Global Political Risk and Currency Momentum *

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Abstract

This paper proposes 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 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.

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There is a growing interest among the policy makers and practitioners about the role of the political environment on the investor's decisions. This paper focuses on the role of global political risk in the foreign exchange market. We investigate how global political shocks influence currency investment strategies and affect their profitability. We mainly focus on currency momentum strategies since there has been limited success to explain their profitability. The absence of a "tangible" fundamental anchor (e.g., Stein, 2009; Lou and Polk, 2013) leads to more unstable profitability and more pronounced vulnerability of momentum strategies to the limits to arbitrage. Existing risk factors that have been able to capture the profitability of other currency strategies do not have a first-order effect on the currency momentum returns both in times-series and cross-sectional dimensions (e.g., Menkhoff, Sarno, Schmeling, and Schrimpf, 2012b).

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, Eichenbaum, and Rebelo, 2011b; Menkhoff et al., 2012b). Its profitability could partially be explained by transaction costs, limits to arbitrage or illiquidity. However, current FX asset pricing models exhibit limited ability in capturing 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 paper, 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 its sensitivity 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 which helps us understand better the determinants of currency risk premia. Furthermore, we construct a two-factor asset pricing model that incorporates the information contained in our global political risk measure. More precisely, the first factor is a *level* factor (i.e. DOL) as originally introduced by Lustig, Roussanov, and Verdelhan (2011) which is measured as the average across portfolios in each period. This traded factor resembles a strategy that buys all foreign currencies and sells the U.S. 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 able to capture political risk surprises around the world. We find that global political risk is priced in the cross-section of currency returns since it is able to explain a significant part of currency excess returns. Winner portfolios load positively on global political risk innovations while loser portfolios load negatively. Our main intuition regarding this finding is linked to the fact that investors require a higher premium for taking on global political risk by holding a portfolio of past *winner* currencies. On the other hand, investors accept a lower return from investing in *loser* portfolios, i.e. past *loser* currencies, as they provide insurance against adverse movements of currency returns in bad states of the world. From the perspective of currency momentum investors bad states of the world are characterized either by increases in political risk in foreign countries or decreases in political risk in the United States, i.e. those periods when capital moves from other countries to U.S. (e.g., flight to quality). 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 on these particular strategies is related to their high profitability (Menkhoff et al., 2012b).[1]

First, we show that global political risk can explain both *time-series* and *cross-sectional* 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. Notably, the predictability mainly comes from the loser portfolios along the time-series dimension. However, it captures only a small part of the time-series variability. Next, we question whether political risk is able to capture the *cross-sectional* variation of currency premia that it is related to currency momentum. We find that momentum returns sorted into portfolios based on exposures to political risk provide an almost monotonic pattern which suggests that investors require a higher premium when currency exposure to political risk increases. In particular, the extreme portfolios render a positive spread that indicates the pricing ability of global political risk. This spread can be explained by the fact that global political risk cannot easily be diversified away in a currency momentum strategy because by construction momentum portfolios consist of currency pairs with correlated past returns.

Our asset pricing model exhibits a strong cross-sectional performance both in statistical and economic terms. In particular, we display results of Fama and MacBeth (1973) regressions as well as GMM procedures (Hansen, 1982) and find highly significant risk factor prices that are related to global political risk. Our results also demonstrate strong cross-sectional behaviour in term of goodness of fit. Specifically, we show that we cannot reject the null that 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. We cannot reject the null that the HJ distance (Hansen and Jagannathan, 1997) is equal to zero and the cross-sectional R^2 range from 66% to 99% for formation periods from one to six months. Our

[1]This is also verified in Figure A1 of our Internet Appendix.

results are similar whether we employ a mimicking portfolio or the raw measure.

Next, 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 different sources 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 (e.g., Mueller, Stathopoulos, and Vedolin, 2013) and reach the same conclusion. These results provide further support to the pricing ability of global political risk for currency momentum.

Finally, we perform additional robustness checks. In oder to make our analysis more realistic, i.e. applied to *tradable* strategies, we apply two filters to the data; (i.) we include only those currencies that belong in the exchange rate regime 3 or 4 of the IMF coarse classification, and (ii.) those with high degree of capital account openness (Chinn and Ito, 2006) following Della Corte, Sarno, Schmeling, and Wagner (2013). We find that the results are 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. We estimate the conditional weights of the mimicking portfolio by using as the 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 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 potential candidates to be the fundamental determinant of the momentum strategy in the foreign exchange market.

In what follows, a literature review on political risk and currency momentum is presented in section 1. We also define our global political risk measure in section 2. In section 3 we provide a brief description of the data as well as the construction of the currency portfolios. Section 4 discusses the empirical results of the paper. Section 5 provides a better understanding of the determinants of currency premia. Section 6 offers some robustness checks. Finally, section 7 gives our conclusion.

1. Related Literature

In this section we review the related studies on political risk and currency momentum so as to set the grounds for our findings. Firstly, we refer the most relevant studies linking political risk to the foreign exchange market and then to currency momentum. While the interpretations of political risk differ in the literature there are two main definitions: The first relates political risk to *"unwanted consequences of political activity"* and the second links it to political events (Kobrin, 1979).

Political Risk. There is an established body of literature on the relation between exchange rates and political risk. In the early FX literature, 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 cross-section of stock returns in Mexico, finding evidence of risk premia that are associated with these risks. Moreover, 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. Another strand of the literature focuses on the political risk premia that it is associated with political news. For example, Boutchkova, Doshi, Durnev, and Molchanov (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 related to 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, Pastor, and Veronesi (2014) show that political uncertainty is priced in the options market and the option with maturity around political events seems to be more expensive.[2] We deviate somewhat from these studies as we do not focus on specific political

[2] For more example please see Gao and Qi (2012); Julio and Yook (2012); Baker, Bloom, and Davis (2012); Belo, Gala, and Li (2013); Cao, Duan, and Uysal (2013).

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. (2011b); Menkhoff et al. (2012b); Asness, Moskowitz, and Pedersen (2013) 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".[3] 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 out-of-sample evidence of profitability for a period that could be 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. Asness et al. (2013) document the prevalence of value and momentum returns across asset classes and the negative correlation between value and momentum. Barroso and Santa-Clara (2013) show that in the equities market an investor could avoid momentum crashes by hedging against momentum-specific risks rather than market risk. This evidence has a direct link to the currency market.

2. Global Political Risk

This section discusses the role of global 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 define our measure of political risk and analyse its dynamics.

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.

Political risk is one of the main determinants of country-specific shocks. For example, Pástor

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

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 show 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, Hermes, and Murinde (2000) show that political risk is a strong determinant of capital flight.[4] 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 affects heavily currency premia in comparison to other country-specific characteristics when the country risk is high.

We introduce a novel measure of global 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. and the rest of the world.[5] In our framework the global political risk may arise either from unanticipated political changes in the U.S. economy or in the rest of the world. Moreover, a country's political risk is mainly determined by its exposure to global political risk rather its own country-specific shocks. Specifically, our proxy for global political conditions is measured by:[6]

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

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 (U.S.) 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.[8] We normalise it with the average political risk on a month-to-month basis so as to check against global political conditions. This normalisation is useful because it gives us the opportunity to capture the simultaneous deterioration of the political conditions between countries with similar characteristics and *vice versa*. In the robustness section we explore alternative definitions of global political risk by

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

[5]Bekaert, Harvey, Lundblad, and Siegel (2014) construct a similar measure to proxy for political risk spreads.

[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. The value weighted index is available upon request.

[7]The political risk measure is from the International Country Risk Guide (ICRG). According to ICRG an *increase* in political risk index is associated with a *decrease* in the political risk measure. Thus, we use the log reciprocal of $ICRG_{it}$ in order to have a measure that increases with political risk, i.e. $\ln(1/ICRG_{i,t}){=}pr_{it}$.

[8]i.e. $\frac{1}{n_t}\sum^{n_t} |pr_{i,t} - pr_{US,t}|$.

omitting the normalisation factor, expanding the set of foreign countries or focusing only on U.S. political risk.

We focus on the global political risk *innovations* (i.e. $\Delta\mathcal{PR}_t$) obtained from a first order autoregressive model to capture political surprises on a global scale.[9] Figure 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, Sarno, Schmeling, and Schrimpf (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)). It can be seen that our measure does not have a strong business cycle component and other risk factors in the foreign exchange market are unrelated to our measure, indicating our attempt to capture different dynamics of currency premia.[10]

[Figure 1 about here.]

3. 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, Eichenbaum, Kleshchelski, and Rebelo (2011a). 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,

[9] Alternatively, one could compute $\Delta\mathcal{PR}_t$ by taking first differences rather than innovations. Our results remain similar regardless of the method being used and they are available upon request.

[10] Apart from the relation with the NBER recessions that we illustrate in figure 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, Rudebusch, and Wu (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.

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 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

$$RX_{t+1} = \frac{F_t - S_{t+1}}{S_t} = \frac{F_t - S_t}{S_t} - \frac{S_{t+1} - S_t}{S_t}. \tag{2}$$

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, Rime, and Sarno (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 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

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

by: $RX^l_{t+1} = (F^b_t - S^a_{t+1})/S^b_t$. Whereas the corresponding short position in the foreign currency (or short in the dollar) will render a *net* excess return of the form: $RX^s_{t+1} = -(F^a_t - S^b_{t+1})/S^a_t$.

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 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:

$$CRX^i_t = sign(RX^i_{t-1})RX^i_t. \qquad (3)$$

The above equation is very similar to the one introduced by Burnside, Eichenbaum, and Rebelo (2011c) 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. $TSMOM^{1,1}_t = \overline{CRX}_t$).

[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.

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

4. Empirical Results

4.1 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 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 global CDS spreads changes. In line with figure 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 1 ABOUT HERE.]

Figure 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 A2 of the Internet Appendix 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 or payment delays dominates in terms of significant correlations. Nonetheless correlations remain low across different components.[14]

[FIGURE 2 ABOUT HERE.]

Table 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

[14] In Figure A3 of the Internet Appendix, we show the turnover of portfolios sorted based on global political risk. The majority of the countries appear in extreme portfolios.

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.[15] 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 about here.]

Panel A of Table 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 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 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:

$$\mathcal{WML}_{t+1}^{f,h} = \alpha^{f,h} + \gamma \mathcal{Z}_t + \varepsilon_{t+1}^{f,h}. \tag{4}$$

$$TSMOM_{t+1}^{1,h} = \alpha^{1,h} + \gamma \mathcal{Z}_t + \varepsilon_{t+1}^{1,h}. \tag{5}$$

[15] In Figure A4 of the Internet Appendix, we show the portfolio turnover of the winner and loser portfolios. Mostly tradable currencies appear in both portfolios.

where f represents the formation period and takes the values 1, 3 and 6[16] 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 1.[17] Table A1 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 A1 we analyze seperately loser and winner portfolios of cross-sectional momentum strategies. We make an important observation; while the returns to 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 A1 about here.]

4.2 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.[18]

[16] To save space we report the results with longer formation periods, i.e. three and six months, in the Internet Appendix Table A1.

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

[18] Smaller window sizes provide slightly weaker results.

$$CRX_t^i = \alpha^i + \beta^{i,PR}\Delta\mathcal{PR}_t + \varepsilon_t^i, \tag{6}$$

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 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 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.[19]

[Table 5 about here.]

4.3 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, Hodrick, Xing, and Zhang (2006).[20] 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:

$$\Delta\mathcal{PR}_{t+1} = a + b'\mathbf{RX}_{t+1} + v_{t+1}, \tag{7}$$

[19] In Figure A5 of the Internet Appendix we show how the rolling betas evolve over time.

[20] Please see Breeden, Gibbons, and Litzenberger (1989); Menkhoff et al. (2012a); Mueller et al. (2013) for more examples of this approach.

where $\mathbf{RX}_{t+1}$ is vector of the six portfolio returns at time $t+1$. Thus, the mimicking portfolio[21] 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:

$$\mathcal{FPR}_{t+1} = -0.19RX^1_{t+1} - 0.06RX^2_{t+1} - 0.01RX^3_{t+1} + 0.05RX^4_{t+1} - 0.14RX^5_{t+1} + 0.33RX^6_{t+1} \quad (8)$$

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.

4.4 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

[21] 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, Siegel, and Xu, 2006). For example, we run a regression of the form: $\Delta\mathcal{PR}_{t+1} = a + b'\mathbf{RX}_{t+1} + c'\mathbf{Z}_t + u_{t+1}$.

zero and satisfy the Euler equation:

$$E[M_{t+1}RX_{t+1}^{j}] = 0 \tag{9}$$

where M_{t+1} denotes a linear SDF in the risk factors ϕ_{t+1}.[22] In particular, the main focus is on the SDF of the following form:

$$M_{t+1} = [1 - b'(\phi_{t+1} - \mu_{\phi})] \tag{10}$$

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:

$$E[RX^{j}] = \lambda'\beta^{j} \tag{11}$$

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.[23] After projecting each currency excess return (RX_t^{j}) 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:

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

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

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

[23] 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.

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:

$$M_{t+1} = 1 - b_{DOL}(DOL_{t+1} - \mu_{DOL}) - b_{\mathcal{FPR}}(\mathcal{FPR}_{t+1} - \mu_{\mathcal{FPR}}). \tag{12}$$

Panel A of table 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.[24] Table 6 displays three panels that correspond to the three momentum strategies of interest. Particularly, the left panel shows results for a momentum strategy with one month formation (f) period and one month holding (h) period

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

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 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. $p = 1, \ldots, 6$),

$$RX^p_{t+1} = \beta^p_0 + \beta^p_{DOL} DOL_{t+1} + \beta^p_{\mathcal{FPR}} \mathcal{FPR}_{t+1} + u^p_{t+1}. \tag{13}$$

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 6 about here.]

In Figure 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 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 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 7 about here.]

5. 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.

5.1 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:

$$RX^i_{t,d+1} = \alpha^i + \beta^i_{1,t} DOL_{t,d+1} + \beta^i_{2,t} HML_{FXt,d+1} + \varepsilon^i_{t,d+1}, \tag{14}$$

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.[25] Thus, the two measures take the following form:

$$IV_{i,t}^{FX} = \sqrt{\frac{1}{T_{i,t}} \sum_{d=1}^{T_{i,t}} \varepsilon_{i,d}^2}, \quad IS_{i,t}^{FX} = \frac{1}{T_{i,t}} \frac{\sum_{d=1}^{T_{i,t}} \varepsilon_{i,d}^3}{(IV_{i,t}^{FX})^3}. \tag{15}$$

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 4 shows average CIP 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 4 about here.]

5.2 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:

$$\sigma_t^{FX} = \frac{1}{T_t} \sum_{d \in T_t} \left[\sum_{k \in K_d} \left(\frac{|\Delta s_d|}{K_d} \right) \right], \quad \xi_t^{FX} = \frac{1}{T_t} \sum_{d \in T_t} \left[\sum_{k \in K_d} \left(\frac{BAS_d^k}{K_d} \right) \right]. \tag{16}$$

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.

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

5.3 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:

$$\gamma_t^{FX} = \frac{1}{N_t^{comb}} \sum_{i=1}^{n_t} \left[\sum_{j>i} \left(RC_t^{ij} \right) \right], \tag{17}$$

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 $\Delta\mathcal{RC}_t^{FX}$.

5.4 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.[26]

Starting with idiosyncratic volatility and skewness *Panels A* and *B* of Table 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

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

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 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 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 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.[27]

[Table 8 about here.]

6. 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.

6.1 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.

[27] 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.

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.[28]

Table 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 4.4. 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 9 about here.]

6.2 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, Liu, and

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

Schwarz, 2010). We therefore perform cross-sectional tests on individual currencies using conditional excess returns. Figure 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 considering each currency in isolation.

[FIGURE 5 ABOUT HERE.]

Next, we ask what is the contribution of country-level political risk in our results. In Figure 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 6 ABOUT HERE.]

6.3 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 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 0.45% for the 6-month formation period to 90% when we evaluate the previous month performance. Figure A6 in the Internet Appendix shows the corresponding pricing error plots. *Panel A* of Table A2 in the Internet Appendix 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 10 about here.]

6.4 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.[29] 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 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 A7 of the Internet Appendix. We also consider longer horizons of 9 and 12 months in *Panel B* of Table A2 in the Internet Appendix. 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 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 11 about here.]

6.5 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 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

[29] See for example Huang, Liu, Rhee, and Zhang (2009); Chen and Petkova (2012).

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 12 about here.]

6.6 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.[30] Figure A9 in the Internet Appendix 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-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.[31]

6.7 Other Measures

We explore how the global political risk measure relates to other measures. Table A3 in the Internet Appendix presents summary statistics of uncertainty measures as well as macroeconomic

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

[31] Asset pricing results are available upon request.

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 A10 in the Internet Appendix 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 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.

We repeat the cross-section asset pricing tests using these alternative measures and report in Figure A4 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 A4 about here.]

7. 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 shedding 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.

References

Addoum, Jawad M, and Alok Kumar, 2013, Political sentiment and predictable returns, *Available at SSRN 2169360* .

Akram, Q. Farooq, Dagfinn Rime, and Lucio Sarno, 2008, Arbitrage in the foreign exchange market: Turning on the microscope, *Journal of International Economics* 76, 237–253.

Alesina, Alberto, and Guido Tabellini, 1989, External debt, capital flight and political risk, *Journal of International Economics* 27, 199–220.

Aliber, Robert Z, 1973, The interest rate parity theorem: A reinterpretation, *The Journal of Political Economy* 81, 1451.

Andrews, Donald W K, 1991, Heteroskedasticity and autocorrelation consistent covariance matrix estimation, *Econometrica* 59, 817–58.

Ang, Andrew, Robert J Hodrick, Yuhang Xing, and Xiaoyan Zhang, 2006, The cross-section of volatility and expected returns, *The Journal of Finance* 61, 259–299.

Ang, Andrew, Jun Liu, and Krista Schwarz, 2010, Using stocks or portfolios in tests of factor models, *Unpublished Working Paper, Columbia University and University of Pennsylvania* .

Asness, Clifford S, Tobias J Moskowitz, and Lasse Heje Pedersen, 2013, Value and momentum everywhere, *The Journal of Finance* 68, 929–985.

Bailey, Warren, and Y Peter Chung, 1995, Exchange rate fluctuations, political risk, and stock returns: some evidence from an emerging market, *Journal of Financial and Quantitative Analysis* 30, 541–561.

Baker, Scott R, Nicholas Bloom, and Steven J Davis, 2012, Measuring economic policy uncertainty, *policyuncertainy. com* .

Barroso, Pedro, and Pedro Santa-Clara, 2012, Beyond the carry trade: Optimal currency portfolios, *Available at SSRN 2041460* .

Barroso, Pedro, and Pedro Santa-Clara, 2013, Momentum has its moments, *Available at SSRN 2041429* .

Bauer, Michael D, Glenn D Rudebusch, and Jing Cynthia Wu, 2014, Term premia and inflation uncertainty: Empirical evidence from an international panel dataset: Comment, *The American Economic Review* 104, 323–337.

Bekaert, Geert, Campbell R Harvey, Christian T Lundblad, and Stephan Siegel, 2014, Political risk spreads, *Journal of International Business Studies* 45, 471–493.

Belo, Frederico, Vito D Gala, and Jun Li, 2013, Government spending, political cycles, and the cross section of stock returns, *Journal of Financial Economics* 107, 305–324.

Blomberg, S Brock, and Gregory D Hess, 1997, Politics and exchange rate forecasts, *Journal of International Economics* 43, 189–205.

Boutchkova, Maria, Hitesh Doshi, Art Durnev, and Alexander Molchanov, 2012, Precarious politics and return volatility, *Review of Financial Studies* 25, 1111–1154.

Boyer, Brian, Todd Mitton, and Keith Vorkink, 2009, Expected idiosyncratic skewness, *Review of Financial Studies* hhp041.

Breeden, Douglas T, Michael R Gibbons, and Robert H Litzenberger, 1989, Empirical tests of the consumption-oriented capm, *The Journal of Finance* 44, 231–262.

Burnside, Craig, Martin Eichenbaum, Isaac Kleshchelski, and Sergio Rebelo, 2011a, Do peso problems explain the returns to the carry trade?, *Review of Financial Studies* 24, 853–891.

Burnside, Craig, Martin Eichenbaum, and Sergio Sergio Rebelo, 2011b, Carry trade and momentum in currency markets, *Annual Review of Financial Economics* 3, 511–535.

Burnside, Craig, Martin S Eichenbaum, and Sergio Rebelo, 2011c, Carry trade and momentum in currency markets .

Cao, Wenbin, Xiaoman Duan, and Vahap B Uysal, 2013, Does political uncertainty affect capital structure choices?, Technical report, Working paper.

Cen, Jason, and Ian W Marsh, 2013, Off the golden fetters: Examining interwar carry trade and momentum, *Available at SSRN 2358456* .

Chen, Zhanhui, and Ralitsa Petkova, 2012, Does idiosyncratic volatility proxy for risk exposure?, *Review of Financial Studies* 25, 2745–2787.

Chinn, Menzie D, and Hiro Ito, 2006, What matters for financial development? capital controls, institutions, and interactions, *Journal of Development Economics* 81, 163–192.

Cochrane, John H., 2005, *Asset Pricing: (Revised)* (Princeton University Press).

Della Corte, Pasquale, Lucio Sarno, Maik Schmeling, and Christian Wagner, 2013, Sovereign risk and currency returns, *Available at SSRN 2354935* .

Dooley, Michael P, and Peter Isard, 1980, Capital controls, political risk, and deviations from interest-rate parity, *The journal of political economy* 88, 370.

Fama, Eugene F, and James D MacBeth, 1973, Risk, return, and equilibrium: Empirical tests, *The Journal of Political Economy* 607–636.

Ferson, Wayne, Andrew F Siegel, and Pisun Tracy Xu, 2006, Mimicking portfolios with conditioning information, *Journal of Financial and Quantitative Analysis* 41, 607–635.

Fu, Fangjian, 2009, Idiosyncratic risk and the cross-section of expected stock returns, *Journal of Financial Economics* 91, 24–37.

Gao, Pengjie, and Yaxuan Qi, 2012, Political uncertainty and public financing costs: Evidence from us municipal bond markets, *Available at SSRN* .

Goyal, Amit, and Pedro Santa-Clara, 2003, Idiosyncratic risk matters!, *The Journal of Finance* 58, 975–1008.

Hansen, Lars Peter, 1982, Large sample properties of generalized method of moments estimators, *Econometrica: Journal of the Econometric Society* 1029–1054.

Hansen, Lars Peter, and Ravi Jagannathan, 1997, Assessing specification errors in stochastic discount factor models, *The Journal of Finance* 52, 557–590.

Huang, Wei, Qianqiu Liu, S Ghon Rhee, and Liang Zhang, 2009, Return reversals, idiosyncratic risk, and expected returns, *Review of Financial Studies* hhp015.

Jagannathan, Ravi, and Zhenyu Wang, 1996, The conditional capm and the cross-section of expected returns, *The Journal of Finance* 51, 3–53.

Jagannathan, Ravi, and Zhenyu Wang, 1998, An asymptotic theory for estimating beta-pricing models using cross-sectional regression, *The Journal of Finance* 53, 1285–1309.

Julio, Brandon, and Youngsuk Yook, 2012, Political uncertainty and corporate investment cycles, *The Journal of Finance* 67, 45–83.

Jurado, Kyle, Sydney C Ludvigson, and Serena Ng, 2013, Measuring uncertainty, Technical report, National Bureau of Economic Research.

Kelly, Bryan, Lubos Pastor, and Pietro Veronesi, 2014, The price of political uncertainty: Theory and evidence from the option market, Technical report, National Bureau of Economic Research.

Kobrin, Stephen J, 1979, Political risk: A review and reconsideration, *Journal of International Business Studies* 67–80.

Lamont, Owen A, 2001, Economic tracking portfolios, *Journal of Econometrics* 105, 161–184.

Lensink, Robert, Niels Hermes, and Victor Murinde, 2000, Capital flight and political risk, *Journal of International Money and Finance* 19, 73–92.

Lou, Dong, and Christopher Polk, 2013, *Comomentum: Inferring arbitrage activity from return correlations* (Paul Woolley Centre for the Study of Capital Market Dysfunctionality; Financial Markets Group).

Lugovskyy, Josephine Cruz, 2012, Political risk: Estimating the risk premium of political regime change .

Lustig, Hanno, Nikolai Roussanov, and Adrien Verdelhan, 2011, Common risk factors in currency markets, *Review of Financial Studies* 24, 3731–3777.

Mancini-Griffoli, Tommaso, and Angelo Ranaldo, 2011, Limits to arbitrage during the crisis: funding liquidity constraints and covered interest parity, *Available at SSRN 1569504* .

Menkhoff, Lukas, Lucio Sarno, Maik Schmeling, and Andreas Schrimpf, 2012a, Carry trades and global foreign exchange volatility, *Journal of Finance* 67, 681–718.

Menkhoff, Lukas, Lucio Sarno, Maik Schmeling, and Andreas Schrimpf, 2012b, Currency momentum strategies, *Journal of Financial Economics* 106, 660–684.

Menkhoff, Lukas, Lucio Sarno, Maik Schmeling, and Andreas Schrimpf, 2014, Currency value, *Available at SSRN 2492082* .

Menkhoff, Lukas, and Mark P Taylor, 2007, The obstinate passion of foreign exchange professionals: technical analysis, *Journal of Economic Literature* 936–972.

Mueller, Philippe, Andreas Stathopoulos, and Andrea Vedolin, 2013, *International correlation risk* (Financial Markets Group, The London School of Economics and Political Science).

Newey, Whitney K, and Kenneth D. West, 1987, A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix, *Econometrica* 55, 703–708.

Okunev, John, and Derek White, 2003, Do momentum-based strategies still work in foreign currency markets?, *Journal of Financial and Quantitative Analysis* 38, 425–448.

Pastor, Lubos, and Pietro Veronesi, 2012, Uncertainty about government policy and stock prices, *The Journal of Finance* 67, 1219–1264.

Pástor, L'uboš, and Pietro Veronesi, 2013, Political uncertainty and risk premia, *Journal of Financial Economics* 110, 520–545.

Shanken, Jay, 1985, Multivariate tests of the zero-beta capm, *Journal of financial economics* 14, 327–348.

Shanken, Jay, 1992, On the estimation of beta-pricing models, *Review of Financial Studies* 5, 1–55.

Stein, Jeremy C, 2009, Presidential address: Sophisticated investors and market efficiency, *The Journal of Finance* 64, 1517–1548.

Table 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. 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 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 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 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 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	α	β_{DOL}	$\beta_{\mathcal{FPR}}$	R^2	α	β_{DOL}	$\beta_{\mathcal{FPR}}$	R^2
P_L	-0.15	0.94	-1.64	0.81	-0.07	0.96	-0.16	0.58	0.02	0.88	-2.45	0.92
	(0.07)	(0.04)	(0.14)		(0.09)	(0.08)	(0.11)		(0.05)	(0.03)	(0.12)	
P_2	0.03	0.99	-0.97	0.78	0.07	0.96	-0.79	0.85	0.12	0.91	-1.08	0.81
	(0.06)	(0.05)	(0.14)		(0.05)	(0.03)	(0.05)		(0.06)	(0.03)	(0.14)	
P_3	0.24	1.01	-0.33	0.82	0.17	0.98	-0.46	0.85	0.19	0.97	-0.29	0.79
	(0.06)	(0.04)	(0.09)		(0.04)	(0.03)	(0.05)		(0.05)	(0.03)	(0.11)	
P_4	0.34	1.02	0.28	0.80	0.25	1.06	0.10	0.81	0.20	1.06	0.77	0.82
	(0.06)	(0.04)	(0.10)		(0.07)	(0.04)	(0.05)		(0.06)	(0.04)	(0.10)	
P_5	0.29	1.00	0.54	0.73	0.38	1.03	0.60	0.83	0.21	1.09	1.21	0.85
	(0.07)	(0.04)	(0.14)		(0.06)	(0.04)	(0.05)		(0.06)	(0.03)	(0.10)	
P_H	0.70	1.03	2.05	0.95	0.67	1.03	0.72	0.75	0.63	1.06	1.87	0.81
	(0.04)	(0.02)	(0.06)		(0.09)	(0.04)	(0.07)		(0.08)	(0.04)	(0.14)	

Table 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 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 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 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 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 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]						

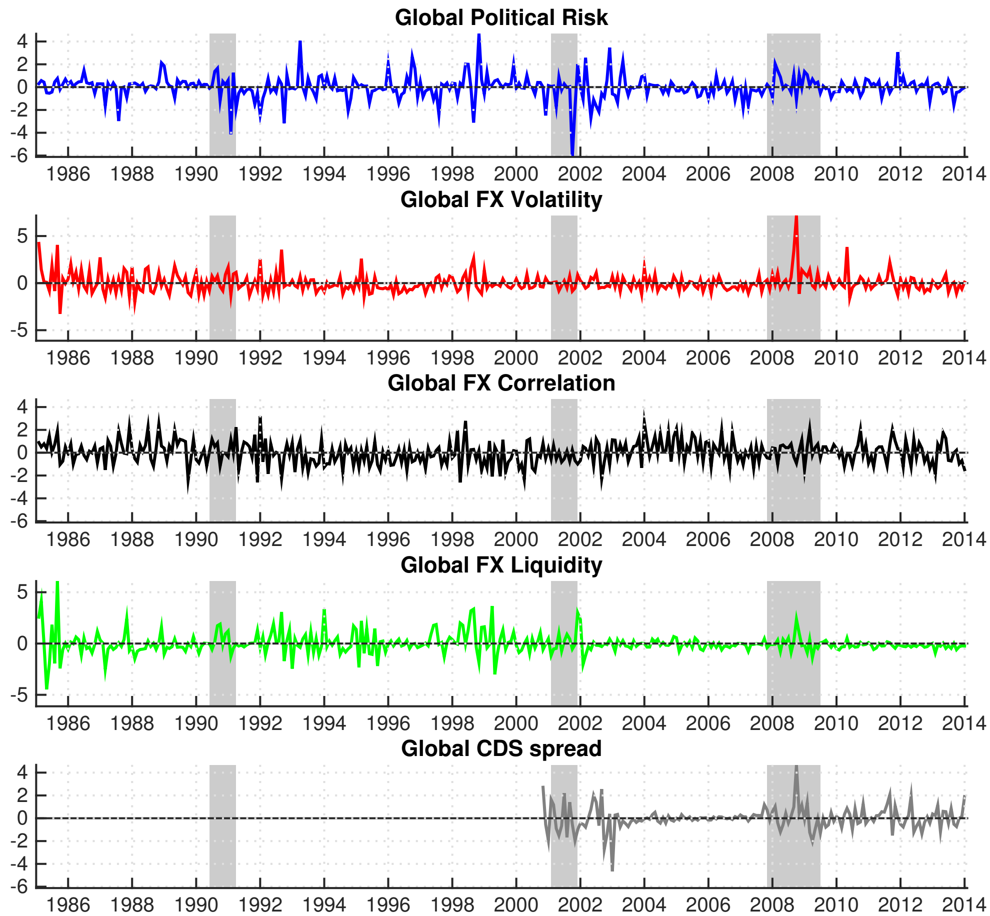


Figure 1. Global Political Risk

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.

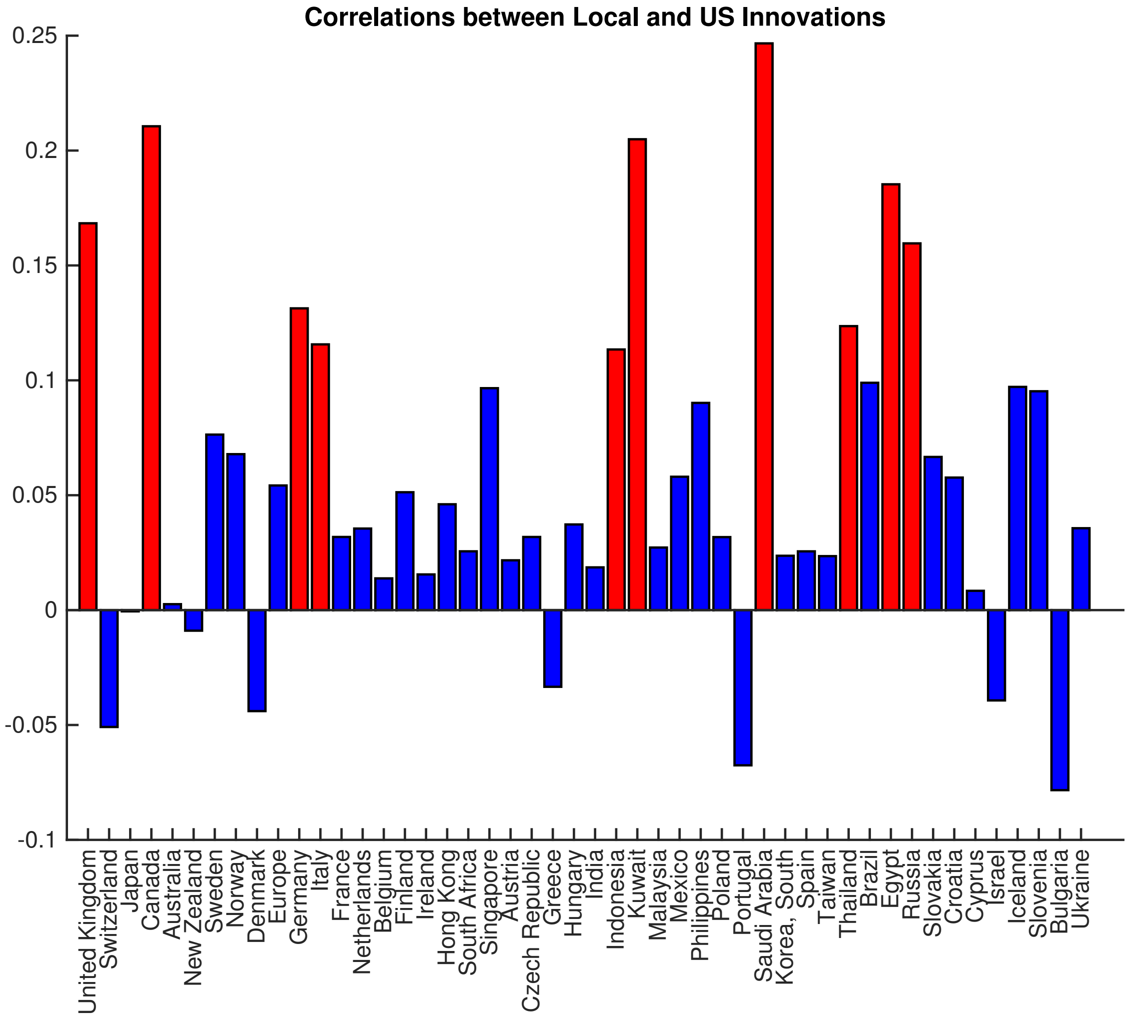


Figure 2. Correlations of US and Foreign Political Risk Innovations

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.

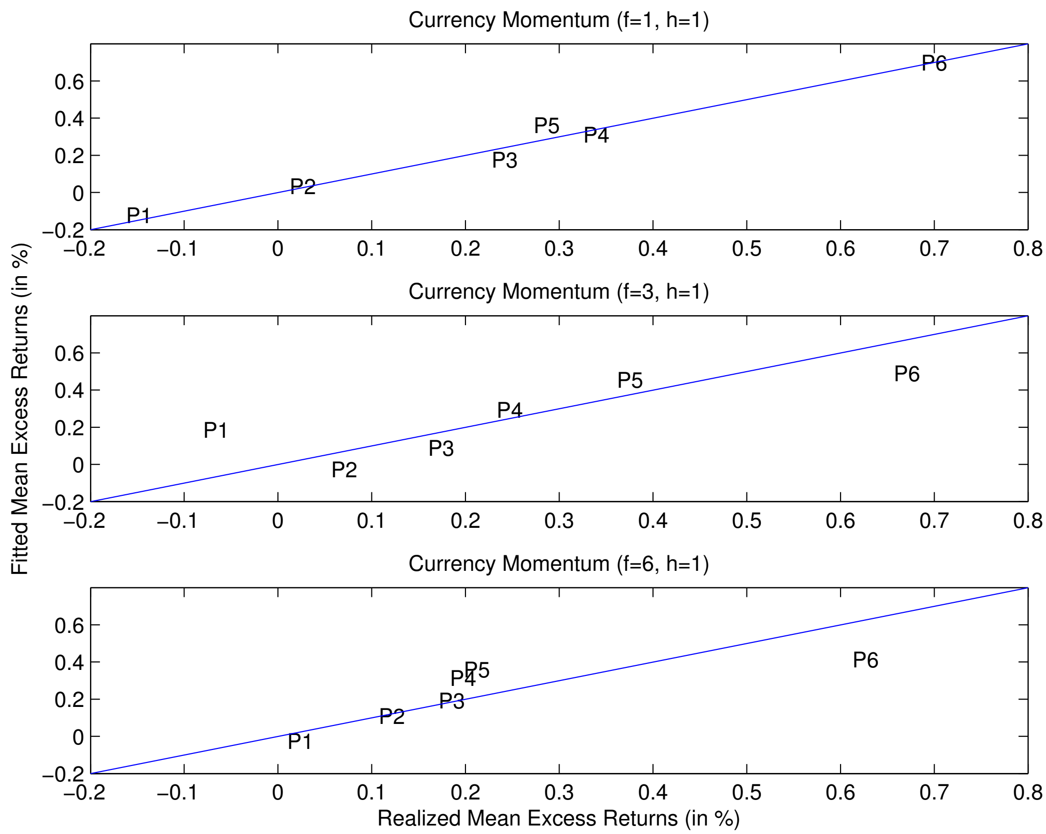


Figure 3. Pricing Error Plots - ***Portfolio Level***

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.

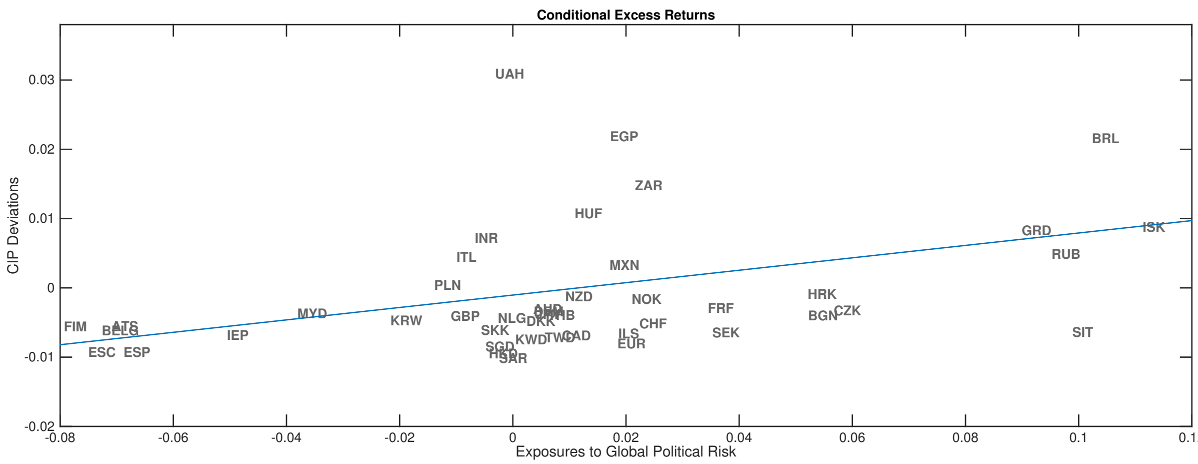


Figure 4. CIP deviations and Global Political Risk Betas

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.

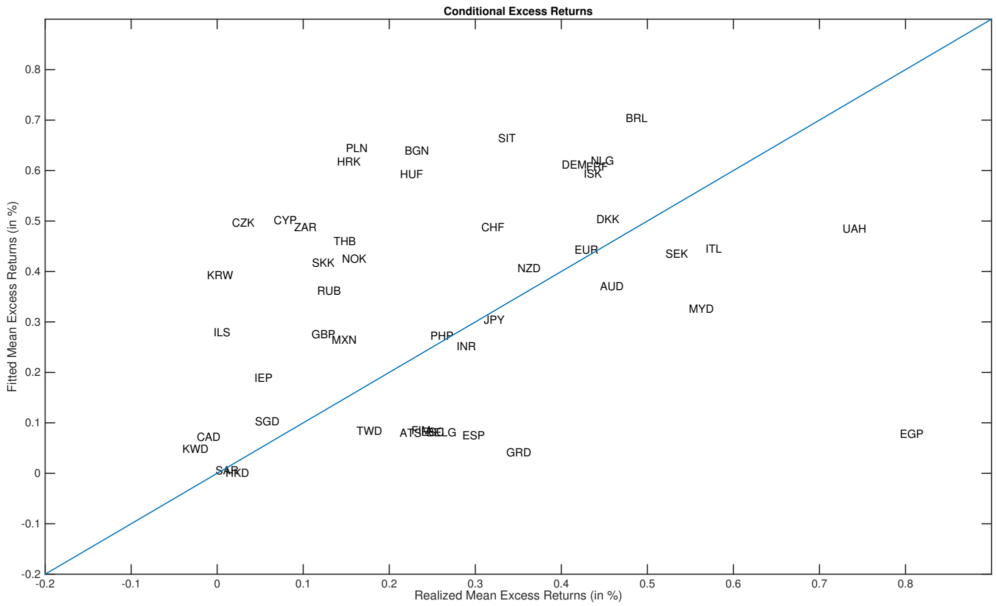


Figure 5. Pricing Error Plots - ***Currency Level***

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.

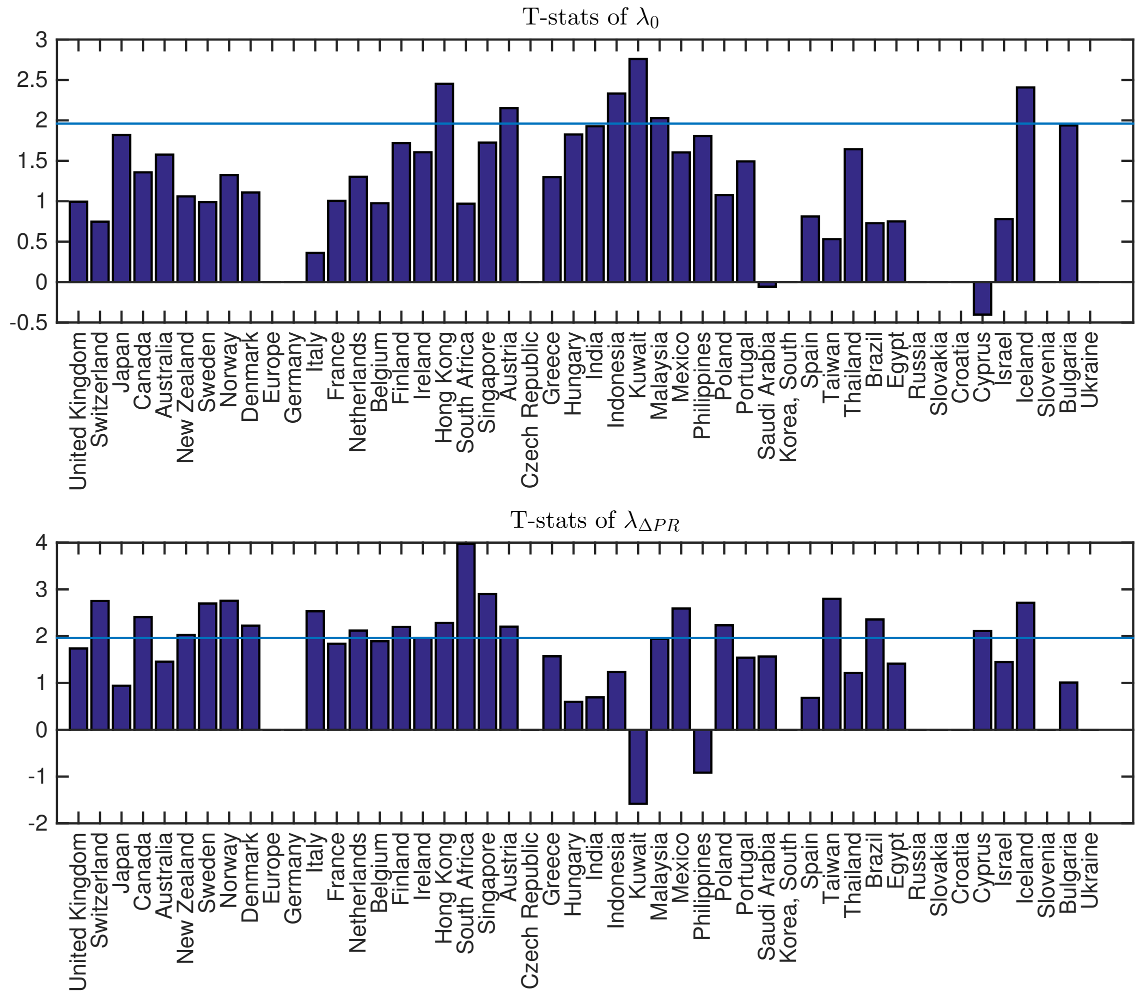


Figure 6. Cross-sectional t-statistics - *Country Level*

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.

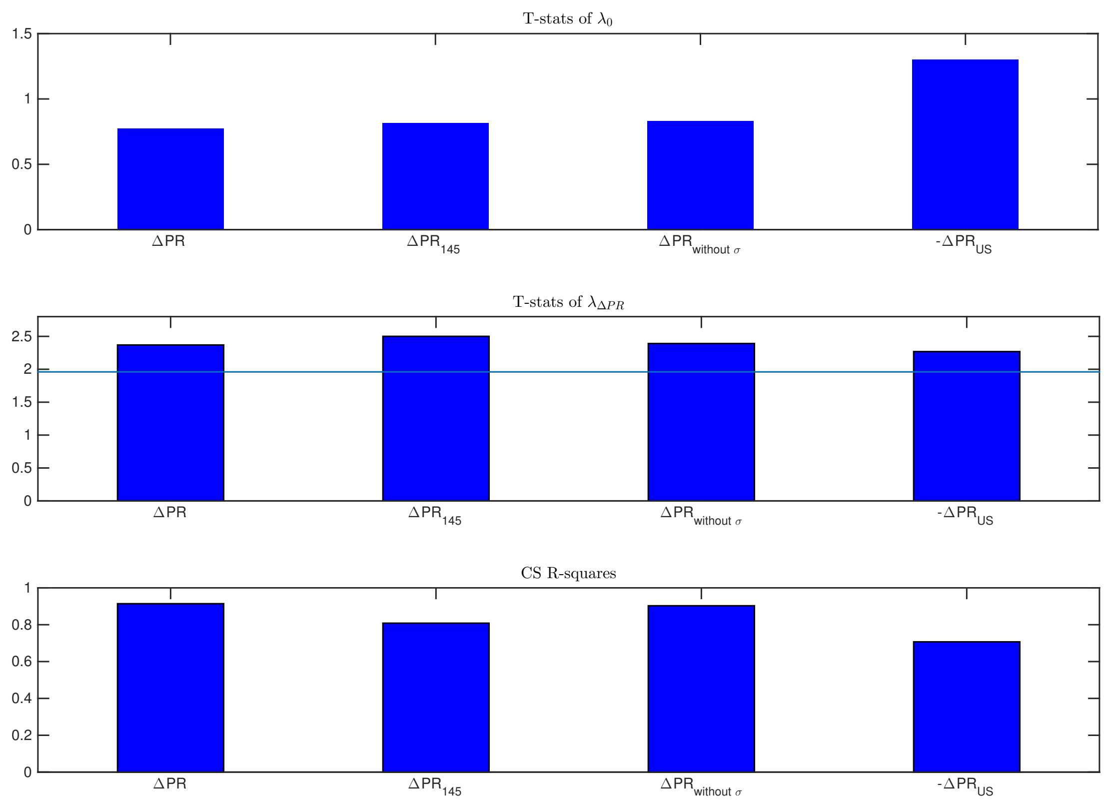


Figure 7. Cross-sectional t-statistics - ***Alternative Definitions of Political Risk***

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.

Internet Appendix to

"Global Political Risk and Currency Momentum"

by

Ilias Filippou   Arie E. Gozluklu   Mark P. Taylor

(Not for publication)

Table A1. 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.

	Without Transaction Costs							*With Transaction Costs*						
	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 ($f = 3$, $h = 1$)														
(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 A2. 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 A3. 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 Jurado, Ludvigson, and Ng (2013) ($\Delta\mathcal{MU}_1$) 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)

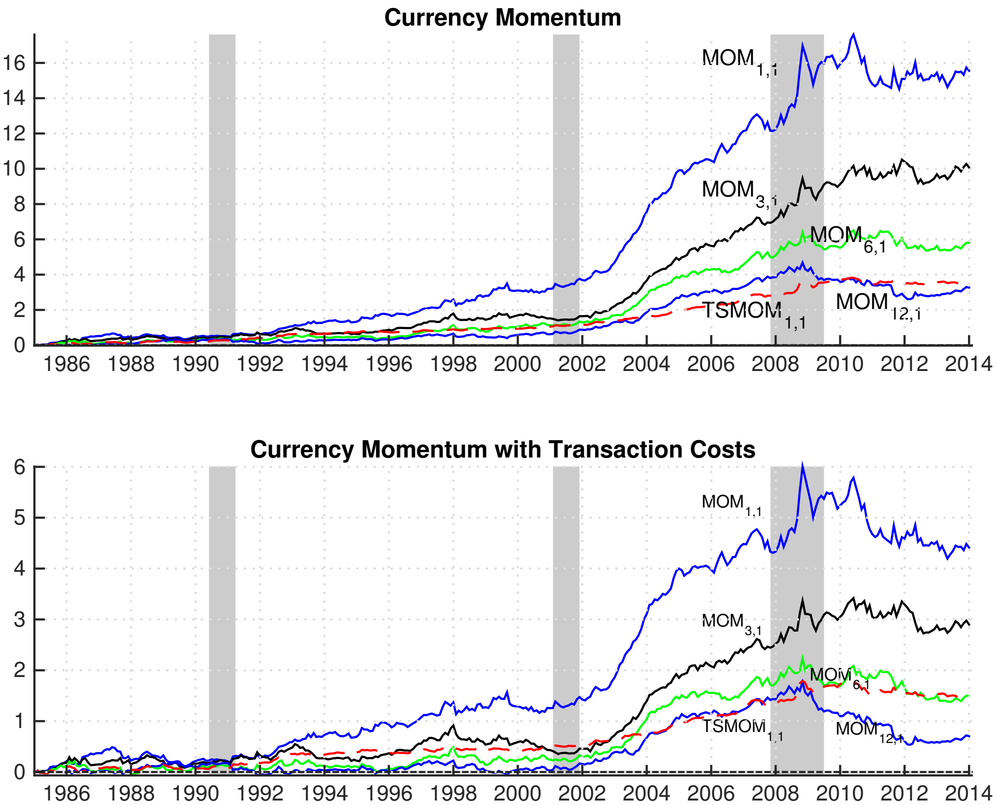


Figure A8. Cumulative Returns of Momentum Portfolios

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.

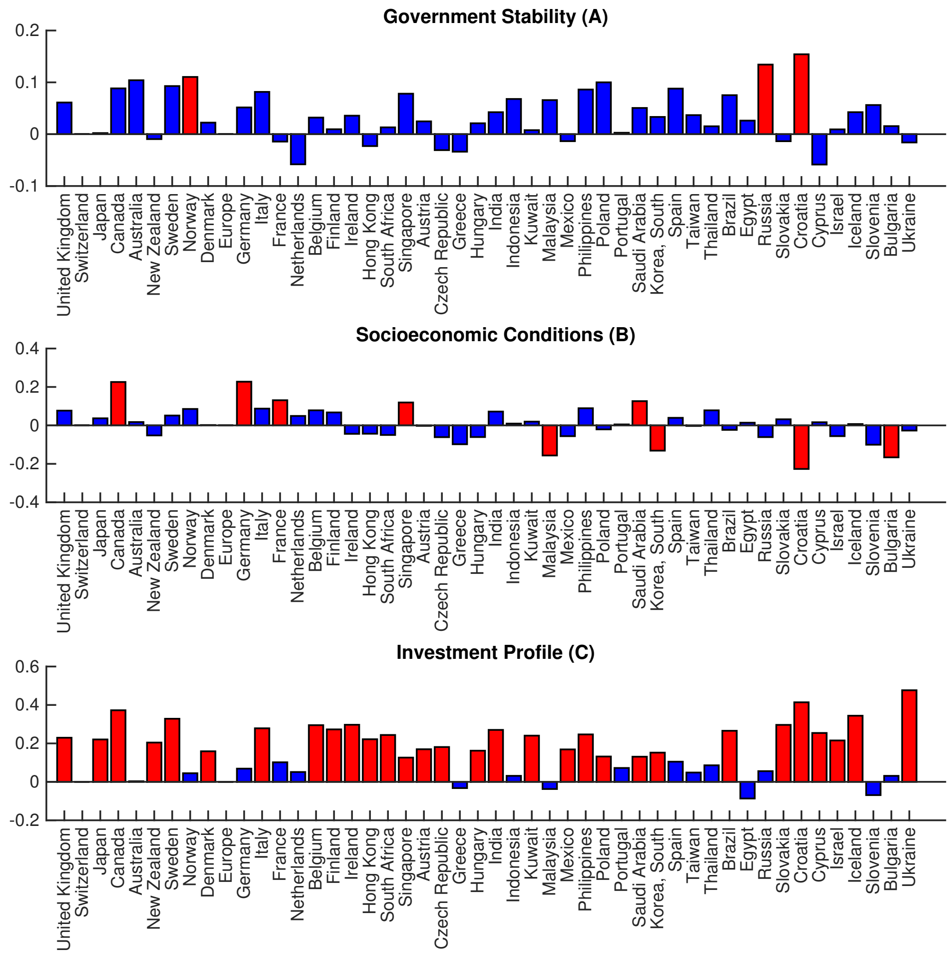


Figure A9. Correlation of U.S. with Foreign Components of Political Risk

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.

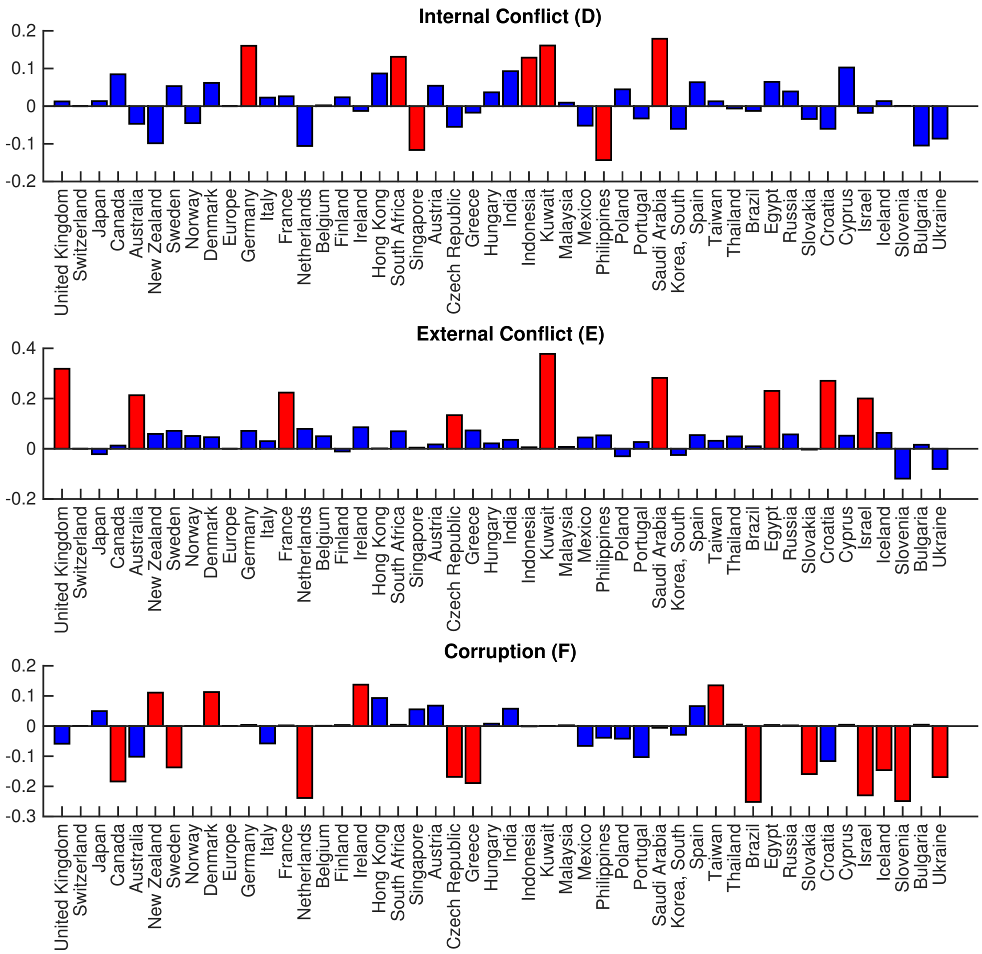


Figure A2. Correlation of U.S. with Foreign Components of Political Risk *(Continued)*

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.

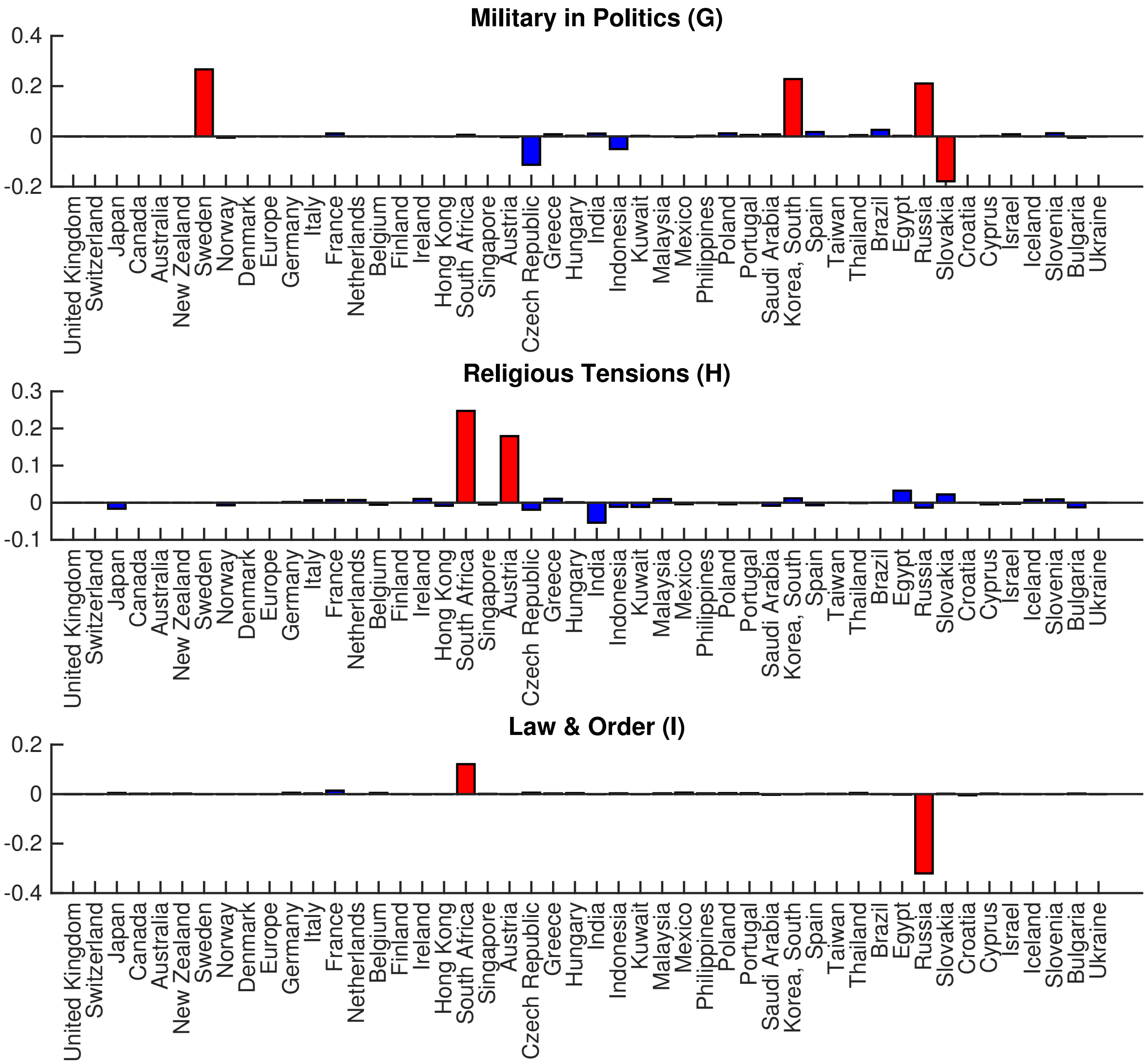


Figure A2. Correlation of U.S. with Foreign Components of Political Risk *(Continued)*

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.

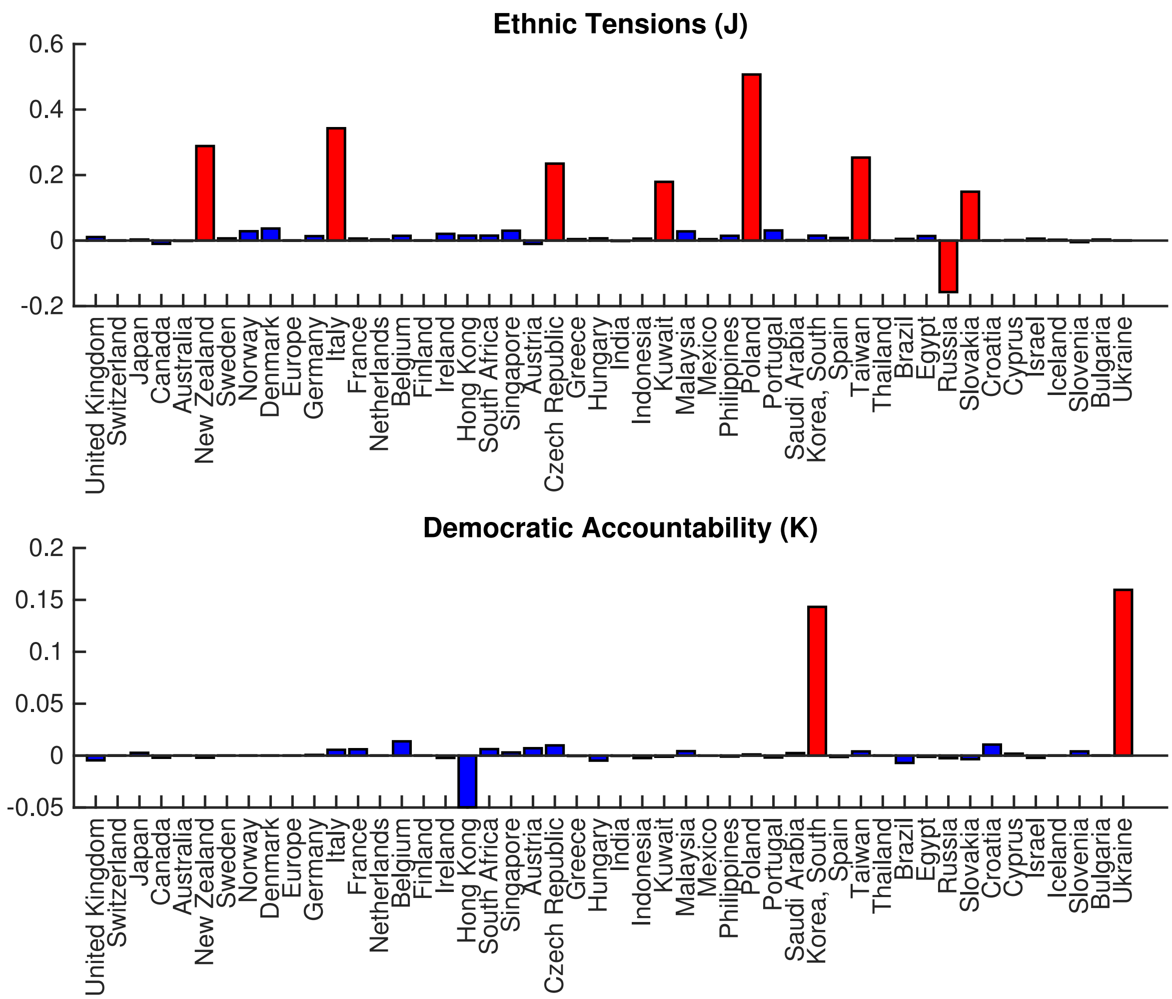


Figure A2. Correlation of U.S. with Foreign Components of Political Risk *(Continued)*

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.

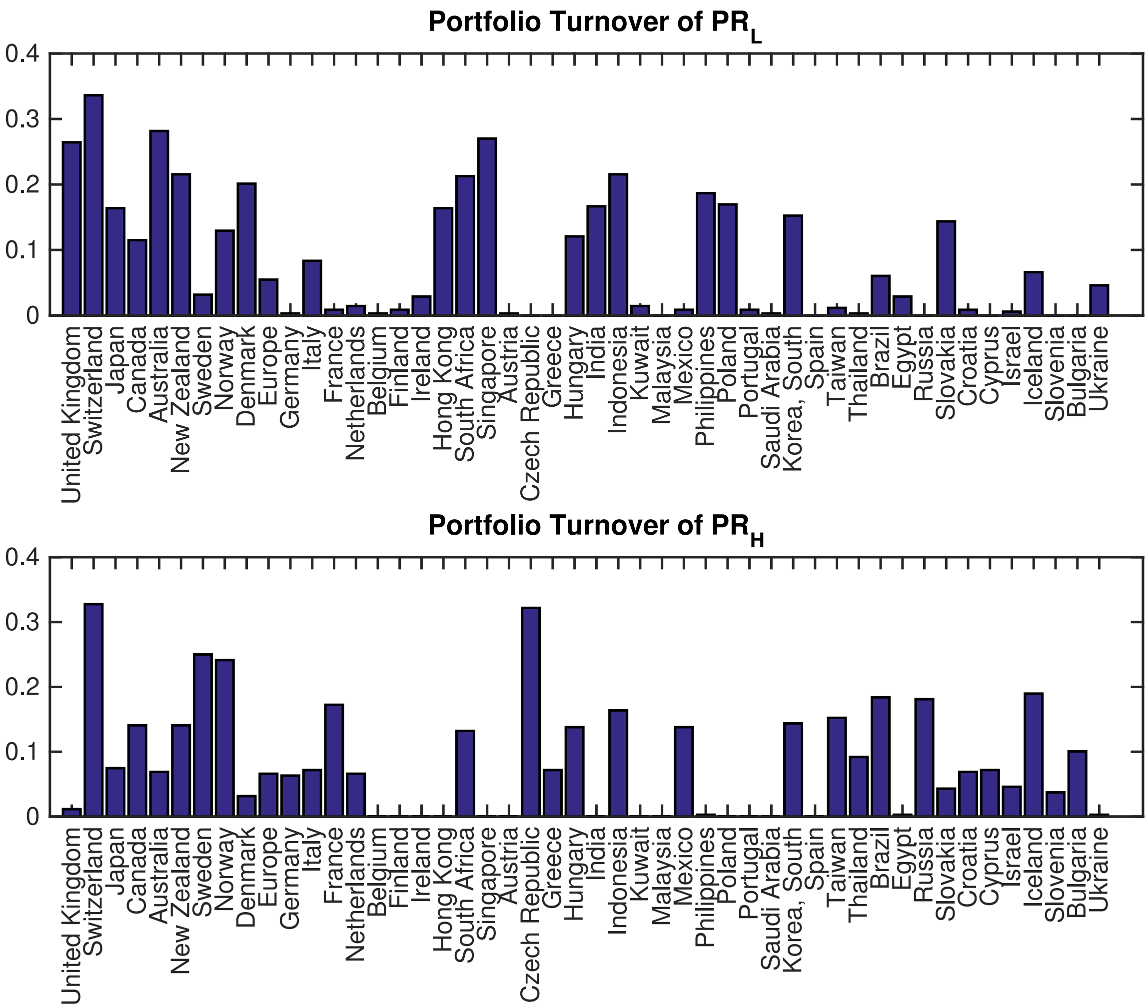


Figure A3. Portfolio Turnover - ***Global Political Risk***

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.

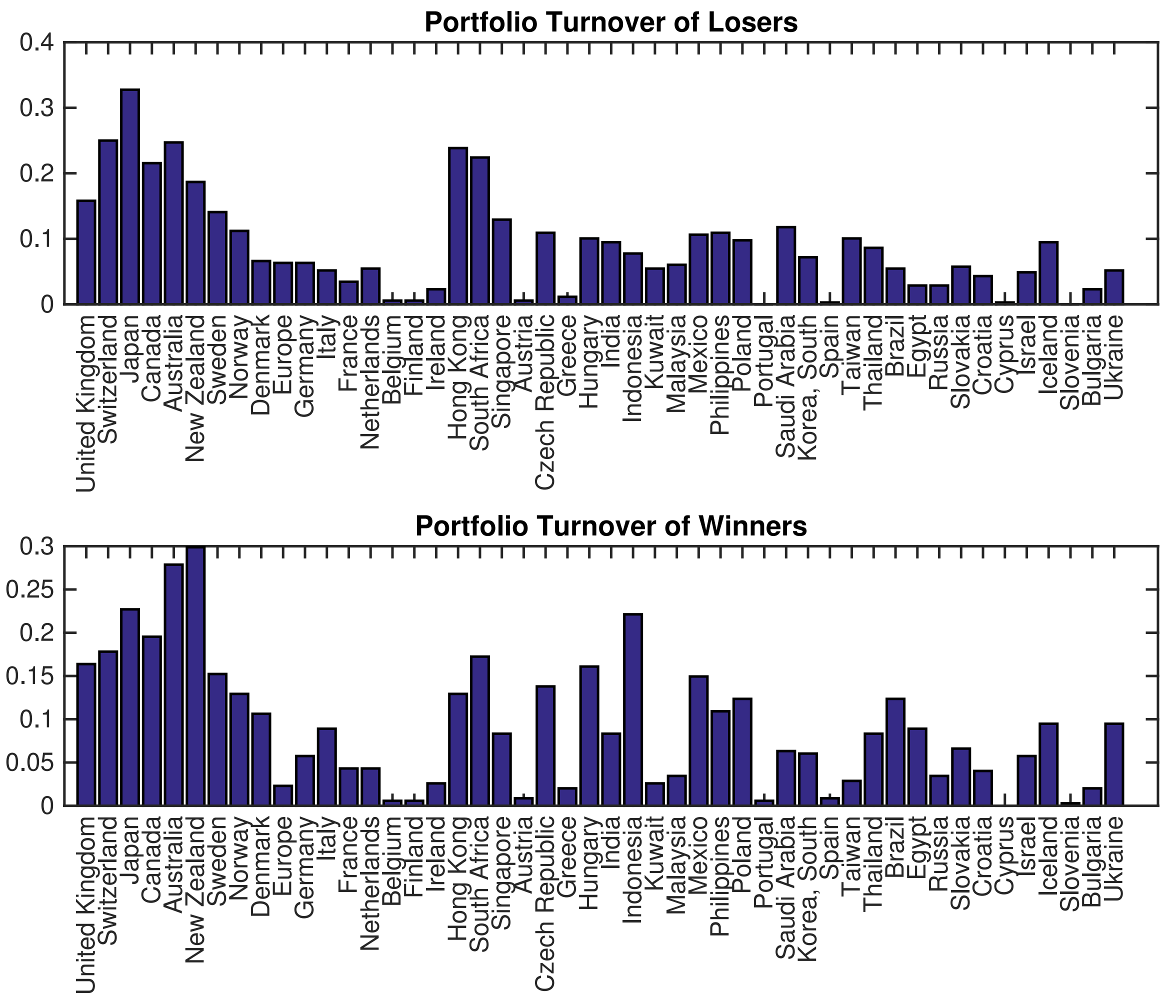


Figure A4. Portfolio Turnover - ***Momentum***

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.

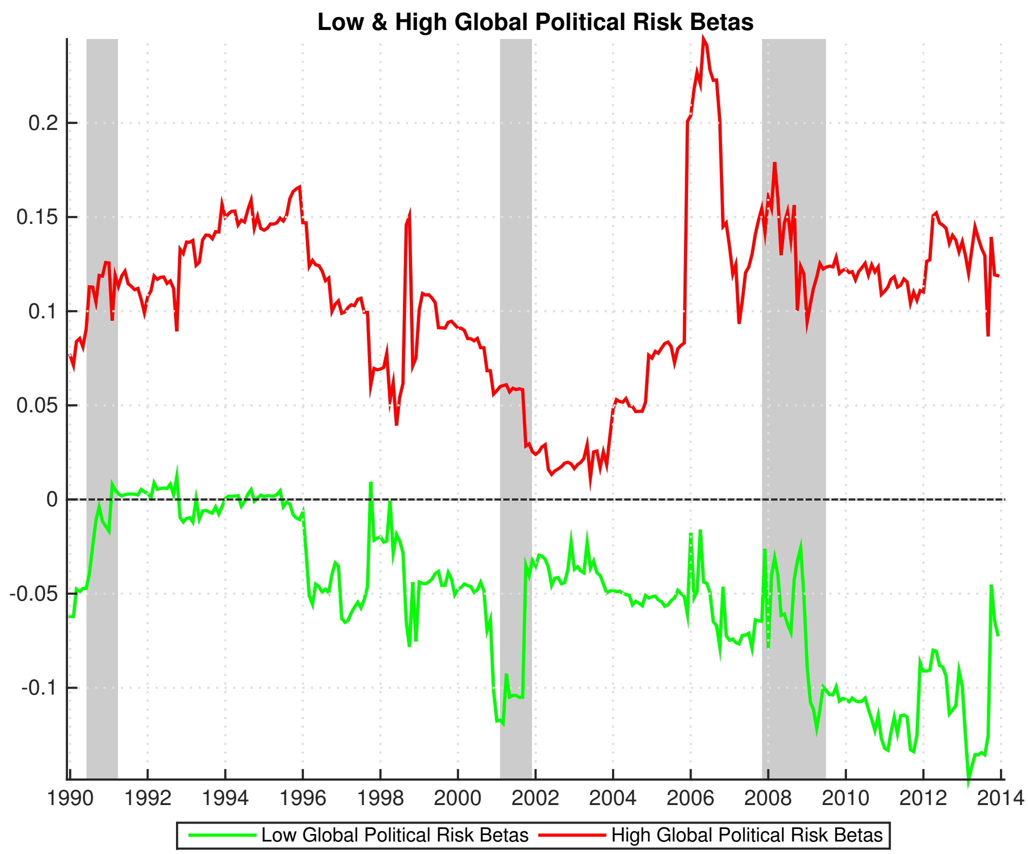


Figure A5. Global Political Risk Betas

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.

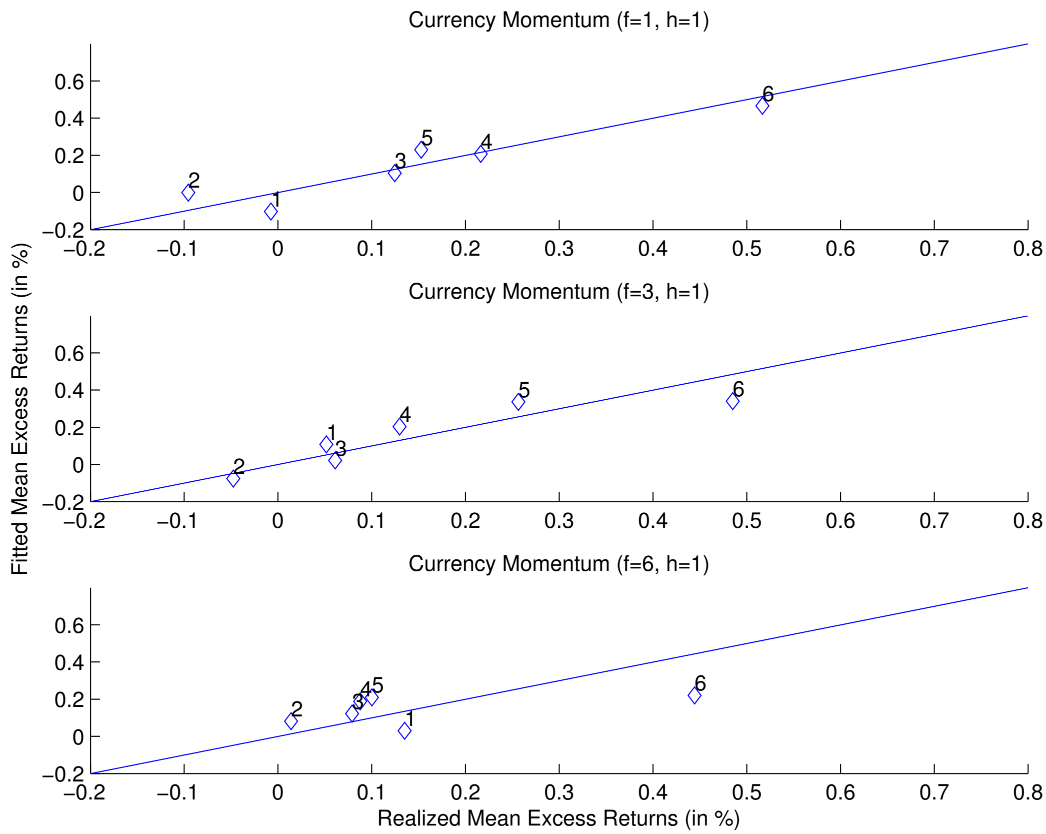


Figure A6. Pricing Error Plots - *Porfolio Level Net Excess Returns*

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.

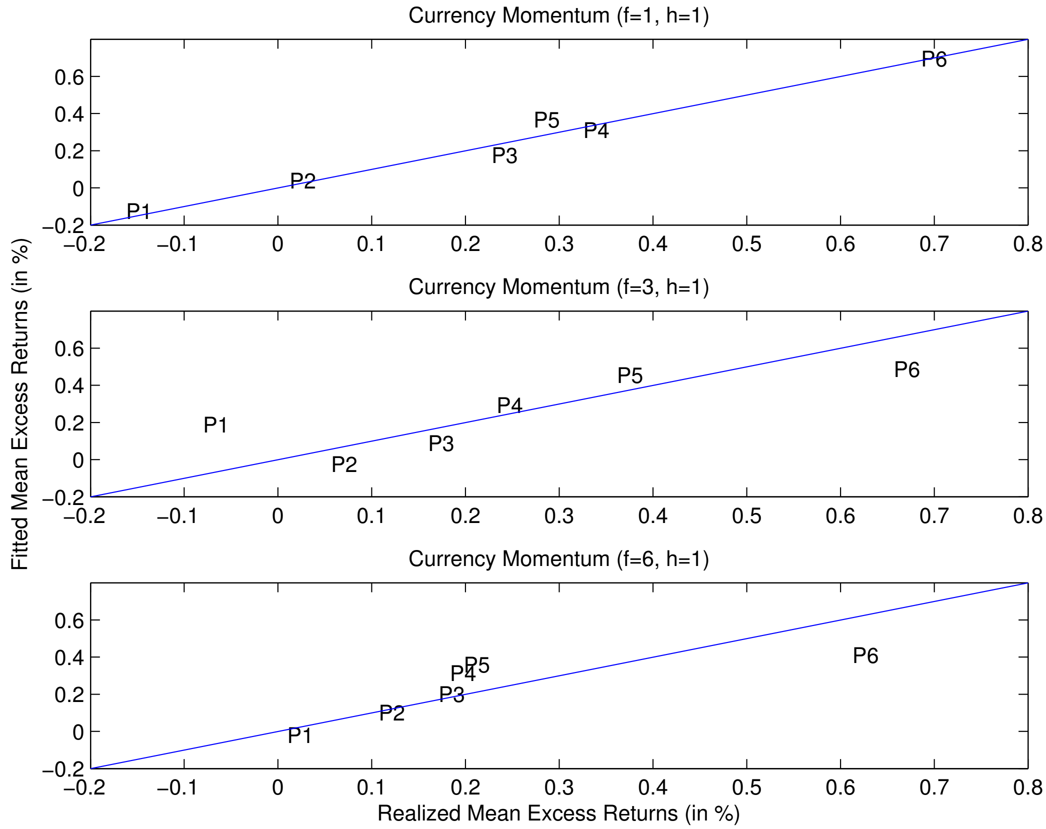


Figure A7. Conditional Pricing Error Plots - ***Portfolio Level***

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.

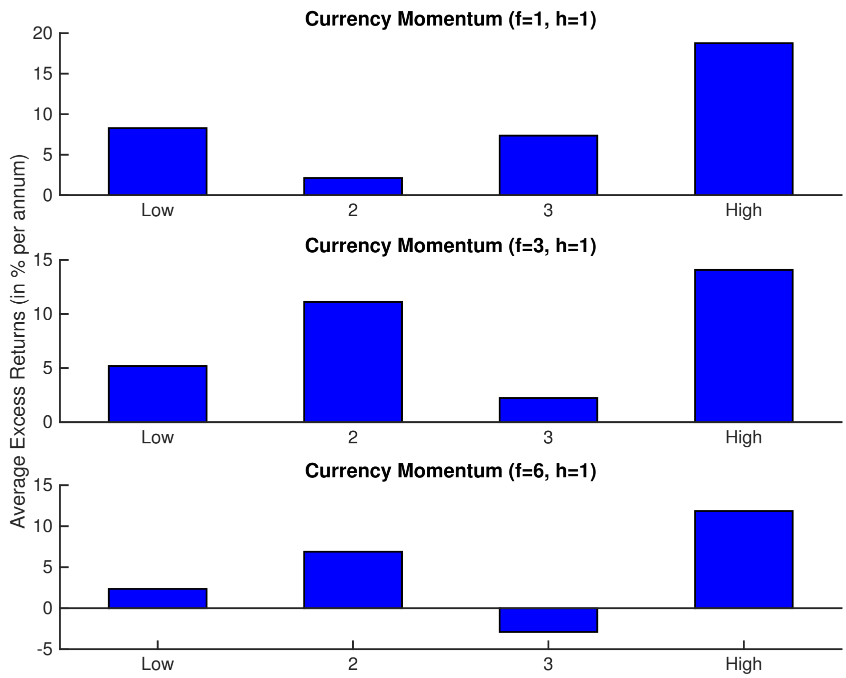
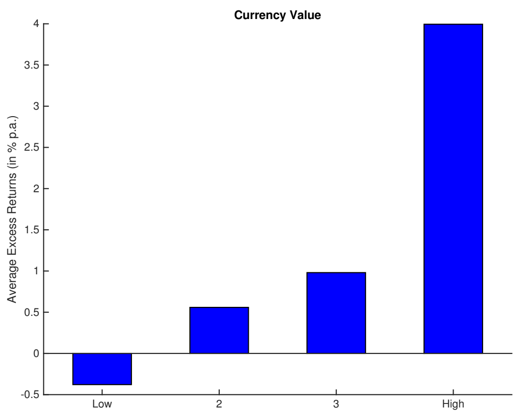
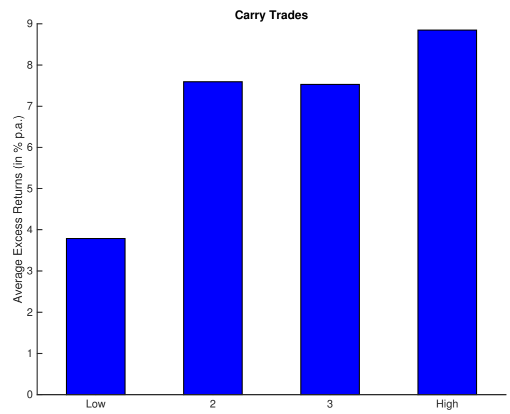


Figure A8. Currency Momentum and Global Political Risk

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 A9. 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.

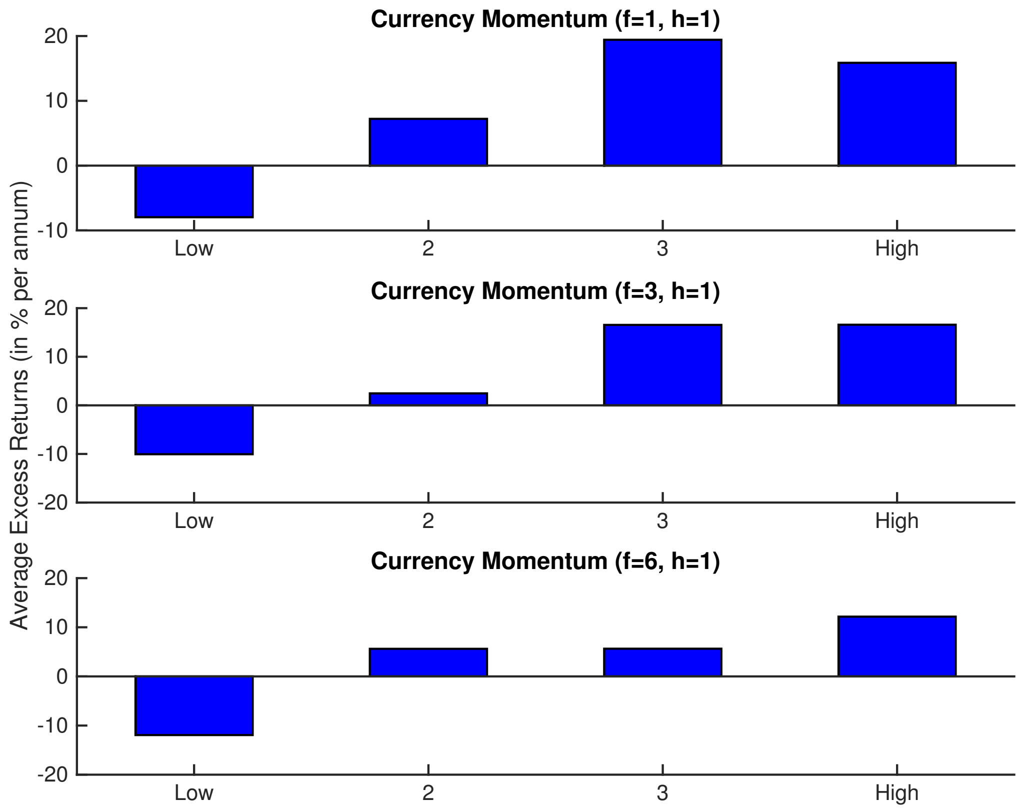


Figure A10. Currency Momentum and Global Political Risk (IFO)

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.