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Abstract

This study investigates how geopolitical risk shapes the relationship between stock and currency markets. We address the limited evidence on their joint dynamics under uncertainty. While prior literature shows that geopolitical risk affects individual financial markets, less is known about its role in the stock–currency interdependence across different economies. Using local Gaussian partial correlations and bootstrap inference for advanced and emerging economies, we analyze nonlinear and asymmetric dependence patterns. Our results show that in advanced economies, stock returns and currency changes are negatively linked, consistent with portfolio balance and flow-oriented theories, whereas emerging markets display positive dependence, reflecting capital flow and risk-based channels. Lead–lag effects reveal that exchange rates dominate in emerging markets, while advanced markets exhibit bidirectional interactions. Under elevated geopolitical risk, dependence strengthens and tail risks become more synchronized, particularly in emerging markets. These findings advance our understanding of cross-market transmission and inform policies on financial stability during geopolitical crises.

Keywords: Stock market; Currency market; Geopolitical risk; Bootstrap analysis; Local Gaussian partial correlation

JEL Codes: Q02; Q43; Q47; E44; G1; C11

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1 Introduction

A key question in international financial research is whether the currency market leads or lags the stock market. Competing theoretical models support different causal directions. The flow-oriented model (Dornbusch and Fischer, 1980) suggests that exchange rate movements influence stock prices, whereas the stock-oriented model (e.g., Gavin, 1989; Branson, 1981; Frankel, 1992; Hau and Rey, 2004) posits the reverse, attributing changes in exchange rates to stock market dynamics. When both mechanisms operate simultaneously, a feedback loop may arise, resulting in a complex and potentially nonlinear relationship. Furthermore, geopolitical risk has been increasingly recognized as a key factor in shaping this interaction (Berkman et al., 2011; Caldara and Iacoviello, 2022). Periods of heightened geopolitical tension often trigger simultaneous reactions in both markets, amplifying volatility and altering the strength and direction of their correlation. Thus, understanding the role of geopolitical uncertainty is essential in assessing both the contemporaneous co-movements and the lead-lag dynamics between exchange rates and stock prices.

This paper considers a broad set of equity-currency pairs and examines their nonlinear contemporaneous and lead-lag relationship. More specifically, we construct aggregate stock and exchange rate indices using a set of 20 countries (10 advanced economies (AEs henceforth) and 10 emerging and developing economies, (EMDEs, henceforth)) and employ a nonlinear local measure of dependence called local Gaussian correlation. Using a bootstrap procedure allows us to distinguish, on the one hand, between positive and negative local dependence quantifying the validity of the correlation estimations by the construction of confidence intervals and, on the other hand, between different states of the market (bulling or bearing).

With regard to the relationship between the stock and foreign exchange markets, there are valid arguments for both positive and negative correlations. For AEs, Hau and Rey (2006) using data from 17 OECD countries, develop a theoretical model that generates a systematic negative relationship between stock and exchange rate returns through order flows in the foreign exchange market, leading to the first hypothesis:

H1: Stock and currency markets in the AEs are negatively correlated.

Yet, the relationship between foreign exchange (FX) and the stock market is of equal significance in EMDEs, since both play an important role in their financial system. Because bond markets in these economies are exposed to factors such as policy changes, managing exchange rates, speculative attacks, and capital inflows and outflows (Reboredo et al., 2016), they are less attractive to international investors compared to equities (Cho et al., 2016). Thus, we expect that the EMDEs currencies appreciate (depreciate) when stock market prices increase (decrease). This aligns with the idea that rising

(falling) stock markets tend to attract (deter) capital inflows, as foreign investors show greater (less) interest in local assets—ultimately increasing (lowering) the value of the domestic currency. This forms our second hypothesis:

H2: Stock and currency markets in the EMDEs are positively correlated.

Furthermore, geopolitical risks are considered key determinants of investment decisions and financial market dynamics, and therefore they will plausibly exert movements in the stock and currency markets (Chen and Siems, 2007; Brounen and Derwall, 2010; Berkman et al., 2011). An increase in geopolitical risk can significantly affect the correlation between the two major financial markets, but the effect differs between AEs and EMDEs. Consequently, our objective is to address this empirical question by adopting the partial local Gaussian correlation approach of Otneim and Tjøstheim (2022), which allows us to simultaneously examine the dependence structure of the two major financial markets for four different market states (bull or bear markets associated with currency appreciation or depreciation), under moderate and high levels of geopolitical uncertainty. To capture global geopolitical risks, we employ the geopolitical risk (GPR) index provided by Caldara and Iacoviello (2022). This index is constructed by using the number of occurrences of words linked to geopolitical tensions (such as wars, terrorist events, and political tensions) that appeared in 11 of the foremost international newspapers. These adverse events induce additional uncertainty in capital markets that strain both domestic and international relations.

Academic research has shown that during times of uncertainty or geopolitical tension, foreign capital tends to shift from EMDEs to AEs, based on the assumption that currencies of developed countries can serve as safe havens when risk aversion increases (Fatum and Yamamoto, 2016; Caldara and Iacoviello, 2022). In this context, in AEs we would expect a stock market decline due to capital flight and a currency appreciation as investors seek safety. Since the stock market is falling while the domestic currency is strengthening, the correlation between the two becomes more negative. EMDEs typically have riskier assets and weaker currencies that are more sensitive to external shocks. Thus, when geopolitical risk rises, stock markets decline as foreign investors pull out capital, and the domestic currency depreciates as capital outflows intensify. Since both the stock market and the currency are falling at the same time, the correlation between the two becomes more positive. This forms our third hypothesis:

H3: When geopolitical risk increases, the correlation becomes more negative in AEs and more positive in EMDEs.

Our baseline results reveal a clear divergence in the contemporaneous relationship between the stock and foreign exchange markets across AEs and EMDEs. For advanced markets, the local Gaussian correlation estimates are consistently negative across the conditional distribution, ranging from approximately -0.25 to -0.45. This negative correlation aligns with the return chasing hypothesis of Hau

and Rey (2006), where rising domestic equity prices attract foreign capital inflows, leading to currency appreciation and thus a negative co-movement between stock returns and exchange rate changes. Additional theoretical support is provided by the portfolio balance and flow-oriented models, which emphasize capital reallocation and trade dynamics in shaping exchange rate movements. In contrast, for the EMDEs, we observe a significant and positive contemporaneous correlation, which can be interpreted through the lens of the portfolio rebalancing theory, whereby stock market booms may trigger capital outflows and currency depreciation, as well as through portfolio balance effects that reflect shifts in investor preferences between domestic and foreign assets.

Considering the exchange rate as the leading market, we find that in advanced countries, moderate currency depreciations precede stock market increases, with significant negative local correlations observed in the right tail of the conditional distribution—consistent with the export competitiveness effect proposed by Dornbusch (1976). However, in EMDEs, the relationship is concentrated in the left tail, where extreme currency appreciations precede stock market declines, reflecting vulnerabilities related to export dependency, interest rate sensitivity, capital flow shifts, and commodity exposure. In contrast, when stock markets are modelled as the leading market, AEs exhibit significant positive local correlations in the right tail, suggesting that stock price increases may lead to currency depreciations, potentially due to capital outflows, monetary policy expectations, or deteriorating trade balances. In EMDEs, the estimated local correlations are weaker and statistically insignificant across the distribution, highlighting the relatively limited role of the stock markets in influencing exchange rates. This asymmetry underscores the structural and institutional differences between country groups, with currency markets playing a more dominant role in EMDEs, while advanced markets exhibit more bidirectional interactions.

Under conditions of elevated geopolitical risk, we reveal distinct patterns in the dependence structure for the two major financial markets between AEs and EMDEs. In advanced countries, we find strong negative local partial correlations during both downturns and booms in equity markets, suggesting an intensified flight-to-quality effect and the role of domestic currencies as safe-haven assets. These results align with the risk-aversion and safe-haven flow mechanisms observed in the literature (e.g., Ranaldo and Söderlind, 2010; Habib and Stracca, 2012). In contrast, EMDEs exhibit consistently positive local dependencies across market regimes, with the strongest effects occurring when stock markets decline and local currencies appreciate. This pattern is consistent with the flow-oriented exchange rate models (Dornbusch and Fischer, 1980) and reflects structural vulnerabilities such as capital flight, foreign debt exposure, current account imbalances, and pro-cyclical monetary responses (e.g., Calvo and Reinhart, 2002; Krugman, 1988). These contrasting dynamics highlight the differentiated roles that financial markets and policy environments play under geopolitical stress between country groups.

The theoretical justification for examining the tail dependence between exchange rate volatility and stock return volatility lies in the interconnectedness of financial markets through mechanisms such as shock transmission, risk, and uncertainty (see for example, [Bekaert and Harvey, 1997](#); [Dungey and Martin, 2007](#); [Diebold and Yilmaz, 2009](#)). During periods of high uncertainty, these interactions are amplified, leading to extreme co-movements between the volatilities of the two variables. Under elevated geopolitical risk, we find a substantial increase in tail dependence in both country groups, with strong co-movements observed across the different market conditions. Our results highlight that in periods of increased global uncertainty, shocks can propagate more synchronously across asset classes, reinforcing the view that financial market volatility is increasingly shaped by global risk factors rather than domestic fundamentals alone.

Finally, using the cross-quantilogram methodology introduced by [Han et al. \(2016\)](#), this study explores the dependence structure in the tails of the joint distribution between stock market returns and exchange rate changes, with a particular focus on the persistence and asymmetry of extreme co-movements. By analyzing high- and low-quantile interactions over a horizon of up to 30 trading days, we uncover notable differences between AEs and EMDEs. In advanced markets, large increases in stock returns tend to coincide with short-term depreciation of the domestic currency, possibly reflecting profit-taking behavior or portfolio rebalancing by foreign investors. In contrast, when stock returns decline sharply, a mild appreciation of the currency is observed, potentially driven by flight-to-safety dynamics. In contrast, in emerging markets, tail dependencies tend to be more persistent and pronounced. Specifically, simultaneous sharp increases in both stock and exchange rate returns can lead to continued currency depreciation over several days, indicating structural vulnerabilities such as shallow markets, policy uncertainty, or limited hedging capacity. Conversely, sharp stock market declines in EMDEs may temporarily reverse exchange rate pressures, suggesting possible investor repositioning or expectations of policy intervention. These findings highlight the importance of accounting for extreme market conditions and tail risks when analyzing asset market inter-linkages, particularly in less mature financial systems.

Our sensitivity analysis shows that our baseline results are robust when using monthly inflation-adjusted series.

The remainder of the paper is organized as follows: Section 2 provides a review of the literature. Section 3 describes the data. Section 4 describes the methodology. Section 5 presents the main empirical results and the robustness tests. The last section concludes.

2 Literature review

In the last decade, there has been a growing empirical literature investigating the cross-market linkages between stock prices and exchange rates ([Ajayi et al., 1998](#); [Granger et al., 2000](#); [Phylaktis and Ravazzolo, 2005](#); [Kodongo and Ojah, 2012](#)). The findings generally suggest that the causal relationship can operate in both directions. For instance, [Hatemi-J and Irandoust \(2002\)](#) find evidence that stock prices lead exchange rate movements in Sweden, showing that stock market gains are followed by a strengthening of the Swedish Krona. [Moore \(2007\)](#), accounting for potential structural breaks, reports a cointegration relationship between equity prices and exchange rates in Hungary and Poland. [Malliaropoulos \(1998\)](#) explores how disparities in international equity returns relate to deviations from relative purchasing power parity among major OECD countries using a VAR framework. Additionally, the dynamics of volatility transmission between the two markets are examined by [Kanas \(2000\)](#), who documents volatility spillovers from stock returns to exchange rate changes.

An extended number of studies have explored the nexus between exchange rates and stock prices for different sets of EMDEs and AEs. These studies may be classified into two broad categories. First, many studies use conventional Granger causality tests, cointegration techniques and vector autoregressive model (VAR) to examine the stock price-exchange rate linkages in the AEs (see for example, [Chen and Chen, 2012](#); [Tsagkanos and Siriopoulos, 2013](#); [Caporale et al., 2014](#); [Inci and Lee, 2014](#)). Along with, a large number of research papers have investigated the stock price-exchange rate nexus for emerging markets (see, [Chkili and Nguyen, 2014](#); [Lin, 2012](#); [Moore and Wang, 2014](#); [Pan et al., 2007](#); [Sui and Sun, 2016](#); [Tang and Yao, 2018](#)). Another branch of literature uses panel techniques (panel unit root and panel cointegration test) to examine the stock market-exchange rate relationship ([Lean et al., 2011](#); [Liang et al., 2013](#); [Wong, 2017](#)).

Recent research is increasingly based on nonlinear modelling approaches to better understand the complex dynamics that connects exchange rates and stock markets (e.g., [Bahmani-Oskooee and Saha, 2016](#); [Liu and Wan, 2012](#); [Salisu and Ndako, 2018](#); [Walid et al., 2011](#)). A central argument in this literature is that conventional linear models may be insufficient if the true relationship is nonlinear, leading to reduced statistical power in unit root, cointegration, and causality tests, and consequently to misleading inferences. In light of this, a number of studies have turned to conditional volatility models to investigate the nature of volatility transmission between the equity and foreign exchange markets ([Andreou et al., 2013](#); [Caporale et al., 2014](#); [Wong, 2017](#); [Zhao, 2010](#)). Although few studies employ quantile regression to examine this linkage ([Tsai, 2012](#)), others have utilized wavelet methods to capture the dynamics in different time and frequency domains ([Andrieş et al., 2014](#); [Afshan et al., 2018](#)).

Our study is closely aligned with research on nonlinear dependence that utilizes copula models,

auto-distance correlation functions, and the cross-quantilogram methodology (Zhou, 2012; Han et al., 2016; Oh and Patton, 2017). Nevertheless, much of the existing literature focuses primarily on estimating and testing dependence between two time series composed of independent and identically distributed variables or on examining serial dependence within a single time series. Han et al. (2016) introduced the cross-quantilogram as a tool to assess quantile-based dependence between two time series, providing insights into directional predictability. However, this approach does not directly quantify the strength of cross-dependence simultaneously or facilitate testing for independence between general stationary time series. In contrast, the local Gaussian correlation framework offers a more intuitive interpretation by directly capturing both average dependence and tail dependence, thereby enhancing the understanding of cross-asset relationships. This local perspective introduces greater flexibility, allowing conditional dependence to vary across different regions of the conditional distribution. Such flexibility is particularly valuable in financial applications, where tail behavior is a key consideration. Additionally, by testing conditional independence in specific parts of the distribution, this approach has the potential to enhance the power of statistical inference.

An expanding stream of research has explored how various forms of uncertainty influence the behavior of macroeconomic and financial variables. Among these, geopolitical risk (GPR)—broadly encompassing threats such as war, terrorism, and inter-state tensions—has been identified as a major factor shaping investor behavior and financial market movements (Berkman et al., 2011; Pástor and Veronesi, 2013). Several studies highlight the effects of GPR on equity market returns and volatility (e.g., Balcilar et al., 2018; Brounen and Derwall, 2010; Chesney et al., 2011) as well as its impact on currency markets (Balcilar et al., 2017). Beyond financial markets, GPR has also been linked to downturns in economic activity (Blomberg et al., 2004; Cheng and Chiu, 2018).

From a theoretical point of view, geopolitical risk can influence exchange rate movements and volatility through a variety of channels, including its dampening effect on international trade, changes in cross-border capital allocation, and its influence on the expectations of market participants (Eckstein and Tsiddon, 2004; Glick and Taylor, 2010; Abadie and Gardeazabal, 2019). For example, a higher GPR is likely to increase trade costs and depress both investment and consumption of foreign goods, thus reducing trade volumes. At the same time, elevated risk can drive investors to reallocate capital away from more exposed economies toward perceived safe havens, resulting in exchange rate fluctuations. The ultimate impact on exchange rates is likely to vary by country, depending on factors such as exposure to geopolitical shocks, macroeconomic fundamentals, currency regime, and the safe-haven status of the currency. In support of this, recent empirical work shows that during periods of increased global risk, capital tends to flow from EMDEs to AEs, whose currencies often function as safe havens (Caldara and Iacoviello, 2022).

The literature on the implications of geopolitical risk in financial markets has largely concentrated on the effects of terrorism. For example, [Karolyi and Martell \(2010\)](#) and [Arin et al. \(2008\)](#) assess how stock markets respond to terrorist incidents. [Johnston and Nedelescu \(2006\)](#) compare market reactions to the September 11 attacks in the United States and the Madrid bombings of 2004, concluding that financial markets face both operational disruptions and increased volatility in the aftermath of such events. In a related study, [Chen and Siems \(2007\)](#) examine the U.S. capital market's response to a series of terrorist and military events between 1915 and 2001, with a special focus on 9/11 and the invasion of Kuwait by Iraq in 1990. Their findings suggest that U.S. markets have become more resilient over time, recovering more rapidly after shocks, a trend they attribute to the robustness of the country's financial infrastructure. [Eldor and Melnick \(2007\)](#), analyzing nearly 640 terrorist attacks in Israel between 1990 and 2003, finds that terrorism exerts a persistent negative impact on the stock market, but has limited influence on the currency market. Their results imply that, while investors react strongly to news related to terrorism, market efficiency remains intact, with no evident desensitization over time.

Recent literature has increasingly examined how geopolitical risk (GPR) interacts with financial markets, often emphasizing its role in amplifying systemic vulnerabilities and triggering cross-market spillovers. [Tuzcuoglu \(2024\)](#) shows that financial stress can magnify adverse shocks through nonlinear spillovers, deepening downturns in interconnected economies. [Banerjee et al. \(2024\)](#) extend this perspective by documenting that GPR serves as a risk transmitter across multiple asset classes, with stronger spillovers during military conflicts. Similarly, [NguyenHuu and Örsal \(2024\)](#) demonstrate that GPR exacerbates financial stress in emerging markets, with foreign exchange markets disproportionately exposed relative to equities. Together, these studies underscore the destabilizing role of GPR in financial systems.

A growing body of research emphasizes the role of exchange rates as a key transmission channel of shocks. [Hossain et al. \(2024\)](#) show that the Russia–Ukraine conflict triggered sharp currency depreciations in energy-dependent and geographically proximate economies, while [Lyke et al. \(2022\)](#) demonstrate that the GPR improves the predictability of exchange rate returns. [Glebocki and Saha \(2024\)](#) find that global uncertainty shocks heighten exchange rate volatility and pressure, particularly in emerging markets, and [Ojea-Ferreiro and Reboredo \(2022\)](#) reveal that exchange rates can either buffer or amplify equity market shocks depending on context. Yet, despite these advances, the joint dynamics of stock and exchange rate markets under different levels of geopolitical risk remain largely underexplored. Addressing this gap, our paper makes three distinct contributions. First, we provide new evidence on

A number of recent studies highlight the importance of distinguishing between types and sources of uncertainty in shaping financial and macroeconomic outcomes (for applications of these measures, see [Kumar et al., 2021, 2023](#); [Kim et al., 2024](#); [Kumar and Mallick, 2024](#)).

the interconnected behavior of stock and exchange rate markets across geopolitical risk regimes, highlighting how these two core markets transmit and amplify uncertainty. Second, unlike much of the existing literature whose samples end before recent high-impact events, our dataset extends through 2024, enabling us to capture the profound effects of the Russia–Ukraine war and other geopolitical disruptions. Third, by analyzing aggregate indicators at the group level rather than at the country level, we offer a more comprehensive view of the structural dynamics within advanced and emerging economies, thereby reducing country-specific noise and uncovering broader patterns of systemic vulnerability.

3 Data

Our sample includes a total of twenty economies that have high trade openness or cross-border financial flows, ten AEs (United States, Canada, Euro area, United Kingdom, Norway, Switzerland, Australia, New Zealand, Japan and Singapore) and ten EMDEs (Mexico, Peru, Argentina, Brazil, Chile, Czech Republic, Poland, South Africa, China and India). All economies included in this study are members of the WTO, represented in MSCI's market indices. Currency linkages often affect groups of nations connected by international trade flows, as these connections assessed through exports to common third markets or bilateral trade relationships. Additionally, fluctuations in capital flows from foreign countries can affect a home country's exchange rate via changes in the terms of trade. This research incorporates both advanced and emerging markets, as dependence may be more pronounced in nations with advanced foreign exchange and stock markets compared to EMDEs. Furthermore, combining AEs and EMDEs not only expands the sample size and enhances the statistical power of the analysis but also allows for generalization of our results for a group of countries.

We download the nominal effective exchange rates and the closing value of the stock market benchmark indices for each country from the Bank of International Settlements and the Datastream, respectively. Based on the availability of the data, we utilize daily data over the period 3/1/2005 to 12/4/2024, which is the same for all analyzed countries. For each market, weekends and national holidays are excluded from the sample. The stock returns and the exchange rate changes are constructed by multiplying the log-difference of the stock index and the nominal exchange rates by 100, respectively.

The aggregate indices for each country group (AEs and EMDEs) are calculated as weighted averages. The respective weights were constructed by calculating the average share of PPP-GDP for each constituent over the years spanning from 2005 to 2024. Subsequently, these weights normalized to ensure that they sum up to unity. The PPP-GDP data are obtained from the World Economic Outlook of

https://www.wto.org/english/thewto_e/whatis_e/tif_e/org6_e.htm and <https://www.msci.com/our-solutions/indexes/market-classification/>

the International Monetary Fund.

Table 1: Descriptive Statistics

	Advanced economies		EMDEs	
	Stock Market	Exchange Rate	Stock Market	Exchange Rate
Mean	0.000	0.000	0.001	0.000
Std. Dev.	0.009	0.001	0.015	0.002
Max	0.079	0.010	0.515	0.013
Min	-0.105	-0.007	-0.092	-0.035
Skewness	-1.309	0.635	16.959	-2.914
Kurtosis	20.297	8.827	606.348	48.756
J-B	0.000	0.000	0.000	0.000
Q(20)	0.000	0.001	0.000	0.450
ARCH	0.000	0.000	0.023	0.055

Table 1 presents the descriptive statistics for stock market and exchange rate returns across AEs and EMDEs. The average returns of the stock markets and those of exchange rates are being close to zero and positive for both markets. Stock market returns in EMDEs show a standard deviation of 0.015 compared to 0.009 in the advanced markets, while exchange rate volatility is also higher (0.002 vs. 0.001). These findings align with the broader literature that documents greater macroeconomic and financial instability in less mature markets. Extremes (maxima and minima) further underscore this volatility asymmetry. The maximum return for emerging market stocks (0.515) is more than six times that of AEs (0.079), and the minimum is also less extreme in AEs (-0.105 vs. -0.092). Exchange rate returns follow a similar pattern, with EMDEs experiencing both higher maximum (0.013) and lower minimum (-0.035) returns. Skewness in advanced markets is moderate: negative for stocks (-1.309) and positive for exchange rates (0.635), suggesting occasional large losses in equities and appreciations in currencies. In contrast, emerging stock markets show extreme positive skewness (16.959), driven by infrequent but exceptionally large gains. Exchange rate returns in EMDEs are strongly negatively skewed (-2.914), indicating a higher frequency of large depreciations. The J-B test outcomes confirm the non-normality hypothesis of the variables, which supports the use of an asymmetrical estimation for examining dependence among the variables. The null hypothesis of no autocorrelations at lag 20 at the 5% significance level is rejected based on the Ljung-Box test for almost all cases (marginally for the exchange rate series in EMDEs at the 5% level). Finally, the null hypothesis of no ARCH effects is rejected at the 5% significance level for both markets.

4 Methodology

4.1 Local Gaussian cross-correlation estimation

Let X_t and Y_t be strictly stationary time series. If we denote $f^{(k)}(x, y) = f_{\{X_t, Y_{t-k}\}}(x, y)$ the density function of X_t, Y_{t-k} , $k \in \mathbb{Z}^*$, then a Gaussian distribution ψ can be fitted in a specific neighborhood of (x, y) , as:

$$\psi((v, \omega), \theta^{(k)}(x, y)) = \frac{1}{2\pi\sigma_1^{(k)}(x, y)\sigma_2^{(k)}(x, y)\sqrt{1-\rho^{(k)}(x, y)^2}} \exp\left[-\frac{1}{2(\rho^{(k)}(x, y)^2)}\right] \quad (1)$$

$$\times \left(\frac{(v - \mu_1^{(k)}(x, y))^2}{\sigma_1^{(k)}(x, y)^2} - 2\rho^{(k)}(x, y) \frac{(v - \mu_1^{(k)}(x, y))(\omega - \mu_2^{(k)}(x, y))}{\sigma_1^{(k)}(x, y)\sigma_2^{(k)}(x, y)} + \frac{(\omega - \mu_2^{(k)}(x, y))^2}{\sigma_2^{(k)}(x, y)^2} \right)$$

where, $\theta(x, y) = (\mu_1^{(k)}(x, y), \mu_2^{(k)}(x, y), \sigma_1^2(x, y), \sigma_2^2(x, y), \rho(x, y))$ is a vector of parameters of the bivariate density ψ . Specifically, $\mu_1^{(k)}(x, y)$ and $\mu_2^{(k)}(x, y)$ are the mean values, $\sigma_1^2(x, y)$ and $\sigma_2^2(x, y)$ are the variances and $\rho(x, y)$ is the local Gaussian correlation. Our focus is on $\rho(x, y) = \rho^{(k)}(x, y)$. We estimate $\theta(x, y)$ using the local log-likelihood of [Hjort and Jones \(1996\)](#). In this case, the local neighborhood can be written as:

$$L_{n,b} = ((\underline{X}_n, \underline{Y}_n), \theta_b(x, y)) = \frac{1}{n} \sum_{t=1}^{n-|k|} K_b(X_t - x, Y_t - y) \log(v((X_t, Y_t), \theta_b(x, y))) \quad (2)$$

$$- \int K_b(v - x, \omega - y) \psi((v, \omega), \theta_b(x, y)) dv d\omega$$

where, $\underline{X}_n = (X_1, \dots, X_n)$, $\underline{Y}_n = (Y_1, \dots, Y_n)$, n is the number of observations and $x, y, v, \omega \in \mathbb{R}$. All parameters of ψ are affected by a bandwidth b , as indicated by θ_b . $K_b(v-x, \omega-y) = (b_1 b_2)^{-1} K(\frac{v-x}{b_1}) K(\frac{\omega-y}{b_2})$ is a product kernel and K is a non-negative kernel function with bandwidth $b = b_n = (b_1, b_2) = (b_{1n}, b_{2n})$.

Following [Lacal and Tjøstheim \(2017\)](#) we define $\theta_{0,b}$ as the minimizer of the following penalty function:

$$\int K_b(v - x, \omega - y) \psi((v, \omega), \theta_b(x, y)) dv d\omega \quad (3)$$

According to [Tjøstheim and Hufthammer \(2013\)](#), it holds that $\theta_{0,b} \rightarrow \theta$ as $b \rightarrow 0$ where θ stands for the true vector of parameters. We obtain the estimates of $\theta_{n,b}(x, y)$ by minimizing the log-likelihood (2). Given the complicated asymptotic expressions for the distributions of the local parameter estimates,

we employ the stationary bootstrap and the moving block bootstrap procedures, as suggested by [Lacal and Tjøstheim \(2019\)](#).

[Lacal and Tjøstheim \(2019\)](#) develop a test to examine the null hypothesis of the pair $\{X_t, Y_{t-k}\}$ being independent against the alternative that $\{X_t, Y_{t-k}\}$ of not being independent. Although the lag k can vary between two points, in practice we choose a specific value (including). For $k = 0$ the test statistic is defined as:

$$T_{n,b} = \int_S h(\theta_{n,b}(x, y)) dF_n(x, y) \quad (4)$$

where, the function h takes on specific forms to test against specified types of dependence, F_n is the empirical distribution function and S is a compact subspace $\mathbb{R}^2$. In addition, [Lacal and Tjøstheim \(2019\)](#) provide a bootstrap version of the test. The two series are block bootstrapped separately to create the bootstrap distribution under H_0 . In this case, the test statistic is given by:

$$T_{n,b}^* = \int_S h(\theta_{n,b}^*(x, y)) dF_n^*(x, y) \quad (5)$$

where, now $F_n^* = \frac{1}{n} \sum_t \mathbb{1}(X_t^* \leq x, Y_t^* \leq y)$.

4.2 The local Gaussian partial correlation and the conditional independence test of [Otneim and Tjøstheim \(2022\)](#)

Let $\mathbf{Y} = (Y_1, \dots, Y_p)$ be a random vector. We consider a partition of $\mathbf{Y}$, (Y_1, Y_2, Y_3) such that the dimension of Y_i is d_i , $i = 1, 2, 3$. Then, we can denote $\mathbf{Y}^{(1)} = (\mathbf{Y}_1, \mathbf{Y}_2) = (Y_1, \dots, Y_{d_1+d_2})$, that is the first two components of the partition of $\mathbf{Y}$, and $\mathbf{Y}^{(2)} = \mathbf{Y}_3 = (Y_{d_1+d_2}, \dots, Y_{d_1+d_2+d_3})$. Based on the above, we can partition the mean vector μ and covariance matrix Σ of $\mathbf{Y}$ as:

$$\mu = \begin{pmatrix} \mu_1 \\ \mu_2 \\ \mu_3 \end{pmatrix}, \Sigma = \begin{pmatrix} \Sigma_{11} & \Sigma_{12} & \Sigma_{13} \\ \Sigma_{21} & \Sigma_{22} & \Sigma_{23} \\ \Sigma_{31} & \Sigma_{32} & \Sigma_{33} \end{pmatrix}$$

where, Σ_{ij} is the covariance matrix of $(\mathbf{Y}_i, \mathbf{Y}_j)$ $i, j = 1, 2, 3$. This setup allows us to differentiate between the concepts of *partial* and *conditional* correlation, which may coincide in the Gaussian distribution as well as in several other joint distributions.

The partial variance-covariance matrix of $\mathbf{Y}^{(1)} = (\mathbf{Y}_1, \mathbf{Y}_2)$ given $\mathbf{Y}^{(2)} = \mathbf{Y}_3$ can be expressed as:

$$\Sigma_{12|3} = \Sigma^{11} - \Sigma^{12} (\Sigma^{22})^{-1} \Sigma^{21}, \quad (6)$$

where, $\Sigma_{12|3}$ denotes the covariance matrix in the conditional (Gaussian) distribution of $\mathbf{Y}^{(1)}$ given $\mathbf{Y}_3$, under the assumption that $\mathbf{Y}$ is jointly normal. Using $\Sigma_{12|3}$, we define the partial correlation matrix between $\mathbf{Y}_1$ and $\mathbf{Y}_2$ given $\mathbf{Y}_3$, as:

$$\mathbf{R}_{12|3} = \mathbf{D}^{-1/2} \Sigma_{12|3} \mathbf{D}^{-1/2} \quad (7)$$

where, $\mathbf{D}$ is the vector of diagonal elements of $\Sigma_{12|3}$. The partial correlation matrix

If the components of $\mathbf{Y}$ are continuous, we are able to approximate the joint density function f_Y of a point y in a neighborhood of y as a multivariate Gaussian density $\phi(y, x)$, which at the point $y = x$ is

$$\phi(y) = \frac{1}{(2\pi)^{p/2} |\Sigma(y)|^{1/2}} \exp \left\{ -1/2 (\mathbf{y} - \mu(\mathbf{y}))^T \Sigma^{-1}(\mathbf{y}) (\mathbf{y} - \mu(\mathbf{y})) \right\} \quad (8)$$

where, $\mathbf{y} = (y_1, \dots, y_p)$, $\mu(\mathbf{y}) = \{\mu_j(y)\}$ and $\Sigma(\mathbf{y}) = \{\sigma_{jk}(y)\}$ for $j, k = 1, \dots, p$. If $x \neq y$, then f_Y is approximated by a family of multivariate Gaussian densities given by a set of smooth parameter functions $\{\mu(\mathbf{y}), \Sigma(\mathbf{y})\}$. Assuming that f_Y is a Gaussian density and that $\phi(\mathbf{y}) = f_Y(\mathbf{y})$, the parameter functions converge to constants.

The estimation of the local parameter functions $\{\mu(\mathbf{y}), \Sigma(\mathbf{y})\}$ becomes straightforward if we transform each Y_j to a standard normal variable $Z_j = \Phi^{-1}(U_j)$ (for more details see, [Otneim and Tjøstheim, 2017, 2018](#)). In this case, U_j is a uniform variable $U_j = F_j(Y_j)$ where, F_j denotes the cumulative distribution function of Y_j . If we define the random vector $\mathbf{Z}$ as transformation of $\mathbf{Y}$ to marginal standard normality:

$$\mathbf{Z} = (\Phi^{-1}F_1(Y_1), \Phi^{-1}F_2(Y_2), \dots, \Phi^{-1}F_p(Y_p))$$

This notation allows us to simplify the local Gaussian approximation (8) by writing the density f_Z of $\mathbf{Z}$ at the point $x = z$ as:

$$f_z(\mathbf{z}) = \phi(\mathbf{z}, \mathbf{R}(\mathbf{z})) = \frac{1}{|2\pi\mathbf{R}(\mathbf{z})|^{1/2}} \exp \left\{ -1/2 \mathbf{z}^T \mathbf{R}^{-1}(\mathbf{z}) \mathbf{z} \right\} \quad (9)$$

from where we can obtain the fixed local means $\mu_j(\mathbf{z}) = 0$ and standard deviations $\sigma_j^2(\mathbf{z}) = 1$, for $j = 1, \dots, p$. $\mathbf{R}(\mathbf{z}) = \{\rho_{jk}(\mathbf{z})\}$ is the local correlation matrix.

If we consider a partition $(\mathbf{Z}^{(1)}, \mathbf{Z}^{(2)}) = (\mathbf{Z}_1, \mathbf{Z}_2, \mathbf{Z}_3)$ of $\mathbf{Z}$, similar to $\mathbf{Y}$, then we can define the local

We will refer to $\mathbf{Z}$ and its probability function F_Z as being on the z -scale.

partial covariance matrix of $\mathbf{Z}^{(1)} \mid \mathbf{Z}^{(2)}$ similarly to the local version of (6):

$$\Sigma_{12|3}(\mathbf{z}) = \mathbf{R}^{11}(\mathbf{z}^{(1)}) - \mathbf{R}^{12}(\mathbf{z}) \left(\mathbf{R}^{22}(\mathbf{z}^{(2)}) \right)^{-1} \mathbf{R}^{21}(\mathbf{z}) \quad (10)$$

In the special case where $d_1 = d_2 = 1$, $\Sigma_{12|3}(\mathbf{z})$ boils down to a 2×2 matrix. In this case, we define the local Gaussian partial correlation $\alpha(\mathbf{z})$ between the two variables in $\mathbf{Z}^{(1)} = (Z_1, Z_2)$ given $\mathbf{Z}^{(2)} = \mathbf{Z}_3$ similar to the ordinary (global) partial correlation provided by (7):

$$\alpha(\mathbf{z}) = \mathbf{R}_{12|3}(\mathbf{z}) = \frac{\{\Sigma_{12|3}(\mathbf{z})\}_{12}}{\{\Sigma_{12|3}(\mathbf{z})\}_{11}^{1/2} \{\Sigma_{12|3}(\mathbf{z})\}_{22}^{1/2}}$$

where in the special case that $\mathbf{Z}^{(2)} = \mathbf{Z}_3$ is scalar reduces to

$$\alpha(\mathbf{z}) = \rho_{12|3}(z_1, z_2 \mid z_3) = \frac{\rho_{12}(z_1, z_2) - \rho_{13}(z_1, z_3) \rho_{23}(z_2, z_3)}{\sqrt{1 - \rho_{13}^2(z_1, z_3)} \sqrt{1 - \rho_{23}^2(z_2, z_3)}}$$

We estimate the local Gaussian partial correlation between Y_1 and Y_2 conditional to $Y^{(2)} = Y_3$, on the $\mathbf{z}$ -scale as:

$$\hat{\alpha}(\mathbf{z}) = \mathbf{R}_{12|3}(\mathbf{z}) = \frac{\{\Sigma_{12|3}(\mathbf{z})\}_{12}}{\{\Sigma_{12|3}(\mathbf{z})\}_{11}^{1/2} \{\Sigma_{12|3}(\mathbf{z})\}_{22}^{1/2}} \quad (11)$$

where at point $\mathbf{y} = \hat{F}(\Phi(\mathbf{z}))$, we obtain the corresponding value of $\hat{\alpha}(\mathbf{y})$ by replacing in the above equation $\mathbf{z} = \Phi^{-1}(\hat{F}(\mathbf{y}))$.

Otneim and Tjøstheim (2022) propose a test for conditional independence based on the local Gaussian partial correlation approach. The test examines the null hypothesis of $H_0 : Y_1 \perp Y_2 \mid \mathbf{Y}_3$ or equivalently the null hypothesis of $H_0 : Z_1 \perp Z_2 \mid \mathbf{Z}_3$ by constructing a test statistic in terms of the marginally Gaussian pseudo observations by aggregating the local measure of dependence over the sample space of $\mathbf{Y}$ (or $\mathbf{Z}$). The test statistic on the $\mathbf{z}$ -scale is:

$$T_{n,b} = \int_S h(\hat{\alpha}_b(\mathbf{z})) dF_n(\mathbf{z})$$

where $h(\cdot)$ denotes an even and non-negative real-valued function and $S \subseteq \mathbf{R}^p$ is an integration area which can be altered in order to test specific portions of the sample space. $T_{n,b}$ converges in probability towards its population value (under the law of large numbers and regularity conditions):

$$T = \int_S h(\alpha(\mathbf{z})) dF_n(\mathbf{z})$$

The null hypothesis, in favor of conditional independence, is rejected when $T_{n,b}$ exceeds the re-

spective critical value (for a more technical description, see [Otneim and Tjøstheim, 2022](#)).

5 Empirical Results

5.1 Baseline results

Figure 1 shows the plots of the local Gaussian correlation $\hat{\rho}(x, x)$, along the diagonal $x = y$, for the X_t = FX rate and the Y_{t-k} = Stock market for $k = 0$ (a contemporaneous relationship between the two markets).

The vertical axis of the local Gaussian correlation diagrams denotes the magnitude of the local correlation estimates between the returns of the two markets, while the horizontal axis shows a vector of (diagonal) gridpoints, that is the returns of both markets on the data rich portion of their conditional distribution. In this manner, we may distinguish between two market states: (i) gridpoints above zero, where the stock returns are positive and the local currency depreciates (exchange rate increases), and (ii) gridpoints below zero, where the stock returns are negative and the local currency appreciates (exchange rate decreases).

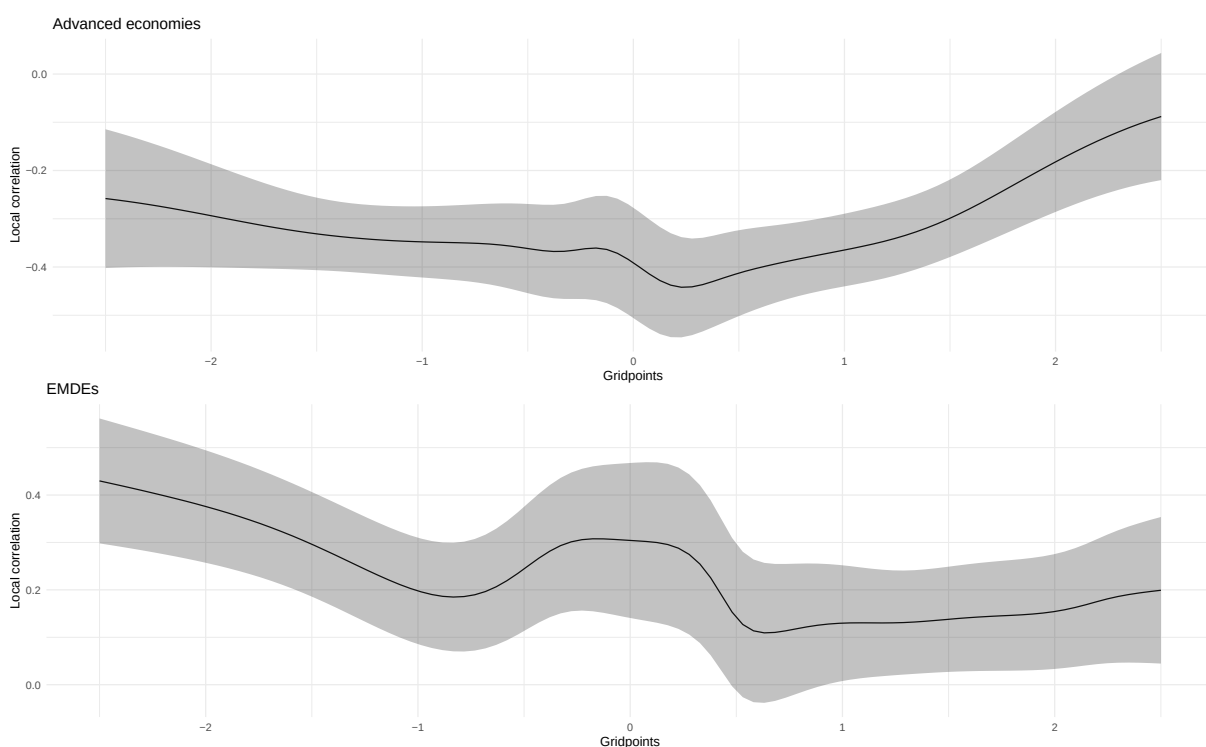
For the contemporaneous relationship between the two markets, the results in Figure 1 show that for the AEs (upper panel), the local correlation estimates are negative throughout the spectrum of the conditional distribution. A negative correlation between the stock and foreign exchange markets indicates that both stock returns and exchange rate changes move in the opposite direction. This is broadly in line with the return chasing effect of [Hau and Rey \(2006\)](#), who postulate that a booming domestic stock market attracts international investors, which in turn leads to an appreciation of the booming country's currency (i.e., a decrease in the nominal exchange rate, which is defined as the number of units of national currency per foreign currency). In such a case, the high stock price coexists with lower exchange rates, thus producing a negative correlation. In a bear market condition, (stock price decrease) investors may sell foreign assets and repatriate funds to invest in the domestic market (the portfolio balance approach). This increases the demand for the local currency, leading to its appreciation. One additional explanation relies on the flow-oriented model, where falling stock prices reflect economic downturns, leading to decreased imports as consumers and businesses cut spending. Lower

In our study, before proceeding to the bivariate and trivariate local correlation analysis, we first test for conditional independence between the two markets. In all cases, the null hypothesis is rejected at the 5% significance level in favor of the conditional dependence (given the global geopolitical risk level for the trivariate case). For the sake of brevity, these results are not presented here but are available upon request.

We used the GARCH-filtered series in order to remove marginal auto-dependence over time and volatility's effects (for more details see, [Støve et al. \(2014\)](#)).

imports reduce the demand for foreign currency, causing the local currency to appreciate. The local Gaussian correlation estimates for the AEs range between -0.25 and -0.35 at the left tail, between -0.4 and -0.45 at the middle, and between -0.35 and -0.2 at the right tail of the distribution. Quantifying these estimates by their confidence intervals, we observe that the contemporaneous relationship is significant across the whole conditional distribution except for very few extreme values on the right tail of the distribution.

Figure 1: Bootstrap local Gaussian correlation estimations for the exchange rates versus stock market for the AEs (upper panel) and EMDEs (lower panel). Shaded area denotes the 95% confidence intervals for the local Gaussian correlation estimates.



The lower panel of Figure 1 illustrates the local Gaussian correlation estimates for the group of EMDEs. We observe significant and positive local correlation estimates across the whole distribution, with estimated values ranging from 0.42 on the left tail to 0.1 on the right shoulder of the distribution. This positive correlation between the two markets can be attributed to the theory of the portfolio rebalancing model of [Hau and Rey \(2006\)](#), who suggest that a surge in domestic stock prices encourages investors to realize their gains and reallocate their capital to other markets which offer better bargains. This will lead to a depreciation of the booming country's currency, thus increasing the country's exposure to exchange rate risks. As a result, rising stock prices can coexist with currency depreciation (i.e., an increase in the exchange rate), which in turn creates a positive correlation between the two

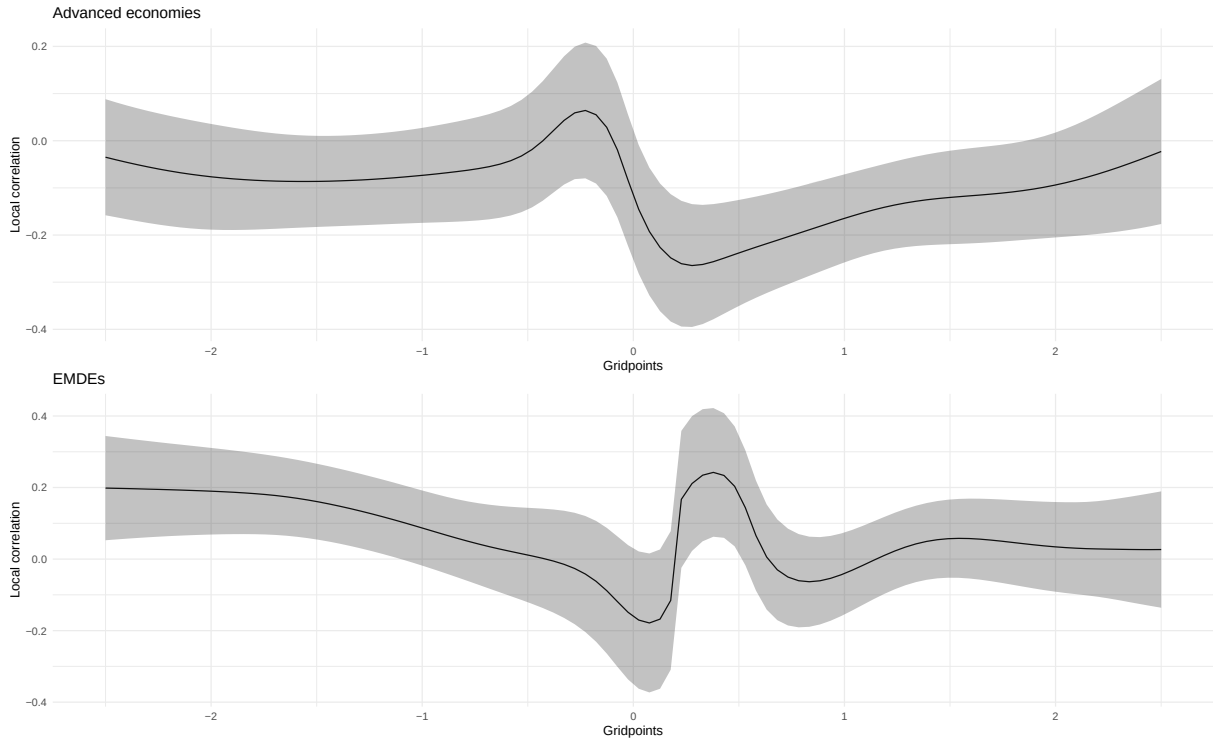
markets. [Mundell \(1963\)](#)'s portfolio balance approach also suggests that investors allocate their wealth across domestic and foreign assets. Changes in stock prices influence the demand for domestic and foreign bonds, impacting the exchange rate. When stock prices increase (bull market), investors may sell domestic stocks to lock in gains and rebalance their portfolios by buying foreign assets. This leads to an increased demand for foreign currency, causing the local currency to depreciate. In a bear market condition (stock price decrease), investors may sell foreign assets and repatriate funds to invest in the domestic market. This increases the demand for the local currency, leading to its appreciation.

Figure 2 illustrates the hypothesis that the currency market is the leading market. The solid lines show the local correlation estimates between the two markets setting $k = -1$ for the stock market.

For the AEs group (upper panel), we observe significant negative local correlation estimates only on the right shoulder of the conditional distribution, with estimated values ranging between 0 and -0.28. This is in line with the export competitiveness effect proposed in [Dornbusch \(1976\)](#), where a local currency depreciation, makes a country's exports cheaper and more competitive in the global market. This can lead to higher sales for export-oriented companies, boosting their revenues and profits. As a result, the stock prices of these companies, and consequently the overall stock market, may rise. Thus, in AEs moderate movements in the exchange rate (currency depreciation) can precede and potentially predict movements in the stock market (increase in stock prices).

For the emerging countries group (lower panel), we observe significant local correlation estimates on the left tail of the conditional distribution, with estimated values ranging from 0.1 to 0.2. This significant impact of an extreme appreciation in exchange rates on falling stock markets may be explained by several factors in EMDEs (see also, [Pan et al., 2007](#)). For example, since many EMDEs rely on exports for economic growth, a stronger local currency makes exports more expensive for foreign buyers, reducing demand and hurting corporate revenues and profits. If the stock market is heavily weighted toward exporting firms (e.g., commodities, manufacturing, or agriculture), their declining earnings can drive the overall market down. Moreover, currency appreciation can be the result of higher domestic interest rates aimed at controlling inflation. Higher interest rates increase borrowing costs for businesses, reducing investment and corporate profitability. Domestic firms with high debt, especially those borrowing in local currency, may see lower stock valuations due to increased financial burdens. Additionally, exchange rate appreciation may attract foreign capital into fixed-income assets (e.g., government bonds) rather than stocks. A shift in capital from equities to bonds can lower stock prices due to weaker demand for shares. Eventually, if an emerging economy depends on commodity exports (e.g., oil, metals, or agricultural products), currency appreciation can reduce local revenues from exports (since commodities are often priced in USD). This can lower profitability for companies in these sectors, leading to stock market declines.

Figure 2: Bootstrap local Gaussian correlation estimations for the lagged exchange rate versus stock market for the AEs (upper panel) and EMDEs (lower panel). Shaded area denotes the 95% confidence intervals for the local Gaussian correlation estimates.

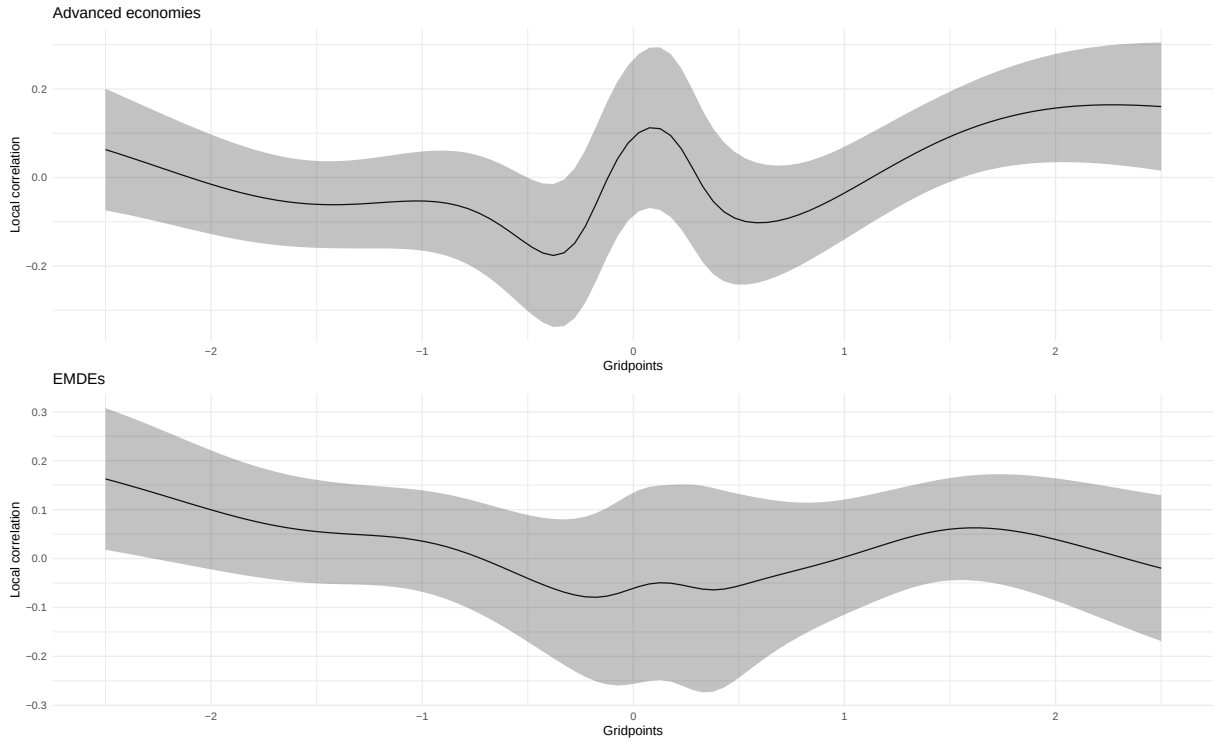


Collectively, the above findings underscore the heterogeneity in exchange rate–stock market dynamics across different economic structures. In advanced markets, moderate currency depreciation acts as a leading signal for stock market gains, while in emerging markets, sharp appreciations may serve as precursors to downturns, reflecting potential vulnerabilities related to export dependence, financial structure, and macroeconomic policy trade-offs.

Figure 3 illustrates the hypothesis that the stock market is the leading market. Again, the solid lines show the local correlation estimations between the two markets setting $k = 1$ for the stock market.

For the advanced countries group (upper panel), we observe significant positive local correlation estimates only on the right tail of the conditional distribution, with estimated values ranging between 0.1 and 0.18. This positive moderate relationship can be explained by a number of reasons, such as capital outflows, policy expectations (signal policy tightening), a worsening trade balance, and speculative positioning. For the EMDEs (lower panel in Figure 3), the local Gaussian correlation estimates range between -0.09 and 0.16, however, zero is included inside the confidence interval across the whole spectrum of the estimated values. This finding highlights the more limited role of the stock markets in EMDEs compared to the currency market.

Figure 3: Bootstrap local Gaussian correlation estimations for the exchange rate versus lagged stock market for the AEs (upper panel) and EMDEs (lower panel). Shaded area denotes the 95% confidence intervals for the local Gaussian correlation estimates.



5.2 Testing for conditional independence between FX and stock market in different levels of geopolitical risk

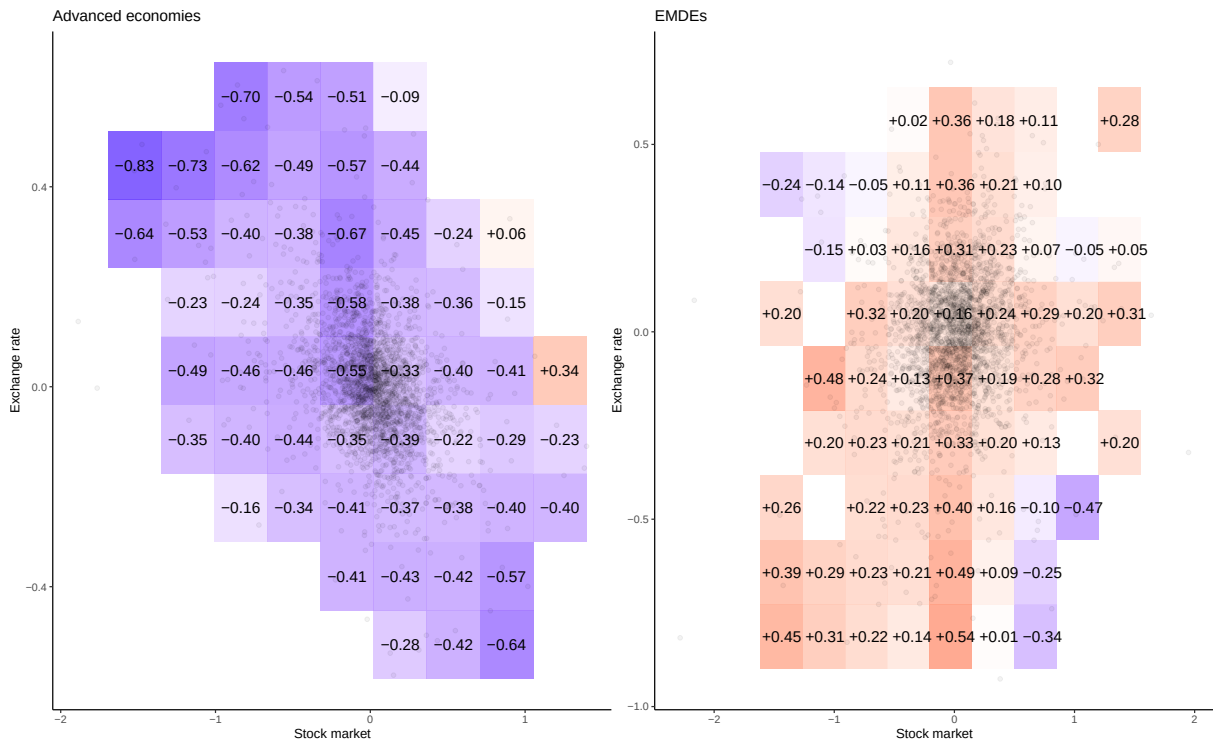
In this section, we use the local Gaussian partial correlation (LGPC) approach of [Otneim and Tjøstheim \(2022\)](#) to illustrate the local partial dependence structure and examine for conditional independence between FX and stock markets given the different levels of geopolitical uncertainty. An advantage of this technique is that it allows us to discuss the dependence and tail dependence of two financial markets for four different market statuses: bull or bear markets associated with currency appreciation or depreciation.

For example, Figure 4 illustrates the trivariate local Gaussian partial correlation between the exchange rate and the stock markets for the AEs (left panel) and EMDEs (right panel) in the plane defined by moderate geopolitical risk levels.

This figure can be divided into four quadrants: the movement from quadrant 1 to 4 follows an anti-clockwise rotation starting from the upper right quadrant to the bottom right quadrant. Thus, the first quadrant, is the upper right quadrant. Both the stock market returns (x -axis) and exchange rate returns (y -axis) have positive returns in quadrant 1: the stock market is booming and the local currency depre-

ciates. The upper left quadrant is the second quadrant, in which the stock market (x -axis) has negative returns while the exchange rate returns (y -axis) are positive: the stock market is in a bear state and the local currency depreciates. The bottom left quadrant is the third quadrant, in which both markets have negative returns: stock market is bearing and the local currency appreciates. The bottom right quadrant is the fourth quadrant, where the stock returns (x -axis) are positive and the exchange rate returns (y -axis) are negative: the stock market is booming and the local currency appreciates.

Figure 4: Local partial dependence map of exchange rates vs stock market on the plane defined by median geopolitical risk levels.



Turning to our results in Figure 4, the LGPC estimates are negative for the group of the AEs (left panel). The lower LGPC estimates are observed in the second quadrant, with LGPC values ranging from -0.23 to -0.83. In this respect, a higher negative dependence between the stock and currency market for the AEs is observed in the state where the stock market is experiencing negative returns and the local currency depreciates. This is in line with the findings of [Cho et al. \(2016\)](#), who observed a negative correlation during market downturns, for a number of AEs, suggesting a flight-to-quality phenomena. The portfolio balance model also contends that investors are risk averse and they move their investments to countries with higher stock returns, which by implication leads to currency appreciation in countries with higher stock returns and depreciation in countries with lower stock returns ([Branson, 1981](#); [Frankel, 1992](#)). Consistently low LGPC estimates are also observed in the second quadrant ranging from

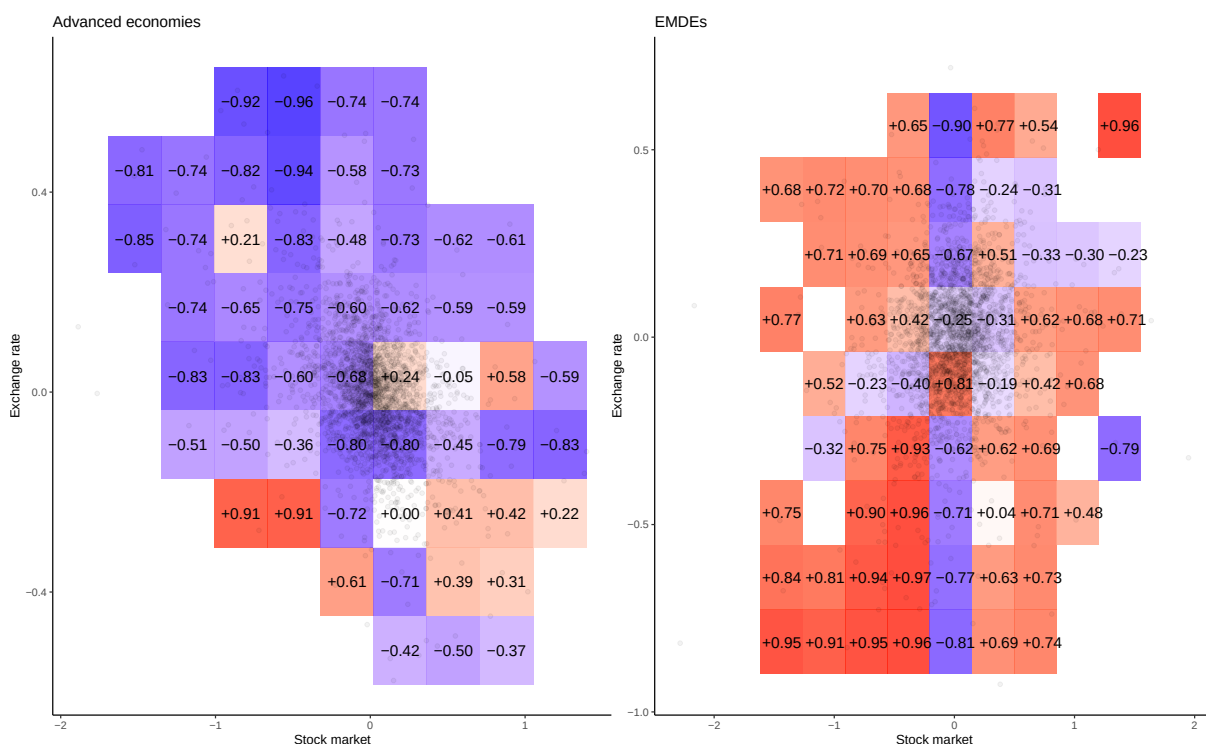
-0.16 to -0.55. In line with our previous findings, declining stock prices in EMDEs signal an economic downturn, prompting consumers and businesses to reduce spending, which lowers import demand. As imports decrease, the need for foreign currency diminishes, leading to an appreciation of the local currency. Moreover, according to the portfolio balance approach, during a bear market, when stock prices decline, investors may liquidate foreign assets and bring funds back to the domestic market, following the portfolio balance approach. This rise in demand for the local currency strengthens its value, leading to appreciation.

Regarding the EMDEs, on the right panel of Figure 4, we document positive LGPC estimates across the whole coordinate plane, with higher values observed in the third quadrant. Thus, for the EMDEs, when geopolitical risk is at a moderate level, we document a higher positive correlation between the exchange rates and stock markets, when the stock market is in a bear state and the local currency appreciates. This is also in agreement to Mundell (1963)'s portfolio balance approach, according to which during a bear market, characterized by declining stock prices, investors liquidate foreign assets and repatriate funds for investment in the domestic market. This repatriation increases the demand for the local currency, resulting in its appreciation.

Figure 5 illustrates the trivariate local Gaussian partial correlation between the exchange rate and stock markets on the plane defined by high geopolitical risk levels. For the AEs, given a high level of geopolitical risk, the two markets possess significant negative dependence when stock market is plummeting and the local currency depreciates (2nd quadrant). This finding implies that the flight-to-quality phenomenon is intensified during periods of high geopolitical risk in advanced markets. High negative LGPC estimates are also observed in the first quadrant, when the stock market is booming and the local currency depreciates, in line with the risk appetite and safe-haven flows hypotheses (see, e.g., Ranaldo and Söderlind, 2010; Habib and Stracca, 2012). In many AEs, the local currency serves as a safe-haven asset. When risk appetite increases (e.g., during a stock market boom), investors may shift capital away from safe-haven assets (such as the local currency) into riskier assets, leading to depreciation. In general, we observe that a higher geopolitical risk is associated with an increased dependence between the two major financial markets in AEs.

The right panel of Figure 5 presents the trivariate local Gaussian partial correlation for the EMDEs in the plane defined by high geopolitical risk levels. The LGPC estimates are positive in all four quadrants with very few exceptions (at the extreme values of the first and fourth quadrant). Thus, higher geopolitical risk is associated with positive dependence between the two major financial markets in emerging countries. In more detail, the higher LGPC estimates are observed in the third quadrant with estimations ranging between 0.42 to 0.97, in which both markets have negative returns: stock market is bearing and the local currency appreciates. This finding is in line with the flow-oriented model of exchange rate

Figure 5: Local partial dependence map of exchange rates vs stock market on the plane defined by high geopolitical risk levels.



determination of [Dornbusch and Fischer \(1980\)](#), which postulates that that currency movements affect international competitiveness and the balance of trade position, and consequently the real output of the country, which in turn affects current and future cash flows of companies and their stock prices. An appreciation of the domestic currency increases prices and this reduces foreign demand, thereby leading to a fall in value and stock. From this point of view, there is a positive relationship between exchange rates and stock prices, with causation running from exchange rates to stock prices. Positive local dependence estimates are found in the second quadrant with LGPC ranging between 0.42 to 0.77(the stock market is in a bear state and the local currency depreciates). This situation of a weakening domestic currency during periods of stock market downturns, may be explained by several theories for EMDEs, such as loss of investor confidence and capital outflows ([Dornbusch et al., 1985](#); [Cho et al., 2016](#)), increased risk perception ([Bekaert and Harvey, 1997](#)), current account imbalances ([Dornbusch and Fischer, 1980](#)), monetary policy responses ([Calvo and Reinhart, 2002](#)) as well as foreign debt dependence ([Krugman, 1988](#)).

Thus, under high geopolitical risk, AEs and EMDEs exhibit contrasting patterns in the relationship between exchange rates and stock markets. In AEs, a significant negative dependence emerges, particularly during market downturns, reflecting a flight-to-quality effect where investors move from equities

to safe-haven currencies. In contrast, EMDEs show a predominantly positive dependence, with both markets often moving in the same direction. This pattern reflects structural vulnerabilities and capital flow dynamics, where geopolitical shocks simultaneously affect investor confidence, exchange rates, and equity valuations.

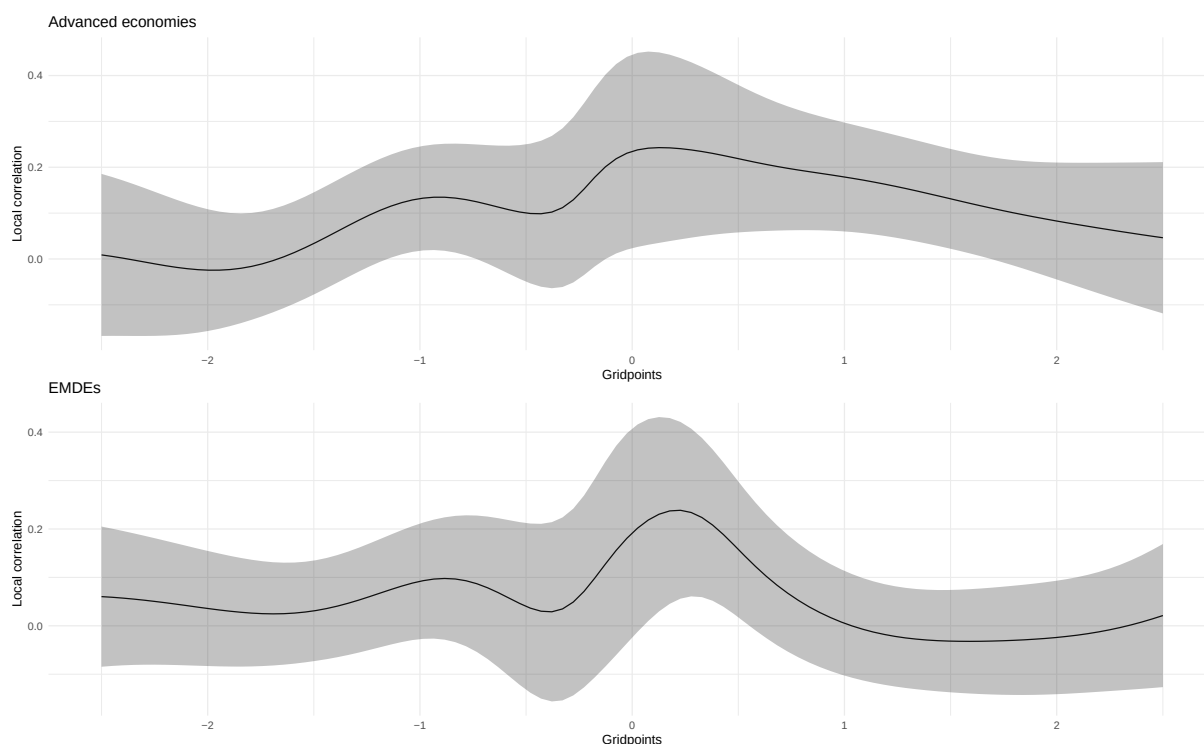
5.3 Examining the tail dependence between exchange rate and stock market volatility

In this section, we examine the tail dependence between exchange rate volatility and stock return volatility for the two country groups. Since mean returns for both variables are close to zero, we use as volatility proxy their squared returns. We would expect the exchange rate volatility and stock return volatility to be interconnected through the transmission of economic shocks (see, [Bekaert and Harvey, 1997](#); [Diebold and Yilmaz, 2009](#)). For instance, sudden changes in exchange rates can affect the profitability of firms engaged in international trade, leading to fluctuations in stock prices. Conversely, stock market volatility can influence investor sentiment and capital flows, which may impact exchange rates ([Dungey and Martin, 2007](#)).

Moreover, both exchange rate volatility and stock return volatility reflect underlying economic and financial uncertainty. Tail dependence, which measures the likelihood of extreme co-movements, is particularly relevant during periods of financial stress or crises when both markets are likely to experience heightened volatility simultaneously ([Forbes and Rigobon, 2002](#)). Additionally, investors often rebalance their portfolios in response to changes in exchange rates, which can lead to correlated movements between stock returns and exchange rates. During extreme market conditions, this rebalancing can amplify tail dependence between the two variables.

For the contemporaneous relationship in volatility between the two markets, the results in Figure 6 show that for the AEs (upper panel), the local correlation estimates are close to zero in the tails of the distribution. The same picture emerges for the EMDEs (lower panel), with insignificant LGPC estimates almost across the whole spectrum of the conditional distribution. We find significant and positive LGPC estimates for the AEs at the right shoulders of the distribution, with estimated values ranging between 0.1 and 0.22. As noted in [Chari et al. \(2024\)](#), in a bullish stock market, investors are generally more optimistic and risk-tolerant. However, if the domestic currency is depreciating even in such a bullish period, it could introduce uncertainty or concern among investors—especially foreign ones—about macroeconomic fundamentals, monetary policy, or external imbalances. This can result in increased capital flow volatility, which increases both stock and currency market fluctuations. Furthermore, a depreciating exchange rate could raise concerns about imported inflation (especially in

Figure 6: Bootstrap local Gaussian correlation estimations for the exchange rates versus stock market volatility for the AEs (upper panel) and EMDEs (lower panel). Shaded area denotes the 95% confidence intervals for the local Gaussian correlation estimates

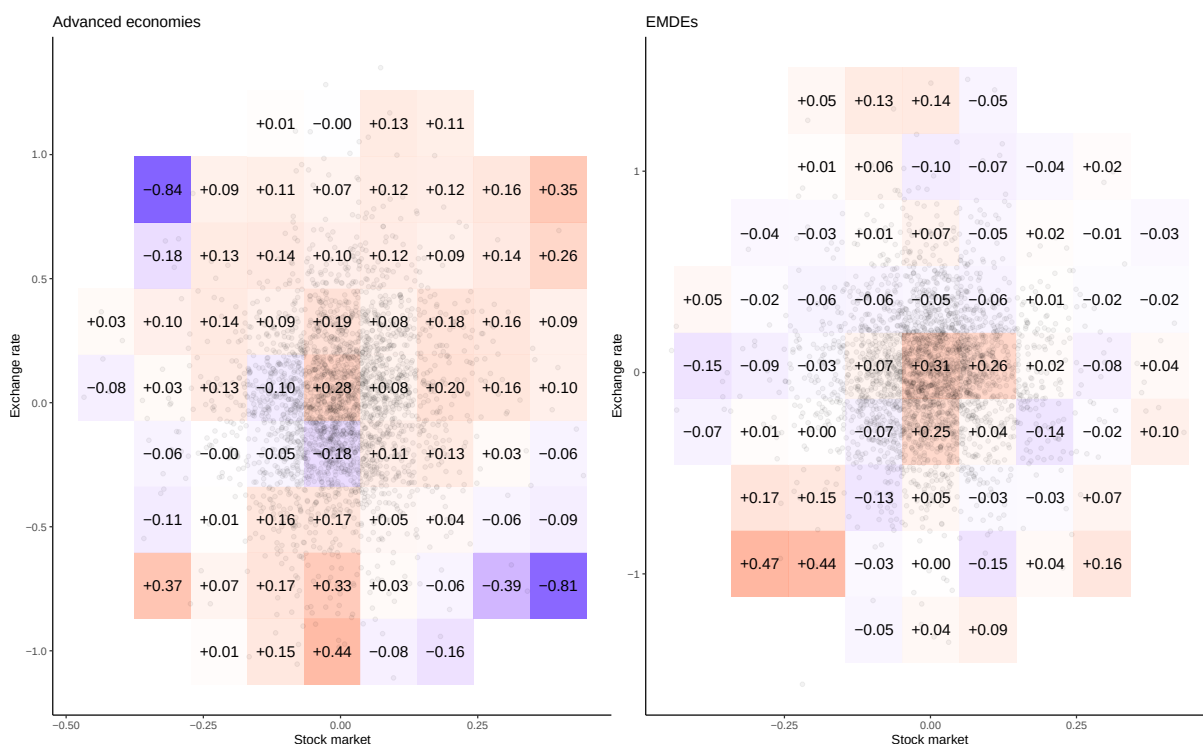


economies heavily dependent on imports). Firms with international exposure (importers or those with foreign-denominated debt) might see their valuations become more volatile, feeding into stock market volatility. Investors may also reassess firm profitability and macro conditions, causing stock prices to fluctuate more (see, [Campa and Goldberg, 1999](#)). In AEs, central banks typically respond to exchange rate depreciations when they affect inflation expectations or financial stability. This potential reaction may generate uncertainty about future interest rates, which can amplify both exchange rate and equity market volatility as investors try to price in future policy shifts.

However, in globally integrated financial markets, a shock—say, a geopolitical event—can cause simultaneous volatility in the currency and equity markets, even when equities generally trend upward ([Kalemli-Ozcan et al., 2009](#); [Tang and Yao, 2022](#)). To test this premise, we employ the local Gaussian Partial correlation estimation for the exchange rate and stock market volatility series. From Figure 7, we observe that the dependence of volatility on the two markets remains low irrespective of the state of the two markets, under the condition of moderate geopolitical risk. However, under high geopolitical risk levels, in Figure 8 we observe that the dependence increases considerably in all four quadrants. If

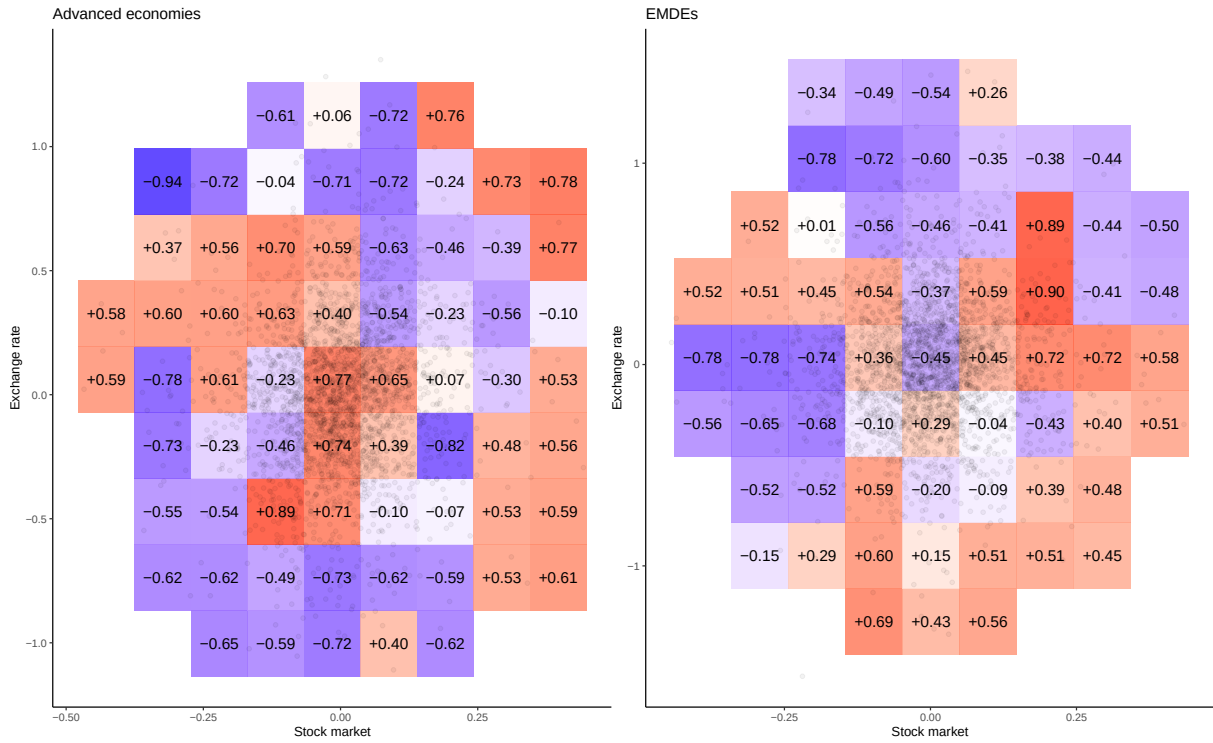
Lag effects were found very close to zero or insignificant and are included in the Appendix.

Figure 7: Local partial dependence map of exchange rates vs stock market volatility on the plane defined by moderate geopolitical risk levels.



the bull market is driven by foreign capital inflows, a currency depreciation could signal that investors are beginning to hedge or reverse those positions, causing volatility in both markets (positive LGPC estimates at the extreme values of the first and fourth quadrant). This finding could also suggest a scenario where growth expectations are high (bull market), but there are concerns about monetary policy credibility, trade competitiveness, or external balances—hence a weaker currency and market volatility. For policymakers, this could indicate the need to monitor capital flows and market perceptions of economic imbalances more closely during bullish periods. For investors, it might be a signal that bullish equity markets do not necessarily reflect macroeconomic stability—exchange rate volatility could be an early warning sign. Moreover, we observe quite similar LGPC estimated values for AEs and EMDEs alike. Thus, under the notion of global financial integration, stocks and currency markets experience more synchronized shocks in volatility stemming from high geopolitical risk.

Figure 8: Local partial dependence map of exchange rates vs stock market volatility on the plane defined by high geopolitical risk levels.



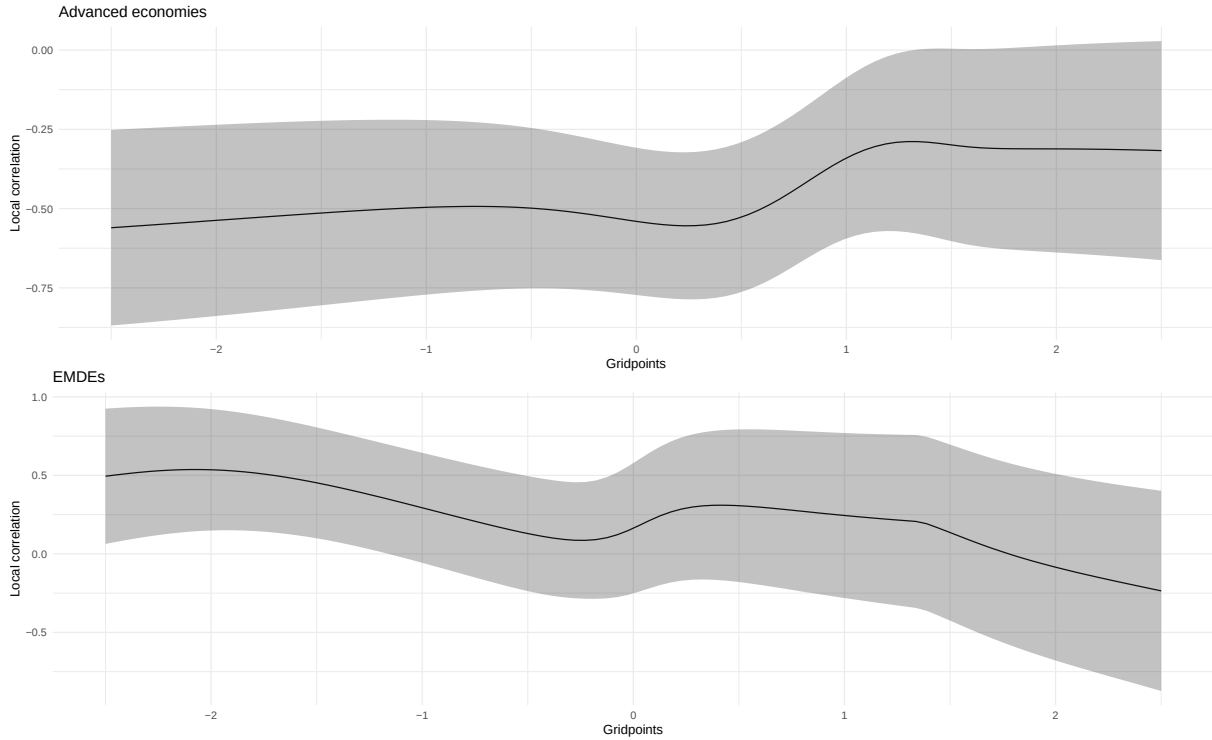
5.4 Robustness analysis

5.4.1 Baseline analysis employing monthly inflation-adjusted series

Next, we conduct a robustness analysis using inflation-adjusted monthly returns in place of daily returns, following the approach of [Billio et al. \(2012\)](#). Given that daily data may be subject to short-term noise and market microstructure effects, the use of monthly returns allows us to assess the stability of our results over a longer horizon. This additional analysis ensures that the observed dependence structures between exchange rates and stock markets are not artifacts of high-frequency fluctuations but reflect more persistent co-movement patterns under varying levels of geopolitical risk.

For the contemporaneous relationship between the two markets, the results in Figure 9 show that for the AEs (upper panel), the local correlation estimates are negative throughout the spectrum of the conditional distribution. However, we observe that the estimated LGPC are higher and significant compared to the daily data with estimated values ranging between -0.27 and -0.52. For emerging countries (lower panel), we observe that the estimated coefficients are larger and statistically significant in the left tail of the distribution, with the estimated coefficients close to 0.5. In this respect, the monthly series show quantitatively similar and even stronger dependence between the two markets.

Figure 9: Bootstrap local Gaussian correlation estimations for the exchange rates versus stock market for AEs (upper panel) and EMDEs (lower panel) monthly series. Shaded area denotes the 95% confidence intervals for the local Gaussian correlation estimates

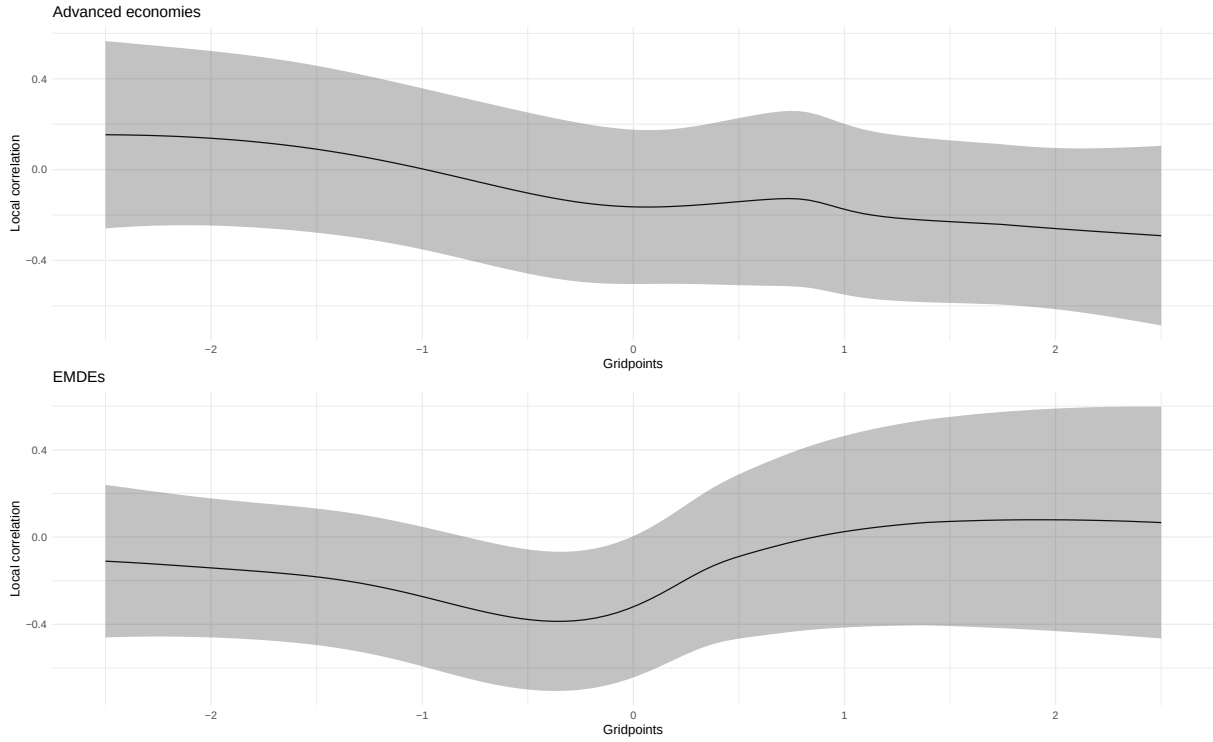


Turning to the lead-lag relationships, Figures 10 and 11 illustrate that the local Gaussian correlation curves are smoother compared to the daily estimates, although with higher confidence intervals. Setting the currency market as the leading market in Fig. 10, we observe that the relationship between the two markets is not significant for both the AEs and EMDEs, across the whole spectrum of conditional distribution. When we set the stock market as the leading market in Fig. 11 we observe a significant and negative dependence on the left shoulder of the conditional distribution, with LGPC estimates close to -0.4. This finding is again in line with our daily analysis, although significant and double in magnitude (see Fig. 3), consistent with the notion that in advanced economies the stock markets lead the currency markets in times of economic downturns.

5.4.2 Testing for conditional independence in different levels of geopolitical risk using monthly inflation adjusted series

In Figs. 12 and 13 are illustrated the trivariate local Gaussian partial correlation between the exchange rate and stock markets for the AEs (left panel) and EMDEs (right panel) in the plane defined by moderate

Figure 10: Bootstrap local Gaussian correlation estimations for the lagged exchange rates versus stock market for the AEs (upper panel) and EMDEs (lower panel) monthly series. Shaded area denotes the 95% confidence intervals for the local Gaussian correlation estimates.



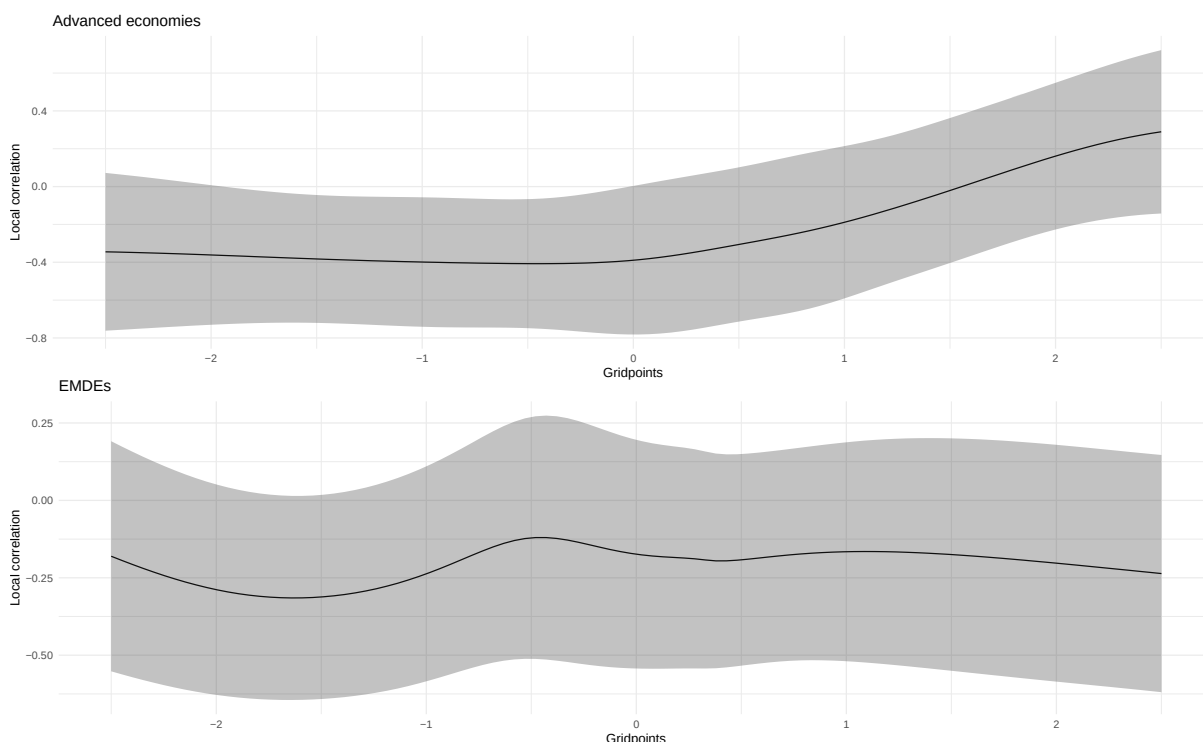
and high geopolitical risk levels, respectively.

Results in Fig. 12, show that the LGPC estimates are negative for the group of the AEs (left panel). The lower LGPC estimates are observed at the second quadrant, with LGPC values ranging from -0.29 to -0.78. Similar to the daily analysis, higher negative dependence between the stock and currency market for the AEs is observed in the state that the stock market is experiencing negative returns and the local currency depreciates. As mentioned above this is consistent with the flight-to quality phenomena as well as the portfolio balance model. These phenomena are further intensified in advanced markets at a state of high geopolitical risk, as is observed in Fig. 13 (left panel), with estimated LGPC values ranging between -0.44 to -0.82.

Turning to the EMDEs, in the right panel in Fig. 12, we observe positive LGPC estimates across almost the whole coordinate plane (except some values in the second quadrant), with higher values observed in the first and third quadrant, consistent with the Mundell (1963)'s portfolio balance approach. However, the estimated positive values are lower than those calculated on daily data (see Fig. 4), ranging between 0 and 0.41.

The right panel of Figure 13 presents the trivariate local Gaussian partial correlation for the EMDEs

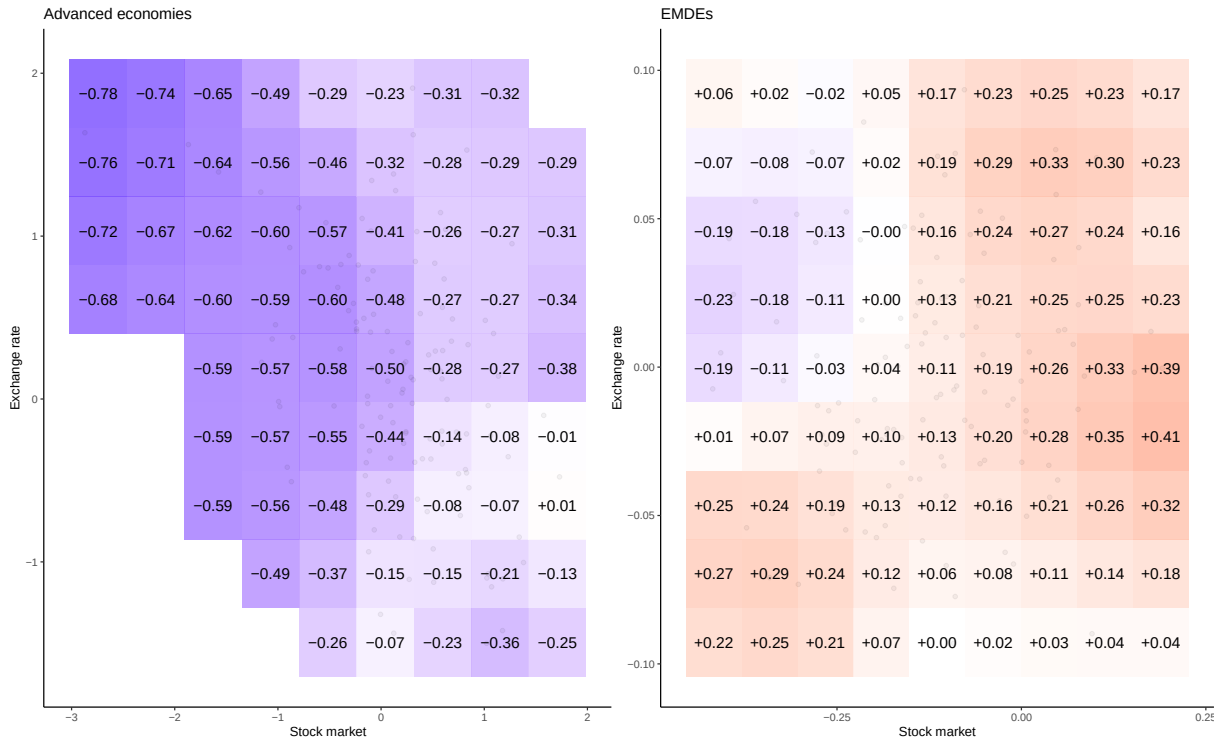
Figure 11: Bootstrap local Gaussian correlation estimations for the exchange rates versus lagged stock market for AEs (upper panel) and EMDEs (lower panel) monthly series. Shaded area denotes the 95% confidence intervals for the local Gaussian correlation estimates



on the plane defined by high geopolitical risk levels. The LGPC estimates are positive in the first and second quadrants, with higher estimates observed in the first quadrant, ranging between 0.19 and 0.70. Thus, under high geopolitical risk, in emerging markets investors may shift out of bonds or currency holdings and turn into stocks of large, politically-connected or resource-based firms, which are seen as better inflation hedges or more resilient. This may result in a weak currency, but in stocks (especially of specific sectors) increase. Moreover, geopolitical tensions often raise global commodity prices, especially energy, metals, and food. If the country is a commodity exporter, depreciation might be driven by global fears, but the stock market benefits due to increasing firm profits in the resource sectors. During high geopolitical risk, depreciation can signal higher future inflation. Equities, especially in sectors with pricing power, can act as a hedge against inflation. As a consequence, investors may move out of cash or bonds and into equities to protect real wealth.

The negative LGPC estimates in the third and second quadrant imply a negative dependence when exchange rate appreciates. In high geopolitical risk environments, currency appreciation accompanied by falling stock prices may indicate, for example, a defensive policy tightening. Authorities may intervene to stabilize the currency (e.g., raise interest rates) in response to geopolitical tensions. Higher

Figure 12: Local partial dependence map of exchange rates vs stock market on the plane defined by median geopolitical risk levels (monthly series).

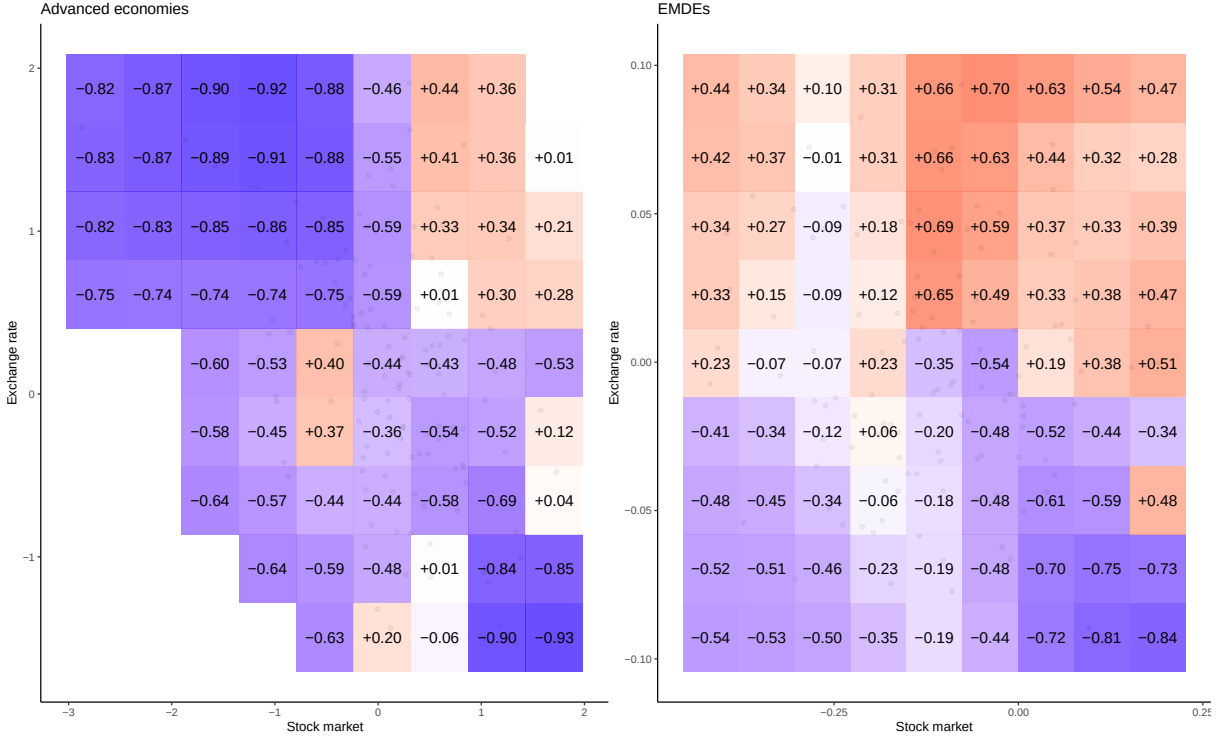


rates lead to stronger currency, but also to tighter monetary conditions, hurting stock valuations (particularly for leveraged firms), which can be considered as a policy trade-off on stabilizing exchange rates at the expense of growth. Moreover, in export oriented countries, geopolitical events can cause terms-of-trade deterioration (e.g., commodity sanctions). Currency appreciates (perhaps due to reduced imports or capital controls), but investors expect earnings to fall, pushing down stock prices. In this case, appreciation is a by-product of disrupted trade or capital flow patterns (Calvo et al., 1993). Moreover, currency appreciation during conditions of high geopolitical risk may be driven by short-term inflows into safer domestic assets (e.g., government bonds), or foreign repatriation of capital. Meanwhile, equity markets decline because investors exit risky local stocks, especially those exposed to domestic consumption or geopolitics. Thus, the currency strengthens due to capital seeking short-term safety, rather confidence in the economy.

5.4.3 Cross-quantilogram results

Linton and Whang (2007) introduced the (auto-)quantilogram as a tool to examine dependence structures across different quantiles of a stationary time series, by utilizing the correlogram of quantile exceedances. Building on this idea, Han et al. (2016) proposed the cross-quantilogram, a multivariate

Figure 13: Local partial dependence map of exchange rates vs stock market on the plane defined by high geopolitical risk levels (monthly series).



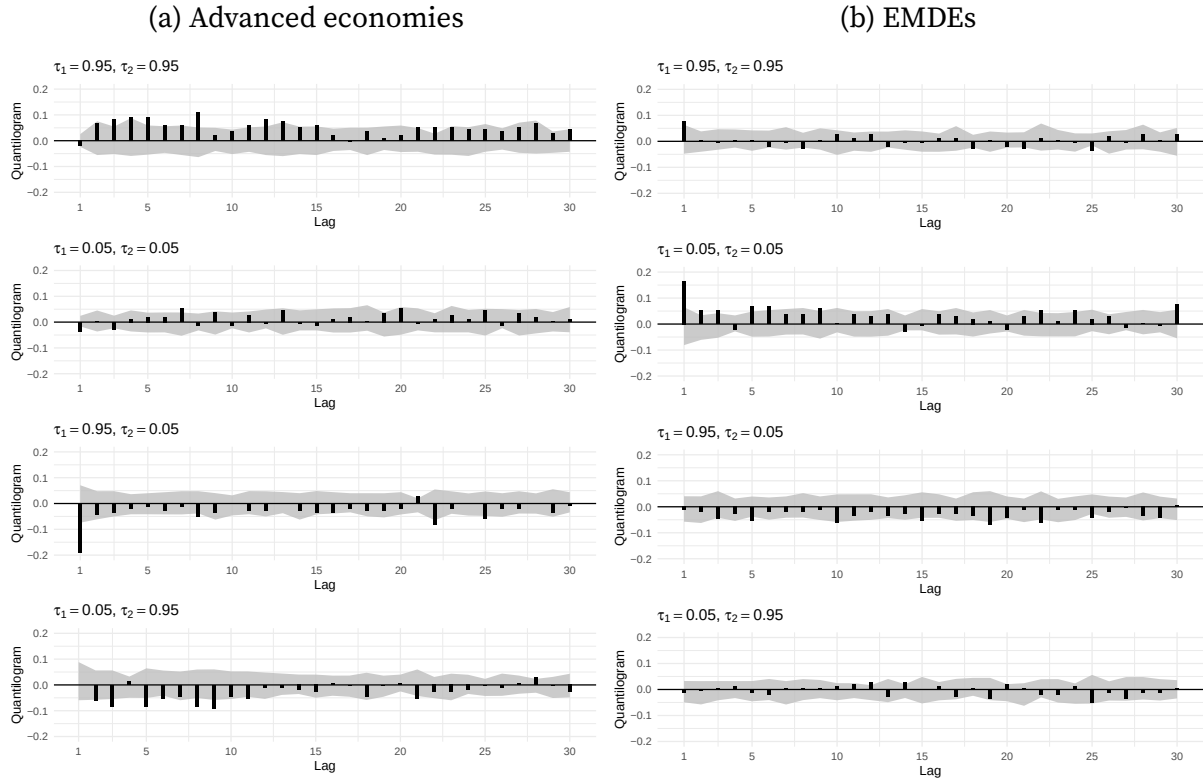
extension that enables the analysis of quantile dependence between two time series. This approach serves multiple purposes: it can be employed to assess quantile-specific dependence, evaluate directional predictability, and perform model specification tests. It can also capture quantile or extreme value dependence between markets based only on their returns.

Our analyses now extend the lag up to 30 and look at various quantiles of exchange rate and stock returns. That is, we let the lag $k=1,2, \dots, 30$, signifying a one month interval for daily observations. The quantile range for exchange rate and stock returns are set to different levels of extreme high and low returns, $[0.95, 0.05]$. The left panel in Figure 14 shows the cross-quantilograms $\hat{\rho}_{\tau_1, \tau_2}(k)$ for the AEs. The first two rows illustrate the hypothesis that both markets are in the high $[\tau_1=0.95, \tau_2=0.95]$ and low quantile $[\tau_1=0.05, \tau_2=0.05]$, respectively. In the third row, the stock market is set in the low quantile and the currency market in the high quantile $[\tau_1=0.95, \tau_2=0.05]$, and in the forth row, the stock market is set in the high quantile and the currency market in the low quantile $[\tau_1=0.05, \tau_2=0.95]$. In each graph, we show the 95% bootstrap confidence intervals for no quantile dependence based on 5000 bootstrapped replicates.

For the AEs (left panel), we observe that in the case when a change in stock returns is in high quan-

Interested readers may refer to the cited publication for technical details

Figure 14: The sample cross-quantilogram $\hat{\rho}_{\tau_1, \tau_2}(k)$, between the stock and currency market, when stock market rapidly increases [$\tau_2=0.95$] or decreases [$\tau_2=0.05$]. Bar graphs describe sample cross-quantilograms for $k = 0, 1, 2, \dots, 30$ and the shaded area denotes the 95% bootstrap confidence intervals, based on 5000 replications.



tile, i.e., [$\tau_2=0.95$], the cross-quantilogram is positive and significant up to five lags (first row of the left panel), and negative and significant for the first two lags (bottom row of the left panel). Thus, in AEs, when the exchange rate is high, and the stock returns increase rapidly the depreciation of the domestic currency will continue for about five days (exchange rate increases). When the exchange rate is low, and the stock returns increase rapidly the depreciation will continue for about two days. In the case that stock returns are set in the low quantile, [$\tau_2=0.05$], (2nd and 3rd row in the left panel), the cross-quantilogram for [$\tau_1=0.05$] and [$\tau_1=0.95$], is negative for both cases but significant only for the former case. This indicates that when stock returns decrease rapidly, the exchange rate depreciation may continue until the next day.

Overall, our results suggest that in advanced markets, large increases in stock returns may signal greater foreign investor inflows or speculative activity, which could put downward pressure on the domestic currency in the short-run, possibly due to expectations of future profit-taking or capital outflows. It may also reflect portfolio rebalancing, where gains in the stock market are accompanied by a reduced demand for the domestic currency. When stock returns fall sharply ($\tau_2=0.05$), the domestic currency

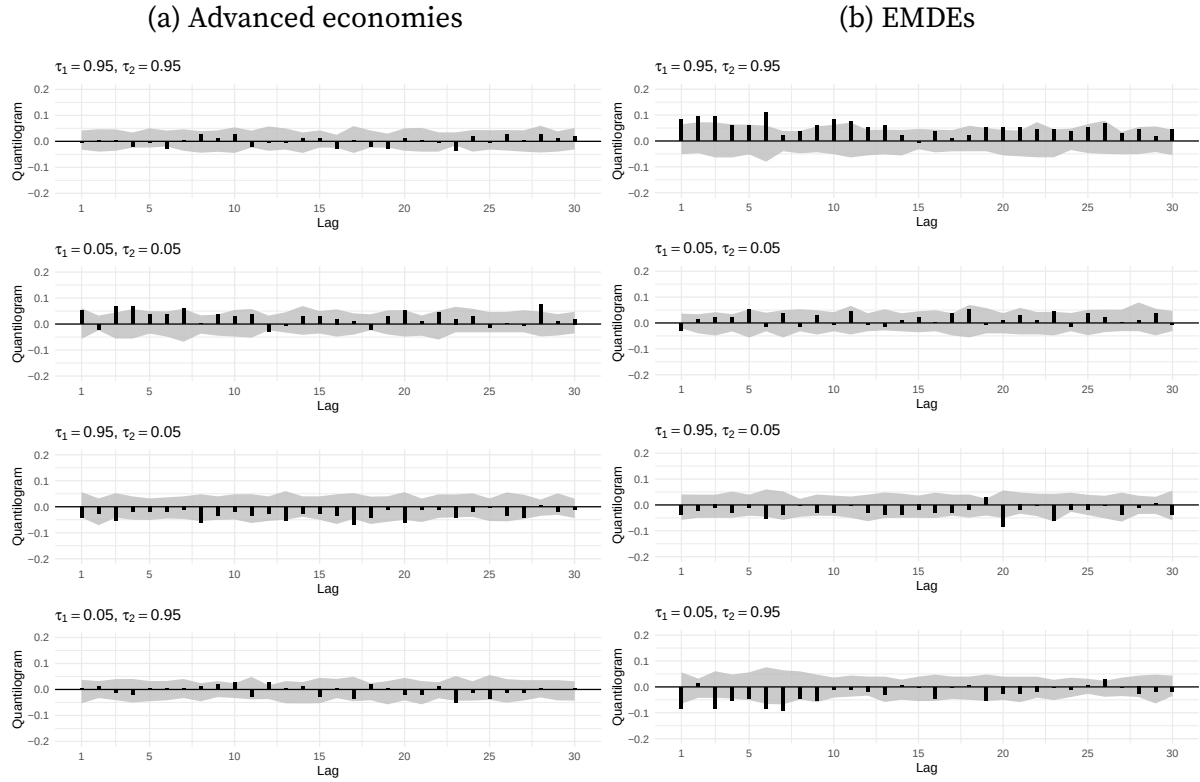
tends to appreciate slightly the next day, especially when the exchange rate is already high ($\tau_1=0.95$). This could be driven by flight-to-safety dynamics, where a drop in asset prices leads to repatriation of capital or increased demand for domestic currency as investors move into less risky assets.

For the EMDEs (right panel), we observe a positive and significant spike at the first lag when both markets lie in the same quantile $[\tau_1=0.95, \tau_2=0.95]$ or $[\tau_1=0.05, \tau_2=0.05]$. The estimate is larger in magnitude when both markets are in the low quantile. This indicates that in emerging markets the exchange rate will appreciate the next day in response to a large decrease in the stock market. This result may reflect the market rebalancing positions, where large drops in stock prices may trigger foreign investors to close short positions in the currency market, creating temporary appreciation pressure. Moreover, sharp market movements may be perceived by market participants as signals for potential central bank interventions or policy adjustments, which could support the domestic currency.

Figure 15 represents the case when a change in exchange rate is set in the high and low quantile, i.e., $[\tau_2=0.05, 0.95]$. For the AEs in panel (a), the cross-quantilogram appears to be broadly insignificant for various quantiles across the different stock market levels. Thus, extreme movements in exchange rates have a limited impact on extreme stock market movements. This complements our previous findings for AEs, that moderate and not extreme movements in the exchange rates may likely predict movements in the stock market. This result also suggests that a high degree of market maturity and insulation, where exchange rate shocks (even large ones) are likely already anticipated, hedged, or otherwise neutralized by diversified investors and central bank credibility. Moreover, the financial systems are more robust in AEs, possibly with deeper derivative markets that help cushion shocks between the FX and equity markets.

For the EMDEs (panel b), we observe that in the case when a change in exchange rate returns is in high quantile, i.e., $[\tau_2=0.95]$, the cross-quantilogram is positive and significant up to six lags (first row from the right panel). Thus, in EMDEs, when the stock returns are high, and the exchange rate returns increase rapidly, the appreciation of the exchange rate will continue for about six days. This could reflect a scenario where strong equity inflows or speculative capital movements drive up stock prices while simultaneously putting pressure on the currency due to profit repatriation or hedging activities. Investors might be selling local currency after gains in the stock market, resulting in sustained depreciation. The persistence suggests that these dynamics may be driven by behavioral or structural factors, such as low market depth, policy uncertainty, or financial frictions, that prevent quick rebalancing. When the stock market is low (last row in panel b), and the exchange rate returns increase rapidly the depreciation will continue over the next day. This indicates that in the face of simultaneous equity sell-offs and currency depreciation, possibly triggered by capital flight or negative sentiment, the depreciation pressure continues but only briefly. It may also reflect prompt monetary or policy re-

Figure 15: The sample cross-quantilogram $\hat{\rho}_{\tau_1, \tau_2}(k)$, between the stock and currency market, when currency market rapidly increases [$\tau_2=0.95$] or decreases [$\tau_2=0.05$]. Bar graphs describe sample cross-quantilograms for $k = 0, 1, 2, \dots, 30$ and the shaded area denotes the 95% bootstrap confidence intervals, based on 5000 replications.



sponses (e.g., central bank intervention, rate hikes, communication strategies) that help stabilize the currency more quickly. Alternatively, it may indicate that investors quickly exit the market, with the most intense pressure concentrated in the initial shock.

6 Conclusions

This study provides a comprehensive analysis of the nonlinear and asymmetric interactions between stock and currency markets in a group of advanced (AEs) and emerging markets and developing (EMDEs) economies, with particular emphasis on the role of geopolitical risk. Employing the advanced framework of local Gaussian partial correlation (LGPC) alongside bootstrap techniques, the findings reveal substantial heterogeneity in financial market linkages across countries and under varying levels of uncertainty.

Our baseline findings show that in AEs, the contemporaneous relationship between stock returns and exchange rate changes is negative, aligning with the “return chasing” hypothesis and the theo-

retical frameworks of portfolio balance and flow-oriented models. Conversely, in emerging markets, the correlation is positive, reflecting capital inflows during bull markets that drive both asset prices and currency values upward. This structural difference highlights the fundamentally distinct nature of financial market functioning across the two groups: while AEs exhibit more complex, bidirectional financial flows, EMDEs are largely driven by currency-sensitive capital movements.

In the analysis of market lead-lag dynamics, we uncover that when exchange rates lead in AEs, a depreciation may enhance export competitiveness and stimulate equity markets. Our results for the EMDEs suggest vulnerability to abrupt currency appreciations that undermine stock market performance—an outcome often linked to external shocks or policy shifts. When stock markets lead, advanced countries exhibit positive tail dependence, potentially due to capital reallocation, signaling of monetary policy changes, or current account effects. In contrast, EMDEs reveal weak and statistically insignificant relationships, underscoring the limited role of equity markets in driving exchange rate dynamics in these economies.

A critical contribution of this paper is the detailed analysis of how geopolitical risk reshapes the stock-exchange rate nexus. Under conditions of high geopolitical risk, advanced markets demonstrate intensified negative dependence across multiple market regimes, especially in downturns, reinforcing the notion of domestic currencies as safe-haven assets. On the other hand, EMDEs display strong and widespread positive dependence under high geopolitical risk, particularly when both markets are under stress, consistent with the structural vulnerabilities of EMDEs. Our findings suggest that EMDEs may be more susceptible to synchronous declines across financial assets when geopolitical uncertainty increases.

Another novel contribution is the analysis of the tail dependence between stock return volatility and exchange rate volatility. We find evidence of significant co-movement under extreme conditions, especially in AEs during bullish equity phases accompanied by currency depreciation. For EMDEs, tail dependence is generally weaker but still present, indicating that volatility synchronization can be exacerbated by structural weaknesses, especially under risk shocks.

Our results have significant policy implications. For policymakers in AEs, the evidence suggests a need to closely monitor exchange rate movements during periods of geopolitical stress, as these can drive equity market responses and investor flows. For EMDEs, the findings highlight the importance of strengthening financial market depth, improving communication of monetary policy, and building buffers against external shocks. Investors, in turn, should account for asymmetric and regime-dependent risks in their global allocation strategies, especially during periods of heightened uncertainty.

Future research could investigate the time-varying nature of these dependencies using dynamic lo-

cal correlation techniques, or extend the analysis to sectoral indices, commodities, and other financial assets. Moreover, disaggregating the types of geopolitical risk (e.g., wars, sanctions, or threats) could further enhance our understanding of how uncertainty translates into market stress. The interaction between induced uncertainties—such as economic policy uncertainty—and geopolitical events also remains an open area of inquiry. We leave these avenues for future research.

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A Appendix

Figure 16: Bootstrap local Gaussian correlation estimations for the lagged exchange rates versus stock market for the AEs (upper panel) and EMDEs (lower panel) economies. Shaded area denotes the 95% confidence intervals for the local Gaussian correlation estimates.

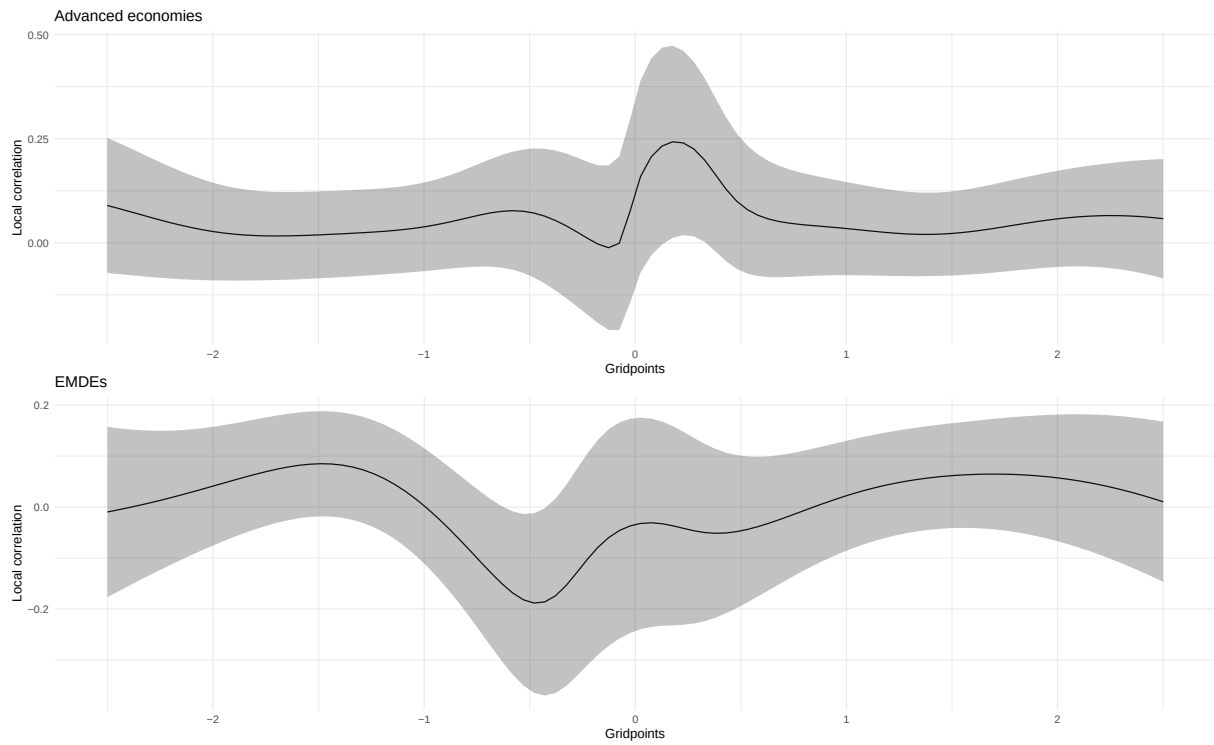


Figure 17: Bootstrap local Gaussian correlation estimations for the exchange rates versus lagged stock market for the AEs (upper panel) and EMDEs (lower panel) economies. Shaded area denotes the 95% confidence intervals for the local Gaussian correlation estimates.

