# Political Risk Everywhere

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March 2023

**Abstract**

We document political risk premia in international equity, bond, and FX markets, and uncover a common factor structure of returns within and across asset classes. We construct a global political risk factor across asset classes (multi-asset P-factor) commanding a significant risk premium of 4.44% per annum, with Sharpe ratio of 0.70. A parsimonious global asset pricing model including the global market and the multi-asset P-factor explains up to 74% of cross-sectional return variation. Our findings shed light on global political risk as an important economic driver of return comovement and increasing integration across asset classes. The results stand with different measures of political risk and are particularly strong within emerging markets.

**JEL Classification:** E62, F30, G15, G18.
**Keywords:** political risk, international equities, bonds, FX, asset pricing.

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# 1 Introduction

Understanding the macroeconomic risks that drive the cross section of expected returns within and across asset classes is a fundamental question in asset pricing (Cochrane, 2011). We identify global political risk as a key driver of returns complementing the growing evidence on multiple determinants affecting jointly several asset classes.[1] Political risk around the world has been increasingly taking center stage in the global financial markets. The global market reactions to recent political events such as Brexit, US or German political elections, or the very recent war in Ukraine, among many other examples, highlight how political risk can lead to sharp increases in global financial markets' comovement across major asset classes. These episodes raise the following question. Is global political risk a major determinant of expected returns *within* and *across* multiple asset classes? An affirmative answer raises a further question on how to price this risk in global financial markets. This paper provides empirical answers to these challenging questions.

Our point of departure is the evidence on the impact of political risk on the economy (Baker, Bloom, and Davis, 2016) and financial markets (Gala, Pagliardi, and Zenios, 2023; Liu and Shaliastovich, 2022; Pástor and Veronesi, 2013). We take the empirical evidence a step further to show that political risk creates common systematic variation *within* and *across* asset classes. We establish global political risk as a determinant of expected returns within the global equity, fixed income, and FX markets, and as a driver of their factor structures and comovement. We document significant political risk premia within each of these asset classes and provide evidence supporting a global view of political risk across asset classes.

The striking comovement of returns across asset classes, which is one of our main findings, suggests the existence of global political risk that is pervasive across all asset classes. To capture this we construct a novel global political factor (multi-asset P-factor) jointly employing returns from equity, bond, and FX markets. We show that stock indices,

[1] Recent literature documenting asset pricing implications of pervasive economic phenomena "everywhere", i.e. jointly across asset classes, includes Asness, Moskowitz, and Pedersen (2013) for value and momentum, Asness, Liew, Pedersen, and Thapar (2021) for deep value, Moskowitz, Ooi, and Pedersen (2012) time-series momentum, Daniel and Moskowitz (2016) momentum crashes, Koijen, Moskowitz, Pedersen, and Vrugt (2018) carry, Frazzini and Pedersen (2014) betting against beta, Bollerslev, Hood, Huss, and Pedersen (2018) volatility, Menkhoff, Sarno, Schmeling, and Schrimpf (2012) global FX volatility, Gao, Lu, and Song (2019) tail risk, Asness, Ilmanen, Israel, and Moskowitz (2015) style, or trend-following investing Babu, Levine, Ooi, Pedersen, and Stamelos (2020), global macroeconomic risks Cooper, Mitrache, and Priestley (2020), and intermediary capital risk He, Kelly, and Manela (2017).

bond indices, and currencies of countries with low political ratings earn higher average returns because they load more on global political risk. The multi-asset P-factor carries a statistically significant risk premium of 4.44% per annum, with Sharpe ratio 0.70, and takes center stage in a parsimonious global two-factor model, along with the global market, at explaining cross-country and cross-assets differences in average returns, reaching a cross-sectional $R^2$ of 0.74.

Our evidence prrovides new insights against the view of strict segmentation among asset classes. We establish global political risk as a driver of the comovement and increasing integration among the three most important asset classes, rationalizing this finding with a parsimonious model that prices jointly many assets across many countries, in a similar spirit to Asness, Moskowitz, and Pedersen (2013). To construct our factor, we measure political risk using several country-level proxies accounting for the its multiple dimensions. Our data sources include the International Country Risk Guide (ICRG), the World Bank, and the Ifo World Economic Survey (WES), for a large cross-section of 42 countries over a long time-series starting in 1992.

We proceed in four steps. First, we focus on the predictability of local currency returns, to disentangle the impact of political risk from that of currency risk on stock and bond returns. We observe that the sizeable cross-country heterogeneity in political risk matches large cross-sectional variation in average returns within each asset class. Sorting countries on the political measures consistently generates novel monotonic cross-sections of average returns. The portfolio that is long in low rated (high political risk) countries outperforms the portfolio that is long in highly rated (low political risk) countries by a statistically significant 13.20% p.a. for equities and 5.40% for bonds, respectively.

Second, using USD returns we gauge the economic magnitude of this predictability from the perspective of a US investor. The portfolio sorts on political risk ratings still produce sizeable spreads in average returns, 5.86% for equities, 3.61% for bonds, and 4.50% for FX, with corresponding Sharpe ratios of 0.48, 0.51 and 0.69, respectively. These values are economically and statistically significant, albeit smaller than the spreads obtained with local currency returns, as expected given that currencies of countries with higher political risk depreciate more against the USD. We further establish that country characteristics, business cycles variables, and exposures to asset-class specific risk factors of prominent asset pricing models cannot account for such return patterns, leading to abnormal returns as large as 7.50% for equities, 5.32% for bonds, and 6.03% for FX.

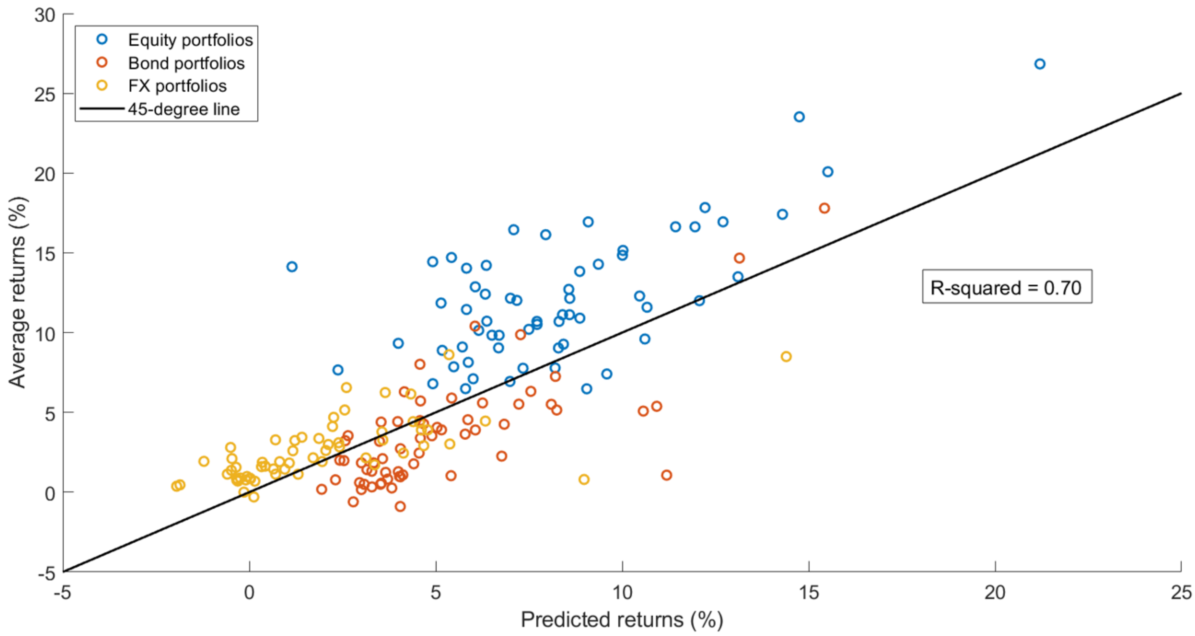
Third, we rationalize these findings with a risk-based view of the impact of political risk on financial markets by constructing the political risk factor (P-factor) within each asset class. The factor mimicking portfolios go long in high political risk countries and short in low political risk countries. They all carry positive and significant risk premia. A global two-factor model that includes the asset-class specific market portfolio and the P-factor explains well the cross-section of political portfolios and country returns. We show that sorted portfolios within each asset class share a strong factor structure, with the first two principal components of portfolio returns consistently accounting for more than 92% of their variation. The first principal component is a level factor, highly correlated with the asset-class specific market portfolio, while the second principal component is a slope factor whose weights line up with average portfolio returns, and it is highly correlated with the asset-class specific P-factor. This evidence is consistent with an APT (Ross, 1976) interpretation of these return patterns in each asset class.

Finally, we uncover a common political factor structure in returns across asset classes as the main finding of our paper. We create the multi-asset P-factor as a risk-parity portfolio of the asset-class specific political factors (Asness, Moskowitz, and Pedersen, 2013) and show that it carries a sizeable risk premium. Its t-statistic is well above the critical threshold of three advocated by Harvey, Liu, and Zhu (2016), which accounts for multiple hypotheses testing. We rule out spanning of the multi-asset P-factor by all other multi-asset factors in the literature (Asness, Moskowitz, and Pedersen, 2013; Frazzini and Pedersen, 2014; Koijen, Moskowitz, Pedersen, and Vrugt, 2018; Moskowitz, Ooi, and Pedersen, 2012). We also compute a global market portfolio as a risk-parity portfolio of the market proxies in each asset class, and conduct formal pricing tests of our global two-factor model jointly on all assets and all countries. Augmenting the global multi-asset market factor with the multi-asset P-factor improves adjusted $R^2$ in the cross-section by an order of magnitude. The pricing ability of our model is summarized in Figure 1, which shows that model predicted returns and average realized returns line up well along the 45-degree line. All results hold true in the base set of the sorted portfolios as test assets and in the extended set where we add country-level stock and bond indices, and currencies.

We conclude with a battery of robustness tests to safeguard against data mining and corroborate our main findings. Specifically, (i) we rule out market segmentation as a potential explanation of our results; (ii) following Lustig, Roussanov, and Verdelhan (2011) we sort countries based on their P-factor exposure, instead of political risk ratings,

Figure 1: **Global multi-asset GPSZ model**

This figure plots the average realized excess returns against the average excess returns predicted by a model that includes the global multi-asset market portfolio and the global multi-asset P-factor, both constructed with equity, bond and FX returns. Test assets are $4 \times 4 \times 3$ portfolios sorted on the four measures of political risk (ICRG, WES politics, WES policy and World Bank politics), as well as the country indices in our sample, in the equity, bond and FX asset classes. Returns are in annualized percentage points. Data are monthly, spanning 1992–2019.




to show that political beta-sorted portfolios produce significant spreads in average returns; and (iii) we follow Avramov, Chordia, Jostova, and Philipov (2012) and provide evidence against spurious political risk factors.

Our work contributes the political uncertainty dimension to a growing body of literature "that is becoming increasingly concerned with pricing global assets across markets" (Asness, Moskowitz, and Pedersen, 2013) and that points towards a common factor structure across countries and across asset classes. Evidence supports increasing partial integration along two dimensions, namely across developed and emerging markets (Pukthuanthong and Roll, 2009) and across asset classes that share common sources of time varying risk premia (Cooper and Priestley, 2013), which justifies the design of global asset pricing models. Specifically, a nexus has been documented between the pricing of stocks and bonds (Koijen, Lustig, and Van Nieuwerburgh, 2017), bonds and currencies (Bansal and Shaliastovich, 2013), stocks and currencies (Carrieri, Errunza, and Majerbi, 2006), and global models have been proposed to price jointly all these asset classes (Asness, Moskowitz, and Pedersen, 2013; Lettau, Maggiori, and Weber, 2014).

Factor identification is central in the finance literature (Pukthuanthong, Roll, and Subrahmanyam, 2019). Beyond asset pricing, factor identification supports portfolio risk management, such as building risk models (Bollerslev, Hood, Huss, and Pedersen, 2018), and to deal with regulatory and CSR requirements on risk exposures, such as in ESG-responsible investing (Pedersen, Fitzgibbons, and Pomorski, 2021). In this paper we focus on the identification of political risk. The theoretical foundations of political risk as a determinant of asset prices were laid recently by Kelly, Pástor, and Veronesi (2016) and documented empirically by Gala, Pagliardi, and Zenios (2023); Liu and Shaliastovich (2022), among others, and in this paper we show that political risk affects returns not only across countries, but also across asset classes. Our factor has a clear economic foundation, as opposed to purely statistical factors.

# 2 Data

We describe our data and methodology for constructing political portfolios and factors within and across asset classes. We report all descriptive statistics in the Data Appendix.

## 2.1 Political risk measures

We use multiple proxies to measure political risk. The ICRG expert assessments (PRS, 2005) is the most widely used measure of political risk adopted in the literature (Bekaert, Harvey, Lundblad, and Siegel, 2014, 2016; Diamonte, Liew, and Stevens, 1996; Erb, Harvey, and Viskanta, 1996), and we use it as our main political risk measure. The Ifo World Economic Survey (Becker and Wohlrabe, 2007) provides ratings for political instability and confidence in government economic policy, and the World Bank (World Bank, 2018) measures perceptions of the likelihood of political instability in a country, and we use them as robustness check.[2]

All data are available for a cross-section of 42 developed and emerging countries in the

[2]The data are available at `https://www.prsgroup.com/explore-our-products/countrydata-online/` (ICRG, subscription required) and `https://databank.worldbank.org/reports.aspx?Report_Name=WGI-Table&Id=ceea4d8b` (World Bank, free access). WES data are accessible in Datastream.

period 1992–2019.[3] ICRG data are at monthly frequency, Ifo WES variables are at semiannual frequency, while the political instability index from the World Bank is available bi-annually from 1996 and annually from 2000. These alternative proxies exhibit a positive correlation, but are far from being perfectly correlated, see Appendix A. The average over time of the cross-sectional correlation for each pair of measures varies from a minimum of 0.32 to a maximum of 0.93, while the cross-sectional average of the time-series correlations for each pair is in the interval 0.14–0.44. The presence of a positive correlation is consistent with the common underlying political risk, while the imperfect correlation allows us to validate the robustness of our results by filtering out noise in their information content.

## 2.2 Asset returns

We follow the MSCI classification to obtain asset returns for 42 developed and emerging countries, spanning the time period from January 1992 to December 2019.

### 2.2.1 Equity returns

We use monthly returns of the MSCI Investable stock market indices, including dividends.[4] For the analysis with USD returns, the global market portfolio is the MSCI All Countries World (ACW) index, and excess returns are computed over the one-month US Treasury bill rate.

### 2.2.2 Bond rreturns

We gather monthly bond data from three different sources. First, we compute total returns from the ICE Bank of America Government Bond Indices, which include bonds with maturity greater than two years. Second, we use the Datastream Benchmark 10-year Government Bond Total Return Indices. Third, we complement our dataset using the yields to maturity of country-level ten-year government bonds from Datastream, imputing the corresponding total bond returns using the second-order approximation of Swinkels

[3]The MSCI classification includes 46 countries, split into 23 developed and 23 emerging markets. We have data for 42 countries for the political ratings, as we exclude four for which WES has no data (Indonesia, Kuwait, Saudi Arabia, Singapore).

[4]MSCI Investable Indices were created in 1994, and we use the standard MSCI Indices for 1992-1993. We use Investable indices to ensure the implementability of the portfolio strategies, especially in emerging markets. Results are robust when replacing Investable with MSCI Standard indices to focus on broad asset pricing implications rather than implementable strategies.

(2019). Details on the sample construction are in Appendix B.

#### 2.2.3 FX returns

We construct our FX sample by first using Datastream monthly spot and forward rates to compute excess returns from forward market investments, and, when forward contracts are not available, we complement our time-series by building excess returns from money-market investments. We validate the construction of our complete dataset by showing that FX returns computed through interest rates differentials are almost perfectly correlated with those constructed with forward contracts. Details on the sample construction are in Appendix B.

### 2.3 Other financial and economic data

We obtain the US risk-free rate, the factors for the International Fama-French five-factor model, augmented with the international version of the momentum factor, from professor Kenneth French website. Returns for the value, momentum, time-series momentum, and betting against beta factors across asset classes are from AQR website. The carry factors for each asset class are downloaded from professor Ralph Koijen website, while the carry trade risk factor in currency markets is from the website of professor Adrien Verdelhan.[5]

We construct the bond factors of Fama and French (1993) "TERM" and "DEF", which are the term spread on U.S. government bonds and the default spread between U.S. corporate bonds and U.S. Treasuries, respectively. The former is computed as the difference between the total return of the S&P US government bond index, which includes all bonds with maturity greater or equal than ten years, and the one-month US risk-free rate. The latter is constructed as the difference between the total return of the S&P US corporate bond index and the S&P US government bond index, both including all bonds with maturity greater or equal to ten years from Datastream. For the other control variables we follow Asness, Moskowitz, and Pedersen (2013), and create global macroeconomic variables as GDP-weighted averages of the corresponding country-specific variables. To construct country weights we use World Bank data of GDP at constant 2010 USD.[6] We retrieve

[5] The data are available from `http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html#Developed` (Fama-French plus momentum factors), `https://www.aqr.com/Insights/Datasets` (value, momentum, time-series momentum and betting-against-beta factors across asset classes), `https://koijen.net/code-and-data.html` (carry across asset classes), and `http://web.mit.edu/adrienv/www/Data.html` (carry trade factor in FX returns).

[6] The data are available from `https://data.worldbank.org/indicator/NY.GDP.MKTP.KD`

from Datastream country-level data on standardized consumer spending, as a proxy for consumption growth. We obtain the dates for peaks and troughs of the business cycle from NBER for the United States and Economic Cycle Research Institute (ECRI) for all other countries available. Country-level quarterly real GDP, monthly CPI, quarterly unemployment rates, and monthly values of the CBOE volatility index VIX are from Datastream.

# 3 Political Risk Premia Within Asset Classes

We provide first strong evidence of political risk premia within each asset class. The return patterns we document remain unexplained by business cycle, economic and financial control variables, or the risk factors of prominent asset pricing models. We report results with portfolio sorts on the ICRG index,[7]. Following Asness, Moskowitz, and Pedersen (2013) we also use a *combo* strategy as an equally weighted combination of the sorts of the four political risk measures.

## 3.1 Portfolio sorts

We form a set of equally weighted political portfolios by ranking securities by the country-specific political risk ratings within each asset class, and sorting them into four groups.[8] We sort into quintiles for the corner portfolios and two equally split quantiles in between, denoting by H and L the top and bottom quantile portfolios with the lowest and highest political risk, respectively.[9]

Table 1 (Panel A) shows the monotonic patterns in local currency returns of portfolios sorted on ICRG political risk ratings and the combo strategy. The spread in average returns between portfolio L and H is always economically and statistically significant at conventional levels. In the equity markets it reaches a high 13.61% with ICRG sorts and 13.20% with combo. Likewise, we observe sizeable spreads in average bond returns, equal to 6.82% with ICRG sorts and 5.40% with combo, respectively. These results in

[7]Results of portfolio sorts on the other three political measures (World Bank political stability, WES political stability, and WES economic policy confidence) are robust and qualitatively similar. They are not reported but are available upon request.

[8]We form equally-weighted portfolios to isolate political risk from size effects. Value-weighting the countries would systematically result into overly concentrated portfolios in a few countries that dominate the world market cap, such as the US.

[9]For bonds in the period 1992-1999, we use, exceptionally, quartiles instead of quintiles to construct the corner portfolios, due to the low number of country bond returns available in the 1990s.

local currencies disentangle the impact of political risk from that of currency risk, and vindicate the importance of political risk for cross-sectional return predictability, in line with Gala, Pagliardi, and Zenios (2023)

[ Insert Table 1 Near Here ]

The cross-sectional predictability can be exploited by US investors, as we show in Panel B of Table 1 with a fairly monotonic pattern in average portfolio USD returns and the spreads between the extreme portfolios remaining statistically significant. The spreads are smaller than those in Panel A, but remain economically significant, with the L-H combo strategy reaching an average return ranging from 5.87% p.a. in the equity market and 3.61% p.a. in the bond market. The smaller spreads in USD are consistent with asset pricing theory and with the empirical evidence provided by Brogaard, Dai, Ngo, and Zhang (2020). The differences are due to the adverse impact of political risk on currency depreciation rates, with the currencies of countries with high political risk depreciating more against the USD.

Interestingly, the spread portfolios of the combo strategies always display lower p-values and higher Sharpe ratios than the corresponding values of the ICRG strategy — the Sharpe ratios are 0.48 vs 0.38 for equities, 0.51 vs 0.42 for bonds, and 0.69 vs 0.62 for FX — in spite of the lower average returns attained by the combos. This is due to the lower volatility of the combo strategies, and to the imperfect correlation between the different proxies of political risk. Figure 2 depicts the time-series dynamics of the combo strategies, which we use as asset-class specific political factors in our pricing tests. The cumulative returns of the combo strategies in the three asset classes grow over time and display a certain degree of comovement, with correlation coefficients in the range 0.38–0.63.[10]

[ Insert Figure 2 Near Here ]

## 3.2 Country characteristics

We investigate possible macroeconomic determinants of the common variation of political risk strategies across countries and asset classes. We run time-series regressions of the USD returns of L-H strategies in Table 1 (Panel B) on a set including a wide array of

[10]The comovement across asset classes is not mechanically driven by the conversion of all equity and bond prices to USD. Even with local currency prices, the sorted portfolios in the different asset classes display sizeable correlation: the average correlation coefficient is 0.45 for P1 (L) and P2, 0.24 for P3 and 0.15 for P4 (H), with maximum correlation of 0.46, 0.54, 0.47 and 0.44, respectively.

macroeconomic variables, computed as GDP-weighted averages of country-level characteristics, and risk factors. Following Asness, Moskowitz, and Pedersen (2013), we use growth in consumer spending as a proxy for consumption growth, a recession dummy (0 peak, 1 trough), real GDP growth, the global equity market portfolio, and the bond factors "TERM" and "DEF" from Fama and French (1993). Furthermore, we add unemployment growth rate (Kilic and Wachter, 2018), inflation (Campbell and Vuolteenaho, 2004), and first differences in the VIX index (Buraschi, Trojani, and Vedolin, 2014).

[ Insert Table 2 Near Here ]

Table 2 shows that the L-H strategy returns in all asset classes remain unexplained by this expansive set of control variables. The $R^2$ of the regressions ranges from 0.00 to a maximum of 0.10 with bonds using the combo strategy. Most of the controls are not statistically significant, and no variable has a joint significant impact on all three asset classes. Overall, these findings rule out macroeconomic factor explanations of the L-H returns for all asset classes.

## 3.3 Risk premia or abnormal returns?

We now investigate whether the profitability of our strategies are due to risk premia on existing factors, or if they can be interpreted as abnormal returns conditional on existing asset pricing models.

### 3.3.1 Test assets

Our base set of test assets includes the 16 sorted portfolios (i.e. four sorted portfolios for each of the four alternative measures) plus the four long-short strategies for each asset class.[11] To corroborate the validity of our findings, we later (Section 3.5) extend this base set of test assets by adding all the 42 country-level returns in each asset class.

### 3.3.2 Risk factors

We control for the risk factors proposed in the literature for each asset class, including value and momentum (Asness, Moskowitz, and Pedersen, 2013), time-series momentum (Moskowitz, Ooi, and Pedersen, 2012), betting against beta (Frazzini and Pedersen, 2014),

[11]We exclude Turkey as its loading on the political factor in the bond markets is very high. Such an outlier would bias the results in favor of our model. For consistency, we also exclude Turkey from the extended set of test assets of equity and FX markets.

and carry (Koijen, Moskowitz, Pedersen, and Vrugt, 2018). We complete this set of asset pricing models by adding the most comprehensive model for each asset class as asset-class specific benchmark. For equities, we use the international version of the five-factor model of Fama and French (2017) augmented with the international version of the momentum factor of Carhart (1997). For bonds, we select a three-factor model that includes the market portfolio, constructed as an equally-weighted average of all bond excess returns in our sample as per Asness, Moskowitz, and Pedersen (2013); Frazzini and Pedersen (2014); Koijen, Moskowitz, Pedersen, and Vrugt (2018), together with the two bond factors "TERM" and "DEF" of Fama and French (1993). For FX, we add the carry factor to a level factor constructed as an equally-weighted market portfolio of the currency excess returns in our sample as per Lustig, Roussanov, and Verdelhan (2011).

#### 3.3.3 Abnormal returns on politically-sorted portfolios

Can the patterns in realized USD returns of Table 1 (Panel B) be attributed to variation in expected returns due to risk premia on existing factors? If the observed patterns were due to abnormal returns with reference to the benchmark models, this would suggest that existing models may be missing risk factors capturing political risk. We address this question by testing whether the political return spreads are explained by exposures to the risk factors in existing asset-class specific models.

We estimate the regression

$$r_{i,t} = \alpha_i + \sum_{j=1}^{K} \beta_{i,j}\, r^*_{j,t} + \epsilon_{i,t}, \tag{1}$$

where $r_{i,t}$ is the monthly excess return on portfolio $i$ at month $t$, $\beta_{i,j}$ is the $i$th portfolio loading on risk factor $j$, and $r^*_{j,t}$ is the monthly excess return of the risk factor $j$. If the average excess returns of the sorted portfolios are explained by exposure to the benchmark risk factors, then the alphas should be statistically indistinguishable from zero.

[ Insert Table 3 Near Here ]

Table 3 shows that the abnormal returns are consistently positive, statistically significant, and close to the time-series average of the strategy returns. For equities, alphas across models for the ICRG strategy range from 6.06% to 8.29%, while for the combo strategy they lie in the interval 5.31%–7.50%. In bond markets, the range is 4.76%–6.29% for ICRG and 3.88%–5.32% for combo. In FX, the range is 6.06%–7.29% for ICRG and

4.97%–6.03% for combo. The information ratios are large, in the interval 0.39–0.63 for equities, 0.47–0.78 for bonds, and 0.82–1.06 for FX. The adjusted $R^2$ are close to zero for all models in equity and bonds, and they are still relatively low for FX, with an average across models of 0.29, with maximum 0.40. In spite of the larger $R^2$ in the FX market, this is the asset class with the largest Sharpe ratios of abnormal returns, and the strongest statistical significance of the alphas. Hence, existing factors fail to explain the sorted portfolio returns.

## 3.4 Factor structures and political factors

So far we have established that neither macroeconomic factors nor loadings on existing risk factors can explain the spreads induced by sorts on political risk measures. We now establish a strong factor structure in portfolios sorted on political risk ratings within each asset class, in the spirit of Lustig, Roussanov, and Verdelhan (2011), and show that the cross-sectional dispersion in loadings on asset-class specific political risk factors is aligned with the cross-sectional heterogeneity in average returns.

[ Insert Table 4 Near Here ]

In Table 4 we report results of principal component analysis of the $4 \times 4$ portfolios sorted on political risk measures. We observe (Panel A) that two factors consistently explain at least 92% of the variation in returns for each asset class. From Panel B we observe that all portfolios load almost equally on the first principal component which can thus be interpreted as a level factor. The second principal component is responsible for 5-10% of common variation in all portfolios, with loadings decreasing monotonically from portfolio L to H uncovering a slope factor within each asset class. Since average excess returns also decrease monotonically across portfolios, the second principal component is the only plausible candidate risk factor that might explain the cross-section of portfolio excess returns within each asset class, as none of the other principal components exhibit monotonic variation in loadings in any of the asset classes.[12]

The principal component analysis suggests two candidate risk factors. We proxy for the level factor through asset-class specific market portfolios. For equities, we use the MSCI All Countries World index in USD, while for each of the other two asset classes we follow Asness, Moskowitz, and Pedersen (2013); Frazzini and Pedersen (2014); Koijen, Moskowitz, Pedersen, and Vrugt (2018); Lustig, Roussanov, and Verdelhan (2011) and

[12]The loadings on the remaining principal components are available upon request.

construct an equally-weighted portfolio of all the excess returns in the sample. Panel C of Table 4 shows that the market proxy is almost perfectly correlated (0.93) with the first principal component. We then construct asset-class specific political factors as the return of the spread portfolios L-H for the combo strategy in each asset class. The correlation of these slope factors with the second principal component in the corresponding asset class is very high, ranging from 0.97 for equities and bonds to 0.82 for FX.

We complement this analysis by computing the correlations of the P-factors with the benchmark risk factors in each asset class (see Appendix Table A2. The absolute value of the correlation coefficients between the P-factor and the other factors in the equity market is a very small 0.08, with comparable magnitudes in the other two asset classes (0.14 for the bond market and 0.16 for the FX market). Interestingly, the correlation of the P-factor in the FX market with the carry slope factor of Lustig, Roussanov, and Verdelhan (2011) is a low 0.24, highlighting the importance to account for both factors in pricing currency returns.

## 3.5 Pricing global political risk within asset classes

We now establish that the sizeable excess returns within each asset class are matched by covariances with the corresponding P-factor. We test a global two-factor model with a market portfolio and an asset-class specific P-factor. We estimate each test asset's loadings on the risk factors by running the first-step time-series regression as in equation (1). We then run a second-step OLS cross-sectional regression of average returns on the factor loadings to estimate the corresponding factor risk premia. We run the regression without intercept (Lustig, Roussanov, and Verdelhan, 2011), account for correlated errors (Cochrane, 2005), and the generated regressor problem from the estimation of factor loadings in the first step (Shanken, 1992). Following Lewellen, Nagel, and Shanken (2010) we include the factors in the set of test assets, and report OLS and GLS $R^2$. We first price the set of test assets consisting of the $4 \times 4$ sorted portfolios and the four corresponding L-H strategies, and then extend the test assets to include the excess returns of the 42 countries in our sample.

[ Insert Table 5 Near Here ]

Table 5 Panel A reports the risk premia of the market portfolio and the asset-class specific P-factor. The political factors carry statistically significant risk premia, with magnitudes close to their average returns. Panel B compares the performance of our two-factor model with the benchmark models. We report both time-series statistics —mean absolute average pricing error (MAPE and GRS test— and cross-sectional statistics —OLS and GLS $R^2$— together with the $R^2$ of a regression of average realized returns on average model-implied returns. It is not our goal to run a horse race across models, but to show instead that the pricing of global political risk seems to be lacking in existing models and adding it in a two-factor model improves several performance metrics.

Our model has significantly lower mean absolute pricing errors than the best-performing benchmark model: 1.09% against 2.55% for the value-momentum model in the equity market, 0.42% vs 2.12% for the betting against beta model in the bond market, and 0.51% compared to the 1.45% of the dollar-carry FX model. The GRS test for our model cannot reject the null hypothesis that all pricing errors are jointly zero for equities and bonds, and while it rejects the null in the FX market, its GRS statistic (1.61) is below the value of 2.71 achieved by the best-performing among the other models. Adding the P-factor to the market portfolio attains a cross-sectional $R^2$ that is larger than existing models (0.66 for equities, 0.85 for bonds, and 0.88 for currencies).

Similar conclusions hold true for the $R^2$ of realized vs predicted returns, with respective values 0.72 vs 0.53 for equities, 0.86 vs 0.45 for bonds, and 0.90 vs 0.35 for currencies. We illustrate pictorially these results in Figure 3 and observe that the test assets line up well along the 45-degree line.

[ Insert Figure 3 Near Here ]

We repeat the test on the extended set of assets. Table 6 Panel A confirms that the asset-class specific P-factors are priced, while Panel B corroborates that the portfolio average realized returns line up well with the predicted returns of our asset-class specific two-factor model. A regression of realized returns on model-predicted returns achieves an $R^2$ equal to 0.57 in the equity market, 0.65 in the bond market, and 0.73 in the FX market. All results are in line with Table 5, corroborating our main findings.

[ Insert Table 6 Near Here ]

# 4 Global Pricing Across Asset Classes

So far we have established the existence of a common P-factor in each asset class. While each factor is asset-class specific, the political ratings are country specific. Our main thesis, reflected in the title of the paper, suggests that we should be able to develop a joint multi-asset pricing model. This is what we do in this section.

We first run a comovement test to establish the explanatory power of political factors constructed from returns in all non-$j$ asset classes to price returns in asset class $j$. Such an out-of-sample test documents the importance of political risk in driving the comovement across asset classes, and it rules out the possibility of results mechanically driven by construction of the political risk factors. We then move to formal asset pricing tests to estimate the political risk premium in a global multi-asset setting.

## 4.1 Comovement test

We explain portfolio returns in asset class $j$ by constructing global versions of the market portfolio and the P-factor using returns only from the non-$j$ asset classes. We run the first-step time-series regression, for each asset $i$ in asset class $j$ and at time $t$,

$$r_{i,j,t} = \alpha_{i,j} + \beta_{i,j,MKT} \sum_{z \neq j} w_z \, MKT_{z,t} + \beta_{i,j,PF} \sum_{z \neq j} w_z \, PF_{z,t} + \epsilon_{i,j,t}, \tag{2}$$

where $z$ denotes all non-$j$ asset classes used to construct the factors for asset class $j$. $MKT_{z,t}$ and $PF_{z,t}$ denote, respectively, returns of the market portfolios and the P-factors. The weights $w_z$ are determined according to an equal-volatility scheme to construct risk-parity portfolios (Asness et al., 2013). For each asset class, we then run a second-step cross-sectional regression to estimate the risk premia. We focus on the set of test assets consisting of the $4 \times 4 \times 3$ sorted portfolios and the corresponding L-H strategies.

[ Insert Table 7 Near Here ]

Table 7 summarizes the results, and we highlight two main findings. First, the MAPEs are economically small for all three asset classes (1.55%, 2.76%, 2.08%, respectively). Comparing the pricing errors of our model from this table with the corresponding pricing errors of the benchmark models in Table 5, where the same portfolios were priced with factors estimated within each asset class, we notice that the errors are always lower for equities, somewhat higher but comparable for bonds, and lower for all but one benchmark model in currency markets.

Second, the large cross-sectional heterogeneity in the loadings on the P-factors constructed in the non-$j$ asset classes matches well the sizeable heterogeneity in average returns in asset class $j$. This is documented by the large OLS and GLS $R^2$ for each asset class, with values, respectively, 50% and 61% for equities, 85% and 69% for bonds, and 76% and 71% for currencies. Figure 6 illustrates this finding by plotting the average realized returns against the predicted returns for our model, with $R^2$ as high as 66%.

These results are remarkable considering that no returns pertaining to asset class $j$ have been used to price the sorted portfolios in $j$, as opposed to Table 5 where we explain the returns of asset class $j$ using factors estimated in the same asset class.

[ Insert Figure 6 Near Here ]

This is not a formal asset pricing test because the right-hand side variables change depending on the left-hand side assets, but it is nevertheless important as it is fully out of sample. Unlike many asset pricing tests conducted in a single asset class, in our comovement test there is no overlap of securities between the test assets used as the dependent variable and the factors used as regressors. This makes a compelling case in favor of a global factor structure across asset classes, which we establish next through formal asset pricing tests.

## 4.2 A global two-factor model

We run principal component analysis on the returns of the $4 \times 4 \times 3$ sorted portfolios from all asset classes. The results, reported in Table 8, confirm the presence of a strong global factor structure in returns.

[ Insert Table 8 Near Here ]

Panel A shows that the first principal component explains 69% of the total return variability, and the first two explain up to 84%. In Panel B we observe that all portfolios load almost equally on the first principal component, while there is a monotonic pattern in the loadings on the second principal component. Those portfolios that load more on the second principal component also display higher average returns across all asset classes.

This evidence motivates the construction of two global factors to capture the level and slope of portfolio returns. We form a global market portfolio and a global political factor as risk-parity portfolios of the asset-class specific market portfolios and P-factors.[13] The global market correlates 99% with the first principal component (and only 2% with

[13]The risk-parity portfolio construction assigns 21.65% weight to the equity factor, 37.60% to the bond factor, and 40.75% to the currency factor. Similar results are obtained when constructing the global factor giving equal weight to each asset class.

the second one), while the global multi-asset P-factor correlates 72% with the second principal component (and only -16% with the first one), suggesting that the market portfolio explains the level of average returns and political risk explains their cross-sectional variation.

[ Insert Figure 4 Near Here ]

Figure 4 plots the time-series dynamics of the global multi-asset P-factor. We notice that the factor grows constantly and smoothly over the 28-year sample period. Table 9 Panel A reports descriptive statistics of the global multi-asset P-factor, together with those of the global market portfolio. They both carry a strongly statistically significant risk premium, 3.83% for the market portfolio and 4.44% for the political factor, with Sharpe ratios of 0.52 and 0.70, respectively. The t-statistic of the multi-asset P-factor is equal to 3.38, well above the critical threshold of three, which accounts for multiple hypotheses testing, advocated by Harvey, Liu, and Zhu (2016). Panel B shows that the global multi-asset P-factor is not spanned (Barillas and Shanken, 2017) by the factors of "everywhere" asset pricing models constructed across asset classes (Asness, Moskowitz, and Pedersen, 2013; Frazzini and Pedersen, 2014; Koijen, Moskowitz, Pedersen, and Vrugt, 2018). The alphas range from 4.62% to 7.99%, all statistically significant, with corresponding information ratios in the range 0.73–1.24. The adjusted $R^2$ are very low, in the interval 0.03–0.16. This empirical evidence is further corroborated by the low correlations of the global multi-asset P-factor with all other factors, reported in Panel C with average absolute correlation coefficients of about 0.15.

[ Insert Table 9 Near Here ]

We further confirm that the global multi-asset P-factor is not spanned by existing factors by constructing mean-variance frontiers with and without the global multi-asset P-factor. Figure 5 shows that adding the global multi-asset political risk factor to the set of existing factors expands the efficient frontier, confirming that the factor is not redundant.

[ Insert Figure 5 Near Here ]

## 4.3 Formal asset pricing tests

We conclude with formal asset pricing tests of our global two-factor model that includes the multi-asset market portfolio and the multi-asset P-factor (henceforth GPSZ multi-asset model), using both the base and extended sets of test assets. We first bundle together all the test assets from each asset class, hence pricing jointly four portfolios for each of the four political risk measures in each of the three asset classes, producing 48 ($= 4 \times 4 \times 3$) test portfolios, and add the 12 ($= 4 \times 3$) spread portfolios consisting of four L-H strategies, obtained with the four different political risk measures, in each of the three asset classes. Our global base set thus includes 60 test assets. We then extend the base set by adding the 126 country returns from all three asset classes.

We compare the performance of GPSZ with that of the benchmark asset pricing models that include factors constructed across asset classes. Our aim is to show the pricing ability of a novel two-factor model to account for political risk and price a set of test assets left unexplained by existing models. We report the results in Table 10. Panel A shows that the global multi-asset P-factor is priced, while Panel B compares our model with the benchmarks. The GRS test cannot reject the null that all pricing errors are jointly zero for our model which displays higher cross-sectional OLS and GLS $R^2$ than the benchmarks. The case for GPSZ is particularly compelling when considering the results with the extended set of assets, where we observe only a slight deterioration in performance compared to the base set.

[ Insert Table 10 Near Here ]

Figure 7 plots the average realized returns against the predicted returns according to each model in the extended set of test assets. This figure clearly illustrates the goodness of fit achieved by the GPSZ multi-asset model, for which the cloud of points lines up much closer to the 45-degree line. Importantly, Table 10 sheds light on the importance to account for political risk in international asset pricing models. A regression of realized returns on predicted returns yields an $R^2$ of 0.41 in the base set of test assets for the global CAPM, against a corresponding value of 0.77 when adding our global multi-asset P-factor. For the extended set of assets, the $R^2$ for CAPM remains virtually unchanged (0.40) and for GPSZ it deteriorates slightly, as expected, but still remains a large 0.70. This finding further highlights the important role of political risk in explaining the cross-sectional variation in average returns across all three asset classes.

[ Insert Figure 7 Near Here ]

# 5 Robustness Tests

We run several tests to reinforce the evidence supporting our thesis. Importantly, we first rule out a potential market segmentation explanation of our results by showing that we observe high cross-sectional heterogeneity in political ratings and average returns even within emerging markets only, and also by showing that the main findings hold within a subsample that includes the most segmented emerging countries while keeping fixed the degree of market segmentation. Second, we show that political ratings help identify each country's exposure to the global political risk factor, and that beta-sorted portfolios generate also monotonic patterns and large spreads in average returns. Third, we run a spurious factor test to show that all political factors constructed within asset classes load on risk and not simply on country characteristics.

## 5.1 Market segmentation

Our results imply that expected country returns incorporate a compensation for exposure to global political risk, but the expected returns of segmented markets would not depend on the covariance with global factors. We run two tests to rule out that market segmentation causes the cross-sectional heterogeneity in average returns obtained by sorting countries on political ratings.

[ Insert Table 11 Near Here ]

First, we perform portfolio sorts only on the subsample of emerging markets according to the MSCI classification. This rules out the possibility that our results are driven by the higher degree of market segmentation of emerging vis-à-vis developed markets. Table 11 Panel A shows that the combo strategies still produce a fairly monotonic pattern in average returns across portfolios, together with an economically large and statistically significant return spread between the corner portfolios, in all asset classes. The Sharpe ratios of the spread portfolios are 0.61 for equities, 0.36 for bonds and 0.84 for currencies. Similar results hold true for the ICRG strategy, although the latter is more volatile since it does not exploit the imperfect correlation among the different political risk measures, and the sample is smaller compared to the base case that includes all the countries.[14]

[14]The only statistically insignificant spread is observed in the bond market, although the average return of the spread portfolio is economically sizeable, 4.36%. This is not surprising, given that many data for bond returns are not available in emerging markets, especially in the 1990s, which reduces the sample size and increases the volatility of the portfolios.

Second, in Panel B, we dig deeper in a subsample of emerging markets characterized by the highest values of capital controls measured by the restriction index on capital flows of Fernández, Klein, Rebucci, Schindler, and Uribe (2016). At each month, we dynamically select those emerging markets with level of capital controls that is greater than the median of all emerging countries. Due to the small sample of countries, we then construct three portfolios, isolating the countries in the top and bottom quintiles of political ratings, and aggregating all the other countries in the middle portfolio. We observe that such a cross-sectional heterogeneity in political risk matches well the sizeable spreads in average returns, while not being associated to large differences in capital controls. The combo strategies attain Sharpe ratios of 0.43 for equities, 0.34 for bonds, and 0.62 for currencies, while the level of market segmentation is essentially constant across portfolios, being 0.89, 0.87 and 0.86 moving from the high political risk to the low political risk portfolio.

## 5.2 Beta-sorted portfolios

Following Lustig, Roussanov, and Verdelhan (2011), we create beta-sorted portfolios and show that the sorting of countries on the ICRG political risk ratings effectively measures country exposures to the political factors. For each asset class, we run rolling-window time-series regressions of each country's excess returns on the asset-class specific global market portfolio and political factor. We estimate the factor loadings with a 36-month window up to time $t-1$ and track the performance of beta-sorted portfolios at $t$. P1 and P4 portfolios include, respectively, countries with exposures in the bottom ($L_\beta$) and top ($H_\beta$) quintiles of the beta distribution, while portfolios P2 and P3 include countries in the two middle equally-spaced groups. The results are shown in Table 12. For each portfolio and each asset class, we report average return, Sharpe ratio, pre-formation betas, post-formation betas estimated by regressing each portfolio's excess returns on the global market portfolio and the political factor over the full sample, and the ICRG political risk ratings observed ex post.

[ Insert Table 12 Near Here ]

First, we observe a monotonic relationship between loadings on the asset-class specific P-factor and average returns in all asset classes, with economically large and statistically significant spreads in average returns between the corner portfolios. The Sharpe ratios of the spread portfolios are 0.34 for equities, 0.63 for bonds, and 0.71 for currencies. These average returns and Sharpe ratios are in line with the corresponding values obtained when sorting on country ratings from Table 1. Second, post-formation betas show the presence of a perfect monotonic pattern in loadings as well as a persistently large exposure to political risk for spread portfolios even out of sample. Third, this observed pattern in betas matches well a similar pattern in ICRG political risk ratings.

These findings show that portfolio sorts on country ratings and sorts based on political risk exposures are clearly related, vindicating the empirical evidence according to which political ratings contain useful information about each country's exposure to the political factors. Countries characterized by higher political risk display higher average returns, and this finding holds consistently across all asset classes.

## 5.3 Risk vs characteristics

We follow Avramov, Chordia, Jostova, and Philipov (2012) to simulate time series of returns for each country, under the null hypothesis that the political ratings are the only drivers of cross-sectional differences in returns. Using these simulated returns we create spurious factors for each of the four political measures, and we then construct a simulated combo factor as an equally-weighted average of the four spurious factors.

Specifically, we first run monthly cross-sectional regressions of country index excess returns on lagged political ratings:

$$r^e_{i,t} = \alpha_t + \beta_t \, \mathrm{Rating}_{i,t-1} + \epsilon_{i,t}. \tag{3}$$

We compute the time averages of cross-sectional intercepts and slope coefficients, and, at each time $t$, we simulate 1000 data drawing vectors of monthly country returns from a multivariate normal distribution that employs the sample variance of country i's regression residuals $\epsilon_{i,t}$ and a diagonal covariance matrix that imposes the restriction of no common variation in the simulated "unexpected" returns. For each of the 1000 simulated data sets, we obtain a political factor. We repeat this process for each of the four political measures, and we create 1000 time-series, of the same length as the actual data. We then construct the 1000 simulated combo factors by taking the average, at each time $t$, of the values of the four factors constructed with the different political measures. This procedure is applied in each of the three asset classes.

[ Insert Table 13 Near Here ]

We price the extended set of test assets using a model that includes the original asset-class specific market portfolio and the simulated political combo factor, repeating the asset pricing tests of subsection 3.5 (Table 6). In Table 13 we report the percentiles of the simulated distribution of the risk premium and cross-sectional adjusted $R^2$ obtained when running the pricing exercise with the simulated combo factor. In the last two rows we report the actual risk premium and cross-sectional adjusted $R^2$ obtained when pricing the real data with the original combo factor (Table 6, Panel B), and the corresponding p-values implied from locating the real data in the distribution of the simulated data.

We observe that the simulated factor does a poor job in explaining the average returns of the test assets, never being able to explain as much cross-sectional variation in average returns as the real factor. The median cross-sectional adjusted $R^2$ is very low compared to the model that includes the original factor: 0.18 for equities, 0.09 for bonds, and 0.12 for currencies, against corresponding values of 0.48, 0.58 and 0.71 for the real factor. The political ratings contain useful information about the riskiness of each country, and the simulated combo factors in every asset class have a sizeable average return, although somewhat lower than that of the real combo factors. As additional evidence, the simulated factors display almost zero correlation with the original factors. The average across simulations of the absolute value of the correlation coefficients between the simulated combo factor and the real combo factor is only 0.04 for equities and bonds, and 0.05 for FX. These findings show that the political factors do not arise spuriously and that political ratings are indeed related to priced political risk.

# 6 Conclusion

This paper contributes the political risk dimension to the empirical asset pricing literature on the economic phenomena that jointly affect several asset classes. Political risk, while originating locally, generates systematic variation across countries that cannot be diversified away. Country-specific political risk shares a common global component, which we show to be priced in the equity, bond, and FX markets. The central finding of this paper is the covariation among returns in the three important asset classes around the world, induced by country exposures to global political risk.

Using a set of 42 developed and emerging countries spanning a twenty-eight year period since 1992, we document political risk premia globally and across asset classes. We uncover a common factor structure among their returns. We reconcile this strong covariance structure within a risk-based view that sheds some light on the importance of global political risk in driving the comovement across asset classes. We document predictable variation in returns within the equity, bond, and FX markets: countries with higher political risk earn higher average returns in each asset class. This return predictability holds true even after accounting for country characteristics and exposures to existing risk factors.

We create a global political factor across asset classes as a linear combination of factor mimicking portfolios of political risk constructed within each asset class. We show that the new multi-asset factor is not spanned by several benchmark factors constructed in the literature across asset classes and it is priced. We introduce the global multi-asset political factor in a parsimonious global two-factor model that is shown to successfully price a wide cross-section of asset returns including equity indices, bond indices, and currencies, being responsible of the covariation among different asset classes. The new factor is not spurious and picks up risk rather than characteristics.

Our results consistently survive a large battery of robustness tests, alleviating data mining concerns. We show that results are robust to several alternative proxies of political risk proposed in the literature, and our findings are not driven by higher market segmentation of emerging markets compared to developed countries, as large political risk premia are observed even within different subsamples of emerging markets.

We have established the importance to account for global political risk in pricing multiple assets across many countries. The novel global political risk factor captures a political risk dimension that is absent from existing models designed to explain the common variation across different asset classes, despite having a sizeable impact on asset prices.

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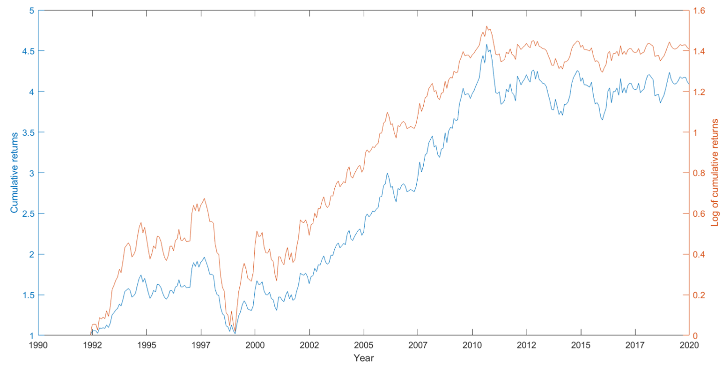
Figure 2: **Time-series dynamics of the combo strategies**

This figure plots the cumulative returns, and the log of the cumulative returns, of the combo strategies constructed in the equity market (Panel A), in the bond market (Panel B) and in the FX market (Panel C). Each combo is as an equally-weighted average of the returns of the four L-H strategies from portfolios sorts on each of the different political risk measures: ICRG, WES politics, WES policy, and World Bank politics. Returns are denominated in USD and include dividends. Data are monthly and span the period 1992-2019.

**(a)** Equity



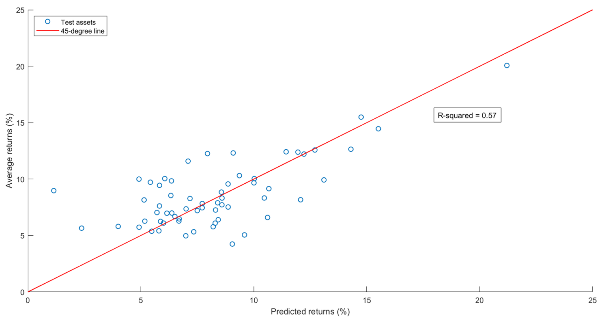

**(b)** Bond


**(c)** FX

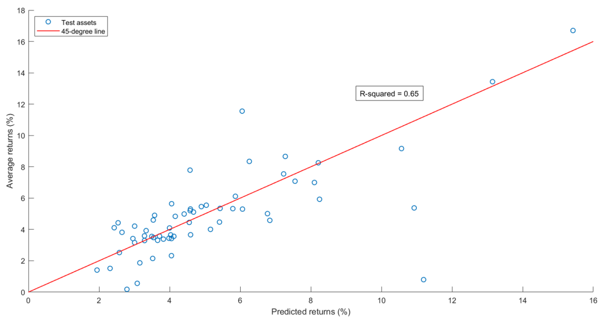
Figure 3: **GPSZ model fit within each asset class**

This figure plots the average realized excess returns against average excess returns predicted by a model that includes the market portfolio and the asset-class specific P-factor. The market portfolios are the MSCI All Countries World for equities, and an equally-weighted average of the excess returns on all countries included within each asset class. The asset-class specific P-factors are constructed as combo strategies that give equal weight to the four L-H strategies from portfolio sorts on each of the different political risk measures: ICRG, WES politics, WES policy, and World Bank politics. We apply the model on the extended set of test assets, which includes these $4 \times 4$ sorted portfolios, the corresponding L-H strategies, and the country indices. Returns are in annualized percentage points. Data are monthly, spanning 1992–2019.

**(a)** Equity




**(b)** Bond




**(c)** FX

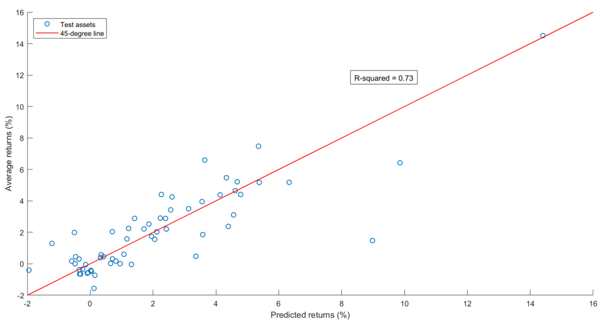


Figure 4: **Global multi-asset P-factor**

This figure plots the cumulative returns, both in levels and in logs, of the global multi-asset P-factor constructed as risk-parity portfolio of the asset-class specific P-factors in equity, bond and FX markets. Data are monthly, spanning 1992–2019.

Figure 5: **Mean-variance frontiers of global multi-asset factors**

This figure plots the efficient frontier obtained using all the "everywhere" factors constructed across asset classes, together with the efficient frontier constructed by adding our multi-asset P-factor. The benchmark factors are MKT (global market portfolio constructed as a risk-parity portfolio of the market portfolios in each asset class), MOM (momentum) and VAL (value) factors from Asness, Moskowitz, and Pedersen (2013), TSM (time-series momentum, from Moskowitz, Ooi, and Pedersen (2012)), BAB (international betting against beta, from Frazzini and Pedersen (2014)), and CAR (carry factor of Koijen, Moskowitz, Pedersen, and Vrugt (2018)). The asterisk denotes the maximum Sharpe ratio portfolio. Data are monthly, spanning 1992–2019.

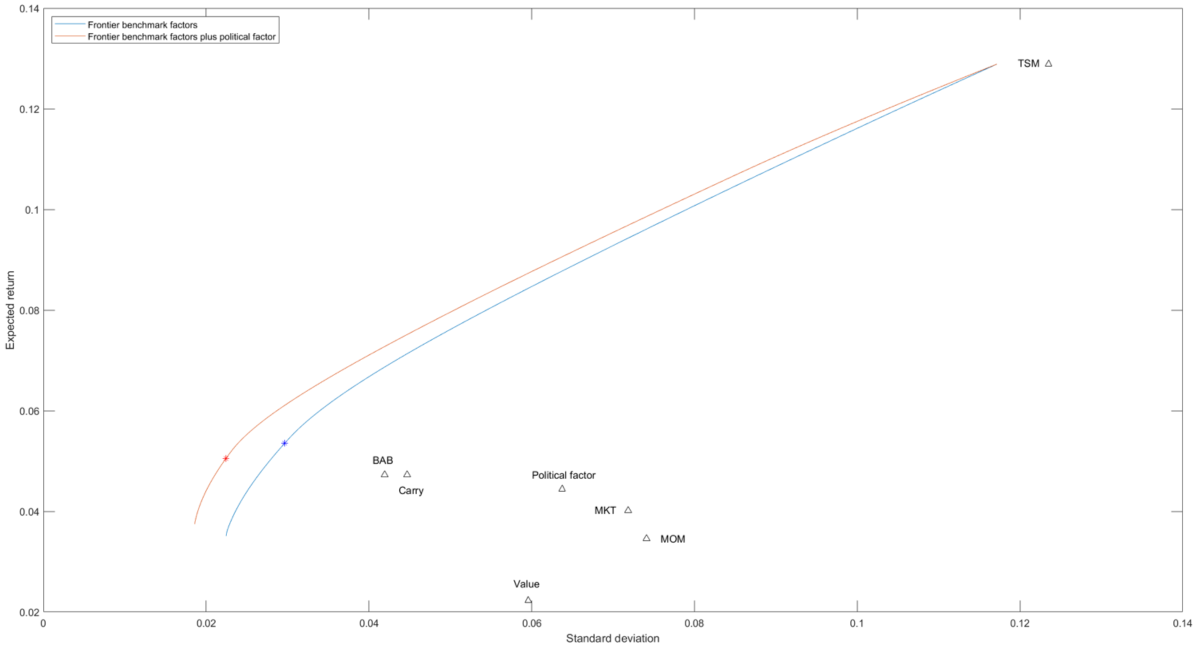


Figure 6: **Comovement test**

This figure plots are the average realized excess returns against average excess returns predicted by a model that includes the global market portfolio and the global multi-asset P-factor, both constructed with returns from the non-$j$ asset classes and used to price returns in asset class $j$. Test assets are $4 \times 4 \times 3$ portfolios sorted on the four measures of political risk (ICRG, WES politics, WES policy and World Bank politics) in the equity, bond and FX asset classes. Returns are in annualized percentage points. Data are monthly, spanning 1992–2019.

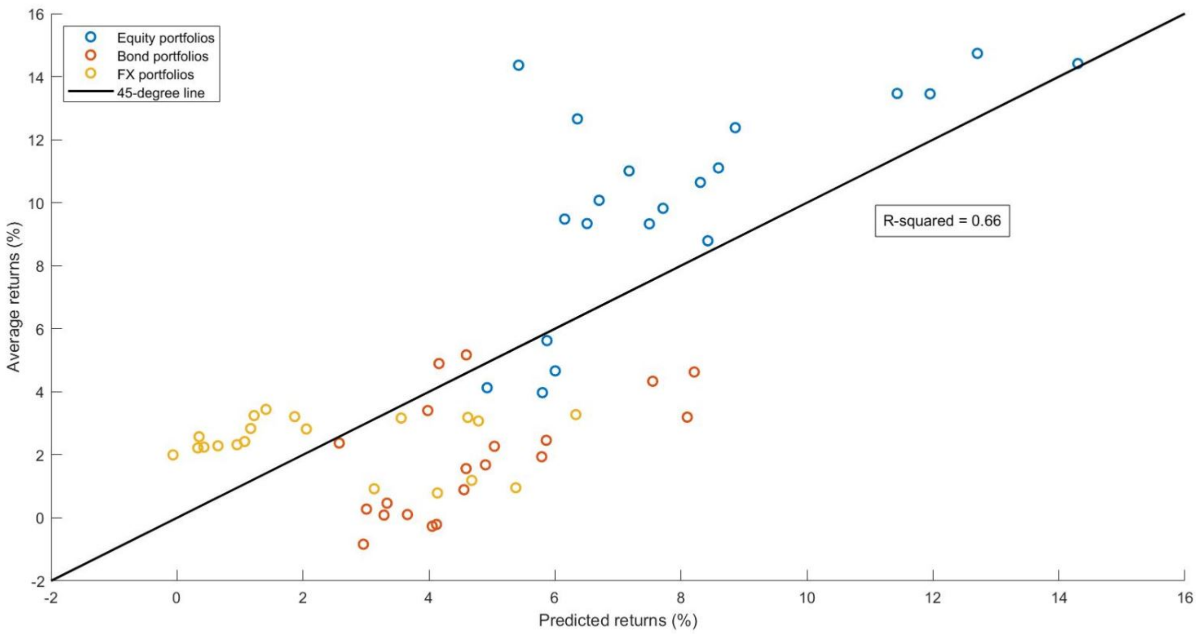
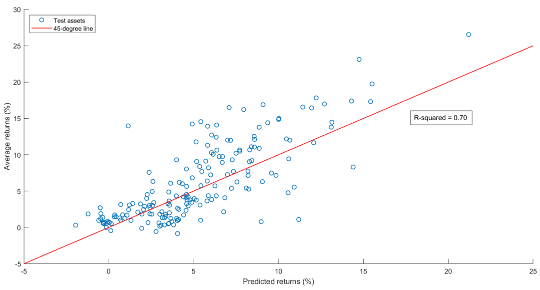


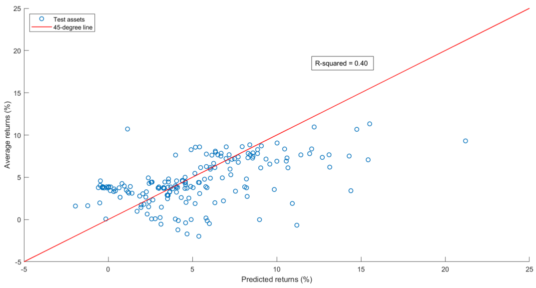
Figure 7: **Cross-sectional fit of global models**

This figure plots the average realized excess returns against average excess returns predicted by each of the global models constructed across asset classes. Our model (GPSZ multi-asset) includes the global market portfolio and the global multi-asset P-factor constructed as risk-parity portfolios of the corresponding asset-class specific P-factors. CAPM includes the global market portfolio. AMP augments the CAPM with the value and momentum everywhere factors of Asness, Moskowitz, and Pedersen (2013), BAB with the betting against beta everywhere factor of Frazzini and Pedersen (2014), and CAR with the carry everywhere factor of Koijen, Moskowitz, Pedersen, and Vrugt (2018). We apply the model on the extended set of test assets, which includes the $4 \times 4 \times 3$ sorted portfolios on each of the four political risk measures within each of the three asset classes (equity, bond and FX), the corresponding L-H strategies, and the excess returns of the country indices for each asset class. Returns are in annualized percentage points. Data are monthly, spanning 1992–2019.

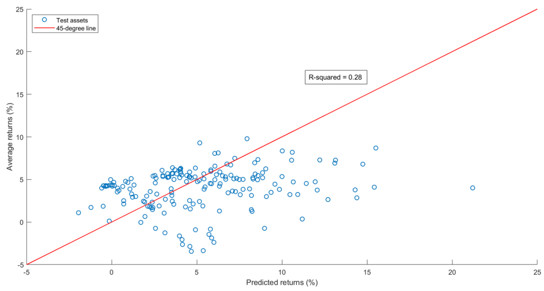
**(a)** GPZ multi-asset model



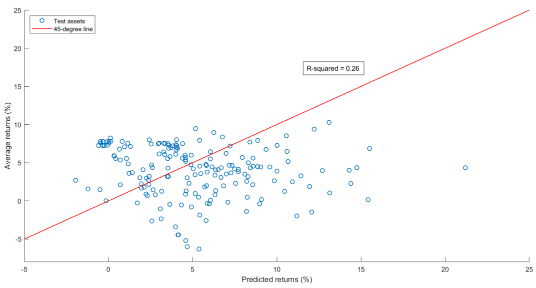

**(b)** CAPM



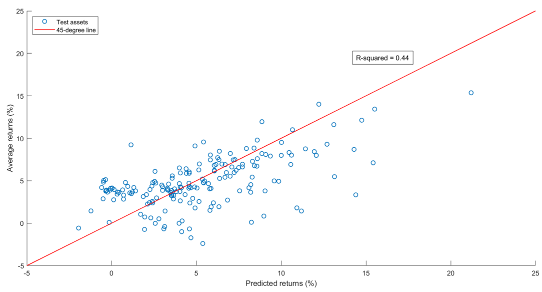

**(c)** AMP




**(d)** BAB




**(e)** CAR



## Table 1 – Portfolio sorts

This table reports the annualized average returns of portfolios sorted on different political risk ratings in international equity and bond markets. "ICRG" denotes the political risk ratings of the International Country Risk Guide, while "Combo" refers to an equally-weighted portfolio of univariate sorts on political risk ratings from, respectively, ICRG, WES policy, WES politics, and World Bank politics. "P1 (L)" refers to the bottom and "P4 (H)" to the top quintiles, and "P2" and "P3" are portfolios in two equally split quantiles in between. ICRG and combo portfolios are rebalanced monthly, while WES portfolios semi-annually and World bank portfolios annually. All returns are in annualized percentages. Panel A reports equity and bond returns denominated in local currency, while Panel B shows USD returns. Equity and bond returns include, respectively, dividends and coupon payments. Newey and West (1987) p-values based on optimal number of lags (Andrews and Monahan, 1992) are in parenthesis, and the asterisk (*) denotes statistical significance at least at the 10% level. Data are monthly, spanning 1992–2019.

(a) Local currency returns

| | Equity | | Bond | |
|---|---|---|---|---|
| | ICRG | Combo | ICRG | Combo |
| P1 (L) | 23.55* | 22.50* | 12.61* | 11.33* |
| | (0.00) | (0.00) | (0.00) | (0.00) |
| P2 | 11.31* | 11.41* | 7.80* | 8.13* |
| | (0.01) | (0.00) | (0.00) | (0.00) |
| P3 | 9.83* | 10.47* | 5.89* | 6.38* |
| | (0.00) | (0.00) | (0.00) | (0.00) |
| P4 (H) | 9.94* | 9.30* | 5.79* | 5.92* |
| | (0.01) | (0.01) | (0.00) | (0.00) |
| L-H | 13.61* | 13.20* | 6.82* | 5.40* |
| | (0.00) | (0.00) | (0.00) | (0.00) |

(b) USD returns

| | Equity | | Bond | | FX | |
|---|---|---|---|---|---|---|
| | ICRG | Combo | ICRG | Combo | ICRG | Combo |
| P1 (L) | 16.69* | 15.34* | 10.60* | 9.82* | 6.33* | 5.15* |
| | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| P2 | 8.75* | 9.81* | 6.98* | 7.57* | 1.22* | 1.65 |
| | (0.05) | (0.02) | (0.00) | (0.00) | (0.35) | (0.18) |
| P3 | 9.89* | 10.10* | 6.05* | 6.17* | 0.33* | 0.83 |
| | (0.01) | (0.01) | (0.00) | (0.00) | (0.83) | (0.58) |
| P4 (H) | 10.82* | 9.49* | 6.44* | 6.21* | 0.95* | 0.65 |
| | (0.01) | (0.02) | (0.00) | (0.00) | (0.60) | (0.70) |
| L-H | 5.87* | 5.86* | 4.16* | 3.61* | 5.38* | 4.50* |
| | (0.09) | (0.03) | (0.04) | (0.01) | (0.00) | (0.00) |
| Sharpe | 0.38 | 0.48 | 0.42 | 0.51 | 0.62 | 0.69 |

## Table 2 – Time-series regressions

This table reports the results of monthly contemporaneous time-series regressions of the excess returns on the L-H strategies reported in Table 1 for the equity, bond and FX markets. Following Asness, Moskowitz, and Pedersen (2013), we create global control variables as GDP-weighted averages of country-specific variables, and we include a measure of consumption growth computed as quarterly growth in standardized consumer spending, a monthly recession dummy (0 = peak, 1 = trough) obtained from NBER dates for the United States and Economic Cycle Research Institute (ECRI) dates outside of the United States, quarterly real GDP growth rate, excess returns on the global market portfolio MSCI All Countries World, and the bond factor returns of Fama and French (1993) "TERM" and "DEF", which represent the term spread on U.S. government bonds and the default spread between U.S. corporate bonds and U.S. Treasuries, respectively. In addition, we also include global GDP-weighted averages of country-specific monthly unemployment growth rates and monthly inflation rates, together with monthly first differences in the CBOE volatility index VIX. The $R^2$ is adjusted for the number of regressors. Newey and West (1987) p-values based on optimal number of lags (Andrews and Monahan, 1992) are in parenthesis, and the asterisk (*) denotes statistical significance at least at the 10% level. Data are monthly, spanning 1992–2019.

| | Equity | | Bond | | FX | |
|---|---|---|---|---|---|---|
| | ICRG | Combo | ICRG | Combo | ICRG | Combo |
| Consumption growth | 0.018 | 0.015 | -0.005 | 0.003 | 0.020 | 0.028 |
| | (0.78) | (0.75) | (0.90) | (0.92) | (0.52) | (0.24) |
| Recession dummy | -0.020 | -0.010 | -0.029* | -0.017 | -0.029* | -0.021* |
| | (0.38) | (0.55) | (0.05) | (0.13) | (0.05) | (0.06) |
| GDP growth | -0.010 | -0.293 | -1.316 | -0.747 | -1.176 | -0.797 |
| | (1.00) | (0.86) | (0.33) | (0.42) | (0.30) | (0.37) |
| Unemployment growth | 0.487 | 0.427* | 0.234 | 0.147 | -0.001 | 0.029 |
| | (0.11) | (0.08) | (0.14) | (0.21) | (1.00) | (0.79) |
| Inflation | 0.016 | 0.193 | -0.322 | -0.407 | -0.138 | -0.200 |
| | (0.98) | (0.71) | (0.36) | (0.12) | (0.77) | (0.56) |
| Mkt ptf | -0.070 | 0.029 | 0.049 | 0.066 | -0.145* | -0.062 |
| | (0.43) | (0.73) | (0.50) | (0.16) | (0.02) | (0.17) |
| $\Delta$VIX | 0.001 | 0.001 | -0.001* | -0.001* | -0.001* | -0.001* |
| | (0.49) | (0.41) | (0.03) | (0.08) | (0.03) | (0.07) |
| TERM | 0.172* | 0.108 | -0.159* | -0.157* | -0.020 | -0.036 |
| | (0.06) | (0.14) | (0.02) | (0.00) | (0.77) | (0.45) |
| DEF | 0.401* | 0.218 | -0.021 | -0.074 | 0.090 | -0.002 |
| | (0.01) | (0.12) | (0.88) | (0.48) | (0.39) | (0.98) |
| Adjusted $R^2$ | 0.00 | 0.00 | 0.07 | 0.10 | 0.02 | 0.01 |

## Table 3 – Abnormal returns

This table reports the average annualized abnormal returns (alphas), adjusted $R^2$ and information ratios (IR) from time-series regressions of the L-H strategies of Table 1 in equity (Panel A), bond (Panel B) and FX (Panel C) markets. We test all asset pricing models constructed across asset classes. For the World CAPM we use the MSCI ACW index in the equity market, and an equally-weighted portfolio of, respectively, bonds and currencies. We augment the CAPM with the value and momentum factors of Asness, Moskowitz, and Pedersen (2013) (VME), with the betting against beta factors of Frazzini and Pedersen (2014) (BAB), and with the carry factors of Koijen, Moskowitz, Pedersen, and Vrugt (2018) (CAR). We also test an asset-class specific benchmark model for each asset class (ACB). For equities, we choose the international five-factor model of Fama and French (2017) augmented with the international version of the momentum factor of Carhart (1997). For bonds, we augment the CAPM with the two bond factors of Fama and French (1993), and for FX we add to the dollar factor estimated in our sample the carry factor of Lustig, Roussanov, and Verdelhan (2011). Returns are in percentages. Newey and West (1987) p-values based on optimal number of lags (Andrews and Monahan, 1992) are in parenthesis, and the asterisk (*) denotes statistical significance at least at the 10% level. Data are monthly, spanning 1992–2016.

(a) Equity

| | ICRG | | | | | Combo | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | CAPM | ACB | VME | BAB | CAR | CAPM | ACB | VME | BAB | CAR |
| $\alpha$ | 6.06* | 8.29* | 6.26* | 7.26* | 6.31 | 5.70* | 7.50* | 5.31* | 6.75* | 5.69* |
| | (0.09) | (0.03) | (0.08) | (0.06) | (0.11) | (0.03) | (0.01) | (0.05) | (0.03) | (0.06) |
| $R^2$ | 0.00 | 0.05 | 0.02 | 0.00 | -0.01 | 0.00 | 0.05 | 0.02 | 0.00 | 0.00 |
| IR | 0.39 | 0.56 | 0.41 | 0.47 | 0.40 | 0.46 | 0.63 | 0.44 | 0.55 | 0.45 |

(b) Bond

| | ICRG | | | | | Combo | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | CAPM | ACB | VME | BAB | CAR | CAPM | ACB | VME | BAB | CAR |
| $\alpha$ | 4.94* | 5.45* | 6.29* | 5.02* | 4.76* | 4.28* | 4.74* | 5.32* | 3.88* | 4.53* |
| | (0.01) | (0.01) | (0.00) | (0.05) | (0.02) | (0.00) | (0.00) | (0.00) | (0.04) | (0.00) |
| $R^2$ | 0.01 | 0.06 | 0.04 | 0.03 | 0.02 | 0.02 | 0.08 | 0.06 | 0.05 | 0.03 |
| IR | 0.50 | 0.57 | 0.65 | 0.47 | 0.48 | 0.61 | 0.70 | 0.78 | 0.51 | 0.64 |

(c) FX

| | ICRG | | | | | Combo | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | CAPM | ACB | VME | BAB | CAR | CAPM | ACB | VME | BAB | CAR |
| $\alpha$ | 6.71* | 6.06* | 7.29* | 6.88* | 6.06* | 5.42* | 4.97* | 6.03* | 5.63* | 4.97* |
| | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| $R^2$ | 0.26 | 0.30 | 0.27 | 0.40 | 0.30 | 0.22 | 0.28 | 0.23 | 0.33 | 0.28 |
| IR | 0.90 | 0.82 | 0.99 | 0.94 | 0.82 | 0.94 | 0.87 | 1.06 | 0.95 | 0.87 |

**Table 4 – Factor structures within asset classes**

This table reports the results of a principal component analysis of the $4 \times 4$ portfolios sorted on the different political risk measures. Panel A shows the percentage of total variance explained by each principal component, Panel B the correlations of each principal component with the market portfolio and the P-factor both constructed within each corresponding asset class, and Panel C the loading of each portfolio on the principal components. Data are monthly, spanning 1992–2019.

| | Equity | | Bond | | FX | |
|---|---|---|---|---|---|---|
| | PC1 | PC2 | PC1 | PC2 | PC1 | PC2 |
| | (a) Factor eigenvalues | | | | | |
| Explained variance (%) | 89.78 | 4.76 | 82.27 | 9.56 | 82.42 | 9.73 |
| Cumulative (%) | 89.78 | 94.54 | 82.27 | 91.83 | 82.42 | 92.15 |
| | (b) Factor loadings | | | | | |
| | ICRG | | | | | |
| P1 (L) | 0.23 | 0.46 | 0.19 | 0.55 | 0.17 | 0.53 |
| P2 | 0.25 | 0.08 | 0.27 | -0.01 | 0.27 | 0.06 |
| P3 | 0.26 | -0.19 | 0.25 | -0.21 | 0.26 | -0.22 |
| P4 (H) | 0.25 | -0.32 | 0.26 | -0.24 | 0.26 | -0.21 |
| | WES politics | | | | | |
| P1 (L) | 0.24 | 0.32 | 0.24 | 0.30 | 0.22 | 0.26 |
| P2 | 0.26 | 0.12 | 0.25 | 0.17 | 0.26 | 0.20 |
| P3 | 0.26 | -0.17 | 0.27 | -0.18 | 0.27 | -0.20 |
| P4 (H) | 0.26 | -0.26 | 0.26 | -0.22 | 0.26 | -0.21 |
| | WES policy | | | | | |
| P1 (L) | 0.24 | 0.27 | 0.25 | 0.16 | 0.23 | 0.20 |
| P2 | 0.26 | 0.04 | 0.26 | 0.11 | 0.27 | -0.01 |
| P3 | 0.26 | -0.07 | 0.26 | -0.07 | 0.27 | -0.04 |
| P4 (H) | 0.25 | -0.21 | 0.26 | -0.20 | 0.27 | -0.16 |
| | World Bank politics | | | | | |
| P1 (L) | 0.23 | 0.43 | 0.20 | 0.47 | 0.19 | 0.51 |
| P2 | 0.24 | 0.07 | 0.26 | 0.07 | 0.25 | 0.12 |
| P3 | 0.25 | -0.18 | 0.26 | -0.16 | 0.26 | -0.18 |
| P4 (H) | 0.24 | -0.29 | 0.25 | -0.25 | 0.25 | -0.24 |
| | (c) Correlations | | | | | |
| Market portfolio | 0.93 | -0.16 | 1.00 | 0.01 | 1.00 | -0.01 |
| Political factor | 0.19 | 0.97 | -0.16 | 0.97 | -0.54 | 0.82 |

### Table 5 – Asset pricing on the base set of test assets

This table reports the results of asset pricing tests run on the base set of test assets, which includes the $4 \times 4$ univariate-sorted portfolios on ICRG, WES policy, WES politics, and World Bank politics, together with the corresponding L-H spread portfolios from each measure. Panel A reports the risk premia of our model with the asset-specific factors (denoted by "GPSZ model") within each asset class, estimated through a two-step OLS regression of average returns on factor loadings, run without the intercept. p-values reported in parenthesis account for correlated errors and the generated regressor problem from the estimation of factor loadings in the first step. We include the factors in the set of test assets. In Panel B we compare the performance of our model with asset-class specific factor models of Table 3. We compute the mean absolute pricing error (MAPE) from time-series regressions, the GRS statistic and its corresponding p-value, and we report OLS and GLS $R^2$ from the second step cross-sectional regression. Panel B also includes the $R^2$ of a regression of average realized returns $\mathbb{E}[r_t]$ on average model predicted returns $\mathbb{E}[\hat{r}_t]$ obtained as the product of the factor loadings and the corresponding time-series factor means. Returns are in percentages, denominated in USD, and include dividends. Risk premia are annualized. The asterisk (*) denotes statistical significance at least at the 10% level. Data are monthly, spanning 1992–2019.

(a) Risk premia with GPSZ model

| | Equity | | Bond | | FX | |
|---|---|---|---|---|---|---|
| | MKT | P-factor | MKT | P-factor | MKT | P-factor |
| Risk premium | 6.10* | 5.59* | 4.88* | 3.81* | 1.86 | 4.31* |
| | (0.05) | (0.03) | (0.00) | (0.01) | (0.14) | (0.00) |

(b) Comparison with benchmark models

| | GPSZ | CAPM | ACB | VME | BAB | CAR |
|---|---|---|---|---|---|---|
| | Equity | | | | | |
| MAPE | 1.09 | 2.78 | 3.34 | 2.55 | 3.40 | 3.05 |
| GRS statistic | 1.06 | 1.45* | 1.98* | 1.30 | 1.93* | 1.69* |
| p-value GRS | 0.39 | 0.10 | 0.01 | 0.18 | 0.01 | 0.03 |
| GLS $R^2$ | 0.24 | 0.10 | 0.69 | 0.81 | 0.19 | 0.66 |
| OLS $R^2$ | 0.66 | 0.17 | 0.80 | 0.55 | 0.31 | 0.16 |
| $R^2$ predicted vs realized | 0.72 | 0.53 | 0.50 | 0.53 | 0.51 | 0.51 |
| | Bond | | | | | |
| MAPE | 0.42 | 2.13 | 2.35 | 2.60 | 2.12 | 2.24 |
| GRS statistic | 0.78 | 7.66* | 2.23* | 3.55* | 1.22 | 40.47* |
| p-value GRS | 0.74 | 0.00 | 0.00 | 0.00 | 0.23 | 0.00 |
| GLS $R^2$ | 0.02 | 0.00 | 0.10 | 0.02 | 0.17 | 0.03 |
| OLS $R^2$ | 0.85 | -0.02 | 0.67 | 0.66 | 0.07 | 0.36 |
| $R^2$ predicted vs realized | 0.86 | 0.45 | 0.45 | 0.44 | 0.45 | 0.45 |
| | FX | | | | | |
| MAPE | 0.51 | 2.38 | 1.45 | 2.65 | 2.52 | 2.11 |
| GRS statistic | 1.61* | 2.91* | 2.71* | 2.82* | 4.50* | 2.90* |
| p-value GRS | 0.05 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| GLS $R^2$ | 0.01 | 0.01 | 0.03 | 0.27 | 0.04 | 0.10 |
| OLS $R^2$ | 0.88 | 0.49 | 0.66 | 0.72 | 0.69 | 0.67 |
| $R^2$ predicted vs realized | 0.90 | 0.28 | 0.16 | 0.35 | 0.27 | 0.22 |

## Table 6 – Asset pricing on the extended set of test assets

This table reports the results of asset pricing tests run on the extended set of test assets, which includes the $4 \times 4$ univariate-sorted portfolios on ICRG, WES policy, WES politics, and World Bank politics, together with the corresponding L-H spread portfolios from each measure and the country excess returns within each asset class. Panel A reports the risk premia of our model with the asset-specific factors of our model with the asset-specific factors (denoted by "GPSZ model"), estimated through a two-step OLS regression of average returns on factor loadings, run without the intercept. p-values reported in parenthesis account for correlated errors and the generated regressor problem from the estimation of factor loadings in the first step. We include the factors in the set of test assets. In Panel B we compare the performance of our model with the asset-class specific factor models of Table 3. We compute the mean absolute pricing error (MAPE) from time-series regressions, the GRS statistic and its corresponding p-value, and we report OLS and GLS $R^2$ from the second step cross-sectional regression. Panel B also includes the $R^2$ of a regression of average realized returns $\mathbb{E}[r_t]$ on average model predicted returns $\mathbb{E}[\hat{r}_t]$ obtained as the product of the factor loadings and the corresponding time-series factor means. Returns are in percentages, denominated in USD, and include dividends. Risk premia are annualized. The asterisk (*) denotes statistical significance at least at the 10% level. Data are monthly, spanning 1992–2019.

(a) Risk premia with the GPSZ model

| | Equity | | Bond | | FX | |
|---|---|---|---|---|---|---|
| | MKT | P-factor | MKT | P-factor | MKT | P-factor |
| Risk premium | 6.33* | 4.82* | 4.70* | 3.63* | 1.89 | 4.06* |
| | (0.04) | (0.06) | (0.00) | (0.02) | (0.12) | (0.00) |

(b) Comparison with benchmark models

| | GPSZ | CAPM | ACB | VME | BAB | CAR |
|---|---|---|---|---|---|---|
| | Equity | | | | | |
| MAPE | 1.90 | 2.52 | 2.86 | 2.51 | 3.08 | 2.70 |
| GRS statistic | 1.05 | 1.23 | 1.07 | 0.82 | 1.19 | 1.30* |
| p-value GRS | 0.39 | 0.13 | 0.35 | 0.83 | 0.18 | 0.08 |
| GLS $R^2$ | 0.74 | 0.65 | 0.87 | 0.91 | 0.71 | 0.85 |
| OLS $R^2$ | 0.48 | 0.16 | 0.39 | 0.29 | 0.15 | 0.17 |
| $R^2$ predicted vs realized | 0.57 | 0.38 | 0.42 | 0.40 | 0.42 | 0.41 |
| | Bond | | | | | |
| MAPE | 1.30 | 2.20 | 2.32 | 2.51 | 2.79 | 2.29 |
| GRS statistic | 1.91* | 1.60* | 1.48* | 1.49* | 2.17* | 1.58* |
| p-value GRS | 0.00 | 0.01 | 0.02 | 0.02 | 0.00 | 0.01 |
| GLS $R^2$ | 0.12 | 0.00 | 0.25 | 0.24 | 0.48 | 0.09 |
| OLS $R^2$ | 0.58 | 0.05 | 0.40 | 0.29 | 0.03 | 0.15 |
| $R^2$ predicted vs realized | 0.65 | 0.36 | 0.31 | 0.31 | 0.37 | 0.33 |
| | FX | | | | | |
| MAPE | 1.00 | 2.39 | 1.55 | 2.64 | 2.57 | 2.07 |
| GRS statistic | 1.98* | 2.23* | 2.24* | 3.44* | 3.32* | 2.74* |
| p-value GRS | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| GLS $R^2$ | 0.06 | 0.01 | 0.02 | 0.09 | 0.09 | 0.07 |
| OLS $R^2$ | 0.71 | 0.05 | 0.37 | 0.42 | 0.36 | 0.40 |
| $R^2$ predicted vs realized | 0.73 | 0.11 | 0.28 | 0.16 | 0.10 | 0.13 |

## Table 7 – Comovement test

This table reports the results of a comovement test run on the base set of test assets, which includes the $4 \times 4$ univariate-sorted portfolios on ICRG, WES policy, WES politics, and World Bank politics, together with the corresponding L-H spread portfolios from each measure. The market portfolio and the political factor used to explain returns in asset class $j$ are constructed with returns of assets that belong only to all other non-$j$ asset classes. We report asset pricing statistics of the comovement test within each asset class, such as the mean absolute pricing error (MAPE) from time-series regressions, the GRS statistic and its corresponding p-value, and the OLS and GLS $R^2$ from the second step cross-sectional regression. Returns are denominated in USD, and include dividends. The asterisk (*) denotes statistical significance at least at the 10% level. Data are monthly, spanning 1992–2019.

| | Equity | Bond | FX |
|---|---|---|---|
| MAPE | 1.66 | 2.76 | 2.08 |
| GRS statistic | 2.14 | 1.53 | 2.36 |
| p-value GRS | 0.003 | 0.071 | 0.001 |
| GLS $R^2$ | 61.30 | 69.22 | 70.76 |
| OLS $R^2$ | 50.43 | 85.24 | 76.13 |

## Table 8 – Global factor structure across asset classes

This table reports the results of a principal component analysis of the 4 × 4 portfolios sorted on the different political risk measures in all asset classes. Panel A shows the percentage of total variance explained by each principal component, Panel B the correlations of each principal component with the market portfolio and the P-factor, both constructed as risk-parity portfolios across asset classes of the corresponding asset-class specific factors, and Panel C the loading of each portfolio on the principal components. Data are monthly, spanning 1992–2019.

(a) Factor eigenvalues

| | PC1 | PC2 |
|---|---|---|
| Explained variance (%) | 68.83 | 15.66 |
| Cumulative (%) | 68.83 | 84.49 |

(b) Factor loadings

| | Equity | | Bond | | FX | |
|---|---|---|---|---|---|---|
| | PC1 | PC2 | PC1 | PC2 | PC1 | PC2 |
| | | | ICRG | | | |
| P1 (L) | 0.12 | 0.22 | 0.12 | 0.08 | 0.12 | 0.10 |
| P2 | 0.14 | 0.19 | 0.16 | -0.10 | 0.17 | -0.03 |
| P3 | 0.14 | 0.17 | 0.13 | -0.17 | 0.16 | -0.15 |
| P4 (H) | 0.14 | 0.16 | 0.14 | -0.18 | 0.15 | -0.15 |
| | | | WES politics | | | |
| P1 (L) | 0.12 | 0.21 | 0.14 | 0.00 | 0.14 | 0.02 |
| P2 | 0.14 | 0.20 | 0.15 | -0.05 | 0.17 | 0.01 |
| P3 | 0.14 | 0.17 | 0.15 | -0.17 | 0.16 | -0.14 |
| P4 (H) | 0.14 | 0.17 | 0.14 | -0.18 | 0.16 | -0.14 |
| | | | WES policy | | | |
| P1 (L) | 0.12 | 0.21 | 0.15 | -0.06 | 0.14 | -0.01 |
| P2 | 0.14 | 0.19 | 0.15 | -0.06 | 0.17 | -0.07 |
| P3 | 0.14 | 0.19 | 0.15 | -0.14 | 0.16 | -0.08 |
| P4 (H) | 0.14 | 0.16 | 0.14 | -0.17 | 0.16 | -0.13 |
| | | | World Bank politics | | | |
| P1 (L) | 0.11 | 0.21 | 0.13 | 0.06 | 0.13 | 0.09 |
| P2 | 0.14 | 0.18 | 0.15 | -0.08 | 0.16 | -0.02 |
| P3 | 0.14 | 0.15 | 0.14 | -0.15 | 0.16 | -0.13 |
| P4 (H) | 0.13 | 0.16 | 0.13 | -0.19 | 0.15 | -0.16 |

(c) Correlations

| | PC1 | PC2 |
|---|---|---|
| Global mkt | 0.99 | 0.02 |
| Global P-factor | -0.16 | 0.72 |

### Table 9 – Global multi-asset P-factor

This table reports the annualized average returns, t-statistics, corresponding Newey and West (1987) p-values based on optimal number of lags (Andrews and Monahan, 1992), and Sharpe ratios of the global market portfolio and multi-asset P-factor, both constructed as risk-parity portfolios across asset classes of the corresponding asset-class specific factors. In Panel B we run spanning regressions of the global P-factor on those factor models described in Table 3 for which the factors have been calibrated "everywhere" across asset classes. We report the abnormal returns (alphas), adjusted $R^2$ and the information ratios. Panel C displays the correlations between the global P-factor and the other global factors constructed across asset classes. The asterisk (*) denotes statistical significance at least at the 10% level. Data are monthly, spanning 1992-2019.

(a) Summary statistics

| | MKT | P-factor |
|---|---|---|
| Avg return | 3.83* | 4.44* |
| | (0.01) | (0.00) |
| t-statistic | 2.66 | 3.38 |
| Sharpe | 0.52 | 0.70 |

(b) Spanning regressions of the global political factor

| | CAPM | VME | BAB | CAR |
|---|---|---|---|---|
| $\alpha$ | 5.03* | 6.45* | 7.99* | 4.62* |
| | (0.00) | (0.00) | (0.00) | (0.00) |
| $R^2$ | 0.03 | 0.06 | 0.16 | 0.04 |
| IR | 0.80 | 1.05 | 1.24 | 0.73 |

(c) Correlations with other global factors

| | P-factor | MKT | MOM | VAL | TSM | BAB |
|---|---|---|---|---|---|---|
| P-factor | | | | | | |
| MKT | -0.17 | | | | | |
| MOM | -0.15 | -0.16 | | | | |
| VAL | 0.04 | 0.10 | -0.68 | | | |
| TSM | -0.16 | -0.05 | 0.63 | -0.33 | | |
| BAB | -0.37 | 0.12 | 0.28 | -0.08 | 0.16 | |
| CAR | 0.02 | 0.36 | 0.00 | -0.01 | 0.06 | 0.14 |

## Table 10 – Global asset pricing

This table reports the results of asset pricing tests run on the base set of test assets, which includes the $4 \times 4$ univariate-sorted portfolios on ICRG, WES policy, WES politics, and World Bank politics, together with the corresponding L-H spread portfolios from each measure and all asset classes, and on the extended set of test assets, which adds the country excess returns for all asset class. Panel A reports the risk premia, estimated through a two-step OLS regression of average returns on factor loadings, run without the intercept. p-values reported in parenthesis account for correlated errors and the generated regressor problem from the estimation of factor loadings in the first step. We include the factors in the set of test assets. In Panel B we compare the performance of the GPSZ model with those factor models described in Table 3 for which the factors have been calibrated "everywhere" across asset classes. We compute the mean absolute pricing error (MAPE) from time-series regressions, the GRS statistic and its corresponding p-value, and we report OLS and GLS $R^2$ from the second step cross-sectional regression. Panel B also includes the $R^2$ of a regression of average realized returns $\mathbb{E}[r_t]$ on average model predicted returns $\mathbb{E}[\hat{r}_t]$ obtained as the product of the factor loadings and the corresponding time-series factor means. Returns are in percentages, denominated in USD, and include dividends. Risk premia are annualized. The asterisk (*) denotes statistical significance at least at the 10% level. Data are monthly, spanning 1992–2019.

(a) Risk premia GPSZ multi-asset model

| | Base set | | Extended set | |
|---|---|---|---|---|
| | MKT | P-factor | MKT | P-factor |
| Risk premium | 2.93* | 3.24* | 3.11* | 2.63* |
| | (0.04) | (0.01) | (0.03) | (0.05) |

(b) Comparison with benchmark models

| | Base set | | | | | Extended set | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | GPSZ | CAPM | VME | BAB | CAR | GPSZ | CAPM | VME | BAB | CAR |
| MAPE | 1.90 | 2.59 | 3.39 | 4.46 | 2.50 | 2.55 | 2.47 | 3.22 | 4.64 | 2.45 |
| GRS statistic | 1.00 | 1.29 | 1.05 | 2.03 | 1.33 | 1.16 | 1.35 | 1.75 | 1.91 | 0.75 |
| p-value GRS | 0.49 | 0.08 | 0.38 | 0.00 | 0.05 | 0.18 | 0.03 | 0.00 | 0.00 | 0.97 |
| GLS $R^2$ | 0.25 | 0.00 | 0.21 | 0.28 | 0.20 | 0.32 | 0.05 | 0.08 | 0.10 | 0.09 |
| OLS $R^2$ | 0.74 | 0.18 | 0.73 | 0.60 | 0.24 | 0.63 | 0.28 | 0.41 | 0.48 | 0.34 |
| $R^2$ predicted vs realized | 0.77 | 0.41 | 0.31 | 0.31 | 0.41 | 0.70 | 0.40 | 0.28 | 0.26 | 0.44 |

## Table 11 – Market Segmentation

This table reports descriptive statistics of portfolio sorts in all emerging markets following the MSCI classification (Panel A), and in a subsample of developing countries characterized by high capital controls (Panel B), where the latter are measured by the overall restriction index on capital flows (Fernández, Klein, Rebucci, Schindler, and Uribe, 2016). In Panel B we dynamically select the countries with a level of capital controls that is greater than the median of all emerging markets. In Panel A "P1 (L)" refers to the bottom and "P4 (H)" to the top quintiles, and "P2" and "P3" are portfolios in two equally split quantiles in between, while in Panel B we restrict the number of portfolios due to the lower number of countries in the sample, denoting by"H" the top quintile, by "L" the bottom quintile, and by "M" the middle 60%. "ICRG" denotes the political risk ratings of the International Country Risk Guide, while "Combo" refers to an equally-weighted portfolio of univariate sorts on political risk ratings from, respectively, ICRG, WES policy, WES politics, and World Bank politics. Newey and West (1987) p-values based on optimal number of lags (Andrews and Monahan, 1992) are in parenthesis. The asterisk (*) denotes statistical significance at least at the 10% level. Returns are in percentages, denominated in USD, and include dividends. Risk premia are annualized. Data are monthly, spanning 1992–2016.

(a) All emerging markets

| | ICRG | | | Combo | | |
|---|---|---|---|---|---|---|
| | Equity | Bond | FX | Equity | Bond | FX |
| P1 (L) | 19.87%* | 12.00%* | 9.13%* | 19.50%* | 10.51%* | 8.01%* |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| P2 | 12.92%* | 9.25%* | 3.02%* | 12.24%* | 9.36%* | 3.08%* |
| | (0.011) | (0.002) | (0.024) | (0.012) | (0.000) | (0.010) |
| P3 | 8.21% | 6.65%* | 1.61% | 9.09%* | 8.22%* | 2.33%* |
| | (0.134) | (0.001) | (0.292) | (0.076) | (0.000) | (0.065) |
| P4 (H) | 11.21%* | 7.64%* | 2.33% | 9.94%* | 6.97%* | 2.13% |
| | (0.032) | (0.001) | (0.117) | (0.041) | (0.001) | (0.143) |
| L-H | 8.65%* | 4.36% | 6.79%* | 9.56%* | 3.53%* | 5.88%* |
| | (0.019) | (0.169) | (0.003) | (0.002) | (0.033) | (0.002) |
| Sharpe | 0.41 | 0.26 | 0.72 | 0.61 | 0.36 | 0.84 |

(b) Subsample of highly segmented emerging markets

| | ICRG | | | | Combo | | | |
|---|---|---|---|---|---|---|---|---|
| | Equity | Bond | FX | CC | Equity | Bond | FX | CC |
| P1 (L) | 23.82%* | 6.89%* | 11.03%* | 0.87* | 19.68%* | 9.69%* | 9.82%* | 0.89* |
| | (0.004) | (0.075) | (0.048) | (0.000) | (0.004) | (0.001) | (0.019) | (0.000) |
| P2 | 9.84%* | 8.99%* | 1.95% | 0.88* | 9.69%* | 8.72%* | 2.26%* | 0.87* |
| | (0.054) | (0.000) | (0.126) | (0.000) | (0.057) | (0.000) | (0.081) | (0.000) |
| P3 (H) | 7.43% | 7.71%* | 4.49%* | 0.82* | 8.68%* | 5.51%* | 2.27% | 0.86* |
| | (0.253) | (0.017) | (0.056) | (0.000) | (0.096) | (0.012) | (0.134) | (0.000) |
| L-H | 16.39%* | -0.82% | 6.55% | 0.06* | 11.00%* | 4.17% | 7.55%* | 0.03* |
| | (0.049) | (0.828) | (0.318) | (0.000) | (0.032) | (0.120) | (0.076) | (0.001) |
| Sharpe | 0.41 | -0.05 | 0.33 | | 0.43 | 0.34 | 0.62 | |

## Table 12 – Beta-sorted portfolios

This table reports descriptive statistics and performance measures of portfolios sorted on country exposures to the asset-class specific global political factor, estimated through rolling-window time-series regressions of country monthly excess returns on the global market portfolio and the political factor estimated in each asset class. Panel A reports results for the equity market, Panel B for bonds, and Panel C for currencies. We estimate betas using data from $t-36$ to $t-1$, sort countries in four groups based on these betas, and then track the performance at time $t$. We report the annualized average returns and Sharpe ratios for each portfolio, together with the corresponding pre-formation betas, the corresponding post-formation betas obtained by regressing each portfolio excess returns on the global market portfolio and the political factor on the full sample, and the corresponding ex-post averge ICRG political risk ratings. P1 and P4 include, respectively, countries with exposures in the bottom ($L_\beta$) and top ($H_\beta$) quintiles of the beta distribution, and "P2" and "P3" are portfolios in two equally split quantiles in between. p-values are in parenthesis and the asterisk (*) denotes statistical significance at least at the 10% level. Returns are in percentages, denominated in USD, and include dividends. Data are monthly, spanning 1992–2019.

| Panel A: Equity | | | | | |
|---|---|---|---|---|---|
| | P1 ($H_\beta$) | P2 | P3 | P4 ($L_\beta$) | $H_\beta - L_\beta$ |
| Avg return | 12.29%* | 5.56% | 8.64%* | 6.51%* | 5.66%* |
| | (0.011) | (0.163) | (0.014) | (0.089) | (0.091) |
| Sharpe ratio | 0.51 | 0.28 | 0.50 | 0.34 | 0.34 |
| Pre-formation beta | 1.31* | 0.41* | -0.01* | -0.30* | 1.61* |
| | (0.000) | (0.000) | (0.004) | (0.000) | (0.000) |
| Post-formation beta | 1.03* | 0.43* | 0.07 | -0.11 | 1.14* |
| | (0.000) | (0.000) | (0.407) | (0.238) | (0.000) |
| Ex-post ICRG rating | 64.01* | 72.63* | 81.55* | 83.78* | -19.77* |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |

| Panel B: Bond | | | | | |
|---|---|---|---|---|---|
| | P1 ($H_\beta$) | P2 | P3 | P4 ($L_\beta$) | $H_\beta - L_\beta$ |
| Avg return | 9.01%* | 5.04%* | 2.60% | 2.19% | 6.82%* |
| | (0.000) | (0.000) | (0.146) | (0.263) | (0.002) |
| Sharpe ratio | 0.76 | 0.74 | 0.29 | 0.23 | 0.63 |
| Pre-formation beta | 1.22* | 0.07* | -0.36* | -0.61* | 1.82* |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Post-formation beta | 0.66* | -0.11* | -0.51* | -0.64* | 1.30* |
| | (0.000) | (0.056) | (0.000) | (0.000) | (0.000) |
| Ex-post ICRG rating | 67.46* | 75.83* | 81.61* | 84.78* | -17.32* |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |

| Panel C: FX | | | | | |
|---|---|---|---|---|---|
| | P1 ($H_\beta$) | P2 | P3 | P4 ($L_\beta$) | $H_\beta - L_\beta$ |
| Avg return | 5.80%* | 1.41% | 1.02% | -1.07% | 6.75%* |
| | (0.001) | (0.162) | (0.488) | (0.562) | (0.001) |
| Sharpe ratio | 0.69 | 0.28 | 0.14 | -0.12 | 0.71 |
| Pre-formation beta | 1.12* | 0.19* | -0.32* | -0.68* | 1.79* |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Post-formation beta | 0.11 | -0.24* | -0.77* | -1.12* | 1.23* |
| | (0.175) | (0.000) | (0.000) | (0.000) | (0.000) |
| Ex-post ICRG rating | 65.91* | 71.98* | 79.86* | 82.91* | -17.00* |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |

## Table 13 – Spurious factor test

This table reports the spurious factor test run on the extended set of test assets, which includes the sorted portfolios and the long-short strategies from Table 1 augmented with the excess returns of the country market indices in our sample, for equities (Panel A), bonds (Panel B) and currencies (Panel C). We simulate country returns under the null hypothesis that they are purely driven by political ratings. The details of the test are described in subsection 5.3. We construct 1000 spurious factors from the simulated data for each of the four political measures, and we construct 1000 spurious combo factors as equal averages of the simulated factors constructed with the four political measures. We then use the simulated combo factors to price the cross-section of test assets. We report the cumulative distribution of the risk premium and cross-sectional adjusted $R^2$ estimated with the simulated factors. The last two rows are the corresponding estimates obtained with the combo factor in real data, and the implied p-values computed by locating them in the distribution of simulated estimates. Returns are in percentages, denominated in USD, and include dividend and coupon payments. Risk premia are annualized. The asterisk (*) denotes statistical significance at least at the 10% level. Data are monthly, spanning 1992–2019.

| | (a) Equity | | (b) Bond | | (c) FX | |
|---|---|---|---|---|---|---|
| | Risk premium | Adj. $R^2$ | Risk premium | Adj. $R^2$ | Risk premium | Adj. $R^2$ |
| Simulated distribution | | | | | | |
| $1^{st}$ percentile | -4.60 | 0.15 | -5.62 | 0.03 | -6.84 | 0.03 |
| $5^{th}$ percentile | -3.20 | 0.15 | -4.39 | 0.03 | -5.80 | 0.03 |
| $10^{th}$ percentile | -2.39 | 0.15 | -3.52 | 0.03 | -4.85 | 0.03 |
| $25^{th}$ percentile | -0.54 | 0.16 | -1.56 | 0.04 | -2.36 | 0.05 |
| $50^{th}$ percentile | 1.78 | 0.18 | 1.27 | 0.09 | 1.50 | 0.12 |
| $75^{th}$ percentile | 4.11 | 0.23 | 3.49 | 0.18 | 5.30 | 0.23 |
| $90^{th}$ percentile | 5.79 | 0.30 | 5.36 | 0.26 | 7.38 | 0.36 |
| $95^{th}$ percentile | 6.78 | 0.35 | 6.12 | 0.35 | 8.09 | 0.44 |
| $99^{th}$ percentile | 8.19 | 0.43 | 7.59 | 0.50 | 9.42 | 0.57 |
| Actual data | | | | | | |
| Estimate | 4.82 | 0.48* | 3.63 | 0.58* | 4.06 | 0.71* |
| Implied p-value | (0.18) | (0.00) | (0.24) | (0.00) | (0.33) | (0.00) |

# Appendix

## A Political risk measures

ICRG aggregates several variables such as "Government Stability", "Socioeconomic Conditions", and "Investment Profile", among others. ICRG ratings range from 0 to 100, with 100 denoting the least politically risky countries. In its Worldwide Governance Indicators (WGI), the World Bank provides publicly available assessments of the "Political Stability and Absence of Violence/Terrorism" in each country, with higher values denoting more politically stable countries.

The World Economic Survey (WES) polls national experts to assess the country economic, financial and political situation. It is conducted by the Ifo Institute for Economic Research in Munich, in cooperation with the International Chamber of Commerce, and financial support from the European Commission. Political instability ratings range from 1 to 9, with 9 denoting the most politically stable countries, while policy confidence ratings range from 0 to 100, with 100 denoting countries with the highest experts' confidence in government economic policy. Data are released in May and November of each year and are updated semiannually. An extensive discussion on and validation of these measures can be found in Gala, Pagliardi, and Zenios (2023).

The average over time of the cross-sectional correlation for each pair of measures varies from a minimum of 0.32 (WES policy-World Bank) to a maximum of 0.93 (ICRG-World Bank). Not surprisingly, economic policy is the variable characterized by the lowest correlation with the other measures – 0.55 with WES politics, 0.36 with ICRG and 0.32 with World Bank – since ICRG and World Bank focus more on political instability rather than policy uncertainty. The average across all of these pairwise cross-sectional correlations is 0.57. The cross-sectional average of the time-series correlations ranges from a minimum of 0.14 (WES policy-World Bank) to a maximum of 0.44 (WES politics-WES policy), with a grand mean across all pairs of 0.30.

# B Sample construction

## B.1 Bond returns

We set up the following algorithm to construct our dataset of country-level bond index returns. We first use the most comprehensive data of country-level total bond returns from the ICE Bank of America Government Bond Indices[15], available from Bloomberg. These are indices of government bonds with maturity greater than two years. When they are not available, we employ the Datastream Benchmark 10-year Government Bond Total Return Indices. For those countries or time periods where neither of these two sources are available, we complement our dataset using the yields to maturity of country-level ten-year government bonds from Datastream, and imputing the corresponding total bond returns using the second-order approximation of Swinkels (2019).

We validate the approximation of bond returns from available yields with two tests. First, we compute the correlations between total bond returns from Datastream, when such data are available, and the imputed returns, and we find an average cross-country correlation of 96%, with maximum of 99% (US) and minimum of 86% (Mexico). Second, we compute the absolute value of the difference between the Datastream total return and the imputed return at each month, and find consistently very low values with cross-country average 0.32%, with maximum 0.98% (Hungary) and minimum 0.15% (US). We first compute returns from local currency prices, and then convert them into USD returns using FX spot rates.

[ Insert Figure A1 Near Here ]

Figure A1 (Panel A) reports the percentage of available bond returns in our dataset per country. Our coverage is complete for many developed markets, whereas we lack data for some emerging markets especially in the 1990's. Panel B shows that the vast majority of data comes from the ICE BofA indices, except for Austria, Belgium, Denmark, Finland and New Zealand, where the Datastream Total Return Index fills around 25% of missing data. Bond returns imputed from yields extend our sample to Colombia and Israel, for which no data were available from the other two sources, and account for around or more than one third of the time-series of some emerging markets such as Russia, Brazil, Chile, India, Malaysia, Philippines and Thailand.

[15] `https://www.theice.com/market-data/indices/fixed-income-indices`, last accessed August 2021.

## B.2 FX returns

We use multiple data sources to construct our dataset also in the FX market. We compute currency depreciation rates against the USD as follows: We first use MSCI spot rates, when not available we employ exchange rates from Barclays BBI, and otherwise we use Refinitiv spot rates. All data are available in Datastream. To construct our dataset of FX excess returns we first use Datastream spot and forward rates to compute excess returns as the returns of a forward market investment that buys the foreign currency in the forward market at time $t$ and then sells it in the spot market at $t+1$,

$$r_{t+1}^{FWD} = \frac{F_t}{S_{t+1}} - 1, \tag{4}$$

where $S$ and $F$ denote, respectively, the spot and forward exchange rates, expressed as units of foreign currency per unit of domestic currency, from the perspective of a US investor. When forward rates are not available, we compute the excess returns from investing in a currency through a money-market investment as

$$r_{t+1}^{MM} = (1 + i_t^*) \frac{S_{t+1}}{S_t} - (1 + i_t), \tag{5}$$

where we denote by $i$ and $i^*$ the interest rates at home and abroad, respectively. For interest rates, we use country-level one-month deposit rates when available (Lustig, Roussanov, and Verdelhan, 2011), otherwise, following Liu and Shaliastovich (2022), we use the local three-month Treasury bill rate, and when the latter are unavailable, we sequentially resort to the one-month interbank rate or the local discount rate available in Datastream.

Our coverage in the time-series is complete for all markets, except for very few cases due to data cleaning. We apply the following screening to rule out that few outliers explain our findings. Similar to Lustig, Roussanov, and Verdelhan (2011) we remove all FX returns in the months of October, November and December 2008 due to widespread violations of the covered interest rate parity (Du, Tepper, and Verdelhan, 2018), and we exclude Turkey in the period October 2000-January 2002. We also remove from the sample Brazil until June 1994 and in January 1999, as well as Egypt in November 2016, because of large outliers due to hyperinflation in Brazil and the 48% devaluation of the Egyptian pound.[16].

[16] See `https://www.reuters.com/article/egypt-economy-currency-idUSL3N27945F`

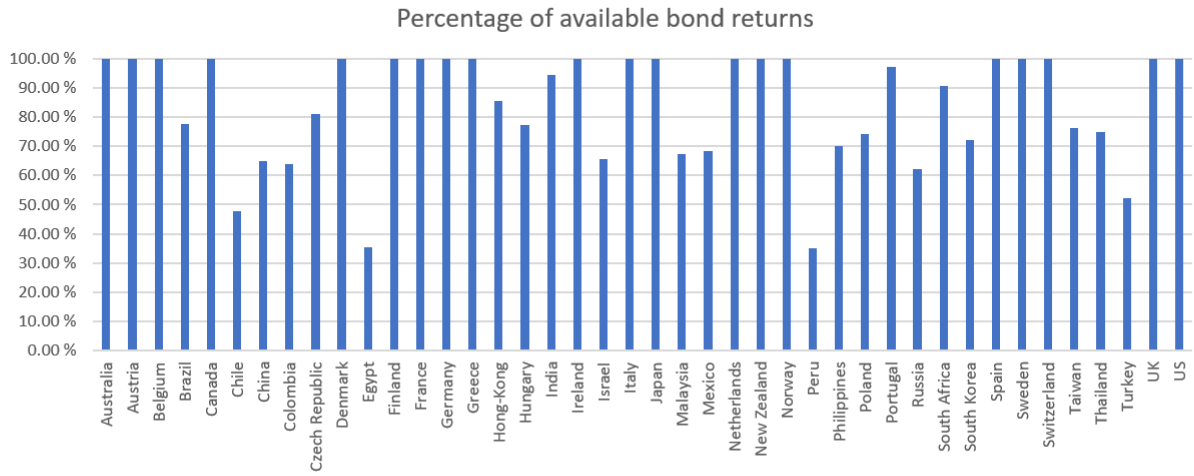
[ Insert Figure A2 Near Here ]

Figure A2 depicts pictorially the distribution of available FX returns in our dataset. As to the data sources, Panel A shows that, while we do not have forward rates for Brazil and Malaysia, currency excess returns computed as forward market investments are the main rule rather than the exception. We have more than 80% of time periods with available forward contracts for all developed markets (except for the Netherlands), and also for several emerging markets. In Panel B we validate the construction of our complete dataset by showing that FX returns computed through interest rates differentials are almost perfectly correlated with those constructed with forward contracts. The average cross-country correlation is 99.5%, with a minimum of 84% (Peru).

Figure A1: **Construction of bond sample**

This figure plots the percentage of bond returns available in the time-series of each country (Panel A), and the proportion of bond returns coming from each of the different data sources (Panel B). We apply the following algorithm to construct the sample of bond returns. Whenever available, we use total bond returns from the ICE Bank of America Government Bond Indices ("ICE BofA"). When these are not available, we employ the Datastream Benchmark 10-year Government Bond Total Return Indices, which we denote by "Datastream TRI". For those countries or time periods where neither of these two sources are available, we complement our dataset with country-level ten-year government bond yields to maturity from Datastream, and then we impute the corresponding total bond returns using the second-order approximation of Swinkels (2019). We denote these time-series by "Datastream YTM". Data are monthly and span the period 1992-2019.

**(a)** Sample distribution per country




**(b)** Data sources

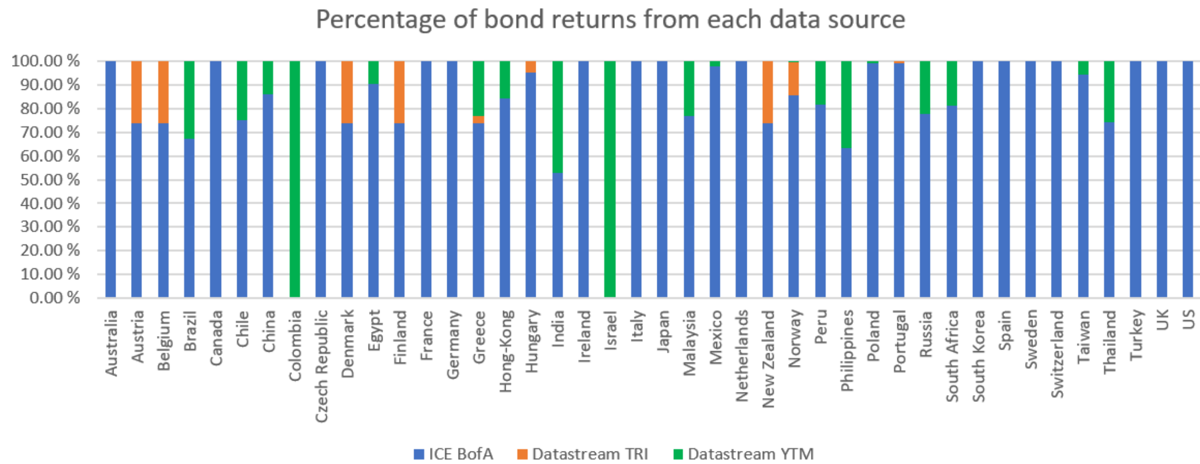
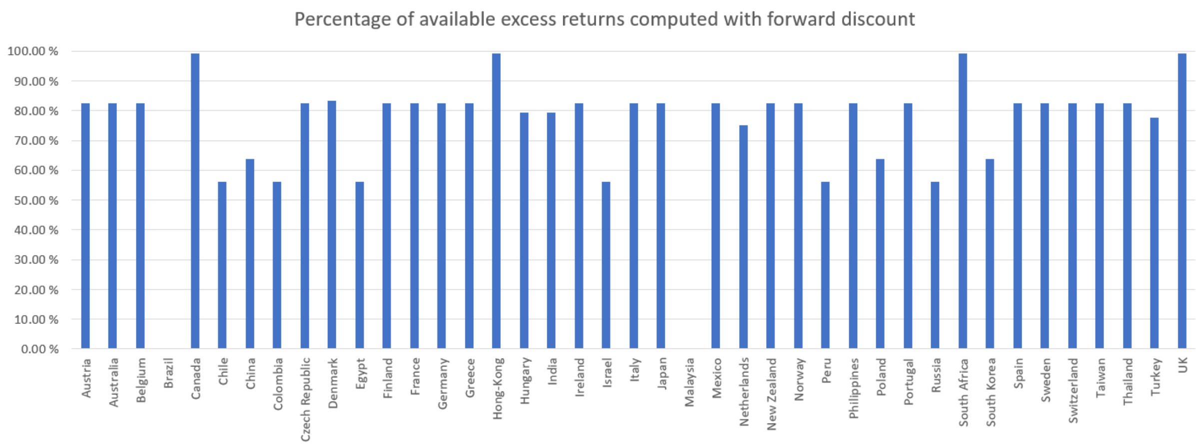


Figure A2: **Construction of FX sample**

Panel A plots the percentage of FX returns constructed as forward market investments in foreign currencies from the perspective of a US investor. Whenever forward contracts are not available, we compute the returns of money-market investments for a US investor who borrows at home and invests the proceedings abroad. The profitability of forward market investments depends on the forward discounts, while that of money-market investments depends on the interest rate differential. The two quantities are related and, if the covered interest rate parity holds, the two methods give the same result. The proportion of excess returns computed as money-market investments can be obtained as one minus the percentage displayed in Panel A. We validate the construction of our sample by displaying in Panel B the correlation coefficients between FX returns obtained as forward market investments vs those computed as money-market investments, for the time periods during which we have both series available in each country. Data are monthly and span the period 1992-2019.

**(a)** Proportion of FX excess returns computed as forward market investments




**(b)** Validation of the construction methodology of the FX excess returns

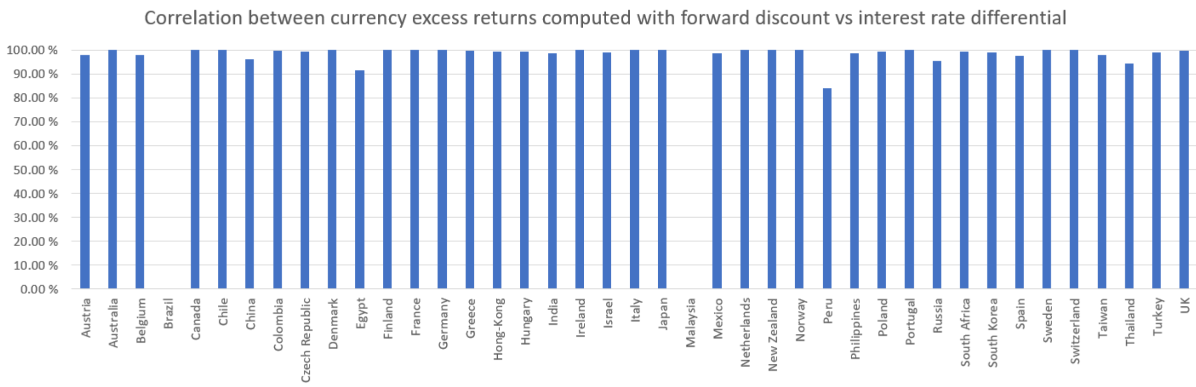


**Table A1 – Descriptive statistics of excess returns in all asset classes**

This table reports descriptive statistics of the equity, bond, and FX excess returns for every country. For each asset class, we report the average return, standard deviation, and Sharpe ratio. Returns are in percentages, denominated in USD, and include dividends. All statistics are annualized. Data are monthly, spanning 1992–2019.

| | Equity | | | Bond | | | FX | | |
|---|---|---|---|---|---|---|---|---|---|
| | Mean | StDev | Sharpe | Mean | StDev | Sharpe | Mean | StDev | Sharpe |
| Australia | 8.59 | 20.06 | 0.43 | 3.25 | 11.75 | 0.28 | 1.95 | 11.00 | 0.18 |
| Austria | 5.18 | 22.03 | 0.23 | 2.81 | 10.09 | 0.28 | -0.77 | 9.23 | -0.08 |
| Belgium | 6.99 | 19.21 | 0.36 | 3.14 | 10.18 | 0.31 | -0.66 | 9.21 | -0.07 |
| Brazil | 14.75 | 37.59 | 0.39 | 12.37 | 31.48 | 0.39 | 4.08 | 16.36 | 0.25 |
| Canada | 7.72 | 18.82 | 0.41 | 2.84 | 8.80 | 0.32 | 0.41 | 7.67 | 0.05 |
| Chile | 6.33 | 22.77 | 0.28 | 1.87 | 14.55 | 0.13 | 1.78 | 9.74 | 0.18 |
| China | 4.92 | 32.56 | 0.15 | 3.00 | 5.48 | 0.55 | -2.15 | 8.17 | -0.26 |
| Colombia | 10.01 | 27.87 | 0.36 | 11.34 | 21.58 | 0.53 | 3.01 | 12.08 | 0.25 |
| Czech Republic | 8.87 | 25.77 | 0.34 | 5.29 | 13.18 | 0.40 | 2.73 | 11.22 | 0.24 |
| Denmark | 9.59 | 18.81 | 0.51 | 2.87 | 9.86 | 0.29 | -0.32 | 9.47 | -0.03 |
| Egypt | 10.67 | 29.22 | 0.37 | 10.36 | 11.62 | 0.89 | 8.63 | 8.01 | 1.08 |
| Finland | 12.07 | 28.12 | 0.43 | 2.89 | 11.05 | 0.26 | -0.99 | 10.18 | -0.10 |
| France | 6.69 | 19.02 | 0.35 | 2.59 | 9.92 | 0.26 | -0.54 | 9.46 | -0.06 |
| Germany | 6.37 | 20.90 | 0.30 | 2.05 | 9.79 | 0.21 | -0.76 | 9.51 | -0.08 |
| Greece | 1.15 | 34.96 | 0.03 | 9.61 | 24.36 | 0.39 | 0.88 | 9.64 | 0.09 |
| Hong-Kong | 8.57 | 24.06 | 0.36 | 2.31 | 6.26 | 0.37 | -0.14 | 0.55 | -0.26 |
| Hungary | 12.22 | 33.49 | 0.37 | 4.45 | 17.90 | 0.25 | 2.90 | 12.09 | 0.24 |
| India | 9.36 | 28.77 | 0.33 | 4.68 | 9.46 | 0.49 | 1.90 | 6.70 | 0.28 |
| Ireland | 7.34 | 21.37 | 0.34 | 3.47 | 12.56 | 0.28 | -0.41 | 9.32 | -0.04 |
| Israel | 5.71 | 21.99 | 0.26 | 7.62 | 13.77 | 0.55 | 1.70 | 7.36 | 0.23 |
| Italy | 5.83 | 24.13 | 0.24 | 3.04 | 12.26 | 0.25 | -0.81 | 9.68 | -0.08 |
| Japan | 2.38 | 18.38 | 0.13 | 0.85 | 11.11 | 0.08 | -2.49 | 10.40 | -0.24 |
| Malaysia | 5.14 | 26.77 | 0.19 | 2.20 | 8.38 | 0.26 | -0.79 | 7.67 | -0.10 |
| Mexico | 7.09 | 26.92 | 0.26 | 3.42 | 14.39 | 0.24 | 3.55 | 13.15 | 0.27 |
| Netherlands | 8.29 | 18.85 | 0.44 | 2.33 | 9.90 | 0.24 | -0.78 | 9.50 | -0.08 |
| New Zealand | 10.61 | 20.26 | 0.52 | 4.62 | 12.87 | 0.36 | 3.71 | 11.62 | 0.32 |
| Norway | 8.40 | 24.29 | 0.35 | 1.25 | 10.99 | 0.11 | 0.26 | 10.60 | 0.02 |
| Peru | 13.11 | 28.68 | 0.46 | 5.19 | 10.50 | 0.49 | 1.60 | 5.77 | 0.28 |
| Philippines | 5.83 | 29.32 | 0.20 | 10.60 | 13.08 | 0.81 | 2.07 | 8.17 | 0.25 |
| Poland | 15.52 | 43.62 | 0.36 | 5.46 | 15.31 | 0.36 | 3.90 | 11.99 | 0.33 |
| Portugal | 4.00 | 21.77 | 0.18 | 4.51 | 13.29 | 0.34 | -0.41 | 9.57 | -0.04 |
| Russia | 21.21 | 46.03 | 0.46 | 5.30 | 20.19 | 0.26 | 13.21 | 24.21 | 0.55 |
| South Africa | 10.02 | 25.66 | 0.39 | 3.65 | 21.20 | 0.17 | 1.56 | 14.53 | 0.11 |
| South Korea | 9.09 | 34.72 | 0.26 | 3.48 | 12.34 | 0.28 | 1.47 | 12.91 | 0.11 |
| Spain | 7.00 | 22.90 | 0.31 | 2.65 | 11.45 | 0.23 | -1.01 | 9.32 | -0.11 |
| Sweden | 10.47 | 23.69 | 0.44 | 1.24 | 11.36 | 0.11 | -1.08 | 11.13 | -0.10 |
| Switzerland | 9.05 | 15.75 | 0.57 | 2.92 | 11.22 | 0.26 | -0.41 | 10.33 | -0.04 |
| Taiwan | 6.06 | 27.85 | 0.22 | 2.92 | 5.69 | 0.51 | -1.35 | 5.12 | -0.26 |
| Thailand | 7.95 | 33.42 | 0.24 | 6.39 | 10.18 | 0.63 | 1.96 | 9.61 | 0.20 |
| Turkey | 15.82 | 49.10 | 0.32 | -0.57 | 24.72 | -0.02 | 8.91 | 16.52 | 0.54 |
| UK | 5.48 | 15.45 | 0.35 | 2.70 | 9.11 | 0.30 | 0.33 | 8.68 | 0.04 |
| US | 8.20 | 14.48 | 0.57 | 2.79 | 4.33 | 0.64 | — | — | — |
| Average | 8.56 | 26.18 | 0.34 | 4.18 | 12.80 | 0.34 | 1.38 | 10.18 | 0.10 |

## Table A2 – Correlations of asset-class specific risk factors

This table reports correlations among the risk factors of the benchmark models and of the global political factor (P-factor), with all factors being computed specifically in the equity (Panel A), bond (Panel B) and FX markets (Panel C). The benchmark factors are MKT (MSCI AC World for equities, and an equally-weighted portfolio of, respectively, all bond excess returns and FX returns in the sample), SMB (small minus big), HML (high minus low), RMW (robust minus weak), CMA (conservative minus aggressive), all from Fama and French (2017), WML (winners minus losers, from Carhart (1997)), MOM (momentum) and VAL (value) factors from Asness, Moskowitz, and Pedersen (2013), TSM (time-series momentum, from Moskowitz, Ooi, and Pedersen (2012)), and BAB (international betting against beta, from Frazzini and Pedersen (2014)), CAR (asset-class specific carry factors of Koijen, Moskowitz, Pedersen, and Vrugt (2018)), TERM (term spread on U.S. government bonds), DEF (default spread between U.S. corporate bonds and U.S. Treasuries), and $HML_{FX}$ (FX carry factor of Lustig, Roussanov, and Verdelhan (2011)). Data are monthly, spanning 1992–2019.

### (a) Equity

| | P-factor | MKT | SMB | HML | RMW | CMA | WML | MOM | VAL | TSM | BAB |
|---|---|---|---|---|---|---|---|---|---|---|---|
| P-factor | | | | | | | | | | | |
| MKT | 0.03 | | | | | | | | | | |
| SMB | 0.16 | -0.11 | | | | | | | | | |
| HML | -0.08 | -0.14 | 0.01 | | | | | | | | |
| RMW | -0.07 | -0.42 | -0.25 | 0.17 | | | | | | | |
| CMA | -0.17 | -0.40 | -0.04 | 0.73 | 0.19 | | | | | | |
| WML | -0.05 | -0.25 | 0.14 | -0.26 | 0.15 | -0.05 | | | | | |
| MOM | -0.03 | -0.16 | 0.06 | -0.09 | 0.23 | -0.03 | 0.52 | | | | |
| VAL | 0.17 | 0.27 | 0.18 | 0.34 | -0.21 | 0.09 | -0.23 | -0.45 | | | |
| TSM | 0.04 | 0.12 | -0.06 | -0.03 | 0.06 | -0.01 | 0.44 | 0.39 | -0.04 | | |
| BAB | -0.07 | -0.25 | 0.22 | 0.45 | 0.43 | 0.39 | 0.26 | 0.19 | 0.09 | 0.08 | |
| CAR | 0.04 | -0.02 | 0.03 | -0.08 | 0.00 | -0.01 | -0.07 | -0.08 | 0.09 | -0.11 | 0.04 |

### (b) Bond

| | P-factor | MKT | TERM | DEF | MOM | VAL | TSM | BAB |
|---|---|---|---|---|---|---|---|---|
| P-factor | | | | | | | | |
| MKT | -0.15 | | | | | | | |
| TERM | -0.23 | 0.21 | | | | | | |
| DEF | 0.21 | 0.25 | -0.56 | | | | | |
| MOM | -0.12 | 0.13 | 0.24 | -0.07 | | | | |
| VAL | 0.00 | -0.08 | -0.24 | 0.09 | -0.26 | | | |
| TSM | -0.22 | 0.15 | 0.65 | -0.39 | 0.38 | -0.21 | | |
| BAB | 0.08 | -0.19 | -0.30 | 0.15 | -0.15 | 0.09 | -0.08 | |
| CAR | -0.09 | 0.21 | 0.26 | -0.13 | 0.24 | -0.27 | 0.20 | -0.08 |

### (c) FX

| | P-factor | MKT | Carry | MOM | VAL | TSM | BAB |
|---|---|---|---|---|---|---|---|
| P-factor | | | | | | | |
| MKT | -0.47 | | | | | | |
| $HML_{FX}$ | 0.24 | 0.26 | | | | | |
| MOM | -0.02 | 0.06 | 0.10 | | | | |
| VAL | 0.00 | -0.04 | -0.18 | -0.46 | | | |
| TSM | -0.08 | -0.02 | 0.02 | 0.69 | -0.30 | | |
| BAB | 0.33 | -0.14 | 0.18 | -0.06 | 0.15 | -0.11 | |
| CAR | 0.01 | 0.36 | 0.66 | 0.15 | -0.25 | 0.00 | 0.16 |