Political Risk Everywhere

Vito D. Gala Giovanni Pagliardi
Ivan Shaliastovich Stavros A. Zenios*

DRAFT of October 2023. Do not quote or distribute.

Abstract

We show that country risk premia include compensation for global political risk. Political risk premia drive international returns within and across asset classes, including equities, bonds, and currencies. A strong factor structure in politically sorted portfolios uncovers systematic variations in global political risk (P-factor). The P-factor commands a significant risk premium of 4.44% per annum with a Sharpe ratio of 0.70, and together with the global market portfolio, it explains up to three-quarters of cross-sectional variation in a large panel of asset returns. The P-factor is unspanned by the existing asset pricing factors, manifests in all asset classes, and is related to systematic variations in expected global growth and aggregate volatility.

JEL Classification: E62, F30, G15, G18.

Keywords: political risk, international equities, bonds, FX, asset pricing.

*Vito D. Gala is at Morningstar Investment Management LLC, USA, vito.gala@gmail.com; Giovanni Pagliardi is at BI Norwegian Business School, giovanni.pagliardi@bi.no; Ivan Shaliastovich is at Wisconsin School of Business, University of Wisconsin-Madison, ivan.shaliastovich@wisc.edu; Stavros A. Zenios is at University of Cyprus, zenios.stavros@ucy.ac.cy, Member of the Cyprus Academy of Sciences, Letter, and Arts, and Non-resident Fellow at Bruegel. Corresponding author: Giovanni Pagliardi, BI Norwegian Business School, Nydalsveien 37, N 0444 Oslo, Norway, Phone: +47 464 10 547. We thank George Constantinides, Bruno Gerard, Richard Priestley, and seminar and conference participants at BI Norwegian Business School, and the School of Economics and Management University of Cyprus, for comments and suggestions. The views contained herein are not necessarily those of Morningstar Investment Management LLC.

1 Introduction

Understanding the fundamental differences in expected returns across risky assets is one of the key questions in financial economics (Cochrane, 2011). A current challenge in this literature is to identify a few systematic factors that could successfully explain the large panel of average returns not only within but also across asset classes.[1] We identify global political risk as one such factor, which, together with the market portfolio, affects systematic variations in risk premia across and within stocks, bonds, and currencies in the global markets.

Global political risk is an often-used but rarely defined label in media, industry, and academic and policy circles. It is anecdotally applied to major political events around the globe, such as Brexit, US elections, or the recent war in Ukraine, to local events, such as the resignation of a prime minister (Berlusconi or Draghi in Italy) or the change of chancellor (Scholz succeeding Merkel in Germany), among many other examples. It is a complex and multi-faceted concept with several ways suggested for measuring it.[2] The main challenges for the literature and the key contributions of our paper are to quantify reliable measures of political risk, document its economic relevance, and show its significance in global financial markets.

The starting point for our analysis is country-level proxies for the multiple dimensions of political risk, namely the International Country Risk Guide-ICRG (PRS, 2005)), the World Bank (World Bank, 2018), and the Ifo World Economic Survey-WES (Becker and Wohlrabe, 2007), for a large cross-section of 42 countries over a 1992-2019 sample period. The country-level rankings based on political risk proxies exhibit a strong factor structure, which suggests common fluctuations in political risk around the world. Motivated by this evidence, we take a “combo” approach and aggregate across the available proxies. This helps to reduce noise and sharpen the identification. However, we show that our results

[1] Recent examples for asset-pricing “everywhere” include 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), intermediary capital risk (He, Kelly, and Manela, 2017).

[2] See political science works by Frei and Ruloff (1988); Jarvis and Griffiths (2007); Jong-A-Pin (2009); Oetzel, Bettis, and Zenner (2001), the second edition of the 1982 book by Kobrin (2022), and the recent book by Sottilotta (2016). From the finance literature, see Bekaert, Harvey, Lundblad, and Siegel (2014); Howell (2014), and from management see Bremmer (2005); Fitzpatrick (1983).

are not driven by any particular political risk proxy.

We provide strong evidence that market investors incorporate concerns about political risks into asset prices. Sorting countries on the political risk measures generate near-monotonic cross-sections of average returns in equity, fixed income, and currency markets in local currency or dollar units. On average, 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. In equity markets, the spread ranges between 8.91% for World Bank and 13.61% for ICRG sorts and reaches 13.20% for a combo average across proxies. Likewise, we observe sizeable spreads in average bond and FX returns of 5.40% and 4.50%, respectively, for a combo approach.

The long-short portfolio return spread in each asset class and for each ranking provides a natural albeit mechanical choice for the risk factor to explain the corresponding cross-section. Rather than generating 4×3 political risk factors, one for each of the three asset classes and four ranking choices, we show that one global P-factor, constructed across all the assets and political risk proxies, does a remarkably good job summarizing the relevant financial market information. In that sense, political risk is "everywhere": it manifests in all the asset classes and proxies and can be meaningfully extracted from any of those, and the asset- or ranking-specific information does not materially enhance its importance.[3]

For the first set of asset-pricing results, we use our benchmark GPSZ model which utilizes a global market and political risk factor to price 60 assets in the base case or 210 assets in the extended set.[4]. We show that stock indices, 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 4.4% using the base set of test assets, with t-statistic well above the critical threshold of three advocated by Harvey, Liu, and Zhu (2016). The GRS test cannot reject the null that all pricing errors are jointly zero for our model, and a cross-sectional R^2 reaches

[3]Specifically, we run an out-of-sample comovement test in the spirit of Asness et al. (2013). in which we use the political risk factor from one asset or rating category to price portfolio sorts on all the remaining ones. Consistent with the global nature of political risk, the predicted and realized returns center around the 45 degree line, with R^2s similar to the benchmark.

[4]The base set consists of the four portfolios from each of the three asset classes for all the four proxies of political risk, and twelve spread portfolios of the four L-H strategies with the four different political risk measures in each of the three asset classes. The extended set adds to the base portfolios the 126 country returns from all three asset classes, 9 global value and 9 global momentum portfolios from Asness, Moskowitz, and Pedersen (2013), and 6 currency portfolios sorted by forward discounts from Lustig, Roussanov, and Verdelhan (2011)

0.74 for base set of assets and 0.62 in the extended set. Panel A of Figure 1 visually demonstrate that the model-predicted and realized average returns cluster around the 45-degree line, within and across asset classes.

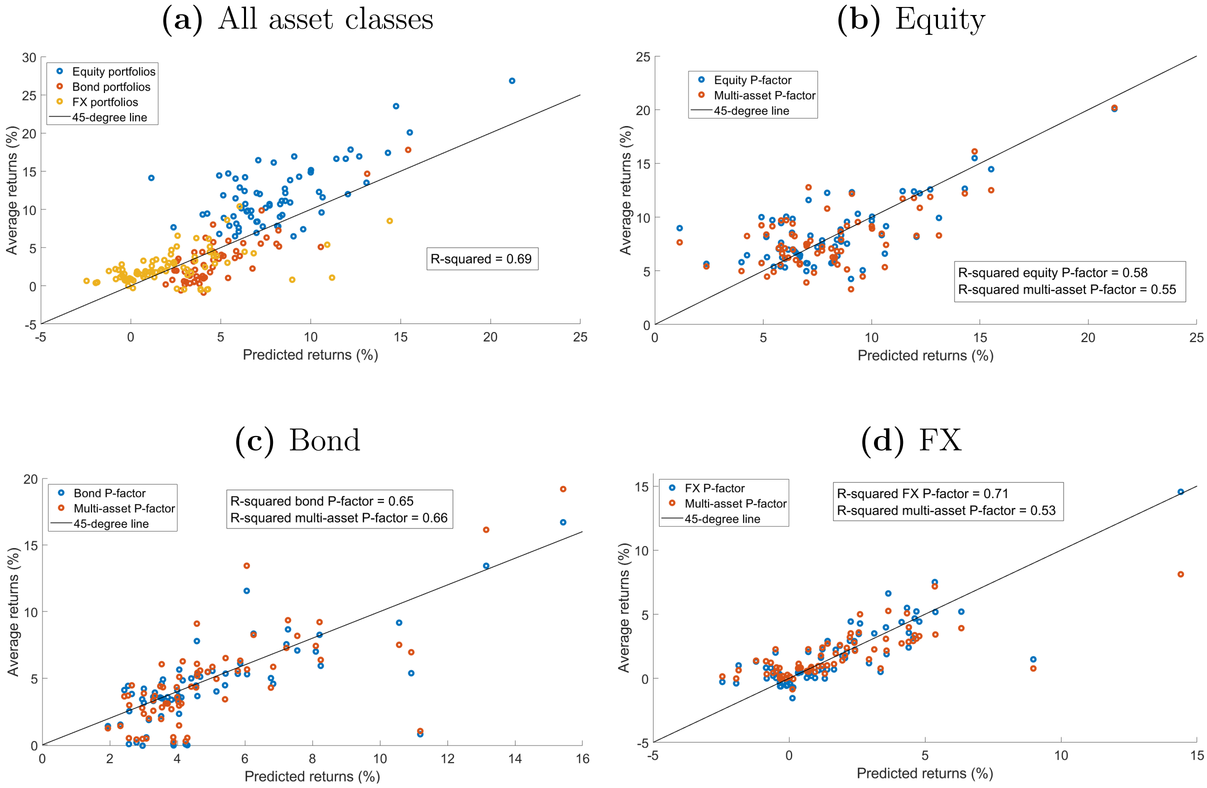
While we do not aim to run a horse race across all the available models of asset returns, we document that the GPSZ model performance substantially improves on the existing factors in the literature. Indeed, the global multi-asset P-factor is not spanned by the traditional factors of "everywhere" asset pricing models constructed across asset classes, such as the global market factor, value and momentum (Asness, Moskowitz, and Pedersen, 2013), time-series momentum (Moskowitz, Ooi, and Pedersen, 2012), betting against beta (Frazzini and Pedersen, 2014), or carry (Koijen, Moskowitz, Pedersen, and Vrugt, 2018). These traditional factors struggle to explain the cross-section of political risk sorted portfolios, each having mean pricing errors larger than the GPSZ model.

We next zoom in on the performance of the model within each asset class or political proxy choice separately. The political risk premium estimates are significant in all three markets, with 3.53% in equities, 3.26% in bonds, and 5.93% in currencies, similar to the multi-asset average. The benchmark global GPSZ model still exhibits lower pricing errors and better or at least comparable cross-sectional R^2 than the best-performing alternative models. This is quite remarkable, given the fact that the model relies on the same two global factors to price securities within each of the three asset classes, while the alternative specifications utilize a variety of asset-specific risk factors. Turning to a variation of the GPSZ model, which uses local rather than global versions of the factors, for each asset class, we show that the biggest improvement comes from using the local market factor, while the gains from asset-specific over multi-asset P-factor are very marginal. Panels B to D of Figure 1 show a similar performance of the model with global or local political risk factors. The differences become even smaller when we consider extracting the P-factor from sorts based on a specific proxy than the combo average. Again, this underscores the main message of the paper that the political risk factor is everywhere.

We present additional evidence to help identify and isolate the channels through which political risk affects prices and examine the economic and statistical margins of its performance. Following Liew and Vassalou (2000), we document that the multi-asset P-factor forecasts global economic growth with positive sign at 3-, 6-, and 12-month horizons. Similarly, the multi-asset P-factor correlates positively with a measure of cross-country capital flows (Miranda-Agrippino and Rey, 2020), and negatively with a measure of global recession and with variables capturing second-moment effects such as the VIX index, global

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, 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.



risk aversion (Bekaert, Engstrom, and Xu, 2022), global volatility (Miranda-Agrippino and Rey, 2020), and global economic policy uncertainty (Baker, Bloom, and Davis, 2016). This helps put our asset-pricing evidence into a risk-based context whereby an increase in the P-factor is associated with systematically good news about the economy and an asset which is positively exposed to the factor under-performs in adverse economic times and earns a positive risk premium.

Finally, we construct several alternative political factors by i) demeaning the ICRG political ratings, ii) orthogonalizing them on the corresponding ICRG economic ratings, and iii) orthogonalizing them on observable macroeconomic variables. We find that all of these political factors are consistently priced with comparable prices of risk. While the first test uncovers the presence of substantial within-country time-series variation in political ratings that can be exploited for pricing, with results not being purely driven by cross-sectional differences in their average values, the other two tests confirm that political variables embed information content that goes above and beyond macroeconomic variables. The multi-asset P-factor remains significant in pricing tests when including other global variables such as the VIX index and an emerging market portfolio, and its performance is mostly driven by the high political risk countries, thus ruling out potential implementability concerns due to trading constraints on short selling.

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, 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 financial market 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 (Cochrane, 2011; 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 dealing 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.

The present paper takes our earlier work (Gala, Pagliardi, and Zenios, 2023) to several new directions. Mainly, we show that political risk affects returns not only across countries in the equities markets, as in the previous paper, but also across asset classes. To arrive at this result, we first recognize that there is no consensus on how to measure political risk, and we go a step further from our earlier work to construct the risk factor as an aggregate of several currently available ratings. In this sense, political risk is everywhere in the available ratings. We also show that political risk affects returns in each asset class separately, echoing Asness et al. (2013), who showed that value and momentum are present in other classes beyond equities, and Koijen et al. (2018) who showed that carry is present beyond FX. These two papers laid the foundation for the extensive "everywhere" literature in footnote 1, and in this paper, we first set the stage to document political risk everywhere. In Table 1, we illustrate the process of constructing the global multi-asset P-factor using multiple ratings, providing also a guide to the organization of our paper. We go further beyond our earlier work to show that political risk predicts global GDP growth and identify several channels, including global volatility, risk aversion, economic policy uncertainty, and cross-border capital flows.

2 Data

We describe the data and empirical methodology for measuring political risk and constructing political portfolios and factors within and across asset classes. All the supportive evidence is relegated to the Appendix.

2.1 Political risk measures

We consider multiple proxies to capture political risk. The ICRG expert assessments (PRS, 2005) are the most common gauge of political risk in the literature, and we use them as our first political risk measure.[5] These ratings are particularly appealing as they have been shown to predict political risk realizations (Bekaert, Harvey, Lundblad, and Siegel, 2014). The Ifo World Economic Survey (Becker and Wohlrabe, 2007) surveys country experts to provide ratings on political instability and confidence in government

[5] See among many others, Gourio, Siemer, and Verdelhan 2015; Herrera, Ordonẽz, and Trebesch 2020.

Table 1 – Constructing the global multi-asset P-factor

This table describes the structure and displays the average return in % of the asset- and rating-specific political risk factors and the global multi-asset P-factor. The 4 x 3 entries in the middle denote *asset-rating P-factors*, i.e., the asset- and rating-specific political risk factors for each asset class using each political rating. These are constructed by portfolio sorts on the country ratings used in this paper (ICRG, WES Politics, WES Policy, World Bank), respectively, and forming portfolios going long in the corresponding asset class of countries with low political ratings (L) and short in the asset class of countries with high ratings (H). The construction of these factors is discussed in section 3.1 with the annual average returns of the L-H portfolios given in Table 2. The last row ("Combo") lists the *asset class P-factors* obtained by equally weighted averaging the rating-specific factors for each asset class. The construction of these factors is also discussed in section 3.1 with the annual average returns of the L-H combo portfolio given in the last column of Table 2. The main factor proposed in this paper is the *global multi-asset P-factor*, listed in the bottom right corner. This is computed as the inverse volatility-weighted average of the last row's asset class-specific factors as discussed in section 3.2. Equivalently, it can be constructed as the equally weighted average of the *multi-asset P-factors* of the last column, obtained by inverse volatility-weighted averaging horizontally for each political rating across asset classes in section 4.4.

		Asset classes			Multi-asset factors
		Equities	Bonds	FX	
Political ratings	ICRG	5.87	4.16	5.38	ICRG P-factor 5.04
	WES politics	4.92	3.98	4.13	WES politics P-factor 4.22
	WES policy	5.80	2.58	3.13	WES Policy P-factor 3.38
	World Bank	6.00	4.59	4.68	World Bank P-factor 4.92
Asset class factors	Combo	Equity P-factor 5.84	Bonds P-factor 3.61	FX P-factor 4.50	**Global multi-asset P-factor 4.44**

economic policy. These ratings were validated by Gala, Pagliardi, and Zenios (2023), who show that global ratings deteriorate with local political shocks having strong spillover effects across countries and rule our reverse causality from sixteen macroeconomic and financial variables. The World Bank (World Bank, 2018) reports the perceptions of its internal experts on the likelihood of political instability in a country.[6]

[6]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.

All the data are available for a cross-section of 42 countries from 1992 to 2019.[7] ICRG data are at a monthly frequency, WES variables are semiannual, and the political instability index from the World Bank is available bi-annually from 1996 and annually since 2000. As we discuss in the Appendix A, the measures of political risk are imperfectly correlated with each other. The average over time of the cross-sectional correlation for each pair of measures varies from 0.32 to 0.93, while the cross-sectional average of the time-series correlations is in the interval 0.14–0.44. Using the asset-market data, the correlations between the political risk measures across the four sources strengthen to a 0.53-0.93 range, as we subsequently show in Section 3.2. A positive correlation between alternative measures gathered from different sources helps validate the notion that they provide consistent, albeit noisy, measures of underlying political risk. As such, in our work, we use both the stand-alone measures and the combo index, which aggregates across all available proxies.

2.2 Political risk measures factor structure

A key premise in our work is that the political ratings from the surveys capture the exposure to systematic, global political risk, and are not merely reflecting idiosyncratic country characteristics.

For an illustration, we depict the GDP-weighted average of the countries' political ratings, aggregated across the available sources, in Figure 2.[8] The index shows clear negative spikes, which correspond to higher political risk, around global political or policy shocks such as Brexit, the Arab Spring, the Eurozone debt crisis, the Lehman Brothers bankruptcy and TARP legislation in late 2008, and the Asian crisis. The index increases with positive news such as the deal on the EU constitution, the agreement on the deputy of the Euro, and Clinton's survival of impeachment charges. Figure 2 also contrasts the time-series dynamics of this global political rating with a smoothed version of our global multi-asset P-factor.[9] The comovement of these two series is apparent and corroborated by a correlation coefficient of 0.59. The P-factor experiences its worst returns in

[7] The MSCI classification includes 23 developed and 23 emerging markets and we exclude the four countries without WES data (Indonesia, Kuwait, Saudi Arabia, Singapore).

[8] Following Baker, Bloom, and Davis (2016) and Caldara and Iacoviello (2022), we first standardize country-level ratings for each of the four political measures. We take a country-level equally weighted average of the standardized ratings of the four measures, and produce a single time-series of political ratings for each country. We average the country-level merged ratings using the country GDP weights.

[9] The smoothed P-factor is constructed as an average of the previous four-year P-factor returns, then rescaled by multiplying these values by 100.

correspondence with a deterioration of global political ratings.

[Insert Figure 2 Near Here]

To start building empirical evidence for this claim, we run a principal component analysis on one of the ratings (ICRG) of all the countries in our sample. On average, the first principal component explains over 50% of the cross-sectional variation in the political ratings across 42 countries, and the fraction goes up to 80% for the three components. The fraction remains quite stable over time, reaches a peak of around 70% for the first principal component, and fluctuates between 70% and 90% over for three components using 10-year rolling windows, as shown in Figure 3. All this evidence suggests a common, systematic nature of political risk across countries.

[Insert Figure 3 Near Here]

In subsequent sections, we expand and sharpen the measurement of systematic political risk by incorporating broad financial market data in addition to the political ratings across countries.

2.3 Asset returns

We follow the MSCI classification to obtain equity, bond, and foreign currency returns for our sample of 42 countries, spanning January 1992 to December 2019.

For equities, we use monthly returns of the MSCI Investable stock market indices, including dividends.[10] 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.

For bond returns, we gather monthly 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 (2019). Details on the sample construction are in Appendix B.

[10]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.

For FX returns, we first use 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 rate differentials are almost perfectly correlated with those constructed with forward contracts. Details on the sample construction are in Appendix B.

2.4 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 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 Ralph Koijen's website, while the carry trade risk factor in currency markets is from the website of Adrien Verdelhan.[11]

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.

Country-level quarterly real GDP and monthly CPI, and monthly values of the CBOE volatility index VIX are from Datastream. We construct a global GDP growth variable and recession dummy using World Bank data of GDP at constant 2010 USD as country weights. We retrieve the global risk aversion index from Nancy Xu's website, the global volatility and global cross-country capital flows from Silvia Miranda-Agrippino's website, and the global economic policy uncertainty (EPU) from Nickolas Bloom's website.[12]

[11]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).

[12]The data are available at `https://data.worldbank.org/indicator/NY.GDP.MKTP.KD` (World

3 Global multi-asset political risk factor

3.1 Political risk portfolios

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.[13] 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.[14] We report results with portfolio sorts on the four political risk measures separately. Following Asness, Moskowitz, and Pedersen (2013) we also use a *combo* strategy as an equally weighted combination of the four portfolio sorts on the different political risk measures.

Table 2 (Panel A) shows the monotonic patterns in local currency returns of portfolios sorted on political risk ratings. The spread in average returns between portfolio L and H is always economically and statistically significant at conventional levels. In equity markets, it ranges between 8.91% for World Bank and 13.61% for ICRG sorts, and reaches a high 13.20% for the combo strategy. Likewise, we observe sizeable spreads in average bond returns, from 3.29% for WES Policy to 6.82% with ICRG sorts, and 5.40% with combo. These results in local currencies disentangle the impact of political risk from that of currency risk, and validate the importance of political risk for cross-sectional return predictability, in line with Gala, Pagliardi, and Zenios (2023)

[Insert Table 2 Near Here]

The cross-sectional predictability can be exploited by the US investors, as we show in Panel B of Table 2. Indeed, average portfolio USD returns exhibit a generally increasing pattern in political risk, and the spreads between the extreme portfolios remain statistically significant. The USD spreads are smaller than those in local currency units, but remain economically significant, with the L-H combo strategy reaching an average return ranging from 5.87% in the equity market to 4.5% in currencies and 3.61% in the bond

Bank GDP), `https://www.nancyxu.net/risk-aversion-index` (global risk aversion), `http://silviamirandaagrippino.com/code-data` (global volatility and cross-country capital flows, data are available only until December 2012), and `https://www.policyuncertainty.com/global_monthly.html` (global economic policy uncertainty).

[13]We follow Lustig et al. (2011) and form equally-weighted portfolios to isolate political risk from size effects. Value-weighting the countries would systematically result in overly concentrated portfolios in a few countries that dominate the world market cap, such as the US.

[14]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.

market. The smaller spreads in USD are consistent with the evidence that the currencies of countries with high political risk depreciate more against the USD; see Brogaard, Dai, Ngo, and Zhang (2020) and the FX results in the Panel B of the Table.

Interestingly, the spread portfolios of the combo strategies have nearly always stronger statistical significance and higher Sharpe ratios than the individual rating strategies — the Sharpe ratios are 0.48 vs a maximum of 0.42 for equities, 0.51 vs 0.55 for bonds, and 0.69 vs 0.62 for FX. Combo strategies exhibit lower volatility than the stand-alone ones, potentially due to the fact that aggregating across various measures help decrease the noise in capturing political risk.[15]

3.2 Global factor structure

The key economic message we establish in this paper is that systematic political risk is pervasive across all asset classes and affects prices in equity, bonds, and FX across countries.

To validate this claim, we consider the entire universe of equity, bond, and currency portfolios sorted on four different proxies of political risk. We then run a principal component analysis on the returns of these $4 \times 4 \times 3$ political-risk sorted portfolios for all asset classes.[16] The results, reported in Table 3, confirm a strong global factor structure in returns.

[Insert Table 3 Near Here]

Panel A shows that the first principal component explains nearly 70% of the total return variation, and the first two explain up to 84%. The marginal contribution of the third principal component drops to under 4%. 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 have lower political ratings and thus exhibit higher average returns across all asset classes.

This evidence motivates the construction of our two global factors akin to the level and

[15] 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 a maximum correlation of 0.46, 0.54, 0.47 and 0.44, respectively.

[16] We do not include "combo" since it is a linear combination of the other four.

slope of portfolio returns.[17] Naturally, the level factor is the market portfolio. To proxy for the market portfolios we take the MSCI All Countries World index for equities, and for fixed income and FX an equally weighted average of, respectively, the bond and currency excess returns in our sample. The second factor is our novel *multi-asset global P-factor*, constructed from the three asset-class specific combo strategy portfolio returns in Panel B of Table 2. We aggregate the asset class specific market and political risk factors to the corresponding global multi-asset ones by taking inverse-volatility portfolios of the asset-class specific market portfolios and political factors, where the weights assigned is the proportion of the total inverse in-sample volatility of all asset classes explained by each asset class (Asness, Moskowitz, and Pedersen, 2013).[18] The global market correlates 99% with the first principal component (and only 2% with 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. Notably, the second principal component exhibits high correlations with the political risk factors within each of the rating source, and not just their global average. The correlations range from 0.54 for the P-factor constructed using the WES Policy measure to 0.70 for the WB Politics.

[Insert Figure 4 Near Here]

Figure 2 shows that the smoothed P-factor follows similar dynamics to the average level of the political ratings across countries. Figure 4 plots the cumulative return on the global market and P-factor together with their asset-class specific counterparts. Consistent with the principal component analysis, the global multi-asset P-factor follows similar dynamics to the asset-class specific P-factors, with correlation coefficients ranging from 0.73 with the equity P-factor to 0.84 with the bond P-factor. Similarly, the global market factor co-moves with the asset class specific market portfolios. This evidence motivates our benchmark choice of the global market and P-factor as the key drivers of the political-risk sorted returns across the three asses classes and across countries. In Sections 4.3 and 4.4 we consider the variations of the model which rely on local versions of these factors.

Table 4 Panel A reports descriptive statistics for the global multi-asset market and P-factor. They both carry a strongly statistically significant risk premium, 3.83% for the

[17]In Sections 4.3 and 4.4 we examine "local" versions of the model with asset-specific market factors and asset- or ranking-specific political risk factors.

[18]The inverse-volatility 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.

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 further shows that the global multi-asset P-factor is not spanned by the traditional factors of asset pricing models constructed across asset classes. In particular, we run four spanning regressions (Barillas and Shanken, 2017) of the P-factor on the "everywhere" global market factor, value and momentum (Asness, Moskowitz, and Pedersen, 2013), or time-series momentum (Moskowitz, Ooi, and Pedersen, 2012), or betting against beta (Frazzini and Pedersen, 2014), or carry (Koijen, Moskowitz, Pedersen, and Vrugt, 2018). Additionally, we run the spanning regression on all the factors above. The alphas range from 4.62% to 8.97%, all statistically significant, with corresponding information ratios in the range 0.73–1.24. The adjusted R^2 are very low, in the interval 0.03–0.19. This empirical evidence is further corroborated by the low correlations of the global multi-asset P-factor with all other factors, with average absolute correlation coefficients of about 0.15.

[Insert Table 4 Near Here]

3.3 Political risk factor and the macroeconomy

The asset-pricing theory dictates that systematic risk factors affect the marginal utility of investors, and thus are related to movements in conditional expectations, volatilities, or higher moments of economic fundamentals. An asset that is exposed to the factor and under-performs in adverse economic times is risky and earns a positive risk premium. We provide here reduced-form evidence for the connection of the political risk factor to global macroeconomic conditions, although we do not provide a fully-fledged economic model to micro-found the factor.

Table 5 documents a relation of the global market and the P-factor to various proxies for the conditional first and second moments of global growth. Panel A shows that both the global multi-asset market and political factor predict global real GDP growth at 3-, 6-, and 12-month horizons, reaching an R^2 of up to 15%. All the loadings are positive and statistically significant; in particular, the P-factor remains significant controlling for the global market factor. The positive sign of the beta coefficients is consistent with a risk-based view that the factors perform poorly (i.e., the market and P-factor returns are low) in bad times of low expected GDP growth.

In a similar vein, Panel B of the Table shows that the two factors significantly underperform in global recessions, measured as the times of global GDP growth falling below the 30th percentile of its unconditional distribution.[19] The P-factor also falls at times of large increases in the VIX, global volatility, global risk aversion, and global EPU. Poor performance of the P-factor is also associated with a lower volume of cross-country capital flows. In all these specifications, the P-factor is a significant determinant of current and expected economic fundamentals beyond the market-level effects. Motivated by this macroeconomic evidence, we next consider the performance of the factors to price the broad cross-section of equity, bond, and currency returns across countries.

[Insert Table 5 Near Here]

4 Cross-sectional pricing of political risk

4.1 Asset-pricing framework

Our benchmark two-factor model (henceforth GPSZ multi-asset model) consists of the multi-asset market portfolio and the multi-asset P-factor of Section 3.2.

Our base set of testing assets includes all four portfolios from each of the three asset classes for the four proxies of political risk, which produces 48 ($= 4 \times 4 \times 3$) test portfolios.[20] We further 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 base set thus includes 60 test assets. We also consider an extended set which includes, in addition to the base portfolios, the 126 country returns from all three asset classes,[21] 9 ($= 3 \times 3$) global value and 9 ($= 3 \times 3$) global momentum portfolios from Asness, Moskowitz, and Pedersen (2013), and 6 currency portfolios sorted by forward discounts from Lustig, Roussanov, and Verdelhan (2011).

Following the standard methodology, we fit the model to the data and perform a statistical

[19] 30th percentile of the distribution provides a reasonable tradeoff between a number of observations and the identification of recession periods. The results are similar for other choices of the cutoff.

[20] We do not include "combo" since it is a linear combination of the other four and is mechanically priced by the P-factor.

[21] We exclude Turkey from the extended set of test assets since its P-factor loading in the bond markets is implausibly high cross-sectional standard deviation from the mean). Including such an outlier would bias the results in favor of our model.

inference. We estimate each test asset's loadings on the risk factors by running the first-step time-series regressions and then running 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 an 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 both the OLS and GLS R^2s.

In our primary analysis, we use the entire set of assets to estimate the model and assess the asset-pricing performance of the global multi-asset market and P-factor. That is, in the spirit of *across asset class* pricing literature, we test the model's ability to jointly price equity, bond, and currency portfolios across countries and rating measures. In Sections 4.3 and 4.4, we examine the asset-pricing performance of the model within each asset class or rating measure separately.

.

4.2 Asset pricing evidence: everywhere

We examine the ability of our two-factor model to price the base and extended sets of assets and compare its performance to that of existing factors constructed across asset classes, such as value and momentum (Asness, Moskowitz, and Pedersen, 2013), time-series momentum (Moskowitz, Ooi, and Pedersen, 2012), betting against beta (Frazzini and Pedersen, 2014), and carry (Koijen, Moskowitz, Pedersen, and Vrugt, 2018).

We report our main empirical results in Table 6. Panel A of the Table documents that both the global market and the P-factor have positive and significant estimates of the risk premia, equal to 2.9% and 3.2% using the base set of assets, and 3.2% and 2.6%, respectively, in the extended set. As shown in Panel B, the GPSZ model delivers the smallest mean absolute pricing errors among the considered specifications, and the GRS test cannot reject the null that all pricing errors are jointly zero for our model. The case for GPSZ is particularly compelling for the extended set of assets, where we observe only a marginal difference in performance compared to the base set.

[Insert Table 6 Near Here]

The cross-sectional R^2 evidence further highlights the importance of including the political risk factor to price the cross-section of country returns. Nearly all of the R^2s are larger for the GPSZ than the other considered models. In particular, a regression of realized returns on predicted base-asset returns reaches an R^2 of 0.41 for the global CAPM and CAR models, against a corresponding value of 0.77 when we combine the global market factor and the P-factor in the GPSZ. The cross-sectional R^2 are just above 0.30 for the other VME and BAB factors. The results are similar for the extended set of assets: the GPSZ delivers an R^2 of nearly 0.70, way above 0.44 for CAR, 0.40 for the CAPM, and under 0.30 for VME and BAB.

The model-comparison results reinforce the evidence in Table 4, which shows that the P-factor is not spanned by the existing asset pricing factors. Indeed, it is not contemporaneously related to the factors, while the alphas in the spanning regressions are large and significant. Overall, while we do not aim to run a horse race across all the available models of asset returns and their multiple combinations, our evidence shows that our novel framework can successfully account for the cross-sectional differences in returns on the political risk-sorted portfolios across asset classes and rating measures, and improves on multiple performance metrics relative to the existing factors in the literature. We next rule out that the model performance is driven by particular asset classes or rating methodologies.

4.3 Asset pricing evidence: within asset classes

We take a similar approach as in the previous section but now zoom in on the performance of the model within each asset class separately. We control again for common risk factors proposed in the literature for every asset class, namely value and momentum (Asness, Moskowitz, and Pedersen, 2013), time-series momentum (Moskowitz, Ooi, and Pedersen, 2012), betting against beta (Frazzini and Pedersen, 2014), and carry (Koijen, Moskowitz, Pedersen, and Vrugt, 2018), but we also add 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). We assess the performance of the benchmark GPSZ model, and its extended version which replaces global market and P-factor by its local, asset-class specific counterparts. For parsimony, we show the results based on the combo strategy sorts; the findings for the individual rating measures are very similar and are reported in the Appendix.

4.3.1 Benchmark models

Table 7 shows that existing models struggle to explain the average portfolio returns on equity, bonds and currencies documented in Table 2 (Panel B). Indeed, the model alphas are consistently positive, statistically significant, and close to the time-series average of the strategy returns. The model alphas range from 5.31% to 7.87% for equity returns, 3.88%–5.56% for bonds, and 4.97%–6.22% for FX. The information ratios are also large, in the interval 0.44–0.66 for equities, 0.51–0.78 for bonds, and 0.87–1.08 for FX. The adjusted R^2 are in single digits for all models in equity, below 0.11 for bonds, and they are still relatively low for FX, ranging between 0.22 and 0.37İn spite of the larger R^2, the FX market is the asset class with the largest Sharpe ratios of abnormal returns and the strongest statistical significance of the alphas.

[Insert Table 7 Near Here]

We next assess the performance of our benchmark GPSZ model, which is based on the global market and P-factor. As shown in Table 8 Panel A, row M_G, P_G, the market and the P-factor carry positive risk premia, with magnitudes close to their average returns. The political risk premium estimates are significant in all three markets, ranging from 3.26% in bonds and 3.53% in equity to 5.93% in FX markets.

[Insert Table 8 Near Here]

Panel B compares the performance of our two-factor model with the existing models in the literature. The benchmark GPSZ model has lower mean absolute pricing errors than the best-performing alternative models: 2.53% against 2.55% for the value-momentum model in the equity market, 1.75% vs 2.12% for the betting against beta model in the bond market, and 1.23% compared to the 1.45% of the dollar-carry FX model. Similarly, our model delivers superior or at least comparable performance in terms of the cross-sectional R^2: considering the R^2 of realized vs predicted returns, the respective values are 0.68 vs 0.53 for equities, 0.66 vs 0.45 for bonds, and 0.33 vs 0.35 for currencies.

We repeat the test on the extended set of assets. The results in Appendix Table A2 Panel A confirm that the P-factor is priced, while Panel B corroborates that the portfolio average realized returns line up well with the predicted returns of our model. While the mean absolute pricing errors somewhat increase relative to the base set of assets and the other models, a regression of realized returns on model-predicted returns achieves an R^2 equal to 0.55 in the equity market, 0.64 in the bond market, and 0.37 in the FX market, well above the corresponding values for existing models.

The performance of our model is quite remarkable in spite of the fact that it relies on the same two global factors to price securities within each of the three asset classes, while the alternative specifications utilize a variety of asset-specific risk factors. It begs the question of whether the performance of the GPSZ model can be further improved by using asset-specific counterparts of the market and the political risk factors, which we address next.

4.3.2 Factor structure within asset classes

Given our original evidence for a factor structure for the entire set of returns, we expect to find a strong factor structure within each class separately. Similar to our across-assets approach in Section 3.2, we run a principal component analysis separately for equity, bond, and FX portfolio returns and find that the two factors consistently explain over 90% of the variation in returns for each asset class; see Table A3. 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 a plausible candidate risk factor that might explain the cross-section of portfolio excess returns within each asset class.

Motivated by the principal component analysis, we construct "local" alternatives for each asset class to the "global" across-asset market and political risk factors of Section 3.2. 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 construct an equally-weighted portfolio of all the excess returns in the sample. Panel C of Table A3 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.

As shown in Table A9 the P-factors constructed within each market are positively correlated with each other, but at the same time, they are not strongly related to the existing factors in the literature. The absolute value of the correlation coefficients between the P-factor and the other factors is under 0.20 in equity markets, under 0.23 in bond markets, and under 0.50 in 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 of accounting for both factors in pricing currency returns.

4.3.3 Factor pricing within asset classes

We next assess the performance of our variations of the GPSZ model using the asset-specific market and P-factor. Table 8 Panel A documents the market risk premia of the factors estimated separately in equity, bond, and FX markets. We consider three versions of the model: the benchmark GPSZ based on the global market and global P-factor (M_G, P_G row); the asset-specific market and global P-factor (M_L, P_G row); and the asset-specific market and asset-specific P-factor (M_G, P_G row). Across the asset classes and model specifications, the market risk premium of political risk is consistently positive and significant and varies between 3.26% and 5.93%. The estimates are larger for local than global factors in equity and bond markets, and the reverse is true in the FX market. The estimates of the market risk premium are more spread out, and vary between insignificant 1.86% to 6.63%.

Panel B documents the performance of the three variants of our model. As noted in the previous section, the benchmark global GPSZ model compares favorably to the existing models in the literature. The "local" versions of the factors further improve the ability of the model to explain the cross-section of asset returns. Going from fully global to fully local factors more than halves the absolute pricing errors in all three markets. The predicted R^2s increase from 0.68 to 0.72 in equity markets, from 0.66 to 0.86 in bond markets, and from 0.33 to a remarkable 0.90 in FX markets.

Much of the improvement in the model performance can be attributed to using the local market factor rather than a switch from global to local P-factor. Indeed, panel B of the Table shows that using local market factor but global political risk factor can account for most of the decrease in the pricing errors in bond and equity markets, and about half of the decrease in FX markets. That underscores the message of the paper that the political risk is "everywhere:" it affects all the asset classes, and is not specific to any asset class in particular.

To show further evidence that we can successfully recover the political risk factor from any of the asset classes, we run an out-of-sample comovement test in the spirit of Asness, Moskowitz, and Pedersen (2013). Specifically, we price each asset class j with a global market portfolio and political factor constructed with returns only from the other two non-j asset classes. Test assets are the 4×4 portfolios sorted on the four measures of political risk in each of the three asset classes, running the model three times separately.

[Insert Figure 5 Near Here]

Figure 5 contrasts the average realized and the predicted returns from the models. All points line up well along the 45-degree line, and a regression of the realized returns on the model's predicted returns yields a high R^2 of 0.66.

4.4 Asset pricing evidence: within ratings

Similar to the analysis of the model performance within each asset class, we next examine the ability of the model to price asset portfolios sorted on each of the political ratings.

Overall, the model prices well the securities sorted using any of the rating choices. As shown in Table 9 Panel A, the estimates of the market price of political risk for the base set of assets range from 2.98% for the WES policy or WES Politics ratings, to 3.26% for ICRG and 3.40% for WB Politics measures. The range of the estimates is even tighter for the extended set of assets, from 2.40% to 2.51%, as shown in Table A4. The estimates of the risk premium for the market factor are clustered around the benchmark values.

[Insert Table 9 Near Here]

Table 9 Panel B assesses the ability of the GPSZ model to price the cross-section of returns within each rating. Similar to the within-asset-class results, the existing models struggle to explain the cross-sectional variation in asset risk premia. GPSZ compares very favorably to them, with a similar performance across all four rating categories. Similar to the overall evidence in Table 6, for the base set of assets, the pricing errors range between 1.65% for WB Politics to 2.07% for ICRG ratings, and all the R^2s are above 70%.[22]

We also considered "local" versions of the political risk factor constructed within each rating category separately, and found very marginal gains, if any, of using ranking-specific rather than "combo" P-factors. To summarize the evidence, Panel B of Figure 5 documents the results for the co-movement test in which we use the political risk factor from one rating category to price portfolio sorts on all the remaining ones. Consistent with the global nature of the political risk, the predicted and realized returns center around the 45-degree line.

5 Political risk: robustness and extensions

In this Section, we consider several strategies to help identify and isolate the effects of political risk and examine economic and statistical margins driving its performance. First, we include additional economic and financial-market factors to control for other sources of aggregate risk. Next, we modify the construction of the P-factor itself to remove mainly country-specific effects. Then, we show that the performance of the P-factor is driven by its long leg and examine potential market segmentation concerns. Finally, we consider the robustness of the evidence to outliers in constructing the P-factor, examine beta-sorted portfolios and the issue of risk versus characteristics.

5.1 Competing systematic risks

A potential concern about our global political risk factor is that it may be picking up other related macroeconomic and financial-market risks. Indeed, we showed in Section 3.3 that the P-factor falls in adverse times of low realized and expected economic growth or high financial volatility. In the cross-section, political risk is related to the level of economic development across countries, and could be proxying for the differences between high and low growth economies.

To address these concerns, in the first set of results we augment our two-factor multi-asset model with either an emerging market portfolio return (EM), or the changes in the US VIX index, global risk aversion, or global EPU.[23] Table 10 reports the asset-

[22]Similar results hold true in the extended set of test assets, see Appendix Table A4.

[23]The results are very similar when we include all the factors together in a single asset pricing model.

pricing evidence across the augmented models. It shows that the multi-asset P-factor is consistently priced across all the specifications, while only the emerging market portfolio carries a significant price of risk.

Overall, adding controls does not diminish the importance of our P-factor, and helps make a stronger case for the pricing of political risk.

[Insert Table 10 Near Here]

5.2 Country-specific effects

In the second set of checks, we modify the construction of the P-factor by removing country-specific effects. In the first specification, we demean each country's ratings by its unconditional average. In this case, we effectively remove the constant fixed effects embedded in the ratings and focus on within-country time-series variation. In the second specification, we regress the country ratings on a constant and country-specific ICRG economic risk ratings and sort portfolios on the regression residuals. Even though we are using the ICRG political ratings, given that ICRG also provides separate ratings on economic risk (Bekaert, Harvey, Lundblad, and Siegel, 2014), this second model serves as an additional robustness check to disentangle political risk from macroeconomic risk fully and, by removing an intercept, constant country fixed effects. In the third specification, we consider observable macroeconomic measures instead of the ICRG economic risk ratings and project political ratings on the country's realized real GDP growth and inflation rate.

For each of these specifications, we start with an ICRG measure as a benchmark indicator of political risk, run the projections, sort securities into portfolios based on the residual ratings, and construct the orthogonalized P-factors. The first immediate consequence of running these projections is that, by removing an intercept, we obtain a well-balanced portfolio composition across the level of macroeconomic development. Indeed, just demeaning the country ratings produces portfolio compositions in which developed markets represent 47%, 58%, 57% and 45% of the total allocation in the portfolios sorted from high to low political risk, respectively. Similar values are obtained with the other two specifications.

[Insert Table 11 Near Here]

Next, we test three versions of our two-factor model in which we replace our multi-asset political factor with each of the three orthogonalized factors. Table 11 reports the risk premia estimated in the base and extended set of test assets. Removing country-specific effects does not diminish the importance of priced global political risk. The market prices of risk of the orthogonalized P-factors range between 5.4% and 5.9% for the base set of assets, and 3.7% and 4.8% in the extended set, and all are highly significant.

Overall, it appears that political ratings embed information content that goes above and beyond global and country-specific macroeconomic risk and that is important to price global cross-asset returns. Further, the performance of the P-factor is not driven entirely by fixed differences in average ratings between countries or groups of countries but also reflect within-country variation in political risk.

5.3 Long and short leg

The benchmark P-factor is constructed as a long-short portfolio return of high versus low political risk countries. As such, an adverse downward move in the factor can reflect the bad news for the high political risk group (long leg), and/or high return for the low risk group (short leg). To help disentangle the two effects, we break down the benchmark P-factor into its long leg (long high political risk countries and short the aggregate market portfolio), and the short leg (long the aggregate market and shorts low political risk countries).

Table 12 Panel A shows that while both legs have positive and significant means, most of the return spread is attributable to high political risk countries. Indeed, the long-leg factor has an average return that is almost three times as large as that of the short-leg: 3.21% against 1.15% p.a. The strategy that goes long high political risk countries and shorts the market reaches a remarkably high t-statistic of 3.99 with a Sharpe ratio of 0.85. Conversely, the corresponding values for the strategy that goes long the market and shorts low political risk countries are much smaller, 1.86 and 0.36.

[Insert Table 12 Near Here]

Cross-sectional tests further support the conclusion that the P-factor performance is driven by its long leg. We test a three-factor model that includes the global multi-asset market portfolio and the two separate legs of the original factor. Panel B reports the estimated risk premia, and Panel C the time-series and cross-sectional pricing statistics. The factor investing in high political risk countries is consistently priced, its statistical significance is strong, and, interestingly, it subsumes the factor investing in low political risk countries.[24] This three-factor model achieves similar, and slightly better, time-series and cross-sectional performance compared to our original two-factor model of Table 6, with MAPE down from 2.36% to 2.14%, cross-sectional GLS R^2 up from 0.35 to 0.38, and cross-sectional OLS R^2 up from 0.62 to 0.67 in the extended set of test assets.

This evidence reinforces our argument that the P-factor reflects adverse economic conditions by picking up the downside risk of high political risk countries. It further has important asset-management considerations: by allowing to harvest the risk premium from the long leg, it avoids the fees embedded in the short leg of the trade.

5.4 Market segmentation

Our benchmark explanation for abnormal returns of high political risk portfolios utilizes the rational risk compensation channel: global political risk rises in adverse economic times, and securities with higher exposure to its fluctuations demand a larger risk premium. One could entertain an alternative story in which market imperfections give rise to the return differential and are at the same time correlated with a country's political risk.

We examine one such channel due to market segmentation. If certain assets are particularly challenging to access due to trading or information costs, the average returns of these securities may contain a market segmentation premium uncorrelated with global risk factors. We run two tests which suggests that market segmentation is unlikely to cause the cross-sectional heterogeneity in average returns on political ratings sorted country portfolios.

[Insert Table 13 Near Here]

First, we perform portfolio sorts only on the subsample of emerging markets according to the MSCI classification. This allows us to assess the possibility that our results are driven by the higher degree of market segmentation of emerging vis-à-vis developed markets. Table 13 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

[24] We also tested two alternative models augmenting the global CAPM with either the factor investing in high political risk countries or the factor investing in low political risk countries. All factors, not only the one constructed from high political risk countries, were consistently priced in the base and extended sets of test assets. This confirms that low political risk countries do have pricing information, but this becomes negligible when accounting for high political risk countries.

ratios of the spread portfolios are 0.61 for equities, 0.36 for bonds and 0.84 for currencies. This evidence is consistent with the findings in Section 5.1 that the emerging market factor, while significantly priced, does not diminish the importance of the political risk factor to explain the cross-section of portfolio returns.

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.

5.5 P-factor robustness to outliers

Subsection 3.3 identifies a link between the multi-asset political factor and the macroeconomy, and Table 5 shows that the factor hits low returns when global shocks occur or in periods of high global uncertainty, consistent with a risk-based interpretation. This suggests that discarding the P-factor returns during these periods should magnify its performance. Motivated by this insight, we report in Table 14 the P-factor statistics when we neglect its returns corresponding to those periods when we observe the highest 20%, 30%, and 40% of values in, respectively, US VIX (Panel A), global risk aversion (Panel B), and global economic policy uncertainty (Panel C). Symmetrically, we also check the P-factor performance when we discard its returns corresponding to the lowest values of these uncertainty indices.

[Insert Table 14 Near Here]

As expected, the P-factor increases (decreases) its average return and Sharpe ratio when removing its returns corresponding to global bad (good) times. The magnitude of this result is remarkable. When discarding the returns corresponding to the top 30% of observations in the US VIX index, the P-factor attains an average return of 5.66% p.a.

with impressive t-statistics of 4.37 and Sharpe ratio of 1.01. Similar results are obtained with global risk aversion or EPU. The evidence that the P-factor stays significant across all specifications and uncertainty measures also suggests that it is robust to outliers.

5.6 Beta-sorted portfolios

Following Lustig, Roussanov, and Verdelhan (2011), we create beta-sorted portfolios and show that the sorting of countries on the ICRG 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_β) and top (H_β) 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 15. 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 15 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 2. 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 political risk ratings.

These findings show that portfolio sorts on country ratings and sorts based on political risk exposures are clearly related, validating 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.

5.7 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:

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

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 16 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 (Table A2). In Table 16 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 A2, 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

Our paper contributes to the empirical asset pricing literature that studies the economic determinants of risk affecting financial markets. Using political ratings of individual countries, we show the evidence for global political risk across and within the equity, bond, and FX markets. Remarkably, the political risk factor manifests itself in all the asset classes and proxies and can be meaningfully extracted from any of those, and the asset- or ranking-specific information does not materially alter its importance. In this sense, political risk is "everywhere".

Our GPSZ model, which consists of the global market and political risk factor, can successfully price a large panel of asset returns within and across stocks, bonds, and currencies, within and across 42 countries, and within and across 4 alternative political risk rankings. Assets 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 using the base set of test assets, with t-statistic well above the critical threshold of three, with a Sharpe ratio of 0.70.

The global political risk factor further predicts global economic growth and correlates with macroeconomic and business-cycle related variables capturing both first- and second-moment effects such as a recession dummy, cross-country capital flows, US and global volatility, global risk aversion, and global economic policy uncertainty. This evidence helps economically interpret the asset-pricing framework, in which the P-factor is associated with systematically good news about the economy and an asset that is positively exposed to the factor and under-performs in adverse economic times is risky and earns a positive risk premium.

Going forward, it would be instructive to provide a full-fledged economic model to microfound the political risk factor and explain its connection to the macroeconomy and financial markets. One can further extend the empirical evidence to other asset classes within or across countries. Finally, it would be interesting to consider the interaction of political risk with other aspects of macroeconomic and financial market fluctuations.

References

Andrews, D. W. and J. C. Monahan (1992): "An improved heteroskedasticity and autocorrelation consistent covariance matrix estimator," *Econometrica*, 60, 953–966.

Asness, C., A. Ilmanen, R. Israel, and T. Moskowitz (2015): "Investing with style," *Journal of Investment Management*, 13, 27–63.

Asness, C., J. Liew, L. H. Pedersen, and A. Thapar (2021): "Deep value," *The Journal of Portfolio Management*, 47, 11–40.

Asness, C. S., T. J. Moskowitz, and L. H. Pedersen (2013): "Value and Momentum Everywhere," *The Journal of Finance*, 68, 929–985.

Avramov, D., T. Chordia, G. Jostova, and A. Philipov (2012): "The world price of credit risk," *The Review of Asset Pricing Studies*, 2, 112–152.

Babu, A., A. Levine, Y. H. Ooi, L. H. Pedersen, and E. Stamelos (2020): "Trends everywhere," *The Journal of Investment Management*, 18.

Baker, S. R., N. Bloom, and S. J. Davis (2016): "Measuring economic policy uncertainty," *The Quarterly Journal of Economics*, 131, 1593–1636.

Bansal, R. and I. Shaliastovich (2013): "A long-run risks explanation of predictability puzzles in bond and currency markets," *The Review of Financial Studies*, 26, 1–33.

Barillas, F. and J. Shanken (2017): "Which alpha?" *The Review of Financial Studies*, 30, 1316–1338.

Becker, S. O. and K. Wohlrabe (2007): "Micro data at the Ifo Institute for Economic Research: The Ifo Business Survey, usage and access," Working Paper 47, Ifo Institute for Economic Research, Munich.

Bekaert, G., E. C. Engstrom, and N. R. Xu (2022): "The time variation in risk appetite and uncertainty," *Management Science*, 68, 3975–4004.

Bekaert, G., C. R. Harvey, C. T. Lundblad, and S. Siegel (2014): "Political risk spreads," *Journal of International Business Studies*, 45, 471–493.

Bollerslev, T., B. Hood, J. Huss, and L. H. Pedersen (2018): "Risk everywhere: Modeling and managing volatility," *The Review of Financial Studies*, 31, 2729–2773.

Bremmer, I. (2005): "Managing risk in an unstable world," *Harvard Business Review.*

Brogaard, J., L. Dai, P. T. H. Ngo, and B. Zhang (2020): "Global political uncertainty and asset prices," *The Review of Financial Studies*, 33, 1737–1780.

Caldara, D. and M. Iacoviello (2022): "Measuring geopolitical risk," *American Economic Review*, 112, 1194–1225.

Carhart, M. M. (1997): "On persistence in mutual fund performance," *The Journal of Finance*, 52, 57–82.

Carrieri, F., V. Errunza, and B. Majerbi (2006): "Does emerging market exchange risk affect global equity prices?" *Journal of Financial and Quantitative Analysis*, 511–540.

Cochrane, J. H. (2005): *Asset Pricing*, Princeton, NJ: Princeton University Press.

——— (2011): "Presidential address: Discount rates," *The Journal of Finance*, 66, 1047–1108.

Cooper, I., A. Mitrache, and R. Priestley (2020): "A global macroeconomic risk model for value, momentum, and other asset classes," *Journal of Financial and Quantitative Analysis.*

Cooper, I. and R. Priestley (2013): "The world business cycle and expected returns," *Review of Finance*, 17, 1029–1064.

Daniel, K. and T. J. Moskowitz (2016): "Momentum crashes," *Journal of Financial Economics*, 122, 221–247.

Du, W., A. Tepper, and A. Verdelhan (2018): "Deviations from covered interest rate parity," *The Journal of Finance*, 73, 915–957.

Fama, E. F. and K. French (1993): "Common risk factors in the returns on stocks and bonds," *Journal of Financial Economics*, 33, 3–56.

Fama, E. F. and K. R. French (2017): "International tests of a five-factor asset pricing model," *Journal of Financial Economics*, 123, 441–463.

Fernández, A., M. W. Klein, A. Rebucci, M. Schindler, and M. Uribe (2016): "Capital control measures: A new dataset," *IMF Economic Review*, 64, 548–574.

Fitzpatrick, M. (1983): "The definition and assessment of political risk in international business: A review of the literature," *Academy of Management Review*, 8, 249–254.

Frazzini, A. and L. H. Pedersen (2014): "Betting against beta," *Journal of Financial Economics*, 111, 1 – 25.

Frei, D. and D. Ruloff (1988): "The methodology of political risk assessment: An overview," *World Futures*, 25, 1–24.

Gala, V. D., G. Pagliardi, and S. A. Zenios (2023): "Global political risk and international stock returns," *Journal of Empirical Finance*, 72, 78–102.

Gao, G. P., X. Lu, and Z. Song (2019): "Tail risk concerns everywhere," *Management Science*, 65, 3111–3130.

Gourio, F., M. Siemer, and A. Verdelhan (2015): "Uncertainty and international capital flows," *Available at SSRN 2626635*.

Harvey, C. R., Y. Liu, and H. Zhu (2016): "... and the cross-section of expected returns," *The Review of Financial Studies*, 29, 5–68.

He, Z., B. Kelly, and A. Manela (2017): "Intermediary asset pricing: New evidence from many asset classes," *Journal of Financial Economics*, 126, 1–35.

Herrera, H., G. Ordoñez, and C. Trebesch (2020): "Political booms, financial crises," *Journal of Political Economy*, 128, 507–543.

Howell, L. D. (2014): "Evaluating political risk forecasting models: What works?" *Thunderbird International Business Review*, 56, 305–316.

Jarvis, D. S. and M. Griffiths (2007): "Learning to fly: The evolution of political risk analysis," *Global Society*, 21, 5–21.

Jong-A-Pin, R. (2009): "On the measurement of political instability and its impact on economic growth," *European Journal of Political Economy*, 25, 15–29.

Kelly, B., L. Pástor, and P. Veronesi (2016): "The price of political uncertainty: theory and evidence from the option market," *The Journal of Finance*, 71, 2418–2480.

Kobrin, S. J. (2022): *Managing Political Risk Assessment Strategic Response to Environmental Change*, Berkeley: University of California Press, second ed.

Koijen, R. S., H. Lustig, and S. Van Nieuwerburgh (2017): "The cross-section and time series of stock and bond returns," *Journal of Monetary Economics*, 88, 50–69.

Koijen, R. S., T. J. Moskowitz, L. H. Pedersen, and E. B. Vrugt (2018): "Carry," *Journal of Financial Economics*, 127, 197–225.

Lettau, M., M. Maggiori, and M. Weber (2014): "Conditional risk premia in currency markets and other asset classes," *Journal of Financial Economics*, 114, 197–225.

Lewellen, J., S. Nagel, and J. Shanken (2010): "A skeptical appraisal of asset pricing tests," *Journal of Financial Economics*, 96, 175–194.

Liew, J. and M. Vassalou (2000): "Can book-to-market, size and momentum be risk factors that predict economic growth?" *Journal of Financial Economics*, 57, 221–245.

Liu, Y. and I. Shaliastovich (2022): "Government policy approval and exchange rates," *Journal of Financial Economics*, 143, 303–331.

Lustig, H., N. Roussanov, and A. Verdelhan (2011): "Common risk factors in currency markets," *The Review of Financial Studies*, 24, 3731–3777.

Menkhoff, L., L. Sarno, M. Schmeling, and A. Schrimpf (2012): "Carry trades and global foreign exchange volatility," *The Journal of Finance*, 67, 681–718.

Miranda-Agrippino, S. and H. Rey (2020): "US monetary policy and the global financial cycle," *The Review of Economic Studies*, 87, 2754–2776.

Moskowitz, T. J., Y. H. Ooi, and L. H. Pedersen (2012): "Time series momentum," *Journal of Financial Economics*, 104, 228–250.

Newey, W. K. and K. D. West (1987): "A simple, positive-definite, heteroskedasticity and autocorrelation consistent covariance matrix," *Econometrica*, 55, 703–708.

Oetzel, J. M., R. A. Bettis, and M. Zenner (2001): "Country risk measures: how risky are they?" *Journal of World Business*, 36, 128–145.

Pedersen, L. H., S. Fitzgibbons, and L. Pomorski (2021): "Responsible investing: The ESG-efficient frontier," *Journal of Financial Economics*, 142, 572–597.

PRS (2005): "About ICRG: the political risk rating." Tech. rep., Available at `http://www.icrgonline.com/page.aspx?pagecrgmethods`.

Pukthuanthong, K. and R. Roll (2009): "Global market integration: An alternative measure and its application," *Journal of Financial Economics*, 94, 214 – 232.

Pukthuanthong, K., R. Roll, and A. Subrahmanyam (2019): "A protocol for factor identification," *The Review of Financial Studies*, 32, 1573–1607.

Shanken, J. (1992): "On the estimation of beta-pricing models," *The Review of Financial Studies*, 5, 1–33.

Sottilotta, C. (2016): *Rethinking Political Risk: Concepts, Theories, Challenges*, London, UK: Taylor & Francis.

Swinkels, L. (2019): "Treasury bond return data starting in 1962," *Data*, 4, 91.

World Bank (2018): "DataBank. Worldwide Governance Indicators (Political Stability and Absence of Violence/Terrorism)," Available at http://databank.worldbank.org/data/reports.aspx?Report_Name=WGI-Table&Id=ceea4d8b, The World Bank.

Figure 2: **Global political ratings and political events**

This figure plots the time-series dynamics of an aggregate global political rating, highlighting the correspondence between its shifts over time with the occurrence of global political events. First, we standardize the political ratings for every country and for each of the four political measures: ICRG political risk, WES policy, WES politics, and World Bank politics. Second, we take a GDP-weighted average of the standardized ratings across countries, thereby constructing four global political measures. Third, we obtain an aggregate combo time series measuring global political risk by taking an equally weighted average of the four standardized global measures constructed in step two. Fourth, we plot the time series of this global political risk rating, identifying good (bad) global political events that match positive (negative) spikes in the global index, which indicate lower (higher) global political risk. We also contrast this series with a smoother version of our multi-asset P-factor, obtained as the average of its previous 4-year returns and rescaled by multiplying these values by 100. The figure also displays the correlation coefficient between the global political rating and the smoothed multi-asset P-factor. All data are converted to semiannual frequency, spanning 1992–2019.

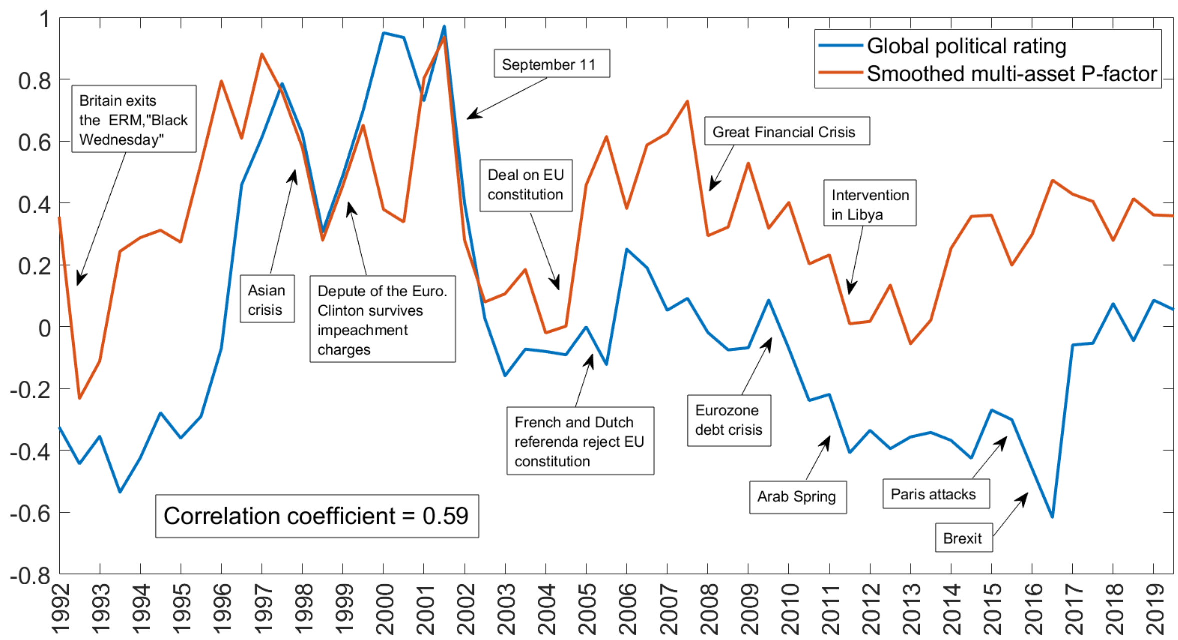


Figure 3: **Principal component analysis of ICRG political ratings**

This figure plots the time-series dynamics of the cumulative percentage of variance explained, respectively, by the first one and the first three principal components when running rolling-window PCA on the ICRG political risk ratings (in blue). We also display the time-series mean of this fraction of explained variance (in black) for both cases. PCA is run with ten-year rolling windows. The x-axis displays the end of each ten-year window and matches the value on the y-axis corresponding to the percentage of variance explained in that ten-year window. PCA is run on the full set of countries in our sample. Data are monthly, spanning 1992–2019.

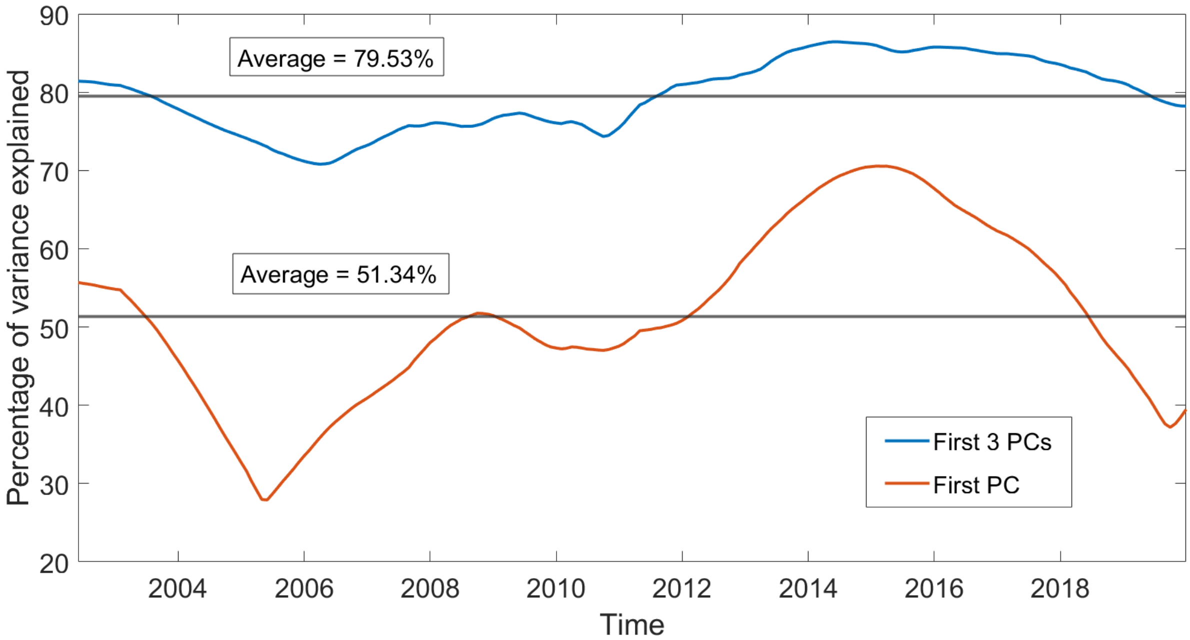
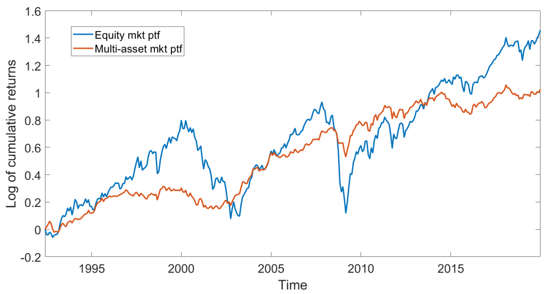


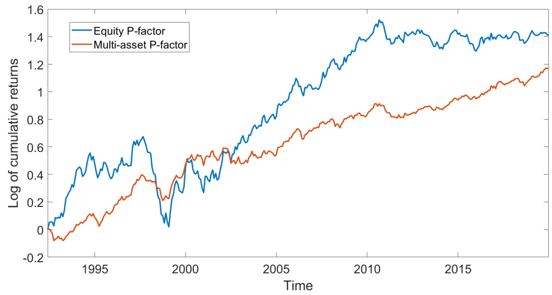
Figure 4: **Asset-class specific vs multi-asset factors**

This figure contrasts the time-series dynamics of the log cumulative returns of each asset-class specific market portfolio (political factor) with, respectively, the global multi-asset market portfolio (political factor). The global multi-asset factors are constructed as inverse-volatility portfolios of the corresponding asset-class-specific factors. The political factor in each asset class is a combo strategy constructed as an equally weighted average of the returns of the four L-H strategies from portfolio sorts on each of the different political risk measures: ICRG political risk, WES politics, WES policy, and World Bank politics. Returns are denominated in USD and include dividends and coupon payments. Data are monthly and span the period 1992-2019.

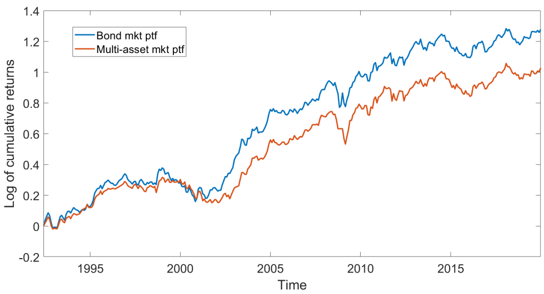
(a) Market equity



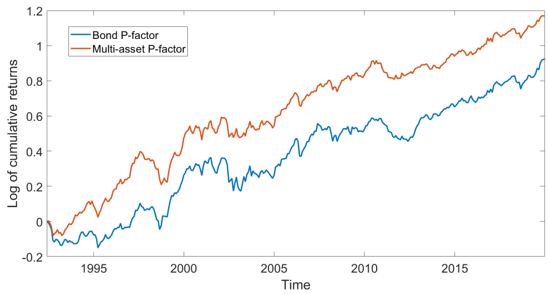
(b) P-factor equity



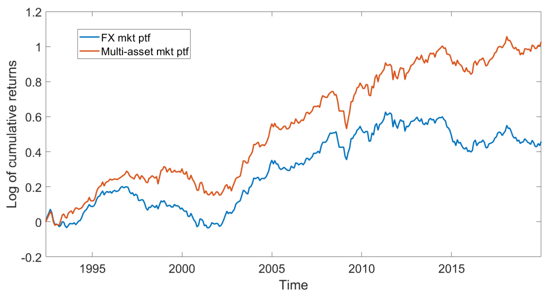
(c) Market bond



(d) P-factor bond



(e) Market FX



(f) P-factor FX

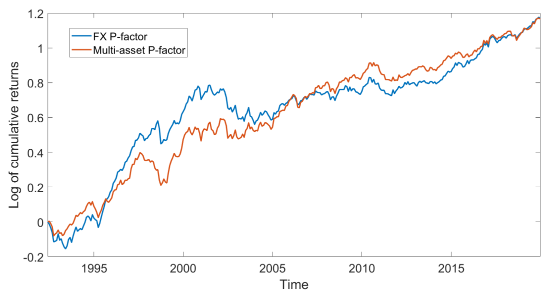
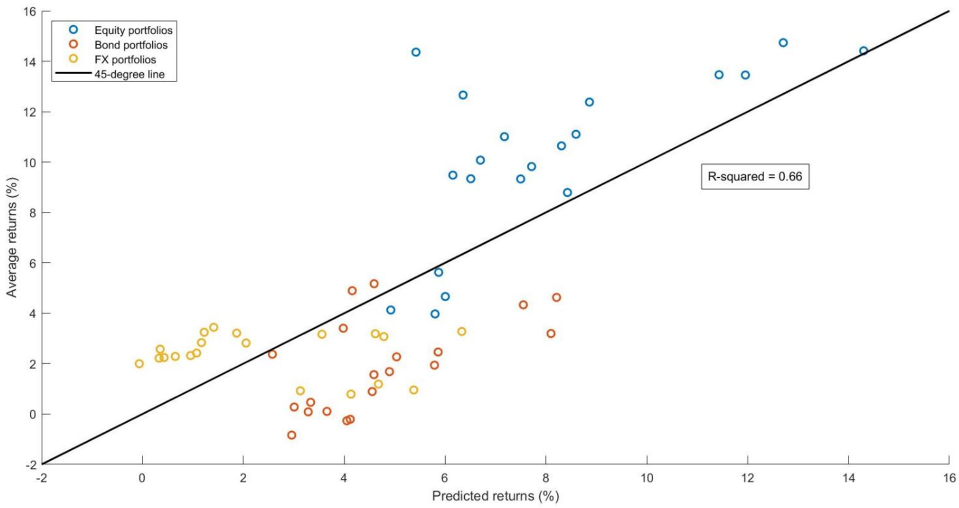


Figure 5: **Comovement tests**

This figure plots the average realized excess returns against average excess returns when running two different comovement tests. Panel A reports the results of a comovement test across asset classes, where we use 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. Panel B reports the results of a comovement test across political ratings, where we use a model that includes the global market portfolio and a global multi-asset P-factor constructed with political ratings from provider j and used to price returns in all the non-j providers. Test assets are $4 \times 4 \times 3$ portfolios sorted on the four measures of political risk (ICRG political risk, WES politics, WES policy, World Bank politics) in the equity, bond, and FX asset classes. Returns are in annualized percentage points. Data are monthly, spanning 1992–2019.

(a) Comovement across asset classes



(b) Comovement across ratings

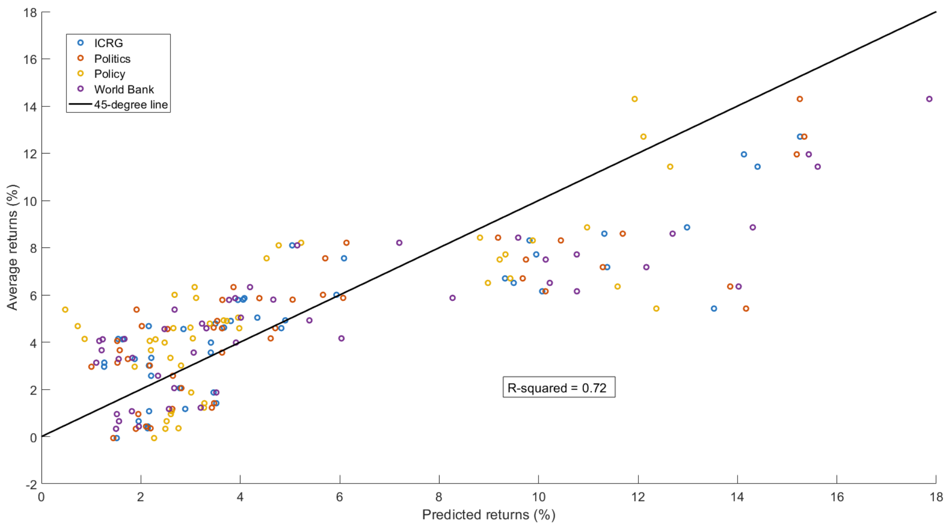


Table 2 – Portfolio sorts

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, "Politics" and "Policy" refer to, respectively, the political stability and economic policy ratings provided by IfO WES, "WB" are the political instability ratings created by the World Bank, and "Combo" refers to an equally-weighted portfolio of the univariate sorts on all these political risk ratings. "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 asterisks (***), (**), and (*) denote statistical significance at the 1%, 5%, and 10% level, respectively. Data are monthly, spanning 1992–2019.

(a) Local currency returns

Equity

	ICRG	WES Politics	WES Policy	WB	Combo
P1 (L)	23.55%***	22.24%***	20.18%***	17.46%***	22.50%***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
P2	11.31%***	12.25%***	12.04%***	8.22%**	11.41%***
	(0.01)	(0.00)	(0.00)	(0.04)	(0.00)
P3	9.83%***	10.70%***	10.59%***	10.02%***	10.47%***
	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)
P4 (H)	9.94%***	8.75%***	9.04%***	8.55%**	9.30%***
	(0.01)	(0.01)	(0.01)	(0.04)	(0.01)
L-H	13.61%***	13.49%***	11.14%***	8.91%***	13.20%***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

Bond

	ICRG	WES Politics	WES Policy	WB	Combo
P1 (L)	12.61%***	11.43%***	9.26%***	11.20%***	11.33%***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
P2	7.80%***	8.33%***	8.40%***	7.20%***	8.13%***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
P3	5.89%***	6.24%***	7.30%***	5.32%***	6.39%***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
P4 (H)	5.79%***	6.02%***	5.97%***	4.91%***	5.92%***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
	6.82%***	5.41%***	3.29%***	6.29%***	5.40%***
L-H	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

Table 2 – (continued)

(b) USD returns

Equity

	ICRG	WES Politics	WES Policy	WB	Combo
P1 (L)	16.69%***	13.82%***	14.34%***	14.74%***	15.34%***
	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)
P2	8.75%**	11.25%***	10.99%***	7.46%	9.81%**
	(0.05)	(0.01)	(0.01)	(0.14)	(0.02)
P3	9.89%***	10.11%***	9.57%**	10.34%**	10.10%***
	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)
P4 (H)	10.82%***	8.90%**	8.54%**	8.74%*	9.49%**
	(0.01)	(0.02)	(0.04)	(0.06)	(0.02)
L-H	5.87%**	4.92%**	5.80%**	6.00%**	5.86%**
	(0.05)	(0.05)	(0.03)	(0.05)	(0.03)
Sharpe	0.38	0.37	0.42	0.41	0.48

Bond

	ICRG	WES Politics	WES Policy	WB	Combo
P1 (L)	10.60%***	10.49%***	8.25%***	9.59%***	9.82%***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
P2	6.98%***	7.43%***	8.18%***	6.93%***	7.57%***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
P3	6.05%***	5.72%***	6.95%***	5.04%***	6.16%***
	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)
P4 (H)	6.44%***	6.51%***	5.68%***	4.99%**	6.21%***
	(0.00)	(0.00)	(0.00)	(0.02)	(0.00)
L-H	4.16%**	3.98%***	2.58%**	4.59%***	3.61%***
	(0.03)	(0.00)	(0.03)	(0.01)	(0.01)
Sharpe	0.42	0.55	0.41	0.51	0.51

FX

	ICRG	WES Politics	WES Policy	WB	Combo
P1 (L)	6.33%***	4.79%***	3.56%**	4.62%***	5.15%***
	(0.00)	(0.00)	(0.02)	(0.00)	(0.00)
P2	1.22%	1.87%	2.05%	1.41%	1.65%
	(0.35)	(0.12)	(0.11)	(0.35)	(0.18)
P3	0.33%	1.07%	1.17%	0.35%	0.83%
	(0.83)	(0.49)	(0.41)	(0.85)	(0.58)
P4 (H)	0.95%	0.65%	0.43%	-0.06%	0.65%
	(0.60)	(0.70)	(0.79)	(0.97)	(0.70)
L-H	5.38%***	4.13%***	3.13%***	4.68%***	4.50%***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Sharpe	0.62	0.62	0.57	0.60	0.69

Table 3 – Global factor structure across asset classes

This table reports the results of a principal component analysis of the $4 \times 4 \times 3$ portfolios sorted on the different political risk measures in all asset classes. Panel A shows the percentage of global variance explained by the first two principal components and their correlations with the market portfolio and the multi-asset P-factors constructed with each of the different political measures. Panel B reports the portfolio loadings on the principal components. Data are monthly, spanning 1992–2019.

(a) PC analysis

	PC1	PC2
Factor eigenvalues		
Explained variance (%)	68.83	15.66
Correlations		
Global mkt	0.99	0.02
ICRG	-0.16	0.66
WES Politics	-0.11	0.65
WES Policy	-0.07	0.54
WB Politics	-0.22	0.70
Combo	-0.16	0.72

(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
Combo						
P1 (L)	0.12	0.21	0.13	0.02	0.13	0.05
P2	0.14	0.19	0.15	-0.08	0.17	-0.03
P3	0.14	0.17	0.14	-0.16	0.16	-0.13
P4 (H)	0.14	0.16	0.14	-0.18	0.16	-0.15

Table 4 – 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 inverse-volatility 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 for which the factors have been calibrated "everywhere" across asset classes. "ALL" denotes the most comprehensive model that includes all the factors of all benchmark models. We report the abnormal returns (alphas), adjusted R^2 and the information ratios. The asterisks (***), (**), and (*) denote statistical significance at the 1%, 5%, and 10% level, respectively. 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	ALL
α	5.03***	6.45***	7.99***	4.62***	8.97***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
R^2	0.03	0.06	0.16	0.04	0.19
IR	0.80	1.05	1.24	0.73	1.42

Table 5 – Global multi-asset P-factor and the macroeconomy

This table reports the results of regressions relating a set of macroeconomic variables on the global multi-asset P-factor and the global multi-asset market portfolio. The former (latter) is computed as a inverse-volatility portfolio of the three asset-class specific P-factors (market portfolios) in the equity, bond, and FX markets. Panel A reports results of a forecasting regression of future global real GDP growth, at 3-, 6-, and 12-month horizons, respectively, on current returns of the multi-asset P-factor and market portfolio. Global GDP growth is computed by aggregating country-level real GDP growth through a GDP-weighted average ("GDP weighted") or equally-weighted average ("equally weighted"). Panel B reports results of contemporaneous regressions of a set of macroeconomic variables on the multi-asset P-factor and market portfolio: a "recession" dummy variable that takes value 1 if global GDP growth falls below percentile 30 of its distribution, and first differences in the US VIX index, in the global risk aversion volatility measure of Bekaert, Engstrom, and Xu (2022), in the global economic policy uncertainty of Baker, Bloom, and Davis (2016), and in the global volatility and global cross-country capital flows variables of Miranda-Agrippino and Rey (2020). Newey and West (1987) p-values based on optimal number of lags (Andrews and Monahan, 1992) are in parenthesis, and the asterisks (***), (**), and (*) denote statistical significance at the 1%, 5%, and 10% level, respectively. GDP data are quarterly, and regressions in Panels A and B are run at quarterly frequency by compounding monthly factor data into quarterly. All data in Panel B are available monthly and regressions are run at monthly frequency. Data span the period 1992–2019.

(a) Forecasting regressions of global economic growth

	GDP weighted			Equally weighted		
	3m	6m	12m	3m	6m	12m
$\beta_{P-factor}$	0.023***	0.044***	0.087***	0.038***	0.064***	0.116***
	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)
β_{MKT}	0.035**	0.071*	0.102***	0.053***	0.093***	0.135***
	(0.05)	(0.06)	(0.01)	(0.00)	(0.02)	(0.00)
R^2	0.08	0.10	0.10	0.15	0.15	0.13

(b) Contemporaneous regressions of global macroeconomic aggregates

	Recession	VIX	Global vol	Risk aversion	EPU	Cross-border flows
$\beta_{P-factor}$	-4.740***	-48.01***	-432.64***	-0.77***	-2.58***	5.60**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.04)
β_{MKT}	-3.366***	-104.76***	-405.98***	-1.35***	1.99***	3.64
	(0.01)	(0.00)	(0.00)	(0.00)	(0.01)	(0.11)
R^2	0.18	0.27	0.12	0.16	0.06	0.03

Table 6 – Global asset pricing

This table reports the results of asset pricing tests run on the base set of test assets, which includes the 4×4×3 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, three value and three momentum portfolios from Asness, Moskowitz, and Pedersen (2013) for each of the three asset classes, and six currency portfolios from Lustig, Roussanov, and Verdelhan (2011). 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 all asset pricing models constructed "everywhere" 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). "ALL" denotes the most comprehensive model that includes all the factors of all benchmark models. 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. We also include 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 and coupon payments. Risk premia are annualized. The asterisks (***), (**), and (*) denote statistical significance at the 1%, 5%, and 10% level, respectively. 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***	3.19**	2.61**
	(0.04)	(0.01)	(0.02)	(0.05)

Table 6 – (continued)

(b) Comparison with benchmark models

Base set	GPSZ	CAPM	VME	BAB	CAR	ALL
MAPE	1.90	2.59	3.39	4.46	2.50	6.00
GRS statistic	1.00	1.29*	1.05	2.03***	1.33**	2.23***
p-value GRS	0.49	0.08	0.38	0.00	0.05	0.00
GLS R^2	0.25	0.00	0.21	0.28	0.20	0.58
OLS R^2	0.74	0.18	0.73	0.60	0.24	0.72
R^2 predicted vs realized	0.77	0.41	0.31	0.31	0.41	0.37

Extended set	GPSZ	CAPM	VME	BAB	CAR	ALL
MAPE	2.36	2.47	3.22	4.64	2.45	5.71
GRS statistic	0.95	1.35**	1.75***	1.91***	0.75	2.54***
p-value GRS	0.63	0.03	0.00	0.00	0.97	0.00
GLS R^2	0.35	0.05	0.08	0.10	0.09	0.15
OLS R^2	0.62	0.28	0.41	0.48	0.34	0.55
R^2 predicted vs realized	0.69	0.40	0.28	0.26	0.44	0.31

Table 7 – Abnormal returns within asset classes

This table reports the average annualized abnormal returns (alphas), adjusted R^2 and information ratios (IR) from time-series regressions of the L-H combo strategies of Table 2 in equity (Panel A), bond (Panel B) and FX (Panel C) markets. We test all asset pricing models constructed across asset classes from Table 6. 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 asterisks (***), (**), and (*) denote statistical significance at the 1%, 5%, and 10% level, respectively. Data are monthly, spanning 1992–2016.

	CAPM	ACB	VME	BAB	CAR	ALL
			a) Equity			
α	5.70%**	7.50%***	5.31%**	6.75%**	5.69%*	7.87%**
	(0.03)	(0.01)	(0.05)	(0.03)	(0.06)	(0.02)
R^2	0.00	0.05	0.02	0.00	0.00	0.08
IR	0.46	0.63	0.44	0.55	0.45	0.66
			b) Bond			
α	4.28%***	4.74%***	5.32%***	3.88%***	4.53%***	5.56%***
	(0.00)	(0.00)	(0.00)	(0.04)	(0.00)	(0.00)
R^2	0.02	0.08	0.06	0.05	0.03	0.11
IR	0.61	0.70	0.78	0.51	0.64	0.77
			c) FX			
α	5.42%***	4.97%***	6.03%***	5.63%***	4.97%***	6.22%***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
R^2	0.22	0.28	0.23	0.33	0.28	0.37
IR	0.94	0.87	1.06	0.95	0.87	1.08

Table 8 – Asset pricing within asset classes: 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 × 4 univariate-sorted portfolios on ICRG political risk, 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 i) a model with the asset-class specific market portfolios (M_L) and political factors (P_L) constructed within each asset class, ii) a model with the asset-class specific market portfolios (M_L) and the global multi-asset political factor (P_G), and iii) our GPSZ model with the multi-asset market portfolio (M_G) and multi-asset political factor (P_G). Risk premia are estimated through a two-step OLS regression of average returns on factor loadings, run without the intercept and including the factors in the set of test assets. In Panel B we report 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, and 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 and coupon payments. Risk premia are annualized. The asterisks (***), (**), and (*) denote statistical significance at the 1%, 5%, and 10% level, respectively. Data are monthly, spanning 1992–2019.

(a) Risk premia

	Equity		Bond		FX	
	MKT	P-factor	MKT	P-factor	MKT	P-factor
M_L,P_L	6.10%**	5.59%**	4.88%***	3.81%***	1.86%	4.31%***
	(0.05)	(0.03)	(0.00)	(0.01)	(0.14)	(0.00)
M_L,P_G	6.63%**	4.13%**	4.87%***	3.62%**	1.87%	5.88%***
	(0.04)	(0.02)	(0.00)	(0.02)	(0.13)	(0.00)
M_G,P_G	2.44%	3.53%**	5.66%***	3.26%**	3.36%**	5.93%***
	(0.15)	(0.04)	(0.00)	(0.03)	(0.03)	(0.00)

Table 8 – (continued)

(b) Comparison with benchmark models

Equity

	M_L,P_L	M_L,P_G	GPSZ	CAPM	ACB	VME	BAB	CAR	ALL
MAPE	1.09%	1.14%	2.53%	2.78%	3.34%	2.55%	3.40%	3.05%	3.79%
GRS	1.06	1.36	1.46*	1.45*	1.98***	1.30	1.93***	1.69**	2.58***
p-value GRS	(0.39)	(0.14)	(0.10)	(0.10)	(0.01)	(0.18)	(0.01)	(0.03)	(0.00)
GLS R^2	0.24	0.44	0.39	0.10	0.69	0.81	0.19	0.66	0.72
OLS R^2	0.66	0.64	0.60	0.17	0.80	0.55	0.31	0.16	0.75
R^2 predicted vs realized	0.72	0.70	0.68	0.53	0.50	0.53	0.51	0.51	0.49

Bond

	M_L,P_L	M_L,P_G	GPSZ	CAPM	ACB	VME	BAB	CAR	ALL
MAPE	0.42%	0.58%	1.75%	2.13%	2.35%	2.60%	2.12%	2.24%	2.88%
GRS	0.78	1.02	1.40	7.66***	2.23***	3.55***	1.22	2.35***	1.31
p-value GRS	(0.73)	(0.44)	(0.12)	(0.00)	(0.00)	(0.00)	(0.23)	(0.00)	(0.17)
GLS R^2	0.02	0.00	0.48	0.00	0.10	0.02	0.17	0.03	0.38
OLS R^2	0.85	0.86	0.85	-0.02	0.67	0.66	0.07	0.36	0.82
R^2 predicted vs realized	0.86	0.85	0.66	0.45	0.45	0.44	0.45	0.45	0.44

FX

	M_L,P_L	M_L,P_G	GPSZ	CAPM	ACB	VME	BAB	CAR	ALL
MAPE	0.51%	0.87%	1.23%	2.38%	2.11%	2.65%	2.52%	2.11%	2.69%
GRS	1.61**	2.06***	1.99***	2.91***	2.89***	2.79***	4.50***	2.89**	4.29***
p-value GRS	(0.05)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
GLS R^2	0.01	0.04	0.70	0.01	0.10	0.27	0.04	0.10	0.55
OLS R^2	0.88	0.83	0.83	0.49	0.67	0.72	0.69	0.67	0.69
R^2 predicted vs realized	0.90	0.69	0.33	0.28	0.22	0.34	0.27	0.22	0.33

Table 9 – Asset pricing within political ratings: 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 4×4 univariate-sorted portfolios on ICRG political risk, 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 global multi-asset GPSZ model used to price the portfolios sorted on each political measure separately. Risk premia are estimated through a two-step OLS regression of average returns on factor loadings, run without the intercept and including the factors in the set of test assets. In Panel B we report 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, and 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 and coupon payments. Risk premia are annualized. The asterisks (***), (**), and (*) denote statistical significance at the 1%, 5%, and 10% level, respectively. Data are monthly, spanning 1992–2019.

(a) Risk premia

	ICRG		WES Politics		WES Policy		WB Politics	
	MKT	P-factor	MKT	P-factor	MKT	P-factor	MKT	P-factor
Risk premium	3.26%**	3.26%**	3.27%**	2.98%**	3.18%**	2.98%*	2.73%*	3.40%**
	(0.04)	(0.03)	(0.04)	(0.05)	(0.04)	(0.07)	(0.07)	(0.02)

(b) Pricing statistics

	ICRG	WES Politics	WES Policy	WB Politics
MAPE	2.07%	1.88%	1.74%	1.65%
GRS	3.28***	2.50***	1.88**	3.12***
p-value GRS	(0.00)	(0.00)	(0.02)	(0.00)
GLS R^2	0.19	0.20	0.25	0.16
OLS R^2	0.64	0.74	0.78	0.66
R^2 predicted vs realized	0.74	0.79	0.82	0.73

Table 10 – Global asset pricing controlling for global variables

This table reports the results of asset pricing tests run on the base set of test assets, which includes the 4 × 4 univariate-sorted portfolios on ICRG political risk, 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, three value and three momentum portfolios from Asness, Moskowitz, and Pedersen (2013) for each of the three asset classes, and six currency portfolios from Lustig, Roussanov, and Verdelhan (2011). We test different models where we augment the GPSZ multi-asset model, which includes the global multi-asset market portfolio ("MKT") and the global multi-asset P-factor, with each of the following global variables: a multi-asset emerging market portfolio ("EM"), and first differences in the US VIX index ("VIX"), in the global risk aversion volatility measure of Bekaert, Engstrom, and Xu (2022) ("Risk av"), and in the global economic policy uncertainty of Baker, Bloom, and Davis (2016) ("EPU"). "EM" is computed as a inverse-volatility portfolio of the emerging market portfolios in the equity, bond, and FX markets. The emerging market portfolio in the equity market is the excess returns of the MSCI Emerging Markets equity index, while in the bond and FX markets, we compute, respectively, the factor excess returns starting from an equally weighted average of the bond and FX returns of the emerging markets in our sample following the MSCI classification. We report the risk premia, estimated through a two-step OLS regression of average returns on factor loadings, run without the intercept and including the factors in the set of test assets. Returns are in percentages, denominated in USD, and include dividends and coupon payments. Risk premia are annualized. The asterisks (***), (**), and (*) denote statistical significance at the 1%, 5%, and 10% level, respectively. Data are monthly, spanning 1992–2019.

	(1)			(2)			(3)			(4)		
	MKT	P-factor	EM	MKT	P-factor	VIX	MKT	P-factor	Risk av	MKT	P-factor	EPU
	Base set											
Risk premium	3.68%***	3.89%***	3.10%*	3.35%**	3.39%***	-0.28%	3.54%***	3.63%***	0.66	3.18%**	3.24%***	8.17
	(0.01)	(0.00)	(0.08)	(0.02)	(0.01)	(1.00)	(0.01)	(0.01)	(0.44)	(0.03)	(0.01)	(0.61)
	Extended set											
Risk premium	3.38%**	3.40%***	4.11%***	3.34%**	3.26%**	-0.36%	3.44%***	3.14%**	0.26	3.32%**	2.57%*	8.17
	(0.02)	(0.01)	(0.01)	(0.02)	(0.02)	(1.00)	(0.01)	(0.02)	(0.71)	(0.02)	(0.06)	(0.61)

Table 11 – P-factor risk premia with orthogonalized political ratings

This table reports results of asset pricing tests when a multi-asset P-factor is constructed from political ratings that are orthogonalized on measures of macroeconomic risk. Pricing tests are run on the base set of test assets, which includes the 4×4 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, augmented with the sorted portfolios and L-H spreads from the orthogonalized ICRG ratings. We also run the same tests on the extended set of test assets, which adds the country excess returns, three value and three momentum portfolios from Asness, Moskowitz, and Pedersen (2013) for each of the three asset classes, and six currency portfolios from Lustig, Roussanov, and Verdelhan (2011). We orthogonalize the political ratings in three ways. In Model (1) we demean them by running country-level time-series regressions of the ICRG political risk scores on a constant. In Model (2) we run country-level time-series regressions of the ICRG political risk ratings on a constant and the ICRG economic risk ratings. In Model (3) we run country-level time-series regressions of the ICRG political risk ratings on a constant, realized GDP growth, and inflation rate. In all specifications we sort countries on the residuals from these regressions, construct the corresponding P-factor, and run cross-sectional pricing tests to estimate the risk premia. The asterisks (***), (**), and (*) denote statistical significance at the 1%, 5%, and 10% level, respectively. Data are monthly, spanning 1992–2019.

	(1)		(2)		(3)	
	MKT	P-factor$_{\perp}^{(1)}$	MKT	P-factor$_{\perp}^{(2)}$	MKT	P-factor$_{\perp}^{(3)}$
			Base set			
Risk premium	3.73%***	5.52%***	3.83%***	5.94%***	3.86%***	5.44%***
	(0.01)	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)
			Extended set			
Risk premium	3.73%***	4.76%***	3.84%***	4.76%***	3.92%***	3.71%***
	(0.01)	(0.00)	(0.01)	(0.00)	(0.01)	(0.01)

Table 12 – Pricing performance of long and short legs of the P-factor

Panel A reports the annualized average return and Sharpe ratio of two alternative factors constructed as the long leg of the global multi-asset P-factor in excess of the global multi-asset market portfolio ("Long–MKT"), and the global multi-asset market portfolio in excess of the short leg of the global multi-asset P-factor ("MKT–Short"). Newey and West (1987) p-values based on optimal number of lags (Andrews and Monahan, 1992) are in parenthesis. In Panel B we estimate the risk premia of a three-factor model, including the global multi-asset market portfolio and the two factors mentioned above. Risk premia estimated through a two-step OLS regression of average returns on factor loadings, run without the intercept and including the factors in the set of test assets. In Panel C we report pricing statistics of this three-factor model such as the mean absolute pricing error (MAPE) from time-series regressions, the GRS statistic and its corresponding p-value, the OLS and GLS R^2 from the second step cross-sectional regression, and 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 and coupon payments. Risk premia are annualized. The asterisks (***), (**), and (*) denote statistical significance at the 1%, 5%, and 10% level, respectively. Data are monthly, spanning 1992–2019.

(a) Factor statistics

	Long–MKT	MKT–Short
Avg return	3.21%***	1.15%*
	(0.00)	(0.07)
Sharpe	0.85	0.36

(b) Risk premia

	Base set			Extended set		
	MKT	Long–MKT	MKT –Short	MKT	Long–MKT	MKT–Short
Risk premium	3.11**	2.31***	-0.79	3.32**	2.12***	-0.55
	(0.03)	(0.01)	(0.22)	(0.02)	(0.01)	(0.43)

(c) Pricing statistics

	Base set	Extended set
MAPE	1.70	2.14
GRS statistic	1.04	0.71
p-value GRS	0.40	0.98
GLS R^2	0.35	0.38
OLS R^2	0.77	0.67
R^2 predicted vs realized	0.80	0.72

Table 13 – 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 asterisks (***), (**), and (*) denote statistical significance at the 1%, 5%, and 10% level, respectively. Returns are in percentages, denominated in USD, and include dividends and coupon payments. 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%***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
P2	12.92%***	9.25%***	3.02%**	12.24%***	9.36%***	3.08%***
	(0.01)	(0.00)	(0.02)	(0.01)	(0.00)	(0.01)
P3	8.21%	6.65%***	1.61%	9.09%*	8.22%***	2.33%*
	(0.13)	(0.00)	(0.29)	(0.08)	(0.00)	(0.06)
P4 (H)	11.21%**	7.64%***	2.33%	9.94%**	6.97%***	2.13%
	(0.03)	(0.00)	(0.12)	(0.04)	(0.00)	(0.14)
L-H	8.65%**	4.36%	6.79%***	9.56%***	3.53%**	5.88%***
	(0.02)	(0.17)	(0.00)	(0.00)	(0.03)	(0.00)
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***
	(0.00)	(0.07)	(0.05)	(0.00)	(0.00)	(0.00)	(0.02)	(0.00)
P2	9.84%**	8.99%***	1.95%	0.88***	9.69%*	8.72%***	2.26%*	0.87***
	(0.05)	(0.00)	(0.13)	(0.00)	(0.06)	(0.00)	(0.08)	(0.00)
P3 (H)	7.43%	7.71%**	4.49%*	0.82***	8.68%*	5.51%***	2.27%	0.86***
	(0.25)	(0.02)	(0.06)	(0.00)	(0.10)	(0.01)	(0.13)	(0.00)
L-H	16.39%**	-0.82%	6.55%	0.06***	11.00%**	4.17%	7.55%*	0.03***
	(0.05)	(0.83)	(0.32)	(0.00)	(0.03)	(0.12)	(0.08)	(0.00)
Sharpe	0.41	-0.05	0.33		0.43	0.34	0.62	

Table 14 – P-factor robustness to outliers

This table reports the statistics of our global multi-asset political factor when we remove its returns corresponding to those months during which the US VIX index (Panel A), the global risk aversion index of Bekaert, Engstrom, and Xu (2022) (Panel B), and the global economic policy uncertainty index of Baker, Bloom, and Davis (2016) (Panel C) fall below or above their k^{th} percentile. Newey and West (1987) p-values based on optimal number of lags (Andrews and Monahan, 1992) are in parenthesis, and the asterisks (***), (**), and (*) denote statistical significance at the 1%, 5%, and 10% level, respectively. Data are monthly, spanning 1992–2016.

(a) US VIX

	Delete if > k			Baseline	Delete if < k		
	k=80%	k=70%	k=60%	k=0%	k=40%	k=30%	k=20%
Avg return	5.54%***	5.66%***	5.09%***	4.44%***	4.27%**	3.93%***	3.44%**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.02)	(0.01)	(0.02)
Sharpe	0.94	1.01	0.96	0.70	0.61	0.58	0.52

(b) Global risk aversion

	Delete if > k			Baseline	Delete if < k		
	k=80%	k=70%	k=60%	k=0%	k=40%	k=30%	k=20%
Avg return	5.69%***	5.63%***	5.99%***	4.44%***	2.89%*	3.76%***	3.95%***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.07)	(0.01)	(0.00)
Sharpe	0.91	0.89	0.92	0.70	0.45	0.59	0.62

(c) Global EPU

	Delete if > k			Baseline	Delete if < k		
	k=80%	k=70%	k=60%	k=0%	k=40%	k=30%	k=20%
Avg return	4.37%***	4.32%***	6.64%***	4.44%***	3.10%**	2.42%*	2.76%**
	(0.00)	(0.01)	(0.00)	(0.00)	(0.02)	(0.07)	(0.04)
Sharpe	0.66	0.63	0.96	0.70	0.53	0.40	0.44

Table 15 – 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_β) and top (H_β) 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 asterisks (***), (**), and (*) denote statistical significance at the 1%, 5%, and 10% level, respectively. Returns are in percentages, denominated in USD, and include dividends and coupon payments. Data are monthly, spanning 1992–2019.

Panel A: Equity					
	P1 (H_β)	P2	P3	P4 (L_β)	$H_\beta - L_\beta$
Avg return	12.29%***	5.56%	8.64%***	6.51%*	5.66%*
	(0.01)	(0.16)	(0.01)	(0.09)	(0.09)
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***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Post-formation beta	1.03***	0.43***	0.07	-0.11	1.14***
	(0.00)	(0.00)	(0.41)	(0.24)	(0.00)
Ex-post ICRG rating	64.01***	72.63***	81.55***	83.78***	-19.77*
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

Panel B: Bond					
	P1 (H_β)	P2	P3	P4 (L_β)	$H_\beta - L_\beta$
Avg return	9.01%***	5.04%***	2.60%	2.19%	6.82%***
	(0.00)	(0.00)	(0.15)	(0.26)	(0.00)
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*
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Post-formation beta	0.66***	-0.11*	-0.51***	-0.64***	1.30***
	(0.00)	(0.06)	(0.00)	(0.00)	(0.00)
Ex-post ICRG rating	67.46***	75.83***	81.61***	84.78***	-17.32***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

Panel C: FX					
	P1 (H_β)	P2	P3	P4 (L_β)	$H_\beta - L_\beta$
Avg return	5.80%***	1.41%	1.02%	-1.07%	6.75%***
	(0.00)	(0.16)	(0.49)	(0.56)	(0.00)
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***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Post-formation beta	0.11	-0.24***	-0.77***	-1.12***	1.23***
	(0.17)	(0.00)	(0.00)	(0.00)	(0.00)
Ex-post ICRG rating	65.91***	71.98***	79.86***	82.91***	-17.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

Table 16 – Spurious factor test

This table reports the spurious factor test run on a set of test assets that includes the sorted portfolios and the long-short strategies from Table 2 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 5.7. 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 asterisks (***), (**), and (*) denote statistical significance at the 1%, 5%, and 10% level, respectively. 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.

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[25], 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.

[25] `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 $t+1$,

$$r_{t+1}^{FWD} = \frac{F_t}{S_{t+1}} - 1, \tag{2}$$

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

$$r_{t+1}^{MM} = (1 + i_t^*)\, \frac{S_{t+1}}{S_t} - (1 + i_t)\,, \tag{3}$$

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.[26].

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

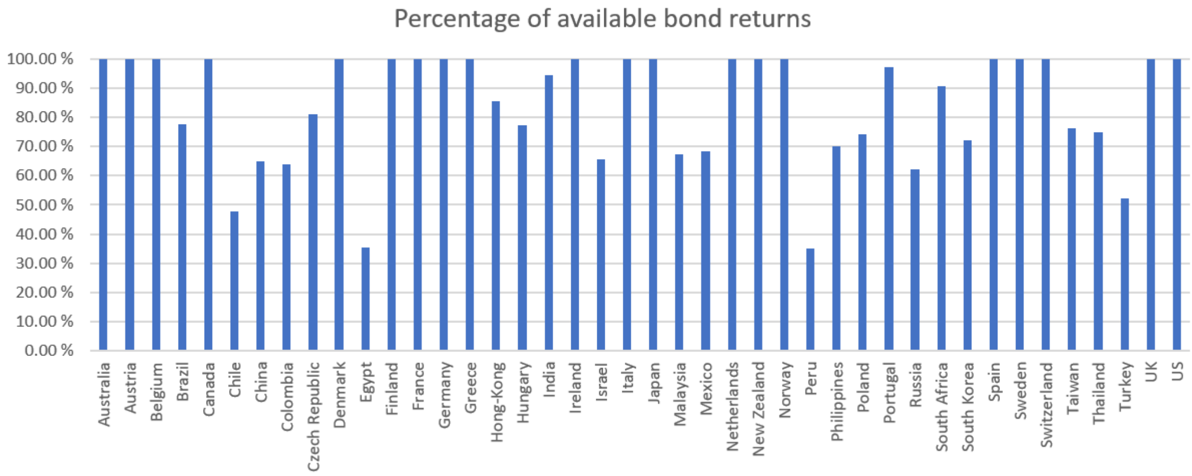
[Insert Figure A2 Near Here]

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

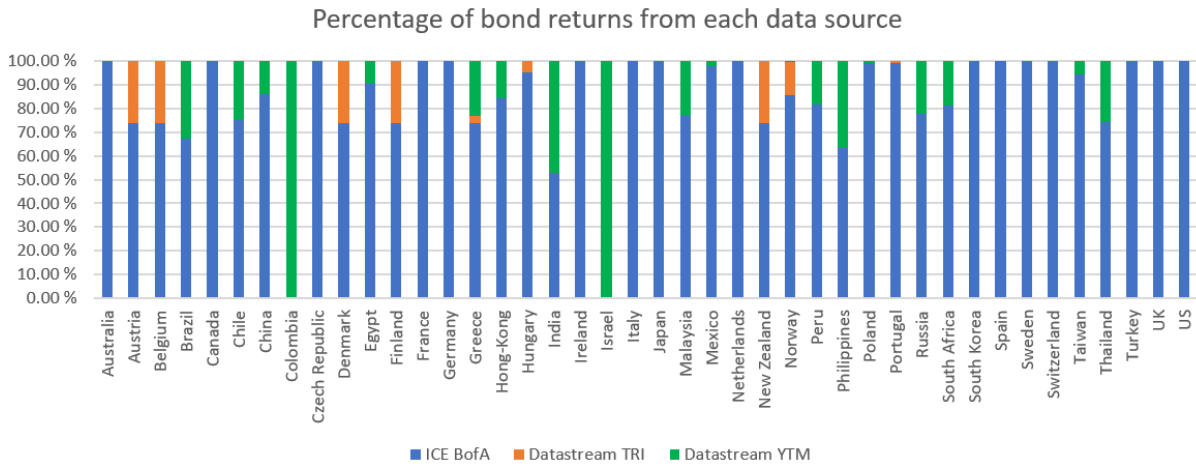
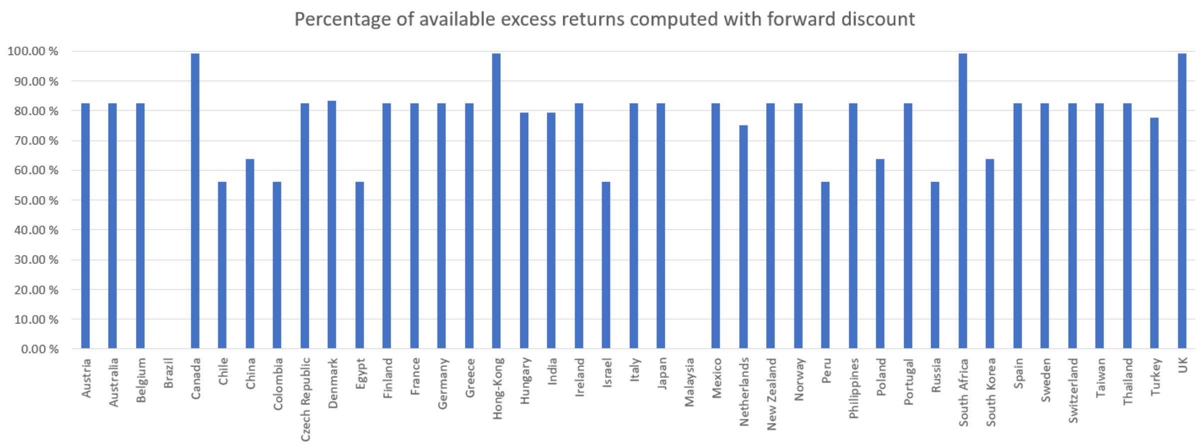


Figure A2: **Construction of FX sample**

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

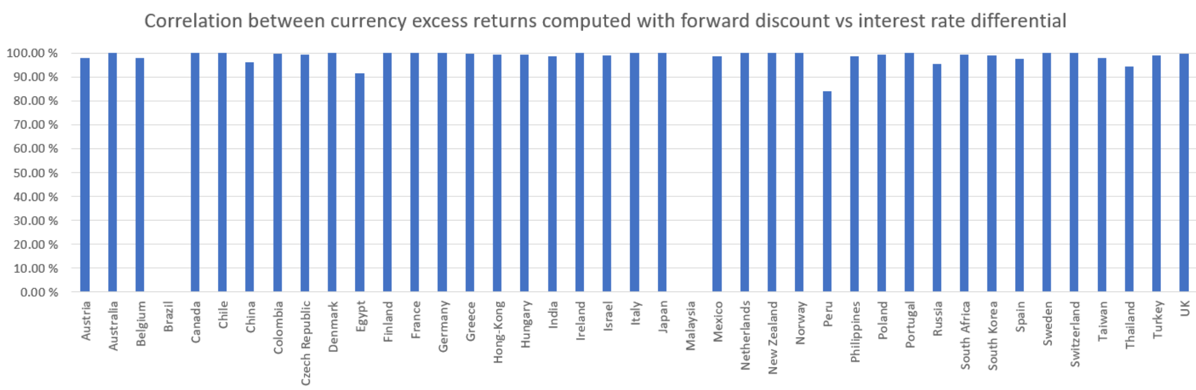


Table A1 – Descriptive statistics of excess returns in all asset classes

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 and coupon payments. 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 – Asset pricing within asset classes: 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 4×4 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 country excess returns within each asset class, three value and three momentum portfolios from Asness, Moskowitz, and Pedersen (2013) within each asset class, and six currency portfolios from Lustig, Roussanov, and Verdelhan (2011) only in FX asset class. Panel A reports the risk premia of i) a model with the asset-class specific market portfolios (M_L) and political factors (P_L) constructed within each asset class, ii) a model with the asset-class specific market portfolios (M_L) and the global multi-asset political factor (P_G), and iii) our GPSZ model with the multi-asset market portfolio (M_G) and multi-asset political factor (P_G). Risk premia are estimated through a two-step OLS regression of average returns on factor loadings, run without the intercept and including the factors in the set of test assets. In Panel B we report 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, and 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 and coupon payments. Risk premia are annualized. The asterisks (***), (**), and (*) denote statistical significance at the 1%, 5%, and 10% level, respectively. Data are monthly, spanning 1992–2019.

(a) Risk premia

Pricing with asset-class specific market portfolios M_L and P-factors P_L

	Equity		Bond		FX	
	M_L	P_L	M_L	P_L	M_L	P_L
Risk premium	6.38%**	4.78%*	4.74%***	3.48%**	1.80%	3.96%***
	(0.03)	(0.06)	(0.00)	(0.02)	(0.14)	(0.00)

Pricing with asset-class specific market portfolios M_L and multi-asset P-factor P_G

	Equity		Bond		FX	
	M_L	P_G	M_L	P_G	M_L	P_G
Risk premium	6.78%**	3.26%**	4.73%***	3.06%**	1.79%	5.21%**
	(0.02)	(0.05)	(0.00)	(0.03)	(0.14)	(0.00)

Pricing with multi-asset market portfolio M_G and multi-asset P-factor P_G

	Equity		Bond		FX	
	M_L	P_G	M_L	P_G	M_L	P_G
Risk premium	2.78%*	2.83%*	5.16%***	2.32%*	2.97%**	5.08%***
	(0.10)	(0.09)	(0.00)	(0.10)	(0.04)	(0.00)

Table A2 – (continued)

(b) Comparison with benchmark models

Equity

	M_L,P_L	M_L,P_G	GPSZ	CAPM	ACB	VME	BAB	CAR	ALL
MAPE	1.85%	1.99%	3.18%	2.42%	2.77%	2.32%	2.99%	2.68%	3.27%
GRS	1.02	1.46**	1.22	1.20	1.08	1.00	1.31*	1.25	1.41**
p-value GRS	(0.44)	(0.02)	(0.14)	(0.17)	(0.33)	(0.48)	(0.07)	(0.11)	(0.03)
GLS R^2	0.74	0.80	0.80	0.65	0.86	0.84	0.71	0.84	0.87
OLS R^2	0.48	0.42	0.44	0.17	0.41	0.28	0.16	0.19	0.44
R^2 predicted vs realized	0.58	0.55	0.55	0.38	0.44	0.40	0.44	0.43	0.46

Bond

	M_L,P_L	M_L,P_G	GPSZ	CAPM	ACB	VME	BAB	CAR	ALL
MAPE	1.51%	1.66%	2.46%	2.28%	2.26%	2.43%	2.81%	2.35%	3.06%
GRS	1.52***	1.54***	2.22***	1.21	2.24***	1.72***	2.59***	2.51***	2.81***
p-value GRS	(0.01)	(0.01)	(0.00)	(0.15)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
GLS R^2	0.09	0.18	0.78	0.00	0.24	0.08	0.52	0.06	0.62
OLS R^2	0.57	0.54	0.53	0.07	0.40	0.28	0.05	0.17	0.48
R^2 predicted vs realized	0.65	0.66	0.64	0.41	0.34	0.33	0.40	0.38	0.33

FX

	M_L,P_L	M_L,P_G	GPSZ	CAPM	ACB	VME	BAB	CAR	ALL
MAPE	1.00%	1.15%	1.50%	2.18%	1.86%	2.40%	2.31%	1.86%	2.31%
GRS	2.14***	2.21***	2.26***	2.54***	2.29***	2.25***	4.59***	2.29***	4.32***
p-value GRS	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
GLS R^2	0.22	0.22	0.07	0.06	0.21	0.28	0.25	0.21	0.32
OLS R^2	0.69	0.57	0.54	0.03	0.43	0.46	0.37	0.43	0.40
R^2 predicted vs realized	0.71	0.53	0.37	0.08	0.12	0.13	0.08	0.12	0.13

Table A3 – Factor structures within asset classes

This table reports the results of a principal component analysis of the 4×4 portfolios sorted on the different political risk measures within each asset class separately. Panel A shows the percentage of total variance explained by the first two principal components and their correlations with the asset-class specific P-factors. Panel B reports the portfolio loadings on these principal components. Data are monthly, spanning 1992–2019.

	Equity		Bond		FX	
	PC1	PC2	PC1	PC2	PC1	PC2
			(a) PC analysis			
Eigenvalues (%)	89.78	4.76	82.27	9.56	82.42	9.73
Correlation	0.19	0.97	-0.16	0.97	-0.54	0.82
			(b) Factor loadings			
			Combo			
P1 (L)	0.23	0.37	0.22	0.37	0.20	0.37
P2	0.26	0.08	0.26	0.09	0.26	0.09
P3	0.26	-0.15	0.26	-0.15	0.27	-0.16
P4 (H)	0.25	-0.27	0.26	-0.23	0.26	-0.20

Table A4 – Asset pricing within political ratings: 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 4×4 univariate-sorted portfolios on ICRG political risk, WES policy, WES politics, and World Bank politics, together with the corresponding L-H spread portfolios from each measure, as well as the country excess returns, three value and three momentum portfolios from Asness, Moskowitz, and Pedersen (2013) for each of the three asset classes, and six currency portfolios from Lustig, Roussanov, and Verdelhan (2011). Panel A reports the risk premia of our global multi-asset GPSZ model used to price the portfolios sorted on each political measure separately. Risk premia are estimated through a two-step OLS regression of average returns on factor loadings, run without the intercept and including the factors in the set of test assets. In Panel B we report 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, and 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 and coupon payments. Risk premia are annualized. The asterisks (***), (**), and (*) denote statistical significance at the 1%, 5%, and 10% level, respectively. Data are monthly, spanning 1992–2019.

(a) Risk premia

	ICRG		WES Politics		WES Policy		WB Politics	
	MKT	P-factor	MKT	P-factor	MKT	P-factor	MKT	P-factor
Risk premium	3.23%**	2.49%*	3.25%**	2.42%*	3.24%**	2.40%*	3.18%**	2.51%*
	(0.02)	(0.08)	(0.02)	(0.09)	(0.02)	(0.09)	(0.02)	(0.08)

(b) Pricing statistics

	ICRG	WES Politics	WES Policy	WB Politics
MAPE	2.53%	2.51%	2.50%	2.49%
GRS	1.60***	1.69***	1.21	1.64***
p-value GRS	(0.00)	(0.00)	(0.11)	(0.00)
GLS R^2	0.12	0.19	0.46	0.22
OLS R^2	0.60	0.60	0.60	0.60
R^2 predicted vs realized	0.67	0.67	0.67	0.67

Table A5 – Global asset pricing controlling for global variables: pricing statistics

This table reports the results of asset pricing tests run on the base set of test assets, which includes the 4 × 4 univariate-sorted portfolios on ICRG political risk, 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, three value and three momentum portfolios from Asness, Moskowitz, and Pedersen (2013) for each of the three asset classes, and six currency portfolios from Lustig, Roussanov, and Verdelhan (2011). We test different models where we augment the GPSZ multi-asset model, which includes the global multi-asset market portfolio ("MKT") and the global multi-asset P-factor, with each of the following global variables: a multi-asset emerging market portfolio ("EM"), and first differences in the US VIX index ("VIX"), in the global risk aversion volatility measure of Bekaert, Engstrom, and Xu (2022) ("Risk av"), and in the global economic policy uncertainty of Baker, Bloom, and Davis (2016) ("EPU"). "EM" is computed as a inverse-volatility portfolio of the emerging market portfolios in the equity, bond, and FX markets. The emerging market portfolio in the equity market is the excess returns of the MSCI Emerging Markets equity index, while in the bond and FX markets we compute, respectively, the factor excess returns starting from an equally weighted average of the bond and FX returns of the emerging markets in our sample following the MSCI classification. We compare the performance of the GPSZ model with those factor models described in Table 7 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 and coupon payments. The asterisks (***), (**), and (*) denote statistical significance at the 1%, 5%, and 10% level, respectively. Data are monthly, spanning 1992–2019.

Base set of test assets

	EM	VIX	Risk av	EPU
MAPE	1.51%	1.56%	1.49%	1.61%
GRS stat	1.32*	1.28*	1.32*	1.45**
GRS p-value	0.07	0.10	0.07	0.03
GLS R^2	0.38	0.21	0.25	0.01
OLS R^2	0.78	0.73	0.74	0.73
R^2 predicted vs realized	0.80	0.78	0.79	0.78

Extended set of test assets

MAPE	1.98%	2.16%	2.07%	2.08%
GRS stat	0.91	1.42**	1.12	2.50***
GRS p-value	0.72	0.02	0.25	0.00
GLS R^2	0.35	0.39	0.35	0.31
OLS R^2	0.64	0.62	0.63	0.60
R^2 predicted vs realized	0.70	0.67	0.69	0.68

Table A6 – Abnormal returns within asset classes and political ratings

This table reports the average annualized abnormal returns (alphas), adjusted R^2 and information ratios (IR) from time-series regressions of the portfolio strategies of Table 2 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 asterisks (***), (**), and (*) denote statistical significance at the 1%, 5%, and 10% level, respectively. Data are monthly, spanning 1992–2016.

(a) Equity

	ICRG						WES Politics					
	CAPM	ACB	VME	BAB	CAR	ALL	CAPM	ACB	VME	BAB	CAR	ALL
α	6.06%*	8.29%**	6.26%*	7.26%*	6.31%	9.06%**	4.68%*	6.13%**	3.79%	5.66%*	4.63%	6.26%*
	(0.09)	(0.03)	(0.08)	(0.06)	(0.11)	(0.04)	(0.09)	(0.04)	(0.17)	(0.07)	(0.14)	(0.06)
R^2	0.00	0.05	0.02	0.00	-0.01	0.07	0.00	0.04	0.02	0.00	0.00	0.07
IR	0.39	0.56	0.41	0.47	0.40	0.60	0.35	0.47	0.29	0.42	0.34	0.48

	WES Policy						World Bank Politics					
	CAPM	ACB	VME	BAB	CAR	ALL	CAPM	ACB	VME	BAB	CAR	ALL
α	5.10%**	8.11%***	4.88%*	7.14%***	4.55%*	8.20%***	6.19%*	6.58%*	5.60%	6.72%*	6.59%*	7.44%*
	(0.04)	(0.00)	(0.06)	(0.01)	(0.10)	(0.00)	(0.09)	(0.10)	(0.12)	(0.10)	(0.10)	(0.10)
R^2	0.01	0.03	0.03	0.02	0.01	0.06	0.00	0.05	0.00	-0.01	0.00	0.05
IR	0.38	0.61	0.37	0.53	0.33	0.61	0.42	0.46	0.38	0.46	0.43	0.51

Table A6 – (continued)

(b) Bond

	ICRG						WES Politics					
	CAPM	ACB	VME	BAB	CAR	ALL	CAPM	ACB	VME	BAB	CAR	ALL
α	4.94%***	5.45%***	6.29%***	5.02%*	4.76%**	7.27%***	4.42%***	4.92%***	5.42%***	3.83%**	5.12%***	5.43%***
	(0.01)	(0.01)	(0.00)	(0.06)	(0.02)	(0.00)	(0.00)	(0.00)	(0.00)	(0.04)	(0.00)	(0.00)
R^2	0.01	0.06	0.04	0.03	0.02	0.08	0.01	0.07	0.05	0.03	0.02	0.08
IR	0.50	0.57	0.65	0.47	0.48	0.71	0.61	0.70	0.77	0.49	0.70	0.72

	WES Policy						World Bank Politics					
	CAPM	ACB	VME	BAB	CAR	ALL	CAPM	ACB	VME	BAB	CAR	ALL
α	2.88%**	3.33%***	3.46%***	1.32%	3.11%**	2.05%	5.67%***	6.00%***	6.73%***	6.47%***	6.19%***	8.69%***
	(0.03)	(0.01)	(0.01)	(0.41)	(0.03)	(0.19)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)
R^2	0.00	0.03	0.03	0.03	0.01	0.05	0.05	0.11	0.07	0.10	0.07	0.17
IR	0.46	0.54	0.56	0.21	0.50	0.34	0.65	0.72	0.79	0.69	0.71	0.98

(c) FX

	ICRG						Politics					
	CAPM	ACB	VME	BAB	CAR	ALL	CAPM	ACB	VME	BAB	CAR	ALL
α	6.71%***	6.06%***	7.29%***	6.88%***	6.06%***	7.57%***	4.95%***	4.69%***	5.45%***	5.43%***	4.69%***	5.80%***
	(0.00)	(0.00)	(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	0.41	0.16	0.21	0.18	0.28	0.21	0.30
IR	0.90	0.82	0.99	0.94	0.82	1.06	0.81	0.76	0.90	0.84	0.76	0.92

	Policy						WB					
	CAPM	ACB	VME	BAB	CAR	ALL	CAPM	ACB	VME	BAB	CAR	ALL
α	3.52%***	3.40%***	3.90%***	3.16%**	3.40%***	3.89%***	5.59%***	4.61%***	6.28%***	6.38%***	4.61%***	5.98%***
	(0.00)	(0.01)	(0.00)	(0.05)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
R^2	0.05	0.08	0.05	0.08	0.08	0.12	0.30	0.40	0.33	0.41	0.40	0.47
IR	0.66	0.63	0.73	0.56	0.63	0.71	0.86	0.74	0.99	0.96	0.74	0.95

Table A7 – P-factor risk premia with orthogonalized political ratings: pricing statistics

This table reports results of asset pricing tests when a multi-asset P-factor is constructed from political ratings that are orthogonalized on measures of macroeconomic risk. Pricing tests are run on the base set of test assets, which includes the 4×4 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, augmented with the sorted portfolios and L-H spreads from the orthogonalized ICRG ratings. We also run the same tests on the extended set of test assets, which adds the country excess returns, three value and three momentum portfolios from Asness, Moskowitz, and Pedersen (2013) for each of the three asset classes, and six currency portfolios from Lustig, Roussanov, and Verdelhan (2011). We orthogonalize the political ratings in three ways. In Model (1) we demean them by running country-level time-series regressions of the ICRG political risk scores on a constant. In Model (2) we run country-level time-series regressions of the ICRG political risk ratings on a constant and the ICRG economic risk ratings. In Model (3) we run country-level time-series regressions of the ICRG political risk ratings on a constant, realized GDP growth, and inflation rate. In all specifications we sort countries on the residuals from these regressions, construct the corresponding P-factor, and run time-series and cross-sectional pricing tests. 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 and coupon payments. The asterisks (***), (**), and (*) denote statistical significance at the 1%, 5%, and 10% level, respectively. Data are monthly, spanning 1992–2019.

	P-factor$^1_\perp$		P-factor$^2_\perp$		P-factor$^3_\perp$	
	Base	Extended	Base	Extended	Base	Extended
MAPE	2.18%	2.33%	2.10%	2.30%	2.31%	2.45%
GRS	1.48***	0.99	1.41**	1.55***	1.48***	1.27*
p-value GRS	(0.01)	(0.53)	(0.03)	(0.01)	(0.01)	(0.08)
GLS R^2	0.02	0.25	0.17	0.27	0.10	0.16
OLS R^2	0.60	0.48	0.55	0.47	0.48	0.38
R^2 predicted vs realized	0.57	0.51	0.59	0.52	0.53	0.47

Table A8 – Correlation among multi-asset political factors constructed with different ratings

This table reports the correlation coefficients of global multi-asset political factors constructed with each of the four political ratings: ICRG political risk ratings, WES politics, WES economic policy, and World Bank politics. "Combo" denotes the factor constructed as an equally weighted average of the returns of the other four factors. All multi-asset political factors are inverse-volatility portfolios of the corresponding asset-class-specific political factors. Data are monthly, spanning 1992–2019.

	ICRG	WES Politics	WES Policy	WB Politics
ICRG				
WES Politics	0.77			
WES Policy	0.56	0.64		
WB Politics	0.93	0.81	0.57	
Combo	0.93	0.90	0.76	0.94

Table A9 – 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)). In Panel D we report the correlations of the asset-class specific political factors. Data are monthly, spanning 1992–2019.

(a) Equity

	P-factor	MKT
P-factor		
MKT	0.03	
SMB	0.16	-0.11
HML	-0.08	-0.14
RMW	-0.07	-0.42
CMA	-0.17	-0.40
WML	-0.05	-0.25
MOM	-0.03	-0.16
VAL	0.17	0.27
TSM	0.04	0.12
BAB	-0.07	-0.25
CAR	0.04	-0.02

(b) Bond

	P-factor	MKT
P-factor		
MKT	-0.15	
TERM	-0.23	0.21
DEF	0.21	0.25
MOM	-0.12	0.13
VAL	0.00	-0.08
TSM	-0.22	0.15
BAB	0.08	-0.19
CAR	-0.09	0.21

Table A9 – (continued)

(c) FX

	P-factor	MKT
P-factor		
MKT	-0.47	
HML_{FX}	0.24	0.26
MOM	-0.02	0.06
VAL	0.00	-0.04
TSM	-0.08	-0.02
BAB	0.33	-0.14
CAR	0.01	0.36

(d) P-factors across asset classes

	Equity	Bond
Equity		
Bond	0.39	
FX	0.36	0.63