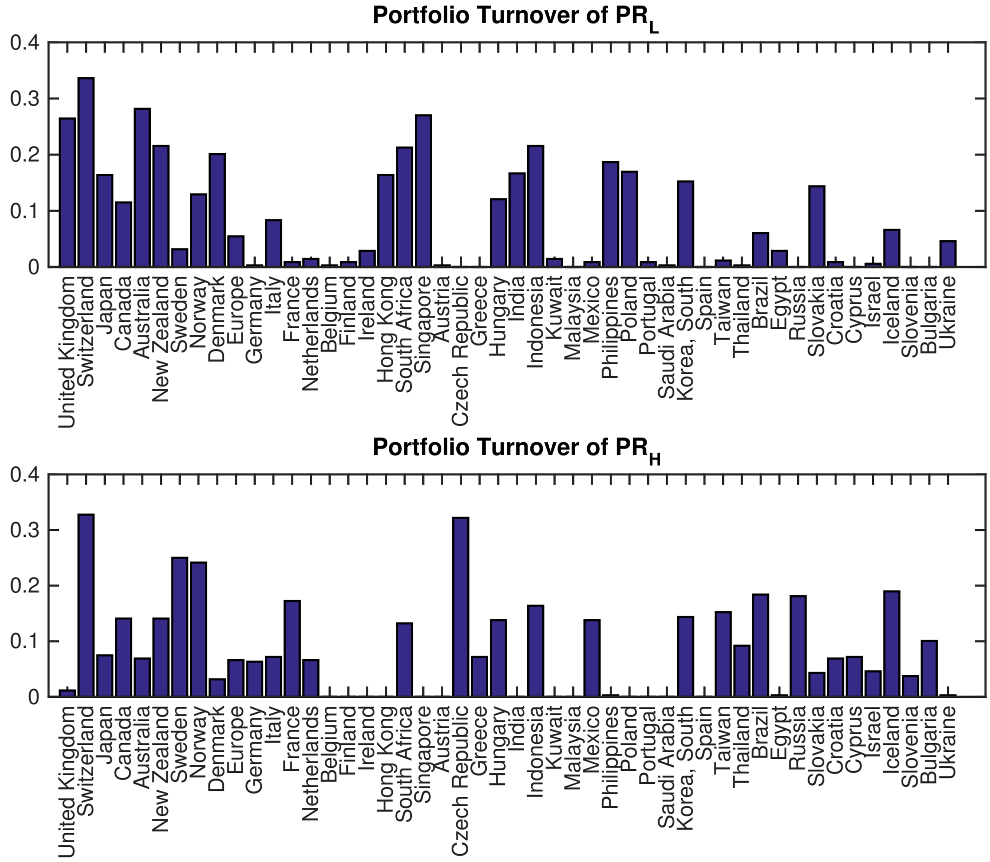


Figure B.3. Portfolio Turnover - *Global Political Risk*

The figure shows the portfolio turnover of currency portfolios sorted on global political risk based on a 60-month rolling window. The data contain monthly series from January 1985 to January 2014.

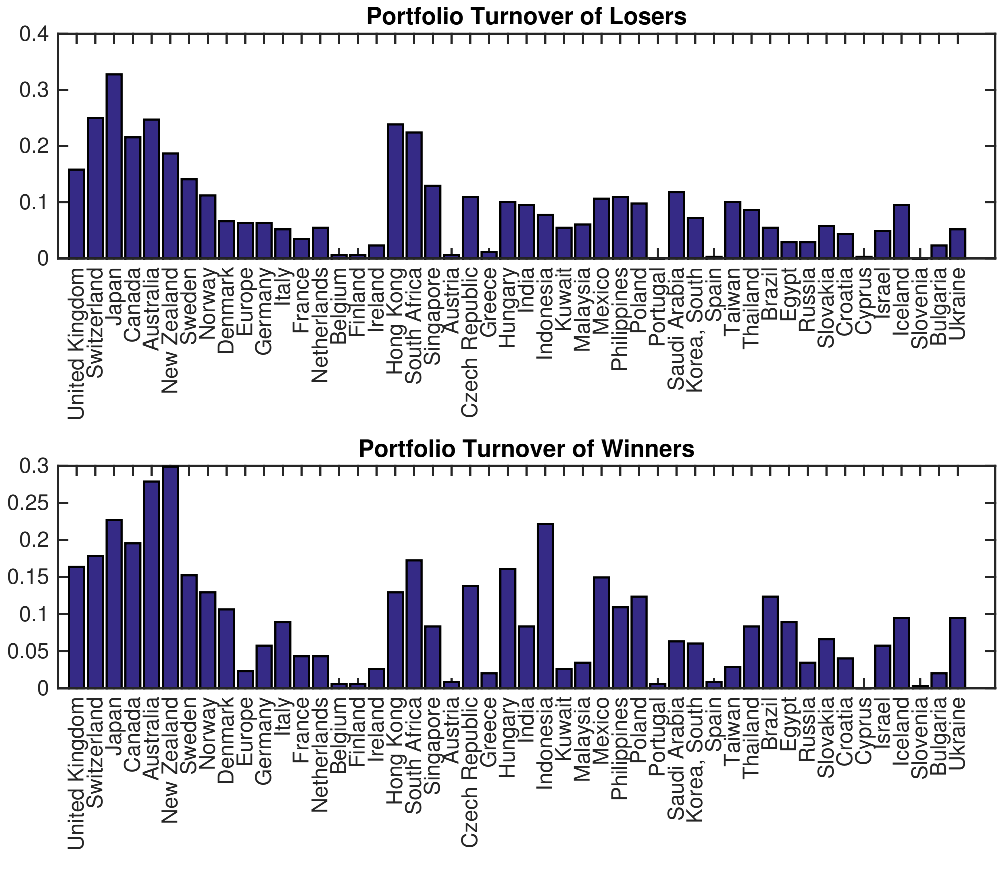


Figure B.4. Portfolio Turnover - *Momentum*

The figure shows the portfolio turnover of currency portfolios sorted on currency momentum, i.e. winners vs. losers. The data contain monthly series from January 1985 to January 2014.

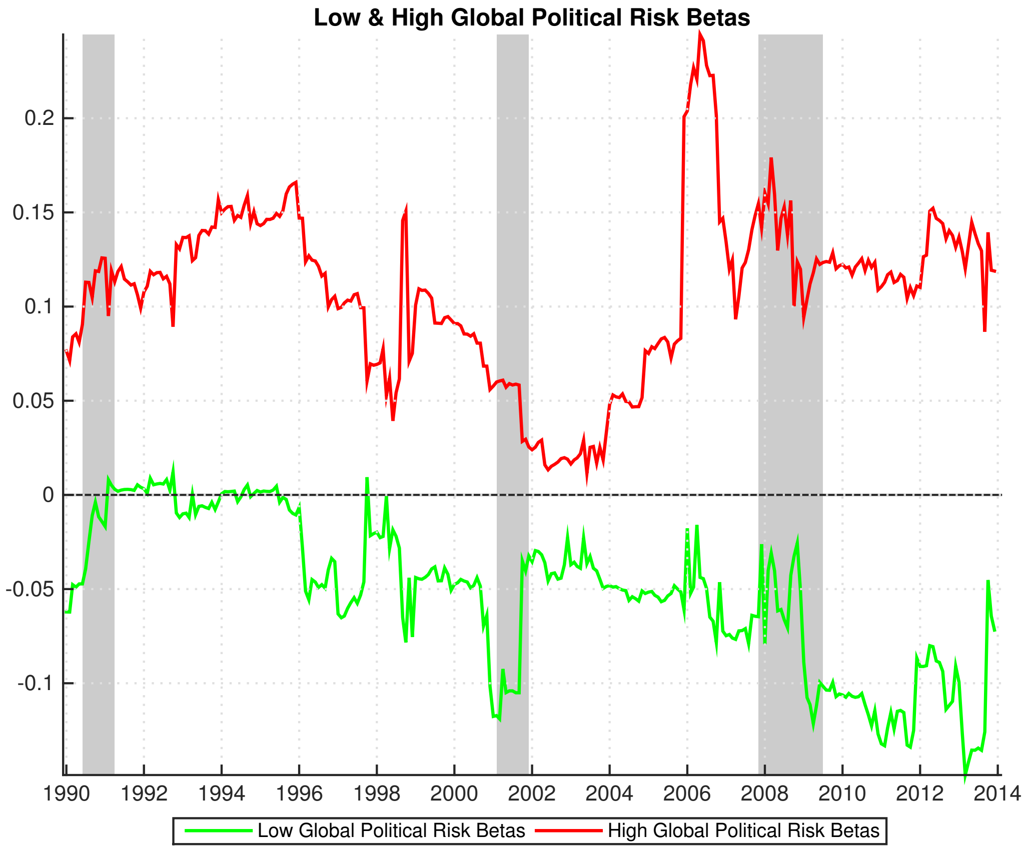


Figure B.5. Global Political Risk Betas

The figure presents average rolling betas of low and high political risk portfolios that are estimated based on a 60-month rolling window. We both consider US and global political risk innovations. The data contain monthly series from January 1985 to January 2014.

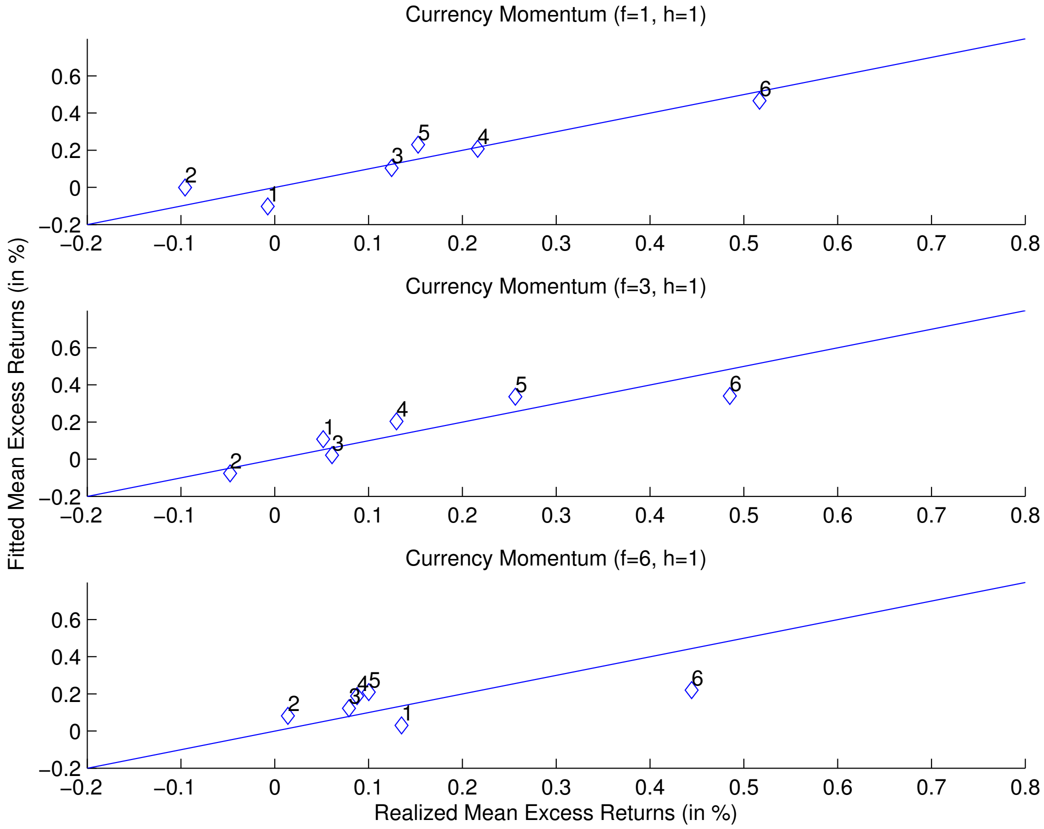


Figure B.6. Pricing Error Plots - *Porfolio Level Net Excess Returns*

The figure displays pricing error plots for the asset pricing models with the DOL as well as the mimicking portfolio of global political risk innovations as the risk factor. We report result for thee currency momentum strategy (i.e. $f = 1, 3, 6$). We take into consideration the implementation cost of each strategy. The data contain monthly series from January 1985 to January 2014.

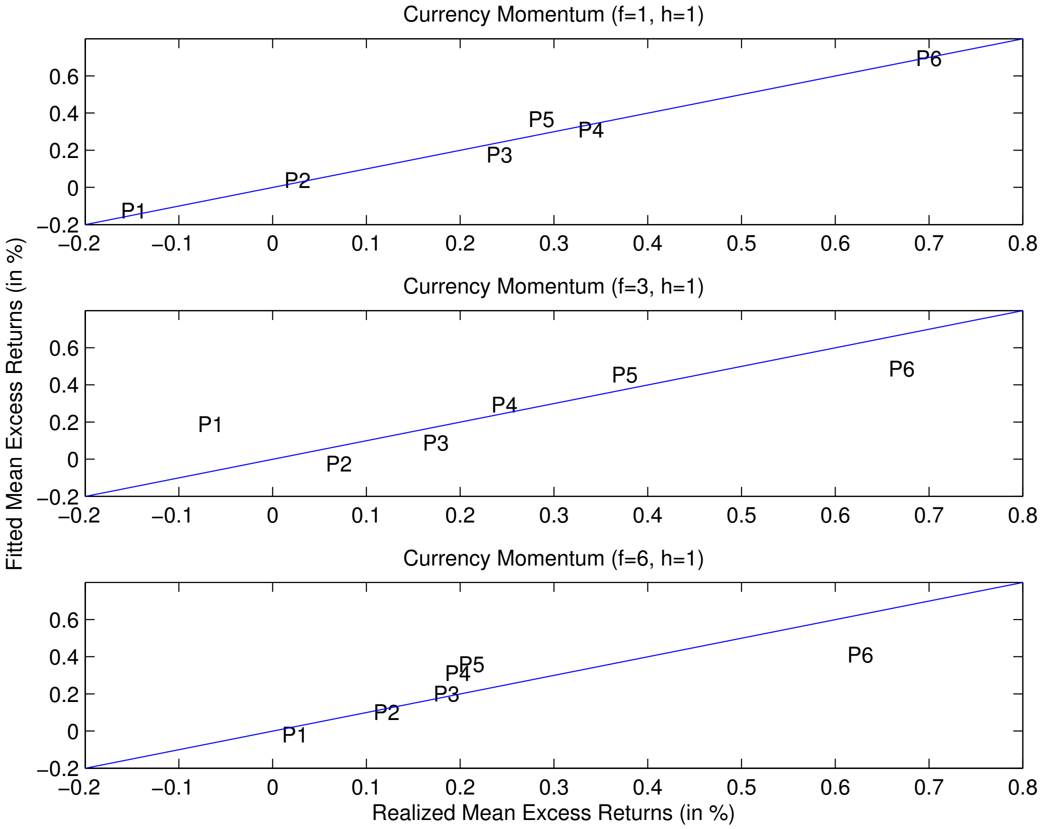


Figure B.7. Conditional Pricing Error Plots - *Portfolio Level*

The figure displays pricing error plots for the asset pricing models with the DOL as well as the conditional (on past returns) mimicking portfolio of global political risk innovations as the risk factor. We report result for thee currency momentum strategy (i.e. $f = 1, 3, 6$). The data contain monthly series from January 1985 to January 2014.

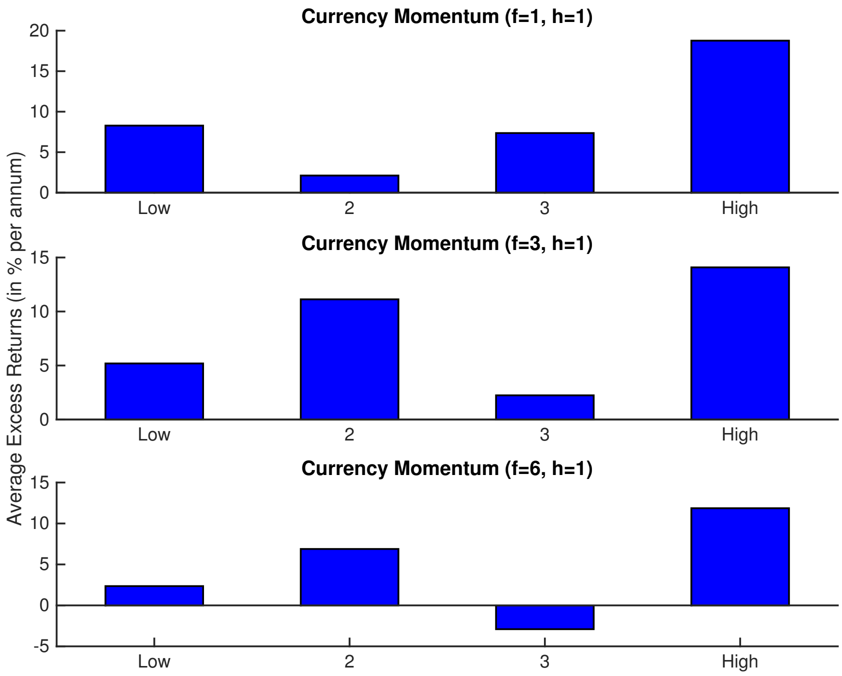
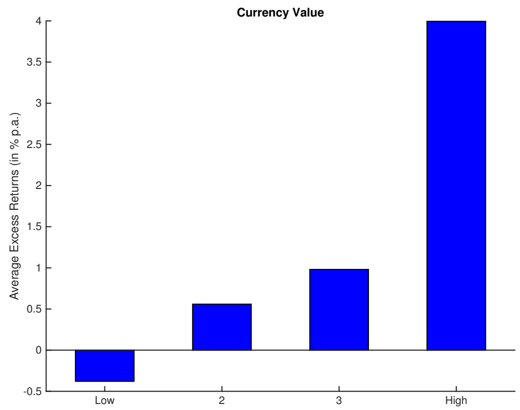


Figure B.8. Currency Momentum and Global Political Risk

The figure visualizes the relationship between global political risk and currency momentum. Particularly, we show annualized average excess returns for currency momentum portfolios conditional on global political risk innovations in the top and bottom quartiles of each sample distribution. Each bar represents annualized mean returns of going long the winner portfolio (based on past returns) and short the loser portfolio (based on past returns) for different formation periods (i.e. $f = 1, 3, 6$). we consider the 33 countries of the filtered data The data contain monthly series from January 1985 to January 2014.



(a) ***Currency Value***

(b) ***Carry Trades - Filtered Data***

Figure B.9. Currency Value, Carry Trades and Global Political Risk

The figure visualizes the relationship between global political risk and currency value as well as currency carry trades. Particularly, we show annualized average excess returns for currency value and carry trade portfolios conditional on global political risk innovations in the top and bottom quartiles of each sample distribution. *Panel A* shows results for the currency value and *Panel B* for currency carry trades. In *Panel A* Each bar represents annualized mean returns of going long the *undervalued* currency (relative to PPP) portfolio and short the *overvalued* (relative to PPP) currency portfolio. In *Panel B* Each bar represents annualized mean returns of going long the *high* interest rate portfolio and *short* the low interest rate portfolio. For the currency value we use a group of 22 currencies, as they are analysed in the text and carry trades are based on the 33 countries of the filtered data. The data contain monthly series from January 1985 to January 2014.

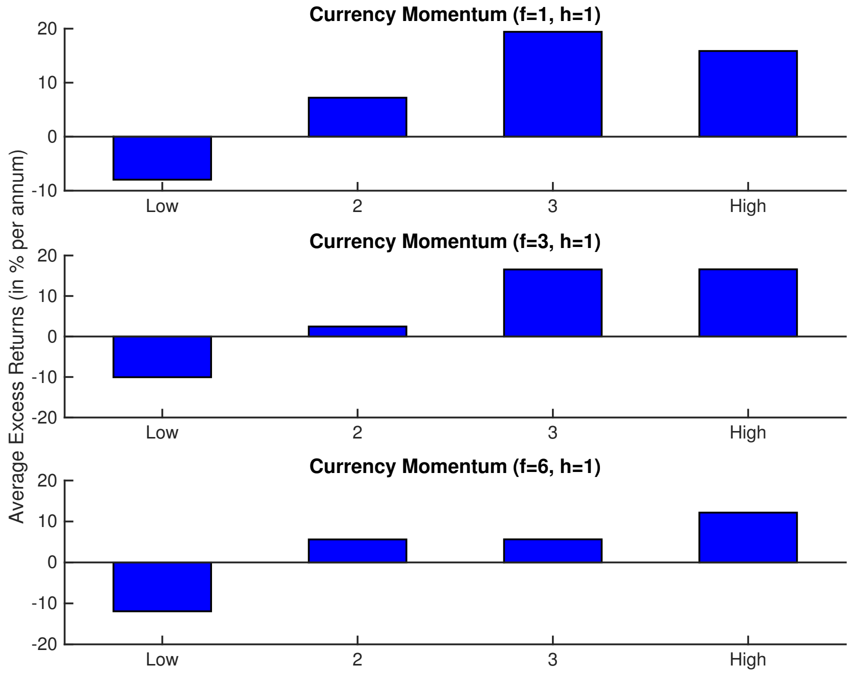


Figure B.10. Currency Momentum and Global Political Risk (IFO)

The figure visualizes the relationship between global political risk (IFO data) and currency momentum returns. Particularly, we show annualized average excess returns for currency momentum portfolios conditional on global political risk innovations in the top and bottom quartiles of each sample distribution. Each bar represents annualized mean returns of going long the loser portfolio and short the winner portfolio for different formation periods (i.e. $f = 1, 3, 6$). *Panel A* shows results for the raw data and *Panel B* for the filtered data. The data contain quarterly series from 1992:Q1 to 2013:Q4.

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