Political Risk and Currency Momentum *

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Abstract

Using a measure of political risk, relative to the U.S., that captures unexpected political conditions, we show that political risk is priced in the cross section of currency momentum and contains information beyond other risk factors. Our results are robust after controlling for transaction costs, reversals and alternative limits to arbitrage. The global political environment affects the profitability of the momentum strategy in the foreign exchange market; investors following such strategies are compensated for the exposure to the global political risk of those currencies they hold, i.e., the past *winners*, and exploit the lower returns of *loser* portfolios. The risk compensation is mainly justified by the different exposures of foreign currencies in the momentum portfolio, to the U.S. political shocks, which is the main component of the global political risk.

Keywords: Currency Momentum, FX Risk Premium, Limits to Arbitrage, Political Risk.

JEL Classification: F31, G11, G12, G15.

1. Introduction

In this paper we report research on the role of political risk in the foreign exchange (FX) market and in particular on the issue of how political shocks influence currency investment strategies and affect their profitability. The FX market is a global decentralized market for the trading of currencies against one another and it is by far the largest financial market in the world in terms of both geographical dispersion and daily turnover, which is in excess of $5 trillion.[1] Nevertheless, despite its size and global importance, the FX market is perhaps one of the least well understood financial markets. For example, while there is some evidence that standard macroeconomic variables may influence the long-run behavior of real and nominal exchange rates, the shorter term disconnect between fundamentals and exchange rate movements is well documented (see, e.g., Taylor, 1995). Similarly, significant departures from the simple (i.e. risk-neutral) efficient markets hypothesis for FX, according to which uncovered interest parity (UIP) should hold and the forward rate should be an optimal predictor of the future spot exchange rate, are also well documented (see, e.g., Hodrick, 1987; Froot and Thaler, 1990; Taylor, 1995; Sarno and Taylor, 2002, for surveys of this literature). Indeed, there is evidence that traders in the FX market have been able to exploit the failure of UIP to pursue profitable trading strategies based on the carry trade (buying high-interest rate currencies against low-interest rate currencies), as well as profitable strategies based on value (selling currencies that appear to be overvalued against currencies that appear to be undervalued according to some fundamental value measure such as purchasing power parity) and momentum (buying currencies that have recently been rising in value against currencies

[1] According to the last Bank for International Settlements' Triennial Survey, daily turnover in the global FX market averaged $5.3 trillion per day in April 2013 (Bank for International Settlements, 2013). See Sager and Taylor (2006), King, Osler, and Rime (2011) and Rime and Schrimpf (2013) for detailed analyses of the structure of the FX market.

that have recently been falling in value) (see, e.g., Rime and Schrimpf, 2013).

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 performance (*losers*); this naive strategy renders high annualized Sharpe ratios and is uncorrelated with the payoffs of other strategies, such as value or carry (Burnside, Eichenbaum, and Rebelo, 2011a; Menkhoff, Sarno, Schmeling, and Schrimpf, 2012b). Its profitability could partially be explained by transaction costs, limits to arbitrage or illiquidity.[2] However, to the best of the present authors' knowledge there is no successful FX asset pricing model that explains both the times-series and the cross-sectional dispersion of currency momentum returns. We attempt to remedy this by investigating how global political shocks may influence currency momentum strategies since there has been limited success to explain their profitability and we argue there may be good reason to suspect that momentum may be influenced by political stability. 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 limits to arbitrage. Existing risk factors that have been able to capture the profitability of other currency strategies have been shown not to have a first-order effect on currency momentum returns either in times-series or in cross-sectional dimensions (e.g., Menkhoff et al., 2012b). Conversely, we show that while political risk has a first-order effect on momentum, it does not have a first-order effect on other currency strategies such as carry and value, as other risk factors explaining those strategies are dominant.

To analyze the question as to whether global political risk prices the cross section of

[2] In particular, Menkhoff et al. (2012b) show that momentum exhibits a significant time-variation that is mainly driven by limits to arbitrage; thus, currency momentum may be more profitable in less developed countries with high risk of capital controls, a fragile political environment and other country risk characteristics that could cause sudden moves in the exchange rate and generate volatility.

currency momentum returns, we develop a novel measure of political risk that captures differences between the political environment of the U.S. economy and that of 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, certainly by a naive investor.[3] We thus examine whether global political shocks affect the profitability of momentum strategies, which helps us understand better the determinants of currency risk premia. We construct a two-factor asset pricing model that incorporates information contained in our global political risk measure. More precisely, the first factor is a *level* factor as originally introduced by Lustig, Roussanov, and Verdelhan (2011), which is measured as the average return 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 (*slope*) factor is our global political risk measure, designed to capture political risk surprises around the world; this factor is highly correlated with the second principal component of currency momentum portfolios. 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 the

[3]A good example is the Brexit referendum outcome on 23rd June 2016 which caught the market participants by surprise and resulted in the largest drop in the British pound over decades.

U.S. or decreases in political risk in the foreign country. We mainly focus on momentum strategies that rebalance portfolios every month and use formation periods 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).[4]

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 as global FX volatility, FX liquidity, FX correlation and changes in credit default swap (CDS) spreads. Notably, the predictability mainly comes from loser portfolios along the time-series dimension, although 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 strong cross-sectional performance both in statistical and in economic terms. In particular, we analyze the results of Fama and MacBeth (1973) regressions as well as generalized method of moments (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 terms of goodness of fit. Specifically, we show that we cannot reject the null hypothesis that all of the pricing errors are

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

jointly equal to zero, as signified in terms of very large *p-values* of the χ^2 test statistic: we cannot reject the null hypothesis that the HJ distance (Hansen and Jagannathan, 1997) is equal to zero and the cross-sectional R^2 ranges from 66% to 99% for formation periods from one to six months. The results are similar whether we employ a mimicking portfolio or the raw measure.

We then 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 or idiosyncratic 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 similar exercises by replacing idiosyncratic volatility with illiquidity, volatility and a correlation variable (e.g., Mueller, Stathopoulos, and Vedolin, 2013) and reach the same conclusion. These results provide further support for 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 exclude currencies of the fixed exchange rate regime, and (ii.) include only those with a high degree of capital account openness (Chinn and Ito, 2006; Della Corte, Sarno, Schmeling, and Wagner, 2013). We find that the results are improved in most cases. In addition, we show that allowing for 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. Again, we find that the results are largely unaffected. Finally, we perform currency-level cross-sectional regressions for conditional returns and again demonstrate the pricing ability of global political risk.

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

The remainder of the paper is set out as follows. In section 2 we set out a brief review of the literature on political risk and currency momentum, while we define and discuss our global political risk measure in section 3. In section 4 we provide a brief description of the data as well as the construction of the currency portfolios. Section 5 discusses the empirical results of the paper. In section 6 we attempt to provide a better understanding of the underlying determinants of currency premia. Section 7 offers some robustness checks. Finally, in section 8, we provide some concluding remarks.

2. Related Literature

In this section we review related studies on political risk and currency momentum in order to set the scene for our investigation. We begin by examining some salient studies linking political risk to the foreign exchange market before turing to the link between to political risk and currency momentum more specifically. While precise interpretations of political risk differ in the literature, there are two main definitions (Kobrin, 1979). The first relates political risk to *"unwanted consequences of political activity"* and the second links it to political events.

Political Risk. There is an established body of literature on the relation between exchange rates and political risk. In early contributions to this literature, Aliber (1973) and Dooley and Isard (1980) consider two main channels of risk that could be linked to deviations from the UIP condition, namely, exchange rate risk and political risk. This separation is further analyzed by Dooley and Isard (1980), who focus on the role of capital controls and the political risk premium. In addition, Bailey and Chung (1995) study the role of political risk and movements in exchange rates in a 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 an FX forecasting model incorporating political risk variables can beat a random walk in an out-of-sample forecasting exercise for three currency pairs.

Political Events. Another strand of this literature focuses on political risk premia associated with political news. For example, Boutchkova, Doshi, Durnev, and Molchanov (2012) investigate how stock market volatility broken down by industry 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 political risk related to announcements of policy changes should lead to a drop in equity prices on average, with an analogous increase in volatility and correlation. In addition, Addoum and Kumar (2013) develop a trading strategy that exploits changes in political events, such as U.S. presidential elections or the beginning and end of a presidential term, demonstrating that investors require a premium under those periods because political uncertainty is higher. Lugovskyy (2012) employs a political risk factor that is a dummy variable of political risk regime changes and finds that there is 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 such that options with maturity around political events appear to be more expensive.[5] We deviate somewhat from these studies as we do not focus on specific political events but, rather, we attempt instead to capture *unexpected* changes in the political environment that drive currency premia.

Currency Momentum. Recent analyses of currency momentum in the foreign exchange rate market research literature include Okunev and White (2003), Burnside, Eichenbaum, and Rebelo (2011a), Menkhoff et al. (2012b) and Asness, Moskowitz, and Pedersen (2013), each of which focuses on the cross-sectional dimension of the momentum strategy. Most of the earlier studies focus on *time-series* momentum, often labeled as a form of "technical analysis".[6] Our methodology is closely related to that one employed by Menkhoff et al. (2012b). In regard to the performance of momentum strategies, Cen and Marsh (2013) show that momentum was more profitable in the interwar period, and provide 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. Bae and Elkamhi (2014) find that a global eqyuity correlation factor jointly explains carry and momentum portfolios in the FX market. Our analysis is different as our factor provides a fundamental determinant of currency 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

[5]For other measures of uncertainty 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).

[6]Surveys of FX market practitioners by Taylor and Allen (1992) and Cheung and Chinn (2001) show that a significant proportion of FX traders use some form of quantitative technical trading rule, with a high proportion using momentum strategies.

than market risk. Asness, Moskowitz, and Pedersen (2013) document the prevalence of value and momentum returns across a range of asset classes (including FX) and the negative correlation between value and momentum; insofar as political risk may be expected to impact negatively on expected value, this would suggest that political risk may generate momentum as investors demand a premium for investing in relatively high political risk currencies.

3. Relative Political Risk

In this section we discuss the role of global political risk in the foreign exchange market and attempt to provide a deeper understanding of the channel through which political risk enters into the currency market and affects investors' decisions. We also define our measure of political risk and analyze 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 for momentum trading, supporting this finding. Thus, it is apparent that currency momentum may be subject to limits to arbitrage while its profitability is heavily determined by country-specific characteristics. For example, these authors demonstrate that momentum exhibits a particular time-variation that stems from country-specific shocks and will thus be more pronounced in highly idiosyncratic volatility portfolios.

Political risk is one of the main determinants of country-specific shocks. For example, Pástor and Veronesi (2013) employ a general equilibrium model to show that in economies with a weak economic profile, political uncertainty requires a risk premium to asset returns 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 characterized 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.[7] Therefore, it is apparent that political risk could serve as a candidate risk factor for currency momentum, since it is a forward-looking measure that heavily affects currency premia in comparison to other country-specific characteristics when country risk is high.

We introduce a novel measure of global political risk that it is defined relative to U.S. political conditions and is designed to capture differences between the political uncertainty of the U.S. and the rest of the world.[8] It is natural to think of political risk relative to the U.S. for two reasons. First, we are dealing with U.S. dollar exchange rates against other currencies and so, although we will for the most part analyze portfolios of currency returns rather than individual currency returns, we will still need a relative measure to reflect the bilateral nature of exchange rates. Second, the role of the U.S. dollar as the global reserve currency, as well as the dominance of the United States in financial markets as well as the global political economy (e.g. the strong effect of U.S. interest rate movements on emerging market capital flows and the U.S. military influence on NATO countries), suggests that a measure of global politcal risk relative to the U.S. is appropriate for analyzing global financial markets in general and currency markets in particular.

We build our measure of global political risk starting with a measure at the country level, which we obtain from the International Country Risk Guide (ICRG) published by the

[7] For further examples see Alesina and Tabellini (1989).

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

PRS Group. The ICRG political risk rating is a long-running dataset, produced monthly for the last three decades and covering over 140 countries, and is widely used in the finance industry as a means of assessing the political stability of countries on a comparable basis. Each month, ICRG country experts assign risk points to a preset group of 12 factors, termed political risk components, by collecting information on each component and converting these into risk points on the basis of a consistent pattern of evaluation.[9] Specifically, our proxy for global political conditions is measured by:[10]

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

where n_t is the total number of available currencies at time t and $pr_{i,t}$ represents our foreign (country i) measure of political risk and $pr_{US,t}$ the US measure, each at time t. The ICRG political risk measure is constructed such that an *increase* in the measure denotes a *reduction* in political risk; thus, we use the log reciprocal of the ICRG measure for country j, $pr(ICRG)_{j,t}$, say, in order to have a measure that increases with political risk, i.e. $pr_{jt} \equiv \ln(1/pr(ICRG)_{j,t})$. The denominator in (1), $\sigma_{i,t}^{\mathcal{PR}}$, is the cross-sectional average of the time t absolute deviation of the foreign (i-th country) measure of political risk from the U.S. measure.[11] We normalise the numerator in (1) with the cross-sectional absolute average political risk on a month-to-month basis so as to highlight country risk relative to global political

[9] For further details of the PRS Group, see https://www.prsgroup.com/; for full details of the ICRG methodology, see http://www.prsgroup.com/wp-content/uploads/2012/11/icrgmethodology.pdf. The 12 weighted variables are: government stability, socioeconomic conditions, investment profile, internal conflict, external conflict, corruption, military in politic, religious tensions, law and order, ethnic tensions, democratic accountability and bureaucracy quality. In turn, each of these is broken down into subcategories.

[10] We also account for differences in *globalisation* across countries by creating a value-weighted global political index, based upon the ICRG risk ratings weighted according to weights determined by the KOF Index of Globalization (http://globalization.kof.ethz.ch/), and we find that the two measures behave similarly. The value weighted index is available upon request.

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

conditions; this is useful because it gives us the opportunity to capture the simultaneous deterioration of political conditions between countries with similar characteristics and *vice versa*.[12]

While (1) gives a measure of global political risk, our focus is on global political risk *innovations* (denoted $\Delta\mathcal{PR}_t$), which we measure as the innovations obtained from a first-order autoregressive model for $\mathcal{PR}_t$.[13] Figure 1 graphs $\Delta\mathcal{PR}_t$ over the period January 1985 to January 2014. Note that a positive value of the innovation represents less political risk associated with the U.S. relative to the rest of the world, and conversely when the innovations are negative. We have also picked out a number of extreme movements in the risk innovations, where they are apparently related to well known political events, and these are labeled in Figure 1.

[FIGURE 1 ABOUT HERE.]

Figure A1 in the Internet Appendix provides a graphical illustration of our global political risk innovations along with other risk factors employed in the literature such as global FX volatility (as in Menkhoff, Sarno, Schmeling, and Schrimpf, 2012a), global FX correlation (e.g. Mueller, Stathopoulos, and Vedolin, 2013)), global FX liquidity innovations (measured as global bid-ask spread (similarly to Menkhoff et al., 2012a, section 4) and global CDS spreads (measured as differences of average CDS spreads across countries, e.g. Della Corte et al., 2013). We see 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 that we are attempting to capture different dynamics of currency premia.[14]

[12] In the robustness section, we explore alternative definitions of global political risk by omitting the normalisation factor, expanding the set of foreign countries or focusing only on U.S. political risk.

[13] 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.

[14] Apart from the relation with the NBER recessions that we illustrate in Figure A2 we also show that our

Table 1 reports descriptive statistics of our 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 accordance with Figure A2, 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 A3 in the Internet Appendix shows the correlation of country-level political risk innovations with respect to U.S. innovations over the sample period. We first note that the correlations are on average low and seldom exceed 25 percent, exceptions being in cases where countries have significant political ties with the U.S., such as the U.K., Canada, Kuwait, Saudi Arabia, Egypt and Russia. In order to understand the source of the correlations we also report in Figure A4 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[15] or payment delays dominates in terms of significant correlations. Nonetheless

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.

[15]For example, firms tend to consider the tax jurisdiction in order to allocate their earning abroad or repatriate them immediately (see e.g., Foley, Hartzell, Titman, and Twite, 2007; Faulkender and Petersen,

correlations remain low across different components.[16]

4. Data and Currency Portfolios

In this section, we provide a detailed description of the data used in our research as well as describe the construction of our momentum strategy portfolios.

Exchange Rate Data. We begin with daily spot and one-month forward exchange rates against the U.S. dollar spanning the period 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 (2011). The main advantage of this approach is that the data is not averaged over each month but represents the rate on the last trading day of each month. The sample is similar to the one employed by Menkhoff et al. (2012a,b) and comprises 48 countries.[17] We apply various filters in the data so as to make the analysis more realistic, focusing on implementable strategies.[18]

2012; Bennedsen and Zeume, 2015). This practice, in principle, could affect currency flows between countries with different tax environments.

[16] In Figure A5 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.

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

[18] 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, and in these cases their exchange rates are excluded from the sample at the later date. We also delete observations 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;

Currency Excess Returns. We denote by S_t and F_t the level of the time t spot and forward exchange rates, respectively. 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 realized excess return (RX_{t+1}) is defined as the payoff of a strategy that buys a foreign currency in the one-month forward market at time t and then sells it in the spot market at maturity at time $t+1$.[19] The excess return can be computed as $RX_{t+1} \equiv \frac{F_t - S_{t+1}}{S_t} = \frac{F_t - S_t}{S_t} - \frac{S_{t+1} - S_t}{S_t}$. 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.[20] 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 from the foreign-domestic risk-free interest rate differential. The implementation cost of the currency strategy is taken into consideration though the use of bid and ask spreads. Particularly, buying the foreign currency forward at time t using the bid price (F_t^b) and selling it at time $t+1$ in the spot market at ask price (S_t^a) is given by: $RX_{t+1}^l = (F_t^b - S_{t+1}^a)/S_t^b$. Whereas the corresponding short position in the foreign currency (or short in the dollar) will render a *net* excess return of the form: $RX_{t+1}^s = -(F_t^a - S_{t+1}^b)/S_t^a$. 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.[21]

Malaysia from August 1998 to June 2005 and Indonesia from December 2000 to May 2007.

[19] The excess return is in fact the *total* return to such a strategy as it involves a zero commitment of funds.

[20] Taylor (1987, 1989) and more recently Akram, Rime, and Sarno (2008) provide a detailed empirical examination of the CIP condition and show that it holds at daily and lower frequencies.

[21] Neely and Weller (2013) argue, based on interviews with traders, that posted bid-ask spreads may systematically overestimate the spreads available in practice and suggest using one third of the posted one-month forward rate bid-ask spread as a more reliable estimate of one-way transactions costs. If this is the case, however, then our allowance for transaction costs, as described above, will only provide a more stringent

Political Risk Data. Our measure of country-level political risk (i.e. $pr_{i,t}$) is constructed using data from the International Country Risk Guide (ICRG). As noted earlier in Section 3 where we describe the construction of our political risk measure in detail, we compute the log inverse of the ICRG measure in order to obtain a measure that increases with with political risk. We then construct our global political risk measure relative to the U.S., $\mathcal{PR}_t$, as in equation (1) and obtain our global political risk innovations measure, $\Delta\mathcal{PR}_t$, from the fitted innovations in an $AR(1)$ model for $\mathcal{PR}_t$.

Momentum Portfolios. At the end of each month t, we allocate currencies into six portfolios 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 ($\mathcal{WML}^{f,h}$) 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) (see e.g., Menkhoff et al., 2012b). In this context we define conditional excess returns as:

$$CRX_t^i \equiv sign(RX_{t-1}^i)RX_t^i. \tag{2}$$

This definiton is very similar to the one introduced by Burnside, Eichenbaum, and Rebelo (2011b) and it resembles a currency momentum strategy as we go *long* the i-th currency when the previous month's return was *positive* and *short* otherwise. However, the dynamics of this strategy differ from those of *cross-sectional* momentum.[22] In particular, we construct an

robustness test.

[22]For a discussion on this issue, see Menkhoff et al. (2012b).

equally weighted portfolio of all the conditional returns and label it as *time-series* momentum (i.e. $TSMOM_t^{1,1} = \overline{CRX}_t$, where the bar denotes the average across portfolios).

5. Empirical Results

5.1 Preliminary Analysis

In this section we evaluate the performance of the most profitable currency momentum portfolios. Furthermore, we report the results of univariate predictive regressions of momentum payoffs with global political risk innovations.

Descriptive Statistics. Table 2 displays summary statistics of the most profitable cross-sectional momentum strategies in the foreign exchange market. More specifically, *Panels A*, *B* and *C* present descriptive statistics of momentum strategies with different formation periods (f) and a holding period (h) of one month (i.e. $\mathcal{WML}^{1,1}$, $\mathcal{WML}^{3,1}$, $\mathcal{WML}^{6,1}$). Consistently with Menkhoff et al. (2012b), we find that currency momentum returns exhibit statistically significant high annualized mean excess returns (before transaction costs) of 10.18% for the formation period of one month, which is the most profitable, and then the profitability decreases monotonically as the formation period increases.[23] The results allowing for transaction costs (supersript τ) partially explain momentum return as the corresponding average *net* excess returns drops to 6.29%. 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.]

[23] In Figure A6 of the Internet Appendix, we show the portfolio turnover of the winner and loser portfolios. Mostly tradable currencies appear in both portfolios.

Panel A of Table A1 in the Internet Appendix shows summary statistics of time-series momentum portfolios with and without transaction costs. As expected, time-series momentum renders an annualized excess return before (after) transaction costs of 5.32% (3.25%) that 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 onto the cross-sectional momentum returns. We find that the two strategies have quite different characteristics, as illustrated by the economically and statistically significant alphas as well as the fact that the adjusted R^2 *decreases* with the formation period. However, the two strategies exhibit a common variation that is revealed from the relatively high adjusted R^2 (i.e. 0.52) when the formation period is one month.

Predictive Regressions. As a first step we question the predictive power of global political risk for both cross-sectional and time-series momentum strategies so as to investigate the time-series variation of momentum returns and 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:

$$\mathcal{Y}_{t+1}^{f,h} = \alpha^{f,h} + \gamma \mathcal{Z}_t + \varepsilon_{t+1}^{f,h}, \quad \text{for} \quad \mathcal{Y} = \mathcal{WML}, TSMOM, \tag{3}$$

where f represents the formation period and takes the values 1, 3 and 6 for the cross-sectional momentum and one for the time-series momentum,[24] 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 previously considered in the literature, summarized in Table 1.[25]

[24]To conserve space we report the results with longer formation periods, i.e. three and six months, in the Internet Appendix Table A2.

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

Table 3 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 poorly in terms of goodness of fit as it exhibits very low R^2, in line with earlier evidence on FX predictability (Menkhoff et al., 2012b; Filippou and Taylor, 2015). In Panel B of Table 3 we analyze seperately loser and winner portfolios of cross-sectional momentum strategies. We can make an important observation from this table: while the returns to winner portfolios are mainly predicted by the changes in FX correlation, only the innovations to global political risk explain the subsequent returns to loser portfolios.[26] This suggests that the main channel through which global political risk rationalizes momentum profitability is the short leg of the cross-sectional momentum strategy. Next, we turn our analysis to a cross-sectional perspective in order to see whether cross-country differences in political risk can capture the cross-sectional variation in currency momentum portfolio performance.

[TABLE 3 ABOUT HERE.]

5.2 Currency Momentum and Global Political Risk

In this section we examine 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 extent a foreign investor could protect herself from adverse political conditions by examining the pricing ability of global political risk innovations for FX momentum portfolios.

[26] Filippou and Taylor (2015) find that U.S. inflation and to a lesser extent global money and credit factors are able to predict currency momentum as well as the short and long legs of the trade.

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 six portfolios at time t based on their past (i.e. $t-1$) betas with global political risk innovations. Following Lustig, Roussanov, and Verdelhan (2011), Menkhoff et al. (2012a) and Mueller, Stathopoulos, and Vedolin (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.[27] The rolling regression takes the form:

$$CRX_t^i = \alpha^i + \beta^{i,PR} \Delta \mathcal{PR}_t + \varepsilon_t^i, \tag{4}$$

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. Here, we ask whether political risk is a priced factor in the cross-section of conditional excess returns. Table 4 displays descriptive statistics of currency portfolios sorted on both global (*Panel A*) and U.S. (*Panel B*) political risk betas. The latter panel is informative since momentum investors take short and long positions w.r.t the base currency (i.e. U.S. dollar). Note that the U.S. political risk is embedded in our global political risk measure (with a negative sign). Excess returns of portfolios sorted on global (U.S.) political risk exposures increase (decrease) as their exposure to political risk increases; indeed, we observe an almost monotonic pattern, verifying the pricing ability of political risk innovations for currency momentum. Particularly, both panels of Table 4 show that when sorting conditional excess returns on global and U.S. political risk betas, it renders a statistically lower (higher) excess return for the low-beta portfolios in comparison to the

[27] Smaller window sizes provide slightly weaker results.

high-beta counterparts. We also report pre- and post- formation betas that increase when moving from low to high beta portfolios.

What does our analysis imply for a momentum investor? Suppose that in the previous period, the USD depreciated against two representative foreign currencies, one in the P_L and the other in the P_H portfolio. The momentum investor would short the USD, and go long both foreign currencies with opposite exposure (i.e. beta) to global (U.S.) political risk innovations. When a negative global political shock hits the markets (that is, ΔPR is increasing), the negative beta for the foreign currency in the P_L portfolio (*Panel A*) implies a hedge against the global shock rendering a lower excess returns due to the depreciating foreign currency against the USD, hence lower excess return is required for this P_L portfolio. On the other hand, the positive beta of the foreign currency in the P_H portfolio is associated with an exposure to the global political shock for which the investor would require a premium to hold the foreign currency.[28]

[Table 4 about here.]

5.3 Factor-Mimicking Portfolio

Our global political risk measure is not a tradable factor and thus we create a mimicking portfolio that helps us overcome this issue and assess the pricing ability of global political

[28]In the same vein, since the global political risk is measured relative to the U.S. political risk it is natural to look at role of the U.S. political risk in isolation. When a negative U.S. political shocks hits the global economy (that is, $\Delta PR^{U.S.}$ is increasing), our portfolio sorts imply that the two representative foreign currencies in portfolios P_L and P_H have opposite exposures to U.S. political risk. Specifically, the currencies in portfolio P_L (P_H) are fundamentally different, as they are more (less) volatile, and more (less) exposed to U.S. political shocks (i.e. higher beta in magnitude). While the increasing U.S. political risk results in an appreciation of the foreign currency in P_H portfolio, the currency in the P_L portfolio tends to depreciates on average. Figure A5 reports the portfolio turnover of the global political risk portfolios ($Panel A$) and Figure A7 of the Internet Appendix shows how the rolling betas evolve over time.

risk innovations (Ang, Hodrick, Xing, and Zhang, 2006).[29] The premise behind the factor-mimicking method is that a traded factor should have an average return that it is similar to one of a traded portfolio, meaning that it can effectively price itself. To construct this, we regress contemporaneously our global political risk measure on excess returns of currency portfolios that are sorted based on their past performances: $\Delta\mathcal{PR}_{t+1} = a + \gamma'\mathbf{RX}_{t+1} + v_{t+1}$ where $\mathbf{RX}_{t+1}$ is the (6×1) vector of portfolio returns at time $t+1$.[30] The mimicking portfolio, $\mathcal{FPR}_{t+1}$ say, is then the linear projection of political risk innovations onto the six portfolio returns, $\mathcal{FPR}_{t+1} \equiv \hat{\gamma}'\mathbf{RX}_{t+1}$, where $\hat{\gamma}$ denotes the fitted value of γ. 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:

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

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 of currencies that are sorted into portfolios based on their previous month return.

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

[30] We also control for other variables (i.e. $\mathbf{Z}$) when estimating the optimal weights of the mimicking portfolios (i.e. γ) such as, past momentum returns (reversals, see section 7), volatility and liquidity. For example, we run a regression of the form: $\Delta\mathcal{PR}_{t+1} = a + \gamma'\mathbf{RX}_{t+1} + \delta'\mathbf{Z}_t + u_{t+1}$. We find that the results remain unchanged (e.g. Lamont, 2001; Ferson, Siegel, and Xu, 2006).

Thus, similarly to Lustig, Roussanov, and Verdelhan (2011), who find that their HML_{FX} factor is highly correlated with the second principal component of interest-rate sorted portfolios and 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.

5.4 FX Asset Pricing Tests

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

Following the asset pricing methodology analyzed in Cochrane (2005) and implemented in many studies in the FX asset pricing literature, such as Lustig, Roussanov, and Verdelhan (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}.[31] If M_{t+1} is the stochastic discount factor (SDF), then since the strategies we consider involve zero net investment, the expected value of $M_{t+1}RX^j_{t+1}$ must be zero, giving the basic Euler equation: $E_t[M_{t+1}RX^j_{t+1}] = 0$, where $E_t[.]$ is the conditional expectations operator, given information at time t. We further assume that the SDF is linear in the risk factors ϕ_{t+1}:[32] $M_{t+1} = [1 - b'(\phi_{t+1} - \mu_\phi)]$, where b denotes the vector of factor loadings and μ_ϕ is the vector of expected values of the pricing factors (i.e. $\mu_\phi = E(\phi_{t+1})$). Multiplying (10) by RX^j_{t+1}, taking unconditional expectations and rearranging, we have $E[RX^j_{t+1}] = b'\Sigma_{Rj\phi}$, where $\Sigma_{Rj\phi}$ is the covariance matrix of the risk factors and excess returns on the j-th portfolio. Let Σ_ϕ

[31] 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.

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

denote the variance-covariance matrix of the risk factors, then from (11) we have the beta pricing model: $E[RX_{t+1}^j] = b'\Sigma_\phi \Sigma_\phi^{-1} \Sigma_{Rj\phi}$ or $E[RX_{t+1}^j] = \lambda' \beta^j$, where $\lambda = \Sigma_\phi b$ represents the vector of factor risk prices and $\beta^j = \Sigma_\phi^{-1} \Sigma_{Rj\phi}$ denotes the vector of regression betas from projecting currency excess returns onto the risk factors contemporaneously.[33] Intuitively, the beta pricing model simply says that the expected excess return will depend upon the co-movement or beta of the return with the risk factors (β^j) and the price of those risk factors (λ), which is itself a function of their impact on the SDF (i.e. b) and their volatility and ability to offset or exacerbate the effects of each other (i.e. Σ_ϕ).

Simultaneous estimation of the factor loadings (b) and the factor means (μ_ϕ), as well as of the individual elements of the factor covariance matrix (Σ_ϕ), may be achieved using the Generalized Method of Moments (GMM) of Hansen (1982). In the present application, estimation is based on the following system of moment conditions:

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

where $g(z_t, \theta)$ is a function of the set of parameters (i.e. $\theta \equiv [b'\mu'\text{vec}(\Sigma_\phi)']'$) and the data (i.e. $z_t \equiv [RX_t^j, \phi_t]$). 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 to 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.[34]

[33] 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.

[34] In the first stage of the GMM estimation (GMM_1) we start with an identity weighting matrix so as to see whether the factors can price the cross-section of the currency excess returns equally well. Then in the second stage (GMM_2) we choose the weighting matrix optimally by minimizing the difference between the objective functions under heteroskedasticity and autocorrelation consistent (HAC) estimates of the long-run covariance matrix of the moment conditions. To do that, we follow the Newey and West (1987) methodology

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-section regressions of average portfolio returns on the factor betas, obtained from the previous step, in order to compute the factor risk prices. In addition, we allow for common mispricing in the currency returns by including a constant, although we find that the cross-sectional estimate of political risk remains highly significant if we exclude it. We also report both Newey and West (1987) as well as Shanken (1992) standard errors so as to account for the potential errors-in-variable issue that might arise due to the fact that the regressors are estimated in the second stage of the FMB procedure.

Cross-Section Analysis. The SDF model takes the following form:

$$M_{t+1} = 1 - b_{DOL}(DOL_{t+1} - \mu_{DOL}) - b_{\mathcal{FPR}}(\mathcal{FPR}_{t+1} - \mu_{\mathcal{FPR}}), \tag{6}$$

where $(b_{DOL} \; b_{\mathcal{FPR}})' = b$ is the vector of factor loadings, DOL_{t+1} denotes a market factor measured as the average excess return across portfolios at time $t+1$, $\mathcal{FPR}_{t+1}$ is the mimicking portfolio return for the risk factors (equation (8)), and μ_{DOL} and $\mu_{\mathcal{FPR}}$ denote their respective means. *Panel A* of Table 5 provides results for the second-pass regression based on the 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 the χ^2 test of the overidentifying restrictions, cross-sectional R^2, HJ

with the optimal number of lags determined following Andrews (1991).

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 hypothesis 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; 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 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 between the estimated SDF of our model in squared terms and a group of acceptable SDFs is equal to zero. We report *p-values* in curly brackets.[35] Table 5 displays three panels that correspond to the three momentum strategies of interest. In particular, the left panel shows results for a momentum strategy with one month formation (f) period and one month holding (h) period whereas the other two panels display cross-sectional estimates for formation periods of 3 and 6 months respectively and monthly rebalancing.

First, we focus on the statistical significance and the sign of the estimates of the factor risk prices of our political risk measure (i.e. $\lambda_{\mathcal{FPR}}$) as well the market factor (i.e. λ_{DOL}). We find that the our estimated political risk prices 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 carry trades (Lustig, Roussanov, and Verdelhan, 2011) but 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 hypothesis that all the pricing errors are equal to zero. We

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

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) strategy is 86%. Finally, regarding HJ distance, we cannot reject the null hypothesis that the HJ distance is equal to zero for all momentum strategies at standard levels of significance. 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.[36]

Regarding the first pass regression, we examine whether the global political risk explains the differences across momentum portfolio excess returns once we control for the DOL_{t+1} factor. With respect to the estimates of the DOL_{t+1} factor beta, we find that they are 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 estimated betas of the mimicking portfolios are highly significant and increase in magnitude as we move from the loser to winner portfolios. Specifically, the estimated betas of the mimicking portfolio for the formation period of one month increase monotonically from -1.64 for the *loser* portfolio to 2.05 for the *winner* portfolio. This finding is consistent across other formation periods, demonstrating that the global political risk betas load negatively on *loser* portfolios and positively on *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.

[36] Figures A7 displays pricing error plots for the asset pricing model.

[TABLE 5 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 global political risk increases, i.e. there is 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. Table 6 reports results for asset pricing tests when the set of two risk factors are the market factor (i.e. DOL_{t+1}) and global political risk innovations (i.e. $\Delta\mathcal{PR}_{t+1}$). In particular, we report cross-sectional results from the FMB regression and find that the estimates of $\lambda_{\mathcal{PR}}$ are highly significant either 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 potential errors-in-variable problem. Regarding the goodness of fit, the χ^2 test statistic indicates that we cannot reject the null hypothesis that all pricing errors are insignificantly different from 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 shown from the very large *p-values*. Thus, we see that the results are similar whether we use global political risk innovations or the mimicking portfolio.

[TABLE 6 ABOUT HERE.]

6. Other Determinants of Currency Premia

In this section we examine the link between global political risk and other risk factors so as to see whether political risk captures the different dynamics of currency premia. Therefore, we perform a double sort of currency excess returns in order to investigate the conditional pricing ability of our measure after controlling for other variables.

Limits to Arbitrage. Political risk is one of the major dimensions of limits to arbitrage in the foreign exchange market that affects 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. In particular, we compute the idiosyncratic volatility and skewness of the Lustig, Roussanov, and Verdelhan (2011) (LRV) model. Lustig, Roussanov, and Verdelhan (2011) show that two risk factors are enough to price the cross-section of currency carry trade returns.[37]

We construct daily level and slope factors obtained from daily currency excess returns sorted on forward discounts of 48 currencies. Daily currency excess returns are regressed each month on a constant and the two factors in order to obtain monthly error terms, $\varepsilon^i_{t,d+1}$,

[37]The first factor is a *level factor* that goes long all the available *foreign* currencies across portfolios each time period, while short-selling the dollar, DOL. The second factor is a *slope* factor that buys a basket of *investment* or high interest rate currencies and sells a *funding* portfolio of low interest rate currencies, a form of carry trade strategy, HML.

where d indexes *daily* observations within each month, t indexes the months and i indexes the currency. We define currency $i's$ idiosyncratic volatility in month t ($IV_{i,t}^{FX}$), as the standard deviation of the daily error terms of the LRV model each month and the corresponding idiosyncratic skewness ($IS_{i,t}^{FX}$) as the third moment of the error term divided by the cubed idiosyncratic volatility.[38]

We also compute average *deviations* from the CIP condition after controlling for transaction costs as another proxy of limits to arbitrage in the currency market (Mancini-Griffoli and Ranaldo, 2011). Figure 2 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 positively sloped regression line, supporting our hypothesis regarding the role of global political risk in currency momentum strategies. This visual evidence is also verified by the significant estimated cross-sectional beta ($\beta = 1.34$, $tstat = 2.55$) and R^2 of 11%.

[Figure 2 about here.]

Global FX Volatility and Liquidity. We examine the behavior 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.[39] As we did for the political risk measure, we compute the innovations of $AR(1)$

[38] 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).

[39] We measure global FX volatility (σ_t^{FX}) and FX liquidity (ξ_t^{FX}) as: $\sigma_t^{FX} = \frac{1}{T_t}\sum_{d\in T_t}\left[\sum_{k\in K_d}\left(\frac{|\Delta s_d|}{K_d}\right)\right]$ and $\xi_t^{FX} = \frac{1}{T_t}\sum_{d\in T_t}\left[\sum_{k\in K_d}\left(\frac{BAS_d^k}{K_d}\right)\right]$ respectively, 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 in this measure is associated with higher levels of illiquidity.

models and denote them as $\Delta\mathcal{RV}_t^{FX}$ and $\Delta\mathcal{L}_t^{FX}$ respectively.

Global FX Correlation. Mueller, Stathopoulos, and Vedolin (2013) show that global FX correlation is priced in the cross-section of carry trade portfolios and that it is a good proxy for global *risk aversion*. It is very important to see the performance of political risk under different states of correlation risk. We use a similar measure with the one introduced by Mueller, Stathopoulos, and Vedolin (2013) and compute global FX correlation risk as: $\gamma_t^{FX} = \frac{1}{N_t^{comb}} \sum_{i=1}^{n_t} \left[\sum_{j>i} \left(RC_t^{ij} \right) \right]$, 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 AR(1) model and denote it $\Delta\mathcal{RC}_t^{FX}$.

Double Sorts. We now turn our 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) first into two portfolios based on the variable of interest and then, within each portfolio, we sort them again into 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.[40]

Starting with idiosyncratic volatility and skewness, *Panels A* and *B* of Table 7 show results of the double sorts on IV ((idiosyncratic volatility) and IS ((idiosyncratic skewness), respectively, along with global political risk exposures. Consistently with Menkhoff et al.

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

(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 test whether this pattern influences our results. We find that in both low and high IV portfolios, currencies with high political risk exhibit higher mean excess returns than the low political risk counterpart, but the difference is more pronounced in high IV portfolios. The results are similar for idiosyncratic skewness, except that the difference across political risk portfolios is greater in low IS portfolios.

Another determinant of currency momentum is illiquidity. Menkhoff et al. (2012b) show that currency momentum is more concentrated among countries with less liquid currencies and a fragile political environment. We therefore need to examine the pricing ability of political risk after controlling for illiquidity. *Panel C* of Table 7 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 in relation to momentum portfolios concerns the level 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 7 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.[41]

[Table 7 about here.]

7. Robustness and other Specification Tests

In this section, we report results of applying a number of checks to examine further the role of political risk in momentum strategies and determine the robustness of our results. In particular, we impose various filters in the data so as to focus on the more easily 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 variables such as 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.

Currency-level Asset Pricing Tests. We ask what is the contribution of country-level political risk in our results. In Figure 3 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 5.4, 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* the United States. As the figure shows, while only few countries are the source of mispricing (i.e., statistically insignificant zero-betas in most cases), many countries contribute significantly to the risk pricing of momentum returns. Our t-statistics

[41] 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.

take into consideration the potential errors-in-variable problem following Jagannathan and Wang (1998). The blue horizontal line corresponds to the 1.96 significance bound.

[FIGURE 3 ABOUT HERE.]

Tradability. One of the main concerns regarding the validity of our results is related to potential impediments in the foreign exchange market that could impede an investor from trading particular currencies; some currencies cannot be traded in large volumes and exhibit a high degree of illiquidity. To alleviate this issue, we follow Della Corte et al. (2013) and allow for currency-time combinations that meet particular conditions. Table A4 in the Internet Appendix reports results of asset pricing tests after imposing the filters. Overall, we find that our asset pricing model performs well in terms of statistical and economic significance.

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 A5 in the Internet Appendix displays results for FMB regressions after considering the implementation cost of the strategy. Figure A8 shows the corresponding pricing error plots. *Panel A* of Table A3 offers results for longer formation periods. Overall, these results show that global political risk is priced in the cross-section of momentum returns even after controlling for transaction costs.

Reversals. In this section, we consider a mimicking portfolio that incorporates conditional information on past returns. In particular, we control for past month excess returns to see whether our results are driven by short-run reversals. Table A6 shows results for FMB regressions after replacing our political risk factor with the *conditional* mimicking portfolio.

We also consider longer horizons of 9 and 12 months in *Panel B* of Table A3. We find that short-run reversals might affect medium horizon momentum strategies but they do not have any effect on the short or long-run formation periods.

Non-linearity. In developing our asset pricing model, we proposed a linear SDF to price momentum returns. However, based on the double-sort evidence reported above, one might argue that there may be a non-linear relationship 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 (Table A7). The pricing implication is slightly stronger when there is an unexpected increase in global political risk. Nevertheless, the linear model remains a good approximation to the true risk pricing relation.

Long-short Strategies. The mechanism we proposed in developing 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 which we examine in the context of global political risk. Figure A11 (Figure A12) provides a visual illustration of annualized mean momentum (value and carry trade strategies) returns conditional on global political risk innovations. Returns of speculative strategies are higher in periods of extreme political risk and perform poorly under low political states indicating the significant role played by political risk in the currency market. Lewellen, Nagel, and Shanken (2010) argue that it is relatively easy to find risk factors that can price test assets with strong factor structure. They suggest that the models should be evaluated on the basis of their GLS R^2 and consider more test assets to address these concerns (Table A8). Overall, we find that our model provides higher cross-sectional R^2 (GLS R^2) compared to other models regardless of the use of the dollar factor.

Other Measures. We explore how the global political risk measure relates to other measures. Table A4 in the Internet Appendix presents summary statistics of uncertainty measures as well as macroeconomic and financial variables.[42] Our analysis also incorporates an alternative data of political risk (IFO World Economic Survey) in Figure A13 and shows that global political risk is present in currency momentum strategies. Before we conclude, we finally consider alternative definitions of our measure of global political risk. First we include the political risk measure for all the 145 countries available in ICRG data. 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 4 the t-statistics of the risk price and the constant (omitting the DOL factor) and the cross-sectional R^2. We see that the original model performs better in terms of the statistical significance of pricing errors, risk price and cross-sectional explanatory power compared to the models with alternative measures of political risk.

[Figure 4 about here.]

8. Conclusion

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.

[42] 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%.

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 shorting 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 short-term currency momentum excess returns. Intuitively, speculative investors will demand a premium for investing on currencies with a large exposure to global political risk, and in particular U.S. political shocks, when placing a bet on short term price continuation.

Limits to arbitrage may drive currency momentum returns of those currencies that exhibit high illiquidity, volatility, correlation and idiosyncratic volatility. We show that political risk is a natural limit to (risky) arbitrage in the FX market, and thus determines the momentum profitability even after accounting for the aforementioned variables capturing a unique dimension of currency premia. The results are robust after controlling for transaction costs, short-run reversals and alternative specifications. Overall, our findings suggest that exposure to political risk is one of the main drivers of momentum profitability and shall be taken into account when placing speculative bets in the foreign exchange market.

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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.

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. 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 $\mathcal{WML}_t^{1,1}$ and *Panel B* for *loser* and *winner* portfolios of the $\mathcal{WML}_t^{1,1}$. 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 4. Portfolios sorted on Political Risk-Betas

This table presents descriptive statistics of currency portfolios sorted on betas with global (*Panel A*) and U.S. (*Panel B*) 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 (Std) and Sharpe ratios, all in percentage points. We also report skewness and kurtosis and standard errors ($s.e$) of the post-formation betas. 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*. We also report annualized pre- and post-formation betas. 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: Global Political Risk Innovations

Portfolios	P_L	$P2$	$P3$	$P4$	$P5$	P_H	Avg	$\mathcal{H}/\mathcal{L}$
	Conditional Excess Returns							
$Mean$	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	-0.59	-0.15	0.08	0.31	0.53	1.26		
Std(pre-β*)*	13.92	6.86	6.48	8.62	9.71	15.38		
post-β	-0.62	-0.15	0.08	0.31	0.55	1.29		
s.e.(post-β*)*	0.21	0.10	0.09	0.12	0.14	0.24		

Panel B: U.S. Political Risk Innovations

Portfolios	P_L	$P2$	$P3$	$P4$	$P5$	P_H	Avg	$\mathcal{H}/\mathcal{L}$
	Conditional Excess Returns							
$Mean$	6.73	3.33	5.22	3.76	2.79	2.72	4.09	-4.01
	[3.96]	[2.35]	[4.30]	[3.31]	[2.25]	[1.81]	[4.25]	[-2.06]
Std	7.82	7.44	6.57	5.70	5.46	7.37	4.98	8.87
SR	0.86	0.45	0.79	0.66	0.51	0.37	0.82	-0.45
$Skew$	0.28	0.89	1.77	0.68	0.55	-0.06	0.81	-0.29
$Kurt$	5.24	7.77	12.85	6.13	5.79	5.76	6.84	5.36
$AC(1)$	0.04	-0.07	0.03	0.09	0.18	0.06	0.09	-0.04
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
pre-β	-0.78	-0.36	-0.19	-0.03	0.11	0.44		
Std(pre-β*)*	9.60	7.76	7.41	5.19	6.07	9.92		
post-β	-0.79	-0.36	-0.20	-0.03	0.12	0.46		
s.e.(post-β*)*	0.15	0.12	0.11	0.08	0.09	0.15		

Table 5. 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. We 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 auto-correlation 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.

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]				

Table 6. FX Asset Pricing Tests: *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. We 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.

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 7. 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]

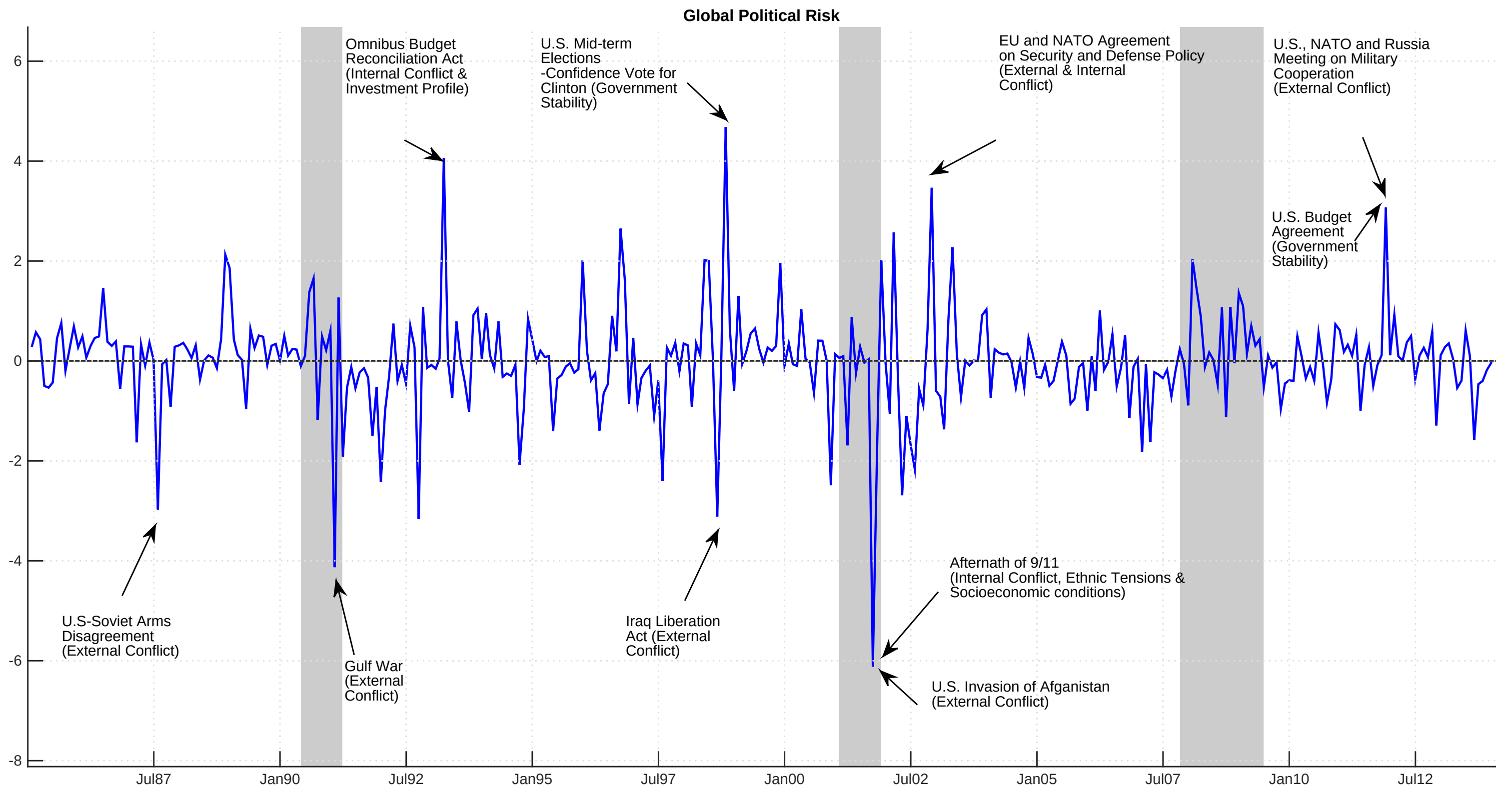

Figure 1. Global Political Risk

The figure presents our global political risk measure. The arrows indicate some global political incidents associated with the extreme spikes. The political risk data is collected from the International Country Risk Guide (ICRG). The data contain monthly series from January 1985 to January 2014.

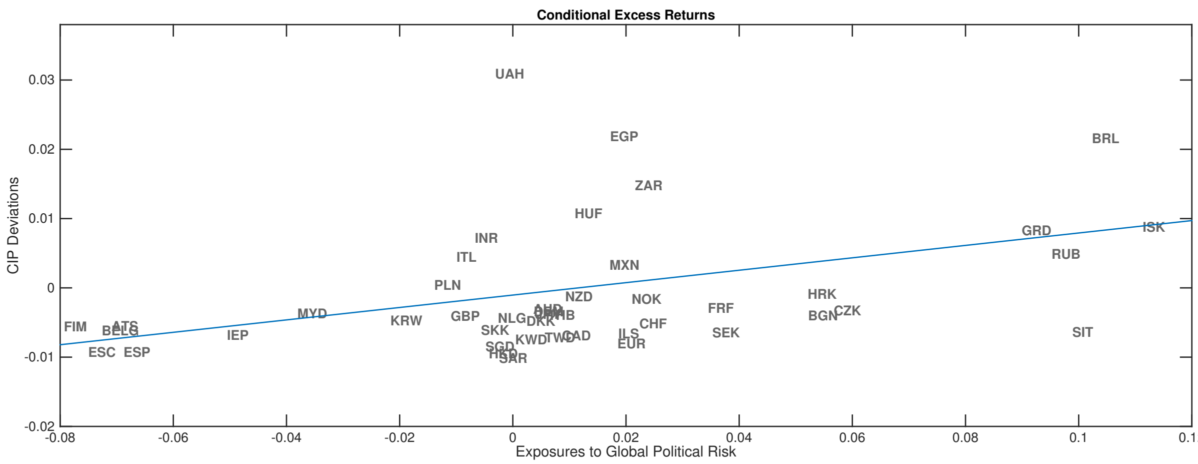

Figure 2. CIP deviations and Global Political Risk Betas

The figure displays average Covered Interest Parity (CIP) deviations along with global political risk exposures for each country in the sample. The CIP deviations are measured by the distance between the forward premium and the interest rate differentials (with respect to the U.S.). The data contain monthly series from January 1985 to January 2014.

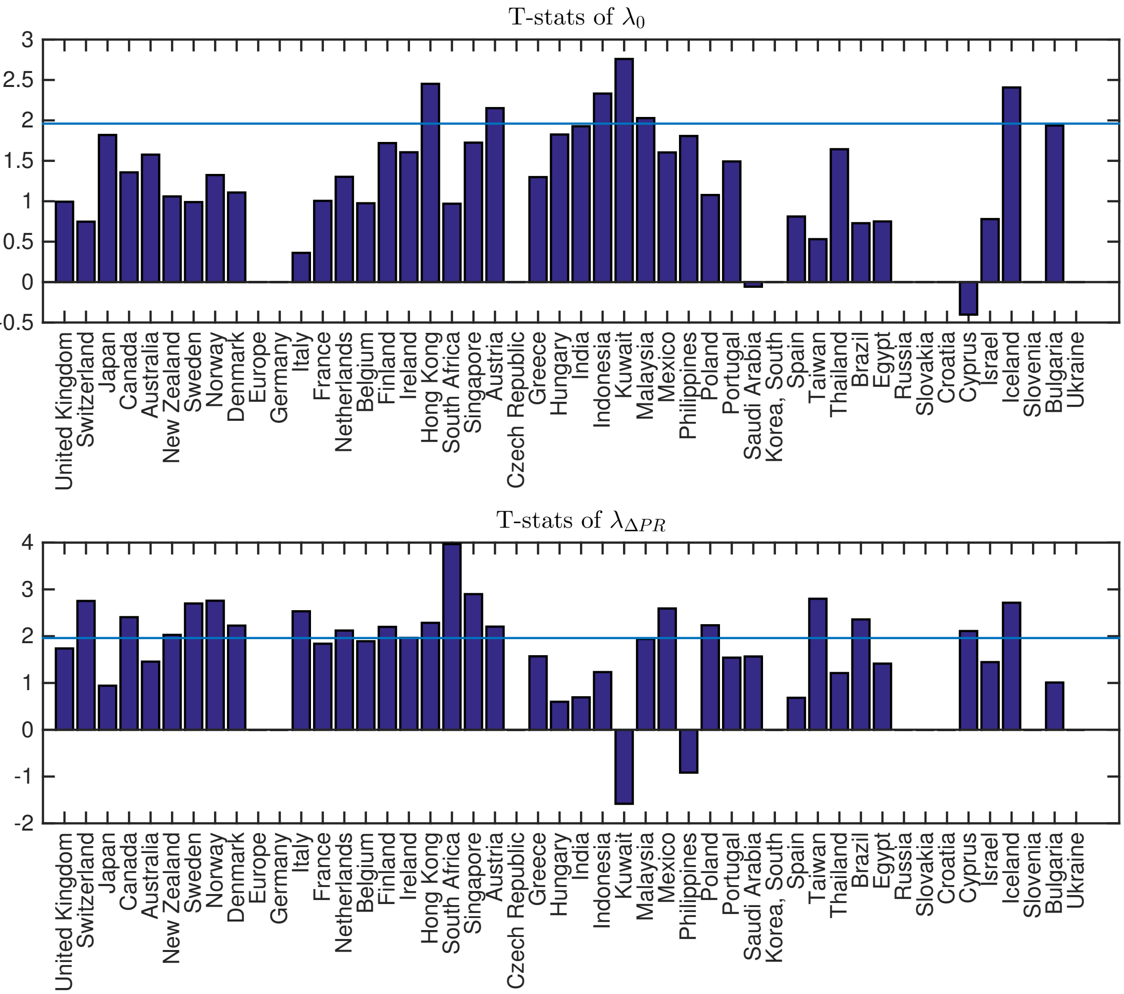

Figure 3. Cross-sectional t-statistics - *Country Level*

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.

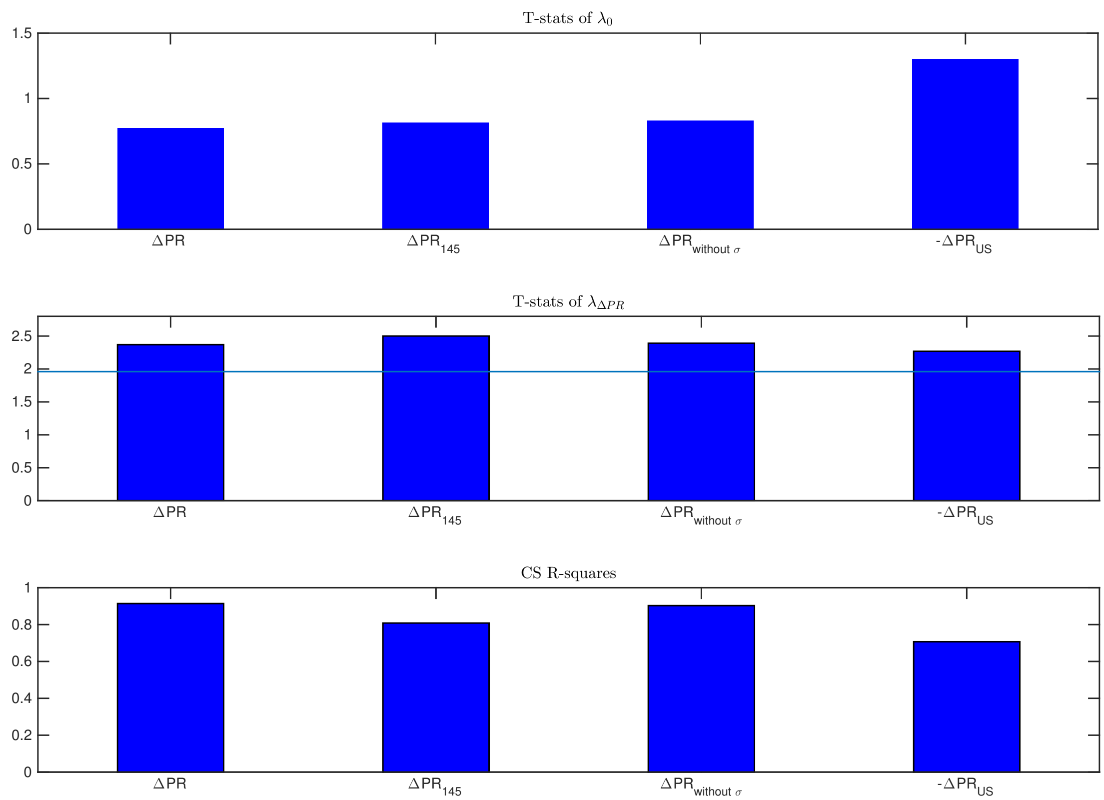

Figure 4. Cross-sectional t-statistics - *Alternative Definitions of Political Risk*

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.