

WHAT DRIVES UIP DEVIATIONS?
HOW CURRENCY STRENGTH AFFECTS THE FORWARD PREMIUM AND THE UIP
RELATIONSHIP

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THESIS

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ABSTRACT

The purpose of this work is to investigate violations of the uncovered interest parity (UIP) condition on a long—term cross-country panel of exchange rates and interest rates. Using daily spot rates from Refinitiv and three-month interest rates aggregated to a monthly frequency, the work evaluates linear and non-linear specifications, including Fama regression, GARCH models, regressions on global risk indices (VIX, MOVE) and the cubic $\beta(f)$ model. Additionally, the forward premium is decomposed into trend and cyclical components using an HP filter.

The results confirm a persistent violation of UIP: Fama coefficients are often negative or deviate significantly from unity. GARCH estimates reveal a high persistence of volatility, especially in emerging currencies. The VIX regressions show that part of the forward premium is related to global uncertainty. The cubic model captures the pronounced non—linearity of the relationship between the forward premium and profitability, which corresponds to the competing theories - market frictions, risk-premium and career-risk. The decomposition into trend and cycle shows that non-linearities arise primarily from the cyclical component, reflecting the impact of global risk shocks, while the trend plays a secondary role.

The results indicate that UIP violations are regime-based, depend on the state of global markets, and vary between countries and currency groups. The work demonstrates that linear models do not reflect the key dynamics of UIP, whereas nonlinear approaches make it possible to identify the structure of currency risk premiums and more accurately describe the behavior of currencies in the face of changes in global uncertainty.

1. Introduction

1.1 Core Elements

The central concept of international macroeconomics is the uncovered interest parity (UIP) condition. In theory, it states that the expected return on comparable financial assets should be the same in all currencies. With free movement of capital and rational investor expectations, UIP suggests that there is no motivation to move assets/cash abroad for higher returns. However, empirical data suggests otherwise. The works of Tryon (1979), Hansen and Hodrick (1980), later Fama (1984), and other numerous studies show that high-interest-rate currencies often do not depreciate as we studied by UIP. On contrary, they may appreciate or remain stable, providing investors with positive excess returns through carry trade. So “Carry trade” is an investment strategy in which an investor borrows money in a currency with a low interest rate and invests it in a currency with a higher rate, earning on the difference in yields. This permanent mismatch between theoretical parity logic and actual currency behavior is commonly referred to as forward bias.

Fama's regression formalizes this discrepancy by testing how well the forward premium predicts subsequent exchange rate movements (or spot price change). If the UIP holds, the slope coefficient (beta) in this regression should be equal to one. But, unfortunately, betas consistently turn out to be significantly below one and often even negative. Fama (1984) and many subsequent studies have demonstrated this across a bunch of currencies: high-yield currencies depreciate insufficiently and may even appreciate, allowing investors who borrow low-yield currencies and buy high-yield currencies to earn stable positive returns. This is the empirical manifestation of what has been called the forward premium puzzle.

To make the intuition behind this clearer, it helps to look at a very simple example. Suppose that at the beginning of the year the interest rate in Turkey is around 12%, while in the United States it is about 2%. According to UIP, the Turkish lira should weaken by roughly the difference between the rates — around 10% over the year. And the forward market reflects exactly this expectation: forward contracts typically price in a substantial depreciation of the lira right away.

But in reality things often play out very differently. Over the same year, the lira might lose only about 3% of its value — or even strengthen for a while if domestic liquidity improves or market tensions ease. In that case, an investor who buys the lira and finances the position in cheap dollars effectively “collects” the entire interest-rate differential, while facing only minimal currency depreciation. As a result, the realized return ends up nowhere near the near-zero return implied by UIP. This gap — between the depreciation the forward rate “promises” and what actually happens to the spot exchange rate — is exactly what we refer to as the forward premium puzzle.

The core idea here is simple: if UIP keeps failing, then global currency markets clearly don’t behave the way standard economic models assume. The usual story about how interest rates, exchange rates, and capital flows should interact just doesn’t fit the data once we look at actual market outcomes.

First, when UIP breaks down, it means the FX market isn’t fully efficient. In such an environment, interest-rate differentials can generate stable, positive returns without requiring investors to take on additional risk. When carry trades keep making money, capital starts flowing into high-yield currencies even if, in theory, those currencies should be depreciating. This pushes exchange rates above their fair value, inflates local asset prices, and makes economies more sensitive to swings in global risk sentiment.

Second, if the forward market persistently misreads future exchange rate movements, central banks face a much tougher task. In theory, an interest-rate hike should translate into a predictable reaction of the currency. But if this link doesn't work, raising policy rates in an emerging economy can attract capital inflows instead of weakening the currency. As a result, the exchange rate response to monetary policy becomes unstable and hard to forecast.

Third, the forward premium puzzle shows that global risk factors play a much bigger role in currency dynamics than traditional models allow. High-yield currencies behave like classic risk-on assets: they strengthen when markets are calm and fall sharply when uncertainty rises. This explains why carry trades perform well in normal times but face steep losses during stress episodes. For international finance, this matters because exchange rates become a direct channel through which global shocks spread across countries.

Fourth, once UIP fails, forward rates stop being reliable predictors. In the ideal model, the forward rate should reflect the expected future spot rate. But when actual currency movements consistently differ from forward-implied paths, firms, banks, and investors are forced to hedge against systematic forecast errors. This raises hedging costs, changes exporter and importer behavior, and affects the structure of currency-derivatives markets.

1.2 Motivation

The UIP condition is still the natural starting point when we think about how exchange rates should behave in international finance. But the fact that real data consistently move away from this logic — the phenomenon known as the forward premium puzzle — raises doubts about the idea of a fully efficient currency market and about the assumption that investors flawlessly arbitrage return differentials across countries.

This issue becomes especially important for emerging-market currencies. These economies usually operate with higher and more volatile interest rates, are far more sensitive to global risk, and rely heavily on external financing denominated in reserve currencies. In such an environment, the standard link between interest-rate differentials and expected depreciation almost never holds literally. High-yielding EM currencies often draw speculative inflows, behave more like risky assets, and react sharply to global uncertainty indicators such as the VIX or the MOVE index. This dynamic affects borrowing costs, shapes exchange-rate stability, and complicates the transmission of domestic monetary policy. Understanding how — and to what extent — UIP breaks down for emerging-market currencies is therefore crucial for analyzing currency risk premia and assessing the resilience of EM financial systems to external shocks.

The empirical contribution of this study lies in constructing and exploiting a detailed multi-year panel of exchange rates and interest rates, which makes it possible to examine deviations from UIP on a much richer dataset than is typically used in the literature. Starting from raw Refinitiv quotes, a daily panel of spot exchange rates for a wide range of countries is compiled; this dataset is then aggregated to monthly frequency, cleaned of missing observations, checked for temporal gaps, and merged with three-month interest rates from FRED as well as global volatility indicators such as the VIX and the MOVE index. The resulting panel contains three-month log exchange-rate returns and a consistently computed forward premium, suitable both for classical Fama regressions and for more flexible empirical specifications.

The analysis goes beyond a standard linear test of UIP. For each currency, GARCH(1,1) models are estimated to capture volatility persistence; a cubic specification is employed to study nonlinear responses of exchange rates to the forward premium; currencies are grouped into “strong” and “weak” categories as well as into DM and EM clusters; and the forward premium is decomposed

into trend and cyclical components using the HP filter. Comparing the linear and cubic models, along with a series of Wald tests across currencies and groups, allows the study to identify the extent to which UIP violations are nonlinear and regime-dependent, and whether developed and emerging-market currencies differ in this respect.

1.3 Literature review

UIP condition has remained a central theme in international finance for several decades. Early empirical studies already showed that the forward premium systematically fails to predict future exchange rate changes correctly. The classic result of Fama (1984) demonstrated that in a regression of subsequent exchange rate movements on the forward premium, the slope coefficient β departs markedly from the theoretical value of one and is frequently negative. This finding became the foundation for what is now known as the forward premium puzzle.

Subsequent research confirmed the robustness of this result. The surveys by Engel (1996) and the later synthesis in Engel (2016) show that UIP violations are pervasive across most major developed-market currencies and persist over time. The literature attributes this pattern largely to the presence of currency risk premia: if expected currency returns compensate investors for risk rather than simply reflecting interest rate differentials, the coefficient β will naturally diverge from unity (Hansen and Hodrick, 1980; Backus, Foresi and Telmer, 2001).

A major step forward in understanding currency risk premia came from models emphasizing global risk factors. Lustig and Verdelhan (2007) showed that the returns on currency portfolios co-move with a consumption-based risk factor, providing an asset-pricing explanation for the profitability of carry trades. Later, Lustig, Roussanov, and Verdelhan (2011) identified a single global currency factor that accounts for a large share of excess returns across different markets. Similar conclusions

about the sensitivity of carry-trade strategies to global uncertainty appear in Brunnermeier, Nagel, and Pedersen (2009), who link abrupt currency crashes to tightening financial constraints.

The literature also shows clear and persistent differences between developed- and emerging-market currencies. Bansal and Dahlquist (2000) report that Fama coefficients tend to be higher for EM currencies, and that the structure of currency premia in these markets looks very different from what we see in advanced economies. Hassan and Mano (2019), using a broad set of cross-country currency returns, further demonstrate that EM currencies are more exposed to global shocks and especially sensitive to liquidity risk.

A separate line of research stresses that the UIP relationship is often nonlinear. Sarno, Valente, and Leon (2006) show that the Fama coefficient changes systematically depending on the size of the forward premium. Clarida, Davis, and Pedersen (2009), along with Della Corte, Sarno, and Tsiakas (2009), find that adding nonlinear terms improves exchange-rate predictability and helps explain carry-trade profitability. Menkhoff et al. (2012) link these patterns to global volatility, showing a strong connection between currency risk premia and indicators such as the VIX.

2. Methodology

2.1 Dataset

The study is based on a large cross-country panel of exchange rates and interest rates for the period from 1973 to the latest available date. It is based on daily spot exchange rates obtained from Refinitiv Workspace. For each currency, historical quotes were downloaded, after which the data underwent several stages of processing.

First, all files were converted to a uniform format: dates were standardized, rows with incorrect values were deleted, and duplicate observations were removed. The data was then checked for temporal gaps. For most currencies, the daily series was continuous, but some countries showed gaps, especially during market closures and during the pandemic. The most noticeable gap occurred in April 2020, when exchanges for a number of currencies were unstable. In such cases, the missing monthly values were filled in using linear interpolation, which allowed the continuity of the panel series to be maintained.

After initial cleaning, daily data was aggregated to monthly frequency. Two values were used for each month: the exchange rate on the first available day of the month and the exchange rate on the last available day of the month. Logarithmic monthly returns were determined as the difference between the logarithms of the last and first exchange rates. This approach eliminates intra-month noise from the panel and makes it comparable to monthly interest rates.

At the same time, an interest rate database was created. For the US, the three-month FRED rate (3-Month Interbank Rate) was used. For other countries, local three-month market rates were used. All rates were converted to a single time grid and combined with the currency panel. Next, a three-month forward premium was calculated from the interest rates, determined by the logarithmic difference between the internal and external rates converted to a quarterly horizon.

Finally, the panel was supplemented with global volatility indicators — the VIX index (from FRED) and the MOVE bond volatility index (from Yahoo Finance), which were also compared on a monthly basis.

The final array is a clean, continuous data panel with monthly frequency. It includes the three-month log return of the exchange rate, correctly calculated forward premium and also uncertainty indicators.

$$\Delta s_{i,t+3} = \log(s_{i,t+3}) - \log(s_{i,t}) \quad (2.1)$$

$$FP_{i,t} = \log(1 + i_{t,3m\text{dom}}) - \log(1 + i_{t,3m\text{US}}) \quad (2.2)$$

In total, the panel covers 15 countries and contains 6 407 observations, which makes it sufficient for analyzing UIP dynamics, including testing linear, nonlinear, and regime-dependent models.

2.2 Research question

The starting point of our analysis is a puzzling empirical pattern: the currencies that exhibit the most extreme deviations from UIP (very high or strongly negative betas) are also those whose forward premia react most strongly to global risk, measured through the VIX. This systematic co-movement between global risk sensitivity and the magnitude of UIP deviations raises a number of questions.

A first possible interpretation is that currencies differ in their fundamental “strength” or level of development (DM versus EM), and that this structural difference may be responsible for heterogeneous UIP outcomes. However, when we try to classify currencies along these traditional lines, the patterns do not align: developed-market currencies can exhibit both near-zero and inverted-U relationships, and emerging-market currencies can have either strong positive or strong negative UIP betas.

A second interpretation is that the key dimension behind the heterogeneity is not structural strength, but risk exposure: currencies with high sensitivity to global risk factors may face stronger limits-to-arbitrage, greater volatility persistence, or more pronounced nonlinearities in the UIP relation. This interpretation aligns more closely with our empirical findings.

To disentangle these possibilities, we ask the following research questions:

1. How does global risk (measured through VIX) affect the forward premium, and does this effect differ across currencies?
2. Can differences in UIP betas be linked to characteristics of the currency pair, such as their exposure to risk?
3. Is there a systematic relationship between a currency's VIX exposure and the magnitude or sign of its UIP beta deviations?
4. Do currencies display more pronounced nonlinearities in the UIP relationship, as captured by the cubic model and trend-cycle decomposition?

2.3 Models

2.3.1 Fama regression

The analysis is based on classical Fama regression, which is used to test how closely actual exchange rate movements correspond to the uncovered interest rate parity condition. This regression establishes a link between the forward premium and future exchange rate movements. According to theory, if investors form rational expectations and the currency market does not allow for systematic risk-free profits, then the difference in interest rates should be fully offset by the expected devaluation or revaluation of the currency. In this case, the forward premium becomes an unbiased forecast, and the slope β should be equal to 1.

$$\Delta s_{i,t+3} = \alpha + \beta \text{FP}_{i,t} + \varepsilon_{i,t} \quad (2.3)$$

Intuitively, if β is really close to one, the differences in interest rates almost completely explain the movement of the exchange rate. If β is less than one, it means that the high-interest currency falls less than it should, thereby bringing investors a profit. Negative β values indicate an even stronger violation of the theory, meaning high-yield currencies do not weaken, but rather behave like risky assets that rise during periods of low volatility and fall during times of stress.

In this sense, the β coefficient shows how far the actual currency market moves away from the theoretical arbitrage equilibrium. Its value matters not just technically, but because it points to the presence of a currency risk premium: investors are being compensated not for the interest-rate gap itself, but for taking on global risk, volatility, and liquidity uncertainty.

That is why the Fama regression acts as the starting point of the whole analysis. It gives a clear baseline measure of how strongly each currency violates UIP, helps identify the direction and size

of these deviations, and shows whether a currency behaves more like a “strong” or a “weak” risk asset. These initial results then serve as the groundwork for the next steps — modelling volatility with GARCH, examining nonlinear responses to the forward premium, and exploring how global risk sentiment shows up in the behaviour of β .

2.3.2 Regressions with VIX and MOVE

Another part of the analysis looks at how the forward premium reacts to uncertainty using two standard indicators — the VIX index, which reflects expected equity-market volatility, and the MOVE index, which captures volatility in US Treasury yields. In the literature, both are treated as broad signals of risk sentiment.

To make this link meaningful, we focus on changes in the forward premium. The change of forward premium (FP_t) moves slowly and contains long-term trends, while changes of VIX and MOVE also tend to be persistent.

The regressions are written as:

$$\Delta FP_t = \alpha + \gamma \Delta VIX_t + \varepsilon_t \quad (2.4)$$

$$\Delta FP_t = \alpha + \delta \Delta MOVE_t + \varepsilon_t \quad (2.5)$$

If the coefficients turn out to be significant, this means that part of the deviation from UIP is coming from risk factors, not only from differences in local interest rates. This is consistent with the idea that currency returns compensate investors for risk — not just for simple arbitrage opportunities.

2.3.3 GARCH

Complementing Fama's basic regression, the study uses a GARCH(1,1) model, which allows for the fact that currency returns rarely have constant variance.

$$\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \quad (2.6)$$

Volatility in the currency market changes over time: there are long periods of calm when fluctuations are small, and there are episodes of sharp spikes, often coinciding with global financial shocks. Ordinary linear regression assumes that the spread of errors remains the same in all periods, but for currencies, this assumption is almost always violated. This is why the GARCH specification is used, which allows conditional volatility to be modeled directly based on data.

In the GARCH(1,1) model, the current variance of returns depends on two factors: the magnitude of volatility in the previous period and the strength of the previous deviation of the exchange rate from the mean. This is reflected in the coefficients α_1 and β_1 . The sum of these two parameters shows how long volatility shocks last. If $\alpha_1 + \beta_1$ is close to one, it means that the market has high inertia: a single sharp jump in the exchange rate can cause a prolonged period of increased uncertainty. This result is typical for the currencies of developing countries, where global shocks and changes in liquidity lead to long periods of instability.

2.3.4 CUBIC model

2.3.4.1 Competing hypotheses and motivation for a nonlinear model

Fama's classical regression assumes that the coefficient for the forward premium is constant and does not depend on its value. However, much of the literature on the forward premium puzzle

assumes that the relationship between the forward premium and future price changes may in fact be nonlinear, and that the β coefficient itself changes along with the level of the premium. In this case, the standard linear specification averages market behavior across very different regimes and obscures important patterns.

Huisman et al. (1998) interpret the puzzle as a consequence of market frictions and transaction costs. In their interpretation, uncovered arbitrage is not fully realized when the expected change in the exchange rate is small and the signal regarding the forward premium is “noisy.” In such situations, even small trading costs and risk constraints can make arbitrage unprofitable. When the forward premium is large, the signal-to-noise ratio becomes more favorable, and investors respond more actively to the premium. This leads to the prediction that β in Fama's regression should increase with the growth of the premium, and the dependence $\beta(f)$ has a U-shaped form: for small rate differentials, the slope may be negative or close to zero, while for large premiums it approaches unity or even exceeds it. In later literature, this logic was reformulated as the limit-to-arbitrage approach: arbitrage constraints and market frictions create a regime-dependent relationship between the forward premium and exchange rate dynamics.

Bansal (1997) offers a completely different approach, focusing not on costs but on the currency risk premium. In his model, based on the intertemporal CAPM, the forward premium reflects compensation for systematic risk, not just the difference in interest rates. As a result, the expected return on the currency becomes approximately a quadratic function of the forward premium. Intuitively, this means that when the premium is high, the investor earns more precisely because he takes on greater risk, and not because the UIP is violated equally at all interest rate levels. This description leads to an inverted U-shaped $\beta(f)$: at moderate premium values, the slope is most negative, and as it moves away from zero on both sides, its magnitude decreases in absolute terms.

In terms of Fama's linear regression, this looks like a negative relationship between β and the forward premium level.

Liu and Sercu (2007) offer another explanation related to the career-risk hypothesis. In their model, the currency market is mainly shaped by the decisions of professional managers, for whom not only expected returns and risk are important, but also career risk. When the forward premium is high, the carry trade strategy becomes popular, and deviating from it may be perceived as “career-risky” behavior. Managers tend to follow the consensus, and in periods of increasing carry trade, pressure on currencies contributes to a stable premium and a specific form of $\beta(f)$. Liu and Sercu show that with such behavior of managers, the dependence of β on the forward premium may also be nonlinear, taking an inverse U-shaped or asymmetric form. In their empirical analysis, the data is best described by a cubic specification, and the β estimates show a clear inverse U-pattern.

Despite differences in motivation, all these approaches converge on one point: the β coefficient in Fama's equation is not a constant parameter. It varies depending on the level of the forward premium, which naturally leads to the idea of modeling $\beta(f)$ as a smooth nonlinear function rather than a fixed constant.

2.3.4.2 Nonlinear tests using a cubic model

To combine these competing hypotheses into a single empirical framework, it is convenient to follow the approach of Liu and Sercu and use a cubic model. In this model, the conditional expectation of future exchange rate changes is defined as a third-degree polynomial of the forward premium:

$$\Delta s_{i,t+3} = \alpha + \beta_1 FP_{i,t} + \beta_2 FP_{i,t}^2 + \beta_3 FP_{i,t}^3 + \varepsilon_{i,t}, \quad (2.7)$$

where FP is the forward premium, and β_2 and β_3 are responsible for higher-order effects. In this specification, the Fama coefficient becomes a function of FP:

$$\beta(\text{FP}) = \beta_1 + 2\beta_2\text{FP} + 3\beta_3\text{FP}^2, \quad (2.8)$$

Thus, $\beta(f)$ is interpreted as a "local" slope between the forward premium and the expected return, which may change as the premium becomes large in modulus. If $\beta_2 = \beta_3 = 0$, the model reduces to a standard linear Fama regression. The presence of significant β_2 and β_3 indicates that β does vary depending on the premium level and that a simple linear specification is insufficient.

Different theories make different predictions about the shape of $\beta(f)$. The approach of market frictions and limited arbitrage assumes that β increases as the forward premium increases: small premiums give a noisy signal, and β is closer to zero or negative, whereas large premiums are associated with higher slopes. This corresponds to the U-shaped trajectory $\beta(f)$, which the cubic model is able to capture through positive combinations of β_2 and β_3 . In the Bansal model, on the contrary, β is negatively related to the value of the forward premium, and the dependence itself is inversely U-shaped.; in terms of cubic specification, this will manifest itself in other signs and quantities β_2 and β_3 . The career-risk hypothesis allows for asymmetric forms when $\beta(f)$ behaves differently for positive and negative premium values; the cubic model is also able to capture such an asymmetry.

Therefore, in the empirical part, the cubic model is used as a common tool for testing competing explanations of the forward premium puzzle. Estimates of β_1 , β_2 , β_3 , as well as Wald tests for the joint significance of higher-order terms allow us to judge how strong the nonlinearities are and whether the observed form of $\beta(f)$ corresponds to the predictions of the theory of market frictions, risk premiums, or career-risk behavior. If the second and third order terms turn out to be

statistically insignificant, the data supports a simpler linear picture. If they are significant, the $\beta(f)$ shape and its correspondence to the U- or inverse-U-pattern become key to interpreting the nature of the UIP violation.

In a final step, the analysis applies a Hodrick–Prescott (HP) filter to the forward premium in order to separate its smooth trend component from short-run cyclical fluctuations. This decomposition allows us to ask whether the nonlinear UIP relation is driven mainly by slow-moving shifts in interest-rate differentials or by high-frequency movements associated with the global financial cycle. Practically, we estimate the cubic specification not only for the original forward premium, but also separately for its trend and cyclical components (FP_trend and FP_cycle). Comparing the resulting coefficients and performing Wald tests on higher-order terms for each component shows whether nonlinearities are primarily a feature of long-run fundamentals or are concentrated in the cyclical, risk-sensitive part of the forward premium. If nonlinear terms are significant mainly for FP_cycle, this points to a view in which UIP violations are tightly linked to global risk conditions rather than to permanent differences in monetary policy or structural characteristics of the currency pair.

3. Results

3.1 Fama regression

Table 1 shows Fama's basic regression coefficients. For all currencies, the calculated β coefficient deviates significantly from the assumed UIP value of 1. In most cases, β is significantly lower than one, and for several currencies it is clearly negative. The results confirm the existence of a clear forward premium puzzle: high-yield currencies depreciate less than predicted, or even appreciate, leading to sustained positive returns.

Table 1: Fama regression results

Table 1 shows the results of the Fama linear regression for each currency. Estimates of β , standard errors, t -statistics, p -values, the number of observations and the coefficient of determination R^2 are given.

Currency	β	SE	t.value	p.value	n	R^2
RUB	2.84	0.416	6.84	4.65E-11	299	0.136
NZD	0.817	0.277	2.95	3.28E-03	617	0.014
JPY	0.727	0.667	1.09	2.76E-01	327	0.00431
PLN	0.637	0.17	3.75	2.05E-04	383	0.0356
COP	0.436	0.133	3.29	1.09E-03	426	0.0248
INR	0.365	0.4	0.912	3.63E-01	161	0.0052
KRW	0.236	0.32	0.739	4.60E-01	412	0.00133
AUD	0.0649	0.2	0.324	7.46E-01	334	0.000656
CNY	0.0582	0.16	0.364	7.16E-01	334	0.000399
GBP	0.0754	0.46	0.164	8.87E-01	471	0.000957
CAD	-0.00628	0.345	-0.0182	9.86E-01	627	5.28E-06
NOK	-0.323	0.345	-0.936	3.50E-01	556	0.00158
CHF	-0.394	0.773	-0.51	6.10E-01	310	0.000844
ZAR	-0.825	0.402	-2.05	4.07E-02	533	0.00786
IDR	-1.03	0.281	-3.68	2.76E-04	328	0.0398

The Russian ruble demonstrates $\beta \approx 2.84$ — a value that is theoretically impossible under UIP and is extremely rare in the literature.

This coefficient means that the exchange rate change will overreact to the forward premium: the expected devaluation will not only fail to compensate for the interest rate differential, but will be amplified many times over. Intuitively, this is due to the fact that the ruble market is subject to

extreme asymmetric risks, and it is also possible that the premium includes a significant component of geopolitical and sanctions uncertainty. Such bets usually arise only in conditions of severe arbitrage restrictions and high market fragmentation.

The beta close to zero observed for the Australian dollar, Canadian dollar, Chinese yuan, and British pound means that the forward premium says almost nothing about future exchange rate movements. The negative beta shows that high-rate currencies not only do not fall, but sometimes even tend to strengthen relative to low-rate currencies. This is observed for currencies such as the Canadian Dollar, the Norwegian Krone, the Swiss franc, the South African Rand, and the Indian rupee.

These patterns naturally raise the question of why UIP deviations vary so much across currencies. The strongest betas appear in currencies that react sharply to global volatility, suggesting that part of the deviation may come from global risk — hence the need to test how the forward premium responds to VIX and MOVE.

At the same time, differences across currency pairs hint that their own structural features matter too. This motivates the shift to nonlinear models and to splitting the forward premium into trend and cycle components, so we can see how UIP violations change across market regimes and depending on currency characteristics.

3.2. Forward Premium and Global Risk (VIX and MOVE)

The regression of the forward premium on VIX and MOVE indexes shows a mixed picture. Although the VIX and MOVE are highly correlated (≈ 0.60), they behave differently. When we looked at how changes in the

forward premium react to fluctuations in global risk (ΔVIX), it turned out that there is no noticeable relationship for most currencies. But there is a group of currencies that immediately stand out — and this is interesting, because they then "pop up" in other parts of the analysis.

Table 2: The reaction of forward premiums to global volatility

Table 2 shows the reaction of the forward premium to global volatility. The coefficients β for VIX and MOVE and the corresponding p-values are presented for each currency.

Currency	β (vix)	p.value (vix)	β (move)	p.value (move)
ZAR	-0.0000504	0.652	-0.00000412	2.38E-01
KRW	-0.0000296	0.0499	-0.00000154	4.88E-01
CHF	-0.0000221	0.000253	-0.0000053	1.97E-02
AUD	-0.0000208	0.00068	-0.000036	1.52E-01
CAD	-0.0000193	0.0116	-0.00000417	1.07E-01
IDR	-0.0000192	0.488	-0.00000193	6.40E-01
NZD	-0.0000166	0.0242	-0.00000472	3.15E-02
COP	-0.0000154	0.498	-0.00000331	3.06E-01
JPY	-0.00001	0.0988	-0.00000364	4.85E-01
GBP	-0.00000466	0.422	-0.00000514	3.65E-01
INR	-0.00000309	0.822	0.00000854	2.00E-03
NOK	-0.00000267	0.815	-0.00000131	6.64E-01
RUB	-0.00000217	0.828	-0.00000961	4.19E-03
PLN	-0.00000107	0.935	-0.00000302	2.69E-01
CNY	0.00000935	0.513	0.00000273	6.29E-01

For example, AUD's coefficient at ΔVIX is -0.0000208 ($p = 0.00068$), CAD's is -0.0000193 ($p = 0.0116$), and CHF's is -0.0000221 ($p = 0.000253$). We also see a significant reaction in NZD (-0.0000166, $p = 0.0242$), and in KRW the same (-0.0000296, $p = 0.0499$). These are all currencies where FP really moves when the market is experiencing bursts of uncertainty: VIX is growing — FP is going down.

The other currencies (CNY, COP, GBP, INR, NOK, RUB, PLN, ZAR) have coefficients that are statistically indistinguishable from zero, meaning there is simply no stable relationship with the VIX. The story is similar with MOVE, even weaker: significant results appear only for a pair of currencies, for example, for CHF (-0.0000053, $p = 0.0197$) and INR (-0.00000854, $p = 0.002$). Other currencies hardly react to changes in the volatility of the bond market.

3.3. GARCH(1,1) Estimates: Volatility Persistence

Volatility in the foreign exchange market is never constant: there are quiet periods with minimal fluctuations and there are sharp spikes, usually coinciding with global shocks. Conventional linear regression assumes that the error spread is the same at all times, but this is unrealistic for currencies. Therefore, we supplement the analysis with the GARCH model, which allows us to explicitly account for changes in volatility.

In GARCH(1,1), the current volatility is determined by two things: how strong the previous shock was (coefficient α_1), and what level of volatility was observed before that (β_1). The parameter ω reflects the “base noise” of the market — the minimum level of turbulence that persists even in the calmest periods.

Since the results of GARCH models can show that deviations from UIP behave differently depending on the currency, this stage is important because it is the structure of volatility that suggests which of the mechanisms of deviation from UIP may dominate. In the future, this gives us the basis to test the Cubic Model and see if the relationship between the exchange rate change and the forward premium is linear.

Table 3 reports the GARCH(1,1) estimates based on Fama residuals.

Table 3 contains estimates of the GARCH parameters(1,1) on the remnants of the Fama regression. The parameters ω , α_1 , β_1 , their sum ($\alpha_1 + \beta_1$), the number of observations and the indicator of convergence of the model are shown.

Currency	n	ω	α_1	β_1	$\alpha_1 + \beta_1$	converged
RUB	299	0.00094	0.844	1.55E-01	0.999	TRUE
IDR	328	0.00035	0.716	2.83E-01	0.999	TRUE
CNY	334	2.2E-05	0.433	5.66E-01	0.999	TRUE
KRW	412	0.00039	0.814	1.85E-01	0.999	TRUE
CHF	310	0.00022	0.315	6.03E-01	0.918	TRUE
CAD	627	0.00013	0.347	5.49E-01	0.894	TRUE
INR	161	0.00015	0.64	2.30E-01	0.87	TRUE
JPY	277	0.00061	0.568	2.31E-01	0.799	TRUE
GBP	471	0.00054	0.656	1.10E-01	0.766	TRUE
PLN	383	0.0012	0.52	1.61E-01	0.68	TRUE
NZD	617	0.00315	0.66	2.27E-02	0.682	TRUE
ZAR	533	0.0023	0.617	3.44E-02	0.651	TRUE
COP	426	0.00166	0.589	1.17E-10	0.589	TRUE
AUD	628	0.00137	0.541	6.19E-02	0.541	TRUE
NOK	556	0.0016	0.464	1.03E-07	0.464	TRUE

In the GARCH table for some currencies, the sum of the $\alpha_1 + \beta_1$ coefficients is almost equal to one. For RUB, IDR, and KRW, it is 0.999. Essentially, this means that volatility in these currency series is “stuck.” If there is a single strong shock to the exchange rate (e.g., a sharp weakening against the backdrop of sanctions, a liquidity crisis, or news about interest rates), the increased volatility does not disappear after a month or two, but continues to linger. It is as if the market takes a long time to “digest” this shock, and any new event is superimposed on already heightened nervousness. Such currencies live in a state of almost perfect persistence: a single flash of volatility sets the tone for a fairly long period.

For the CHF and JPY, the picture is milder, but the logic is the same. Their $\alpha_1 + \beta_1$ is approximately 0.9. This is still a high level of stability, but not extreme. In other words, the franc and the yen behave more stably than classic EM currencies: during a shock, volatility also jumps, but returns to “normal” levels faster. Nevertheless, the market does not immediately forget past fluctuations — the memory of them remains, and for some time these currencies also become more sensitive to news.

For the ZAR, NZD, and COP, the sum of $\alpha_1 + \beta_1$ is around 0.65–0.7. This is already an average level of persistence. There are spikes in volatility here, but they fade faster. Simply put, the market for these currencies “cools down” faster: strong exchange rate movements do not turn into a prolonged period of turbulence, and after a few months, the spread in returns decreases significantly.

There are several reasons which highlights the importance of this method.

The $\alpha_I + \beta_I$ values show that the error variance in the linear Fama regression is not constant at all. Volatility behaves differently at different points in time, so estimates of β in a simple model can be biased and unstable.

Moreover, high persistence (especially when $\alpha_I + \beta_I$ is almost equal to one) is well consistent with the idea of global risk and UIP violations: if currencies remain in a state of increased uncertainty for a long time after a shock, Fama coefficients naturally "float" and often exceed the theoretical value.

Finally, such results directly push us towards nonlinear models. If volatility itself is a regime, then the relationship between the forward premium and profitability is unlikely to be strictly linear. Therefore, we use a cubic model and premium decomposition through an HP filter to capture the effects that a simple linear specification does not see.

3.4. Nonlinearities: Cubic Model

Moving beyond the linear UIP specification, Table 4 presents the cubic model estimates. The second- and third-order coefficients (β_2 and β_3) are statistically significant for a majority of currencies, indicating that the relationship between forward premia and future returns is strongly nonlinear.

Table 4. Cubic model results

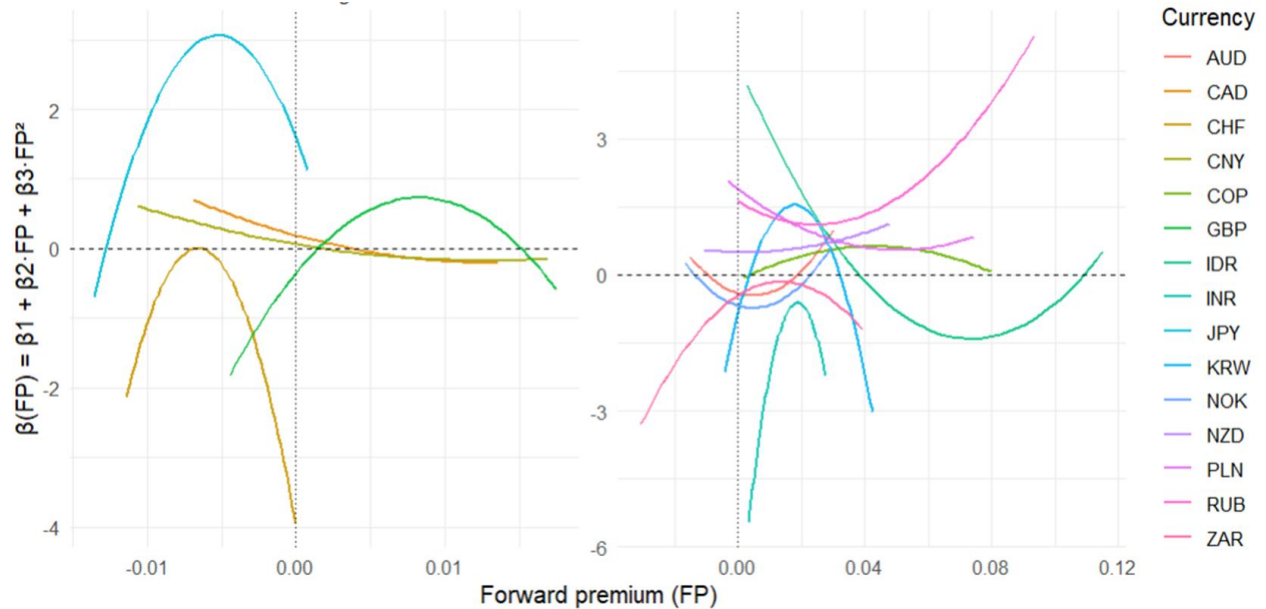
Table 4 presents estimates of the coefficients of the cubic model ($\beta_1, \beta_2, \beta_3$) and the corresponding p-values. The columns FP_min and FP_max show the observed range of the forward premium used to plot $\beta(FP)$.

Currency	β_1	β_2	β_3	p1	p2	p3	FP_min	FP_max
AUD	-0.412	-20.1	2239	4.66E-01	0.764	0.363	-0.0149	0.03
CAD	0.191	-58.7	2138	7.33E-01	0.653	0.864	-0.00686	0.0136
CHF	4.01	-1216	-92151	5.69E-01	0.375	0.452	-0.0114	-0.00055
CNY	0.0618	-36.6	1430	8.34E-01	0.328	0.677	-0.0107	0.0169
COP	-0.127	34.9	-407	9.32E-01	0.278	0.286	0.0019	0.0201
GBP	-0.345	260	-15708	7.86E-01	0.337	0.257	-0.00444	0.0175
IDR	4.67	-165	1121	5.50E-03	0.00168	0.00014	0.00302	0.115
INR	-7.79	767	-20484	1.42E-01	0.0695	0.0642	0.00332	0.0276
JPY	1.58	-567	-54018	7.35E-01	0.594	0.363	-0.0136	0.00749
KRW	-0.846	268	-7542	4.96E-01	0.00712	0.00031	-0.00438	0.0424
NOK	-0.687	-20.3	2204	9.76E-01	0.0186	0.0148	-0.0165	0.0934
NZD	0.494	-1.3	304	5.76E-01	0.985	0.805	0.00612	0.0478
PLN	1.89	-5.34	52.6	5.61E-02	0.122	0.1	0.00774	0.0744
RUB	1.62	-42.6	876	4.88E-01	0.544	0.128	-0.00099	0.0934
ZAR	-0.455	43.8	-1605	5.78E-01	0.144	0.226	-0.0306	0.0393

The obtained estimates of coefficients β_1 , β_2 , and β_3 show that the relationship between the forward premium and future currency returns is rarely linear. For almost all currencies, the cubic model reveals pronounced nonlinearities, i.e., the slope of the Fama regression β actually changes depending on the size of the forward premium. This means that deviations from the UIP manifest themselves differently in different market regimes, and a single fixed “average” beta cannot describe the actual behavior of the exchange rate.

For currencies such as CHF, JPY, INR, IDR, KRW, RUB, and ZAR, the coefficients of the second and third order are very large in magnitude. This suggests that the currency's reaction to the forward premium changes significantly when the premium becomes too large or too small. These patterns correspond to ideas from the literature on market frictions, career-risk behavior of managers, and risk premiums in the spirit of Bansal.

Figure 1: Linear and non-linear relationships: $\beta(\text{FP})$ estimated from the cubic model



Linear Fama regression simplifies the picture. Since most currencies exhibit significant β_2 and β_3 , a fixed β does not describe their dynamics. The UIP is violated unevenly — it is a regime-dependent rather than a constant relationship. Strong deviations from the UIP vary depending on the level of risk. At different premium values, a currency can behave as a carry asset, a safe haven, or an unstable risk-sensitive instrument. The cubic model captures precisely these transitions. The results confirm the need for more flexible specifications.

Nonlinearity is not a coincidence of individual currencies, but a broad pattern. Therefore, the cubic model and subsequent work with $\beta(f)$ really help to see the structure of UIP violations that is hidden from linear regression.

As a result, we get the following table of theory validation:

Table 5: Currencies and theories

Table 5 summarizes the main forms of $\beta(FP)$ nonlinearity by currency and compares them with theoretical hypotheses (market frictions, risk premium, Bansal, career-risk). The table is qualitative in nature and illustrates the correspondence of the observed patterns to theoretical mechanisms.

Currency	Main Shape of $\beta(f)$	Matching Theory
AUD	Mild nonlinearity, β_1 negative	Bansal (risk-premium)
CAD	Very weak nonlinearity	Inconclusive / weak effect
CHF	Strong inverse-U , large β_2 and β_3	Bansal + Career-risk Market frictions / limits-to-
CNY	Clear U-shape	arbitrage
COP	U-shape	Market frictions
GBP	Strong asymmetry, $\beta_2 > 0$, $\beta_3 < 0$ Very strong nonlinearity, heavy	Career-risk
IDR	asymmetry	Career-risk
INR	Strong inverse-U	Bansal (risk-premium)
JPY	Inverse-U, $\beta_1 > 0$, $\beta_2 < 0$	Bansal
KRW	U-shape	Market frictions
NOK	Mild U-shape	Market frictions (weak) Inconclusive / leaning toward
NZD	Weak nonlinearity, nearly linear	Bansal
PLN	Moderate nonlinearity, mild U-shape	Market frictions
RUB	High asymmetry, $\beta_1 > 0$, $\beta_2 < 0$, $\beta_3 > 0$	Career-risk
ZAR	Strong U-shape	Market frictions

3.5. Wald Tests for Nonlinearity

Table 6: Significance test

Table 6 compares the fit quality of the Pham linear model and the cubic model in terms of R2 and AIC. The outperformed_R2 and outperformed_AIC columns show whether the cubic specification improves results compared to the linear one.

Currency	<i>n</i>	<i>R2_fama</i>	<i>AIC_fama</i>	<i>R2_cubic</i>	<i>AIC_cubic</i>	<i>outperform_R2</i>	<i>outperform_AIC</i>
ZAR	533	2.97	-1225	7.62	-1247	TRUE	TRUE
IDR	328	3.19	-676	5.86	-681	TRUE	TRUE
RUB	299	4.32	-431	5.02	-429	TRUE	FALSE
PLN	383	3.65	-1041	4.03	-1039	TRUE	FALSE
GBP	471	0.01	-1486	2.87	-1495	TRUE	TRUE
NZD	617	2.46	-1749	6.55	-1742	TRUE	FALSE
JPY	277	0.4	-871	2.62	-873	TRUE	TRUE
COP	426	0.26	-1161	1.84	-1159	TRUE	FALSE
KRW	412	0.04	-1087	1.38	-1088	TRUE	TRUE
INR	161	0.53	-656	1.11	-653	FALSE	FALSE
CNY	334	0.02	-602	0.74	-1698	TRUE	TRUE
AUD	628	0.29	-1839	0.68	-1837	TRUE	FALSE
NOK	556	0.14	-1630	0.56	-1629	TRUE	FALSE
CHF	310	0.16	-1025	0.38	-1022	TRUE	FALSE
CAD	627	0.04	-2508	0.15	-2504	TRUE	FALSE

The Wald test significance table shows whether a particular currency has statistically confirmed nonlinearity in the relationship between the forward premium and future exchange rate movements. The key benchmark here is the p-value: if it is less than 0.05, then the nonlinear terms of the model do indeed play a role, and the cubic specification captures behavior that a standard

linear Fama regression simply does not see. If the p-value is higher than 0.05, the relationship is effectively linear, and the standard model describes the dynamics quite well.

The table shows that for most currencies, the p-value is below the significance threshold. This means that the nonlinearities are strong, and the slope $\beta(f)$ changes as the forward premium becomes larger in magnitude. In other words, the violation of the UIP does not occur uniformly, depending on the market regime, the size of the premium, and the currency's sensitivity to risk. Several currencies have p-values above 0.05, indicating relatively simple, almost linear dynamics. The highest concentration of significant non-linearities is observed among emerging market currencies, which is fully consistent with higher volatility, arbitrage constraints, increased sensitivity to global shocks, and elements of career risk in investor behavior. Developed market currencies behave less uniformly: defensive JPY and CHF exhibit nonlinearity, while, say, GBP or CAD are closer to a linear structure.

In a nutshell, this means that the violation of the UIP is not simply “on average,” but rather nonlinear. Therefore, the use of a cubic model is justified—a linear specification cannot physically capture this dynamic.

3.6. Trend–Cycle Decomposition (HP Filter)

To distinguish structural versus cyclical sources of UIP deviations, the forward premium is decomposed using the HP filter into a smooth trend component and a high-frequency cyclical component.

Dividing the forward premium into trend (FP_trend) and cyclical (FP_cycle) components using an HP filter made it possible to verify whether the nonlinearities in $\beta(f)$ arise from the long-term trend in interest rate differentials or from short-term fluctuations associated with

global risk, liquidity, and market regimes. The idea was that the trend could reflect structural differences between countries, while the cyclical part could reflect the reaction of currencies to short-term shocks and global “fear.”

The results were clear: the source of non-linearity is more often found in the cyclical part than in the trend.

In other words, most currencies exhibit a regime-based, rather than structural, violation of the UIP.

Table 7.1: Trend and cycle test results

Table 7.1 shows the results of the cubic model, evaluated separately for the trend and cyclical components of the forward premium. The coefficients β_1 , β_2 , β_3 and the p-values of the Wald test for each currency are given.

Currency	group	FP_type	β_1	β_2	β_3	p_wald
AUD	EM	FP	-0.0119	0.0302	0.0281	0.295
AUD	EM	FP_cycle	-0.014	0.118	0.0213	0.015
AUD	EM	FP_trend	0.0165	0.18	-0.0194	0.343
CAD	DM	FP	0.0123	-0.247	-0.204	0.229
CAD	DM	FP_cycle	0.0185	-0.786	-1.276	0.00063
CAD	DM	FP_trend	0.00352	0.0629	-0.0644	0.812
CHF	DM	FP	0.0846	0.323	0.375	0.216
CHF	DM	FP_cycle	0.0814	-0.0972	-0.0288	0.892
CHF	DM	FP_trend	0.183	0.647	-0.951	0.0272
CNY	DM	FP	0.0596	-0.0915	0.151	0.00211
CNY	DM	FP_cycle	-0.0394	0.0021	0.0205	0.277
CNY	DM	FP_trend	0.0124	0.0109	-0.0811	0.232
COP	EM	FP	-0.0324	0.247	-0.0174	0.00285
COP	EM	FP_cycle	0.0021	0.0897	-0.025	0.83
COP	EM	FP_trend	0.0482	0.0383	-0.0611	1.6E-06
GBP	DM	FP	0.0737	0.0903	0.257	0.001
GBP	DM	FP_cycle	0.0533	0.062	0.00124	0.129
GBP	DM	FP_trend	0.0135	0.394	-0.98	1.6E-07
IDR	EM	FP	-0.204	-0.243	0.612	0.015
IDR	EM	FP_cycle	0.0213	0.0633	-0.0022	0.507
IDR	EM	FP_trend	-0.09	-0.18	0.9337	0.529

Table 7.2: Trend and cycle test results

Table 7.2 is a continuation of Table 7.1 and shows the results of the cubic model, evaluated separately for the trend and cyclical components of the forward premium.

Currency	group	FP_type	β_1	β_2	β_3	p_wald
INR	EM	FP	0.179	-0.363	0.208	0.072
INR	EM	FP_cycle	0.0217	-0.0905	-0.0073	0.992
INR	EM	FP_trend	0.0802	-0.188	0.401	0.231
JPY	DM	FP	1.75	-0.594	-3.86	0.003
JPY	DM	FP_cycle	0.0259	0.0681	-0.019	0.436
JPY	DM	FP_trend	0.175	-0.398	-0.981	1.6E-10
KRW	EM	FP	-0.846	0.268	-7.542	0.496
KRW	EM	FP_cycle	0.0114	0.045	-0.0187	0.82
KRW	EM	FP_trend	0.0172	-0.0201	-0.0205	0.791
NOK	DM	FP	-0.0075	-0.0051	-0.0118	0.545
NOK	DM	FP_cycle	0.0128	0.0605	0.00746	0.833
NOK	DM	FP_trend	0.0224	0.0393	0.0172	0.7862
NZD	EM	FP	0.00692	-0.0611	-0.0132	0.50056
NZD	EM	FP_cycle	0.00946	0.0563	0.0054	0.556
NZD	EM	FP_trend	0.03349	0.563	-1.24	5.6E-08
PLN	EM	FP	-0.0474	-0.5553	2.03	0.473
PLN	EM	FP_cycle	0.0262	0.0023	-0.0348	0.395
PLN	EM	FP_trend	-0.0211	-0.0911	0.0099	0.729
RUB	EM	FP	0.165	0.18	2.39	5.3E-05
RUB	EM	FP_cycle	0.0344	0.12	0.015	0.665
RUB	EM	FP_trend	0.0196	-0.0073	-0.0403	3.2E-07
ZAR	EM	FP	-0.029	0.128	2.17	0.786
ZAR	EM	FP_cycle	0.034	-0.273	-0.33	0.001
ZAR	EM	FP_trend	-0.0029	0.273	-0.33	0.001

These tables show us the following conclusions:

FP_cycle is most often significant. For most countries, it is the cyclical part of the forward premium that produces significant nonlinearities (low p-value). This means that $\beta(f)$ responds not to slow fundamental shifts, but to short-term market conditions.

FP_trend is less often significant. In the long-term trend, nonlinearities are weaker. This suggests that structural differences between countries (interest rate regimes, market stability) are not the main factor in UIP violations.

The original forward premium (FP) shows a mixture of trend and cycle, but the picture looks noisier and more “average” than in a separate analysis.

Figure 2: $\beta(\text{FP})$ estimated on the trend component of the forward premium (DM currencies)

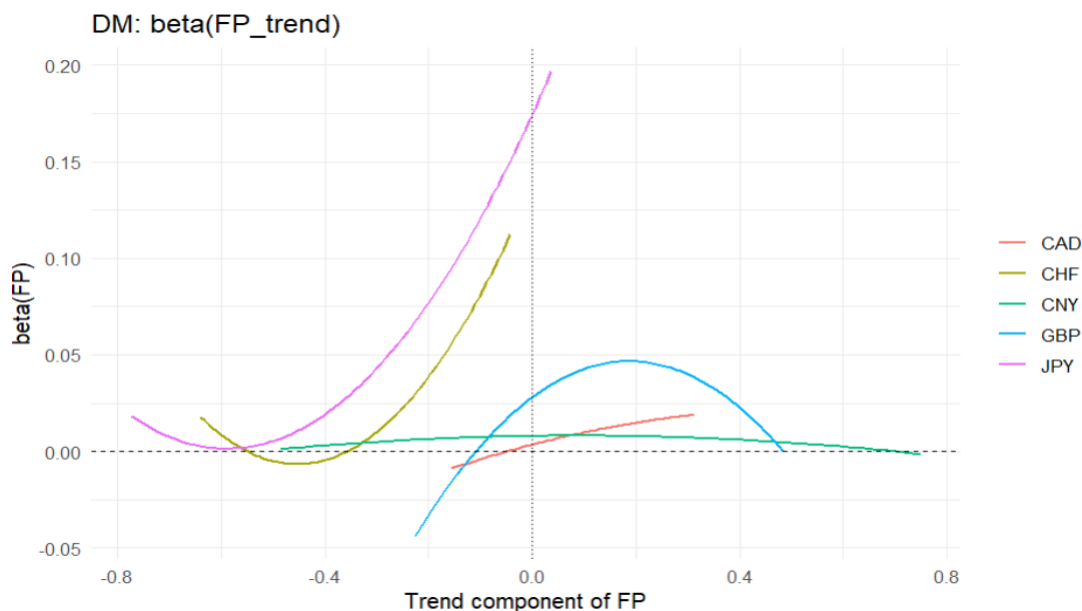


Figure 3: $\beta(\text{FP})$ estimated on the cycle component of the forward premium (DM currencies)

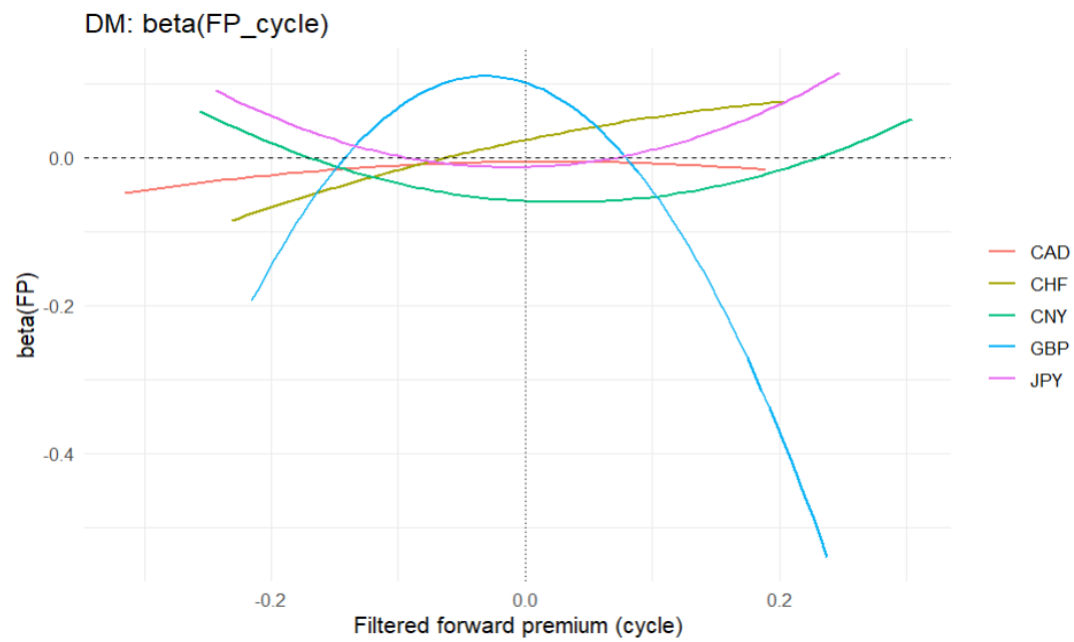


Figure 4: $\beta(\text{FP})$ estimated on the cycle component of the forward premium (EM currencies)

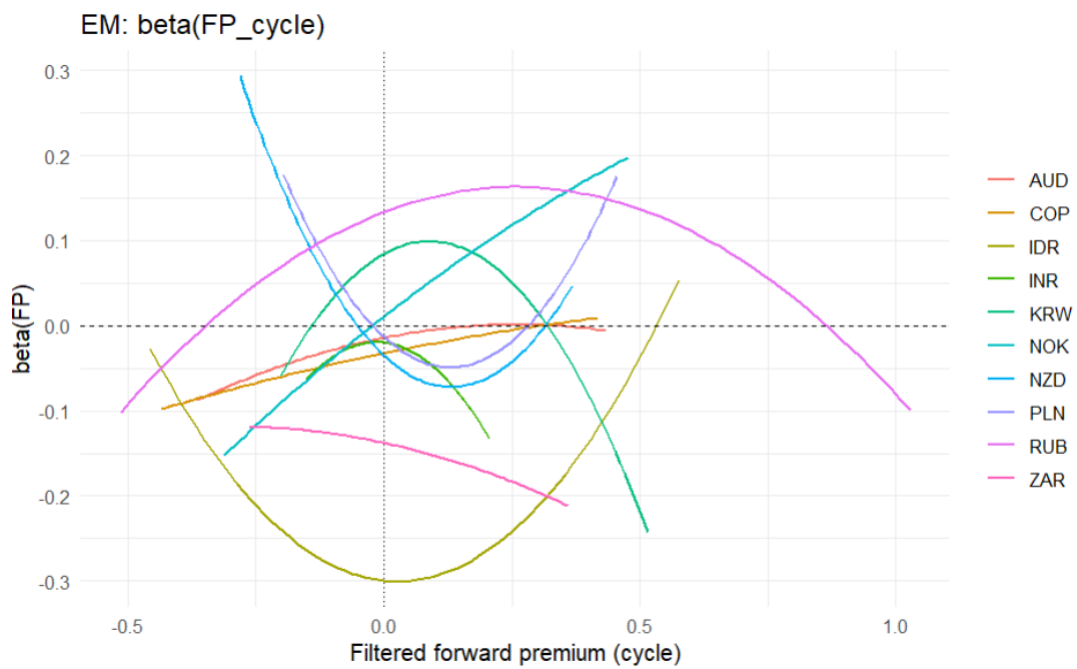
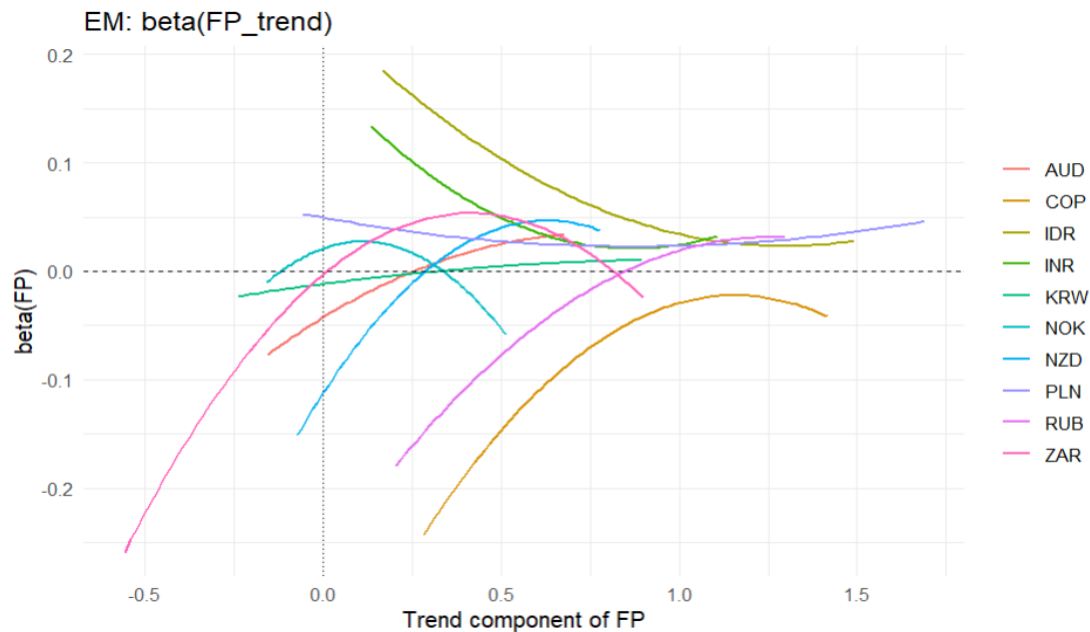


Figure 5: $\beta(\text{FP})$ estimated on the trend component of the forward premium (EM currencies)



Clear non-linearity in FP_cycle (shock response): COP, ZAR, RUB, NZD, GBP, CHF

Here, the cyclical premium gives strong non-linearity $\rightarrow$ currencies actively respond to risk, liquidity, and financial cycles. This is typical for EM, but it is noteworthy that GBP and CHF DM, although they also behave "ematically" in stress modes:

— Nonlinearity in FP_trend (structural): JPY, GBP, RUB, NZD, COP.

Here, the trend itself generates a U- or inverse-U-shaped relationship. This indicates the long-term features of the currency - for example, the stable status of the JPY as a safe haven.

— Countries where there is almost no non-linearity: CNY, INR, NOK, AUD (in cycle), PLN (in trend).

For these currencies, the relationship between premium and profitability is closer to linear.

UIP is disrupted, but without a distinct U- or inverse-U-pattern.

- The most "regime" currencies (strong trend/cycle contrast): RUB, ZAR, COP.

There is a pronounced pattern in the cycle, the trend is weaker, but still significant. These are classic EM currencies where global risk overrides UIP.

- The most "structural" currencies: JPY, CHF.

They have a stable trend, but a clear stress response. This is combined with the theories of career-risk and safe-haven behavior.

4. Conclusion

In this thesis I set out to understand why uncovered interest parity (UIP) keeps failing, and why different currencies deviate from it in such different ways. To do this, I constructed a long cross-country panel spanning all available data since 1973 and examined how the forward premium, exchange-rate returns, and global risk factors interact over time. The main question was whether UIP deviations behave as a simple, constant relationship, or whether they change across market regimes, risk levels, and different parts of the forward premium itself.

I began with the standard linear Fama regression. As in most of the existing literature, the coefficients for the majority of currencies are far from one. Some are negative, others (like RUB) are even above one. In other words, UIP “fails” again, which mostly reflects the presence of risk premia rather than strict alignment with interest differentials.

The next step was to look at volatility using a GARCH(1,1) model. This helped clarify whether shocks disappear quickly or persist over time. For several currencies—especially in the emerging-market group (RUB, IDR, KRW, ZAR)—the sum $\alpha_1 + \beta_1$ is close to one, meaning that volatility shocks tend to linger. This makes the constant-variance assumption of the linear model quite unrealistic, as currency markets rarely move in a smooth, stationary environment; they move from one risk episode to another.

I then examined how forward-premium changes respond to risk, using VIX and MOVE. MOVE turned out to explain very little (which is not surprising), but changes in VIX did show a meaningful effect for a selective group of currencies. CHF, JPY, AUD, CAD, NZD, KRW and

some EM currencies exhibit forward-premium responses to shifts in global uncertainty. At the same time, a simple classification such as “safe haven vs. non-safe haven” did not provide a clean structure. The reactions appear to be regime-dependent and currency-specific rather than tied to fixed labels.

The nonlinear analysis produced the most nuanced insights. The cubic UIP specification revealed that $\beta(\text{FP})$ is rarely a constant. Instead, it varies with the level of the forward premium, often forming U-shaped, inverse-U-shaped, or asymmetric patterns. These shapes resemble the mechanisms discussed in different theoretical frameworks: market-friction stories tend to generate U-shapes, Bansal-type models give inverse-U patterns, and career-risk considerations can lead to asymmetric slopes. These estimates are not meant to prove one specific theory. Rather, they indicate that currencies may rely on different mechanisms at different points in time and under different market conditions.

Decomposing the forward premium into trend and cycle using the HP filter turned out to be especially helpful. Almost all of the pronounced nonlinearities appear in the cyclical component—the short-term fluctuations that tend to capture global shocks, news, and rapid reassessments of risk. The trend component, by contrast, is often quite flat. This suggests that UIP deviations are mainly a short-run phenomenon linked to global uncertainty, not something driven by long-run fundamentals.

Some emerging-market currencies (RUB, ZAR, COP) exhibit nonlinearities in both the trend and the cycle, which fits their profile: domestic vulnerabilities combined with exposure to global

shocks. Safe-haven currencies like CHF and JPY behave differently. Their trends are relatively stable, while the cyclical component responds to spikes in global volatility.

Overall, the results indicate that UIP deviations are not uniform, nor are they constant over time. Linear Fama regressions capture the broad anomaly but overlook the regime-dependent and nonlinear dynamics behind it. Combining volatility modeling, risk measures, and nonlinear specifications provides a more complete picture: UIP deviations seem to be shaped by global uncertainty, short-term market conditions, and heterogeneous currency behaviors, rather than a single universal mechanism.

In this sense, the UIP puzzle appears less like a fixed anomaly and more like a shifting, evolving phenomenon tied closely to financial cycles. The contribution of this work is to bring classical UIP tests together with volatility models and nonlinear approaches, showing how different theories may apply to different currencies at different times.