Political Risk Everywhere

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Abstract

Country risk premia reflect compensation for global political risk. A strong factor structure in political-risk sorted equity, bond, and currency portfolios gives rise to a global political risk P-factor, which commands a significant risk premium of 4.4% with a Sharpe ratio of 0.7. Along with the global market, it explains up to three-quarters of the cross-sectional variation within and across a large panel of international asset returns. The P-factor is distinct from existing asset pricing factors, is pervasive across asset classes and political ratings, and is related to systematic variations in expected global growth and aggregate volatility.

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1 Introduction

Understanding the fundamental differences in expected returns across risky assets is one of the key questions in financial economics. 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 global market risk, drives systematic variations in risk premia across and within stocks, bonds, and currencies in the international 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 wars in Ukraine and Middle East, to local events, such as snap elections (following the resignation of Truss in the UK or Macron's decision to call snap elections in France), among many other examples. Political risk spurred a vibrant literature in finance, laying its theoretical foundations for asset pricing (Pástor and Veronesi, 2012), providing empirical evidence (Brogaard, Dai, Ngo, and Zhang, 2020; Kelly, Pástor, and Veronesi, 2016; Liu and Shaliastovich, 2022) including spillovers (Gala, Pagliardi, and Zenios, 2023), and using advanced analytics on policy news (Baker, Bloom, and Davis, 2016). Acknowledging the complex and multi-faceted nature of political risk, several measures have been proposed in the literature.[2] Our key contributions are to quantify reliable measures of political risk, show its significance in global financial markets, and document its economic relevance.

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 long sample period. The country-level rankings based on political risk proxies exhibit a strong factor structure,

[1] The asset-pricing "everywhere" literature includes Asness, Moskowitz, and Pedersen (2013) for value and momentum, Asness, Liew, Pedersen, and Thapar (2021) for deep value, Moskowitz, Ooi, and Pedersen (2012) time-series momentum, Daniel and Moskowitz (2016) momentum crashes, Koijen, Moskowitz, Pedersen, and Vrugt (2018) carry, Frazzini and Pedersen (2014) betting against beta, Bollerslev, Hood, Huss, and Pedersen (2018) volatility, Menkhoff, Sarno, Schmeling, and Schrimpf (2012) global FX volatility, Gao, Lu, and Song (2019) tail risk, Asness, Ilmanen, Israel, and Moskowitz (2015) style, trend-following investing (Babu, Levine, Ooi, Pedersen, and Stamelos, 2020), global macroeconomic risks (Cooper, Mitrache, and Priestley, 2020), or 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 one by Sottilotta (2016). From the finance literature, see Bekaert, Harvey, Lundblad, and Siegel (2014); Howell (2014), and from management see Bremmer (2005); Fitzpatrick (1983).

suggesting common fluctuations in political risk worldwide. Motivated by this evidence, we take a "combo" approach and aggregate proxies to reduce noise and sharpen identification while also showing that our results are not driven by any particular proxy. While a country-specific component of political risk likely exists, our goal is to price the uncovered global systematic component.

Armed with proxies for political risk, we provide strong evidence that market investors incorporate concerns about political risks into asset prices, leading high political-risk countries to earn systematically high average returns. Sorting countries on the political risk measures generates 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 that in highly-rated (low political risk) countries. In equity markets, the return 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 economically sizeable and statistically significant spreads in average bond and FX returns of 5.40% and 4.50%, respectively, for the combo.

The portfolios sorted on political risk proxies share a strong factor structure across asset classes, with the first two principal components accounting for about 84% of variation in equity, fixed income, and currency political portfolio returns. The first principal component is a level factor, essentially the global market portfolio. The second principal component is a slope factor whose weights line up with average portfolio returns. This evidence suggests a standard APT (Ross, 1976) approach to explaining political returns.

Motivated by the strong factor structure in returns, we use the long-short spread portfolio for each asset class and rating category to construct asset- and rating-specific political risk factors, along with the global multi-asset political factor (P-factor). As shown in Table 1, which summarizes the corresponding average returns, political risk is "everywhere." Sizeable political risk premia are pervasive across all asset classes and ratings. Importantly, political risk can be meaningfully identified from any of those, and asset- or rating-specific information does not materially alter its importance. Rather than focusing on 4×3 political risk factors separately, one for each of the three asset classes and four rating choices, we center our analysis on the global multi-asset P-factor. We show that the global multi-asset P-factor, constructed across all asset classes and ratings, does a remarkably good job of extracting the political risk information embedded in global financial markets. It carries a significant risk premium of 4.44% p.a. and is highly correlated with the slope factor driving the common variation in returns across political portfolios.

Table 1 – Global political risk premia

This table reports risk premia for the P-factors within and across asset classes and ratings. The 4×3 entries in the middle denote the asset- and rating-specific political risk premia within each asset class (equities, bonds, and currencies) and each political rating (ICRG, WES Politics, WES Policy, World Bank). These are constructed as spread portfolios going long in countries with low political ratings (L) and short in countries with high political ratings (H); see section 3.1. The last row ("Combo") reports equally weighted averages of rating-specific P-factors within each asset class. The last column ("Multi-asset factors") reports inverse volatility-weighted averages of asset class-specific P-factors within each rating category; see section 3.2. Likewise, the "Global multi-asset P-factor," listed in the bottom right corner, is computed as the inverse volatility-weighted average of the asset class P-factors. All political risk premia computed as average returns in % are statistically significant at the 5% level or less.

		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
Combo factors		Equity P-factor 5.86	Bonds P-factor 3.61	FX P-factor 4.50	**Global multi-asset P-factor** **4.44**

We formally test our benchmark two-factor multi-asset model (henceforth GPSZ), which consists of the multi-asset market portfolio and the multi-asset P-factor. For the first set of asset-pricing results, we use the model to price large sets of test assets, up to 210 assets, across equity, fixed income, and currency markets. 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% with a t-statistic of 3.38, above the critical threshold of three advocated by Harvey, Liu, and Zhu (2016), and a Sharpe ratio of 0.70. These magnitudes are even more remarkable when discarding returns corresponding to periods of high market volatility —top 30% of observations in the US VIX Index— with the global P-factor attaining an average return of 5.66% p.a. with t-statistic of 4.37 and Sharpe ratio of 1.01. The GRS test cannot reject the null that all pricing errors are jointly zero for our model, with cross-sectional R^2 reaching up to 0.74.

While we do not aim to run a horse race across all 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 do not explain the cross-section of political risk sorted portfolios, each having mean pricing errors larger than the GPSZ model.

Next, we zoom in on the model's performance within each asset class or political proxy separately. The political risk premium estimates are significant in all three markets, and the benchmark global GPSZ model exhibits lower pricing errors and better or at least comparable cross-sectional R^2 than the best-performing alternative model.[3] 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 asset-class-specific factors rather than multi-asset versions of the factors, we show that the most significant improvement comes from using the market factor. At the same time, the gains from asset-specific over multi-asset P-factor are marginal. We also find that our pricing results are not driven by any particular political risk rating across the three proxies or the sub-components of the ICRG ratings. This evidence underscores the central message of the paper that the political risk factor is everywhere.

To provide an economic interpretation of our results, we show that fluctuations in political risk anticipate changes in global economic conditions. Following Liew and Vassalou (2000), we show that the P-factor forecasts global economic growth with positive signs at 3-, 6-, and 12-month horizons. Similarly, it 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 VIX, global 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 evidence is consistent with a risk-based explanation for the global political risk premium whereby positive P-factor returns are associated with systemati-

[3]To safeguard against any potential mechanical relationship between the risk factors and test assets, we also successfully run an "out-of-sample" comovement test in the spirit of Asness, Moskowitz, and Pedersen (2013). We use the political risk factor from one asset or rating category to price successfully portfolio sorts on all the remaining ones; see subsections 4.3.3 and 4.4.

cally good news —high growth, low uncertainty— about the global economy. Investors command a positive premium as compensation for un-diversifiable global political risk, and any asset that covaries positively with the global P-factor earns higher returns.

We next show that the P-factor predicts various out-of-sample proxies of global political risk, including the global geopolitical risk index of Caldara and Iacoviello (2022), but it has no significant predictive power on economic risk ratings, confirming its forward-looking nature and ability to isolate political information. We then document that it remains significant in pricing tests including economic and financial-market variables to control for other sources of aggregate risk, such as the VIX index and an emerging market portfolio. We also construct several alternative P-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 these factors are consistently priced with comparable risk prices. 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 beyond macroeconomic variables.

We conclude with several extensions to corroborate our main finding of a risk-based explanation of political returns and safeguard against data mining. Specifically, i) we consider the robustness to outliers in constructing the P-factor and find, as expected, increases (decreases) of its average return and Sharpe ratio when removing global bad (good) times; 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 hence it is the covariation with the global factor that affects country expected returns; iii) show that the performance of the P-factor is preserved in its long-only version, thus ruling out potential implementability concerns due to trading constraints on short selling and reinforcing our argument that it reflects adverse economic conditions by picking up the downside risk of high political risk countries; and iv) follow Avramov, Chordia, Jostova, and Philipov (2012) to address the issue of risk versus characteristics and provide evidence against spurious political risk factors.

Related literature

Our work contributes the political uncertainty dimension to a growing body of literature that is "increasingly concerned with pricing global assets across markets" (Asness, Moskowitz, and Pedersen, 2013) and that points towards a common factor structure across countries and 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), justifying 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). Global models have been proposed to price jointly all these asset classes (Asness, Moskowitz, and Pedersen, 2013; Korsaye, Trojani, and Vedolin, 2023; Lettau, Maggiori, and Weber, 2014). Beyond asset pricing, factor identification supports portfolio management, such as building risk models (Bollerslev, Hood, Huss, and Pedersen, 2018), and dealing with CSR requirements on risk exposures as in ESG-responsible investing (Pedersen, Fitzgibbons, and Pomorski, 2021). In this paper, we focus on the identification of political risk.

Our paper is related to Gala, Pagliardi, and Zenios (2023), who used WES ratings to show that political risk is priced in global equity markets. Our work considerably broadens the evidence and scope for global political risk and uncovers its "everywhere" nature. Indeed, we show that political risk affects returns both within and across a large international panel of equity, bond, and currency portfolios and provide a parsimonious global multi-asset model for pricing international assets successfully. 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. We further contribute to the debate on measuring political risk and show consistent evidence across distinct political risk ratings. Finally, we interpret our results within a broader macro-finance framework and show that our measure of political risk is related to current and future global economic growth and aggregate proxies of risk and uncertainty.

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 ratings

We rely on the following sources to capture political risk: International Country Risk Guide-ICRG, the World Bank, and the Ifo World Economic Survey-WES.

The ICRG expert assessments (PRS, 2005) are the most common gauge of political risk in the literature.[4] They aggregate across 12 component variables such as "Government Stability", "Socioeconomic Conditions", and "Investment Profile"; we examine the relative importance of each sub-group in Section 4.4.2. The ICRG ratings are appealing as they have been shown to predict political risk realizations (Bekaert, Harvey, Lundblad, and Siegel, 2014). The ICRG also collects economic ratings which assess a country's current economic strengths and weaknesses by weighting five observable macroeconomic indicators. We contrast the two ratings and show that the economic ratings do not subsume relevant dimensions of political risk.[5]

The Ifo World Economic Survey (Becker and Wohlrabe, 2007) surveys country experts to provide ratings on political instability and confidence in government economic policy. These ratings were validated by Gala, Pagliardi, and Zenios (2023), who showed that global ratings deteriorate with local political shocks having strong spillover effects across countries and rule out 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]

All the data are available for 42 countries from 1992 to 2019.[7] ICRG data are at a

[4]See among many others, Erb, Harvey, and Viskanta 1996; Gourio, Siemer, and Verdelhan 2015; Herrera, Ordoñez, and Trebesch 2020.

[5]Appendix Table A1 provides a description of the components of the political rating, their interpretation and subcomponents. Appendix Table A2 summarizes the components of the ICRG economic rating.

[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.

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

monthly frequency, WES variables are semiannual, and the World Bank index has been available bi-annually since 1996 and annually since 2000.

As discussed in Appendix A, the political risk ratings are positively correlated. The time-series average of the cross-sectional correlation for each rating pair varies from 0.32 to 0.93, and a cross-sectional average of the time-series correlations is in the interval from 0.14 to 0.44. A positive correlation between alternative measures from different sources supports that they provide consistent, albeit noisy, measures of underlying political risk. In our work, we use both the stand-alone measures and a combo index, which aggregates across all available proxies.

2.1.1 Global political events and political ratings

Following Baker, Bloom, and Davis (2016) and Caldara and Iacoviello (2022), we plot in Figure 1 the time-series of the combo index aggregated across the available sources.[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, and the Asian crisis. The index increases with positive news such as the deal on the EU constitution, the agreement on launching the Euro, and Clinton's survival of impeachment charges.

[Insert Figure 1 Near Here]

Figure 1 also shows that the smoothed P-factor follows similar dynamics to the average level of political ratings across countries. The correlation between the rating- and return-based political risk factors is almost 60% and we observe that the P-factor experiences its worst returns at times of deteriorating global political conditions. We investigate further the relation of the P-factor to global economic and political variables in Section 5.

2.1.2 Factor structure in political ratings

The fluctuations in ratings across countries follow a strong factor structure, with a few common components explaining a majority of the cross-country variation. The ICRG 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 first three components.

[8] We proceed as follows. First, we standardize country-level ratings for each of the four political measures. Second, we construct four global political measures by taking a GDP-weighted average of the standardized ratings across countries. Third, we obtain an aggregate combo time series measuring global political risk as an equally weighted average of the four standardized global measures.

The fraction remains quite stable over time, reaches a peak of around 70% for the first principal component, and fluctuates between 70% and 90% for the first three components using 10-year rolling windows, as shown in Figure 2. This evidence is important, because it suggests that political ratings from the surveys reflect exposures to systematic, global political risk factors and do not merely capture idiosyncratic country characteristics. Motivated by this evidence, we use financial market data to isolate and measure the compensation for systematic political risk.

[Insert Figure 2 Near Here]

2.2 Asset returns

We 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.[9] 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 over 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 sample construction are in Appendix B.

For FX returns, we use Datastream monthly spot and forward rates to compute excess returns from forward market investments. 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 sample construction are in Appendix B. Descriptive statistics of excess returns in each asset class are in Appendix Table A3.

[9] 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.

2.3 Other financial and economic data

We obtain the US risk-free rate, the factors for the International Fama-French five-factor model, augmented with the international version of the momentum factor, from Kenneth French's website. Returns for the value, momentum, time-series momentum, and betting against beta factors across asset classes are from the 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.[10]

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. 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 to ten years from Datastream, and the one-month US risk-free rate. The latter is the difference between the total return of the S&P US corporate bond index and the S&P US government bond index.

Country-level quarterly real GDP, 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 GDP data at constant 2010 USD as country weights. We retrieved the global risk aversion index from Nancy Xu's website; the global volatility and cross-country capital flows from Silvia Miranda-Agrippino's website, and the global economic policy uncertainty (EPU) from Nicholas Bloom's website.[11]

[10] 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).

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

3 Global multi-asset political risk factor

3.1 Political risk portfolios

We form a set of equally weighted political portfolios by sorting securities by the country-specific political risk ratings within each asset class into four groups.[12] We sort into quintiles for the corner portfolios and two equally split quantiles in between, denoting by H and L the top and bottom quintile portfolios with the lowest and highest political risk, respectively.[13] We separately report results with portfolio sorts on the four political risk measures. 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 portfolios 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 of 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 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 market. The smaller spreads in USD are consistent with the evidence that the high political risk currencies depreciate more against the USD; see Brogaard, Dai, Ngo, and Zhang (2020)

[12] 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.

[13] For bonds in 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.

and the FX results in Panel B of the Table.

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, as aggregating across various measures helps decrease the noise in capturing political risk.[14]

3.2 Global factor structure and the P-factor

The key economic message of our paper is that systematic political risk is pervasive across all asset classes and affects prices in equity, bonds, and FX across countries. To establish this claim, we consider the 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 sorted portfolios.[15] 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 slope of portfolio returns.[16] Naturally, the level factor is the market portfolio. We proxy the equity market portfolio using the MSCI All Countries World index for equities. For fixed income and FX, we take an equally weighted average of, respectively, the bond and currency excess returns in our sample. The second factor is our *multi-asset global*

[14]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.

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

[16]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.

P-factor, constructed from the three asset-class 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 correspond to the normalized inverse volatility of each asset class (Asness, Moskowitz, and Pedersen, 2013).[17] The global market correlates 99% with the first principal component (and only 2% with the second one). In contrast, 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 sources. The correlations range from 0.54 for the P-factor constructed using the WES Policy measure to 0.70 for the WB Politics. In line with the APT (Ross, 1976), we interpret the global P-factor as an observable proxy for the underlying slope factor mimicking priced global political risk.

[Insert Figure 3 Near Here]

Figure 3 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 asset classes and countries. In Sections 4.3 and 4.4, we consider the variations of the model, which rely on local versions of these factors.

[Insert Table 4 Near Here]

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 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).

[17]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. Qualitatively similar results are obtained when constructing the global factor with equal weights to each asset class.

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. Panel B shows that the global multi-asset P-factor is not spanned by the traditional factors of asset pricing models constructed across asset classes. The alphas range from 4.62% to 8.97%, all statistically significant, with corresponding information ratios in the range of 0.73–1.24, and the adjusted R^2 are very low. 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.

4 Cross-sectional pricing of political risk

4.1 Global asset-pricing model

Motivated by our portfolio evidence, we argue that the two candidate factors, the global market and the P-factor, help isolate relevant systematic risks to explain the broad cross-section of asset returns across countries. In performing asset pricing tests, we expect pricing errors to be jointly zero and model-implied estimates of risk premia to align closely with average returns in the data.

We formally test the model. Our base set of test assets includes all four portfolios from each of the three asset classes for the four proxies of political risk, that is 48 ($= 4 \times 4 \times 3$) portfolios.[18] 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 further includes the 126 country returns from all three asset classes,[19] 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

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

[19]We exclude Turkey from the extended set of test assets since its P-factor loading in the bond markets is implausibly high. 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 the *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, 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).

We report our main empirical results in Table 5. Panel A 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% in 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. 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 5 Near Here]

The cross-sectional R^2 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 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 VME and BAB factors. The results are similar for the extended set of assets: GPSZ delivers an R^2 of nearly 0.70, versus 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 existing asset pricing factors do not span the P-factor. 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 particular asset classes or rating methodologies drive the model performance.

4.3 Asset pricing evidence: within asset classes

We now zoom in on the performance of the model within each asset class separately, following the approach of the previous section. 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). We also add the most comprehensive model for each asset class as an 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 use 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 local version, which replaces the global market and P-factor with its local, asset-class-specific counterparts. For parsimony, we show the results with the combo strategy sorts. Results with the individual rating measures are similar and are reported in Appendix Table A4.

4.3.1 Existing models

Table 6 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 0.37. In 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 6 Near Here]

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 A5. All portfolios load almost equally on the first principal component, which can 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 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 A5 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 A6, 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 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 to price currency returns.

4.3.3 Factor pricing within asset classes

We next assess the performance of variations of the GPSZ model using the asset-specific market and P-factor. This test also addresses the question of whether the performance of GPSZ can be further improved by using asset-specific counterparts of the market and the political risk factors.

Table 7 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%.

[Insert Table 7 Near Here]

Panel B documents the performance of the three variants of our two-factor model. The benchmark GPSZ model has lower mean absolute pricing errors than the best-performing benchmark model: 2.53% against 2.55% for the value-momentum model in the equity market, 1.75% vs. 2.12% for the betting against the beta model in the bond market, and

1.23% compared to the 1.45% of the dollar-carry FX model. Similarly, GPSZ 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.

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 only 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 factors but global political risk factors 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 political risk is "everywhere": it affects all the asset classes and is not specific to any asset class in particular.

In Figure 4 (Panel A), we visually demonstrate that the global model-predicted and realized average returns line up along the 45-degree line, within and across asset classes. Panels B to D show a similar performance of the model with local political risk factors.

[Insert Figure 4 Near Here]

We provide further evidence that we can successfully recover the political risk factor from any of the asset classes by running 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. Figure 5 Panel A contrasts the average realized and the predicted returns from the models. All points line up nicely 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.

[Insert Figure 5 Near Here]

We repeat the asset pricing test on the extended set of assets. The results (Appendix Table A7, Panel A) confirm that the P-factor is priced. 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 of 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.

4.4 Asset pricing evidence: within ratings

Similar to the analysis within each asset class, we next examine the ability of the model to price asset portfolios sorted on each of the political ratings. We also extend the "everywhere" dimension of our findings into the components of the composite ICRG political risk rating.

4.4.1 Asset pricing within ratings

Overall, the GPSZ model prices well the securities sorted using any of the rating choices. As shown in Table 8 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 A8. The estimates of the risk premium for the market factor are clustered around the benchmark values.

[Insert Table 8 Near Here]

Table 8 Panel B assesses the ability of GPSZ 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 5, 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%.[20]

We also considered "local" versions of the political risk factor constructed within each of the four rating categories separately.[21] In asset pricing tests we found only marginal gains, if any, from using ranking-specific rather than "combo" P-factors. To summarize the evidence, Panel B of Figure 5 documents the results for the comovement test in which

[20] Similar results hold in the extended set of test assets; see Appendix Table A8.

[21] The correlations between the political factors in each pair constructed from these four factors are sizeable and in the range 0.56–0.93, and the correlations with the "combo" factor range in 0.76–0.94; see Appendix Table A9.

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.

4.4.2 ICRG components

The ICRG ratings aggregate across 12 different components of political risk, which provide another dimension to examine the nature and magnitude of political risk compensation. As shown in Appendix Table A10, the components of the ICRG ratings display an even stronger factor structure than the aggregate index. For example, the first principal component of "Investment profile" explains 75% of the total cross-country rating variation, with the first three principal components reaching 90%. This is consistent with the financial openness observed across the globe during the last decades, which is associated with the attractiveness of a country for foreign direct investments (Bekaert, Harvey, Lundblad, and Siegel, 2011).

At the same time, the time-series trends across the components feature only modest correlation. This is consistent with the difference in the nature of risk the sub-categories capture, as well as the data and measurement limitations. Indeed, some rating sub-categories change infrequently and produce low portfolio turnover, unlike for the aggregate index where on average 20% of countries move across portfolios every year.[22]

We follow our benchmark approach and construct global multi-asset political factors within each of the rating components and run spanning regressions on a two-factor model including the global market portfolio and a global multi-asset P-factor constructed with the composite ICRG political risk rating. The average P-factor returns are positive for each subgroup, and are similar to the one constructed from the composite rating. At the same time, none of them generates abnormal returns once we control for the global P-factor based on the composite ICRG index.

Consistent with our previous analysis, this corroborates that political risk is again "everywhere": it is consistently priced by the investors, and no single dimension stands out for asset-pricing. All political ratings share common information on which the corresponding factor mimicking portfolios are loading, which helps explain the observed spreads in the cross section of international returns.

[22]Results for principal component analysis are reported in Appendix Table A10, for spanning tests in Appendix Table A11, and for country turnover in Appendix Table A12.

5 Political risk factor and the macroeconomy

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. In this section, we provide reduced-form evidence on the mechanism connecting political risk and asset returns, consistent with a risk-based explanation of our findings.

First, we show that the global multi-asset P-factor relates to various proxies of the conditional first and second moments of the global growth distribution. Next, we include additional economic and financial-market factors to control for other sources of global risk. Then, we modify the construction of the P-factor itself to remove mainly country-specific effects. We conclude with tests ruling out an alternative explanation of our findings whereby the cross-sectional return predictability arises from differential cross-country degrees of market segmentation.

5.1 Political risk and global conditions

Table 9 Panel A shows that both the global multi-asset market and political factors 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, and the P-factor remains significant when 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.

[Insert Table 9 Near Here]

In a similar vein, Panel B shows that the two factors significantly under-perform in global recessions, measured as the times of global GDP growth falling below the 30th percentile of its unconditional distribution.[23] The P-factor also falls at times of significant increases in the VIX, global volatility, global risk aversion, and global EPU. Poor performance of the P-factor is also associated with low cross-country capital flows. In all these specifications, the P-factor is a significant determinant of current and expected economic fundamentals beyond market-level effects.

[23] 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.

A potential concern is that the P-factor may be picking up other related macroeconomic and financial-market risks rather than political risk. 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, we undertake two tests. First, we show that the global multi-asset P-factor truly captures global political information, as it forecasts various proxies of global political risk. Second, we provide evidence that the P-factor retains strong pricing ability of cross-sectional returns when controlling for other global economic and financial variables.

Table 10 shows that the P-factor captures political information that goes beyond market risk and cannot be inferred by simply inspecting country macroeconomic fundamentals or economic ratings. We test the predictive power of the P-factor to forecast future global political risk, proxied by the global geopolitical risk index of Caldara and Iacoviello (2022). We control for the global market portfolio and the current value of the predictive variable. The P-factor is statistically significant at both short and long horizons. The market portfolio does not have any predictive power, confirming again that political risk is instrinsically different from market risk.

[Insert Table 10 Near Here]

We also go a step further and contrast the predictability of the global ICRG political risk and ICRG economic risk, both constructed by taking cross-sectional averages of their respective country-level ICRG ratings. Consistent with previous evidence, the P-factor predicts future global political risk while the market does not. Interestingly, the P-factor predicts economic ratings to a much lesser extent, not showing any predictive power at the three-month horizon, and being statistically significant only one year ahead.[24] The return-based P-factor proves to be a forward-looking measure of global political risk, capturing information beyond market effects and economic risk.

We also 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.[25] Table 11 reports the asset-pricing evidence across the augmented models. It shows that the multi-asset P-factor is consistently priced across all the specifications.[26]

[24] In unreported results we also find that, in turn, none of these global political variables can instead forecast future P-factor returns.

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

[26] Appendix Table A13 reports the statistics for the corresponding time-series and cross-sectional asset pricing tests.

[Insert Table 11 Near Here]

Overall, this set of results highlights the forward-looking nature of our return-based P-factor and confirms that adding controls does not diminish its importance.

5.2 Country-specific effects

In the next 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, thus focusing on within-country time-series variation. In the second specification, we regress ICRG political risk ratings on a constant and country-specific ICRG economic risk ratings and sort portfolios on the regression residuals. Given that ICRG also provides separate ratings on economic risk (Bekaert, Harvey, Lundblad, and Siegel, 2014), this second model helps disentangle political risk from macroeconomic risk and, by removing an intercept, constant country fixed effects. In the third specification, we consider observable macroeconomic measures instead of the ICRG economic 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 corresponding P-factors based on orthogonalized ratings. First, by removing an intercept, we confirm a well-balanced portfolio composition across the level of macroeconomic development. Indeed, simply demeaning the country ratings generates political sorted portfolios with developed markets' weights ranging between 45%–58%. Similar values are obtained with the other two specifications.

[Insert Table 12 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 12 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.[27]

Overall, political ratings embed information content that goes above and beyond global

[27] Appendix Table A14 reports the statistics for the corresponding time-series and cross-sectional asset pricing tests.

and country-specific macroeconomic risks, and that is important to price global cross-asset returns. Further, the performance of the P-factor is not driven entirely by differences in average ratings among countries or groups of countries but also reflects within-country variation in political risk.

5.3 Market segmentation

Our benchmark explanation for abnormal returns of high political risk portfolios is based on 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 potentially correlated with a country's political risk ratings can give rise to the return differential.

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

Second, in Panel B, we dig deeper into a subsample of emerging markets characterized by the highest values of capital controls as 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 a level of capital controls that is greater than the median of all emerging countries. Due to the small sample of countries, we then constructed 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 large cross-sectional heterogeneity in political risk, which matches well the sizeable spreads in average returns while not being associated with large differences in capital controls. The combos attain Sharpe ratios of 0.43 for equities, 0.34 for bonds, and 0.62 for currencies, while the level of segmentation is essentially constant across portfolios.

6 Extensions and robustness

We extend our analysis along three directions to corroborate the validity of our risk-based mechanism and ensure the robustness of the P-factor. Motivated by the link between political risk and global economic growth, we start by showing that the risk-adjusted returns of the global multi-asset P-factor are magnified when we exclude periods of low global economic growth or high aggregate volatility. We then provide additional evidence in favor of a risk-based explanation of our findings through the construction of beta-sorted portfolios, which confirms that it is the country covariation with the common political risk factor that determines their expected returns. Finally, we reinforce our claim that the P-factor reflects adverse economic conditions by showing that it mostly loads on the downside risk of the high political risk countries and that it does not arise spuriously.

6.1 P-factor robustness to outliers

Subsection 5.1 identifies a link between the multi-asset political factor and the macroeconomy, and Table 9 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 exclude 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. 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 confirms that it is robust to outliers.

6.2 Beta-sorted portfolios

Following Lustig, Roussanov, and Verdelhan (2011), we create beta-sorted portfolios and show that the sorting of countries on the ICRG political risk ratings effectively measures country exposures to the political factors. For each asset class, we run rolling-window time-series regressions of each country's excess returns on the asset-class-specific global market portfolio and political factor. We estimate the factor loadings with a 36-month window up to time $t-1$ and track the performance of beta-sorted portfolios at t. P1 and P4 portfolios include, respectively, countries with exposures in the bottom (L_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, and 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 based 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 political factors. Countries characterized by higher political risk display higher average returns, and this finding holds consistently across all asset classes.

6.3 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 P-factor into a long leg of high political risk countries and a short leg of low political risk countries.

Table 16 (Panel A) shows that both legs have positive and significant risk premia, with the long leg having a higher premium (5.25% p.a.) than either the market (3.37%) or the short leg (3.17%). 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 time series and cross-sectional pricing statistics.[28] This three-factor model achieves similar time-series and cross-sectional performance to the GPSZ two-factor model of Table 5, with MAPE reduced from 2.36% to 2.25% and cross-sectional GLS and OLS R^2, respectively, slightly reduced from 0.35 to 0.28 or unchanged in the extended set of test assets.

[Insert Table 16 Near Here]

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: it is possible to harvest political risk premia even from long-only portfolios, thus avoiding altogether any shorting costs.

6.4 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.

[28] 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 were consistently priced in the base and extended sets of test assets.

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

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

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 17 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. In Table 17, 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 actual data with the original combo factor, and the corresponding p-values implied from locating the actual data in the distribution of the simulated data.

We observe that the simulated factor does a poor job of explaining the average returns of the test assets, explaining significantly less cross-sectional variation in average returns than the real factor. The median cross-sectional adjusted R^2 is very low compared to the model with 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.

7 Conclusion

Our paper contributes to the "everywhere" empirical asset pricing literature that studies the economic determinants of risk affecting financial markets across asset classes. Using political ratings of individual countries, we provide evidence of priced 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 can be meaningfully extracted from any of the political risk proxies. The asset- or ranking-specific information does not materially alter its importance. In this sense, political risk is "everywhere".

Consistently with a standard APT interpretation, our GPSZ model, which consists of the global market and political risk factor, can successfully price a large panel of international asset returns within and across stocks, bonds, and currencies and within and across four alternative political risk ratings. Assets of countries with low political ratings earn higher average returns because they load more on global political risk. The global multi-asset P-factor carries a statistically significant risk premium of 4.44% per annum, with a t-statistic well above the critical threshold of three and a Sharpe ratio of 0.70.

The global political risk factor further predicts global economic growth and correlates with macroeconomic and business cycle variables capturing both first- and second-moment effects such as a recession dummy, cross-country capital flows, 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.

Given the pervasive nature of global political risk in financial markets, promising avenues for further research would undoubtedly include economic models to micro-found the sources of global political risk and its connections to the economy.

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Figure 1: **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 and the occurrence of global political events. We first standardize country-level ratings 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 to construct four global political measures. Third, we obtain an aggregate combo time series measuring global political risk as an equally weighted average of the four standardized global measures. 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 to 2019.

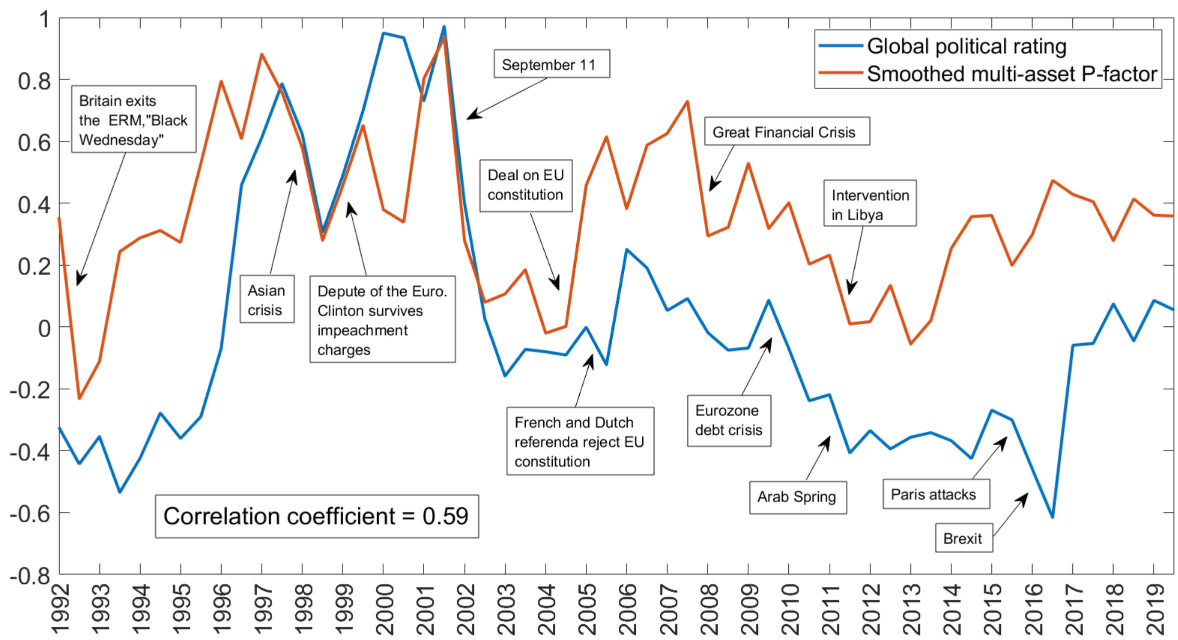


Figure 2: **Principal component analysis of ICRG political ratings**

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 to 2019.

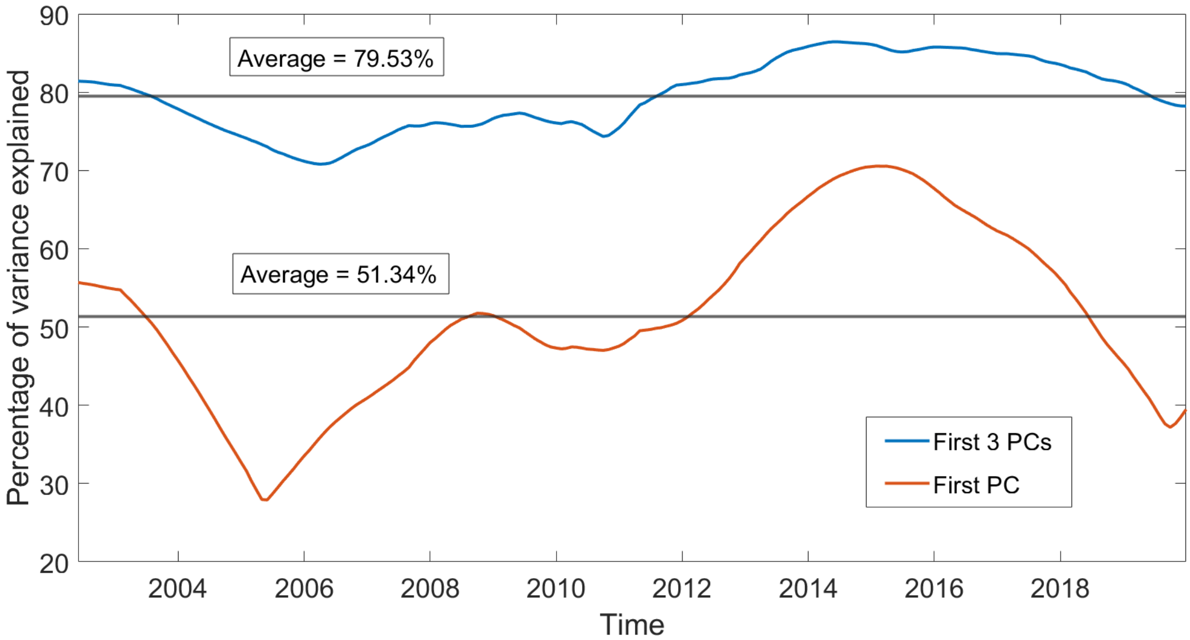
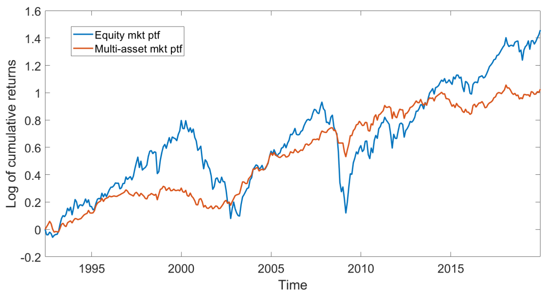


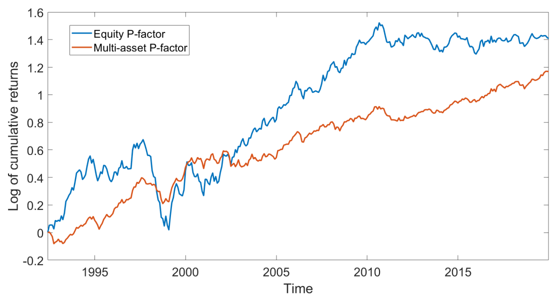
Figure 3: **Asset-class specific vs multi-asset factors**

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.

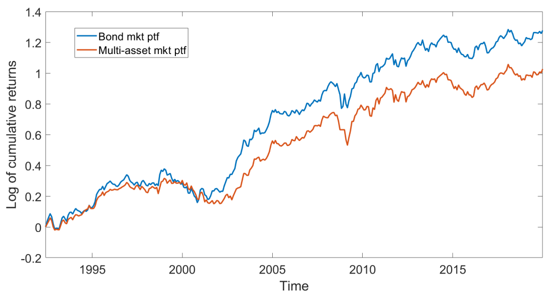
(a) Market equity



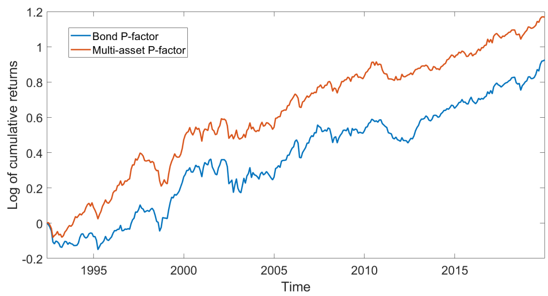
(b) P-factor equity



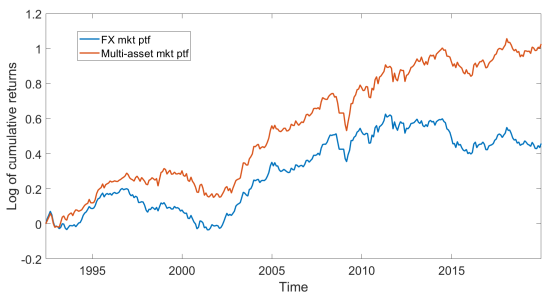
(c) Market bond



(d) P-factor bond



(e) Market FX



(f) P-factor FX

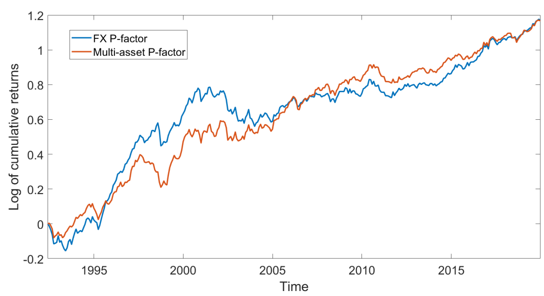


Figure 4: **Global multi-asset GPSZ model**

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, 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 to 2019.

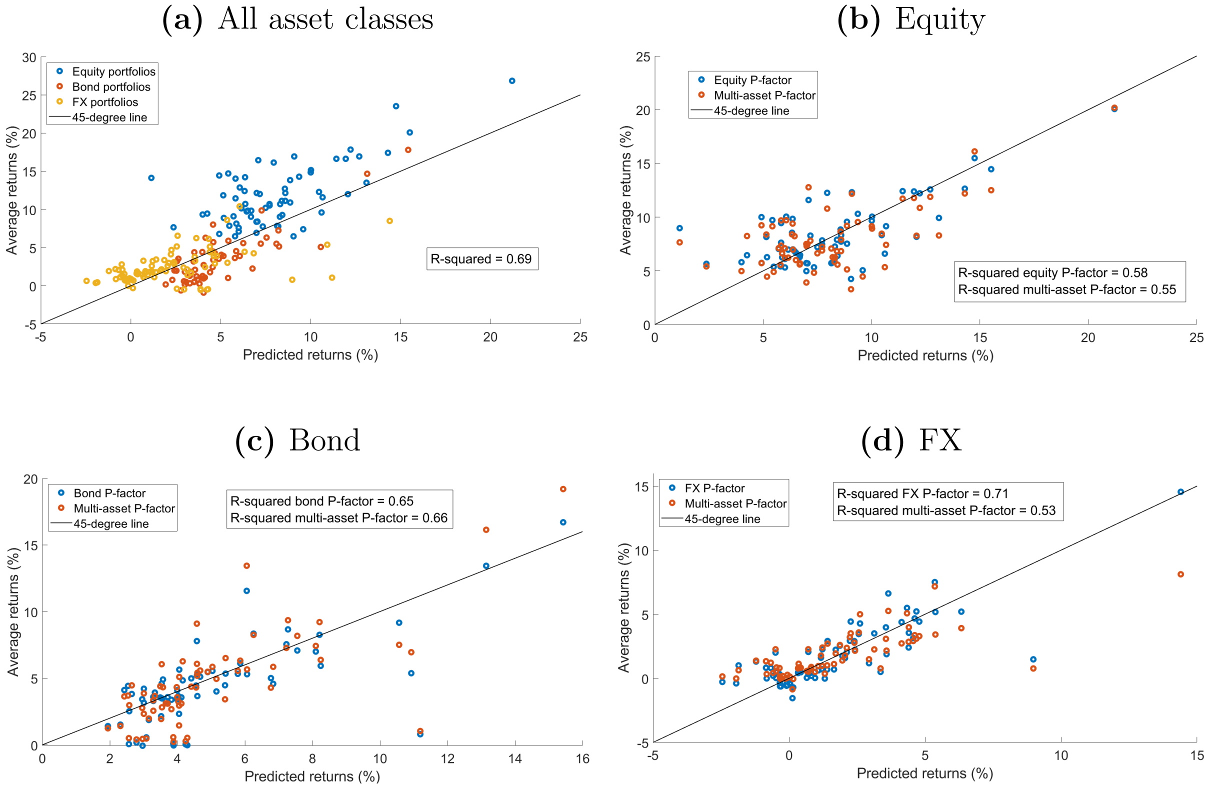
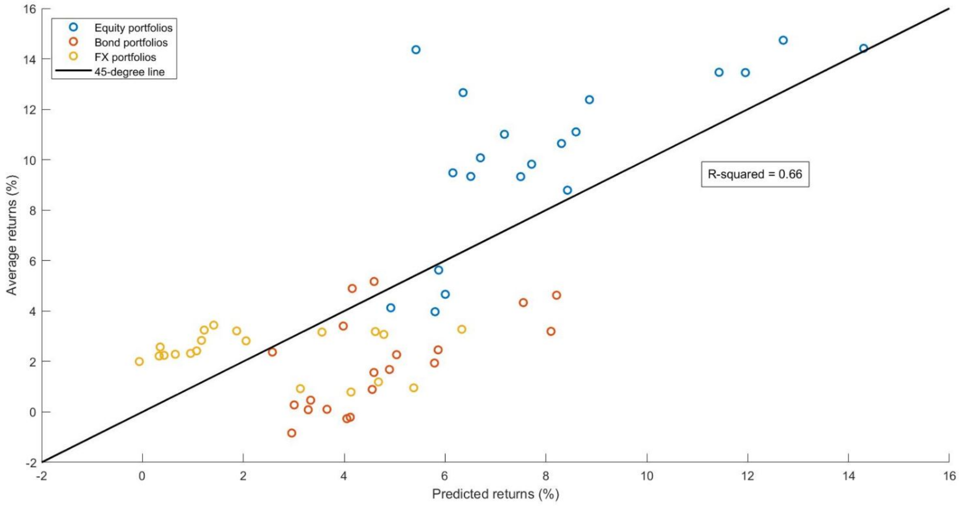


Figure 5: **Comovement tests**

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 to 2019.

(a) Comovement across asset classes



(b) Comovement across ratings

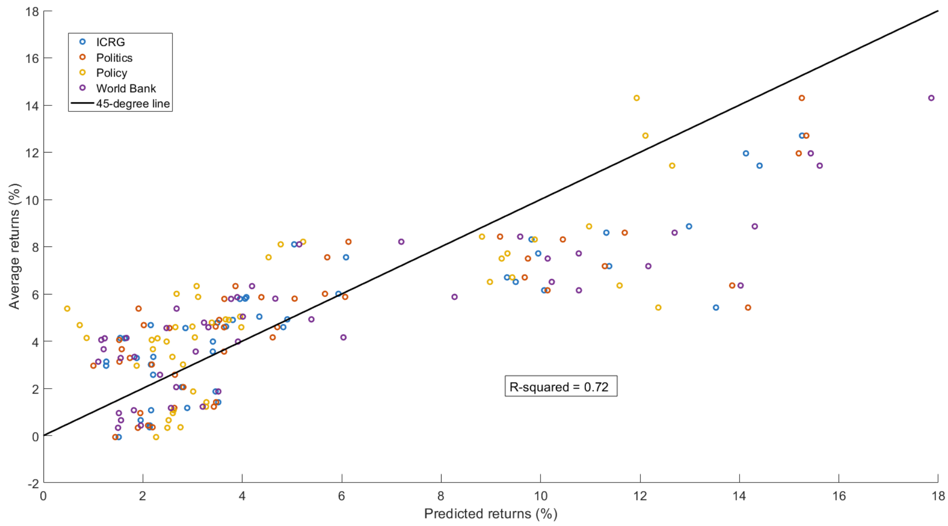


Table 2 – Portfolio sorts

This table reports the annualized average returns of portfolios sorted on different political risk ratings in international equity, bond, and FX 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 are semi-annual and World Bank portfolios are annual. 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 to 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)

(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 to 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 an 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% levels, 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 asset pricing

This table reports the results of asset pricing tests run on the base set of test assets, which includes the $4\times4\times3$ 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 bonds and currencies, respectively. 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% levels, 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)

(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 6 – 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 5. 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 to 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 7 – 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% levels, respectively. Data are monthly, spanning 1992 to 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)

(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 8 – 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% levels, respectively. Data are monthly, spanning 1992 to 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 9 – 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 an 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 the 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 one 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 the quarterly frequency by compounding monthly factor data into quarterly. All data in Panel B are available monthly, and regressions are run at a 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 10 – Global multi-asset P-factor and future global political risk

This table reports the results of predictive regressions of a set of proxies for global political risk on the global multi-asset P-factor and the global multi-asset market portfolio. The former (latter) is computed as an inverse-volatility portfolio of the three asset-class-specific P-factors (market portfolios) in the equity, bond, and FX markets. We report results of forecasting regressions of the global geopolitical risk index of Caldara and Iacoviello (2022), the global ICRG political risk ratings, and the global ICRG economic risk ratings. The global geopolitical risk index is at monthly frequency, while country-level ICRG ratings are available monthly and the global indices are constructed as equally-weighted averages of their country-level counterparts. We run the predictive regressions at the 3- and 12-month horizons, excluding the top 1% of geopolitical risk observations as large outliers. In all predictive regressions we control for the current value of the left-hand side variables due to their persistency over time. 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 span the period 1992–2019.

	Geopolitical risk index		ICRG Political rating		ICRG Economic rating	
	3m	12m	3m	12m	3m	12m
$\beta_{P-factor}$	-403.84***	-316.33**	5.60***	9.84**	0.65	9.89***
	(0.00)	(0.04)	(0.00)	(0.03)	(0.77)	(0.01)
β_{MKT}	-10.05	-183.24	1.20	-0.26	-1.20	10.48*
	(0.93)	(0.16)	(0.47)	(0.93)	(0.67)	(0.08)
β_{Rating_t}	0.60***	0.36**	0.95***	0.77***	0.90***	0.40***
	(0.00)	(0.02)	(0.00)	(0.00)	(0.00)	(0.00)
R^2	0.17	0.07	0.93	0.69	0.84	0.20

Table 11 – 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 an 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% levels, respectively. Data are monthly, spanning 1992 to 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 12 – P-factor risk premia with orthogonalized political ratings

This table reports the 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% levels, respectively. Data are monthly, spanning 1992 to 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 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 is measured by the overall restriction index on capital flows (Fernández, Klein, Rebucci, Schindler, and Uribe, 2016). Portfolios are sorted on the Combo factor, referring to an equally-weighted portfolio of univariate sorts on political risk ratings from, respectively, ICRG, WES policy, WES politics, and World Bank politics. 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%. 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% levels, respectively. Returns are in percentages, denominated in USD, and include dividends and coupon payments. Risk premia are annualized. Data are monthly, spanning 1992 to 2016.

(a) All emerging markets

	Equity	Bond	FX
P1 (L)	19.50%***	10.51%***	8.01%***
	(0.00)	(0.00)	(0.00)
P2	12.24%***	9.36%***	3.08%***
	(0.01)	(0.00)	(0.01)
P3	9.09%*	8.22%***	2.33%*
	(0.08)	(0.00)	(0.06)
P4 (H).	9.94%**	6.97%***	2.13%
	(0.04)	(0.00)	(0.14)
L-H.	9.56%***	3.53%**	5.88%***
	(0.00)	(0.03)	(0.00)
Sharpe	0.61	0.36	0.84

(b) Subsample of highly segmented emerging markets

	Equity	Bond	FX	CC
P1 (L)	19.68%***	9.69%***	9.82%**	0.89***
	(0.00)	(0.00)	(0.02)	(0.00)
P2.	9.69%*	8.72%***	2.26%*	0.87***
	(0.06)	(0.00)	(0.08)	(0.00)
P3 (H)	8.68%*	5.51%***	2.27%	0.86***
	(0.10)	(0.01)	(0.13)	(0.00)
L-H	11.00%**	4.17%	7.55%*	0.03***
	(0.03)	(0.12)	(0.08)	(0.00)
Sharpe	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 to 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 into 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 average 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 to 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 – Pricing performance of long and short legs of the P-factor

In Panel A, we estimate the risk premia of a three-factor model, including the global multi-asset market portfolio and two alternative factors constructed as the long and the short legs of the global multi-asset P-factor excess return, "Long" and "Short," respectively. 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. Newey and West (1987) p-values based on optimal number of lags (Andrews and Monahan, 1992) are in parenthesis. In Panel B 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% levels, respectively. Data are monthly, spanning 1992 to 2019.

(a) Risk premia

	Base set			Extended set		
	MKT	Long	Short	MKT	Long	Short
Risk premium	3.37%**	5.25%***	3.17%*	3.22%**	5.21%***	3.06%*
	(0.02)	(0.00)	(0.07)	(0.02)	(0.00)	(0.08)

(b) Pricing statistics

	Base set	Extended set
MAPE	1.68	2.25
GRS statistic	12.42	3.14
p-value GRS	0.00	0.00
GLS R^2	0.23	0.28
OLS R^2	0.75	0.62
R^2 predicted vs realized	0.77	0.67

Table 17 – 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 6.4. We construct 1000 spurious factors from the simulated data for each of the four political measures and 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% levels, respectively. Data are monthly, spanning 1992 to 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)

Online Appendix

A Political risk measures

ICRG aggregates several political variables and its 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's 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 nine 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[29], 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 periods where neither of these two sources is 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 a maximum of 99% (US) and a 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 a cross-country average of 0.32%, with a maximum of 0.98% (Hungary) and a minimum of 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 1990s. 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.

[29] `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 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 is 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 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 removed 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.[30].

[Insert Figure A2 Near Here]

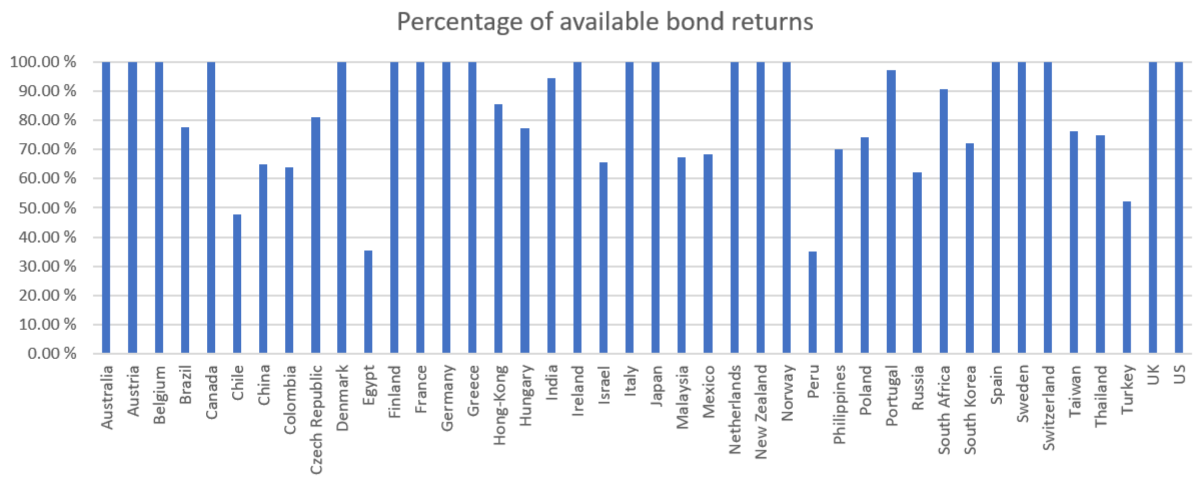
[30]See `https://www.reuters.com/article/egypt-economy-currency-idUSL3N27945F`

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% 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 rate 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 periods where neither of these two sources is available, we complement our dataset with country-level ten-year government bond yields to maturity from Datastream. 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

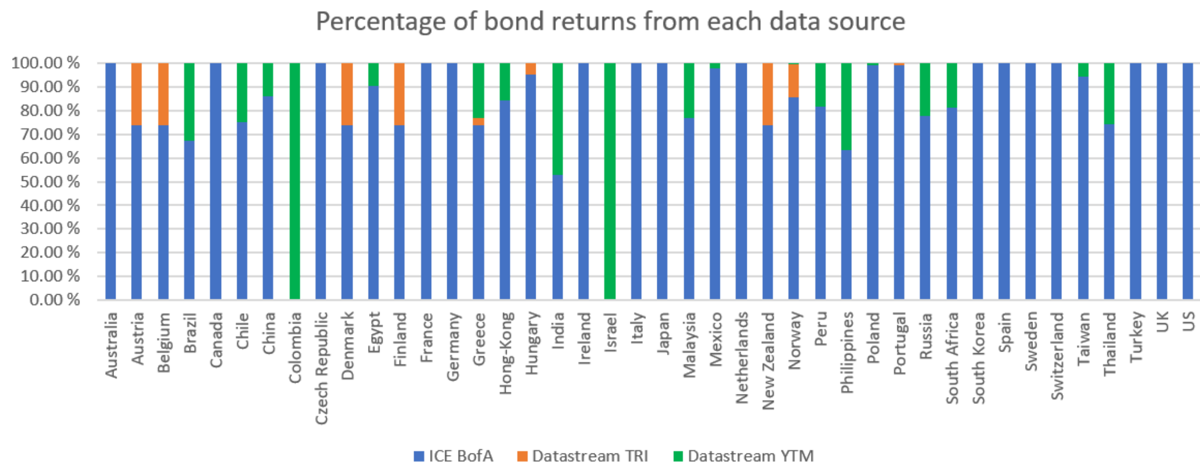
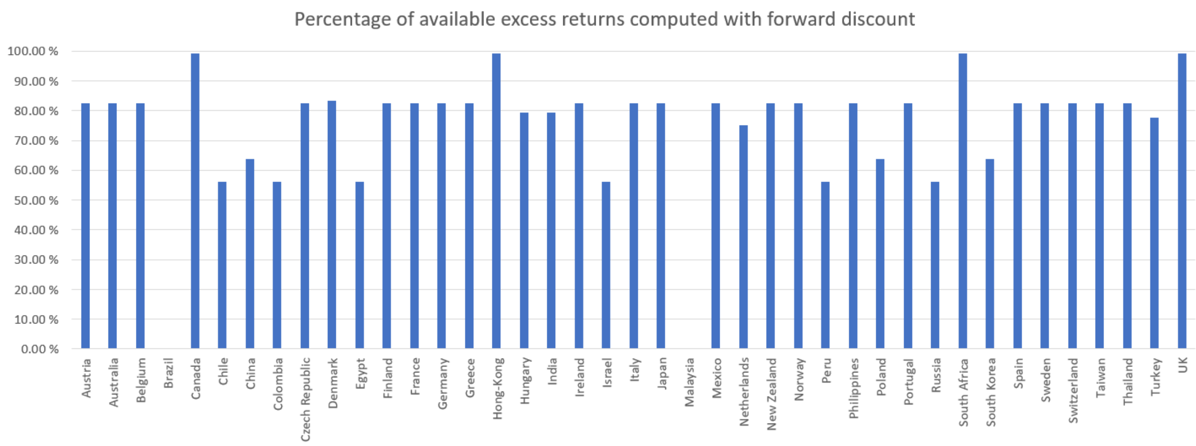


Figure A2: **Construction of FX sample**

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 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

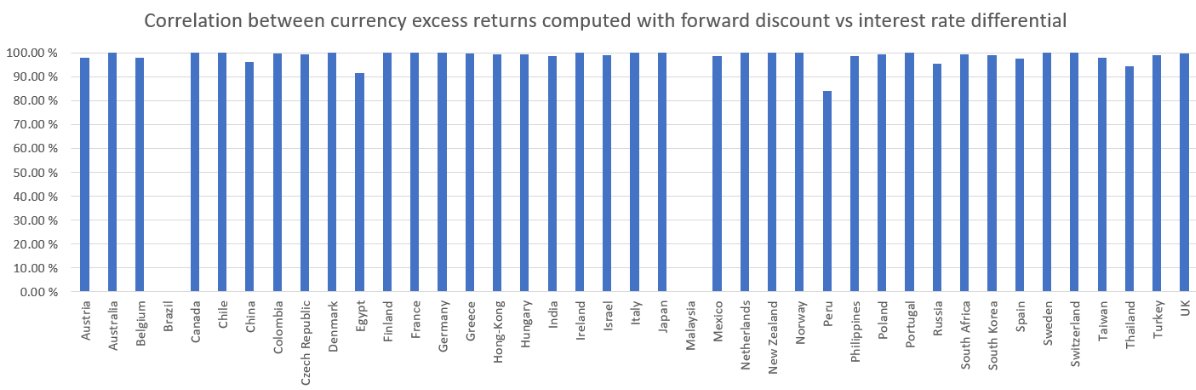


Table A1 – Components of the ICRG political risk ratings

This table summarizes the components of the ICRG political risk rating, which is constructed as a weighted average of its components. The first five components carry a weight of 12%, while all the others weigh 6%.

Component	Description	Subcomponents
Government stability	Assessment both of the government's ability to carry out its declared program(s), and its ability to stay in office	Government cohesion; Legislative strength; Popular support
Socioeconomic conditions	Assessment of the socioeconomic pressures at work in society that could constrain government action or fuel social dissatisfaction	Unemployment; Consumer confidence; Poverty
Investment profile	Assessment of factors affecting the risk to investment that are not covered by other political, economic and financial risk components	Contract viability/Expropriation; Profit repatriation; Payment delays
Internal conflict	Assessment of political violence in the country and its actual or potential impact on governance	Civil war/Coup threat; Terrorism/Political violence; Civil disorder
External conflict	Assessment both of the risk to the incumbent government from foreign action, ranging from non-violent to violent external pressures	War; Cross-border conflict; Foreign pressures
Corruption	Assessment of corruption within the political system, for example in the form of demands for special payments and bribes connected with import and export licenses, exchange controls, tax assessments, police protection, or loans	
Military in politics	Assessment the involvement of the military in politics, which, even at a peripheral level, is a diminution of democratic accountability	
Religious tensions	This risk ranges from inexperienced people imposing inappropriate policies through civil dissent to civil war	
Law and order	Assessment of both judicial system and crime rate in terms of whether the law is routinely ignored without effective sanction (for example, widespread illegal strikes)	Strength and impartiality of the legal system; Popular observance of the law
Ethnic tensions	Assessment of the degree of tension within a country attributable to racial, nationality, or language divisions	
Democratic accountability	Measure of how responsive government is to its people	
Bureaucracy quality	Assessment of the degree to which bureaucracy has the strength and expertise to govern without drastic changes in policy or interruptions in government services	

Table A2 – Components of the ICRG economic risk ratings

This table summarizes the components of the ICRG economic risk rating, which is constructed as a weighted average of its components. The first component carries a weight of 10%, the subsequent three are at 20% each, and the last component weights 30%.

Component	**Description**
GDP per head	Converted into US dollars at the average exchange rate for that year. Expressed as a percentage of the average of the estimated total GDP of all the countries covered by ICRG
Real GDP growth	Annual change in the estimated GDP, at constant 1990 prices, of a given country. Expressed as a percentage increase or decrease
Inflation rate	Unweighted average of the Consumer Price Index. Calculated as a percentage change
Budget balance	Estimated central government budget balance (including grants) for a given year in the national currency. Expressed as a percentage of the estimated GDP for that year in the national currency
Current account	Estimated balance on the current account of the balance of payments for a given year, converted into US dollars at the average exchange rate for that year. Expressed as a percentage of the estimated GDP of the country concerned, converted into US dollars at the average rate of exchange for the period covered

Table A3 – 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 to 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 A4 – 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 bonds and currencies, respectively. 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 to 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

(continued)

(b) Bond

	ICRG					
	CAPM	ACB	VME	BAB	CAR	ALL
α	4.94%***	5.45%***	6.29%***	5.02%*	4.76%**	7.27%***
	(0.01)	(0.01)	(0.00)	(0.06)	(0.02)	(0.00)
R^2	0.01	0.06	0.04	0.03	0.02	0.08
IR	0.50	0.57	0.65	0.47	0.48	0.71

WES Politics					
CAPM	ACB	VME	BAB	CAR	ALL
4.42%***	4.92%***	5.42%***	3.83%**	5.12%***	5.43%***
(0.00)	(0.00)	(0.00)	(0.04)	(0.00)	(0.00)
0.01	0.07	0.05	0.03	0.02	0.08
0.61	0.70	0.77	0.49	0.70	0.72

	WES Policy					
	CAPM	ACB	VME	BAB	CAR	ALL
α	2.88%**	3.33%***	3.46%***	1.32%	3.11%**	2.05%
	(0.03)	(0.01)	(0.01)	(0.41)	(0.03)	(0.19)
R^2	0.00	0.03	0.03	0.03	0.01	0.05
IR	0.46	0.54	0.56	0.21	0.50	0.34

World Bank Politics					
CAPM	ACB	VME	BAB	CAR	ALL
5.67%***	6.00%***	6.73%***	6.47%***	6.19%***	8.69%***
(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)
0.05	0.11	0.07	0.10	0.07	0.17
0.65	0.72	0.79	0.69	0.71	0.98

(c) FX

	ICRG					
	CAPM	ACB	VME	BAB	CAR	ALL
α	6.71%***	6.06%***	7.29%***	6.88%***	6.06%***	7.57%***
	(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
IR	0.90	0.82	0.99	0.94	0.82	1.06

Politics					
CAPM	ACB	VME	BAB	CAR	ALL
4.95%***	4.69%***	5.45%***	5.43%***	4.69%***	5.80%***
(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
0.16	0.21	0.18	0.28	0.21	0.30
0.81	0.76	0.90	0.84	0.76	0.92

	Policy					
	CAPM	ACB	VME	BAB	CAR	ALL
α	3.52%***	3.40%***	3.90%***	3.16%**	3.40%***	3.89%***
	(0.00)	(0.01)	(0.00)	(0.05)	(0.01)	(0.00)
R^2	0.05	0.08	0.05	0.08	0.08	0.12
IR	0.66	0.63	0.73	0.56	0.63	0.71

WB					
CAPM	ACB	VME	BAB	CAR	ALL
5.59%***	4.61%***	6.28%***	6.38%***	4.61%***	5.98%***
(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
0.30	0.40	0.33	0.41	0.40	0.47
0.86	0.74	0.99	0.96	0.74	0.95

Table A5 – 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 to 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 A6 – 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 to 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

(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

Table A7 – Asset pricing within asset classes: extended set of test assets

This table reports the results of asset pricing tests 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 within each asset class (Asness, Moskowitz, and Pedersen, 2013), and six currency portfolios in FX asset class (Lustig, Roussanov, and Verdelhan, 2011). Panel A reports the risk premia of models with i) the asset-class specific market portfolios (M_L) and political factors (P_L) constructed within each asset class and ii) 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, OLS and GLS R^2 from the second step cross-sectional regression, and the R^2 of 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% levels, respectively. Data are monthly, spanning 1992 to 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_G	P_G	M_G	P_G	M_G	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)

(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 A8 – Asset pricing within political ratings on an 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% levels, respectively. Data are monthly, spanning 1992 to 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 A9 – 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 to 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 A10 – Principal component analysis on ICRG components

This table reports results from principal component analysis run on the set of 42 countries for each of the ICRG components. Panel A includes the percentages of variance explained by the each of the first three principal components, as well as their sum, all expressed in percentage points. Panel B reports the pairwise correlations between the time-series of the principal component scores obtained from PCA run on each of the ICRG components separately. The aggregate index is denoted by "ICRG", while the components are labelled as follows: "BC" stands for "Bureaucracy quality", "CO" for corruption, "DA" for "Democratic accountability", "ET" for "Ethnic tensions", "EC" for "External conflict", "GS" for "Government stability", "IC" for "Internal conflict", "IP" for "Investment profile", "LO" for "Law and order", "MP" for Military in politics, "RT" for "Religious tensions", and "SC" for "Socioeconomic conditions". Data are monthly, spanning 1992 to 2019.

(a) Percentage of variance explained

	ICRG	BQ	CO	DA	ET	EC	GS	IC	IP	LO	MP	RT	SC
PC 1	40.56	75.87	52.16	35.43	56.12	47.74	50.81	47.74	75.00	49.05	49.69	60.74	44.94
PC 2	16.07	10.46	21.46	26.84	14.78	12.98	8.88	12.98	11.44	21.81	20.57	12.62	22.65
PC 3	13.84	4.66	5.39	13.53	7.98	11.27	6.11	11.27	3.50	10.55	15.16	9.00	8.47
PC 1, 2, 3	70.46	90.99	79.00	75.79	78.88	71.99	65.80	71.99	89.94	81.41	85.42	82.36	76.06

(b) Correlation between scores of the first principal components

	ICRG	BQ	CO	DA	ET	EC	GS	IC	IP	LO	MP	RT	SC
ICRG		0.17	-0.08	-0.03	0.21	0.19	0.90	0.56	0.23	0.30	-0.25	0.50	0.10
BQ			-0.92	0.92	-0.85	-0.88	0.42	-0.68	0.91	-0.79	0.84	-0.60	0.88
CO				-0.94	0.94	0.90	-0.24	0.68	-0.96	0.88	-0.92	0.70	-0.95
DA					-0.93	-0.92	0.16	-0.74	0.92	-0.86	0.93	-0.78	0.91
ET						0.95	0.04	0.85	-0.89	0.97	-0.98	0.89	-0.92
EC							-0.05	0.88	-0.84	0.90	-0.95	0.86	-0.88
GS								0.28	0.33	0.12	-0.09	0.37	0.21
IC									-0.58	0.87	-0.86	0.87	-0.68
IP										-0.83	0.86	-0.66	0.95
LO											-0.97	0.85	-0.88
MP												-0.87	0.91
RT													-0.71

Table A11 – Spanning regressions on political factors constructed with the ICRG components

This table reports results from spanning regressions of the multi-asset P-factors constructed with each of the ICRG components on a two-factor model that includes the global multi-asset market portfolio and the global multi-asset P-factor constructed with the aggregate ICRG political risk rating. We proceed in three steps. First, we sort countries on, respectively, each ICRG component. Second, for each ICRG component, we construct a long-short factor-mimicking portfolio and compute its return in the equity, bond, and FX asset classes. Third, for each ICRG component, we construct a global multi-asset factor as an inverse-volatility portfolio of the corresponding three asset-class specific factors. We regress each of these global multi-asset factors on the global multi-asset market portfolio and a global multi-asset P-factor constructed sorting countries on the aggregate ICRG political risk ratings, and we report the annualized abnormal return, time-series adjusted R^2, and information ratio. The multi-asset political factors constructed with the ICRG components are labelled as follows: "BC" stands for "Bureaucracy quality", "CO" for corruption, "DA" for "Democratic accountability", "ET" for "Ethnic tensions", "EC" for "External conflict", "GS" for "Government stability", "IC" for "Internal conflict", "IP" for "Investment profile", "LO" for "Law and order", "MP" for Military in politics, "RT" for "Religious tensions", and "SC" for "Socioeconomic conditions". 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% levels, respectively. Data are monthly, spanning 1992 to 2019.

	BQ	CO	DA	ET	EC	GS	IC	IP	LO	MP	RT	SC
α	-2.31%	1.40%	0.24%	0.31%	1.69%*	-0.43%	0.35%	-0.44%	-1.86%*	-0.86%	1.48%	0.63%
	(0.45)	(0.12)	(0.74)	(0.74)	(0.09)	(0.78)	(0.69)	(0.76)	(0.08)	(0.23)	(0.13)	(0.52)
R^2	0.38	0.65	0.71	0.45	0.44	0.08	0.77	0.54	0.72	0.79	0.43	0.63
IR	-0.20	0.31	0.06	0.06	0.39	-0.07	0.10	-0.07	-0.40	-0.26	0.34	0.15

Table A12 – Country turnover in politically sorted portfolios

This table reports country turnover for the portfolios sorted on each of the political measures and the ICRG components. At every time t, and for each portfolio j, we compute the number of countries that are included in portfolio j at time t and that were also in portfolio j at $t-12$, with time expressed in months. We then calculate a time series of annual country turnover by dividing this number by the total amount of countries included in portfolio j in $t-12$. We report the time-series average of this ratio for each portfolio. "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" 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, and "WB" are the political instability ratings created by the World Bank. The ICRG components are labelled as follows: "BC" stands for "Bureaucracy quality", "CO" for corruption, "DA" for "Democratic accountability", "ET" for "Ethnic tensions", "EC" for "External conflict", "GS" for "Government stability", "IC" for "Internal conflict", "IP" for "Investment profile", "LO" for "Law and order", "MP" for Military in politics, "RT" for "Religious tensions", and "SC" for "Socioeconomic conditions". Data span the period 1992–2019.

	P1 (L)	P2	P3	P4 (H)	Avg
	Political risk measures				
ICRG	15.77%	21.66%	27.16%	22.37%	21.74%
Politics	0.00%	0.00%	0.00%	0.00%	0.00%
Policy	0.00%	0.00%	0.00%	0.00%	0.00%
WB	0.00%	0.00%	0.00%	0.00%	0.00%
	ICRG components				
BQ	6.43%	7.92%	8.62%	1.66%	6.16%
CO	18.59%	11.27%	10.65%	8.82%	12.33%
DA	10.71%	16.93%	19.51%	4.28%	12.86%
ET	9.14%	8.84%	11.26%	5.11%	8.59%
EC	22.01%	25.18%	47.14%	10.06%	26.10%
GS	64.18%	42.84%	58.45%	45.28%	52.68%
IC	23.32%	24.35%	44.76%	17.37%	27.45%
IP	30.73%	24.01%	31.70%	31.48%	29.48%
LO	9.26%	11.47%	11.84%	2.63%	8.80%
MP	7.71%	8.13%	9.09%	0.80%	6.43%
RT	9.00%	13.88%	11.46%	1.70%	9.01%
SC	14.70%	25.96%	34.29%	34.74%	27.42%

Table A13 – 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 an 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 6 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% levels, respectively. Data are monthly, spanning 1992 to 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 A14 – P-factor risk premia with orthogonalized political ratings: pricing statistics

This table reports the 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% levels, respectively. Data are monthly, spanning 1992 to 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