Geopolitical Risk in Currency Markets*

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Abstract

We document that sorting currencies into portfolios on the exposure of their expected returns to the level of global geopolitical turmoil yields a substantial return spread that cannot be explained by loadings to standard currency risk factors. We, then, propose a traded currency factor that reflects global geopolitical risk and show that it is priced in the cross-section of currency returns. On average, developed country currencies hedge geopolitical risk, whereas emerging country currencies are geopolitically risky, with emerging currencies exhibiting larger cross-sectional variation in geopolitical risk exposure than developed currencies. When we implement the USD-neutral geopolitical trade strategy using bonds, we find that using long-maturity bonds and short-maturity bonds yield similar USD returns, suggesting that geopolitical shocks have a permanent, rather than a transitory, impact on pricing kernels. Finally, we show that geopolitical risk factor loadings are related to the sensitivity of expected capital flows to geopolitical turmoil: countries that tend to attract higher-than-average net capital flows in times of turmoil have currencies that hedge geopolitical risk, whereas countries that experience the opposite have geopolitically risky currencies.

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1 Introduction

Geopolitical developments have important implications for economic activity and asset prices, making geopolitical risk relevant for investors, firms, and policymakers. In recent work, Caldara and Iacoviello (2022) document that adverse geopolitical shock realizations are associated with drops in investment, employment, and stock prices. Relatedly, Caldara, Conlisk, Iacoviello and Penn (2026) show that adverse geopolitical events lead to an increase in global inflation, with the rise in inflation accompanied by higher inflation uncertainty and declines in economic activity and the volume of international trade.

Crucially, countries are not exposed to global geopolitical fluctuations to the same degree: some countries are widely considered safe havens, while others are perceived to be geopolitically risky. Although cross-country differences in exposure to geopolitical risk are likely to affect the pricing of all asset classes, exchange rates are uniquely sensitive to those differences. This is because exchange rates represent the relative valuation of currencies, so their fluctuations reflect cross-sectional differences in exposure to global shocks. For that reason, currency returns provide an ideal asset class for investigating cross-country heterogeneity in global geopolitical risk exposure.

To study the impact of geopolitical risk on currency returns, we consider a novel cross-section of currency portfolios that differ in the exposure of their expected excess returns on global geopolitical tensions. In particular, we form "geopolitical exposure portfolios" by sorting currencies into portfolios on the rolling forecast coefficient of their excess returns on GPT, the global geopolitical threats index developed by Caldara and Iacoviello (2022). Currencies with positive forecast coefficients have expected excess returns that are increasing in the level of GPT and, hence, are highly exposed to global geopolitical tension, whereas the opposite is true for currencies with negative forecast coefficients.

We find that the average excess returns of the geopolitical exposure portfolios are monotonically increasing in the geopolitical exposure of their excess returns, so the dollar-neutral strategy that invests in high-exposure currencies and shorts low-exposure currencies, denoted

by $GHML$, yields an annualized return of 3.28%. Strikingly, the $GHML$ average return does not reflect exposure to standard currency risk factors: the loadings of $GHML$ on the Lustig, Roussanov and Verdelhan (2011) dollar and carry factors (DOL and CAR, respectively) are economically small and statistically non-significant, so the $GHML$ strategy has an annualized alpha of 2.76%.

We, then, explore whether $GHML$ can be considered a currency risk factor. First, we document that exposure to the $GHML$ factor can help explain our novel cross-section of currency returns in statistical terms. To that end, we show that there is a positive cross-sectional association between $GHML$ loadings and excess return geopolitical exposure: high-exposure currencies have high $GHML$ betas, whereas low-exposure currencies have low $GHML$ loadings. This finding is robust to controlling for the DOL and CAR factors, as DOL is a level factor for geopolitical portfolio returns, whereas CAR loadings are economically small across portfolios. Importantly, when we control for all three factors, portfolio alphas become statistically non-significant, indicating that the three factors are able to jointly account for the magnitude of the excess returns of our geopolitical exposure portfolios. Interestingly, sorting currencies into portfolios on their nominal interest rate or their dollar beta does not generate differences in geopolitical risk exposure, so standard portfolio sorts are not conducive to uncovering the effect of geopolitical risk on currency returns. When we estimate the price of the $GHML$ factor using different sets of test portfolios, we find that its price is close to its unconditional return, consistent with the fact that it is a traded factor.

A natural interpretation of the $GHML$ factor is that it reflects geopolitical risk. The time series of the $GHML$ excess returns is consistent with that interpretation. For example, in September 2001, the month of the terrorist attack on the World Trade Center, the monthly excess return of the $GHML$ strategy was -7.37% (a staggering -88.44% in annualized terms). During the same month, the monthly GPT index jumped from 55.23 to 260.17, an increase of 371.07%. Another salient data point is the Russian invasion of Ukraine, in February 2022: the $GHML$ strategy recorded large negative excess returns just before, during, and shortly after the invasion, rebounding only after geopolitical tensions eased and the GPT index

increased. More formally, we demonstrate that the $GHML$ factor captures global geopolitical risk by regressing currency excess returns on contemporaneous log changes in GPT and sorting currencies into portfolios on the regression slope coefficient. Positive-coefficient currencies are those that do well when GPT increases, and therefore hedge geopolitical risk, whereas negative-coefficient currencies do badly in those times, so they are geopolitically risky. Consistent with our conjecture, we find that positive-coefficient currency portfolios have low average excess returns and negative $GHML$ loadings, whereas negative-coefficient currency portfolios have high average excess returns and positive $GHML$ loadings, with the return spread between positive- and negative-coefficient currency portfolios being -1.98% and their $GHML$ loading spread being -0.52.

When we consider developed and emerging country currencies separately, we find statistically and economically meaningful differences in their geopolitical risk properties: the former, on average, hedge geopolitical risk, whereas the latter, on average, are geopolitically risky. In particular, the $GHML$ loading of the equally-weighted portfolio of all developed currencies (denoted by DEV) is negative (-0.04) and significant at the 1% level, whereas the $GHML$ loading of the equally-weighted portfolio of all emerging currencies (EMG) is positive (0.07) and significant at the 5% level. Hence, the strategy that invests in emerging currencies and shorts developed currencies (EMG - DEV) has a positive $GHML$ loading (0.12), which partly accounts for the 1.70% return spread between the two portfolios. Both sets of currencies exhibit non-trivial heterogeneity in their geopolitical risk loadings: the $GHML$ loadings range from -0.37 to 0.12 for developed currency portfolios and from -0.30 to 0.86 for emerging currency portfolios. Hence, emerging currencies are both geopolitically riskier than developed currencies on average, and they feature substantially larger cross-sectional variation in their geopolitical risk exposure.

Next, we implement the USD-neutral "geopolitical trade" strategy using long-maturity bonds. In particular, we consider a strategy that invests in the (zero-coupon) 10-year bonds of currencies with high geopolitical exposure and shorts the 10-year bonds of low-exposure currencies, liquidating the position after one month. We find that the strategy is quite

profitable for a US investor, earning a monthly USD return of 3.58%, in annualized terms. We, then, decompose that USD return into two parts: a local currency return difference, which compensates investors for exposure to interest rate risk, and an FX excess return, which compensates investors for exposure to currency risk and reflects the return of the geopolitical trade strategy using short-maturity bonds. We find that the USD return of the geopolitical trade is almost entirely due to latter component: the currency premium is 3.85%, whereas the term premium difference is -0.28%. In the terminology of Lustig, Stathopoulos and Verdelhan (2019), the term structure of the risk premia of the geopolitical trade strategy is flat: the USD return is about the same when using either short-maturity or long-maturity bonds.

As discussed in Lustig et al. (2019), if international financial markets are complete and long-maturity bonds proxy for infinite maturity bonds, the short end of the term structure of long-short bond strategies reflects differences in countries' exposure to all priced shocks, whereas the long end of the term structure reflects differences in exposure only to permanent priced shocks, i.e., shocks that have a permanent impact on countries' pricing kernels. Hence, the flatness of the term structure of "geopolitical trade" premia suggests that geopolitical shocks are permanent, rather than transitory, shocks. It follows that our findings have important theoretical implications: in any model that includes geopolitical shocks, those shocks need have permanent effects in pricing kernels, otherwise the model will be unable to match the empirical evidence on bond returns. Furthermore, our findings indicate that geopolitical shocks are of first-order economic importance: to the extent that pricing kernels reflect the marginal utility of wealth, as standard macro-finance models suggest, the persistence of geopolitical shocks implies that adverse geopolitical developments have substantial long-term welfare consequences for countries and that policies or arrangements that mitigate geopolitical risk have long-term welfare benefits.

Next, we turn to international capital flows. In particular, we investigate whether the exposure of capital flows to geopolitical turmoil is associated with the geopolitical risk loading of currency returns. For our exercise, we sort currencies into portfolios on the geopolitical ex-

posure of their expected net capital flow ratio to the level of geopolitical tension, as measured by the forecast coefficient of net international capital flows (scaled by GDP) on the GPT index. A positive forecast coefficient implies that net capital flows tend to increase in GPT, so countries with positive coefficients are geopolitical "safe havens", attracting higher-than-average net flows in periods of geopolitical turmoil. On the other hand, negative forecast coefficients indicate less-than-average net flows in times of turmoil and, hence, correspond to geopolitical "danger zones". We find a negative cross-sectional relationship between net capital flow forecast coefficients and $GHML$ loadings: safe haven currencies have a $GHML$ loading 0.32 lower than danger zone currencies, suggesting that the currencies of countries that attract more capital flows in times of turmoil are less exposed to global geopolitical risk than the currencies of geopolitical danger zones.

When we decompose international capital flows into FDI and portfolio flows and sort currencies into portfolios on the forecast coefficient of each type of net flows, we find that the relationship between capital flow forecast coefficients and $GHML$ loadings is driven by portfolio flows, whereas the geopolitical exposure of expected FDI flows and the geopolitical risk loadings of currencies are cross-sectionally unrelated.

Finally, we explore the drivers of cross-sectional heterogeneity in geopolitical risk exposure by considering different portfolio sorts and documenting whether they generate variation in $GHML$ loadings. We find that sorting currencies into portfolios on the forecast coefficient of their returns on the text-based war discourse measure of Hirshleifer, Mai and Pukthuanthong (2024) generates a meaningful spread in $GHML$ betas, consistent with our interpretation of $GHML$ as a geopolitical risk factor. Next, in order to examine whether global geopolitical risk and policy uncertainty are connected, we sort on the forecast coefficient of currency excess returns on policy uncertainty measures. In particular, we consider two text-based measures: the Economic Policy Uncertainty (EPU) index of Baker, Bloom and Davis (2016) and the Trade Policy Uncertainty (TPU) index of Caldara, Iacoviello, Molligo, Prestipino and Raffo (2020). In both cases, we find no substantial variation in $GHML$ loadings across portfolios, suggesting that expected excess return exposure to policy uncertainty differs from

return exposure to geopolitical risk. For our final exercise, we sort currencies into portfolios on the magnitude of country-specific, rather than global, geopolitical risk measures. Those measures are also developed by Caldara and Iacoviello (2022) and measure the intensity of media coverage of particular countries in the context of news items focusing on geopolitical developments. We show that we are unable to generate a meaningful spread in $GHML$ betas, indicating that currency return exposure to global geopolitical risk cannot be proxied by text-based measures that reflect country-specific media coverage.

Our paper contributes to a growing literature that explores the effects of geopolitical risk on economic activity and financial markets. In terms of real effects, geopolitical risk reduces corporate investment (Wang, Wu and Xu (2024)), curtails bank lending (Niepmann and Shen (2025)), and depresses international trade (Khalil, Osten and Strobel (2025)). When geopolitical tension escalates to war, the economic impact is particularly severe: Barro (2006) documents that wars entail large contractions of economic activity, and Federle, Meier, Müller, Mutschler and Schularick (2025) find that, in war-site economies, wars are associated with output drops of about 10% and consumer price increases of about 20%, on average, with sharp drops in capital stock, total factor productivity, and equity returns.

As regards equity markets, there is evidence that geopolitical risk measures have forecasting power for stock returns (Ma, Lu and Tao (2022)) and that increases in geopolitical risk are negatively associated with stock prices (Federle, Meier, Müller and Sehn (2024)) and positively associated with stock market volatility (Zhang, He, He and Li (2023)). Gonçalves, Melone and Ricciardi (2025) show that sorting equity and bond portfolios on their GPT growth beta generates a return spread that cannot be accounted by standard risk factors and that GPT has forecasting ability for country-level equity returns. Other research focuses on the effects on geopolitical risk on bond prices (Hegde, Kalimipalli and Liao (2025)), oil prices (Liu, Ma, Tang and Zhang (2019)), gold prices (Baur and Smales (2020)), commodity prices (Umar, Bossman, Choi and Teplova (2022)), and cryptocurrency prices (Long, Demir, Bedowska-Sojka, Zaremba and Shahzad (2022), Chibane and Janson (2025)).

With respect to currency returns, the existing literature finds that measures of geopolitical

turmoil have forecasting power for both currency returns (Iyke, Phan and Narayan (2022)) and exchange rate volatility (Salisu, Cunado and Gupta (2022)) and that the impact of geopolitical shocks differs greatly across currencies (Bossman, Gubareva and Teplova (2023), Hossain, Masum and Saadi (2024), Yilmazkuday (2025)). Liu and Zhang (2024) propose a geopolitical risk factor constructed by sorting currencies into portfolios on country-specific geopolitical risk measures and show that it reflects idiosyncratic and regional geopolitical shocks, but not global shocks. Geopolitical risk also affects international capital flows: Feng, Han, Vigne and Xu (2023) document that, when geopolitical turmoil increases, international capital flows contract, with geopolitical threats having a stronger impact than geopolitical acts.

The research that traces the impact of geopolitical developments on asset prices can be considered a part of the emerging field of geoeconomics, which is the study of the interlinkages between geopolitics and economics. Mohr and Trebesch (2025) provide a comprehensive review of the geoeconomics literature. Clayton, Maggiori and Schreger (2026) introduce a theoretical framework of the sources and uses of geoeconomic power, illustrating the ability of hegemonic powers to coordinate threats across disparate economic relationships as a means to enforce their demands and extract benefits. Pflueger and Yared (2025) propose a dynamic two-country model which links government financing and geopolitical rivalry through the pricing of sovereign debt in international bond markets. Eichengreen, Minesso, Mehl, Vansteenkiste and Vicquéry (2024), focusing on the interwar period (1914-1945), document that the impact of different types of sanctions (import restrictions, export restrictions, asset freezes, and trade embargoes) on exchange rates are consistent with the predictions of theoretical models (Lorenzoni and Werning (2023), Itskhoki and Mukhin (2025)).

A related strand of the literature focuses on political risk, providing evidence that it is priced in currency markets. In particular, Filippou, Gozluklu and Taylor (2018) combine country-level data from the International Country Risk Guide (ICRG) in order to construct a measure of global political risk and show that exposure to that risk can help explain the return cross-section of currency momentum portfolios. More broadly, Gala, Pagliardi, Shaliastovich and

Zenios (2025) construct a global political factor by employing risk measures from the ICRG, the World Bank, and the Ifo World Economic Survey (WES) and document that it explains a significant share of the cross-sectional return variation across stock, bond, and currency portfolios. Finally, Dodd, Fernandez-Perez and Sosvilla-Rivero (2025) show that commodity returns and the currency returns of commodity-exporting countries become disconnected when political risk increases.

Finally, our paper contributes to the part of the international finance literature that focuses on the cross-section of currency returns and the pricing of currency risk. A non-exhaustive list of related work includes papers that explore the properties of portfolios of currencies sorted on consumption growth risk exposure (Lustig and Verdelhan (2007)), interest rates (Lustig et al. (2011)), exposure to FX volatility risk (Menkhoff, Sarno, Schmeling and Schripmf (2012a)), currency momentum (Menkhoff, Sarno, Schmeling and Schripmf (2012b)), country size (Hassan (2013)), global imbalances (Della Corte, Riddiough and Sarno (2016)), currency value (Menkhoff, Sarno, Schmeling and Schripmf (2017)), exposure to FX correlation risk (Mueller, Stathopoulos and Vedolin (2017)), trade composition (Ready, Roussanov and Ward (2017))), trade network centrality (Richmond (2019)), economic momentum (Dahlquist and Hasseltoft (2020)), the output gap (Colacito, Riddiough and Sarno (2020)), and sovereign credit risk (Della Corte, Sarno, Schmeling and Wagner (2022)).

The rest of this paper is organized as follows. Section 2 introduces the geopolitical exposure portfolios and the $GHML$ factor, and documents that $GHML$ is a priced factor that reflects global geopolitical risk. Section 3 establishes a cross-sectional relationship between the exposure of expected capital flows to global geopolitical turmoil and the $GHML$ loading of currency returns. Finally, Section 4 explores the geopolitical riskiness of different sets of currency portfolios, and Section 5 concludes.

2 Geopolitical risk and currency returns

We document that sorting currencies into portfolios on the exposure of their expected excess returns to the level of global geopolitical turmoil generates a substantial return spread that cannot be explained by their loadings on standard currency risk factors. Then, we show that $GHML$, the return of the strategy that invests in high-exposure currencies and shorts low-exposure currencies, is a priced factor in the cross-section of currency returns and that it reflects global geopolitical risk, and we estimate the price of that factor. Finally, we document that, when we implement the same strategy using long-maturity bonds, the average USD return is comparable to the return earned using short-maturity bonds, suggesting that geopolitical shocks have a permanent effect on pricing kernels.

2.1 Geopolitical exposure portfolios

We start by introducing a novel cross-section of currency portfolios: portfolios that differ in the exposure of their expected excess returns on geopolitical tension, as measured by the forecast coefficient of currency excess returns on a measure of the level of global geopolitical threats.

Caldara and Iacoviello (2022) define geopolitical risk as "the threat, realization, and escalation of adverse events associated with wars, terrorism, and any tensions among states and political actors that affect the peaceful course of international relations". For our analysis, we focus on the Caldara and Iacoviello (2022) global geopolitical threats index, denoted by GPT. For each month t, GPT_t represents (after normalization) the share of articles that mention geopolitical threats in leading newspapers, published in the United States, Canada, and the United Kingdom, during month t.[1] Although the newspapers in the dataset have global readership, their geographic location and language of publication suggests that their articles are likely to be biased towards threats that are salient for investors in North America

[1] In particular, GPT represents the share of articles that mention five categories of threats: war threats, peace threats, military buildups, nuclear threats, and terror threats.

and Britain. For our analysis, we take the perspective of an American investor and consider currency returns against the US dollar.

It is worth noting that GPT is one of the two components of the overall Caldara and Iacoviello (2022) geopolitical risk index, GPR. The other component is the geopolitical acts index (GPA), which measures the share of articles that mention current adverse geopolitical events (and, in particular, the beginning or escalation of war, as well as terror acts). We choose to focus on GPT as the forecast signal because it encodes information about the likelihood of adverse future geopolitical realizations and, hence, is likely to have a stronger association with expectations of future currency returns compared to measures that reflect information about events that have already occurred. Indeed, Gonçalves et al. (2025) find that GPT is able to forecast equity returns more strongly and consistently than GPA, and that GPT aligns more strongly than GPA with how firms and investors perceive geopolitical risk and act upon it.[2]

For our main analysis, we focus on the monthly horizon. For currency i, the log excess return for month $t+1$ is given by

$$rx^i_{t+1} = s^i_{t+1} - f^i_t = \Delta s^i_{t+1} + (s^i_t - f^i_t), \tag{1}$$

where s^i_{t+1} is the log spot exchange rate at the end of month $t+1$ and f^i_t is the 1-month forward exchange rate at the end of month t, with both rates expressed in US dollars per unit of currency i. The first component of excess returns, Δs^i_{t+1}, is the (log) nominal exchange rate change and the second component, $s^i_t - f^i_t$, is the (log) forward discount. In the remainder of our paper, we refer to the forward discount component as the nominal interest rate differential (IRD) between currency i and the US dollar, implicitly imposing the covered interest rate parity condition $s^i_t - f^i_t \approx r^i_t - r_t$, where r^i_t (r_t) is the 1-month riskless interest rate of currency i (the US dollar) at the end of month t. We consider the currencies of 41 developed and emerging countries, as well as the euro. Our sample period is

[2] As part of our robustness checks, discussed later in this section, we also consider portfolio sorts that use GPR or GPA as the forecast signal.

from January 1985 to December 2024, with the start of the sample period being determined by the beginning of the GPT data series. After the introduction of the euro, we exclude the data of eurozone countries and keep only the euro series. We provide details of our data sources in Internet Appendix A.

For each currency i, we run the set of rolling forecasting regressions

$$rx_{t+1}^{i} = \alpha^{i} + \theta^{i,GPT} GPT_{t} + \eta_{t+1}^{i}, \tag{2}$$

using a 36-month rolling window of monthly observations. The slope coefficient measures the conditional exposure of the expected monthly excess return of currency i to geopolitical tension: positive (negative) θ^{GPT} values reflect expected excess returns that are increasing (decreasing) in the level of global geopolitical tension. Then, at the end of each month t, we sort the available currencies into five equally-weighted portfolios on their excess return forecast coefficient, and refer to those as "geopolitical exposure portfolios": Portfolio 1 includes the lowest-θ^{GPT} currencies and Portfolio 5 the highest-θ^{GPT} currencies.

The time series of the forecast coefficient of each portfolio, calculated as the equally-weighted average of the forecast coefficient of the currencies included in the portfolio, is plotted in Figure 1. As seen in the figure, Portfolio 1 tends to have a negative θ^{GPT}, i.e., it includes currencies that have lower-than-average expected excess returns when geopolitical tensions are high. In contrast, Portfolio 5 tends to have a positive θ^{GPT}, so it includes currencies that do better, on average, in times of geopolitical turmoil. By construction, the forecast coefficient of Portfolio 5 is always higher than that of Portfolio 1, so the long-short currency portfolio $GHML$ (defined as Portfolio 5 minus Portfolio 1) is a strategy that always has a positive conditional θ^{GPT}. Notably, $GHML$ is a US dollar-neutral strategy: both legs of the strategy are short on the US dollar, so the USD position of $GHML$ is zero.

Since we need 36 months of data for our pre-formation regressions, the sample period of portfolio excess returns starts in February 1988 and ends in December 2024, for a total of 443 monthly observations. The summary statistics of the excess returns of the five geopolitical

exposure portfolios and the long-short strategy $GHML$ are presented in Panel A of Table 1. Our sorting generates average excess returns that are monotonically increasing in geopolitical exposure, ranging from -0.02% (Portfolio 1) to 3.26% (Portfolio 5) in annualized terms. When we decompose the portfolio average excess returns into average nominal exchange rate changes and average nominal interest rate differentials, we do not find a monotonic pattern for either FX changes or interest rate differentials, with the latter fact suggesting that our portfolio sort differs from the standard sort on nominal interest rates.[3] The $GHML$ strategy has an average excess return of 3.28%, an excess return standard deviation of 8.37%, and a Sharpe ratio of 0.39, all in annualized terms. Both components of the average $GHML$ excess return are positive, with the largest component being the average interest rate differential (3.07%), whereas the average FX change accounts for 0.21%. Although the excess returns of all five geopolitical exposure portfolios exhibit negative skewness, indicating an asymmetry towards large negative realizations, the return distribution of the long-short portfolio $GHML$ is almost completely symmetric, exhibiting negligible skewness. Finally, the excess kurtosis of $GHML$ returns is 1.08, lower than the excess kurtosis of Portfolios 1 to 5, suggesting that the long-short strategy diversifies away extreme excess return realizations in either direction.

To determine whether the cross-sectional variation in the excess returns of the geopolitical exposure portfolios can be explained by differences in exposure to the well-known Lustig et al. (2011) dollar (DOL) and carry (CAR) currency risk factors, we calculate portfolio factor loadings and report our findings in Panel B of Table 1. The DOL factor is an equally weighted average of all available currency excess returns, whereas the CAR factor is constructed by sorting currencies into five equally-weighted portfolios on their nominal interest rate and going long Portfolio 5 (high interest rate currencies) and short Portfolio 1 (low interest rate currencies).

We find that, in the cross-section of the geopolitical exposure portfolios, DOL is clearly a level factor and, therefore, cannot explain any return differences: all five portfolios have a

[3]Later in this section, we consider interest rate-sorted portfolios and confirm that their properties differ markedly from those of our geopolitical exposure portfolios.

DOL loading very close to 1 (ranging from 0.93 to 1.09), so the $GHML$ loading on the DOL factor is statistically indistinguishable from zero. Given that most of the excess return of the $GHML$ portfolio is due to the interest rate differential between the long and the short legs of the strategy, one might expect that the $GHML$ portfolio would have positive exposure to the CAR factor. However, that is not the case: the loading of $GHML$ on CAR is economically small and statistically insignificant. Indeed, exposure to the CAR factor appears largely unable to account for the excess returns of our geopolitical exposure portfolios: the loading on CAR is statistically different from zero for only two out of the five portfolios and is economically small for all five of them. Finally, there is no clear cross-sectional pattern in either the DOL or the CAR portfolio loadings. Given the statistically insignificant loading of the $GHML$ strategy on both factors, it is not surprising that its monthly alpha of 0.23% (2.76% in annual terms) accounts for almost the entirety of its average excess return. Consistent with that finding, the regression adjusted R^2 for $GHML$ is a paltry 2%, indicating that exposure to DOL and CAR risk explains a negligible share of the variation in $GHML$ returns.

2.2 The $GHML$ factor and the cross-section of currency returns

To understand the sources of variation in our new cross-section of currency returns, we calculate the principal components of the excess returns of the five portfolios. The results are presented in Table 2. The first principal component, which explains about 75% of the overall variation in excess returns, is clearly a level factor, as the loadings of the five portfolios on the first PC exhibit very limited cross-sectional dispersion, ranging from 0.39 to 0.48. On the other hand, the second principal component, which accounts for about 12% of the variation, appears to be a slope factor: the portfolio loadings on the second PC exhibit a monotonic pattern and a substantial spread, ranging from -0.41 (for Portfolio 1) to 0.78 (for Portfolio 5). It is worth noting that the correlation between the second principal component and the $GHML$ return is 0.94, suggesting that the two series are quite similar. For that reason, we next explore whether $GHML$ is a priced factor for currency returns.

Our proposed factor, $GHML$, is almost orthogonal to both DOL and CAR: its unconditional correlation with the former is -0.09 and with the latter is 0.06, indicating that it represents a new source of systematic variation in currency returns. To explore whether $GHML$ has pricing ability for the cross-section of currency returns, we start by running time-series regressions of the returns of our geopolitical exposure portfolios on the $GHML$ return (also including a constant). Our findings are presented in the first five columns of Table 3. Portfolio loadings on $GHML$ increase monotonically from Portfolio 1 (-0.49) to Portfolio 5 (0.51), suggesting a strong positive cross-sectional association between average currency returns and $GHML$ betas.

Next, we control for exposure to dollar and carry risk by also including the two Lustig et al. (2011) factors as regressors. Our findings are reported in columns six to ten of Table 3. It is clear that including the two additional factors does not materially change our findings: the portfolio return loadings on $GHML$ continue to be economically large, statistically significant, and to exhibit monotonicity, ranging from -0.42 (Portfolio 1) to 0.58 (Portfolio 5). Consistent with our findings in Panel B of Table 1, the DOL loadings of all five portfolios are statistically significant and have estimated values very close to one, whereas all CAR loadings are economically small. However, the inclusion of the DOL and CAR factors increases the share of the explained variation of the excess returns of the geopolitical exposure portfolios: when only $GHML$ is included in the regression, the adjusted R^2s range from 0.00 to 0.24, whereas when DOL and CAR are added, the adjusted R^ss increase considerably, ranging from 0.80 to 0.91. Furthermore, when all three factors are included, all five portfolios have economically small and statistically non-significant alphas, suggesting the $GHML$, DOL and CAR factors are sufficient to account for the magnitude of the average excess returns of our portfolios.

One potential concern is that the positive cross-sectional relationship between θ^{GPT} forecast coefficients and $GHML$ betas may mechanically arise from cross-sectional heterogeneity in conditional return volatility. In particular, the excess return forecast coefficient can be

decomposed into the product of a correlation term and a volatility term:

$$\theta^{i,GPT} = \frac{cov(rx^i_{t+1}, GPT_t)}{var(GPT_t)} = \rho(rx^i_{t+1}, GPT_t)\frac{\sigma(rx^i_{t+1})}{\sigma(GPT_t)}. \quad (3)$$

It follows that our portfolio sort reflects cross-sectional differences in both conditional return volatility and conditional return correlation with the GPT index. If the cross-sectional variation in θ^{GPT} arises mainly from heterogeneity in the volatility term, then we are essentially sorting on conditional return volatility. In that case, variation in $GHML$ loadings would mainly reflect differences in the magnitude (rather than the direction) of return fluctuations, with more volatile currencies having higher $GHML$ loadings. On the other hand, if most of the variation in θ^{GPT} is due to differences in the correlation term, then there is meaningful cross-sectional heterogeneity in the exposure of currency excess returns to geopolitical tensions, and $GHML$ loadings reflect those cross-sectional differences.

To shed some light on that issue, we sort currencies into portfolios on each of the two components of the 36-month rolling forecast coefficient θ^{GPT}, and report the factor loadings of those portfolios in Table 4. In particular, Panel A focuses on portfolios sorted on the 36-month rolling correlation of excess returns with the lagged GPT index, whereas Panel B on portfolios sorted on the ratio of 36-month rolling excess return volatility over the 36-month rolling volatility of the lagged GPT index.

As seen in Panel A, sorting currencies into portfolios on their rolling correlation term generates substantial heterogeneity in their $GHML$ loadings. When $GHML$ is the only factor considered, the portfolios' $GHML$ loadings are monotonically increasing in the magnitude of the rolling correlation, ranging from -0.36 (Portfolio 1) to 0.34 (Portfolio 5). The magnitudes of the $GHML$ loadings of the portfolios do not change much when we also control for the DOL and CAR factors: in that case, the $GHML$ loadings range from -0.29 (Portfolio 1) to 0.40 (Portfolio 5). Overall, we find that there is a tight cross-sectional relationship between return correlation with GPT levels and $GHML$ loadings: the currencies with the highest (lowest) return correlation with GPT are those with the highest (lowest) $GHML$ loadings.

Hence, sorting on just the correlation component of the return forecast coefficient is very similar to sorting on the overall magnitude of the forecast coefficient.

In contrast, as seen in Panel B of Table 4, sorting currencies into portfolios on their rolling volatility ratio fails to produce a meaningful spread in $GHML$ loadings. In particular, the univariate $GHML$ betas of all portfolios are economically small (ranging from -0.17 to 0.07) and statistically insignificant. Furthermore, those $GHML$ loadings do not exhibit a discernible cross-sectional pattern, suggesting that the level of currency return volatility is not associated with the degree of exposure to the $GHML$ factor across portfolios. Finally, the regression adjusted R^2s are tiny for all five portfolios, indicating that exposure to the $GHML$ factor is unable to explain the time-series variation in their excess returns. When we include the DOL and CAR factors in the regression, our findings regarding the cross-section of $GHML$ loadings do not materially change: $GHML$ loadings continue to be economically small and to lack a monotonic pattern across portfolios, although now three of the five portfolios have a $GHML$ beta that is statistically significant.

We conclude that the positive association between θ^{GPT} forecast coefficients and $GHML$ betas across currency portfolios is not a mechanical artifact of cross-sectional differences in currency return volatility. Rather, it arises from differences in the correlation of returns with GPT levels and, hence, it reflects cross-sectional heterogeneity in the magnitude of currency return exposure to geopolitical turmoil.

2.3 The $GHML$ factor and geopolitical risk

So far, we have documented that exposure to the $GHML$ factor can help explain our novel cross-section of currency returns, indicating that it represents a source of return comovement that is important for statistically characterizing the returns of our geopolitical exposure portfolios. However, we have been silent on one important economic question: is it a risk factor and, if so, which systematic risk does it reflect?

A reasonable conjecture is that it reflects global geopolitical risk. As we demonstrate in a

simple no-arbitrage model, discussed later in this section and presented in detail in Appendix C, if geopolitical risk is priced by investors and if the price of that risk is increasing in the level of geopolitical tension, then the currencies that yield higher-than-average (lower-than-average) excess returns in times of elevated geopolitical turmoil are those that are more (less) geopolitically risky. In that case, our portfolio sort reflects heterogeneity in geopolitical risk exposure and the $GHML$ factor is the mimicking portfolio of priced global geopolitical risk.

The time series of $GHML$ realizations is consistent with the interpretation of $GHML$ as a geopolitical risk factor. Consider the Russian invasion in Ukraine, a recent major geopolitical development. In December 2021, Russia accumulated troops near its borders with Ukraine and issued several demands. After a few weeks of tension, Russia invaded Ukraine on February 24, 2022, with the first weeks of the war characterized by significant uncertainty as regards the military involvement of third countries allied with the two participants. Indeed, the GPT index spiked during that period, with the same being true for the two other Caldara and Iacoviello (2022) global indices, GPA and GPR. In particular, the monthly GPT index monotonically increased from 121.50 (in November 2021) to 403.71 (in March 2022). Despite the continuation of the war, the geopolitical turmoil gradually eased over the next four months, with the GPT index monotonically declining from 403.71 in March 2022 to 141.24 in July 2022. Consistent with our interpretation, $GHML$ returns were negative in each of the four months from December 2021 to March 2022, with the economic magnitude of those declines being large. In particular, the average monthly $GHML$ log excess return during that period was -16.46% in annualized terms. In contrast, during the period in which geopolitical tensions eased (April to July 2022), investing in $GHML$ was a very profitable strategy: a US investor would achieve an average monthly log excess return of 22.72% in annualized terms.

To formally explore whether our conjecture has merit, we sort currencies into portfolios using their return comovement with GPT log changes and test whether our sorting generates heterogeneous exposure to the $GHML$ factor. In particular, for each currency i, we run

rolling contemporaneous regressions of the form

$$rx_{t+1}^{i} = \alpha^{i} + \beta^{i,GPT} \Delta \log GPT_{t+1} + \epsilon_{t+1}^{i}, \tag{4}$$

using a 36-month rolling window of monthly observations. The slope coefficient is the conditional beta of the monthly excess return of currency i with respect to monthly log GPT changes. Then, at the end of each month, we sort currencies into five equally-weighted portfolios on their log GPT beta. Portfolio 1 includes the lowest-β^{GPT} currencies, i.e., the currencies which perform the worst when global geopolitical tension increases and, thus, can be considered the most exposed to geopolitical risk. The opposite is true for Portfolio 5: it includes the highest-β^{GPT} currencies, i.e., the currencies that have the least exposure to geopolitical risk. If our $GHML$ factor reflects geopolitical risk, we expect to find a negative cross-sectional relationship between β^{GPT} and $GHML$ loadings: low-β^{GPT} currencies (geopolitically risky) should have high $GHML$ loadings, whereas high-β^{GPT} currencies (geopolitically safe) should have low $GHML$ loadings.

We report our findings in Table 5. We find that sorting on β^{GPT} generates a return spread: geopolitically risky currencies (Portfolio 1) have an average excess return that is 1.98% higher, in annualized terms, than geopolitically safe currencies (Portfolio 5). As seen in Panel B of the table, that return spread reflects differences in risk exposure across portfolios and, in particular, differences in exposure to the $GHML$, DOL, and CAR factors. When we account for exposure to those three factors, none of the portfolio alphas (including the alpha of the strategy that goes long Portfolio 5 and short Portfolio 1) are statistically different from zero, suggesting that there is no remaining unexplained return variation. Importantly, the cross-sectional pattern of $GHML$ loadings is consistent with our conjecture: Portfolio 1 has a positive (0.31) and statistically significant $GHML$ loading, whereas Portfolio 5 has a negative (-0.52) and significant $GHML$ loading. In other words, geopolitically risky (safe) currencies load positively (negatively) on the $GHML$ factor, in line with our interpretation of the $GHML$ factor as a geopolitical risk factor. More strikingly, the $GHML$ loadings of

our β^{GPT}-sorted portfolios are monotonically decreasing in the portfolio β^{GPT}, suggesting that $GHML$ factor loadings tightly track the magnitude of geopolitical risk exposure.

2.4 The $GHML$ loadings of benchmark currency portfolios

To illustrate why our novel portfolio sort is critical for uncovering exposure to the $GHML$ factor, we calculate the factor loadings of portfolios that have been widely used in the literature as test assets for currency return pricing models. In particular, we sort currencies into portfolios using either their nominal interest rate or their dollar beta: interest rate-sorted portfolios and dollar beta-sorted portfolios are known to exhibit substantial variation as regards their CAR and DOL loadings, respectively, and, for that reason, are instrumental for pinning down the prices of those factors. However, as we show below, sorting currencies into portfolios using either nominal interest rates or dollar betas does not generate substantial heterogeneity in $GHML$ loadings, obfuscating the importance of the $GHML$ factor for the cross-section of currency returns.

Interest rate-sorted portfolios and dollar beta-sorted portfolios are monthly rebalanced. Interest rate-sorted portfolios are formed by sorting currencies into portfolios on their nominal interest rate differential at the end of each month, following Lustig et al. (2011). In particular, Portfolio 1 (Portfolio 5) includes the currencies with the lowest (highest) nominal interest rate. As regards dollar beta-sorted portfolios, we follow Verdelhan (2018). First, for each currency i, we run the set of rolling contemporaneous regressions

$$\Delta s^i_{t+1} = \alpha^i + \beta^i(r^i_t - r_t) + \gamma^i(r^i_t - r_t)Carry_{t+1} + \delta^i Carry_{t+1} + \tau^i Dollar_{t+1} + \epsilon^i_{t+1},$$

using a 60-month rolling window, where $Carry$ and $Dollar$ is the nominal exchange rate change component of the CAR and DOL excess return, respectively. It follows that τ^i is the conditional dollar beta of currency i. Then, at the end of each month, we sort currencies into portfolios on τ^i: Portfolio 1 (Portfolio 5) includes the currencies with the lowest (highest) dollar beta.

Our findings are presented in Table 6: Panel A reports the factor loadings of interest rate-sorted portfolios, and Panel B the loadings of dollar beta-sorted portfolios. As seen in Panel A, when only $GHML$ is included as a factor, the $GHML$ loadings of interest rate-sorted portfolios are economically small and statistically non-significant, and regression adjusted R^2s are tiny. When we include the DOL and CAR factors in the regressions, adjusted R^2s become large (ranging from 0.84 to 0.95), the DOL factor is a level factor, and CAR is a slope factor with loadings that perfectly align cross-sectionally with interest rate differentials, consistent with the findings in Lustig et al. (2011). However, $GHML$ loadings continue to be small and to not have a clear pattern, suggesting that interest rate-sorted portfolios do not exhibit meaningful variation in $GHML$ exposure and that interest rates and $GHML$ loadings are cross-sectionally unrelated.

Next, we turn to dollar beta-sorted portfolios. As seen in Panel B, when we consider $GHML$ as the only pricing factor, the portfolio factor loadings are non-significant and the regression adjusted R^2s are very small across all five portfolios. When we also include the DOL and CAR factors, regression R^2s increase substantially, loadings on the CAR factor are small, but exhibit no pattern, and the DOL is a slope factor, as expected. In particular, the portfolio loadings on the DOL factor are monotonically increasing in the portfolios' conditional dollar beta, consistent with the findings in Verdelhan (2018). However, the $GHML$ loadings of dollar beta-sorted portfolios are all statistically insignificant, suggesting the absence of a statistically non-zero spread in geopolitical risk exposure across portfolios.

In sum, the standard portfolio sorts considered in the international asset pricing literature are not conducive to uncovering differences in exposure to geopolitical risk, underscoring the importance of our novel portfolio sort.

2.5 Price of risk estimation

Having established the importance of exposure to the $GHML$, DOL, and CAR factors for currency returns, we now formally calculate the unconditional price of those risk factors. As

standard in the international asset pricing literature, for this exercise we consider currency excess returns in levels (rather than logs), so that we don't have to assume that the stochastic discount factor (SDF) and currency returns are jointly log-normal. The Euler equation that the excess return of currency i (in levels), Rx^i, has to satisfy in order to preclude arbitrage opportunities is

$$E_t\left[M_{t+1}Rx^i_{t+1}\right] = E_t\left[(1 - b(F_{t+1} - \mu_F))Rx^i_{t+1}\right] = 0. \tag{5}$$

where the SDF M is a linear function of factors F, b are SDF factor loadings, and μ_F are factor means. This is a linear factor model that implies that unconditional risk premia are linearly associated with unconditional factor loadings:

$$E\left[Rx^i\right] = \lambda'\beta^i, \tag{6}$$

where $\lambda = E[(F_t - \mu_F)(F_t - \mu_F)']b$ is the vector of the factor prices and β^i is the vector of the factor loadings of Rx^i. We estimate factor prices and factor loadings using the generalized method of moments (GMM) estimation method of Hansen (1982). For the GMM estimation, we use the identity matrix as the weighting matrix, so that all test portfolios are treated equally in the estimation.

We consider four estimation exercises, which differ on the set of currency portfolios used as test assets. For our first exercise, we consider only the 5 geopolitical exposure currency portfolios. Next, we use both the 5 geopolitical exposure portfolios and 5 interest rate-sorted portfolios, for a total of 10 test assets. Our third test also includes 10 test assets: 5 geopolitical exposure portfolios and 5 dollar beta-sorted portfolios. Finally, our benchmark estimation includes 15 test assets: 5 geopolitical exposure portfolios, 5 interest rate-sorted portfolios, and 5 dollar beta-sorted portfolios.

Our estimation output is presented in Table 7. Each of the four panels corresponds to a different estimation exercise. In each panel, we report the estimated values of SDF factor loadings b and prices of risk λ, the cross-sectional adjusted R^2, the square root of the mean

squared pricing errors (RMSE), and the p-value of the χ^2 test statistic under the null hypothesis that all cross-sectional pricing errors are zero. In parentheses, we report standard errors for the SDF factor loadings b and the prices of risk λ. We consider three specifications: one with DOL and CAR as pricing factors, one with DOL and $GHML$, and one with all three factors.

Panel A of Table 7 reports our findings when the test assets are the geopolitical exposure portfolios. When only DOL and CAR are included as pricing factors, the CAR factor has a positive and statistically significant price and SDF loading. In particular, the monthly price of the CAR factor is 0.71% (8.51% annualized), in line with its unconditional annualized mean of 8.46% (in levels), and its SDF loading is positive and significant at the 10% level, suggesting that it has non-trivial return pricing ability. On the other hand, the DOL factor is neither priced nor has pricing ability, with both its price and its SDF loading being statistically indistinguishable from zero. When we consider only the two standard currency factors, asset pricing errors are large and the cross-sectional R^2 is only 25%, underscoring the inability of the two factors to adequately address our novel currency return cross-section. When we replace CAR with our $GHML$ factor, the $GHML$ factor has a positive and significant SDF loading and a monthly price of 0.31% (3.70% annualized), very close to its unconditional annualized average of 3.58% (in levels). Crucially, the cross-sectional R^2 rises to 93%, suggesting that the two factors combined can explain almost all of the cross-sectional variation in the excess returns of the geopolitical exposure portfolios. Consistent with that, the χ^2 test statistic indicates that the null hypothesis of zero pricing errors cannot be rejected. Finally, when all three factors are included, the cross-sectional R^2 reaches 99%, so the addition of the CAR factor has a relatively small effect on model fit. Furthermore, only the $GHML$ factor is priced or has a statistically significant SDF loading.

As seen in Panel B of Table 7, adding the 5 interest rate-sorted currency portfolios to the set of test assets highlights the importance of the CAR factor for pricing currency returns. That is not surprising: as seen in Panel A of Table 6, interest rate-sorted portfolios mainly differ in their CAR exposure, so explaining any cross-section of currency returns that includes

interest rate-sorted portfolios requires including the CAR factor. When only the DOL and CAR factors are included, the CAR factor has a positive and significant SDF loading and the cross-sectional R^2 of the model is 85%. When we exclude the CAR factor, replacing it with our $GHML$ factor, the cross-sectional R^2 drops to 31% and the null hypothesis of zero pricing errors is firmly rejected. The best-performing specification is the one that includes all three factors: in that case, both the CAR and the $GHML$ factor have positive and significant SDF loadings, indicating that both factors help price the test portfolios, and the cross-sectional R^2 rises to 97%.

Panel C shows the performance of the model when we consider the 5 geopolitical exposure portfolios and the 5 dollar beta-sorted portfolios as test assets. The best-performing specification, with a cross-sectional R^2 of 89%, is the one that includes all three factors. As we see, since the test assets do not include interest rate-sorted portfolios, the importance of CAR is diminished. Only $GHML$ has a positive and significant price and SDF loading, whereas both DOL or CAR are neither priced nor have pricing ability for currency returns.

Finally, Panel D reports the model statistics for the largest set of test assets (15 portfolios). When we include DOL, CAR and $GHML$ as factors, which is the best-performing specification, only the latter two are priced and have a statistically significant SDF loading. The monthly price of CAR is 0.70% (8.41% annualized) and the monthly price of $GHML$ is 0.33% (3.90% annualized), with both prices being very close to the corresponding unconditional factor means. Including all three factors helps price assets well: the cross-sectional R^2 is 96% and the null hypothesis that all pricing errors are zero cannot be rejected. Figure 2 shows the pricing errors when all three factors are included: the x-axis measures the average realized excess return of each portfolio, whereas the y-axis the model-predicted average excess return, so pricing errors are measured by the deviation from the 45°line. Given the very high cross-sectional R^2, it is not surprising that the currency portfolios' realized and model-implied average excess returns line up almost perfectly.

2.6 Developed and emerging countries

Do developed country currencies differ from emerging country currencies in geopolitical risk exposure? A reasonable conjecture is that, on average, the currencies of emerging countries should be more affected by global geopolitical shocks then those of developed countries, as the former tend to have less resilient capital markets, weaker institutions, and less diversified economies than the latter. To explore that issue, we focus on two currency portfolios: an equally-weighted portfolio of all developed country currencies (denoted by DEV) and an equally-weighted portfolio of all emerging country currencies (EMG). Our findings are reported in Table 8.

Panel A documents the summary statistics of the excess returns of the DEV and EMG portfolios and of their difference EMG - DEV, i.e., of the currency strategy that invests in EMG and shorts DEV. A US investor holding an equally-weighted portfolio of developed country currencies experiences an average monthly excess return of -0.29%, in annualized terms. Although developed country currencies have a slight interest rate differential of 0.25% (in annual terms) over the USD, those currencies tend to depreciate by 0.54% against the USD, bringing the overall portfolio return to negative territory. On the other hand, a US investor that invests in an equally-weighted portfolio of emerging country currencies earns an average annualized return of 1.42%, as the large interest rate difference of emerging country currencies over the USD (5.14%) is only partially offset by their average depreciation (3.72%). As a result, the EMG-DEV strategy yields an annualized monthly excess return of 1.70%, as both its legs are profitable on average.

To explore whether the return spread between the EMG and the DEV portfolios arises from differences in geopolitical risk exposure, we calculate their factor loadings and present our findings in Panel B of Table 8. As we see in the first column, investing in developed county currencies entails global geopolitical risk hedging: the $GHML$ loading of the DEV portfolio is negative (-0.04) and significant at the 1% level. Furthermore, developed country currencies are associated with higher-than-average DOL risk (the DOL loading is 1.14, higher than

the global average of 1) and a hedging position on CAR risk (the CAR loading is -0.22, and statistically significant). In contrast, emerging country currencies expose US investors to geopolitical risk: the $GHML$ loading of the EMG portfolio is positive (0.07) and significant at the 5% level. In addition, the EMG portfolio is less exposed than average to DOL risk (DOL loading of 0.78) and is positively and significantly exposed to CAR risk (CAR loading of 0.13). It follows that EMG - DEV, the strategy that invests in emerging country currencies and shorts developed country currencies, has positive exposure to geopolitical risk ($GHML$ loading of 0.12) and CAR risk (CAR loading of 0.36) and negative exposure to DOL risk (DOL loading of -0.37). In other words, part of the 1.70% return spread between emerging and developed country currencies can be attributed to the higher geopolitical risk exposure of the former, with another part of the spread contributed by differences is CAR risk, and a partial offsetting effect generated by differences in DOL risk. Overall, we find that the average emerging country currency is more geopolitically risky than the average developed country currency.

However, it is unlikely that the entire cross-country heterogeneity in $GHML$ loadings, documented in Table 3, arises solely from differences between those two sets of currencies. Rather, it is reasonable to assume that some of that heterogeneity is due to differences in geopolitical risk exposure within each set of countries. After all, developed countries differ from each other in many ways that would affect the exposure of their currency to geopolitical shocks, and the same is true for emerging countries. To explore how much developed country currencies differ from each other in terms of geopolitical risk exposure, we sort those currencies into 4 portfolios on θ^{GPT}, the 36-month rolling GPT forecast coefficient of their excess returns, and report their factor loadings in Panel A of Table 9. We also report the factor loadings of the strategy the invests in Portfolio 4 and shorts Portfolio 1 and, thus, quantifies the geopolitical risk exposure heterogeneity within the set of developed country currencies. When we only include the $GHML$ factor in our regressions, portfolio loadings are monotonically increasing in θ^{GPT}, consistent with our findings for the cross-section of all currencies. Developed country currencies exhibit substantial heterogeneity in their exposure

to geopolitical shocks, with some of them hedging geopolitical risk and some of them being positively exposed to it. In particular, $GHML$ loadings range from -0.37 (Portfolio 1) to 0.12 (Portfolio 4), generating a $GHML$ loading spread of 0.49, statistically significant at the 1% level. When we also include the DOL and CAR factors as regressors, our conclusions not materially change: $GHML$ loadings continue to be monotonically increasing and to exhibit a statistically significant spread of 0.49. Developed-country portfolios exhibit two interesting features as regards their DOL loadings. First, those loadings do not differ much across portfolios, indicating that DOL is a level factor across developed country currencies. Second, the point estimates of all four of them are above 1, suggesting that the above-average DOL exposure of the DEV portfolio is not driven by a handful of high-DOL countries, but, rather, is a pervasive attribute of developed country currencies. Finally, we find that all four developed country portfolios have negative and statistically significant CAR loadings. Hence, developed country currencies hedge CAR risk, regardless of their exposure to geopolitical risk, leading to the conclusion that the negative CAR loading of the DEV portfolio reflects a consistent feature of developed countries, rather than an artifact of averaging.

We, then, repeat the exercise for emerging countries and report our findings in Panel B of Table 9. We find that sorting emerging country currencies into portfolios on the 36-month rolling GPT forecast coefficient of their excess returns generates a monotonic pattern in $GHML$ loadings, regardless on whether we control for exposure to the DOL and CAR factors or not. The $GHML$ loading spread across portfolios is quite large: 0.86 when we consider the $GHML$ factor in isolation and 0.85 when we add the other two factors. That spread arises due to the existence of both hedging currencies and risky currencies in the set of emerging country currencies: the $GHML$ loading of Portfolio 1 is negative and significant, whereas the $GHML$ loading of Portfolio 4 is positive and significant, both when we control for DOL and CAR exposure and when we do not. Notably, emerging countries exhibit much higher heterogeneity in geopolitical risk exposure compared to developed countries: it is worth recalling that the $GHML$ loading spread across developed countries is only 0.49, about half the value of the corresponding spread for emerging countries. Hence, not only

are emerging currencies more geopolitically risky on average than developed currencies, but they also feature much larger variation in their risk exposure. Finally, emerging currency portfolios feature lower-than-1 DOL loadings and positive (and in some, but not all, cases significant) CAR loadings, in line with the EMG portfolio properties.

It is worth noting that, for the factor regressions presented in Table 9, we employ our benchmark factors ($GHML$, DOL, and CAR), constructed using the currencies of all the countries in our sample, developed and emerging. In Internet Appendix B, we calculate portfolio loadings on factors constructed using only the set of currencies under focus (i.e., we use developed currency factors when we focus on developed currency portfolios, and emerging currency factors when we consider emerging currency portfolios), and show that our findings do not materially change.

2.7 Bond returns and the persistence of geopolitical shocks

Our analysis so far has been focused on the geopolitical risk exposure of currency excess returns, i.e., of excess returns that a US investor realizes when investing in short-term foreign currency riskless assets and shorting USD riskless assets (regardless of whether those returns are achieved by trading such short-term assets directly or by entering FX forward contracts). We now turn to exploring the exposure of longer-term foreign assets on geopolitical risk and, in particular, we consider the geopolitical risk exposure of long-term riskless zero-coupon bonds. Focusing on long-maturity bonds yields two important benefits. First, it substantially broadens our analysis by incorporating an asset class of great interest to global investors. Second, as discussed in Lustig et al. (2019), considering the short-term returns of long-maturity zero-coupon bonds allows us to draw important conclusions about the persistence of priced shocks, under certain assumptions.

Consider the k-period maturity riskless zero-coupon bond of currency i, with its face value normalized to one unit of currency i. The price of that bond at the end of period t, expressed in units of currency i, is denoted by $P_t^{(k),i}$. It follows that the one-period log return of that

bond, in terms of currency i units, is

$$r_{t+1}^{(k),i} = \log\left[\frac{P_{t+1}^{(k-1),i}}{P_t^{(k),i}}\right]. \tag{7}$$

Hence, the local currency one-period log excess return, which compensates the foreign investor for exposure to local interest rate risk, is given by

$$rx_{t+1}^{(k),i} = r_{t+1}^{(k),i} - r_t^i, \tag{8}$$

where r_t is the one-period log riskless rate of currency i. From the perspective of a US investor, however, buying the k-period maturity zero-coupon bond of currency i, selling it after one period, and converting the payoff to US dollars entails being exposed to both (foreign) interest rate risk and currency risk. In particular, the one-period USD log excess return of that bond can be decomposed into a bond local currency log excess return and a currency log excess return, as follows:

$$rx_{t+1}^{(k),i,\$} = r_{t+1}^{(k),i} + \Delta s_{t+1}^i - r_t = \left(r_{t+1}^{(k),i} - r_t^i\right) + \left(\Delta s_{t+1}^i + r_t^i - r_t\right) = rx_{t+1}^{(k),i} + rx_{t+1}^{FX}, \tag{9}$$

where r_t^i is the one-period log USD riskless rate. It follows that the USD log return difference between investing in foreign currency zero-coupon bonds and USD zero-coupon bonds of the same maturity for one period is given by

$$rx_{t+1}^{(k),i,\$} - rx_{t+1}^{(k)} = (rx_{t+1}^{(k),i} - rx_{t+1}^{(k)}) + rx_{t+1}^{FX}, \tag{10}$$

where $rx_{t+1}^{(k)} = r_{t+1}^{(k)} - r_t$ is the log excess return of k-period maturity zero-coupon USD bonds. As seen in the expression above, the bond USD log return difference, which is the one-period log return that a US investor earns by investing in k-maturity foreign currency bonds and shorting k-maturity USD bonds, can be decomposed into two parts. The first component is the local currency bond log return difference, which reflects differences in compensation for exposure to interest rate risk across the two countries. The second component is the FX

excess return, which compensates investors for exposure to currency fluctuations. In other words, the first component reflects the one-period return of a US investor who invests in foreign currency bonds and shorts USD bonds, but fully hedges currency risk. On the other hand, the second component reflects the return of the same investor when fully hedging interest rate risk (both domestic and foreign), which is equivalent to trading one-period bonds.

For our analysis, we proceed as follows. As before, for each currency i, we run the family of predictability regressions described by Equation 1 and sort currencies into portfolios on the currency excess return forecast coefficient $\theta^{i,GPT}$. However, instead of calculating short-term bond return differences, as we did before, we now calculate long-term bond return differences, as in Equation 10. In particular, we consider strategies that trade 10-year zero-coupon bonds, buying them at the end of each month, and liquidating the position at the end of the following month. We calculate zero coupon bond returns using zero coupon sovereign bond yield curve data from Bloomberg – the details are provided in Internet Appendix A.

Our findings are presented in Panel A of Table 10. We find that the one-month return that a US investor earns by going long a foreign 10-year bond and shorting the domestic 10-year bond varies substantially across countries, depending on the geopolitical exposure of their currency. In particular, investing in the bonds of low-exposure currencies (Portfolio 1) and shorting domestic bonds is unprofitable for a US investor, as it earns an average one-month return of -1.25%, in annualized terms. When the US investor invests in the bonds of countries with higher-exposure currencies, the return differential improves monotonically with geopolitical exposure, reaching 2.33% for the highest-exposure currencies. As a result, the return difference between Portfolio 5 and Portfolio 1, which reflects the performance of a USD-neutral strategy that invests in the bonds of countries with the highest geopolitical currency exposure and shorts the bonds of countries with the lowest exposure, is 3.58%. The annualized return standard deviation of that strategy is 11.30%, yielding a Sharpe ratio of 0.32, roughly equal to the Sharpe ratio of the strategy implemented with short-term bonds (as seen in Panel A of Table 1).

Panel B of Table 10 presents the factor loadings of the different long-short bond portfolios. Of particular interest is the USD-neutral "geopolitical trade" bond strategy (Portfolio 5 - Portfolio 1): its $GHML$ loading is 0.72, significant at the 1% level, which largely accounts for its positive excess return. Both the long and the short leg of that strategy contribute to its positive geopolitical risk exposure. In particular, investing in the bonds of low-exposure currencies and shorting USD bonds (Portfolio 1) hedges geopolitical risk ($GHML$ loading of -0.56), whereas investing in the bonds of high-exposure currencies and shorting USD bonds (Portfolio 5) exposes investors to geopolitical risk ($GHML$ loading of 0.17), so both shorting Portfolio 1 and investing in Portfolio 5 entail positive $GHML$ betas.

It is important to note that the USD return difference between the bonds of high- and low-exposure currencies can be entirely attributed to the currency excess return component: the average FX excess return of the geopolitical trade is 3.85%, whereas the local currency return difference is -0.28%. The magnitude of the average FX return of the geopolitical trade is consistent with the magnitude documented in Table 1, although two calculations use different data sources (and somewhat different sample countries and periods), confirming the robustness of our prior results. Notably, the negligible local currency bond return difference suggests that compensation for interest rate risk is roughly equalized across geopolitical exposure bond portfolios. Indeed, local currency return differences across the 5 portfolios range from -0.21% to 0.47%: foreign term premia are almost equal with US term premia (and, therefore, among themselves) across portfolios, suggesting that country differences in geopolitical currency exposure are not associated with differences in term premia across countries.

In Table 11, we separately consider the risk properties of the two components of bond USD return differences: Panel A focuses on bond local currency return differences, whereas Panel B considers currency excess returns. We find that the currency excess return component accounts for the bulk of the geopolitical risk exposure, which is consistent with the almost zero return of the currency-hedged strategy. In particular, across portfolios, the $GHML$ loading of the currency excess return component ranges from -0.37 (Portfolio 1) to 0.21 (Portfolio 5),

tracking the monotonic pattern of $GHML$ loadings of bond USD return differences, shown in Panel B of Table 10. As a result, the $GHML$ loading of the FX return component of the USD-neutral geopolitical trade is -0.59, corresponding to more than 80% of the geopolitical risk loading of that strategy. On the other hand, the currency-hedged geopolitical trade strategy is barely exposed to geopolitical risk, with a $GHML$ beta of only 0.14.

In short, as regards both average excess returns and geopolitical risk exposure, it makes little difference whether an investor implements the geopolitical trade with long-term or short-term bonds, as both the risk exposure and the risk compensation are mostly due to the FX excess return component. The corollary is obvious: executing the geopolitical trade with long-maturity bonds, but hedging the FX component, produces almost zero geopolitical risk exposure and negligible excess returns.

Crucially, the properties of the geopolitical trade differ markedly from the properties of bond strategies considered by Lustig et al. (2019). In particular, Lustig et al. (2019) consider two strategies: the first strategy entails investing in the bonds of high-interest rate countries and shorting the bonds of low-interest rate countries (which, for short-maturity bonds, is the well-known "currency carry trade"), whereas the second strategy invests in the bonds of countries with a flat yield curve (low yield curve slope) and shorts the bonds of countries with a steep yield curve (high yield curve slope). They find that, for both those strategies, the local currency return difference component is large and negative for bonds of long maturities, offsetting the positive currency excess return component and producing roughly zero USD returns at the long end of the term structure. As Lustig et al. (2019) put it, the term structure of the premia of those strategies is downward-sloping: positive for short-maturity bonds and zero for long-maturity bonds. In contrast, we find that sorting currencies into portfolios on their geopolitical exposure (i.e., the forecast coefficient of their excess returns on the GPT index) yields no such offsetting effect for the corresponding bond strategy – in other words, the term structure of premia is flat.

Apart from being of interest to global investors, the slope of the term structure of risk premia can yield important economic insights, as it is informative about the temporal properties

of priced risk. As Lustig et al. (2019) discuss, under the assumptions that international financial markets are complete and that long-maturity bonds are sufficiently good proxies of infinite maturity bonds, the short end of the term structure (i.e., the FX excess return) of long-short bond strategies reflects differences in countries' exposure to priced shocks, whereas the long end of the term structure (i.e., the overall USD return) reflects differences in countries' exposure only to permanent priced shocks. This is because, when implementing those strategies using long-term bonds, exposure to priced transitory shocks becomes fully hedged, so investors are only compensated for being exposed to permanent shocks, i.e., shocks that have a permanent impact on countries' pricing kernels.

It follows that the flatness of the term structure of geopolitical trade premia suggests that geopolitical shocks are permanent shocks, i.e., they have permanent, non-reversible, effects on countries' pricing kernels. As discussed in Alvarez and Jermann (2005), permanent shocks do not affect the local currency prices of long-maturity bonds, i.e., long-term bonds are essentially riskless as regards permanent shocks in local currency terms and, hence, become essentially identical to short-term bonds in that respect. Hence, the reason that it is almost immaterial whether an investor implements the geopolitical trade with long-term or short-term bonds is that, in the absence of a transitory component in geopolitical shocks, short-term bonds and long-term bonds of the same currency are essentially identical as regards the impact of geopolitical shocks on their USD prices and, hence, they have almost the same geopolitical risk loadings.

Our empirical findings have important theoretical implications: they suggest that any model that includes geopolitical shocks (either directly or arising as a combination of other fundamental shocks) needs to ensure that those shocks are permanent in nature, i.e., that they entail a non-reversible impact on countries' pricing kernels. In economic terms, our findings indicate that geopolitical shocks are of first-order importance: to the extent that pricing kernels are connected to the marginal utility of wealth of a representative agent, as standard macro-finance models posit, the persistence of geopolitical shocks implies that adverse geopolitical developments do not entail just short-term welfare losses, but, rather, they have

substantial long-term welfare consequences for countries. A direct corollary of that insight is that eliminating geopolitical risk entails significant welfare gains across time, so policies or institutional arrangements that mitigate geopolitical risk have long-term welfare benefits.

2.8 No-arbitrage model

We rationalize our empirical findings with a simple no-arbitrage model, discussed in detail in Internet Appendix C. Our model features a global economy with one domestic country and multiple foreign countries, financial market completeness, and stochastic discount factor (SDFs) heterogeneity across countries, as in Lustig et al. (2011).

In the model, countries differ in their SDF exposure to a global geopolitical shock, with the exposure of each country having both a fixed and a time-varying component. Due to the latter, the cross-sectional distribution of exposure to global geopolitical risk exhibits time variation. The price of geopolitical risk is regulated by a global state variable that reflects the level of global geopolitical tension and can be mapped empirically to the GPT index. Crucially, the price of geopolitical risk is countercyclical, as adverse realizations of the global geopolitical shock increase the level of the global state variable.

Our key empirical findings are consistent with the model. In particular, we show that sorting currencies into portfolios on the forecast coefficient of their excess returns on the global state variable is equivalent to sorting on their exposure to global geopolitical risk, so a strategy that invests in high-coefficient currencies and short low-coefficient currencies, which we denote by $GHML$, is a mimicking portfolio of the global geopolitical shock. Furthermore, we show that currency portfolios sorted on the conditional beta of their excess returns with respect to changes in the level of the global state variable exhibit heterogeneous exposure to global geopolitical risk, as the betas are cross-sectionally negatively associated with $GHML$ loadings, consistent with our empirical findings.

2.9 Robustness exercises

In Internet Appendix B, we present a number of robustness checks and additional results. First, we show that sorting currencies into portfolios using the GPT forecast coefficient of exchange rate changes, rather than excess returns, generates findings very similar to our benchmark results. Second, we demonstrate that our findings are robust to sorting currencies into portfolios on the exposure of their excess returns to alternative measures of geopolitical turmoil and, in particular, to the Caldara and Iacoviello (2022) GPA and GPR indices – the former reflects geopolitical acts, whereas the latter reflects both geopolitical acts and geopolitical threats. Third, we demonstrate that sorting currencies into portfolios on their rolling $GHML$ loading generates a substantial return spread that reflects positive exposure to the $GHML$ factor, consistent with our factor pricing results. We also show that our main findings continue to hold when we consider longer-horizon (and, in particular, 3-month or 12-month) excess returns.

Finally, we explore whether sorting currencies into portfolios on the unconditional exposure of their expected excess returns to geopolitical turmoil (i.e., on the unconditional forecast coefficient of excess returns on GPT levels) generates a meaningful spread in $GHML$ loadings. We find that sorting on unconditional geopolitical exposure generates a negligible return spread and an economically small spread in $GHML$ loadings, indicating that geopolitical exposure is a time-varying trait, rather than a fixed attribute, of currencies.

3 Geopolitical turmoil and capital flows

So far, we have considered how geopolitical turmoil affects the pricing of currency risk. Now, we turn to exploring whether geopolitical turmoil affects international capital flows and, if so, whether capital flow exposure to geopolitical turmoil and currency return exposure to geopolitical risk are connected.

For our exercise, we collect monthly data on international portfolio and foreign direct invest-

ment (FDI) flows for 19 countries from the OECD Monthly Capital Flow Dataset, described in De Crescenzio and Lepers (2025). For each country, capital inflows (outflows) are defined as the sum of portfolio and FDI inflows (outflows), and net capital flows equal the difference between capital inflows and outflows. Finally, the net capital flow ratio of country i at month t, ncf_t^i, is defined as the ratio of net capital flows over the country's GDP: $ncf_t^i = NCF_t^i/GDP_t^i$. We provide more details on our international capital flow data in Internet Appendix A.

We sort currencies into portfolios on the geopolitical exposure of their expected net capital flow ratio to the level of global geopolitical tension. As a first step, we run rolling 36-month forecast regressions of the type

$$ncf_{t+1}^i = \alpha^i + \phi^{i,GPT} GPT_t + \eta_{t+1}^i. \tag{11}$$

A positive (negative) forecast coefficient indicates that the expected net international capital flow ratio of country i is increasing (decreasing) in the level of global geopolitical turmoil. In other words, countries with a positive forecast coefficient have higher-then-average international capital flows during periods of elevated geopolitical threats and, thus, can be considered geopolitical "safe haven" countries. On the other hand, countries with a negative forecast coefficient experience less-than-average net capital flows in times of turmoil and, hence, are geopolitical "danger zones".

At the end of each month, we sort currencies into three portfolios on their rolling ϕ^{GPT}: Portfolio 1 includes the currencies with the lowest 36-month rolling forecast coefficients (i.e., danger zone currencies), whereas Portfolio 3 contains the highest-coefficient currencies (i.e., safe haven currencies). We also consider the US dollar-neutral SMD (Safe Minus Danger) currency strategy, which invests in Portfolio 3 and shorts Portfolio 1. Our sample period begins in April 2004 and ends in December 2024. The summary statistics of the portfolio returns are reported in Panel A of Table 12. Notably, the currencies of safe haven countries (Portfolio 3) have much lower excess returns than those of danger zones (Portfolio 1), so

the excess return of the SMD strategy is -2.27% in annualized terms, with an annualized Sharpe ratio of -0.29.

Are the currencies of safe haven countries less exposed to geopolitical risk than the currencies of danger zones? If so, we expect to find a negative cross-sectional relationship between ϕ^{GPT} and $GHML$ loadings: safe haven currencies should have low loadings on the $GHML$ factor, whereas danger zone currencies should exhibit high $GHML$ loadings. Panel B of Table 12 reports the factor betas of the three ϕ^{GPT}-sorted portfolios, as well as of the SMD strategy.

Consistent with our conjecture, $GHML$ loadings decline monotonically from Portfolio 1 (0.14) to Portfolio 3 (-0.13), generating a loading spread of -0.27, significant at the 1% level: safe haven currencies hedge geopolitical risk, whereas danger zone currencies are positively exposed to geopolitical risk. On other hand, the SMD strategy has a negligible loading on the CAR factor, suggesting that there is no meaningful difference in exposure to carry risk between safe haven and danger zone currencies. We also find that the SMD strategy has a negative loading on the DOL factor, suggesting that safe haven currencies comove with the US dollar (which is the short leg of the DOL factor) more than danger zone currencies. However, the DOL loading of the SMD strategy is economically small and marginally statistically significant.

We conclude that sorting currencies into portfolios on the geopolitical exposure of net capital flows generates heterogeneity mostly regarding the geopolitical riskiness of their returns, suggesting a tight link between capital flow sensitivity to geopolitical turmoil and geopolitical currency risk: countries that attract capital flows in times of geopolitical turmoil have currencies that hedge geopolitical risk, whereas countries that experience capital flight in those times have geopolitically risky currencies.

Which type of international capital flows drives that link? In other words, are the geopolitical risk properties of currencies associated with the geopolitical sensitivity of countries' portfolio flows or FDI flows? To answer that question, we consider two additional portfolio sorts, one based on the geopolitical exposure of net FDI flows and the other on the geopolitical

exposure of net portfolio flows. In particular, we start by calculating two new measures for each country: the net FDI flow ratio $nfdi$ (defined as net FDI flows over GDP) and the net portfolio flow ratio $nptf$ (defined as net portfolio flows over GDP). Then, we run 36-month rolling forecast regressions, as in Equation 11, but replacing the dependent variable by either $nfdi$ or $nptf$, and sort currencies into portfolios on the GPT forecast coefficient.

The factor loadings of those portfolios are presented in Table 13: Panel A refers to portfolios sorted on the geopolitical exposure of FDI flows, whereas Panel B refers to portfolios sorted on the geopolitical exposure of net portfolio flows. As seen in Panel A, sorting on the geopolitical exposure of FDI flows does not generate a statistically significant spread in $GHML$ loadings, suggesting that the geopolitical sensitivity of FDI flows is not connected to the geopolitical risk properties of currencies.

On the other hand, sorting on the geopolitical exposure of net portfolio flows yields a substantial spread in $GHML$ loadings. In particular, as seen in Panel B of Table 13, the currencies of low-exposure countries (Portfolio 1) are geopolitically risky, with a $GHML$ loading of 0.13 (significant at the 1% level), whereas the currencies of high-exposure countries (Portfolio 3) are geopolitical hedges, having a $GHML$ loading of -0.11 (also significant at the 1% level). It follows that a strategy that invests in the currencies of countries that have higher-than-average net portfolio flows in times of geopolitical turmoil and shorts the currencies of countries that experience lower-than-average net portfolio flows in those times has a negative and significant $GHML$ coefficient (-0.24), indicating that it acts as a geopolitical risk hedge, tending to outperform in times of elevated geopolitical turbulence.

For robustness, we repeat our analysis using quarterly data from the IMF Balance of Payments dataset. Using quarterly data allows us to expand the set of countries we include in our analysis and increase the sample period, at the cost of having fewer observations. We find that our main results continue to hold: the currencies of "safe havens" hedge geopolitical risk, whereas the currencies of "danger zones" are geopolitically risky, with the relationship being driven by portfolio, rather than FDI, flows. Our results are reported and discussed in more detail in Internet Appendix B.

4 Currency portfolios and geopolitical risk

So far, we have identified a new cross-section of currency portfolios that exhibits substantial heterogeneity as regards geopolitical risk exposure. One question worth considering is whether different sets of currency portfolios also exhibit such heterogeneity and, therefore, help us understand the attributes that characterize cross-sectional variation in exposure to global geopolitical risk. To that end, we consider different types of portfolio sorts and explore whether those sorts generate variation in $GHML$ loadings. We find that sorting currencies into portfolios on the forecast coefficient of their excess returns on a war-related discourse measure generates a wide spread in $GHML$ betas, consistent with the hypothesis that $GHML$ is a geopolitical risk factor. On the other hand, currency portfolio sorts on the return forecast coefficients of policy uncertainty measures (and, in particular, text-based economic and trade policy uncertainty measures) do not lead to substantial variation in $GHML$ loadings, suggesting that exposure to uncertainty differs from exposure to geopolitical risk. Finally, we show that sorting currencies into portfolios on country-specific GPR measures does not generate a spread in $GHML$ loadings, suggesting that currency exposure to global geopolitical risk cannot be proxied by measures that reflect media coverage.

4.1 Sorting on exposure to the war discourse measure

Since the $GHML$ factor is a geopolitical risk factor, any portfolio sort that generates cross-sectional heterogeneity to geopolitical risk exposure should generate large variation in $GHML$ loadings. To test that hypothesis, we sort currencies into portfolios on the forecast coefficient of their return on the Hirshleifer et al. (2024) war discourse measure (War). War is a monthly text-based measure, having higher values during periods in which the New York Times coverage focuses more on war-related news stories. In more detail, War is the latent weight of war-related media discourse, extracted from New York Times articles using a semi-supervised topic model. Importantly, as documented in Hirshleifer et al. (2024), War has substantial predictive power for asset returns: it positively predicts stock market returns

and negatively predicts bond returns.

As a first step, for each currency i, we consider 36-month rolling excess return forecasting regressions of the type

$$rx^i_{t+1} = \alpha^i + \theta^{i,War} War_t + \eta^i_{t+1}. \tag{12}$$

The θ^{War} coefficient measures the sensitivity of expected excess returns to the intensity of the war discourse in the media: currencies with high (low) β^{War} are expected to have higher-than-average (lower-than-average) returns when the war discourse measure is high. Then, each month t, we sort currencies into five portfolios on their θ^{War}_t forecast coefficient. Given that war risk is a significant element of geopolitical risk, our conjecture is that exposure to geopolitical risk is increasing in θ^{War}, with high-θ^{War} currencies having a higher $GHML$ loading than low-θ^{War} currencies.

To test our conjecture, we regress the excess returns of the θ^{War}-sorted portfolios on the currency risk factors and report their factor loadings in Table 14. The time series for War starts in January 1985 and ends in October 2019, so the excess return sample period is from February 1988 to October 2019. The first six columns present the output of regressions that include only $GHML$ (and a constant) as a regressor for each of the five β^{War}-sorted portfolios and the long-short strategy that invests in the high-θ^{War} currencies (Portfolio 5) and shorts the low-θ^{War} currencies (Portfolio 1). Consistent with our hypothesis, $GHML$ loadings are monotonically increasing in θ^{War} and range from -0.26 (Portfolio 1) to 0.37 (Portfolio 5). When we also include the DOL and CAR factors as regressors (last six columns of Table 14), our results do not change much: $GHML$ loadings continue to exhibit monotonicity and to have a cross-sectional spread of 0.62, suggesting that sorting currencies into portfolios on the war discourse forecast coefficient of their excess returns yields substantial cross-sectional variation in geopolitical risk exposure. On the other hand, sorting on θ^{War} does not generate a substantial spread in either DOL or CAR loadings. In particular, the spread in DOL loadings is both economically small and statistically significant, and the spread in CAR loadings, albeit marginally significant, is not economically large.

In sum, we find that sorting on the exposure of currency expected excess returns on the Hirshleifer et al. (2024) war discourse measure generates a meaningful spread in $GHML$ loadings, but not in either DOL or CAR loadings, in line with our interpretation of $GHML$ as a global geopolitical risk factor.

4.2 Sorting on exposure to uncertainty measures

Since geopolitical turmoil may be associated with uncertainty, it is worth exploring whether measures associated with those two concepts are related in the context of currency returns. To do so, we sort currencies into portfolios based on their return forecast coefficient on uncertainty measures and check whether such sorts generate a spread in $GHML$ loadings. In particular, we consider two U.S. policy uncertainty measures: the Economic Policy Uncertainty (EPU) index of Baker et al. (2016) and the Trade Policy Uncertainty (TPU) index of Caldara et al. (2020). Both measures are text-based and reflect the frequency of occurrence of newspaper articles that include terms associated with U.S. economic and trade policy uncertainty, respectively.

For each of those measures, we consider 36-month rolling return forecast regressions of the type

$$rx^i_{t+1} = \alpha^i + \theta^{i,x} x_t + \eta^i_{t+1}, \tag{13}$$

where $x = \{EPU, TPU\}$, and sort currencies into portfolios based on their rolling forecast coefficient. Table 15 reports our findings: Panels A and B show the factor loadings of currency portfolios sorted on their rolling θ^{EPU} and θ^{TPU}, respectively. In each panel, the first six columns report the regression output when only $GHML$ is included as a factor, whereas the last six columns report the output of regressions that include the DOL, CAR and $GHML$ factors. The excess return sample period is from February 1988 to December 2024.

Overall, we find that return exposure to U.S. economic or trade policy uncertainty is unable to generate meaningful variation in $GHML$ loadings. In particular, sorting on the θ^{EPU}

forecast coefficient yields economically small $GHML$ betas across all five portfolios, with the $GHML$ beta spread between high-θ^{EPU} and low-θ^{EPU} currencies being statistically insignificant. When we sort on θ^{TPU}, we get non-significant $GHML$ loadings across all five portfolios. We conclude that there is no association between expected return exposure to policy uncertainty and geopolitical risk loading in the cross-section of currency returns.

Notably, both measures considered here regard U.S. policy uncertainty. Although the United States is a major economic power and its policy decisions have a significant impact on the global economy, it worth exploring the possibility that, although global geopolitical risk does not appear to be associated with U.S.-based uncertainty, it may be connected with global uncertainty. For that reason, in Internet Appendix B, we consider two global uncertainty measures: the Global Economic Policy Uncertainty Index of Baker et al. (2016), which is a GDP-weighted average of the country-level Economic Policy Uncertainty Index of 18 countries, and the World Uncertainty Index of Ahirt, Bloom and Furceri (2022), which is constructed using frequency counts of the word "uncertainty" (and related variants) in the country reports of the Economist Intelligence Unit for 143 countries. We find that sorting currencies into portfolios on the rolling forecast coefficient of their excess returns on either of those two measures does not generate a meaningful spread in $GHML$ loadings, consistent with our findings for the U.S. uncertainty measures.

4.3 Sorting on country-level GPR measures

In addition to constructing global geopolitical risk indices, Caldara and Iacoviello (2022) also construct country-specific measures of geopolitical risk. Each country-specific GPR index is calculated as the monthly share of newspaper articles that satisfy two conditions: first, they meet the criteria for inclusion in the global GPR index, and, second, they mention the name (or the name of major cities) of the country. Hence, the country-specific GPR indices are measures of the geopolitical risk associated with particular countries. Notably, Caldara and Iacoviello (2022) construct a single country-specific GPR index per country:

their index reflects both acts and threats, and they do not calculate separate country-specific GPT (threats) and GPA (acts) subindices.

To explore whether the Caldara and Iacoviello (2022) country-specific GPR measures are informative about currency exposure to global geopolitical risk (i.e., about the $GHML$ loadings of currency returns), each month we sort currencies into portfolios using countries' (one-month) lagged GPR index and calculate portfolio returns and factor betas. Our findings are presented in Table 16: Portfolio 1 (Portfolio 5) includes the currencies with the lowest (highest) GPR index each month. Panel A, which reports the summary statistics of portfolio excess returns, makes it clear that sorting on country-specific GPR measures does not generate a meaningful return spread: the average excess return of the currencies of high-GPR countries (0.97% in annualized terms) is almost identical to the average excess return of low-GPR currencies (0.96%). Furthermore, as seen in Panel B of Table 16, there is no statistically significant difference in the exposure of high-GPR and low-GPR currencies to global geopolitical risk: the $GHML$ loading of a strategy that invests in high-GPR currencies (Portfolio 5) and shorts low-GPR currencies (Portfolio 1) is statistically indistinguishable from zero, suggesting that country-specific GPR indices do not proxy for $GHML$ loadings.

One possibility worth considering is that the monthly level of a country's GPR measure, which reflects newspaper coverage in a single month, may be a noisy proxy of the country's exposure to geopolitical turmoil. For that reason, we check the robustness of our findings by sorting currencies into portfolios using the 36-month rolling mean of the corresponding country's GPR measure, which averages out random fluctuations in news coverage. As shown in Internet Appendix B, we find that sorting on the rolling mean of country-specific GPR measures yields very similar results to sorting on monthly GPR measures, confirming that the exposure of a country's currency to global geopolitical risk is distinct from the intensity of media coverage of the country's geopolitical developments.

In related work, Liu and Zhang (2024) sort currencies into portfolios on country-specific geopolitical risk measures, document a large return spread between high-measure and low-

measure currencies, and propose a traded geopolitical risk factor constructed by investing in high-measure currencies and shorting low-measure currencies. Although the country-specific measures of Liu and Zhang (2024) are calculated by exactly the same methodology as the country-specific measures of Caldara and Iacoviello (2022), the two types of measures differ on the news dataset employed in the analysis: Caldara and Iacoviello (2022) rely on the articles of ten major English-language newspapers, whereas Liu and Zhang (2024) retrieve news items from the Access World News database, which includes a wider array of news sources, many of them foreign-language. Interestingly, when Liu and Zhang (2024) decompose their country-specific measures into a global, a regional, and an idiosyncratic component, they find that sorting currencies into portfolios on either the regional or the idiocyncratic component generates a return spread, but sorting on the global component does not, concluding that their findings are due to cross-country differences in idiosyncratic and regional geopolitical risk.

In conclusion, the Liu and Zhang (2024) factor reflects local and regional geopolitical shocks, as a result of the fact that their portfolio sort generates substantial heterogeneity in non-global geopolitical risk, but limited variability regarding global geopolitical risk.[4] In contrast, our $GHML$ factor is, by construction, a global factor, reflecting global shocks: it is constructed by sorting currencies into portfolios on the slope coefficient of excess return forecasting regressions on GPT, a global index.

5 Conclusion

We document that $GHML$, a USD-neutral currency strategy that invests in currencies with higher-than-average expected excess returns in times of geopolitical turmoil and shorts currencies that have lower-than-average expected excess returns in those times, is a priced

[4]For the purposes of identifying heterogeneity in exposure to such shocks, the country-specific Liu and Zhang (2024) measures, constructed from a large number of local news sources, are likely better than the country-specific Caldara and Iacoviello (2022) measures, which rely on a small set of international newspapers, which would explain why sorting currencies into portfolios on the former generates a return spread, but sorting on the latter does not.

factor in the cross-section of currency returns. We, further, show that $GHML$ reflects global geopolitical risk, with risky currencies having a positive $GHML$ loadings and geopolitical hedges having a negative $GHML$ loading. When we implement the same strategy using long-maturity bonds, we find that the average return does not change significantly: the "geopolitical trade" delivers similar premia whether implemented with short- or long-term bonds, as its return and risk exposure are almost entirely driven by the currency excess return component, rather than by differences in local currency term premia. The flat term structure of geopolitical premia suggests that geopolitical shocks are persistent priced shocks, affecting countries' pricing kernels in a long-lasting fashion. Finally, we document a negative cross-sectional relationship between the exposure of expected net capital flows to geopolitical turmoil and $GHML$ currency loadings, suggesting that geopolitical turmoil jointly affects international capital flows and the pricing of currency risk.

Although we are able to rationalize our empirical findings with a reduced-form no-arbitrage model, we do not attempt to endogenize the drivers of cross-country heterogeneity in exposure to global geopolitical shocks. This is an important question that we leave to future research. A model that fully addresses that topic would likely need to consider the determinants of (potentially time-varying) economic, financial, and political links across countries and their joint impact on international capital flows and exchange rate determination. More generally, future research that introduces models that embed geopolitical shocks as persistent components of countries' pricing kernels can help economists and policymakers characterize the short- and long-term asset pricing and welfare effects of geopolitical shocks, as well as quantify the welfare gains from policies and institutional arrangements which mitigate geopolitical risk.

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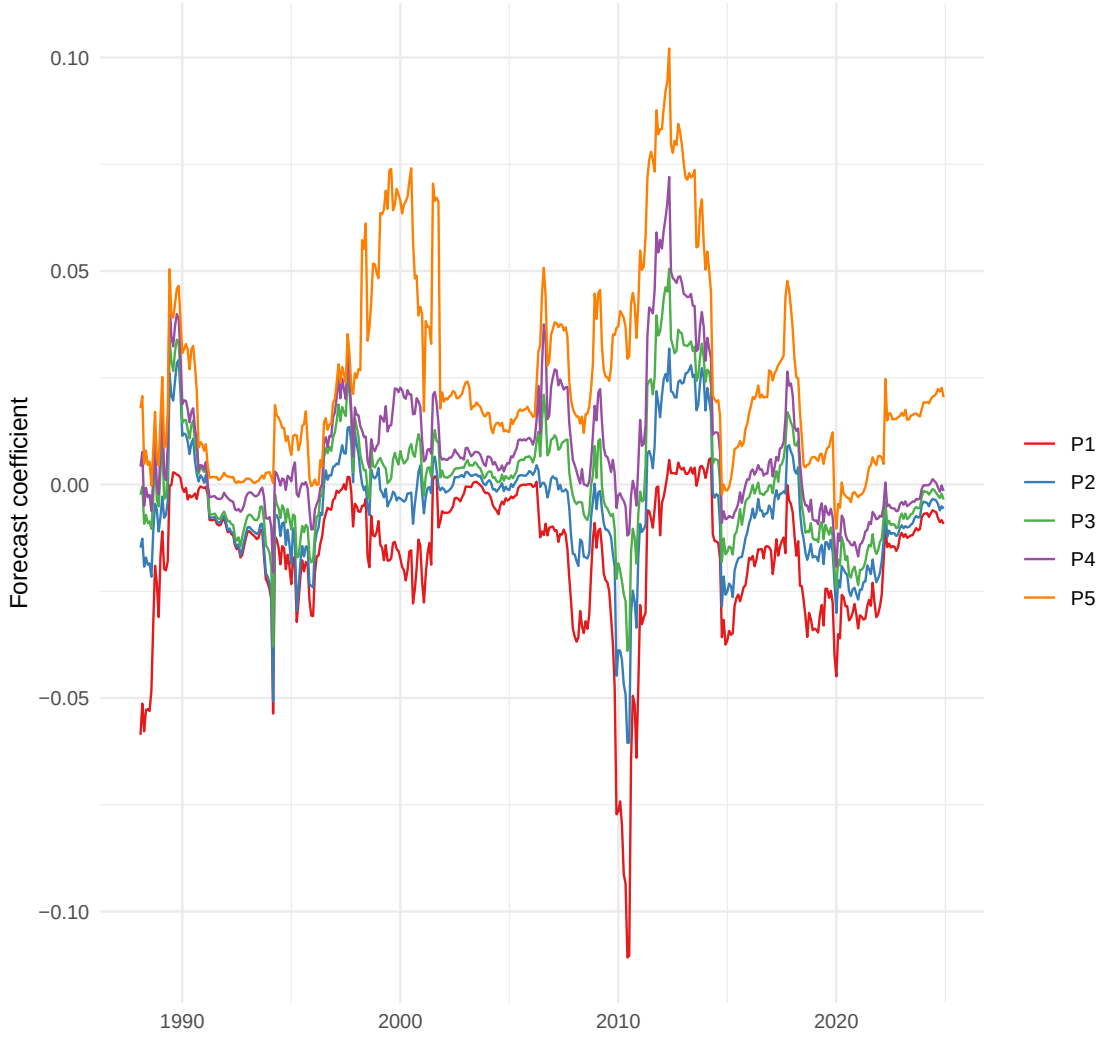
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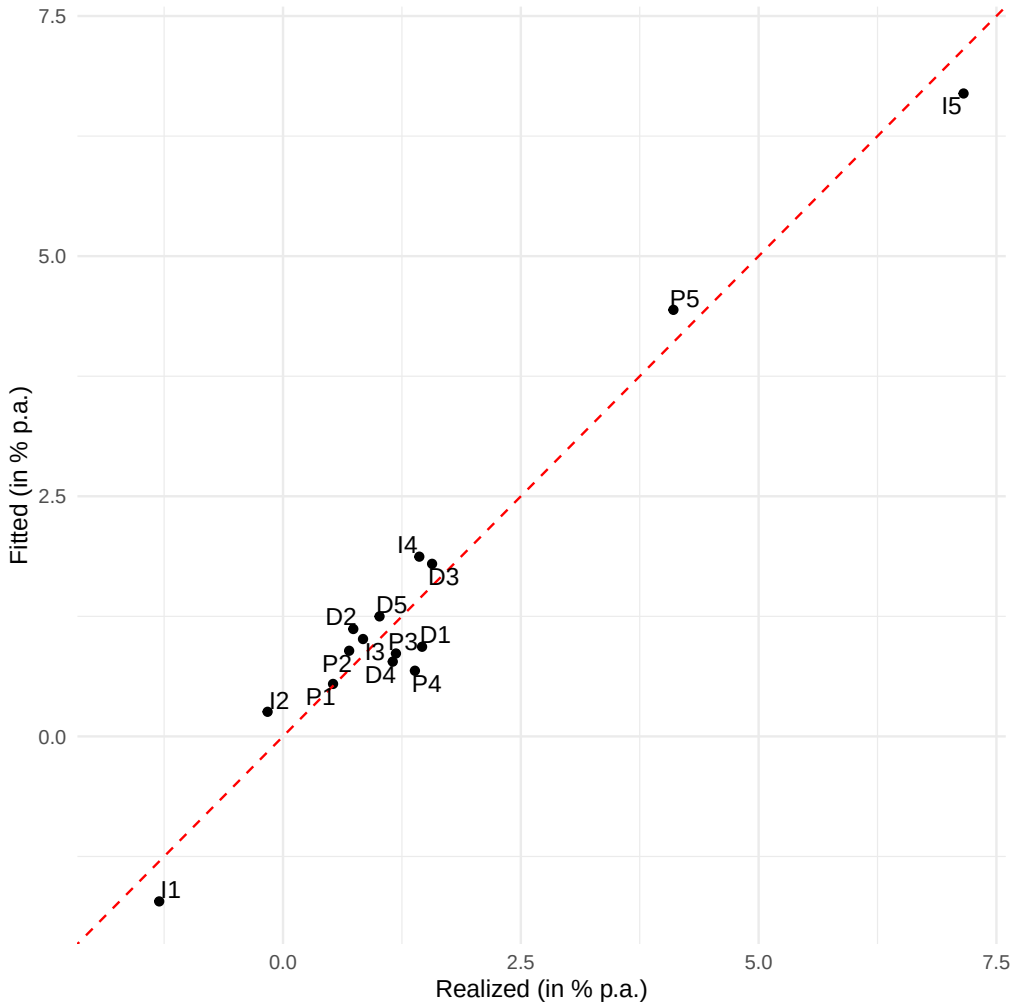
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Fig. 1: Excess return forecast coefficients of geopolitical exposure portfolios



The figure plots the rolling forecast coefficients of the excess returns of geopolitical exposure currency portfolios. Each month, currencies are sorted into portfolios on the slope coefficient in a 36-month rolling forecasting regression of monthly excess returns on a measure of global geopolitical threats. Portfolio 1 (P1) includes the currencies with the lowest forecast coefficient, whereas Portfolio 5 (P5) includes the currencies with the highest forecast coefficient each month. Portfolios are monthly rebalanced and equally-weighted. For each portfolio, the rolling forecast coefficient is the equally-weighted average of the rolling forecast coefficients of the currencies in the portfolio.

Fig. 2: Fitted vs. realized excess returns of currency portfolios



The figure plots average fitted against average realized excess returns of currency portfolios. Excess returns are annualized and expressed in percentage terms. Fitted returns are the average excess returns implied by a three-factor model that includes the geopolitical ($GHML$) factor, the dollar (DOL) factor, and the carry (CAR) factor. Portfolios P1 to P5 denote geopolitical exposure currency portfolios, i.e., portfolios of currencies sorted on the slope coefficient in a 36-month rolling forecasting regression of monthly excess returns on a measure of global geopolitical threats. Portfolio 1 (P1) includes the currencies with the lowest forecast coefficient, whereas Portfolio 5 (P5) includes the currencies with the highest forecast coefficient, each month. Portfolios I1 to I5 denote portfolios of currencies sorted on their log nominal interest rate difference with the United States. Portfolio 1 (I1) includes the currencies with the lowest difference, whereas Portfolio 5 (I5) includes the currencies with the highest difference, each month. Portfolios D1 to D5 denote portfolios of currencies sorted on their dollar beta. Portfolio 1 (D1) includes the currencies with the lowest dollar beta, whereas Portfolio 5 (D5) includes the currencies with the highest dollar beta, each month. Portfolios are monthly rebalanced and equally-weighted.

Table 1: Geopolitical exposure currency portfolios

Panel A: Summary statistics						
	P1	P2	P3	P4	P5	GHML
Mean rx	-0.02	0.05	0.77	0.82	3.26	3.28
Mean Δs	-2.60	-1.74	-1.50	-1.18	-2.39	0.21
Mean IRD	2.58	1.80	2.26	2.00	5.65	3.07
Std deviation	8.53	7.88	8.05	7.29	8.60	8.37
Sharpe ratio	-0.00	0.01	0.10	0.11	0.38	0.39
Skewness	-0.68	-0.59	-0.40	-0.45	-0.42	-0.07
Exc. kurtosis	3.33	2.36	1.14	1.76	1.88	1.08
Panel B: Factor loadings						
	P1	P2	P3	P4	P5	GHML
Constant	-0.10	-0.07	0.03	0.08	0.13	0.23^{**}
	(0.07)	(0.05)	(0.06)	(0.05)	(0.08)	(0.11)
DOL	1.06^{***}	1.02^{***}	1.09^{***}	0.96^{***}	0.93^{***}	-0.13
	(0.07)	(0.06)	(0.03)	(0.05)	(0.07)	(0.13)
CAR	0.01	-0.02	-0.09^{**}	-0.14^{***}	0.10	0.09
	(0.05)	(0.04)	(0.04)	(0.03)	(0.08)	(0.11)
Obs.	443	443	443	443	443	443
Adj. R^2	0.74	0.79	0.83	0.78	0.60	0.02

The table reports summary statistics (Panel A) and factor loadings (Panel B) of the monthly excess returns of geopolitical exposure currency portfolios, i.e., portfolios of currencies sorted on the slope coefficient in a 36-month rolling forecasting regression of monthly currency excess returns on a measure of global geopolitical threats. The sample period is February 1988 to December 2024. Portfolio 1 (P1) includes the currencies with the lowest forecast coefficient, whereas Portfolio 5 (P5) includes the currencies with the highest forecast coefficient each month. Portfolios are monthly rebalanced and equally-weighted. $GHML$ is the long-short strategy that invests in Portfolio 5 and shorts Portfolio 1. Standard errors are reported in parentheses. One, two, and three stars denote statistical significance at the 1%, 5%, and 10% level, respectively.

Table 2: Excess return PCs of geopolitical exposure portfolios

	PC1	PC2	PC3	PC4	PC5
Portfolio 1	0.44	-0.41	-0.58	-0.51	0.20
Portfolio 2	0.46	-0.35	0.00	0.78	0.24
Portfolio 3	0.48	-0.17	0.32	-0.12	-0.79
Portfolio 4	0.46	0.27	0.60	-0.31	0.51
Portfolio 5	0.39	0.78	-0.44	0.16	-0.14
% variance	0.75	0.12	0.06	0.04	0.03
Cum % variance	0.75	0.87	0.93	0.97	1.00

The table reports the principal component coefficients of the log excess returns of geopolitical exposure currency portfolios, i.e., portfolios of currencies sorted on the slope coefficient in a 36-month rolling forecasting regression of monthly currency excess returns on a measure of global geopolitical threats. The sample period is February 1988 to December 2024. Portfolio 1 (P1) includes the currencies with the lowest forecasting coefficient, whereas Portfolio 5 (P5) includes the currencies with the highest forecasting coefficient each month. Portfolios are monthly rebalanced and equally-weighted. The two last rows report the percentage share and the cumulative percentage share of the total variance explained by the corresponding principal component.

Table 3: Factor loadings of geopolitical exposure portfolios

	P1	P2	P3	P4	P5	P1	P2	P3	P4	P5
Constant	0.13	0.07	0.11	0.05	0.13	−0.00	−0.04	0.05	0.04	−0.00
	(0.12)	(0.11)	(0.11)	(0.11)	(0.12)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
GHML	−0.49***	−0.24**	−0.17	0.06	0.51***	−0.42***	−0.16***	−0.09***	0.14***	0.58***
	(0.09)	(0.10)	(0.11)	(0.09)	(0.09)	(0.03)	(0.03)	(0.02)	(0.03)	(0.03)
DOL						1.01***	1.00***	1.08***	0.98***	1.01***
						(0.04)	(0.05)	(0.03)	(0.04)	(0.04)
CAR						0.05*	−0.00	−0.09**	−0.15***	0.05*
						(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Obs.	443	443	443	443	443	443	443	443	443	443
Adj. R^2	0.23	0.06	0.03	0.00	0.24	0.91	0.82	0.84	0.80	0.91

The table reports the factor loadings of the monthly excess returns of geopolitical exposure currency portfolios, i.e., portfolios of currencies sorted on the slope coefficient in a 36-month rolling forecasting regression of monthly currency excess returns on a measure of global geopolitical threats. The sample period is February 1988 to December 2024. Portfolio 1 (P1) includes the currencies with the lowest forecasting coefficient, whereas Portfolio 5 (P5) includes the currencies with the highest forecasting coefficient each month. Portfolios are monthly rebalanced and equally-weighted. The first five columns report the portfolio loadings when the log excess return of each portfolio is regressed on a constant and the geopolitical ($GHML$) factor, whereas the last five columns report the portfolio loadings when log excess return of each portfolio is regressed on a constant, and the geopolitical ($GHML$), dollar (DOL) and carry (CAR) factors. Standard errors are reported in parentheses. One, two, and three stars denote statistical significance at the 1%, 5%, and 10% level, respectively.

Table 4: Portfolios sorted on components of the geopolitical exposure forecast coefficient

Panel A: Portfolios sorted on rolling correlation										
	P1	P2	P3	P4	P5	P1	P2	P3	P4	P5
Constant	0.10	0.11	0.11	0.09	0.11	0.01	0.00	0.03	0.02	−0.01
	(0.10)	(0.12)	(0.12)	(0.13)	(0.10)	(0.05)	(0.06)	(0.05)	(0.06)	(0.05)
GHML	−0.36***	−0.25**	−0.12	0.06	0.34***	−0.29***	−0.17***	−0.04	0.15***	0.40***
	(0.08)	(0.10)	(0.11)	(0.10)	(0.08)	(0.03)	(0.02)	(0.03)	(0.03)	(0.03)
DOL						0.85***	1.10***	1.11***	1.11***	0.91***
						(0.04)	(0.03)	(0.03)	(0.03)	(0.03)
CAR						0.00	−0.00	−0.06*	−0.08**	0.03
						(0.03)	(0.04)	(0.04)	(0.03)	(0.03)
Obs.	443	443	443	443	443	443	443	443	443	443
Adj. R^2	0.17	0.06	0.01	0.00	0.13	0.84	0.84	0.83	0.80	0.81
Panel B: Portfolios sorted on rolling volatility ratio										
	P1	P2	P3	P4	P5	P1	P2	P3	P4	P5
Constant	0.07	0.05	0.03	0.13	0.22	0.05	0.07*	−0.01	0.05	−0.11
	(0.06)	(0.10)	(0.13)	(0.14)	(0.16)	(0.04)	(0.04)	(0.06)	(0.06)	(0.08)
GHML	0.00	−0.09	−0.17	−0.15	0.07	0.03	−0.01	−0.08***	−0.05**	0.14***
	(0.03)	(0.07)	(0.11)	(0.12)	(0.16)	(0.02)	(0.02)	(0.03)	(0.03)	(0.05)
DOL						0.39***	0.91***	1.16***	1.31***	1.32***
						(0.02)	(0.03)	(0.04)	(0.03)	(0.05)
CAR						−0.04**	−0.18***	−0.12***	−0.09**	0.30***
						(0.02)	(0.02)	(0.04)	(0.04)	(0.06)
Obs.	443	443	443	443	443	443	443	443	443	443
Adj. R^2	−0.00	0.01	0.03	0.02	0.00	0.55	0.83	0.84	0.87	0.80

The table reports the factor loadings of the monthly excess returns of currency portfolios. The sample period is February 1988 to December 2024. Panel A refers to portfolios sorted on the 36-month rolling correlation of monthly currency excess returns with a lagged measure of global geopolitical threats. Portfolio 1 (P1) includes the currencies with the lowest correlation coefficient, whereas Portfolio 5 (P5) includes the currencies with the highest correlation coefficient each month. Panel B refers to portfolios sorted on the ratio of the 36-month rolling volatility of monthly currency excess returns over the 36-month rolling volatility of a lagged measure of global geopolitical threats. Portfolio 1 (P1) includes the currencies with the lowest volatility ratio, whereas Portfolio 5 (P5) includes the currencies with the highest volatility ratio each month. Portfolios are monthly rebalanced and equally-weighted. In each panel, the first five columns report the portfolio loadings when the log excess return of each portfolio is regressed on a constant and the geopolitical ($GHML$) factor, whereas the last five columns report the portfolio loadings when log excess return of each portfolio is regressed on a constant, and the geopolitical ($GHML$), dollar (DOL) and carry (CAR) factors. Standard errors are reported in parentheses. One, two, and three stars denote statistical significance at the 1%, 5%, and 10% level, respectively.

Table 5: Portfolios sorted on conditional $\Delta \log GPT$ beta

Panel A: Summary statistics						
	P1	P2	P3	P4	P5	P5 - P1
Mean rx	2.89	0.50	-0.49	0.88	0.90	-1.98
Mean Δs	-1.99	-1.73	-2.31	-1.55	-1.96	0.04
Mean IRD	4.88	2.23	1.82	2.43	2.86	-2.02
Std deviation	7.89	7.51	8.21	8.03	8.67	8.29
Sharpe ratio	0.37	0.07	-0.06	0.11	0.10	-0.24
Skewness	-0.32	-0.65	-0.55	-0.49	-0.66	-0.13
Exc. kurtosis	1.86	2.98	1.73	2.13	3.10	1.80
Panel B: Factor loadings						
	P1	P2	P3	P4	P5	P5 - P1
Constant	0.01	0.03	-0.07	0.04	0.03	0.01
	(0.07)	(0.06)	(0.07)	(0.05)	(0.07)	(0.10)
GHML	0.31^{***}	0.05	-0.01	-0.11^{***}	-0.21^{***}	-0.52^{***}
	(0.05)	(0.03)	(0.03)	(0.03)	(0.04)	(0.07)
DOL	0.86^{***}	1.00^{***}	1.08^{***}	1.07^{***}	1.06^{***}	0.21^{**}
	(0.06)	(0.03)	(0.04)	(0.03)	(0.05)	(0.09)
CAR	0.11^{*}	-0.13^{***}	-0.10^{**}	-0.04	0.02	-0.08
	(0.06)	(0.03)	(0.05)	(0.03)	(0.04)	(0.07)
Obs.	443	443	443	443	443	443
Adj. R^2	0.68	0.80	0.79	0.86	0.79	0.32

The table reports summary statistics and factor loadings of the monthly excess returns of portfolios of currencies sorted on the slope coefficient in a 36-month rolling contemporaneous regression of their monthly excess returns on log changes of GPT, a measure of global geopolitical threats. The sample period is February 1988 to December 2024. Portfolio 1 (P1) includes the currencies with the lowest coefficient, whereas Portfolio 5 (P5) includes the currencies with the highest coefficient, each month. Portfolios are monthly rebalanced and equally-weighted. Standard errors are reported in parentheses. One, two, and three stars denote statistical significance at the 1%, 5%, and 10% level, respectively.

Table 6: Interest-rate sorted and dollar beta-sorted portfolios

Panel A: Interest rate-sorted portfolios										
	P1	P2	P3	P4	P5	P1	P2	P3	P4	P5
Constant	−0.13	−0.03	0.07	0.10	0.49***	0.03	−0.02	−0.00	−0.03	0.03
	(0.10)	(0.10)	(0.12)	(0.12)	(0.14)	(0.04)	(0.04)	(0.04)	(0.05)	(0.04)
GHML	−0.04	−0.07	−0.14	−0.14	0.02	0.06***	0.01	−0.07***	−0.06***	0.06***
	(0.07)	(0.08)	(0.09)	(0.11)	(0.12)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
DOL						0.94***	0.99***	1.02***	1.12***	0.94***
						(0.02)	(0.02)	(0.03)	(0.03)	(0.02)
CAR						−0.41***	−0.17***	−0.05**	0.03	0.59***
						(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Obs.	443	443	443	443	443	443	443	443	443	443
Adj. R^2	−0.00	0.00	0.02	0.02	−0.00	0.92	0.86	0.87	0.84	0.95
Panel B: Dollar beta-sorted portfolios										
	P1	P2	P3	P4	P5	P1	P2	P3	P4	P5
Constant	0.08	0.04	0.10	0.08	0.06	0.03	−0.03	−0.01	0.03	−0.02
	(0.07)	(0.11)	(0.13)	(0.14)	(0.15)	(0.06)	(0.06)	(0.06)	(0.05)	(0.07)
GHML	0.03	−0.04	−0.07	−0.15	−0.15	0.06	0.03	0.01	−0.04	−0.04
	(0.04)	(0.08)	(0.11)	(0.12)	(0.14)	(0.04)	(0.03)	(0.03)	(0.03)	(0.04)
DOL						0.39***	0.90***	1.12***	1.33***	1.44***
						(0.03)	(0.03)	(0.04)	(0.04)	(0.04)
CAR						0.02	−0.05*	−0.01	−0.15***	−0.11**
						(0.04)	(0.03)	(0.04)	(0.05)	(0.05)
Obs.	443	443	443	443	443	443	443	443	443	443
Adj. R^2	0.00	0.00	0.00	0.01	0.01	0.38	0.79	0.81	0.86	0.85

The table reports the factor loadings of the monthly excess returns of currency portfolios. The sample period is February 1988 to December 2024. Panel A refers to portfolios sorted on their log nominal interest rate difference with the United States. Portfolio 1 (P1) includes the currencies with the lowest difference, whereas Portfolio 5 (P5) includes the currencies with the highest difference each month. Panel B refers to portfolios sorted on their dollar beta coefficient. Portfolio 1 (P1) includes the currencies with the lowest coefficient, whereas Portfolio 5 (P5) includes the currencies with the highest coefficient each month. Portfolios are monthly rebalanced and equally-weighted. In each panel, the first five columns report the portfolio loadings when the log excess return of each portfolio is regressed on a constant and the geopolitical ($GHML$) factor, whereas the last five columns report the portfolio loadings when log excess return of each portfolio is regressed on a constant, and the geopolitical ($GHML$), dollar (DOL) and carry (CAR) factors. Standard errors are reported in parentheses. One, two, and three stars denote statistical significance at the 1%, 5%, and 10% level, respectively.

Table 7: Price of risk

Panel A: Geopolitical exposure portfolios (5 test assets)

λ_{DOL}	λ_{CAR}	λ_{GHML}	b_{DOL}	b_{CAR}	b_{GHML}	R^2	RMSE	χ^2 pval
0.143 (0.121)	0.709** (0.356)		0.002 (0.034)	0.129* (0.067)		24.970	0.094	0.129
0.129 (0.107)		0.308** (0.120)	0.040 (0.028)		0.056*** (0.021)	92.970	0.029	0.764
0.136 (0.112)	0.368 (0.357)	0.308*** (0.120)	0.025 (0.032)	0.059 (0.068)	0.051** (0.021)	98.900	0.011	0.876

Panel B: Geopolitical exposure and interest rate-sorted portfolios (10 test assets)

λ_{DOL}	λ_{CAR}	λ_{GHML}	b_{DOL}	b_{CAR}	b_{GHML}	R^2	RMSE	χ^2 pval
0.138 (0.121)	0.729*** (0.136)		−0.000 (0.030)	0.133*** (0.024)		84.840	0.074	0.242
0.140 (0.108)		0.382*** (0.123)	0.044 (0.028)		0.069*** (0.021)	31.250	0.157	0.000
0.139 (0.119)	0.701*** (0.133)	0.323** (0.126)	0.008 (0.030)	0.123*** (0.024)	0.048** (0.022)	97.030	0.033	0.549

Panel C: Geopolitical exposure and dollar beta-sorted portfolios (10 test assets)

λ_{DOL}	λ_{CAR}	λ_{GHML}	b_{DOL}	b_{CAR}	b_{GHML}	R^2	RMSE	χ^2 pval
0.138 (0.121)	0.740** (0.307)		−0.000 (0.033)	0.135** (0.058)		22.830	0.071	0.393
0.108 (0.106)		0.320*** (0.121)	0.034 (0.028)		0.058*** (0.021)	76.040	0.039	0.346
0.127 (0.114)	0.464 (0.305)	0.314*** (0.122)	0.018 (0.031)	0.078 (0.058)	0.050** (0.021)	89.410	0.026	0.792

Panel D: Geopolitical exposure, interest rate-sorted, and dollar beta-sorted portfolios (15 test assets)

λ_{DOL}	λ_{CAR}	λ_{GHML}	b_{DOL}	b_{CAR}	b_{GHML}	R^2	RMSE	χ^2 pval
0.136 (0.121)	0.730*** (0.138)		−0.001 (0.030)	0.133*** (0.024)		83.610	0.063	0.488
0.122 (0.108)		0.395*** (0.124)	0.039 (0.028)		0.071*** (0.021)	28.330	0.132	0.000
0.137 (0.119)	0.701*** (0.135)	0.325** (0.128)	0.008 (0.030)	0.123*** (0.024)	0.048** (0.022)	95.790	0.032	0.780

The table reports the estimated values of SDF factor loadings b and prices of risk λ for each of the currency factors, the cross-sectional adjusted R^2 of test asset returns, the square root of the mean squared pricing errors (RMSE), and the p-value of the χ^2 test statistic under the null hypothesis that all cross-sectional pricing errors are zero. We consider three currency factors: the geopolitical ($GHML$) factor, the dollar (DOL) factor, and the carry (CAR) factor. Panel A reports the results when the test assets are 5 geopolitical exposure currency portfolios. Panel B reports the results when the test assets are 5 geopolitical exposure currency portfolios and 5 interest rate-sorted currency portfolios. Panel C reports the results when the test assets are 5 geopolitical exposure currency portfolios and 5 dollar beta-sorted currency portfolios. Panel D reports the results when the test assets are 5 geopolitical exposure currency portfolios, 5 interest-rate sorted currency portfolios, and 5 dollar beta-sorted currency portfolios. Portfolios are monthly rebalanced and equally-weighted. One, two, and three stars denote statistical significance at the 1%, 5%, and 10% level, respectively.

Table 8: Developed and emerging country portfolios

Panel A: Summary statistics			
	DEV	EMG	EMG - DEV
Mean rx	-0.29	1.42	1.70
Mean Δs	-0.54	-3.72	-3.19
Mean IRD	0.25	5.14	4.89
Std deviation	7.97	6.23	5.48
Sharpe ratio	-0.04	0.23	0.31
Skewness	-0.25	-0.61	0.03
Exc. kurtosis	0.72	2.54	0.90
Panel B: Factor loadings			
	DEV	EMG	EMG - DEV
Constant	0.04	-0.05	-0.09
	(0.03)	(0.04)	(0.07)
GHML	-0.04^{***}	0.07^{**}	0.12^{**}
	(0.02)	(0.04)	(0.05)
DOL	1.14^{***}	0.78^{***}	-0.37^{***}
	(0.02)	(0.05)	(0.06)
CAR	-0.22^{***}	0.13^{***}	0.36^{***}
	(0.02)	(0.04)	(0.06)
Obs.	443	443	443
Adj. R^2	0.94	0.83	0.44

The table reports summary statistics and factor loadings of the monthly excess returns of portfolios of developed country currencies (DEV) and emerging country currencies (EMG). The sample period is February 1988 to December 2024. Portfolios are monthly rebalanced and equally-weighted. Standard errors are reported in parentheses. One, two, and three stars denote statistical significance at the 1%, 5%, and 10% level, respectively.

Table 9: Factor loadings of developed and emerging country geopolitical exposure portfolios

	Panel A: Developed country currencies									
	P1	P2	P3	P4	P4-P1	P1	P2	P3	P4	P4-P1
Constant	0.06	−0.04	0.07	−0.00	−0.06	0.04	−0.02	0.10	0.05	0.01
	(0.13)	(0.13)	(0.14)	(0.12)	(0.07)	(0.05)	(0.07)	(0.07)	(0.05)	(0.07)
GHML	−0.37***	−0.19*	−0.09	0.12	0.49***	−0.28***	−0.08***	0.01	0.21***	0.49***
	(0.09)	(0.11)	(0.12)	(0.09)	(0.07)	(0.03)	(0.03)	(0.04)	(0.04)	(0.06)
DOL						1.13***	1.20***	1.23***	1.04***	−0.09
						(0.03)	(0.04)	(0.04)	(0.04)	(0.06)
CAR						−0.16***	−0.23***	−0.26***	−0.26***	−0.10**
						(0.03)	(0.04)	(0.05)	(0.03)	(0.04)
Obs.	443	443	443	443	443	443	443	443	443	443
Adj. R^2	0.12	0.03	0.00	0.01	0.35	0.83	0.78	0.80	0.79	0.38
	Panel B: Emerging country currencies									
	P1	P2	P3	P4	P4-P1	P1	P2	P3	P4	P4-P1
Constant	0.07	0.07	0.17*	0.21	0.14	−0.10	−0.03	0.08	−0.09	0.01
	(0.12)	(0.08)	(0.10)	(0.14)	(0.12)	(0.09)	(0.07)	(0.07)	(0.10)	(0.12)
GHML	−0.30***	−0.10	0.03	0.56***	0.86***	−0.24***	−0.06	0.08**	0.60***	0.85***
	(0.08)	(0.07)	(0.07)	(0.14)	(0.10)	(0.06)	(0.04)	(0.04)	(0.09)	(0.10)
DOL						0.84***	0.65***	0.73***	0.87***	0.03
						(0.07)	(0.06)	(0.06)	(0.09)	(0.10)
CAR						0.12**	0.06	0.01	0.34***	0.21**
						(0.06)	(0.04)	(0.05)	(0.08)	(0.09)
Obs.	443	443	443	443	443	443	443	443	443	443
Adj. R^2	0.09	0.02	−0.00	0.19	0.48	0.64	0.54	0.59	0.64	0.51

The table reports the factor loadings of the monthly excess returns of developed and emerging country geopolitical exposure currency portfolios, i.e., portfolios of currencies sorted on the slope coefficient in a 36-month rolling forecasting regression of monthly currency excess returns on a measure of global geopolitical threats. The sample period is February 1988 to December 2024. In each panel, Portfolio 1 (P1) includes the currencies with the lowest forecast coefficient, whereas Portfolio 5 (P5) includes the currencies with the highest forecast coefficient each month. Portfolios are monthly rebalanced and equally-weighted. Panel A refers to developed-country currency portfolios, whereas Panel B emerging-country currency portfolios. In each panel, the first five columns report the portfolio loadings when the log excess return of each portfolio is regressed on a constant and the geopolitical ($GHML$) factor, whereas the last five columns report the portfolio loadings when log excess return of each portfolio is regressed on a constant, and the geopolitical ($GHML$), dollar (DOL) and carry (CAR) factors. Standard errors are reported in parentheses. One, two, and three stars denote statistical significance at the 1%, 5%, and 10% level, respectively.

Table 10: Geopolitical exposure bond portfolios

Panel A: Summary statistics						
	P1	P2	P3	P4	P5	P5 - P1
$rx^{(10),i,\$} - rx^{(10)}$	-1.25	-0.16	0.36	2.00	2.33	3.58
$rx^{(10),i} - rx^{(10)}$	0.06	-0.01	0.47	0.41	-0.21	-0.28
rx^{FX}	-1.31	-0.15	-0.11	1.59	2.54	3.85
Std deviation	14.37	10.41	10.55	9.90	12.04	11.30
Sharpe ratio	-0.09	-0.02	0.03	0.20	0.19	0.32
Skewness	-1.01	-0.17	-0.17	-0.19	-0.66	0.29
Exc. kurtosis	8.52	3.87	4.81	5.18	5.10	5.76
Panel B: Factor loadings						
	P1	P2	P3	P4	P5	P5 - P1
Constant	-0.34^{**}	-0.15	-0.04	0.05	-0.09	0.25
	(0.16)	(0.14)	(0.11)	(0.11)	(0.16)	(0.17)
GHML	-0.56^{***}	-0.14^{*}	-0.01	0.09	0.17^{*}	0.73^{***}
	(0.07)	(0.07)	(0.07)	(0.06)	(0.10)	(0.11)
DOL	1.34^{***}	1.04^{***}	1.13^{***}	1.10^{***}	1.23^{***}	-0.11
	(0.08)	(0.10)	(0.09)	(0.07)	(0.10)	(0.12)
CAR	0.43^{***}	0.12^{*}	-0.04	-0.04	0.11	-0.32^{***}
	(0.10)	(0.07)	(0.07)	(0.06)	(0.07)	(0.10)
Obs.	324	324	324	324	324	324
Adj. R^2	0.60	0.50	0.49	0.53	0.51	0.29

The table reports summary statistics (Panel A) and factor loadings (Panel B) of monthly USD bond return differences of geopolitical exposure bond portfolios, i.e., differences in the USD returns of portfolios of 10-year sovereign bonds sorted on the slope coefficient in a 36-month rolling forecasting regression of monthly currency excess returns on a measure of global geopolitical threats against the USD return of the 10-year sovereign US bond. The sample period is January 1998 to December 2024. Portfolio 1 (P1) includes the currencies with the lowest forecast coefficient, whereas Portfolio 5 (P5) includes the currencies with the highest forecast coefficient each month. Portfolios are monthly rebalanced and equally-weighted. $GHML$ is the long-short strategy that invests in Portfolio 5 and shorts Portfolio 1. Standard errors are reported in parentheses. One, two, and three stars denote statistical significance at the 1%, 5%, and 10% level, respectively.

Table 11: Geopolitical exposure bond portfolios: return decomposition

Panel A: Local currency bond return differences ($rx^{(10),i} - rx^{(10)}$)						
	P1	P2	P3	P4	P5	P5 - P1
Constant	-0.28^{**}	-0.21^{*}	-0.10	-0.11	-0.20^{*}	0.08
	(0.13)	(0.12)	(0.09)	(0.09)	(0.11)	(0.11)
GHML	-0.19^{***}	-0.01	-0.02	-0.03	-0.05	0.14^{**}
	(0.06)	(0.05)	(0.06)	(0.05)	(0.07)	(0.06)
DOL	0.21^{***}	-0.02	0.02	-0.00	0.11	-0.10
	(0.07)	(0.06)	(0.06)	(0.06)	(0.08)	(0.07)
CAR	0.43^{***}	0.27^{***}	0.19^{***}	0.20^{***}	0.24^{***}	-0.20^{***}
	(0.07)	(0.05)	(0.05)	(0.05)	(0.06)	(0.06)
Obs.	324	324	324	324	324	324
Adj. R^2	0.21	0.10	0.04	0.06	0.09	0.07
Panel B: FX excess returns (rx^{FX})						
	P1	P2	P3	P4	P5	P5 - P1
Constant	-0.06	0.05	0.06	0.16^{***}	0.11	0.17^{*}
	(0.06)	(0.06)	(0.07)	(0.06)	(0.08)	(0.10)
GHML	-0.37^{***}	-0.13^{***}	0.00	0.12^{***}	0.21^{***}	0.59^{***}
	(0.04)	(0.03)	(0.03)	(0.03)	(0.04)	(0.07)
DOL	1.13^{***}	1.07^{***}	1.12^{***}	1.10^{***}	1.13^{***}	-0.00
	(0.04)	(0.05)	(0.05)	(0.03)	(0.05)	(0.07)
CAR	-0.00	-0.15^{***}	-0.23^{***}	-0.25^{***}	-0.13^{***}	-0.13^{**}
	(0.03)	(0.03)	(0.04)	(0.03)	(0.04)	(0.06)
Obs.	324	324	324	324	324	324
Adj. R^2	0.86	0.81	0.79	0.82	0.78	0.44

The table reports factor loadings of the components of monthly USD bond return differences of geopolitical exposure bond portfolios, i.e., differences in the USD returns of portfolios of 10-year sovereign bonds sorted on the slope coefficient in a 36-month rolling forecasting regression of monthly currency excess returns on a measure of global geopolitical threats against the USD return of the 10-year sovereign US bond. Panel A refers to differences in the local currency returns of geopolitical exposure bond portfolios against the USD return of the 10-year sovereign US bond, whereas Panel B refers to the currency excess return component of monthly USD bond return differences of geopolitical exposure bond portfolios. The sample period is January 1998 to December 2024. Portfolio 1 (P1) includes the currencies with the lowest forecast coefficient, whereas Portfolio 5 (P5) includes the currencies with the highest forecast coefficient each month. Portfolios are monthly rebalanced and equally-weighted. $GHML$ is the long-short strategy that invests in Portfolio 5 and shorts Portfolio 1. Standard errors are reported in parentheses. One, two, and three stars denote statistical significance at the 1%, 5%, and 10% level, respectively.

Table 12: Portfolios sorted on net capital flow geopolitical exposure

Panel A: Summary statistics				
	P1	P2	P3	SMD
Mean rx	1.56	-0.69	-0.71	-2.27
Mean Δs	-2.28	-5.80	-2.79	-0.51
Mean IRD	3.84	5.11	2.08	-1.76
Std deviation	9.02	9.91	8.24	7.81
Sharpe ratio	0.17	-0.07	-0.09	-0.29
Skewness	-0.42	-1.09	-0.38	0.21
Exc. kurtosis	1.49	5.31	0.74	1.85
Panel B: Factor loadings				
	P1	P2	P3	SMD
Constant	0.08	-0.24^{*}	-0.03	-0.10
	(0.10)	(0.14)	(0.09)	(0.14)
GHML	0.14^{**}	0.05	-0.13^{**}	-0.27^{***}
	(0.07)	(0.05)	(0.05)	(0.08)
DOL	1.15^{***}	1.06^{***}	0.97^{***}	-0.18^{*}
	(0.05)	(0.05)	(0.07)	(0.10)
CAR	-0.06	0.21^{**}	-0.07	-0.01
	(0.06)	(0.09)	(0.06)	(0.09)
Obs.	249	249	249	249
Adj. R^2	0.72	0.63	0.67	0.07

The table reports summary statistics and factor loadings of the monthly excess returns of currency portfolios sorted on the slope coefficient in a 36-month rolling forecasting regression of the monthly net capital flows of the corresponding country on a measure of global geopolitical threats. The sample period is April 2004 to December 2024. Portfolio 1 (P1) includes the currencies with the lowest forecasting coefficient, whereas Portfolio 3 (P3) includes the currencies with the highest forecasting coefficient, each month. Portfolios are monthly rebalanced and equally-weighted. Standard errors are reported in parentheses. One, two, and three stars denote statistical significance at the 1%, 5%, and 10% level, respectively.

Table 13: Portfolios sorted on geopolitical exposure of capital flow components

Panel A: Sorting on exposure of net FDI flows				
	P1	P2	P3	P3 - P1
Constant	−0.06	−0.04	−0.09	−0.03
	(0.13)	(0.10)	(0.08)	(0.16)
GHML	0.10	−0.03	−0.01	−0.11
	(0.08)	(0.06)	(0.04)	(0.09)
DOL	1.03***	1.01***	1.18***	0.15**
	(0.06)	(0.07)	(0.04)	(0.07)
CAR	0.19*	0.05	−0.17***	−0.36***
	(0.11)	(0.07)	(0.04)	(0.12)
Obs.	249	249	249	249
Adj. R^2	0.63	0.65	0.76	0.11
Panel B: Sorting on exposure of net portfolio flows				
	P1	P2	P3	P3 - P1
Constant	−0.05	−0.07	−0.05	−0.00
	(0.11)	(0.09)	(0.08)	(0.15)
GHML	0.13*	0.01	−0.11***	−0.24***
	(0.07)	(0.05)	(0.04)	(0.08)
DOL	1.17***	0.99***	0.93***	−0.23**
	(0.05)	(0.06)	(0.06)	(0.09)
CAR	−0.04	0.12***	−0.01	0.03
	(0.07)	(0.04)	(0.06)	(0.10)
Obs.	249	249	249	249
Adj. R^2	0.75	0.73	0.71	0.09

The table reports factor loadings of the monthly excess returns of currency portfolios. The sample period is April 2004 to December 2024. Currencies are sorted into portfolios on the slope coefficient in a 36-month rolling forecasting regression of the monthly net FDI flows (Panel A) or monthly net poftfolio flows (Panel B) of the corresponding country on a measure of global geopolitical threats. Portfolio 1 (P1) includes the currencies with the lowest forecasting coefficient, whereas Portfolio 3 (P3) includes the currencies with the highest forecasting coefficient, each month. Portfolios are monthly rebalanced and equally-weighted. Standard errors are reported in parentheses. One, two, and three stars denote statistical significance at the 1%, 5%, and 10% level, respectively.

Table 14: Portfolios sorted on the return forecast coefficient of the war discourse measure

	P1	P2	P3	P4	P5	P5-P1	P1	P2	P3	P4	P5	P5-P1
Constant	0.12	0.10	0.13	0.07	0.15	0.03	0.00	0.04	0.07	0.00	−0.04	−0.04
	(0.13)	(0.14)	(0.13)	(0.13)	(0.12)	(0.09)	(0.07)	(0.05)	(0.06)	(0.08)	(0.06)	(0.10)
GHML	−0.26**	−0.18*	−0.08	0.15	0.37***	0.62***	−0.25***	−0.17***	−0.07**	0.16***	0.37***	0.62***
	(0.10)	(0.11)	(0.11)	(0.09)	(0.11)	(0.08)	(0.03)	(0.02)	(0.03)	(0.03)	(0.06)	(0.08)
DOL							1.06***	1.08***	1.12***	0.95***	0.88***	−0.17
							(0.06)	(0.03)	(0.04)	(0.05)	(0.07)	(0.11)
CAR							−0.01	−0.11***	−0.11***	−0.06	0.14**	0.15*
							(0.05)	(0.03)	(0.04)	(0.04)	(0.06)	(0.09)
Obs.	381	381	381	381	381	381	381	381	381	381	381	381
Adj. R^2	0.06	0.03	0.00	0.03	0.13	0.37	0.78	0.86	0.84	0.76	0.74	0.39

The table reports the factor loadings of the monthly excess returns of currency portfolios sorted on the slope coefficient in a 36-month rolling forecasting regression of monthly currency excess returns on the war discourse measure (War) of Hirshleifer et al. (2024). The sample period is February 1988 to October 2019. Portfolio 1 (P1) includes the currencies with the lowest forecasting coefficient, whereas Portfolio 5 (P5) includes the currencies with the highest forecasting coefficient each month. Portfolios are monthly rebalanced and equally-weighted. The first five columns report the portfolio loadings when the log excess return of each portfolio is regressed on a constant and the geopolitical ($GHML$) factor, whereas the last five columns report the portfolio loadings when log excess return of each portfolio is regressed on a constant, and the geopolitical ($GHML$), dollar (DOL) and carry (CAR) factors. Standard errors are reported in parentheses. One, two, and three stars denote statistical significance at the 1%, 5%, and 10% level, respectively.

Table 15: Sorting on return forecast coefficients of U.S. uncertainty measures

Panel A: Portfolios sorted on EPU forecast coefficient						
	P1	P2	P3	P4	P5	P5-P1
Constant	−0.04	0.14***	0.05	−0.08	0.00	0.05
	(0.07)	(0.05)	(0.06)	(0.06)	(0.08)	(0.11)
GHML	−0.01	−0.07**	−0.05*	0.03	0.14*	0.14
	(0.06)	(0.04)	(0.03)	(0.03)	(0.08)	(0.12)
DOL	0.88***	1.01***	1.13***	1.07***	0.99***	0.11
	(0.06)	(0.05)	(0.03)	(0.04)	(0.08)	(0.13)
CAR	0.10**	−0.04	−0.10***	−0.09**	−0.02	−0.12
	(0.04)	(0.03)	(0.04)	(0.04)	(0.05)	(0.07)
Obs.	443	443	443	443	443	443
Adj. R^2	0.67	0.82	0.84	0.81	0.63	0.03
Panel B: Portfolios sorted on TPU forecast coefficient						
	P1	P2	P3	P4	P5	P5-P1
Constant	−0.07	0.02	0.05	0.03	0.04	0.11
	(0.07)	(0.05)	(0.06)	(0.06)	(0.08)	(0.12)
GHML	0.04	−0.01	−0.03	0.01	0.04	−0.01
	(0.06)	(0.02)	(0.03)	(0.03)	(0.07)	(0.12)
DOL	1.17***	1.11***	1.00***	0.93***	0.86***	−0.30***
	(0.05)	(0.03)	(0.03)	(0.03)	(0.06)	(0.10)
CAR	0.11**	−0.06**	−0.13***	−0.10***	0.05	−0.06
	(0.05)	(0.03)	(0.03)	(0.03)	(0.07)	(0.11)
Obs.	443	443	443	443	443	443
Adj. R^2	0.77	0.86	0.81	0.77	0.61	0.07

The table reports the factor loadings of the monthly excess returns of currency portfolios. The sample period is February 1988 to December 2024. Panels A and B report the factor loadings of portfolios sorted on the slope coefficient in a 36-month rolling forecasting regression of monthly currency excess returns on the U.S. Economic Policy Uncertainty (EPU) index and U.S. Trade Policy Uncertainty (TPU) index, respectively. In each panel, Portfolio 1 (P1) includes the currencies with the lowest forecasting coefficient, whereas Portfolio 5 (P5) includes the currencies with the highest forecasting coefficient each month. Portfolios are monthly rebalanced and equally-weighted. Standard errors are reported in parentheses. One, two, and three stars denote statistical significance at the 1%, 5%, and 10% level, respectively.

Table 16: Portfolios sorted on country-level GPR index

Panel A: Summary statistics						
	P1	P2	P3	P4	P5	P5 - P1
Mean rx	0.96	0.25	1.89	0.94	0.97	0.02
Mean Δs	-1.68	-2.63	-2.17	-4.55	-2.23	-0.55
Mean IRD	2.64	2.88	4.06	5.49	3.21	0.57
Std deviation	7.84	8.39	8.77	7.44	7.45	5.95
Sharpe ratio	0.12	0.03	0.22	0.13	0.13	0.00
Skewness	-0.58	-1.14	-0.19	-1.13	-0.27	0.10
Exc. kurtosis	2.07	5.85	2.74	3.07	2.20	3.83
Panel B: Factor loadings						
	P1	P2	P3	P4	P5	P5 - P1
Constant	0.05	-0.08	0.05	-0.07	-0.03	-0.08
	(0.05)	(0.09)	(0.05)	(0.06)	(0.06)	(0.09)
GHML	-0.04^{*}	-0.01	-0.04	0.06^{*}	0.01	0.05
	(0.02)	(0.04)	(0.03)	(0.03)	(0.04)	(0.05)
DOL	1.06^{***}	1.03^{***}	1.13^{***}	0.88^{***}	0.88^{***}	-0.18^{***}
	(0.03)	(0.06)	(0.03)	(0.04)	(0.05)	(0.06)
CAR	-0.08^{***}	0.03	0.03	0.09^{*}	0.06	0.14^{*}
	(0.02)	(0.03)	(0.03)	(0.05)	(0.07)	(0.08)
Obs.	443	443	443	443	443	443
Adj. R^2	0.84	0.73	0.81	0.70	0.69	0.06

The table reports summary statistics (Panel A) and factor loadings (Panel B) of the monthly excess returns of currency portfolios sorted on the corresponding country's GPR index. The sample period is February 1988 to December 2024. Portfolio 1 (P1) includes the currencies with the lowest GPR index, whereas Portfolio 5 (P5) includes the currencies with the highest GPR index, each month. Portfolios are monthly rebalanced and equally-weighted. Standard errors are reported in parentheses. One, two, and three stars denote statistical significance at the 1%, 5%, and 10% level, respectively.

Internet Appendix

A Data

In this section, we describe the data we use for the calculation of currency excess returns and international capital flows.

A.1 Currency excess returns

Our sample includes the currencies of 41 developed and emerging countries, as follows: Australia, Belgium, Brazil, Canada, Chile, China, Colombia, Denmark, Egypt, France, Germany, Hong Kong, Hungary, India, Indonesia, Ireland, Israel, Italy, Japan, Malaysia, Mexico, Netherlands, New Zealand, Norway, Philippines, Poland, Portugal, Romania, Russia, Singapore, South Africa, South Korea, Spain, Sweden, Switzerland, Taiwan, Thailand, Tunisia, Turkey, Ukraine, and the United Kingdom. We also include the euro. After the formation of the eurozone, we exclude the data of all countries that are eurozone members and, instead, include the eurozone as a single country. The developed country sample includes 17 countries (Australia, Belgium, Canada, Switzerland, Germany, Denmark, Spain, France, United Kingdom, Ireland, Israel, Italy, Japan, Netherlands, Norway, Portugal, and Sweden), as well as the eurozone, whereas the rest of the countries in our sample are considered emerging countries. Following Lustig et al. (2011), we include currencies that are fully or partially pegged to the US dollar (e.g., the Hong Kong dollar), as forward FX contracts for those currencies are easily accessible to investors.

We collect end-of-the-month spot and forward exchange rate data, with our sample period beginning in January 1985 and ending in December 2024. However, due to limits in data availability, we do not have spot and forward data for all month-currency pairs in our sample, so our panel is unbalanced. Spot FX market data are from WM/Reuters: for data availability reasons, we calculate spot exchange rates against the USD by using WM/Reuters data on spot exchange rates against the GBP and imposing triangular arbitrage, supplementing with WM/Reuters data on spot exchange rates against the USD. 1-month, 3-month, and 12-month forward FX market data are from WM/Reuters, Refinitiv, and Barclays. In particular, we use WM/Reuters data on forward exchange rates against the USD, supplementing with USD forward data from Refinitiv and Barclays. When forward data from any of the aforementioned sources are not available, we use WM/Reuters data on non-deliverable forward rates against the USD, Refiniv data on forward rates against the GBP (in which case we calculate USD forward rates by imposing triangular arbitrage), and Refiniv data on forward points against the USD. For our main analysis, which focuses on 1-month currency excess returns, we use 1-month forward data. We use 3-month and 12-month forward data for the calculation of 3-month and 12-month excess returns, respectively, discussed in Internet Appendix B. We clean the spot and forward FX rate dataset by eliminating observations below 0.0001, as calculations become very imprecise due to rounding. Furthermore, in the forward FX rate dataset, we eliminate all observations that are part of a series of three or more identical consecutive observations, as they are very likely to be erroneous.

When forward rates are unavailable, but eurocurrency rates are available, we use the covered interest rate parity condition to proxy the 1-month currency excess return by

$$rx^i_{t+1} \approx \Delta s_{t+1} + r^i_t - r_t, \tag{14}$$

where r^i_t (r_t) is the 1-month nominal rate of currency i (US dollar) at the end of month t. We similarly calculate 3-month and 12-month currency excess returns using 3-month and 12-month eurocurrency rates. To that end, we collect 1-month, 3-month, and 12-month eurocurrency rates for the currencies of Australia, Belgium, Canada, Denmark, France, Germany, Hong Kong, Italy, Japan, Netherlands, New Zealand, Norway, Portugal, South Africa, Sweden, Switzerland, Singapore, Spain, and the United Kingdom, as well as for the euro, from FT/LSEG.

A.2 Bond returns

We collect end-of-month zero coupon sovereign bond yield data from Bloomberg for 33 countries: Australia, Belgium, Brazil, Canada, Chile, China, Colombia, Denmark, France, Germany, Hong Kong, Hungary, Indonesia, Ireland, Israel, Italy, Japan, Malaysia, Mexico, Netherlands, New Zealand, Norway, Philippines, Poland, Portugal, Singapore, Sweden, South Africa, South Korea, Spain, Switzerland, United Kingdom, and the United States. The sample period is December 1994 to December 2024, but our panel is unbalanced, with some countries entering the sample after December 1994. Our yield curve data include 15 maturities: 3 months, 6 months, 1 year, 2 years, 3 year, 4 years, 5 years, 6 years, 7 years, 8 years, 9 years, 10 years, 15 years, 20 years, and 30 years. We calculate zero coupon bond prices for all maturities ranging from 1 months to 360 months by linearly interpolating bond yields for all missing maturities. After the introduction of the euro (January 1999), we proxy euro bond returns by German sovereign bond returns.

A.3 International capital flows

Monthly international capital flow data data are from the OECD Monthly Capital Flow Dataset, with the sample being January 1995 to December 2024. The details of that dataset are discussed in De Crescenzio and Lepers (2025). For each country, we collect portfolio inflows and outflows and FDI inflows and outflows. For each country, capital inflows are the sum of portfolio and FDI inflows – capital outflows are calculated analogously. For each type of flows, net flows are defined as inflows minus outflows. Due to limits in data availability, we have both portfolio flow and FDI flow data (and, therefore, we can calculate net capital flows) for the following 17 countries: Brazil, Chile, Denmark, Germany, Hungary, India, Japan, Philippines, Poland, Portugal, Romania, South Korea, Spain, Sweden, Thailand, Turkey, and Ukraine. In addition, we use portfolio flow data for Canada and FDI flow data for Italy. All types of international capital flow ratios scale capital flow levels by monthly GDP levels. For each country, we impute the monthly GDP series by dividing the country's quarterly GDP (from IMF) by three and applying the imputed level to all three months included in the corresponding quarter. When quarterly GDP data are not available, the monthly GDP for all the months in a given year is imputed by dividing the country's annual

GDP by 12. To convert quarterly or annual IMF GDP data, reported in local currency units, to US dollars, we use the end-of-the-period exchange rate from the IMF.

Quarterly international capital flow data are from IMF Balance of Payments dataset. The sample period is 1988:Q3 to 2024:Q4. Consistent with our monthly data definitions, we define total capital inflows (outflows) to be the sum of portfolio inflows (outflows) and gross FDI inflows (outflows). We include the capital flows of 31 countries (Australia, Belgium, Brazil, Canada, Chile, Colombia, Denmark, France, Germany, Hungary, India, Indonesia, Ireland, Israel, Italy, Japan, Mexico, Netherlands, New Zealand, Norway, Poland, Portugal, Romania, South Africa, South Korea, Spain, Sweden, Switzerland, Thailand, Turkey, and the United Kingdom), as well as the eurozone.

B Robustness checks and additional empirical findings

In this section, we report several robustness checks and additional empirical findings. First, we document that sorting currencies into portfolios using the GPT forecast coefficient of exchange rate changes generates results very similar to those we get by sorting on the forecast coefficient of currency excess returns. Then, we show that sorting currencies into portfolios using their GPA or the GPR return forecast coefficient generates a spread in $GHML$ loadings, and that sorting currencies into portfolios on their rolling $GHML$ beta generates a return spread that mostly compensates investors for positive exposure to the $GHML$ factor, in line with our factor pricing results. We also show that our main empirical findings are robust to using factors that include only developed or only emerging country currencies. Furthermore, we demonstrate that our main findings are robust when we consider 3-month or 12-month, rather than 1-month, excess returns. On the other hand, when we sort currencies into portfolios on the unconditional GPT forecast coefficient of their excess returns, we find a small spread on their exposure to global geopolitical risk, showcasing the importance of the time variation in the geopolitical exposure of currency expected excess returns. Next, we document that our findings on the properties of the excess returns of currency portfolios sorted on the forecast coefficient of international capital flows on GPT are robust to using quarterly flow data. Furthermore, we show that sorting currencies into portfolios on the exposure of their excess returns on measures of global uncertainty does not generate a spread in $GHML$ loadings. Finally, when we sort currencies into portfolios on the 36-month rolling mean of the corresponding country's GPR index, we find no meaningful spread in geopolitical risk exposure, suggesting that country-level GPR rolling means are unconnected to $GHML$ currency loadings.

B.1 Geopolitical exposure portfolios using FX changes

The only risky component of currency excess returns is the exchange rate change, as interest rate differentials are known at the end of month t. For that reason, we need to ensure that sorting on the GPT forecast coefficient of FX changes yields results similar to our baseline portfolio sort that uses β^{GPT}, the GPT forecast coefficient of excess returns. To that end,

for each currency i, we run 36-month rolling forecast regressions of the type

$$\Delta s^i_{t+1} = \alpha^i + \delta^{i,GPT} GPT_t + \eta^i_{t+1}, \tag{15}$$

and, at each month t, we sort currencies into five portfolios on δ^{GPT}_t, the conditional forecast coefficient of FX changes.

We report the summary statistics of those alternative geopolitical exposure portfolios in Panel A of Table A1. We also consider $GHML^{FX}$, a strategy that invests in high-δ^{GPT} currencies (Portfolio 5) and shorts low-δ^{GPT} currencies (Portfolio 1). We find that the annualized return spread across portfolios is 3.20%, almost identical to the return spread our standard geopolitical exposure portfolios. To explore whether that return spread can be explained to exposure to the two Lustig et al. (2011) currency factors, we turn to Panel B. We find that the $GHML^{FX}$ strategy has an economically large (2.52% in annualized terms) and statistically significant excess return, suggesting that the standard factors are unable to account for the return spread of δ^{GPT}_t-sorted portfolios.

For that reason, we follow the approach adopted in the main text of our paper and examine whether $GHML^{FX}$ can be used as a factor that helps statistically characterize the excess returns of δ^{GPT}_t-sorted portfolios. Table A2 reports our findings. The first five columns document the portfolio factor loadings on our $GHML^{FX}$ factor, whereas the last five columns show the portfolio loadings when we include all three ($GHML^{FX}$, DOL and CAR) factors. When we only consider the $GHML^{FX}$ factor, we find that the factor loadings are monotonically increasing in δ^{GPT}. When we include the other two factors, the $GHML$ loadings continue to exhibit monotonicity. The DOL factor is a level factor whereas the CAR loadings of all portfolios are economically small. Hence, the factor loadings of the δ^{GPT}-sorted portfolios are very similar to those of our standard geopolitical exposure portfolios.

Finally, we examine whether our alternative geopolitical exposure portfolios exhibit heterogeneity in $GHML$ factor loadings. Given the similarity of those portfolios with our standard geopolitical exposure portfolios, we expect both a monotonic pattern and a significant spread in $GHML$ betas across portfolios. As shown in Table A3, both our conjectures are confirmed. In particular, the univariate $GHML$ loadings increase monotonically from -0.46 to 0.48, generating a spread of 0.94, statistically significant at the 1% level. Those findings are robust to controlling for the DOL and CAR factors: $GHML$ loadings continue to be monotonic and now range from -0.39 to 0.54, producing a statistically significant loading spread of 0.94.

B.2 Using alternative geopolitical turmoil measures

For our baseline exercise, we sort currencies into portfolios on the rolling 36-month GPT forecast coefficient of their excess returns. As detailed in Caldara and Iacoviello (2022), the GPT index is a measure of global geopolitical threats and one of the two components of the overall geopolitical risk index, GPR. The other GPR component is a measure of global geopolitical acts, GPA. To evaluate the robustness of our main findings to using alternative measures of geopolitical turmoil, we replace GPT as an excess return forecast signal by either GPA or GPR and sort currencies into portfolios on each of the two forecast coefficients. In each case, Portfolios 1 and 5 include the low-coefficient and high-coefficient currencies, respectively. Furthermore, we consider two currency strategies, $GHML^{GPA}$ and

$GHML^{GPR}$: the former goes long the currencies with the highest GPA forecast coefficients (Portfolio 5) and shorts the currencies with the lowest GPA forecast coefficients (Portfolio 1), whereas the latter does the same using GPR forecast coefficients.

First, we consider whether $GHML^{GPA}$ and $GHML^{GPR}$ statistically characterize the excess returns of the respective set of currency portfolios. To that end, we calculate the $GHML^{GPA}$ ($GHML^{GPR}$) loadings of portfolios sorted on their GPA (GPR) forecast coefficient. Our findings are reported in Table A4: Panel A refers to the former, whereas Panel B refers to the latter. In both cases, we get monotonically increasing factor loadings, regardless of whether we control for the DOL and CAR factors or not. In particular, in the cross-section of currency portfolios sorted on the GPA forecast coefficient, the $GHML^{GPA}$ loadings range from -0.62 to 0.38 when we do not include additional factors and from -0.41 to 0.59 when we do. When we switch our focus on portfolios sorted on the GPR forecast coefficient, we get similar results: univariate $GHML^{GPR}$ loadings monotonically increase from -0.55 to 0.45 and multivariate loadings increase from -0.39 to 0.61.

Are those two cross-sections of portfolios characterized by heterogeneity in $GHML$ loadings? The answer is provided in Table A5, with Panel A focusing on portfolios sorted on the GPA forecast coefficient and Panel B on portfolios sorted on the GPR forecast coefficient.

As seen in Panel A, the informational content of the GPA index for currency expected excess returns is not very different of that of the GPT index. Sorting currencies into portfolios on the exposure of their expected excess returns on the level of geopolitical acts generates substantial heterogeneity in $GHML$ loadings: currencies with high conditional GPA forecast coefficients (Portfolio 5) have significantly higher $GHML$ loadings compared to currencies with low GPA forecast coefficients (Portfolio 1), regardless on whether we control for DOL and CAR exposure or not. In particular, the $GHML$ loadings range from -0.26 to 0.25 when we do not control for exposure to additional factors, and from -0.18 to 0.30 when we do. Hence, the long-short strategy that invests in Portfolio 5 and shorts Portfolio 1 has an economically large and statistically significant $GHML$ coefficient, regardless of whether we control for DOL and CAR exposure of not.

Given our results so far and taking into account that the GPR index includes information in both the GPA and the GPT index, we expect to find that sorting currencies into portfolios on the conditional GPR forecast coefficient of their excess returns yields a large spread on conditional $GHML$ betas. The results in Panel B of Table A5 confirm our intuition. High-coefficient currencies have a much higher $GHML$ loading than low-coefficient currencies, with the $GHML$ loading spread between Portfolio 5 and Portfolio 1 being 0.83 when we do not control for other factors and 0.81 when we do.

B.3 Portfolios sorted on $GHML$ betas

We provide additional evidence for the pricing ability of $GHML$ in currency markets by turning to currency portfolios sorted on their $GHML$ beta. For each currency, we calculate the univariate $GHML$ beta of its log excess return using a 36-month rolling window. Then, at each month t, we sort currencies into five portfolios based on their conditional $GHML$ beta: Portfolio 1 includes the low-beta currencies and Portfolio 5 the high-beta currencies. If $GHML$ is a priced risk factor and, hence, currency exposure to $GHML$ is compensated by

a risk premium, then sorting currencies on their $GHML$ beta should generate a substantial cross-sectional spread in average excess returns.

The properties of $GHML$ beta-sorted currency portfolios are presented in Table A6. Since we lose 36 months of observations for the calculation of the conditional betas, the excess return sample period starts in February 1991 and ends in December 2024, for a total of 407 monthly observations. Panel A reports the summary statistics of the portfolio excess returns. Although the average excess returns do not exactly line up with pre-formation $GHML$ betas, the spread between high-beta (Portfolio 5) and low-beta (Portfolio 1) currencies is 1.72% in annualized terms.

The post-formation factor loadings of the portfolios are reported in Panel B. We find that post-formation $GHML$ betas are monotonically increasing across portfolios, suggesting the pre-formation betas and post-formation betas line up. In particular, Portfolio 1 has a post-formation $GHML$ beta of -0.11 and Portfolio 5 a beta of 0.31, so the $GHML$ beta of the high-minus-low strategy (Portfolio 5 - Portfolio 1) is 0.42, significant at the 1% level. In the cross-section of $GHML$ beta-sorted currency portfolios, the DOL factor is a level factor, whereas CAR loadings are economically small. In particular, DOL loadings are all close to 1, but exhibit some cross-sectional variation (ranging from 0.85 to 1.11), so the long-short strategy has a small, but negative and significant, DOL loading. In contrast, all CAR loadings are close to zero and (with one exception) statistically non-significant.

We conclude that sorting currencies into portfolios on their $GHML$ rolling beta generates a substantial return spread that mainly reflects positive exposure to the $GHML$ factor, consistent with our factor pricing results.

B.4 Developed and emerging country factors

In our main analysis, we consider traded currency factors (in particular, DOL, CAR, and $GHML$) constructed by sorting all countries' currencies into portfolios, so our benchmark factors are essentially "all-country" factors. To check the robustness of our main results to factors constructed on different subsets of currencies, we proceed as follows. First, we construct "developed-country" ("emerging-country") factors by sorting only developed (emerging) country currencies into portfolios. Then, we sort the developed (emerging) country currencies of our sample into 4 portfolios on θ^{GPT}, the 36-month rolling GPT forecast coefficient of their excess returns, and report the unconditional loadings of the portfolio excess returns on the "developed-country" ("emerging-country") factors. Our findings are presented in Table A7: Panel A reports the loadings of developed currency portfolios on developed-country factors, whereas Panel B does the same for emerging currencies.

As seen in Panel A, the portfolio loadings on the developed-country $GHML$ factor are monotonically increasing in θ^{GPT}. When we also control for exposure to developed-country DOL and CAR factors, we find that $GHML$ holdings continue to be monotonically increasing, the developed-country DOL factor is a level factor across developed country portfolios, and the developed-country CAR factor latter has negligible (and non-significant) loadings across portfolios. Panel B documents similar findings for the currencies of emerging countries. In particular, portfolios of emerging currencies sorted on the rolling GPT forecast coefficient of their excess returns exhibit a monotonic pattern in emerging-country $GHML$ loadings,

regardless on whether we control for exposure to the emerging-country DOL and CAR factors or not. Furthermore, there is little cross-sectional variation in DOL and CAR factor loadings: DOL acts as a level factor, whereas CAR exposure is economically small across portfolios.

In summary, we confirm that our main findings are robust to restricting our focus to either developed or emerging country factors.

B.5 Longer-horizon portfolio returns

Our main analysis focuses on 1-month portfolio returns. In order to explore whether our findings hold for longer holding periods, we now consider 3-month and 12-month overlapping returns. In particular, for each month t, we run 36-month forecast regressions using 1-month returns (Equation 2) and sort currencies into five portfolios on their rolling forecast coefficient β_t^{GPT}, as in our main analysis. However, we now calculate either 3-month or 12-month returns: for $h = \{3, 12\}$, the log excess returns for the portfolios sorted on month t are calculating by equally weighting the h-month excess returns included in each portfolio, given by $(s_{t+h}^i - s_t^i) - (r_{t,h}^i - r_{t,h}^{US})$. Since our returns are overlapping, we have 441 monthly observations of 3-month returns and 432 monthly observations of 12-month returns. Our factors are constructed similarly: for each factor, we calculate 3-month or 12-month overlapping returns.

Table A8 reports the summary statistics of longer-horizon returns of the aforementioned geopolitical exposure portfolios, with Panel A referring to 3-month returns and Panel B to 12-month returns. The 3-month return spread (i.e., the excess return of the $GHML$ strategy) is 2.59% in annualized terms, whereas the 12-month return spread is 2.93%, both of which being similar in magnitude to the 1-month return spread.

Tables A9 and A10 report the factor loadings of the 3-month and 12-month excess returns of the geopolitical exposure portfolios. We find that both the 3-month and the 12-month excess returns of the geopolitical exposure portfolios have factor loadings with properties very similar to those of the monthly portfolio returns: $GHML$ loadings are increasing in β^{GPT}, DOL is a level factor, and CAR loadings are economically small.

B.6 Sorting on unconditional geopolitical exposure

One question worth addressing is the following: how much of the performance of the $GHML$ strategy is due to portfolio rebalancing due to changes in conditional geopolitical forecasting coefficients, and how much is due to unconditional differences in geopolitical predictability across currencies? In other words, is being a high-exposure (Portfolio 5) or low-exposure (Portfolio 1) currency more of a time-varying attribute or more of a fixed characteristic of currencies? To answer that question, we calculate the unconditional θ^{GPR} coefficient for each currency and form fixed-composition portfolios using that coefficient as the sorting variable. Since we use the entire sample for calculating the unconditional forecast coefficients, this is not an implementable trading strategy. Still, this exercise is valuable for determining the nature of the geopolitical exposure of currency returns.

Our findings are reported in Table A11. As seen in Panel A, sorting on unconditional forecast coefficients generates a negligible return spread: Portfolio 5, which includes the currencies with the highest unconditional forecast coefficients, yields an average annualized excess return of 3.20%, which is only 0.36% higher than the average return of low-coefficient (Portfolio 1) currencies. The 0.36% return spread can be decomposed into a 5.23% average interest rate differential and a -4.86% average exchange rate change. Unsurprisingly, the Sharpe ratio of the strategy that goes long Portfolio 5 and short Portfolio 1 is only 0.05 in annualized terms, indicating the absence of almost any compensation for bearing the return fluctuations of that strategy. Given that, as seen in Table 1, the conditional strategy (i.e., $GHML$) yields an annualized return of 3.28%, we can conclude that chasing fluctuations in the conditional exposure to geopolitical turmoil accounts for the bulk of the $GHML$ average return.

In Panel B of Table A11, we report the factor loadings of the currency portfolios sorted on unconditional GPT forecast coefficients. Although high-coefficient currencies (Portfolio 5) have a higher $GHML$ loading than low-coefficient currencies (Portfolio 1), the spread in $GHML$ exposure is economically small (0.21), albeit highly statistically significant. In fact, the return spread between high- and low-coefficient currencies is mainly due to their CAR spread (0.45), suggesting that sorting on the unconditional GPT forecast coefficient has significant overlap with sorting on nominal interest rates.

B.7 Using quarterly international capital flow data

We sort currencies into portfolios on the slope coefficient of rolling forecast regressions of countries' quarterly net capital inflow ratio on the GPT level, and calculate the factor loadings of their quarterly non-overlapping excess returns. The forecast regression rolling window is 24 quarters. Furthermore, we repeat that exercise for the net FDI flow and the net portfolio flow ratios. Table A12 reports the factor loadings of the excess returns of those currency portfolios. In particular, Panels A, B, and C refer to portfolios sorted on the forecast coefficient of net capital flow, net FDI flow, and net portfolio flow ratios, respectively. The sample period is 1994:Q3 to 2024:Q4, so there are 122 quarterly excess return observations available.

Panel A of Table A12 shows that the strategy that invests in currencies that tend to have higher-than-average net capital flows when geopolitical turmoil is high ("safe haven" currencies) and shorts currencies that tend to have lower-than-average net capital flows in those times ("danger zone" currencies) hedges geopolitical risk, as it has a $GHML$ loading of -0.15, significant at the 1% level. Furthermore, as seen in Panels B and C of Table A12, sorting on the forecast coefficient of net FDI flows does not generate a statistical significant spread in $GHML$ loadings, whereas sorting on the forecast coefficient of net portfolio flows does. In particular, the strategy that goes long on currencies that tend to attract high-than-average net portfolio flows in times of elevated geopolitical threats and short on currencies that tend to do the opposite has a $GHML$ loading of -0.10, statistically significant at the 5% level.

Overall, our findings are consistent with the results we get when we use monthly capital flow data, as presented in Tables 12 and 13 of the main text.

B.8 Sorting on exposure to global uncertainty measures

In order to explore whether currency exposure to global uncertainty is associated with geopolitical risk currency loadings, we consider two text-based global uncertainty measures, the Global Economic Policy Uncertainty Index of Baker et al. (2016) and he World Uncertainty Index of Ahirt et al. (2022), and sort currencies into portfolios on the 36-month rolling forecast coefficient of their excess returns on each measure (θ^{GEPU} and θ^{WUI}, respectively).

Our findings are reported in Table A13: Panel A (Panel B) presents the factor loadings of currency portfolios sorted on rolling θ^{GEPU} (θ^{WUI}), with the sample period starting in February 2000 (February 2011) and ending in December 2024. When we sort currencies into five portfolios on the GEPU rolling forecast coefficient, all $GHML$ loadings are economically small (ranging from -0.03 to 0.07) and almost all are statistically insignificant. As a result, investing in high-exposure currencies (Portfolio 5) and shorting low-exposure currencies (Portfolio 1) yields a $GHML$ beta of 0.02, statistically indistinguishable from zero. The same is true when we sort on the WUI forecast coefficient: $GHML$ loadings across the five portfolios range from -0.06 to 0.13, with the long-short USD-neutral strategy having a $GHML$ beta of -0.03, statistically insignificant.

In summary, differences in exposure to global uncertainty do not appear to be linked to differences in geopolitical risk loadings across currencies.

B.9 Sorting on rolling means of country-specific GPR measures

We sort currencies into portfolios using the 36-month rolling mean of the corresponding country's GPR index, and present our findings in Table A14. Panel A reports the properties of portfolio returns, documenting that there is essentially no return spread between the currencies of countries with high GPR rolling means (Portfolio 5) and those of countries with low GPR rolling means (Portfolio 5). To answer whether sorting on GPR rolling averages generates a meaningful spread in $GHML$ loadngs, we turn to Panel B. We see that the strategy that goes long the high-mean GPR currencies and shorts the low-mean GPR currencies does not load on the $GHML$ factor at all, indicating that the currencies of countries with high GPR rolling averages have the same exposure to geopolitical risk as the currencies of countries with low GPR averages. We conclude that countries' GPR rolling means do not proxy for the $GHML$ exposure of their currencies.

C No-arbitrage model

To rationalize our empirical findings, we propose a multi-country no-arbitrage model. In the model, financial markets are complete, but stochastic discount factors (SDFs) differ across countries, in the spirit of Lustig et al. (2011).

C.1 Setting

The global economy includes $N+1$ countries, indexed by i, with country $i=0$ being the domestic country and countries $i=1,...,N$ foreign countries.

The log SDF of country i, m^i_{t+1}, satisfies

$$-m^i_{t+1} = \chi z^i_t + \frac{\zeta^i + \theta x^i_t}{2} z^g_t + \sqrt{\gamma z^i_t} u^i_{t+1} + \sqrt{(\zeta^i + \theta x^i_t) z^g_t} u^g_{t+1}. \tag{16}$$

The set of shocks u^i, $i=0,1,...,N$, are country-specific shocks, whereas u^g is a global geopolitical shock, common across countries. Shocks u^i and u^g are i.i.d. standard normal. Note that a negative (positive) realization of any shock increases (decreases) m^i, so negative realizations denote adverse realizations from the perspective of investor i.

For each country i, there is a state variable z^i, which reflects the level of country-specific volatility and regulates the price of u^i shocks in that country. The state variable z^i is stationary, with law of motion

$$z^i_{t+1} = (1-\phi)\bar{z} + \phi z^i_t - \sigma\sqrt{z^i_t} u^i_{t+1}, \tag{17}$$

where $\phi \in (0,1)$, $\bar{z} > 0$, and $\sigma > 0$. Importantly, z^i is countercyclical: a negative u^i realization raises the level of z^i and, hence, the price of u^i risk next period. The parameters of the z^i law of motion (in particular, ϕ, $\bar{z}$, and σ) are identical across countries, so cross-country differences in z^i arise solely due to differences in u^i realizations.

In addition, there is a global state variable, z^g, which reflects the level of global geopolitical tension and regulates the price of global geopolitical shocks u^g across countries. Empirically, the global state variable z^g can be mapped to the Caldara and Iacoviello (2022) global geopolitical threats (GPT) index. The global state variable z^g is also stationary, with law of motion

$$z^g_{t+1} = (1-\phi^g)\bar{z}^g + \phi^g z^g_t - \sigma^g\sqrt{z^g_t}(\rho u^g_{t+1} + \sqrt{1-\rho}\varepsilon_{t+1}), \tag{18}$$

where $\phi^g \in (0,1)$, $\bar{z}^g > 0$, $\rho \in (0,1)$, and $\sigma^g > 0$. The innovations of z^g are a weighted average of the global geopolitical shock u^g and the unpriced global shock ε (which is i.i.d. standard normal). Hence, the level of global geopolitical tension z^g is not driven solely by geopolitical shocks: z^g can rise either due to a negative realization of the global geopolitical shock u^g or due to a negative realization of the unpriced global shock ε.

The exposure of each country to the global geopolitical shock u^g has a fixed component and a time-varying component. The fixed component depends on parameter ζ^i, the value of which can differ across countries. The time-varying component is a driven by the country-specific stationary state variable x^i, which has law of motion

$$x^i_{t+1} = \phi^x x^i_t + \sigma^x u^{i,x}_{t+1}, \tag{19}$$

where $\phi^x \in (0,1)$, $\sigma^x > 0$, and $u^{i,x}$ is an i.i.d. standard normal shock. Note that the parameters of the x^i law of motion (ϕ^x and σ^x) are identical across countries. The unconditional mean of x^i is zero for all countries, so the unconditional exposure of country i to geopolitical risk is ζ^i. However, the cross-sectional distribution of exposure to global geopolitical risk is

time-varying, as the cross-sectional rank of a country's exposure to geopolitical risk solely also depends on the cross-sectional rank of its state variable x^i.

C.2 Interest rates and exchange rates

The log risk-free rate of country i is

$$r_t^i = -E_t(m_{t+1}^i) - \frac{1}{2} var_t(m_{t+1}^i) = \left(\chi - \frac{\gamma}{2}\right) z_t^i. \tag{20}$$

Note that a country's exposure to geopolitical risk has nothing to do with its risk-free rate: in our model, risk-free rates convey no information regarding countries' geopolitical risk exposure. Furthermore, since $E[z_t^i] = \bar{z}$ for all i, all countries have the same unconditional interest rate mean. Those assumptions are adopted to keep the model simple and focused: our aim is to provide a framework that rationalizes our empirical findings regarding the geopolitical exposure portfolios. Since those portfolios have minimal exposure to carry risk, adding features that would help the model also rationalize the empirical properties of interest rate-sorted portfolios, albeit straightforward, would be superfluous in our context.

In what follows, we omit the superscript from domestic variables for notational convenience. Due to the assumption of market completeness, log real exchange rate changes are given by

$$\Delta s_{t+1}^i = m_{t+1}^i - m_{t+1}. \tag{21}$$

The realized log excess return that the domestic investor receives when investing in currency i is

$$rx_{t+1}^i = \Delta s_{t+1}^i + r_t^i - r_t, \tag{22}$$

so log currency returns are exposed to both domestic and foreign country-level shocks, as well as the global geopolitical shock:

$$rx_{t+1}^i - E_t(rx_{t+1}^i) = \sqrt{\gamma z_t} u_{t+1} - \sqrt{\gamma z_t^i} u_{t+1}^i + \left(\sqrt{\zeta + \theta x_t} - \sqrt{\zeta^i + \theta x_t^i}\right) \sqrt{z_t^g} u_{t+1}^g. \tag{23}$$

From the perspective of the domestic investor, the log excess return achieved by investing in a foreign currency is always positively exposed to domestic country-specific shocks and negatively exposed to the foreign country's country-specific shocks. However, the sign of the excess return exposure to global geopolitical shocks is not fixed, but depends on the relative magnitude of the geopolitical risk loading of the domestic and the foreign SDFs. In particular, when the domestic SDF loading is higher (which happens when $\zeta + \theta x_t > \zeta^i + \theta x_t^i$), then the foreign currency depreciates against the domestic currency upon a negative realization of the global geopolitical shock, so the foreign currency is geopolitically risky for the domestic investor. On the other hand, when the foreign SDF loading is higher ($\zeta^i + \theta x_t^i > \zeta + \theta x_t$), the foreign currency is a hedge against global geopolitical shocks.

The conditional currency risk premium (in levels, as the Jensen term is included) is

$$rp_t^i = E_t(rx_{t+1}^i) + \frac{1}{2} var_t(rx_{t+1}^i) = -cov_t(rx_{t+1}^i, m_{t+1}), \tag{24}$$

which yields

$$rp_t^i = \gamma z_t + \left[\left(\sqrt{\zeta + \theta x_t} - \sqrt{\zeta^i + \theta x_t^i}\right)\sqrt{\zeta + \theta x_t}\right] z_t^g. \tag{25}$$

The first term reflects the risk premium that the domestic investor requires for exposure to country-specific domestic shocks (i.e., u shocks): since the foreign currency depreciates against the domestic currency upon a negative realization of u, the domestic investor requires a positive compensation for assuming that risk. The second term is the premium for exposure to the global geopolitical shock, with the expression inside the brackets being the forecast coefficient of the currency excess return on the state variable z_t^g. The forecast coefficient (and, hence, the geopolitical risk premium) can be positive or negative, depending on whether the foreign currency is geopolitically risky or a geopolitical hedge. When the foreign currency is geopolitically risky ($\zeta + \theta x_t > \zeta^i + \theta x_t^i$), the domestic investor requires a positive premium to hold the foreign currency and the forecast coefficient is positive. On the other hand, when the foreign currency is a geopolitical risk hedge ($\zeta^i + \theta x_t^i > \zeta + \theta x_t$), the foreign currency has a negative geopolitical risk premium and the forecast coefficient is negative.[5]

C.3 Currency portfolios

An immediate corollary of the discussion above is that sorting currencies into portfolios on their geopolitical forecast coefficient is equivalent to sorting on their geopolitical risk premium: high (low) forecast coefficient currencies have high (low) premia. Hence, the geopolitical exposure portfolios, discussed in the main text of our paper, are designed to produce cross-sectional variation in exposure to global geopolitical risk.

To see that, consider the innovation of the equally-weighted log excess return of any currency portfolio P:

$$rx_{t+1}^P - E_t(rx_{t+1}^P) = \sqrt{\gamma z_t} u_{t+1} + \left(\sqrt{\zeta + \theta x_t} - \sqrt{\zeta^P + \theta x_t^P}\right)\sqrt{z_t^g} u_{t+1}^g, \tag{26}$$

where $\sqrt{\zeta^P + \theta x_t^P} \equiv \frac{1}{N_P}\sum_{i \in P}\sqrt{\zeta^i + \theta x_t^i}$ and N_p is the number of currencies in portfolio P. Note that, as is standard, we implicitly assume that N_p is large enough so that foreign country-specific shocks (which are independent of each other and of all other shocks) are diversified away: $\frac{1}{N_P}\sum_{i \in P}\sqrt{\gamma z_t^i} u_{t+1}^i \approx 0$.

The first term reflects the exposure of the portfolio excess return to the domestic country-specific shock u. Notably, that term is identical across currency portfolios, so long-short currency strategies (i.e., strategies that go long a currency portfolio P_L and short a currency portfolio P_S) have no exposure to domestic country-specific risk and earn no related premium. On the other hand, portfolios differ on their exposure to the global geopolitical shock u^g, which depends on the value of $\sqrt{\zeta^P + \theta x_t^P}$. In particular, portfolios with cross-sectionally

[5] Focusing on log (rather than level) currency excess returns, as we do in our empirical analysis, yields very similar results. In particular, the log risk premium is $E_t(rx_{t+1}^i) = \frac{1}{2}var_t(m_{t+1}) - \frac{1}{2}var_t(m_{t+1}^i) = \frac{1}{2}\gamma(z_t - z_t^i) + \frac{1}{2}\left[(\zeta + \theta x_t) - (\zeta^i + \theta x_t^i)\right] z_t^g$, so the geopolitical forecast coefficient and the geopolitical risk premium are both positive when $\zeta + \theta x_t > \zeta^i + \theta x_t^i$, and both negative when $\zeta^i + \theta x_t^i > \zeta + \theta x_t$. In fact, sorting currencies on the geopolitical forecast coefficient of log returns yields exactly the same portfolios as sorting on the geopolitical forecast coefficient of level returns. For that reason, in what follows, we make no distinction between the two sorts.

low $\sqrt{\zeta^P + \theta x_t^P}$ terms, which are those that include currencies with cross-sectionally high geopolitical forecast coefficients, have cross-sectionally high loadings on the geopolitical shock and, thus, are geopolitically risky in relative terms. Conversely, portfolios of currencies with cross-sectionally low geopolitical forecast coefficients are geopolitical hedges.

It follows that a strategy that invests in high geopolitical forecast coefficient currencies (Portfolio H) and shorts low coefficient currencies (Portfolio L), denoted by $GHML$, is solely exposed to global geopolitical risk. Indeed, the innovation of the log excess return of that strategy is

$$rx_{t+1}^{GHML} - E_t(rx_{t+1}^{GHML}) = \left(\sqrt{\zeta^L + \theta x_t^L} - \sqrt{\zeta^H + \theta x_t^H}\right)\sqrt{z_t^g}u_{t+1}^g. \tag{27}$$

Since, as discussed above, $\sqrt{\zeta^L + \theta x_t^L} > \sqrt{\zeta^H + \theta x_t^H}$, the excess return innovation is perfectly positively correlated with the global geopolitical shock u^g. Therefore, shocks in rx^{GHML} reflect global geopolitical shocks.

Furthermore, the equally-weighted portfolio that goes long all foreign currencies, denoted by DOL, has excess return innovation

$$rx_{t+1}^{DOL} - E_t(rx_{t+1}^{DOL}) = \sqrt{\gamma z_t}u_{t+1} + \left(\sqrt{\zeta + \theta x_t} - \overline{\sqrt{\zeta^i + \theta x_t^i}}\right)\sqrt{z_t^g}u_{t+1}^g, \tag{28}$$

where $\overline{\sqrt{\zeta + \theta x_t^i}} \equiv \frac{1}{N}\sum_{i=1}^N \sqrt{\zeta^i + \theta x_t^i}$. Therefore, the geopolitical riskiness of the DOL portfolio hinges on the relative geopolitical SDF loading of the domestic country. When the domestic country has a higher (lower) SDF loading on the global geopolitical shock than the average foreign country, then the DOL portfolio excess return has a positive (negative) loading on u^g and is, thus, geopolitically risky (a geopolitical hedge). If the domestic country has the same SDF loading on the global geopolitical shock as the average foreign country, then the DOL portfolio is only exposed to the domestic country-specific risk and has no exposure to the global geopolitical shock, an assumption that is consistent with the empirically observed lack of correlation between the DOL and $GHML$ returns.

Adopting that assumption, the conditional DOL and $GHML$ betas of currency portfolios P, sorted on the geopolitical forecast coefficient of excess returns, are

$$\beta_t^{P,DOL} = 1, \qquad \beta_t^{P,GHML} = \frac{\sqrt{\zeta + \theta x_t} - \sqrt{\zeta^P + \theta x_t^P}}{\sqrt{\zeta^L + \theta x_t^L} - \sqrt{\zeta^H + \theta x_t^H}}. \tag{29}$$

In the cross-section of the geopolitical exposure portfolios, DOL is a level factor: the excess returns of all portfolios have the same exposure to domestic country-specific risk as the equally-weighted DOL portfolio, so they have a unit loading on DOL. On the other hand, $GHML$ is a slope factor, as there is a positive cross-sectional association between geopolitical forecast coefficients and $GHML$ betas. In particular, portfolios that include currencies with a cross-sectionally high geopolitical forecast coefficient, which are geopolitically risky, have a positive $GHML$ loading, whereas the portfolios that include currencies with a low forecast coefficient have a negative $GHML$ loading, as they are geopolitical hedge assets.

Finally, we consider the properties of portfolios sorted on the conditional beta of currency returns on z^g changes, empirically mapped to changes in the GPT measure. For currency i,

the conditional Δz^g beta is

$$\beta_t^{i,g} = \frac{cov_t\left(rx_{t+1}^i, \Delta z_{t+1}^g\right)}{var_t\left(\Delta z_{t+1}^g\right)} = \frac{\sqrt{\zeta^i + \theta x_t^i} - \sqrt{\zeta + \theta x_t}}{\rho \sigma^g}. \tag{30}$$

It is easy to see that Δz^g betas and geopolitical forecast coefficients are negatively associated in the cross-section of currencies. Currencies with cross-sectionally low geopolitical forecast coefficients (and, hence, low $GHML$ loadings) have relatively high conditional Δz^g betas, whereas the opposite is true for currencies with high forecast coefficients. In short, the model generates a negative cross-sectional relationship between Δz^g betas and $GHML$ betas, consistent with our empirical findings.

C.4 Bond prices

The price of the riskless zero coupon bond of country i with one-period maturity and face value equal to one unit of currency i, denoted by $P^{(1),i}$, satisfies

$$P_t^{(1),i} = \mathbb{E}_t\left[M_{t+1}^i\right], \tag{31}$$

so its log price is given by

$$p_t^{(1),i} \equiv \log[P_t^{i,(1)}] = E_t(m_{t+1}^i) + \frac{1}{2} var_t(m_{t+1}^i) = -r_t^i = -\left(\chi - \frac{\gamma}{2}\right) z_t^i. \tag{32}$$

The prices of zero coupon bonds of higher maturities are pinned down by the Euler equation

$$P_t^{(k),i} = \mathbb{E}_t\left[M_{t+1}^i P_{t+1}^{(k-1),i}\right]. \tag{33}$$

We conjecture that zero coupon bond prices are exponentially affine, satisfying

$$P_t^{(k),i} = e^{-B_0^{k,i} - B_1^{k,i} z_t^i}. \tag{34}$$

Applying that conjecture, the Euler equation above yields the following recursive relationships for coefficients $B_0^{k,i}$ and $B_1^{k,i}$:

$$B_0^{k,i} = B_0^{k-1,i} + (1-\phi)\bar{z} B_1^{k-1,i}, \tag{35}$$

and

$$B_1^{k,i} = \left(\chi - \frac{\gamma}{2}\right) + (\phi + \sqrt{\gamma}\sigma) B_1^{k-1,i} - \frac{\sigma^2}{2}(B_1^{k-1,i})^2, \tag{36}$$

where $B_0^{1,i} = 0$ and $B_1^{1,i} = \chi - \frac{\gamma}{2}$. Notably, under our parametrization (in which the values of parameters ϕ, $\bar{z}$, σ, γ, and χ are common across countries), coefficients $B_0^{k,i}$ and $B_1^{k,i}$ are the same across countries, so cross-country differences in zero coupon bond prices arise only because of differences in the realizations of the z^i processes. For that reason, we omit country superscripts from those coefficients in the remainder of our discussion.

Importantly, zero coupon bond prices (and, hence, their returns) are not exposed to the

global geopolitical shock u^g, but only to country-specific shocks u^i (through the dependence on z^i). In other words, interest rate risk only reflects country-specific shocks, and, for that reason, sorting countries into portfolios on the geopolitical exposure of their currencies does not generate a spread in local currency term premia.

Indeed, the one-period local currency log return of a k-period maturity zero coupon bond is given by

$$rx_{t+1}^{(k),i} = \log\left[\frac{P_{t+1}^{(k-1),i}}{P_t^{(k),i}}\right] = B_0^k + B_1^k z_t^i - B_0^{k-1} - B_1^{k-1} z_{t+1}^i. \tag{37}$$

Hence, the local currency term premium of k-period maturity bonds, in levels, is

$$rp_t^{(k),i} = E_t(rx_{t+1}^{(k),i}) + \frac{1}{2} var_t(rx_{t+1}^{(k),i}) = -cov_t(rx_{t+1}^{(k),i}, m_{t+1}^i) = B_1^{k-1}\sqrt{\gamma}\sigma z_t^i, \tag{38}$$

so local currency term premium differences with respect to U.S. bonds satisfy

$$rp_t^{(k),i} - rp_t^{(k)} = B_1^{k-1}\sqrt{\gamma}\sigma(z_t^i - z_t). \tag{39}$$

Under the assumption that the number of currencies, N_p, in each geopolitical exposure currency portfolio is large, local currency term premium differences are almost identical across portfolios,

$$rp_t^{(k),P} - rp_t^{(k)} \equiv \frac{1}{N_p}\sum_{i\in P}(rp_t^{(k),i} - rp_t^{(k)}) = B_1^{k-1}\sqrt{\gamma}\sigma\left(\frac{1}{N_p}\sum_{i\in P} z_t^i - z_t\right) \approx B_1^{k-1}\sqrt{\gamma}\sigma\left(\bar{z} - z_t\right), \tag{40}$$

so the "geopolitical trade", which invests in the bonds of countries with high-exposure currencies and shorts the bonds of low-exposure currencies, generates a local currency term premium that is close to zero.

Finally, following Alvarez and Jermann (2005), we decompose each country's pricing kernel into a permanent and a transitory component. For country i, the transitory component is

$$\Lambda_t^{\mathbb{T},i} = \lim_{k\to\infty}\frac{\beta^{t+k}}{P_t^{(k),i}} = \lim_{k\to\infty}\beta^{t+k}e^{B_0^k + B_1^k z_t^i}, \tag{41}$$

where β is a constant that satisfies the following condition (Assumption 1 in Alvarez and Jermann (2005)):

$$0 < \lim_{k\to\infty}\frac{P_t^{(k),i}}{\beta^k} < \infty. \tag{42}$$

To satisfy the condition above, we pick $\beta = e^{-(1-\phi)\bar{z}B_1^\infty}$, where B_1^∞ satisfies the quadratic expression in Equation 36 for $k \to \infty$. Indeed, as seen in Equation 35, our choice of β fully offsets the linear growth in coefficient B_0^k as the bond maturity approaches infinity:

$$\lim_{k\to\infty}(B_0^k - B_0^{k-1}) = (1-\phi)\bar{z}B_1^\infty. \tag{43}$$

It follows that the transitory component of the log SDF of country i is

$$m_{t+1}^{\mathbb{T},i} \equiv \log\left[\frac{\Lambda_{t+1}^{\mathbb{T},i}}{\Lambda_t^{\mathbb{T},i}}\right] = \log\beta + B_1^{\infty}(z_{t+1}^i - z_t^i) = \log\beta + B_1^{\infty}((1-\phi)(\bar{z} - z_t^i) - \sigma\sqrt{z_t^i}u_{t+1}^i), \quad (44)$$

so it includes only its country-specific shock u^i. On the other hand, global geopolitical shocks u^g appear only in the permanent log SDF component, given by

$$m_{t+1}^{\mathbb{P},i} = m_{t+1}^i - m_{t+1}^{\mathbb{T},i}. \quad (45)$$

Table A1: Geopolitical exposure portfolios using FX changes

Panel A: Summary statistics						
	P1	P2	P3	P4	P5	GHML^{FX}
Mean rx	0.14	0.22	0.86	0.40	3.34	3.20
Mean Δs	-2.42	-1.48	-1.30	-1.87	-2.30	0.13
Mean IRD	2.56	1.70	2.17	2.27	5.64	3.08
Std deviation	8.62	7.88	7.89	7.10	8.63	8.50
Sharpe ratio	0.02	0.03	0.11	0.06	0.39	0.38
Skewness	-0.66	-0.34	-0.40	-0.48	-0.45	-0.16
Exc. kurtosis	2.33	1.70	1.36	1.50	1.99	1.05
Panel B: Factor loadings						
	P1	P2	P3	P4	P5	GHML^{FX}
Constant	-0.09	-0.04	0.04	0.03	0.13	0.21^{*}
	(0.08)	(0.05)	(0.06)	(0.05)	(0.08)	(0.12)
DOL	1.07^{***}	1.04^{***}	1.06^{***}	0.94^{***}	0.94^{***}	-0.14
	(0.07)	(0.05)	(0.04)	(0.04)	(0.07)	(0.13)
CAR	0.01	-0.05	-0.08^{*}	-0.12^{***}	0.11	0.10
	(0.05)	(0.04)	(0.04)	(0.03)	(0.08)	(0.11)
Observations	443	443	443	443	443	443
R^2	0.74	0.81	0.83	0.79	0.61	0.02

The table reports summary statistics (Panel A) and factor loadings (Panel B) of the monthly excess returns and factor loadings of currency portfolios sorted on the slope coefficient in a 36-month rolling forecasting regression of monthly FX changes on a measure of global geopolitical threats. The sample period is February 1988 to December 2024. Portfolio 1 (P1) includes the currencies with the lowest forecast coefficient, whereas Portfolio 5 (P5) includes the currencies with the highest forecast coefficient each month. Portfolios are monthly rebalanced and equally-weighted. GHML^{FX} is the long-short strategy that invests in Portfolio 5 and shorts Portfolio 1. Standard errors are reported in parentheses. One, two, and three stars denote statistical significance at the 1%, 5%, and 10% level, respectively.

Table A2: Factor loadings of geopolitical exposure portfolios using FX changes

	P1	P2	P3	P4	P5	P1	P2	P3	P4	P5
Constant	0.14	0.08	0.11	0.02	0.14	0.01	−0.00	0.05	0.01	0.01
	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
$GHML^{FX}$	−0.50***	−0.24**	−0.15	0.05	0.50***	−0.43***	−0.17***	−0.07**	0.13***	0.57***
	(0.09)	(0.10)	(0.10)	(0.08)	(0.09)	(0.03)	(0.02)	(0.03)	(0.03)	(0.03)
DOL						1.02***	1.02***	1.06***	0.96***	1.02***
						(0.03)	(0.03)	(0.03)	(0.04)	(0.03)
CAR						0.05**	−0.03	−0.08*	−0.14***	0.05**
						(0.03)	(0.02)	(0.04)	(0.03)	(0.03)
Obs.	443	443	443	443	443	443	443	443	443	443
Adj. R^2	0.24	0.07	0.02	0.00	0.24	0.92	0.84	0.84	0.81	0.92

The table reports the factor loadings of the monthly excess returns of currency portfolios sorted on the slope coefficient in a 36-month rolling forecasting regression of monthly FX changes on a measure of global geopolitical threats. The sample period is February 1988 to December 2024. Portfolio 1 (P1) includes the currencies with the lowest forecasting coefficient, whereas Portfolio 5 (P5) includes the currencies with the highest forecasting coefficient each month. Portfolios are monthly rebalanced and equally-weighted. The first five columns report the portfolio loadings when the log excess return of each portfolio is regressed on a constant and the geopolitical ($GHML^{FX}$) factor, whereas the last five columns report the portfolio loadings when log excess return of each portfolio is regressed on a constant, and the geopolitical ($GHML^{FX}$), dollar (DOL) and carry (CAR) factors. Standard errors are reported in parentheses. One, two, and three stars denote statistical significance at the 1%, 5%, and 10% level, respectively.

Table A3: Factor loadings of geopolitical exposure portfolios using FX changes

	P1	P2	P3	P4	P5	P5-P1	P1	P2	P3	P4	P5	P5-P1
Constant	0.14	0.09	0.11	0.02	0.15	0.01	0.00	0.00	0.05	0.00	0.00	−0.00
	(0.12)	(0.11)	(0.11)	(0.11)	(0.11)	(0.06)	(0.06)	(0.05)	(0.05)	(0.05)	(0.06)	(0.07)
GHML	−0.46***	−0.26***	−0.15	0.06	0.48***	0.94***	−0.39***	−0.18***	−0.07**	0.14***	0.54***	0.94***
	(0.09)	(0.10)	(0.10)	(0.09)	(0.09)	(0.04)	(0.03)	(0.02)	(0.03)	(0.03)	(0.03)	(0.04)
DOL							1.02***	1.02***	1.06***	0.96***	1.01***	−0.01
							(0.03)	(0.04)	(0.03)	(0.04)	(0.04)	(0.03)
CAR							0.05	−0.03	−0.08*	−0.13***	0.07*	0.02
							(0.03)	(0.03)	(0.04)	(0.03)	(0.04)	(0.04)
Obs.	443	443	443	443	443	443	443	443	443	443	443	443
Adj. R^2	0.20	0.07	0.02	0.00	0.21	0.86	0.88	0.84	0.84	0.81	0.88	0.86

The table reports the factor loadings of the monthly excess returns of currency portfolios sorted on the slope coefficient in a 36-month rolling forecasting regression of monthly FX changes on a measure of global geopolitical threats. The sample period is February 1988 to December 2024. Portfolio 1 (P1) includes the currencies with the lowest forecasting coefficient, whereas Portfolio 5 (P5) includes the currencies with the highest forecasting coefficient each month. Portfolios are monthly rebalanced and equally-weighted. The first six columns report the portfolio loadings when the log excess return of each portfolio is regressed on a constant and the geopolitical ($GHML$) factor, whereas the last six columns report the portfolio loadings when log excess return of each portfolio is regressed on a constant, and the geopolitical ($GHML$), dollar (DOL) and carry (CAR) factors. Standard errors are reported in parentheses. One, two, and three stars denote statistical significance at the 1%, 5%, and 10% level, respectively.

Table A4: Portfolios sorted on GPA and GPR return forecast coefficients

Panel A: Portfolios sorted on GPA forecast coefficient										
	P1	P2	P3	P4	P5	P1	P2	P3	P4	P5
Constant	0.13	0.09	0.10	0.13	0.13	−0.04	−0.00	0.02	0.11**	−0.04
	(0.11)	(0.12)	(0.11)	(0.10)	(0.11)	(0.04)	(0.05)	(0.06)	(0.04)	(0.04)
$GHML^{GPA}$	−0.62***	−0.38***	−0.32***	−0.13*	0.38***	−0.41***	−0.14***	−0.09***	0.10***	0.59***
	(0.09)	(0.10)	(0.09)	(0.07)	(0.09)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
DOL						0.99***	1.08***	1.05***	0.98***	0.99***
						(0.03)	(0.03)	(0.04)	(0.03)	(0.03)
CAR						0.07***	−0.06**	−0.08**	−0.14***	0.07***
						(0.02)	(0.03)	(0.04)	(0.03)	(0.02)
Obs.	443	443	443	443	443	443	443	443	443	443
Adj. R^2	0.37	0.16	0.12	0.02	0.18	0.93	0.88	0.83	0.81	0.91
Panel B: Portfolios sorted on GPR forecast coefficient										
	P1	P2	P3	P4	P5	P1	P2	P3	P4	P5
Constant	0.14	0.03	0.10	0.12	0.14	−0.02	−0.07	0.03	0.12**	−0.02
	(0.12)	(0.11)	(0.10)	(0.11)	(0.12)	(0.05)	(0.05)	(0.06)	(0.05)	(0.05)
$GHML^{GPR}$	−0.55***	−0.34***	−0.27***	−0.06	0.45***	−0.39***	−0.18***	−0.08***	0.10***	0.61***
	(0.10)	(0.10)	(0.10)	(0.06)	(0.10)	(0.02)	(0.03)	(0.02)	(0.03)	(0.02)
DOL						1.04***	0.97***	1.10***	0.92***	1.04***
						(0.03)	(0.04)	(0.03)	(0.04)	(0.03)
CAR						0.06**	−0.02	−0.08**	−0.16***	0.06**
						(0.03)	(0.03)	(0.04)	(0.03)	(0.03)
Obs.	443	443	443	443	443	443	443	443	443	443
Adj. R^2	0.27	0.13	0.07	0.00	0.20	0.93	0.83	0.85	0.78	0.92

Panels A and B report the factor loadings of the monthly excess returns of currency portfolios sorted on the slope coefficient in a 36-month rolling forecasting regression of monthly currency excess returns on GPA and GPR, respectively. The sample period is February 1988 to December 2024. In each panel, Portfolio 1 (P1) includes the currencies with the lowest forecasting coefficient, whereas Portfolio 5 (P5) includes the currencies with the highest forecasting coefficient each month. Portfolios are monthly rebalanced and equally-weighted. In each panel, the first five columns report the portfolio loadings when the log excess return of each portfolio is regressed on a constant and the geopolitical ($GHML^{GPA}$ or ($GHML^{GPR}$) factor, whereas the last six columns report the portfolio loadings when log excess return of each portfolio is regressed on a constant, and the geopolitical ($GHML^{GPA}$ or ($GHML^{GPR}$), dollar (DOL) and carry (CAR) factors. Standard errors are reported in parentheses. One, two, and three stars denote statistical significance at the 1%, 5%, and 10% level, respectively.

Table A5: Portfolios sorted on GPA and GPR return forecast coefficients

Panel A: Portfolios sorted on GPA forecast coefficient												
	P1	P2	P3	P4	P5	P5-P1	P1	P2	P3	P4	P5	P5-P1
Constant	0.10	0.07	0.08	0.12	0.12	0.02	−0.03	0.00	0.03	0.11**	−0.05	−0.02
	(0.13)	(0.13)	(0.11)	(0.10)	(0.11)	(0.10)	(0.06)	(0.05)	(0.06)	(0.05)	(0.08)	(0.11)
GHML	−0.26**	−0.16	−0.13	−0.03	0.25***	0.51***	−0.18***	−0.07**	−0.05*	0.04	0.30***	0.48***
	(0.12)	(0.12)	(0.10)	(0.08)	(0.09)	(0.11)	(0.03)	(0.03)	(0.03)	(0.03)	(0.07)	(0.10)
DOL							1.13***	1.13***	1.07***	0.94***	0.79***	−0.35***
							(0.05)	(0.04)	(0.04)	(0.03)	(0.08)	(0.13)
CAR							0.02	−0.08**	−0.08**	−0.13***	0.14**	0.11
							(0.03)	(0.03)	(0.04)	(0.03)	(0.06)	(0.08)
Obs.	443	443	443	443	443	443	443	443	443	443	443	443
Adj. R^2	0.06	0.02	0.02	−0.00	0.07	0.23	0.81	0.86	0.82	0.80	0.61	0.30
Panel B: Portfolios sorted on GPR forecast coefficient												
	P1	P2	P3	P4	P5	P5-P1	P1	P2	P3	P4	P5	P5-P1
Constant	0.16	0.05	0.10	0.10	0.09	−0.06	0.03	−0.04	0.04	0.10*	−0.07	−0.10
	(0.13)	(0.12)	(0.11)	(0.11)	(0.12)	(0.06)	(0.05)	(0.05)	(0.06)	(0.05)	(0.07)	(0.07)
GHML	−0.40***	−0.26**	−0.15	0.05	0.43***	0.83***	−0.32***	−0.18***	−0.06**	0.12***	0.49***	0.81***
	(0.10)	(0.10)	(0.11)	(0.08)	(0.09)	(0.05)	(0.02)	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)
DOL							1.11***	1.00***	1.12***	0.91***	0.93***	−0.18**
							(0.03)	(0.04)	(0.03)	(0.03)	(0.06)	(0.07)
CAR							0.03	−0.03	−0.09**	−0.16***	0.12**	0.09**
							(0.03)	(0.03)	(0.04)	(0.03)	(0.05)	(0.04)
Obs.	443	443	443	443	443	443	443	443	443	443	443	443
Adj. R^2	0.14	0.07	0.02	0.00	0.18	0.68	0.89	0.83	0.84	0.79	0.80	0.70

Panel A and B report the factor loadings of the monthly excess returns of currency portfolios sorted on the slope coefficient in a 36-month rolling forecasting regression of monthly currency excess returns on GPA and GPR, respectively. The sample period is February 1988 to December 2024. In each panel, Portfolio 1 (P1) includes the currencies with the lowest forecasting coefficient, whereas Portfolio 5 (P5) includes the currencies with the highest forecasting coefficient each month. Portfolios are monthly rebalanced and equally-weighted. In each panel, the first six columns report the portfolio loadings when the log excess return of each portfolio is regressed on a constant and the geopolitical ($GHML$) factor, whereas the last six columns report the portfolio loadings when log excess return of each portfolio is regressed on a constant, and the geopolitical ($GHML$), dollar (DOL) and carry (CAR) factors. Standard errors are reported in parentheses. One, two, and three stars denote statistical significance at the 1%, 5%, and 10% level, respectively.

Table A6: Portfolios sorted on conditional $GHML$ beta

Panel A: Summary statistics						
	P1	P2	P3	P4	P5	P5 - P1
Mean rx	0.62	0.12	1.04	-0.85	2.34	1.72
Mean Δs	-2.04	-2.81	-1.58	-2.49	-2.57	-0.53
Mean IRD	2.66	2.93	2.62	1.64	4.91	2.25
Std deviation	9.14	8.68	7.67	7.18	8.02	9.52
Sharpe ratio	0.07	0.01	0.14	-0.12	0.29	0.18
Skewness	-0.66	-0.52	-0.51	-0.57	-0.34	0.16
Exc. kurtosis	2.58	1.37	2.01	3.55	2.36	0.77
Panel B: Univariate factor loadings						
	P1	P2	P3	P4	P5	P5 - P1
Constant	0.13	0.08	0.14	-0.03	0.13	0.00
	(0.15)	(0.13)	(0.11)	(0.11)	(0.12)	(0.12)
GHML	-0.25^{**}	-0.23^{**}	-0.19^{*}	-0.13	0.21^{**}	0.47^{***}
	(0.11)	(0.11)	(0.10)	(0.08)	(0.11)	(0.11)
Obs.	407	407	407	407	407	407
Adj. R^2	0.05	0.05	0.04	0.02	0.05	0.17
Panel C: Multivariate factor loadings						
	P1	P2	P3	P4	P5	P5 - P1
Constant	0.03	0.00	0.07	-0.06	-0.00	-0.04
	(0.09)	(0.06)	(0.06)	(0.04)	(0.07)	(0.13)
GHML	-0.11^{*}	-0.08^{**}	-0.06^{*}	0.00	0.31^{***}	0.42^{***}
	(0.06)	(0.03)	(0.03)	(0.03)	(0.07)	(0.12)
DOL	1.11^{***}	1.15^{***}	1.01^{***}	0.97^{***}	0.85^{***}	-0.26^{*}
	(0.07)	(0.03)	(0.04)	(0.05)	(0.08)	(0.13)
CAR	-0.02	-0.05	-0.05	-0.11^{***}	0.09	0.11
	(0.05)	(0.03)	(0.04)	(0.03)	(0.06)	(0.10)
Obs.	407	407	407	407	407	407
Adj. R^2	0.72	0.82	0.80	0.80	0.61	0.20

The table reports summary statistics and factor loadings of the monthly excess returns of currency portfolios sorted on the 36-month rolling univariate $GHML$ beta. The sample period is February 1991 to December 2024. Portfolio 1 (P1) includes the currencies with the lowest rolling beta, whereas Portfolio 5 (P5) includes the currencies with the highest rolling beta, each month. Portfolios are monthly rebalanced and equally-weighted. In Panel B, the log excess return of each portfolio is regressed on a constant and the geopolitical ($GHML$) factor, whereas in Panel C the log excess return of each portfolio is regressed on a constant, and the geopolitical ($GHML$), dollar (DOL) and carry (CAR) factors. Standard errors are reported in parentheses. One, two, and three stars denote statistical significance at the 1%, 5%, and 10% level, respectively.

Table A7: Factor loadings of developed and emerging country geopolitical exposure portfolios

Panel A: Developed country currencies								
	P1	P2	P3	P4	P1	P2	P3	P4
Constant	0.01	−0.07	0.05	0.01	0.02	−0.05	0.06	0.02
	(0.12)	(0.12)	(0.14)	(0.12)	(0.03)	(0.05)	(0.04)	(0.03)
GHML	−0.69***	−0.26**	−0.13	0.31***	−0.50***	−0.05*	0.09***	0.50***
	(0.09)	(0.13)	(0.14)	(0.09)	(0.02)	(0.03)	(0.03)	(0.02)
DOL					0.94***	1.06***	1.08***	0.94***
					(0.01)	(0.03)	(0.02)	(0.01)
CAR					−0.00	−0.03	0.02	−0.00
					(0.02)	(0.04)	(0.03)	(0.02)
Obs.	443	443	443	443	443	443	443	443
Adj. R^2	0.28	0.04	0.01	0.07	0.96	0.84	0.87	0.95
Panel B: Emerging country currencies								
	P1	P2	P3	P4	P1	P2	P3	P4
Constant	0.09	0.05	0.16	0.09	−0.07	0.00	0.11*	−0.07
	(0.12)	(0.09)	(0.10)	(0.12)	(0.06)	(0.06)	(0.06)	(0.06)
GHML	−0.28***	−0.01	0.05	0.72***	−0.38***	−0.06**	−0.01	0.62***
	(0.11)	(0.05)	(0.05)	(0.11)	(0.04)	(0.02)	(0.02)	(0.04)
DOL					1.05***	0.83***	0.88***	1.05***
					(0.08)	(0.08)	(0.05)	(0.08)
CAR					0.11***	−0.05	−0.04	0.11***
					(0.04)	(0.04)	(0.04)	(0.04)
Obs.	443	443	443	443	443	443	443	443
Adj. R^2	0.13	−0.00	0.00	0.49	0.84	0.61	0.65	0.91

The table reports the factor loadings of the monthly excess returns of developed and emerging country geopolitical exposure currency portfolios, i.e., portfolios of currencies sorted on the slope coefficient in a 36-month rolling forecasting regression of monthly currency excess returns on a measure of global geopolitical threats. The sample period is February 1988 to December 2024. Portfolio 1 (P1) includes the currencies with the lowest forecast coefficient, whereas Portfolio 5 (P5) includes the currencies with the highest forecast coefficient each month. Portfolios are monthly rebalanced and equally-weighted. In Panel A (Panel B), currency factors are constructed using only developed (emerging) country currencies. In each panel, the first five columns report the portfolio loadings when the log excess return of each portfolio is regressed on a constant and the geopolitical ($GHML$) factor, whereas the last five columns report the portfolio loadings when log excess return of each portfolio is regressed on a constant, and the geopolitical ($GHML$), dollar (DOL) and carry (CAR) factors. Standard errors are reported in parentheses. One, two, and three stars denote statistical significance at the 1%, 5%, and 10% level, respectively.

Table A8: Geopolitical exposure portfolios – longer-horizon returns

Panel A: 3-month excess returns						
	P1	P2	P3	P4	P5	GHML
Mean rx	0.31	0.07	0.24	0.60	2.90	2.59
Mean Δs	-2.10	-1.57	-1.90	-1.32	-2.26	-0.16
Mean IRD	2.41	1.64	2.14	1.92	5.16	2.75
Std deviation	9.42	8.25	8.56	7.64	9.02	8.46
Sharpe ratio	0.03	0.01	0.03	0.08	0.32	0.31
Skewness	-0.96	-0.30	-0.56	-0.47	0.04	0.12
Exc. kurtosis	5.29	1.92	2.37	0.74	1.17	1.14
Panel B: 12-month excess returns						
	P1	P2	P3	P4	P5	GHML
Mean rx	0.10	-0.30	-0.16	0.47	3.04	2.93
Mean Δs	-2.16	-1.74	-2.04	-1.39	-1.62	0.53
Mean IRD	2.26	1.44	1.88	1.86	4.66	2.40
Std deviation	8.66	8.26	8.50	7.72	10.54	8.53
Sharpe ratio	0.01	-0.04	-0.02	0.06	0.29	0.34
Skewness	0.08	0.01	-0.06	-0.07	0.64	0.82
Exc. kurtosis	-0.07	0.11	0.40	-0.06	1.74	1.98

Panels A and B report the summary statistics of overlapping 3-month and 12-month excess returns, respectively, of geopolitical exposure currency portfolios, i.e., portfolios of currencies sorted on the slope coefficient in a 36-month rolling forecasting regression of currency excess returns on a measure of global geopolitical threats. The sample period for the 3-month returns is April 1988 to December 2024 and the sample period for the 12-month returns is January 1989 to December 2024. Portfolio 1 (P1) includes the currencies with the lowest forecast coefficient, whereas Portfolio 5 (P5) includes the currencies with the highest forecast coefficient each month. Portfolios are monthly rebalanced and equally-weighted. $GHML$ is the long-short strategy that invests in Portfolio 5 and shorts Portfolio 1.

Table A9: Factor loadings of 3-month returns of geopolitical exposure portfolios

	P1	P2	P3	P4	P5	P1	P2	P3	P4	P5
Constant	0.44	0.18	0.22	0.16	0.44	0.09	0.02	0.01	0.08	0.09
	(0.39)	(0.45)	(0.44)	(0.48)	(0.39)	(0.18)	(0.13)	(0.16)	(0.16)	(0.18)
GHML	-0.55^{***}	-0.25^{**}	-0.24^{*}	-0.01	0.45^{***}	-0.42^{***}	-0.13^{***}	-0.11^{***}	0.10^{***}	0.58^{***}
	(0.16)	(0.13)	(0.12)	(0.12)	(0.16)	(0.04)	(0.03)	(0.03)	(0.04)	(0.04)
DOL						1.03^{***}	1.02^{***}	1.05^{***}	0.97^{***}	1.03^{***}
						(0.04)	(0.04)	(0.04)	(0.05)	(0.04)
CAR						0.03	-0.09^{***}	-0.06	-0.13^{***}	0.03
						(0.04)	(0.03)	(0.04)	(0.05)	(0.04)
Obs.	441	441	441	441	441	441	441	441	441	441
Adj. R^2	0.24	0.07	0.05	-0.00	0.18	0.91	0.85	0.84	0.80	0.91

The table reports the factor loadings of the overlapping 3-month excess returns of geopolitical exposure currency portfolios, i.e., portfolios of currencies sorted on the slope coefficient in a 36-month rolling forecasting regression of monthly currency excess returns on a measure of global geopolitical threats. The sample period is April 1988 to December 2024. Portfolio 1 (P1) includes the currencies with the lowest forecast coefficient, whereas Portfolio 5 (P5) includes the currencies with the highest forecast coefficient each month. Portfolios are monthly rebalanced and equally-weighted. $GHML$ is the long-short strategy that invests in Portfolio 5 and shorts Portfolio 1. Standard errors are reported in parentheses. One, two, and three stars denote statistical significance at the 1%, 5%, and 10% level, respectively.

Table A10: Factor loadings of 12-month returns of geopolitical exposure portfolios

	P1	P2	P3	P4	P5	P1	P2	P3	P4	P5
Constant	0.84	−0.03	0.16	0.30	0.84	0.57	0.07	−0.14	0.46	0.57
	(1.92)	(1.56)	(1.46)	(1.31)	(1.92)	(0.55)	(0.43)	(0.67)	(0.38)	(0.55)
GHML	−0.25	−0.09	−0.11	0.06	0.75***	−0.34***	−0.13***	−0.20***	0.03	0.66***
	(0.17)	(0.14)	(0.14)	(0.09)	(0.17)	(0.05)	(0.05)	(0.06)	(0.04)	(0.05)
DOL						1.02***	1.02***	0.96***	0.95***	1.02***
						(0.06)	(0.06)	(0.05)	(0.05)	(0.06)
CAR						−0.01	−0.12***	0.00	−0.13***	−0.01
						(0.07)	(0.04)	(0.09)	(0.04)	(0.07)
Obs.	432	432	432	432	432	432	432	432	432	432
Adj. R^2	0.06	0.01	0.01	0.00	0.37	0.88	0.82	0.77	0.80	0.92

The table reports the factor loadings of the overlapping 12-month excess returns of geopolitical exposure currency portfolios, i.e., portfolios of currencies sorted on the slope coefficient in a 36-month rolling forecasting regression of monthly currency excess returns on a measure of global geopolitical threats. The sample period is January 1989 to December 2024. Portfolio 1 (P1) includes the currencies with the lowest forecast coefficient, whereas Portfolio 5 (P5) includes the currencies with the highest forecast coefficient each month. Portfolios are monthly rebalanced and equally-weighted. $GHML$ is the long-short strategy that invests in Portfolio 5 and shorts Portfolio 1. Standard errors are reported in parentheses. One, two, and three stars denote statistical significance at the 1%, 5%, and 10% level, respectively.

Table A11: Portfolios sorted on unconditional geopolitical exposure

Panel A: Summary statistics						
	P1	P2	P3	P4	P5	P5 - P1
Mean rx	2.84	1.15	2.25	1.17	3.20	0.36
Mean Δs	-0.07	0.57	0.13	-1.36	-4.93	-4.86
Mean IRD	2.91	0.58	2.12	2.53	8.13	5.23
Std deviation	8.34	8.50	7.66	7.38	8.37	7.25
Sharpe ratio	0.34	0.14	0.29	0.16	0.38	0.05
Skewness	-0.39	-0.11	-0.36	-0.33	-1.08	-0.20
Exc. kurtosis	1.27	1.54	1.05	1.76	4.17	2.23
Panel B: Factor loadings						
	P1	P2	P3	P4	P5	P5 - P1
Constant	0.10^{**}	0.03	0.04	-0.02	-0.14^{**}	-0.24^{**}
	(0.05)	(0.04)	(0.04)	(0.05)	(0.06)	(0.09)
GHML	-0.08^{***}	-0.03	-0.05^{**}	0.02	0.13^{***}	0.21^{***}
	(0.03)	(0.03)	(0.02)	(0.03)	(0.04)	(0.05)
DOL	1.04^{***}	1.09^{***}	1.01^{***}	0.98^{***}	0.88^{***}	-0.16^{*}
	(0.04)	(0.04)	(0.03)	(0.05)	(0.05)	(0.09)
CAR	-0.07	-0.22^{***}	-0.01	-0.09^{**}	0.38^{***}	0.45^{***}
	(0.05)	(0.03)	(0.02)	(0.04)	(0.05)	(0.08)
Obs.	443	443	443	443	443	443
Adj. R^2	0.84	0.87	0.89	0.84	0.80	0.33

The table reports summary statistics (Panel A) and factor loadings (Panel B) of the monthly excess returns of currency portfolios sorted on the slope coefficient in an unconditional forecasting regression of monthly currency excess returns on a measure of global geopolitical threats. The sample period is February 1988 to December 2024. Portfolio 1 (P1) includes the currencies with the lowest forecast coefficient, whereas Portfolio 5 (P5) includes the currencies with the highest forecast coefficient. Portfolios are equally-weighted. P5-P1 is the long-short strategy that invests in Portfolio 5 and shorts Portfolio 1. Standard errors are reported in parentheses. One, two, and three stars denote statistical significance at the 1%, 5%, and 10% level, respectively.

Table A12: Sorting on geopolitical exposure of quarterly capital flows

Panel A: Sorting on exposure of net capital flows				
	P1	P2	P3	SMD
Constant	0.05	−0.10	0.25**	0.20
	(0.23)	(0.20)	(0.12)	(0.28)
GHML	0.06	−0.08*	−0.09**	−0.15***
	(0.04)	(0.05)	(0.04)	(0.04)
DOL	1.10***	0.92***	1.03***	−0.07
	(0.07)	(0.06)	(0.05)	(0.09)
CAR	−0.07	0.02	−0.24***	−0.17**
	(0.07)	(0.06)	(0.04)	(0.07)
Obs.	122	122	122	122
Adj. R^2	0.83	0.78	0.86	0.17
Panel B: Sorting on exposure of net FDI flows				
	P1	P2	P3	P3 - P1
Constant	−0.00	−0.08	0.30**	0.30
	(0.18)	(0.16)	(0.15)	(0.23)
GHML	−0.04	−0.06**	−0.01	0.03
	(0.06)	(0.03)	(0.04)	(0.08)
DOL	1.12***	0.95***	0.98***	−0.13
	(0.06)	(0.04)	(0.06)	(0.09)
CAR	−0.00	−0.02	−0.27***	−0.27***
	(0.07)	(0.04)	(0.06)	(0.09)
Obs.	122	122	122	122
Adj. R^2	0.84	0.85	0.82	0.21
Panel C: Sorting on exposure of net portfolio flows				
	P1	P2	P3	P3 - P1
Constant	0.06	−0.05	0.21*	0.15
	(0.23)	(0.18)	(0.12)	(0.29)
GHML	0.04	−0.08	−0.07	−0.10**
	(0.05)	(0.06)	(0.04)	(0.05)
DOL	1.01***	0.97***	1.07***	0.05
	(0.07)	(0.06)	(0.05)	(0.09)
CAR	−0.13*	0.07	−0.24***	−0.12
	(0.07)	(0.06)	(0.05)	(0.07)
Obs.	122	122	122	122
Adj. R^2	0.79	0.81	0.87	0.07

The table reports factor loadings of the quarterly excess returns of currency portfolios sorted on the slope coefficient in a 24-quarter rolling forecasting regression of the quarterly net capital flows (Panel A), net FDI flows (Panel B), or net portfolio flows (Panel C) of the corresponding country on a measure of global geopolitical threats. The sample period is 1994:Q3 to 2024:Q4. Portfolio 1 (P1) includes the currencies with the lowest forecasting coefficient, whereas Portfolio 3 (P3) includes the currencies with the highest forecasting coefficient, each quarter. Portfolios are quarterly rebalanced and equally-weighted. Standard errors are reported in parentheses. One, two, and three stars denote statistical significance at the 1%, 5%, and 10% level, respectively.

Table A13: Sorting on forecast coefficients of global uncertainty measures

Panel A: Portfolios sorted on GEPU forecast coefficient						
	P1	P2	P3	P4	P5	P5-P1
Constant	−0.03	0.01	0.06	−0.03	−0.03	−0.00
	(0.06)	(0.07)	(0.06)	(0.08)	(0.09)	(0.13)
GHML	−0.01	0.07*	−0.03	0.00	0.01	0.02
	(0.05)	(0.04)	(0.02)	(0.04)	(0.07)	(0.12)
DOL	0.96***	1.08***	1.09***	1.03***	0.95***	−0.02
	(0.06)	(0.05)	(0.04)	(0.06)	(0.09)	(0.14)
CAR	0.07	−0.05	−0.12***	−0.06	0.10*	0.03
	(0.04)	(0.03)	(0.03)	(0.05)	(0.06)	(0.08)
Obs.	299	299	299	299	299	299
Adj. R^2	0.74	0.81	0.84	0.75	0.63	−0.01
Panel B: Portfolios sorted on WUI forecast coefficient						
	P1	P2	P3	P4	P5	P5-P1
Constant	0.13	−0.01	−0.08	0.05	−0.11	−0.24
	(0.09)	(0.06)	(0.09)	(0.06)	(0.09)	(0.16)
GHML	−0.02	0.13***	−0.00	−0.06	−0.05	−0.03
	(0.04)	(0.04)	(0.05)	(0.04)	(0.06)	(0.07)
DOL	0.93***	0.99***	1.02***	1.03***	1.04***	0.11
	(0.06)	(0.04)	(0.03)	(0.04)	(0.04)	(0.09)
CAR	−0.07**	−0.11**	−0.06	−0.09***	0.32***	0.39***
	(0.03)	(0.04)	(0.05)	(0.03)	(0.08)	(0.10)
Obs.	167	167	167	167	167	167
Adj. R^2	0.75	0.83	0.82	0.87	0.84	0.24

The table reports the factor loadings of the monthly excess returns of currency portfolios. Panels A and B report the factor loadings of portfolios sorted on the slope coefficient in a 36-month rolling forecasting regression of monthly currency excess returns on the Global Economic Policy Uncertainty (GEPU) index and the World Uncertainty Index (WUI), respectively. The sample period is February 2000 to December 2024 for Panel A and February 2011 to December 2024 for Panel B. In each panel, Portfolio 1 (P1) includes the currencies with the lowest forecasting coefficient, whereas Portfolio 5 (P5) includes the currencies with the highest forecasting coefficient each month. Portfolios are monthly rebalanced and equally-weighted. Standard errors are reported in parentheses. One, two, and three stars denote statistical significance at the 1%, 5%, and 10% level, respectively.

Table A14: Portfolios sorted on rolling mean of country-level GPR index

Panel A: Summary statistics						
	P1	P2	P3	P4	P5	P5 - P1
Mean rx	0.50	1.47	0.68	1.60	0.52	0.03
Mean Δs	-2.13	-0.92	-2.79	-4.88	-2.61	-0.47
Mean IRD	2.63	2.39	3.47	6.47	3.13	0.50
Std deviation	7.99	8.01	9.10	7.25	7.33	6.17
Sharpe ratio	0.06	0.18	0.07	0.22	0.07	0.00
Skewness	-1.23	-0.32	-0.34	-0.94	-0.47	1.45
Exc. kurtosis	4.93	0.44	2.31	3.17	2.09	9.69
Panel B: Factor loadings						
	P1	P2	P3	P4	P5	P5 - P1
Constant	−0.03	0.07	−0.05	−0.00	−0.04	−0.02
	(0.07)	(0.05)	(0.06)	(0.08)	(0.07)	(0.11)
GHML	−0.03	−0.05	0.06	0.03	−0.01	0.03
	(0.03)	(0.04)	(0.05)	(0.03)	(0.04)	(0.05)
DOL	1.03***	1.04***	1.18***	0.85***	0.87***	−0.16**
	(0.05)	(0.04)	(0.04)	(0.04)	(0.05)	(0.08)
CAR	−0.01	−0.02	0.00	0.10*	0.04	0.05
	(0.03)	(0.03)	(0.05)	(0.05)	(0.07)	(0.09)
Obs.	443	443	443	443	443	443
Adj. R^2	0.80	0.80	0.80	0.70	0.70	0.03

The table reports summary statistics (Panel A) and factor loadings (Panel B) of the monthly excess returns of currency portfolios sorted on the 36-month rolling mean of the corresponding country's GPR index. The sample period is February 1988 to December 2024. Portfolio 1 (P1) includes the currencies with the lowest GPR index rolling mean, whereas Portfolio 5 (P5) includes the currencies with the highest GPR index rolling mean, each month. Portfolios are monthly rebalanced and equally-weighted. Standard errors are reported in parentheses. One, two, and three stars denote statistical significance at the 1%, 5%, and 10% level, respectively.