The Impact of Currency Carry Trade Activity on the Transmission of Monetary Policy*

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Abstract

In this paper, we examine how carry trade activity affects the transmission of monetary policy in currency markets. We analyze a large set of currencies against the U.S. dollar. The U.S. dollar appreciates in response to a conventional monetary policy shock but depreciates to an information shock. Currencies typically involved in the carry trade tend to respond stronger to both shocks, while safe-haven currencies exhibit different adjustment dynamics. To infer these effects from the data, a threshold vector autoregressive model is fitted to discriminate between different regimes of carry trade activity. Finally, a currency trading strategy created on the day of central bank announcements, which takes into consideration the joint co-movement of interest rates and stock prices, outperforms strategies based on carry trade or on the dollar risk factor in terms of the Sharpe ratio and downside risk.

Keywords: Currency markets, Carry Trade Strategy, Monetary Policy, Threshold VAR

JEL Codes: C32, E52, F31

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We want to thank Georg Cejnek, Pia Heckl, Ingrid Kubin, Hanno Lustig, Daria Prem, Otto Randl, Ákos Török, Andrea Vedolin, and Josef Zechner for helpful suggestions and valuable comments.
Disclaimer: The views expressed in this paper do not necessarily reflect those of the Oesterreichische Nationalbank or the Eurosystem.

1 Introduction

Currency markets are shaped by a variety of factors and influenced by the current monetary policy stance. Economic theory suggests that a tightening of monetary policy leads to an appreciation of the domestic currency.[1] However, empirical evidence shows that the domestic currency may also depreciate after a monetary policy tightening, as shown in Fig. 1a for a set of currencies vis-à-vis the U.S. dollar.[2] The two subperiods are characterized by either positive or negative co-movement between interest rates and stock prices around the Federal Reserve (Fed) announcements, indicating the presence of *information* effects. At the same time, the level of interest rates is closely related to speculative currency trading, such as the currency carry trade that seeks to exploit existing global interest rate differentials. The implementation of this simple strategy generates excess returns. Fig. 1b shows a clear connection between the average interest rate differential and an indicator for carry trade activity, the net open interest. This paper thus investigates the role of monetary policy for a broad range of currencies vis-à-vis the U.S. dollar and the importance of carry trade activity for monetary policy transmission.

So far, the interest in carry trade activity and monetary policy actions received rather limited attention in the literature. While Brunnermeier *et al.* (2008) show that high carry trade activity is associated with elevated volatility in exchange rate markets, the impact of monetary policy has so far not been investigated. Monetary policy surprises may alter the profit of currency speculations substantially, either through direct effects on the exchange rate or the underlying fundamentals. Subsequently, carry trade can be particularly exposed to monetary policy actions, because unexpected interest rate changes may be related to a sudden deterioration in currency markets. Hence, this paper tackles the following research questions: What is the effect of different monetary policy shocks on exchange rate markets? How does carry trade activity impact the responsiveness of exchange rates to different monetary policy shocks?

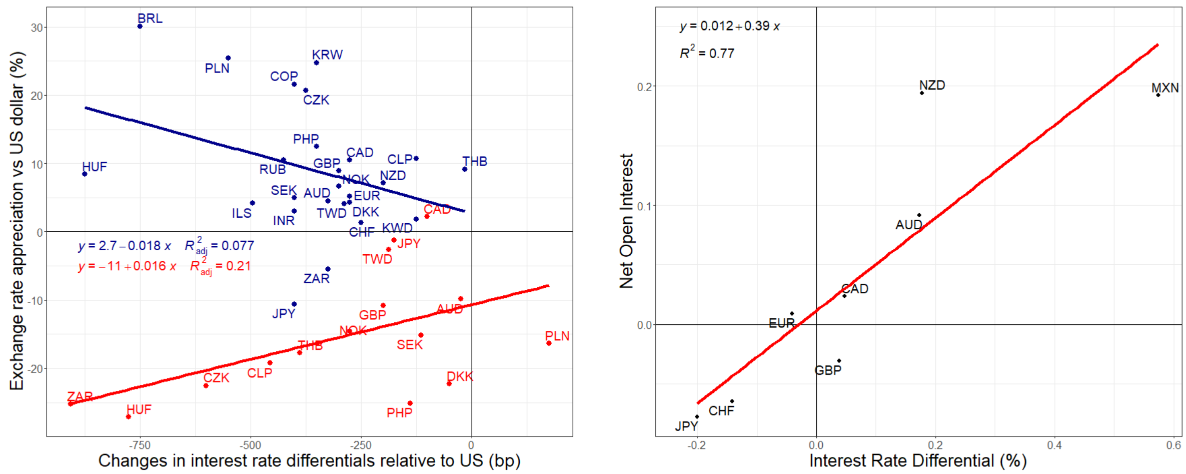
This paper thus investigates empirically the relationship between U.S. monetary policy and foreign exchange rates vis-à-vis the U.S. dollar in a set of 31 advanced and emerging economies. First, we develop a linear vector autoregressive (VAR) model to measure the effects of monetary policy and information shocks on exchange rates. Second, we utilize a non-linear threshold VAR model to examine the effects of these shocks on exchange rates given the role of carry trade activity. Our VAR setup builds on the recent findings of Jiang *et al.* (2021), who relate the U.S. dollar exchange rate to the concept of *convenience yields* of U.S. Treasuries, serving as safe and highly liquid assets, and are thus able to fully incorporate the important global role of the U.S. dollar. For the identification of monetary policy shocks, we use the procedure provided by Jarociński and Karadi (2020) to differentiate between monetary and information shocks by exploiting the co-movement between interest rate and stock market surprises. While a negative co-movement points towards a conventional monetary policy shock, a positive co-movement can be seen as a non-monetary shock, which we denote as an *information* shock.[3] More specifically, we examine the impact of both of these surprises

[1] See, for instance, Dornbusch (1976), Eichenbaum and Evans (1995), Faust and Rogers (2003), Rogers *et al.* (2018).

[2] We regress the exchange rate appreciation against the U.S. dollar on the average change in the interest rate differentials relative to the U.S. (bps). The regressions differ in their sample period: The red (blue) line refers to the period from 1998 to 2000 (2003 to 2006) and mark both periods associated with U.S. monetary policy tightening.

[3] We follow the bulk of the literature, which denotes this shock as an *information* or *growth* shock. The common interpretation is that a central bank reveals non-public information, thus shaping private sectors' expectations (Melosi, 2017; Nakamura and Steinsson,

Figure 1: Exchange Rates, Interest Rate Differentials, and Net Open Interest.



(a) Exchange Rates and Interest Rate Differentials. **(b)** Net Open Interest and Interest Rate Differentials.

Notes: Panel (a) regresses the foreign exchange rate appreciation against the USD (%) on the change in the interest rate differentials relative to the US (bps). red shows the averages from Dec. 2003 until Dec. 2006, while blue the period from Dec. 1998 until Dec. 2000. Panel (b) regresses the average net open interest in the foreign exchange future markets on average interest rate differentials relative to the US (bps). Net open interest is the difference between the long and short futures position of noncommercial traders divided by the total open interest. R^2_{adj} denotes the adjusted R^2.

across different carry trade activity regimes for a subset of currencies being either used as an investment or a funding currency (against the U.S. dollar). To proxy for carry trade activity, we employ the net open interest that is defined as the difference between long- and short-futures position of non-commercial traders in the foreign currency divided by the total open interest of all traders (Brunnermeier *et al.*, 2008; Fong, 2013).

As highlighted partly in Fig. 1a, we expect that a monetary tightening episode typically leads to a deterioration in economic conditions and an appreciation of the U.S. dollar as U.S. Treasuries become more attractive. However, a monetary tightening accompanied by an increase in stock prices points in the opposite direction, namely an improvement in the respective sentiments where the U.S. dollar will depreciate. This is mainly due to a substitution effect of safe assets' demand by search-for-yield motives. As we will outline in the next section, there is a growing body of literature supporting this view. Subsequently, we expect that monetary policy and information shocks lead to different exchange rate adjustment dynamics. Furthermore, given the presence of the carry trade, the question arises of how foreign exchange investors react to these shocks. Sudden changes in interest rates may make it necessary for investors to unwind their positions, which puts additional pressure on the respective exchange rate. We thus expect different dynamics whether investors borrow (”funding currency”) or invest (”investment currency”) in a given currency against the U.S. dollar.

We find that both shocks are transmitted through the exchange rate channel, but with opposite signs. While a typical monetary policy shock leads to an appreciation of the U.S. dollar, an information shock reveals a pattern of depreciation. However, the magnitude of reactions is currency specific, which may be

2018; Cieslak and Schrimpf, 2019). Recently, this has been challenged by Bauer and Swanson (forthcoming), pointing to a "Fed response to news" channel, where both the central bank and the market react to incoming economic news in the days and weeks leading up to an announcement. The central bank reacts more strongly to these news than the public had expected. As a result, professional forecasters revise their forecasts, leading to a procyclical correlation with monetary policy surprises.

attributed to the currency's attractiveness for speculative purposes. We continue the analysis by examining the role of the carry trade in transmitting these shocks. In the non-linear model, we find strong support for three regimes with substantially different reactions of typical funding/investment currencies involved in the carry trade. While the upper and lower regimes correspond to high carry trade activity, the second regime resembles an indeterminacy region accounting for the uncertainty of our threshold variable in describing carry trade activity.[4] Moreover, for their specific reactions to monetary policy and information shocks, it is important whether the currency currently serves as a funding or an investment currency. Currencies, typically classified as carry trade investment currencies, depreciate stronger after a monetary policy shock if they are involved in carry trade. Likewise, they depreciate less strongly in periods when they are used as funding currencies. This supports the evidence of a sharp depreciation of currencies typically engaged in carry trade when a negative shock occurs. At the same time, the impact of a monetary policy shock on typical safe-haven currencies in times of economic turmoil is not significant. One explanation is the higher investors' demand for these currencies, which thus mitigates the U.S. dollar appreciation. Instead, the information shock leads to a significant foreign currency appreciation, when traditional carry trade currencies are used as investment currencies (i.e., in the third regime), while safe-haven currencies do not show a significant reaction.

Finally, we construct a foreign exchange trading strategy that trades on the day of central bank announcements and takes the co-movement of interest rates and stock prices into consideration. Since we empirically demonstrate that the U.S. dollar appreciates when the rise in interest rates is accompanied by a fall in equity prices around Fed meetings, taking this information into account allows investors to avoid periods of sharp foreign currency depreciation. As a result, the new strategy, where the nature of the shock is incorporated, outperforms the conventional carry trade and a strategy based on the dollar factor in terms of the Sharpe ratio and the downside risk. It furthermore enables the investor to protect her portfolio from large losses to which a traditional currency trading strategy is typically exposed to.

To summarize, our study makes three key contributions to the literature on exchange rate dynamics. First, we demonstrate that the nature of monetary policy shocks is a critical factor in determining how exchange rates respond. Specifically, we find that monetary policy and information shocks can lead to either an appreciation or depreciation of the U.S. dollar, respectively. This suggests that the information shock can also be transmitted through the exchange rate channel. Second, we show that the impact of both types of shocks is strongly influenced by the prevailing carry trade regime, i.e., whether a currency is being used as a funding or investment currency in a carry trade. We observe that when a currency is subject to pronounced carry trade activity, its reactions to both types of shocks are amplified. Our findings, therefore, provide insights into the causes of currency crashes. Third, based on these insights, we develop a trading strategy to assess whether we can outperform a simple benchmark portfolio. We find that using the surprises as signals to create the portfolio leads to improved performance in terms of the Sharpe ratio and skewness. Finally, our analysis is based on an exchange rate model that takes into account the central role of the U.S. dollar in the global financial system. This allows us to consider the various drivers of exchange rate movements, including the U.S.'s role as a supplier of safe and highly liquid assets.

[4] In the respective carry trade regimes, the first and third regime correspond to the currency being used either as a funding or investment currency.

The remainder of the paper is structured as follows. In Section 2, we discuss the relevant literature on the relationships between exchange rate dynamics, monetary policy, and carry trade. We proceed in Section 3 with a discussion of the underlying exchange rate model, the employed variables as well as our empirical framework. Section 4 discusses the findings both from the linear and nonlinear specification. Section 5 investigates currency anomalies across regimes and Section 6 presents our trading strategy. Finally, Section 7 concludes.

2 Monetary Policy, Foreign Exchange Rate Markets, and Carry Trade

In this section, we embed our research questions into the literature and link them with the theories provided. As our research and the respective questions lie in the intersection of macroeconomics and finance, we will start with an overview of how the two identified dimensions of monetary policy affect exchange rate markets. Consequently, we link these findings to recent advances in the understanding of exchange rate fluctuations from a finance perspective. Finally, taking the global importance of the U.S. dollar into account, we build on Jiang *et al.* (2021), and thus discuss the research associated with this special role more closely.

The identification of exogenous movements in monetary policy actions by the central bank is a decisive issue in the current monetary literature. In a central contribution, Jarociński and Karadi (2020) confirm the importance of considering the stock price reaction in addition to the response of interest rates around policy announcements. In particular, they examine the high-frequency co-movements of interest rates and stock prices within a 30-minute window around FOMC (Federal Open Market Committee) meetings. If the increase in interest rates is accompanied by a decrease in stock prices, the authors define it as a conventional monetary policy shock, leading to a significant decline in economic activity and the price level. However, if the co-movement is positive, Jarociński and Karadi (2020) claim that the central bank reveals information about the economic outlook, suggesting the presence of a central bank information shock that has a (weakly) positive effect on economic activity. In a similar vein, Cieslak and Schrimpf (2019) analyze asset price variations on policy announcement dates based on co-movement of stock and bond yields. The authors decompose central bank announcements into monetary policy, economic growth, and risk premium news and are able to show that these effects – or as we deem them as *information* effects – are likely drivers of asset prices. By focusing more on a specific unconventional policy tool to steer long-term expectations about the policy rate path (i.e., forward guidance that builds on committing to a certain interest rate path over a longer horizon), Lunsford (2018) documents similar evidence and relates it to investors' reassessment of output and inflation expectations. This empirical evidence has spurred some discussion. Bauer and Swanson (forthcoming) argue that both the central bank and professional forecasters react to incoming news prior to an announcement. However, since the central bank reacts more strongly to the preceding economic news than the private sector, the market revises its expectations. This leads to the procyclical correlation with monetary policy surprises. To summarize, the conventional effects of monetary policy tightening lead to a decline in stock prices in response to the decline in present value of future cash flows due to a higher discount rate. If the co-movement is positive instead, the central bank, therefore, reveals surprising information that was not anticipated by investors before.

As open economies' financial and real sectors are linked, monetary policy decisions may not only affect the domestic but also foreign economies. Ultimately, this gives rise, inter alia, to concepts like the uncovered interest parity (UIP) that governs the relationship between interest rates and exchange rates. Adding the aspects of monetary policy, the classical reaction of a floating exchange rate to a standard monetary policy tightening leads to an appreciation of the domestic currency, as reported, for instance, in Kim and Roubini (2000), Favero and Marcellino (2001) or Faust *et al.* (2007). However, quite early empirical evidence points to certain failures of theoretical predictions, like the failure of the UIP (Genberg, 1978; Stockman, 1980; Fama, 1984). For instance, exchange rates (henceforth, FX) frequently exhibit high volatility and currency returns often feature fat tails and asymmetry, which does not square with Gaussian normality. As we will elaborate below, the U.S. dollar has a special role in the global economy and is thus of special interest.

From a standard monetary policy perspective, policy tightening from the Federal Reserve leads to a significant appreciation of the U.S. dollar due to the increased attractiveness of U.S. Treasuries. For a significant interest rate differential where the domestic rate exceeds the foreign one, research has shown the failure of the UIP giving rise to the so-called *forward premium puzzle* (shown in, among others, Eichenbaum and Evans, 1995; Faust and Rogers, 2003; Rogers *et al.*, 2018). However, since it has been demonstrated that central bank announcements may also feature information effects, one also can expect different effects on exchange rates. This particular question received rather limited attention in the literature so far, and to the best of our knowledge, only with classic reserve currencies like the U.S. dollar, the Euro, or the Pound sterling. A paper related to our research shows that the dollar appreciated during the Great Recession despite an easing monetary policy stance contradicting standard theory (Stavrakeva and Tang, 2019). They relate the results to the information – or in their words the signaling – effect that dominates the monetary policy effect due to "calendar-based" forward guidance. This seems particularly prevalent during periods of high uncertainty about macroeconomic fundamentals. They argue that central bank announcements during the Great Recession revealed information about future economic growth that affected investor expectations and increased investor risk aversion. Recently, Pinchetti and Szczepaniak (2021) put this idea further for a panel of developed and emerging market currencies. They also find a U.S. dollar depreciation after an information effect and relate this result to an increasing investors' risk appetite. Finally, Franz (2020) points towards the importance of currency characteristics when analysing FX responses to monetary policy and information shocks. Especially the latter seem to affect currencies in a heterogeneous way, depending on how they are typically employed in trading strategies. While these papers are the closest to our research, we deviate along two other important dimensions. On the one hand, we analyse the impact of monetary policy announcements for a large set of developed and emerging market currencies *separately*. On the other hand and also in stark contrast to Franz (2020), we explicitly consider the effect of shocks to follow a nonlinear process, as we will lay out below.

Another stylized fact of FX dynamics concerns the emergence of a sudden and unexpected depreciation of a currency. This phenomenon is particularly observed for high-yielding currencies, also known as those that "go up by the stairs and down by the elevator" – a common expression among FX traders. Along with risk-based aspects that may explain currency crashes (see, among others, Brunnermeier *et al.*, 2008; Ang and Chen, 2010; Della Corte *et al.*, 2016; Menkhoff *et al.*, 2017), some behavioral explanations seem promising.

Especially, the impact of so-called herding behavior in exchange rate markets became under scrutiny (for instance, Frankel *et al.*, 1986; Sokolovski, 2007; De Grauwe and Kaltwasser, 2012; Hasselgren, 2020). Within this strand of literature, a certain trading strategy stands out: *the carry trade*. Investors pursuing this kind of strategy – carry traders – take advantage of an interest rate differential between two currencies. They borrow in a currency with a low interest rate and simultaneously invest in a currency that features a high interest rate. If both currencies feature a relatively stable dynamic, exploiting the deviations from the efficient market hypothesis, like the deviations of UIP, carry traders are able to gain significant excess returns as shown in Burnside *et al.* (2006) and Lustig *et al.* (2011).

However, this strategy might be responsible for bubble creation and the high crash risks for certain currencies (shown, e.g., in Plantin and Shin, 2008; Kaizoji, 2010; Spronk *et al.*, 2013). Moreover, as Sokolovski (2007) argues, during times of high carry trade activity – or "crowdedness" as he names it –, large negative shocks affecting the interest rate force carry traders to unwind their positions to prevent a loss. Ultimately, if the mass of traders pursuing this strategy is large enough, the exchange rate might suddenly experience a substantial depreciation. Additionally, a (potentially non-linear) relationship between a "crowdedness" measure and the carry trade returns emerge. Supporting the latter finding, Plantin and Shin (2008) show with a dynamic asset pricing model that episodes of strong negative exchange rate movements are triggered by high carry trade activity given certain funding constraints. Building on this result, Brunnermeier *et al.* (2008) demonstrate empirically that carry trade activity is positively correlated with the interest rate differential and negatively related to the currency returns' skewness. Moreover, carry trade activity seem to be a significant predictor of currency returns, which challenges the efficient market hypothesis. However, measuring carry trade activity is a challenging task. Brunnermeier *et al.* (2008) and Fong (2013), for instance, proxy it based on futures position data of noncommercial traders reported by Commodity Futures Trading Commission (CFTC). According to CFTC, noncommercial traders are those, who use futures contracts not for hedging purposes, implying that they use these contracts for speculative reasons.

Finally, as our analysis concerns currency markets and puts an emphasis on the global importance of the U.S. dollar, some thoughts on the respective model stances are in order. First, the U.S. dollar is an important reserve and invoicing currency (Goldberg and Tille, 2009) and second, the U.S. economy and its central bank are key drivers of the global financial cycle (Miranda-Agrippino and Rey, 2020). Moreover, during times of financial distress or uncertainty, U.S. assets are in high demand as they are safe and liquid (see, among others, Chahrour and Valchev, 2018; Du *et al.*, 2018; Gopinath and Stein, 2021). Hence, the U.S. dollar is deemed to enjoy an "exorbitant privilege" (Gourinchas and Rey, 2007), which we want to take properly into account. For this reason, we neither rely on Taylor rule (Molodtsova *et al.*, 2008; Molodtsova and Papell, 2009; Molodtsova *et al.*, 2011) nor on long-run monetary models (MacDonald and Taylor, 1994; Mark and Sul, 2001; Rapach and Wohar, 2002; 2004; Dick *et al.*, 2015; Huber and Zörner, 2019) but on the model proposed in Jiang *et al.* (2021). Based on the concept of convenience yields, they augment the models of Campbell and Clarida (1987) and Clarida and Gali (1994), and are able to show both empirically and theoretically that the log spot exchange rate of the U.S. dollar is a composite of the convenience yield, the interest rate differential and the risk premium attached to a foreign currency. Thus, our multivariate model follows this definition of an exchange rate and also builds upon the concept of convenience yields.

3 Methodological Framework

In the following sections, we lay out the employed data and transformations, how we derive key variables in our specification, as well as the methodological framework. Before we introduce our estimated empirical model, namely a linear and a threshold vector autoregression, we provide an overview of our variables and the convenience yield of U.S. Treasuries.

3.1 Data and Empirical Specification

The sample period for the estimation covers January 1990 to June 2019. All models feature the following set of endogenous variables $\boldsymbol{y}_t = [ir_t^{US}, ir_t^*, x_t^{Treas}, rp_t^*, spot_t]$, where we collect the domestic and the foreign interest rate, ir_t^{US} and ir_t^*, the respective exchange rate vis-à-vis the U.S. dollar, $spot_t$, and estimate the two remaining latent variables, the Treasury basis x_t^{Treas}, and the currency risk premium rp_t^*. This ultimately reflects the explanation of spot rate dynamics derived in Jiang *et al.* (2021).

For the linear specification, we consider a large set of currencies being comprised of 10 developed market (DM) and 21 emerging market (EM) currencies: Australian dollar (AUD), Brazilian real (BRL), Canadian dollar (CAD), Croatian kuna (HRK), Swiss franc (CHF), Chilean peso (CLP), Colombian peso (COP), Czech koruna (CZK), Danish krone (DKK), the Euro (EUR), Pound sterling (GBP), Hungarian forint (HUF), Indonesian rupiah (IDR), Israeli shekel (ILS), Indian rupee (INR), Japanese yen (JPY), South Korean won (KRW), Kuwaiti dinar (KWD), Mexican peso (MXN), Malaysian ringgit (MYR), Norwegian krone (NOK), New Zealand dollar (NZD), Philippine peso (PHP), Polish zloty (PLN), Russian ruble (RUB), Swedish krona (SEK), Singapore dollar (SGD), Thai baht (THB), Taiwan dollar (TWD), South African rand (ZAR), and the U.S. dollar (USD). The U.S. dollar is considered to be the domestic currency. All currencies are expressed per unit of the U.S. dollar, i.e., an increase in the spot exchange rate indicates an appreciation of the U.S. dollar. Daily spot, one-week, one-month, and twelve-month forward mid-rates are retrieved from Datastream (WM/Reuters and Barclays Bank International).[5] To estimate monthly returns, end-of-month data is used.

Tab. 1 shows some summary statistics of monthly currency excess returns for emerging and developed currencies. The returns are on average low and exhibit high volatility that is especially observed for the emerging economies. With the sole exception of the Japanese yen and the Swiss franc, returns are negatively skewed. Furthermore, they demonstrate high kurtosis, indicating fat tails. Overall, the summary statistics show that currencies are prone to sharp sudden depreciations.

For the non-linear specification, we have to constrain the sample due to the availability of futures data needed for the construction of our threshold variable. The threshold governing variable captures carry trade activity of currency i against the U.S. dollar and is proxied by the net open interest (NOI_{it}). This variable was successfully implemented by Brunnermeier *et al.* (2008) to proxy the activity of carry traders against the U.S. dollar. For the construction of this variable, we rely on the currency futures positions of the U.S. Commodity Futures Trading Commission (CFTC). Given the availability of CFTC data, the sample used to evaluate the impact of monetary and non-monetary policy shocks over currency regimes (i.e., our nonlinear specification) is restricted to eight currencies: AUD, CAD, CHF, EUR, GBP, JPY, NZD, and MXN. Although CFTC reports

[5] Typically, we use the respective treasury interest rate. If no foreign treasury interest rate is available, we stick to the interbank rate.

the data on a weekly basis, end-of-month data is used. We follow the approach of Brunnermeier *et al.* (2008) and define it as the difference between the long and short futures positions of noncommercial traders divided by total open interest, such that

$$NOI_{it} = \frac{Long_{it} - Short_{it}}{TotalOpenInterest_{it}}. \quad (3.1)$$

A positive NOI_{it} means that investors sell the U.S. dollar and buy the foreign currency i. Thus implying that the latter can be considered as an *investment currency* in a carry trade. In contrast, a negative NOI indicates that investors buy the U.S. dollar and sell the foreign currency. As a result, the foreign currency serves now as a *funding currency*. Although it is in principle possible, that a currency can be identified either as a funding *or* an investment currency, we introduce a third state where we remain agnostic about the currency characteristic. This allows us to take the shortcoming of the NOI as a carry trade activity indicator into account. Moreover, with this approach, we ensure that only a significant amount of carry trade activity results in a currency being classified as either a funding or investment currency.

Tab. 1 reveals the positive correlation between the forward discount and the net open interest (NOI), indicating that non-commercial traders are involved in the carry trade. JPY and CHF, which are often considered as funding currencies for carry trade, have negative net open interest, i.e., these currencies are sold on average, whereas AUD, MXN, and NZD - typical investment carry trade currencies - have a positive average net open interest. Moreover, Tab. 1 indicates that there is a positive cross-sectional correlation between average returns and the NOI. In addition, a negative correlation between currency skewness and the NOI confirms the evidence in the existing literature that carry trade activity may lead to currency crashes (Brunnermeier *et al.*, 2008). Therefore, the analysis of the impact of monetary policy and information shocks depending on the net open interest contributes to a better understating of currency fluctuations.

3.2 Definition of the Convenience Yield

Our set of endogenous variables consists of five variables in total and resembles the approach by Jiang *et al.* (2021). While the domestic and foreign interest rates as well as the spot exchange rate, is relatively standard and observed, we need to elicit two additional latent variables: the *Treasury basis* and the *risk premium*. With this, we deviate from typical exchange rate models and provide more details. Based on the finding that variations in the U.S. *convenience yield* can explain a significant share of exchange rate fluctuations, their micro-founded model provides an evaluation of the fundamental value of the U.S. dollar. The specification is derived from a foreign bond investor's Euler equation and arrives at the fundamental value of the U.S. dollar as a function of the sum of future interest rate differences, the sum of the future currency risk premia, and the sum of future convenience yield differences.[6] The key mechanism takes the special role of the U.S. dollar into account and resembles that increases in the convenience yield result into an appreciation of the U.S. dollar. Hence the main appeal of this model is that a nominal exchange rate vis-à-vis the U.S. dollar can

[6] The following Equation 3.2 corresponds to equation (14) of Jiang *et al.* (2021, p.1062). We omit the exact theoretical derivation here and refer the interested reader to section III of the respective paper.

Table 1: Summary Statistics of Currency Returns

	Starting Date	Mean	SD	Skewness	Kurtosis	$f_t - s_t$	NOI
AUD	1990-01	1.81	11.27	-0.50	2.70	0.17	0.10
BRL	2004-03	6.74	15.41	-0.49	1.26	0.72	
CAD	1990-01	-0.04	7.83	-0.56	4.27	0.03	0.01
CHF	1990-01	-0.09	10.78	0.02	1.21	-0.12	-0.09
CLP	2004-03	1.15	11.89	-1.26	5.24	0.17	
COP	2004-03	1.69	13.61	-0.17	0.48	0.27	
CZK	1996-12	1.34	12.11	-0.25	0.52	0.05	
DKK	1996-12	-1.22	9.78	-0.11	0.96	-0.06	
EUR	1999-01	-1.07	9.22	-0.10	1.39	-0.08	0.06
GBP	1990-01	0.22	9.27	-0.72	2.51	0.10	-0.01
HRK	2004-03	0.38	10.09	-0.48	1.23	0.08	
HUF	1997-10	2.73	13.40	-1.01	3.77	0.38	
IDR	2000-11	21.44	18.41	0.16	1.49	1.97	
ILS	2004-03	1.61	8.07	-0.24	0.67	0.01	
INR	1997-10	1.67	7.21	-0.22	2.73	0.39	
JPY	1990-01	-1.34	10.62	0.30	2.00	-0.19	-0.10
KRW	2002-02	1.46	11.07	-0.37	4.49	0.07	
KWD	1996-12	0.50	2.26	-1.13	15.13	0.05	
MXN	1996-12	2.91	10.50	-0.87	2.47	0.58	0.17
MYR	2005-06	0.90	7.74	-0.42	2.20	0.11	
NOK	1996-12	-0.62	11.12	-0.16	0.74	0.06	
NZD	1990-01	2.46	11.57	-0.33	2.16	0.21	0.21
PHP	1996-12	0.79	8.10	-1.05	5.99	0.32	
PLN	2002-02	2.74	13.82	-0.78	1.96	0.18	
RUB	2004-03	0.94	14.53	-0.71	3.76	0.53	
SEK	1996-12	-1.95	10.95	-0.02	0.44	-0.04	
SGD	1996-12	-0.64	6.00	-0.25	2.39	-0.06	
THB	1996-12	1.10	10.60	-0.56	17.87	0.17	
TRY	2003-12	1.96	15.92	-1.82	8.79	0.93	
TWD	1996-12	-1.61	5.37	-0.04	3.48	-0.08	
ZAR	1996-12	1.86	16.12	-0.41	0.72	0.58	0.07

Notes: This table shows the mean, the standard deviation, the skewness, and the kurtosis for monthly log excess returns, rx_{t+1}. $f_t - s_t$ corresponds to the average forward discount in percent. The last column represents the average net open interest, NOI. Mean and standard deviation are annualized and in percent. The base currency is U.S. dollar.

be thus decomposed as follows:

$$s_t = \mathbb{E}_t \sum_{\tau=0}^{\infty} (\lambda_{t+\tau}^{\$,*} - \lambda_{t+\tau}^{*,*}) + \mathbb{E}_t \sum_{\tau=0}^{\infty} (y_{t+\tau}^{\$} - y_{t+\tau}^{*}) - \mathbb{E}_t \sum_{\tau=0}^{\infty} rp_{t+\tau}^{*} + \bar{s}, \tag{3.2}$$

where s_t is the logarithm of the spot rate expressed in foreign currency per unit of the U.S. dollar, $\lambda_t^{\$,*} - \lambda_t^{*,*}$ is the difference between convenience yield of the foreign investor for the investment in U.S. Treasury bonds and convenience yield for the investment in the foreign bonds, and $y_t^{\$} - y_t^{*}$ is the difference in the U.S. and foreign government bond yields. Lastly, rp_t^* is the realized risk premium earned by the foreign investor for going long U.S. safe assets. The term $\lim_{T\to\infty} \mathbb{E}[s_{t+T}] = \bar{s}$ is a constant if the nominal exchange rate is stationary, which we assume. Such an exchange rate decomposition consists of a cash flow component that reflects the interest rate differential, a convenience yield component, and a discount rate component that tracks the currency risk premia.

However, both the convenience yield and the risk premium are not observable and thus have to be estimated. Again, we rely on Jiang *et al.* (2021) to estimate these quantities. To achieve that, let us also define the *Treasury basis* as follows

$$x_t^{Treas} \equiv (y_t^{\$} - y_t^{*}) + (f_t^1 - s_t) \tag{3.3}$$

where f_t^1 and s_t are the logarithm of the one-year forward rate and the logarithm of the spot exchange rate, $y_t^{\$}$ and y_t^* are U.S. and foreign one-year government bond yields, respectively. Therefore, the treasury basis is the difference between the yield on U.S. Treasuries and a synthetic dollar yield of a foreign government bond. The latter is hedged back into dollars, denoted by the difference of the forward and the spot rate of the U.S. dollar. As an interim result, we observe that a negative basis implies a more expensive U.S. Treasury relative to a foreign one. Combining this fact with the foreign investor's current and future expected value of an exchange rate (i.e., her respective Euler equation) helps to derive the *convenience yield*, which is then simply proportional to the Treasury basis

$$x_t^{Treas} \equiv (y_t^{\$} - y_t^{*}) + (f_t^1 - s_t) = -(1-\beta^*)(\lambda_t^{\$,*} - \lambda_t^{*,*}) \quad \Longleftrightarrow \quad (\lambda_t^{\$,*} - \lambda_t^{*,*}) = -\frac{x_t^{Treas}}{(1-\beta^*)} \tag{3.4}$$

where $0 < \beta^* < 1$ indicates the foreign investor's preference for synthetically created dollar deposit relative to the U.S. Treasury investment. Two extreme values highlight the meaning of β^*. A $\beta^* = 0$ would imply that U.S. Treasuries create no additional benefit in terms of convenience yields. Jiang *et al.* (2021) dub this as *dollarness*. On the contrary, if β^* approaches unity, investors start appreciating the safety and liquidity of U.S. assets. In the latter case, we thus observe a convenience yield. By estimating the β^* with monthly data across currencies in our sample, we find $\beta^* = 0.68$ as outlined in App. A. This insight helps to define the *risk premium* as the log excess return minus the Treasury basis, i.e.,

$$rp_t^* = rx_t - \frac{1}{1-\beta^*} x_{t-1}^{Treas}. \tag{3.5}$$

The log currency excess return earned from the long position in the foreign currency is defined as the interest rate differential less the rate of depreciation, i.e., $rx_{t+1} = i_t^* - i_t - (s_{t+1} - s_t)$.

By substituting two components of Eq. (3.2) by Eq. (3.4) and Eq. (3.5), the logarithm of the nominal U.S. exchange rate vis-à-vis a foreign currency can be represented as

$$s_t = -\mathbb{E}_t \sum_{\tau=0}^{\infty} \frac{x_{t+\tau}^{Treas}}{1-\beta^*} + \mathbb{E}_t \sum_{\tau=0}^{\infty} (y_{t+\tau}^{\$} - y_{t+\tau}^*) - \mathbb{E}_t \sum_{\tau=0}^{\infty} rp_{t+\tau}^* + \bar{s}. \tag{3.6}$$

With this approach, we properly take the important global role of the U.S. dollar into account and deviate from standard exchange rate models, like the UIP, Taylor rule based or long-run monetary models that fail to do so.

3.3 Econometric Framework

The main focus of this paper is to analyse the effect of the monetary policy announcements on the exchange rate. To identify the structural shocks of interest, we follow the approach of Jarociński and Karadi (2020) in both the linear and non-linear version of the vector autoregression. Hence, for a general version, let $\{\boldsymbol{y}_t\}_{t=1}^T$ denote an $n_y \times 1$ vector of endogenous macroeconomic and financial variables. In our empirical setting, as outlined above, $\boldsymbol{y}_t = [ir_t^{US}, ir_t^*, x_t^{Treas}, rp_t^*, spot_t]$. Furthermore, let $\{\boldsymbol{m}_t\}_{t=1}^T$ be a $n_m \times 1$ vector of exogenous high-frequency instruments capturing intraday surprises occurring at FOMC announcements, in what follows later $\boldsymbol{m}_t = [m_t^{\text{ff}}, m_t^{\text{SP500}}]$. We gather all variables in the $n \times 1$ vector $\boldsymbol{Y}_t = \left(\boldsymbol{m}_t', \boldsymbol{y}_t'\right)'$. Then the linear specification reads as follows

$$\begin{pmatrix} \boldsymbol{m}_t \\ \boldsymbol{y}_t \end{pmatrix} = \underbrace{\begin{pmatrix} \boldsymbol{0} \\ \boldsymbol{c}^y \end{pmatrix}}_{=\boldsymbol{c}} + \sum_{j=1}^{p} \underbrace{\begin{pmatrix} \boldsymbol{0} & \boldsymbol{0} \\ \boldsymbol{A}_j^{my} & \boldsymbol{A}_j^{yy} \end{pmatrix}}_{=\boldsymbol{A}_j} \begin{pmatrix} \boldsymbol{m}_{t-j} \\ \boldsymbol{y}_{t-j} \end{pmatrix} + \underbrace{\begin{pmatrix} \boldsymbol{\varepsilon}_t^m \\ \boldsymbol{\varepsilon}_t^y \end{pmatrix}}_{=\boldsymbol{\varepsilon}_t}, \qquad \boldsymbol{\varepsilon}_t \sim \mathcal{N}\left(\boldsymbol{0}, \boldsymbol{\Sigma}\right), \tag{3.7}$$

where $\boldsymbol{c}^y$ denotes the $n_y \times 1$ vector of constants, $\boldsymbol{A}_j^{yy}$ is the $n_y \times n_y$ matrix of coefficients for lag j, $\boldsymbol{A}_j^{my}$ denotes an $n_m \times n_y$ matrix of coefficients, and $\boldsymbol{\Sigma}$ is an $n \times n$ variance-covariance matrix. We assume that the surprises in $\boldsymbol{m}_t$ have zero mean and do not depend on the lags of either $\boldsymbol{m}_t$ or $\boldsymbol{y}_t$. These restrictions are plausible as long as financial market surprises are unpredictable.

When moving to the non-linear version of the model, we keep the parametric restrictions in $\boldsymbol{c}$ and $\boldsymbol{A}_j$ in each regime. We allow for three regimes, which are distinguished by the regime indicator NOI_t. We suppress the indicator i because we estimate the model for each exchange rate combination separately. Hence, the threshold vector autoregression with $R = 3$ regimes for a specific currency reads

$$\boldsymbol{Y}_t = \begin{cases} \boldsymbol{c}_1 + \sum_{j=1}^{p} \boldsymbol{A}_{1j} \boldsymbol{Y}_{t-j} + \boldsymbol{\varepsilon}_t, & \boldsymbol{\varepsilon}_t \sim \mathcal{N}(\boldsymbol{0}, \boldsymbol{\Sigma}_1) \qquad \text{if } \gamma_0 < NOI_{t-1} \leq \gamma_1, \\ \boldsymbol{c}_2 + \sum_{j=1}^{p} \boldsymbol{A}_{2j} \boldsymbol{Y}_{t-j} + \boldsymbol{\varepsilon}_t, & \boldsymbol{\varepsilon}_t \sim \mathcal{N}(\boldsymbol{0}, \boldsymbol{\Sigma}_2) \qquad \text{if } \gamma_1 < NOI_{t-1} \leq \gamma_2, \\ \boldsymbol{c}_3 + \sum_{j=1}^{p} \boldsymbol{A}_{3j} \boldsymbol{Y}_{t-j} + \boldsymbol{\varepsilon}_t, & \boldsymbol{\varepsilon}_t \sim \mathcal{N}(\boldsymbol{0}, \boldsymbol{\Sigma}_3) \qquad \text{if } \gamma_2 < NOI_{t-1} < \gamma_R, \end{cases} \tag{3.8}$$

where $\boldsymbol{c}_r$ is an $n \times 1$ regime-specific constant, $\boldsymbol{A}_{rj}$ an $n \times n$ regime-specific coefficient matrix for lag j, and $\boldsymbol{\Sigma}_r$ an $n \times n$ regime-specific variance-covariance matrix with $r = \{1, 2, 3\}$. The definition of the coefficients corresponds to their linear counterparts.

Both models are estimated with Bayesian techniques. We resort to a relatively standard independent Normal-inverse-Wishart prior setup. We abstain from using the conjugate Normal-inverse-Wishart prior, because we want to impose different priors on the own and cross-equation coefficients in the (T)VAR. Thus, we use the horseshoe (HS) shrinkage prior on the coefficients.[7]

The prior structure of the model can be summarized as follows. Let $\boldsymbol{\alpha}_r = \text{vec}(\boldsymbol{c}_i, \text{vec}\,(\boldsymbol{A}_{r1}), \ldots, \text{vec}\,(\boldsymbol{A}_{rp}))$ denote the $k \times 1$ vector of coefficients with $k = n(n+1)p$ for regime r. Then

$$\alpha_{rj} \mid \lambda_{rj}^2, \tau_i \sim \mathcal{N}(\underline{\alpha_{rj}}, \lambda_{rj}^2 \tau_r^2), \qquad \lambda_{rj} \sim C^+(0,1), \qquad \tau_r \sim C^+(0,1), \qquad j = 1, \ldots, K, \tag{3.9}$$

where $C^+(0,a)$ denotes the half-Cauchy distribution on the positive real numbers with scale parameter a. λ_{rj} denotes the *local* shrinkage parameter that is coefficient specific and τ_r is a *global* shrinkage term that pulls all elements in $\boldsymbol{\alpha}_r$ towards zero. Hence, $\underline{\alpha_{rj}} = 0$. The variance-covariance matrix $\boldsymbol{\Sigma}_r$ follows

$$\boldsymbol{\Sigma}_r \sim iW(\underline{\nu}, \underline{\boldsymbol{S}}), \qquad r = 1, 2, 3, \tag{3.10}$$

where $\nu = n+2$ and $\boldsymbol{S} = \text{diag}(s_1^2, \ldots, s_n^2)$, where s_l^2 denotes the variance of the residuals of an AR(4) process of variable l ($l = 1, \ldots, n$). This is relatively standard according to Kadiyala and Karlsson (1997) and concludes the prior setup for the (T)VAR coefficients. The linear VAR follows the same prior specification, except that the regime-dependent subscript r is dropped. For the TVAR, we also have to estimate the regime parameters $\boldsymbol{\gamma} = (\gamma_0, \gamma_1, \gamma_2, \gamma_R)$. On each threshold parameter, we construct a prior that has full support over the constrained space $\{-\infty = \gamma_0 < \gamma_1 < \gamma_2 < \gamma_R = \infty\}$. We achieve this by constructing a sequence of independent Gaussian priors,

$$\gamma_r \sim \mathcal{N}(0, \psi_r^2), \qquad r = 1, 2, 3, \tag{3.11}$$

where ψ_r^2 is a prior scaling factor that is set to a rather large value (in our empirical application, we specify $\psi^2 = 10^2$).

Since the conditional posterior distribution is of no well-known form, sampling this parameter is a non-trivial task. Typically, scholars achieve sampling of the relevant conditional posterior by employing a Random-Walk Metropolis-Hastings step (Chen and Lee, 1995; Alessandri and Mumtaz, 2017; Böck and Zörner, 2019). However, with more than two regimes the implementation of the Metropolis-Hastings algorithm led to perform poorly in terms of convergence. Therefore, we use instead the strategy of Huber and Zörner (2019), who exploit the fact that the support of γ_r is bounded conditional on γ_{r-1} and γ_{r+1} (except for γ_0 and γ_R) and thus resort to the Griddy Gibbs sampler (Ritter and Tanner, 1992). This sampler approximates the true cumulative distribution function (CDF) of the full conditional posterior distribution by means of a piecewise linear function, and then use the resulting approximation to obtain draws by applying inverse transform sampling.

The full exposition of the MCMC algorithm is described in Appendix B. The MCMC algorithm samples iteratively from the full conditional posterior distributions. We repeat this procedure 25,000 times and

[7] Although Chan (2022) introduces the asymmetric conjugate prior, we abstain from using this prior due to two reasons. First, the HS shrinkage prior has proven to have excellent shrinkage properties and works well in VAR settings (Follett and Yu, 2019). Furthermore, the HS prior offers the advantage of being free of user-chosen hyperparameters. Finally, in the threshold version of the model we loose conjugacy anyway.

discard the first 10,000 draws as burn-ins. To assess whether the sampler has converged sufficiently, we report convergence diagnostics in Appendix C.

3.4 Identification

The identification of monetary policy and information shocks in this model is achieved by the use of two proxies, m_t^{ff} and m_t^{SP500}. These proxies capture high-frequency movements in the policy rate and in the stock market. Additionally, we use sign restrictions to distinguish clearly between two shocks.

The respective surprises build upon Gürkaynak *et al.* (2005). These high-frequency surprises are financial asset price changes in a narrow window surrounding FOMC monetary policy announcements and labeled as *surprises*. The narrow window is defined as 10 minutes before and 20 minutes after the announcement. These asset price changes reflect the exogenous changes in expectations solely due to monetary policy announcements. We use high-frequency surprises in the policy indicator and in the S&P 500. Specifically, for the surprises in the policy indicator we follow Nakamura and Steinsson (2018) and used as in Jarociński and Karadi (2020), which use the first principal component of five high-frequency surprises: the current-month fed funds future, the 3-month fed funds future, and the eurodollar futures at the horizons of two, three, and four quarters.[8]

Jarociński and Karadi (2020) document *wrong-signed* stock market responses to announcements; a positive co-movement between interest rates and stock prices. This has given rise to non-monetary policy shocks. Hence, to distinguish between a *negative co-movement shock* (referred to a monetary policy shock) and a *positive co-movement shock* (referred to an information shock), they propose sign restrictions.

We thus distinguish between the high-frequency surprises with sign restrictions to achieve clear identification of monetary policy and information shocks. We compute posterior draws of the shocks and the associated impulse response assuming a uniform prior on the space of rotations conditionally on satisfying the sign restrictions (Rubio-Ramirez *et al.*, 2010). Hence note, that these restrictions only provide set identification and not point identification.

4 Results

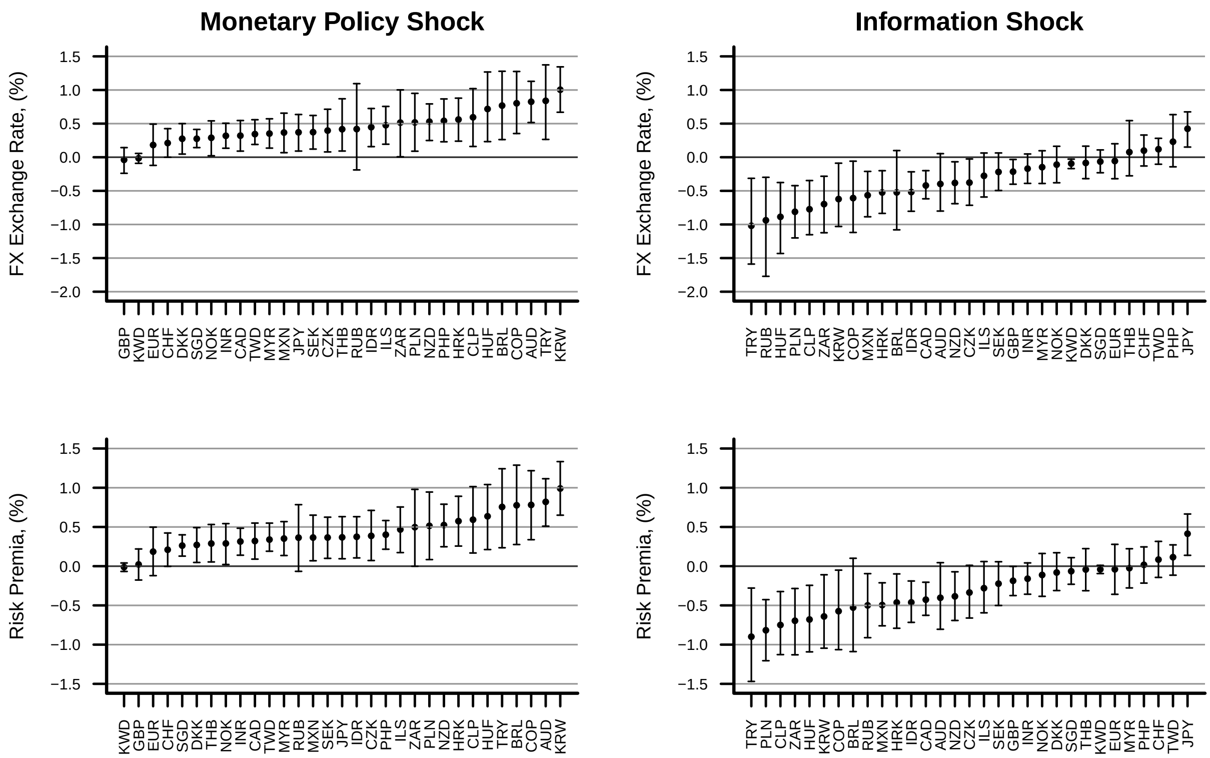
In this section, we proceed with the discussion of our results of a simulation of a contractionary shock from the Federal Reserve. First, we provide evidence that both monetary policy and information shocks transmit via the exchange rate channel. In the consecutive subsection, we show the impact of carry trade activity on these results by discussing our results from the nonlinear TVAR model.

4.1 Evidence from the Linear Model

In Fig. 2 the maximum responses of exchange rates and currency risk premia to the monetary policy (first column) and information (second column) shocks are shown. Clearly, high-frequency co-movement of interest rates and stock prices around central bank announcements contains important information for exchange rates.

[8] As noted by Jarociński and Karadi (2020), the advantage of this indicator is that it captures partly forward guidance. The disadvantage is that it relies on the eurodollar futures, which are not as liquid as the federal funds futures.

Figure 2: Maximum Impulse Responses of Exchange Rates and Risk Premia

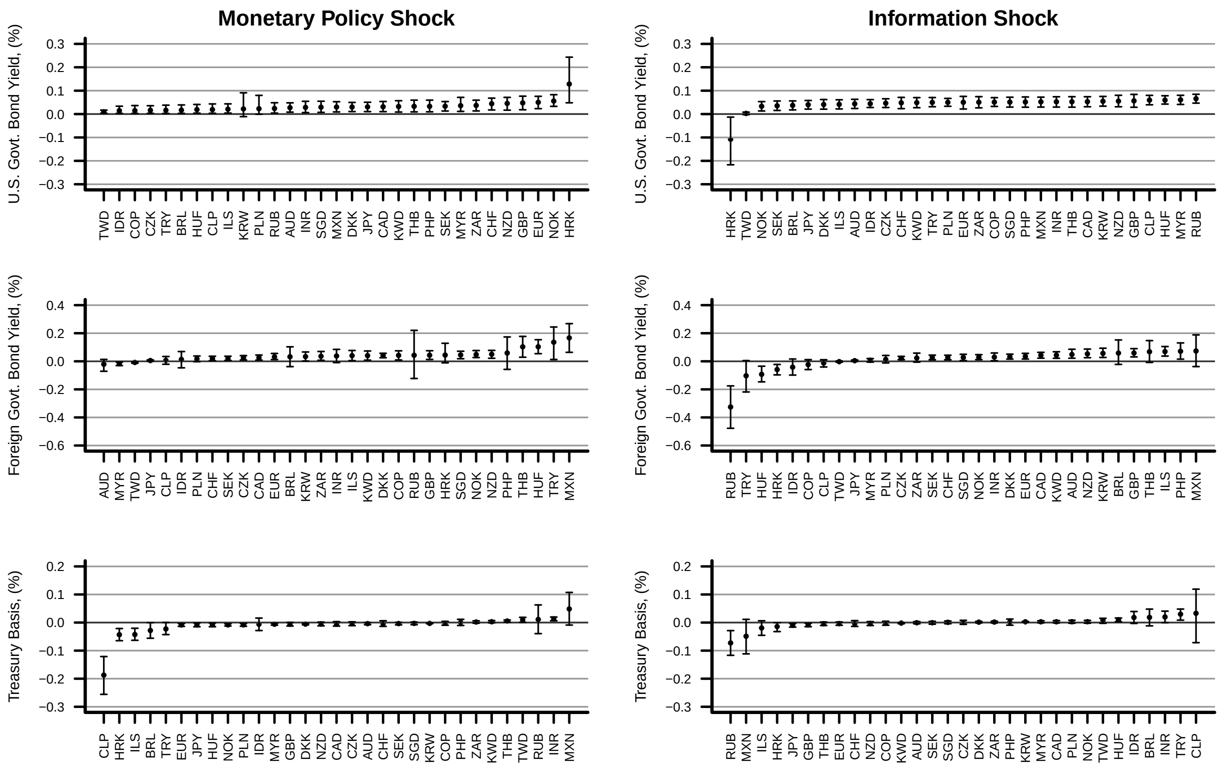


Notes: The upper panel shows the percentage change of the exchange rate vis-à-vis the U.S. dollar, while the lower panel the respective risk premium after a restrictive one standard deviation monetary policy shock (left column) or information shock (right column). Maximum responses are shown with their corresponding 80% credible set. For the abbreviations, we refer to Sec. 3.1.

Monetary policy tightening accompanied by a decrease in the stock market prices, representing a "pure" monetary policy shock, leads to a U.S. dollar appreciation that is a widely known phenomenon in the literature. However, the simultaneous increase in interest rates and stock prices has an opposite effect that leads to a U.S. dollar depreciation and an appreciation of the respective foreign currency. For example, for the New Zealand dollar, a monetary policy shock is associated with a maximum appreciation of the U.S. dollar by 52 basis points, while an information shock leads to a depreciation of the U.S. dollar by 38 basis points. The effects of monetary policy and information shocks are consistent across developed and emerging market currencies. Although for currencies, such as CHF, JPY, EUR, the impact of the information shock is slightly positive, the results do not contradict the main finding, since these currencies have different risk structures. Furthermore, these are typical currencies involved in carry trade strategies, which we will explore further below. The impact of shocks on the spot exchange rate has a direct implication for currency risk premia. Since the risk premia represent the long position in the U.S. dollar, for, e.g., the TRY/USD pair it increases by 75 basis points due to the monetary policy shock and decreases by 89 basis points after the information shock. For the majority of currencies, the results are statistically significant and reveal the expected pattern.

The reaction of U.S. and foreign government bond yields do not reveal any substantial differences across shocks. Fig. 3 shows that both shocks are associated with the increase in foreign and U.S. interest rates. This

Figure 3: Maximum Impulse Responses of U.S. and Foreign Govt. Bond Yields and the Treasury Basis



Notes: The upper panel shows the percentage change of 1-year US government bond yields, the middle panel the respective foreign bonds, and the lower panel the Treasury basis after a restrictive one standard deviation monetary policy shock (left column) or information shock (right column). Maximum responses are shown with their corresponding 80% credible set. For the abbreviations, we refer to Sec. 3.1.

result is expected due to the Fed's tightening and is quantitatively slightly higher when it is accompanied by an increase in the stock market. For the majority of currencies, both shocks only influence the Treasury basis negligibly. Nevertheless, the monetary policy shock leads in general to a decrease in the Treasury basis, thus confirming the special role of the U.S. during times of economic uncertainty. Since a monetary policy tightening shock leads to a deterioration in economic conditions, the Treasury basis significantly widens for CLP, HRK, ILS, and BRL. At the same time, an information shock leads to a statistically significant increase of the Treasury basis for TRY as well as INR.

Overall, these findings support the idea that central bank announcements contain information that affect exchange rate dynamics. Specifically, a distinction between shocks – monetary policy and information shocks – reveals different exchange rate reactions, which are significant for almost all currencies in our sample. The magnitude across currencies, however, shows substantial heterogeneity. This intermediate result points towards the importance of distinguishing between the two shocks originating from a central bank for policymakers and investors alike. Therefore, including these insights in some trading strategies may pay off in terms of returns and risk as we will show in Sec. 6.

Table 2: Summary Statistics of Currency Returns

	Total					*Regime 1*				*Regime 3*			
	Starting Date	Mean	SD	Skewness	Kurtosis	Mean	SD	Skewness	Kurtosis	Mean	SD	Skewness	Kurtosis
AUD	1990-01-01	1.835	11.324	-0.465	5.458	0.495	11.468	0.189	3.017	4.993	14.337	-1.044	6.044
CAD	1990-01-01	0.064	7.831	-0.575	7.096	-0.400	8.219	0.143	4.675	1.700	8.304	-0.361	2.787
CHF	1990-01-01	0.126	10.591	0.009	4.316	0.735	9.250	-0.131	3.899	-3.582	10.840	-0.151	4.215
EUR	1999-01-01	-0.284	9.568	-0.147	4.150	-5.156	10.891	-0.126	4.108	3.011	8.444	-0.048	3.410
GBP	1990-01-01	-0.581	8.626	-0.375	4.312	-2.063	9.743	-0.479	4.337	0.788	7.270	-0.455	3.479
JPY	1990-01-01	-1.237	10.391	0.299	5.194	-4.157	10.265	1.183	7.766	-3.284	11.660	-0.174	3.090
MXN	2008-01-01	2.981	11.163	-1.115	3.785	1.637	11.999	-0.294	0.596	-2.528	13.144	-1.123	1.919
NZD	1999-01-01	2.931	11.628	-0.342	5.009	8.499	14.272	-0.068	4.989	5.341	12.628	-0.589	3.499

Notes: This table shows the mean, the standard deviation, the skewness, and the kurtosis for monthly log excess returns, rx_{t+1}, for the *Total* sample as well as for *Regime 1* and *Regime 3*. Mean and standard deviation are annualized and in percent. The base currency is U.S. dollar. Summary statistics for *Regime 2* are omitted to enhance readability.

4.2 Currency Allocation Across Regimes

Our nonlinear model stance allows us to gauge the effect of carry trade activity on the shock transmission by employing the net open interest (NOI_t) as a threshold variable. As a first result, we find that the regime allocation strongly depends on the respective currency, as shown in Tab. 2. Here, we present summary statistics of monthly currency excess returns across different regimes, while in App. D the respective graphical representation for each currency can be found. *Total* represents some descriptive statistics for the whole sample. *Regime 1* corresponds to the period when a currency is considered as a funding currency with respect to the U.S. dollar, while *Regime 3* corresponds to the period when a currency is considered as an investment currency with respect to the U.S. dollar. As elaborated above, we consider a currency as neither a funding nor an investment currency if it is allocated in *Regime 2*, for which we omit descriptive statistics here, but can be found in Appendix E.

As depicted in Tab. 1, the returns are low and exhibit high volatility on average for the *Total* sample. Returns are negatively skewed, except for JPY and CHF, and in general leptokurtic. However, by taking into consideration the regime allocation, some striking features appear. First, while there is no clear pattern for the mean return and the volatility, skewness is negative and always lower (except for EUR) in the third regime. In this regime the investor buys the foreign currency and sells the U.S. dollar. For typical carry trade investment currencies (like AUD, NZD, and MXN), the skewness is highly negative when investors go long the foreign currencies and short the U.S. dollar. This result implies that these currencies are prone to high losses when carry trade activity is high and a central bank shock occurs. Furthermore, it shows that the third regime contributes the most to total negative skewness in the sample. This finding empirically confirms that carry trade activity is associated with currency crashes and may therefore act as a destabilising force in the FX market (Brunnermeier *et al.*, 2008). In contrast, for currencies such as JPY and CHF the positive skewness stems from the first regime, when serving as funding currencies.

Regarding the probability of each currency being allocated into a particular regime, some features are worth to be highlighted. For the majority of currencies, times of enhanced economic volatility and uncertainty as well as of high U.S. dollar appreciation are allocated in *Regime 1*. Times of economic recession are frequently accompanied by a USD appreciation due to "flight-to-safety" motives, as the U.S. is the global provider of safe assets. Unlike all other currencies, however, the JPY appreciates in times of recession, as it they are predominantly assigned to *Regime 3*. The JPY is considered as an investment currency during this period, also incorporating the role as a "safe haven" in the foreign exchange market. Moreover, since 2015, typical carry trade investment currencies have been assigned to the first or second regime and are no longer considered as investment currencies, supporting recent evidence that the carry trade strategy has lost most of its attractiveness in terms of profitability after the Global Financial Crisis (Falconio, 2021). This may also be attributed to the general low interest rate environment worldwide, which in turn triggered a search-for-yield behaviour. Both the estimated NOI thresholds separating the regimes and the respective regime allocation figures for each currency under scrutiny can be found in Appendix D.

4.3 Influence of Carry Trade on the Shock Transmission

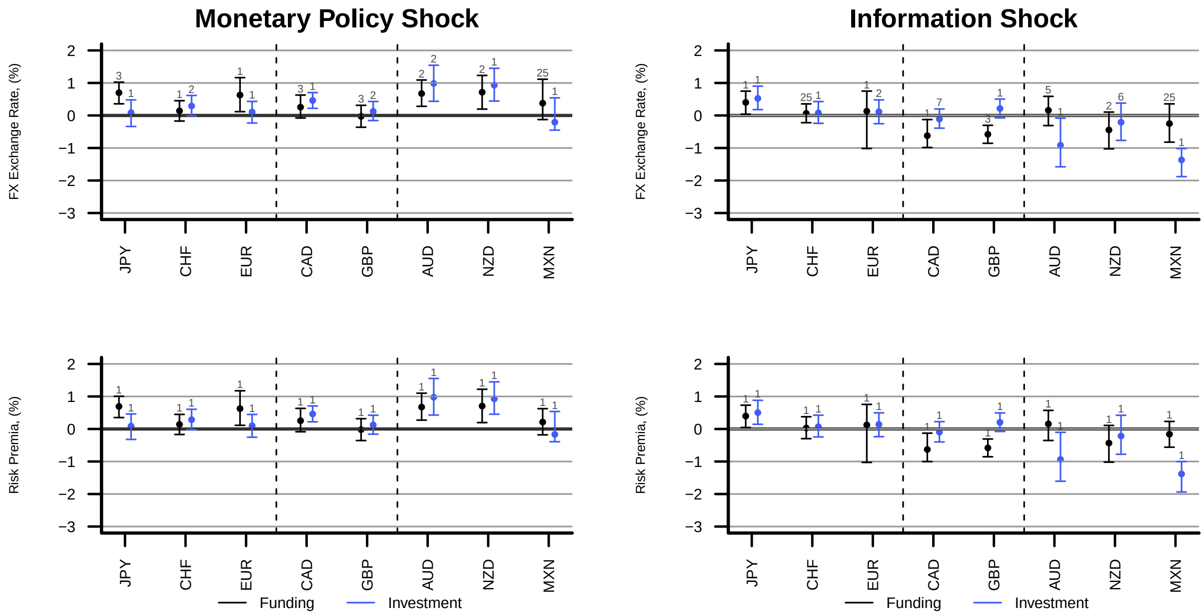
Equipped with information about the regime allocation, we are now ready to inspect the effects of our shocks across the first and third regimes, i.e., whether a currency serves as a funding (Regime 1) or an investment currency (Regime 3) against the U.S. dollar on the announcement day. Note, that for this exercise we only have results for eight currencies due to the availability of the regime indicator. The results for the second regime, where the characteristic of the currency is not determined, are presented in Appendix E.

In Fig. 2 we present the maximum response of exchange rates and currency risk premia to monetary policy (left) and information shocks (right), together with their typical positions in carry trade portfolios (dashed lines). Moreover, we indicate the horizon where the maximum response occurs. JPY, CHF, and EUR are usually sold in the carry trade as they offer lower interest rates compared to the U.S. dollar, while AUD, NZD, and MXN are normally bought. First, we observe that the effects of monetary policy (left) and information shocks (right) appear to be slightly different for CHF, EUR, and JPY. This can be explained by a different risk structure of these currencies, as they are often considered as safe-haven or hedging currencies. Another common characteristic of these currencies is that they are used as funding currencies in the carry trade.

However, the difference between currencies depending on the regime is remarkable. When a monetary policy shock occurs, AUD and NZD depreciate more when they are involved in the carry trade (i.e., being in the *investment* regime). The depreciation is higher by 21 and 30 basis points, respectively. This finding supports the idea that carry trade currencies in times of high carry trade activity are prone to a sharp depreciation when a shock occurs. However, foreign currencies also depreciate when currencies are in the *Funding* regime. This can be related to the "flight-to-safety" motives, as monetary policy shocks lead to a deterioration in economic conditions (Jarociński and Karadi, 2020). For the typical carry trade funding currencies, such as JPY, CHF, and EUR, the effect of a monetary policy shock is different. When these currencies are in the *Investment* regime, the U.S. dollar appreciation is small. This can be attributed due to the currencies' risk characteristics. For example, JPY and CHF are considered "safe-haven" currencies and tend to appreciate in times of economic turmoil. This mitigates the effects of the appreciation of the U.S. dollar.

The second column of Fig. 4 shows the maximum responses to the information shock following central bank announcements. In contrast to the monetary policy shock, typical carry trade investment currencies significantly appreciate. The appreciation varies between 22 and 137 basis points when being in the *Investment*

Figure 4: Maximum Impulse Responses of Exchange Rates and FX Risk Premia

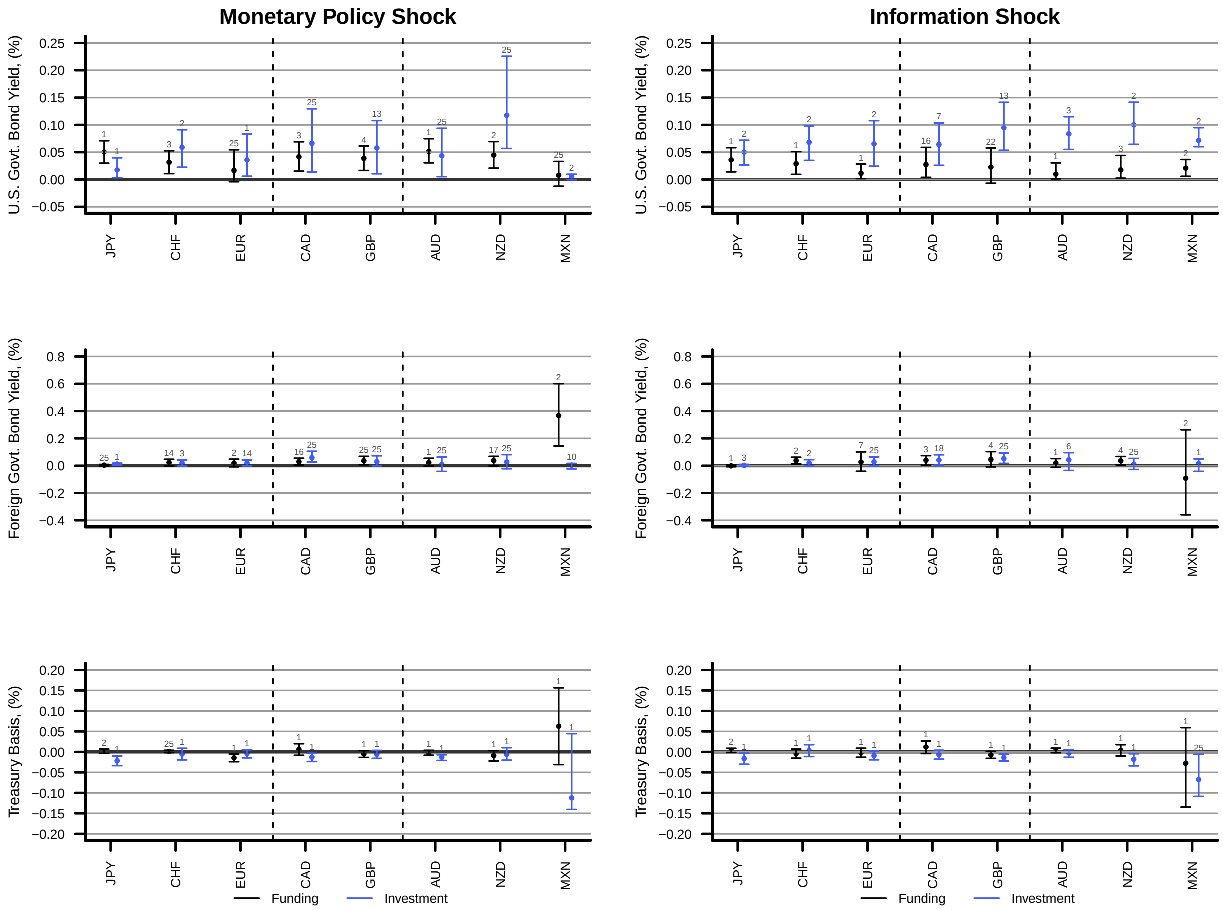


Notes: The upper panel shows the percentage change of the exchange rate vis-à-vis the U.S. dollar, while the lower panel the respective risk premium after a restrictive one standard deviation monetary policy shock (left column) or information shock (right column). Maximum responses are shown with their corresponding 80% credible set and numbers indicate the period, where the reaction occurs. The black line indicates reactions in Regime 1 (i.e., FX is a funding currency) and the blue line in Regime 3 (i.e., FX is an investment currency). Horizontally dashed lines separate currencies according to their typical usage, either as a funding (left) or an investment (right) currency in the carry trade strategy. For the abbreviations, we refer to Sec. 3.1.

regime, while remaining rather small and insignificant in the *Funding* regime. As the latter for AUD, NZD, and MXN involves times of economic instability (as depicted in Fig. D1), the insignificant foreign currency appreciation may be subject to higher risk aversion during this regime. However, when used as an investment currency, i.e., being in the *Investment* regime, the shock is perceived as positive sentiment and the appreciation of the foreign currency is amplified by the carry traders. For the typical carry trade funding currencies, the information shock leads to a U.S. dollar appreciation, whereas its effect is not different from zero in the *Investment* regime for CHF and EUR. One result is slightly puzzling. Although the Mexican peso is considered as a "typical" carry trade currency, the impact of a monetary policy shock seems to be not significant. This may be related to the responsiveness of interest rates to a contractionary U.S. monetary policy shock and should be thus further investigated in a different setup. Nevertheless, the MXN appreciates significantly in case of an information shock, which points towards the investors' desire to switch to high-yielding currencies when economic conditions improve. The response of the currency risk premia is proportional to that of the exchange rates, since the risk premia is driven by currency fluctuations.

With respect to the U.S. Treasury yields we observe that, regardless of the regime, both types of shocks have an increasing effect. However, during periods when currencies are in the *Investment* regime this effect appears to be slightly stronger. This may be related to the regime overlap with economic cycles. The impact of shocks on the foreign interest rate reveals a similar pattern. Finally, both shocks lead to the widening in the Treasury basis. However, in total, the impact of shocks seems to be not very sizeable and often not different

Figure 5: Maximum Impulse Responses of U.S. and foreign Interest Rates and Treasury Basis to a Monetary Policy and Information Shock



Notes: The upper panel shows the percentage change of 1-year US government bond yields, the middle panel the respective foreign bonds, and the lower panel the Treasury basis after a restrictive one standard deviation monetary policy shock (left column) or information shock (right column). Maximum responses are shown with their corresponding 84% credible set. The black line indicates reactions in Regime 1 (i.e., FX is a funding currency) and the blue line in Regime 3 (i.e., FX is an investment currency). Horizontally dashed lines separate currencies according to their typical usage, either as a funding (left) or an investment (right) currency in the carry trade. For the abbreviations, we refer to Sec. 3.1.

from zero. Finally, as shown in the appendix, the impact of the shocks in the second regime, for all variables in the system is very small and often statistically insignificant.

5 Currency Anomalies Across Regimes

Given our evidence so far, it is apparent that exchange rate dynamics after policy shocks follow a nonlinear process depending on the carry trade activity. We use this finding to delve deeper into the potential mechanisms by investigating two widely-studied currency anomalies. Both the exchange rate disconnect and the forward premium puzzle are deviations of exchange rates from their respectively implied fundamental value. To establish a connection to our previous finding, we discriminate between the identified regimes highlighting the potential effects of high carry trade activity on the dynamics.

It has been widely shown in the literature that currencies tend to deviate from their fundamental value. That is macroeconomic variables ultimately forming the fundamental value are not able to explain or predict fluctuations in exchange rates at short horizons (see, inter alia, Meese and Rogoff, 1983a;b). This section analyzes whether these deviations can be explained by carry trade activity and examines whether Taylor rule fundamentals augmented by interest rates can indeed predict exchange rate changes.

We model the evolution of a log spot exchange rate with three explanatory variables, namely the interest rate differential, the inflation differential, and the output gap differential respectively (as proposed by, e.g., Molodtsova and Papell, 2009). However, we now discriminate between the previously identified carry trade regimes, $r = \{1, 2, 3\}$, such that

$$\Delta s_{t+1} = \alpha_r + \beta_{1,r}(i_t^* - i_t) + \beta_{2,r}(\pi_t^* - \pi_t) + \beta_{3,r}(y_t^* - y_t) + \varepsilon_{t+1}. \tag{5.1}$$

Here, α_r is a regime-specific intercept, $\beta_{i,r}$ are regime-specific coefficients, $i_t^* - i_t$ is the difference between the foreign and U.S. 3-month Treasury yield, $\pi_t^* - \pi_t$ is the difference between the logarithm of foreign and U.S. inflation rates, and $y_t^* - y_t$ is the output gap differential, computed by the difference between foreign and domestic industrial production. The log inflation differential is estimated using the log of the foreign and U.S. consumer price indices as $\pi_t^* - \pi_t = (p_t^* - p_{t-1}^*) - (p_t - p_{t-1})$. To measure the output gap, we use the Hodrick-Prescott filter (Hodrick and Prescott, 1997). Namely, we estimate the deviation of actual output, measured by industrial production, from the Hodrick-Prescott implied trend with a smoothing parameter $\lambda = 14400$. The results of this regression are reported in Tab. 3.

Panel A of Tab. 3 represents the regression coefficients when the total sample is used for the analysis. It is obvious that macroeconomic variables lack statistical significance and thus the regression has a very low explanatory power. Apparently, for the whole sample, the exchange rate model in Eq. (5.1) performs poorly. However, when the regime allocation is taken into consideration, the results substantially differ depending on whether currency is in the *Investment* or *Funding* regime (Regime 3 or 1, respectively). The former is associated with the case when investor largely invests in a target currency and sells the U.S. dollar, presenting a carry trade for high-yielding currencies. Tab. 3 shows that during this regime, macroeconomic fundamentals have no power to predict exchange rates. The adjusted R^2 is very low or even negative. It is in line with the theory that during times of high carry trade activity, the currency is driven away from its fundamental value. However, if we consider the regime when the target currency is a funding currency, corresponding to the low carry trade activity, macroeconomic variables are indeed significant for explaining the spot variation. For EUR, the model explains around 7% of the total variation in exchange rates. The output gap appears to be relevant for CAD and EUR, while the inflation differential for JPY and MXN. As a result, it suggests that during times of high carry trade activity, currencies deviate from their fundamental value, leading to the exchange rate disconnect, while during the regime of low speculative activity spot rates can be reflected by the underlying fundamentals. The results from Tab. 3 can partially also explain the greater depreciation of typical carry trade currencies due to monetary policy tightening in the *Investment* regime presented in Sec. 4. Since currencies deviate more from their fundamental value in this regime, they depreciate stronger when a

Table 3: Determination of the Currency's Fundamental Value

	Dependent variable:					
	Δs_{t+1}					
	AUD	CAD	EUR	GBP	JPY	MXN
Panel A: Total Sample						
$i_t^* - i_t$	1.72	−3.09	1.28	1.05	−0.54	0.40
	(1.32)	(3.44)	(1.41)	(1.36)	(0.97)	(0.53)
$\pi_t^* - \pi_t$	−0.09	−1.06	1.07	−0.58	1.30^{**}	−0.27
	(0.69)	(0.85)	(0.72)	(0.56)	(0.53)	(0.53)
$y_t^* - y_t$	−0.03	0.10	0.18^{***}	0.11^{*}	0.12	0.0001
	(0.08)	(0.09)	(0.07)	(0.06)	(0.08)	(0.11)
Adjusted R^2	-0.004	0.004	0.03	0.01	0.02	-0.01
Observations	323	195	262	287	323	287
Panel B: Regime 1						
$i_t^* - i_t$	4.75^{**}	-12.88^{**}	1.49	0.81	−1.52	4.93
	(2.32)	(4.96)	(2.47)	(2.91)	(1.40)	(3.40)
$\pi_t^* - \pi_t$	−0.48	−0.43	1.13	−1.09	1.98^{***}	4.16^{***}
	(0.96)	(1.20)	(1.09)	(0.82)	(0.74)	(1.27)
$y_t^* - y_t$	0.03	0.27^{*}	0.36^{***}	0.05	0.20	0.19
	(0.15)	(0.16)	(0.12)	(0.18)	(0.19)	(0.28)
Adjusted R^2	0.01	0.06	0.07	-0.01	0.04	0.17
Observations	134	89	113	137	140	67
Panel C: Regime 3						
$i_t^* - i_t$	−0.15	−1.14	1.91	2.29	0.45	0.23
	(2.79)	(5.31)	(2.32)	(1.74)	(2.32)	(3.72)
$\pi_t^* - \pi_t$	0.77	−1.01	0.98	0.74	1.03	−1.29
	(1.39)	(1.25)	(1.21)	(0.88)	(0.99)	(1.30)
$y_t^* - y_t$	−0.21	0.03	−0.10	0.05	0.08	−0.16
	(0.19)	(0.19)	(0.11)	(0.13)	(0.14)	(0.31)
Adjusted R^2	-0.01	-0.03	-0.01	-0.003	-0.01	-0.02
Observations	116	83	104	119	124	61
Note:					$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$	

Notes: This table shows regression coefficients from Eq. (5.1) for the total sample (Total), as well as for Regime 1 and Regime 3. The intercept, although estimated, is not reported in the table.

shock occurs. However, in the first regime, currencies are more related to their fundamentals and the impact of the unexpected event is smaller. Therefore, the currency's involvement in the carry trade is linked to the exchange rate disconnect puzzle, serving as potential reason for a sudden currency depreciation.

Another very prominent currency market anomaly is the deviation from the uncovered interest rate parity (UIP). According to this concept, the nominal exchange rate should adjust to the interest rate differential such that a currency with a higher nominal interest rate should depreciate. However, it has been empirically shown that it does not hold and currencies with higher interest rates have an appreciation tendency (Fama, 1984; Boudoukh *et al.*, 2016; Dahlquist and Pénasse, 2022). Since a large interest differential is desirable from the viewpoint of a carry trade investor, high carry trade activity might be a crucial factor for a currency's dynamic. To analyse the influence of carry trades, we implement the regression brought forward by Fama (1984) to examine if the UIP holds depending on whether the currency is considered as funding or investment

Table 4: Analysis of the Forward Premium Puzzle

	Dependent variable:							
	Δs_{t+1}							
	AUD	CAD	CHF	EUR	GBP	JPY	MXN	NZD
Panel A: Total Sample								
$f_t - s_t$	−0.71	−0.83	−0.74	−2.18**	−0.39	−0.88	−0.22	−0.61
	(0.74)	(0.83)	(0.82)	(1.10)	(0.75)	(0.82)	(0.40)	(0.61)
Observations	419	419	419	419	419	419	288	419
Adjusted R^2	-0.0002	0.0000	-0.0005	0.01	-0.002	0.0003	-0.002	0.0000
Panel B: Regime 1								
$f_t - s_t$	−4.01*	2.07	−2.14*	−1.56	−0.62	1.23	−6.79**	−1.42
	(2.26)	(2.55)	(1.26)	(2.92)	(1.70)	(1.37)	(3.16)	(2.54)
Observations	134	151	172	113	171	140	67	115
Adjusted R^2	0.02	-0.002	0.01	-0.01	-0.01	-0.001	0.05	-0.01
Panel C: Regime 3								
$f_t - s_t$	0.35	−3.36	0.71	−2.06	1.02	−1.31	2.02	5.23
	(2.77)	(2.21)	(1.44)	(1.89)	(1.19)	(2.06)	(3.24)	(3.69)
Observations	116	134	154	104	152	124	61	102
Adjusted R^2	-0.01	0.01	-0.005	0.002	-0.002	-0.005	-0.01	0.01

*p<0.1; **p<0.05; ***p<0.01

Notes: This table shows regression coefficients from Eq. (5.2) for the total sample (Total), as well as for Regime 1 and Regime 3. The intercept, although estimated, is not reported in the table.

with respect to the U.S. dollar:

$$s_{t+1} - s_t = \alpha_r + \beta_r (f_t - s_t) + \varepsilon_{t+1}, \tag{5.2}$$

where α_r is a regime-specific intercept, β_r is a regime-specific slope coefficient, f_t is the logarithm of forward, and s_t is the logarithm of spot rate, forming the forward premium respectively. For the uncovered interest rate parity to hold, the slope coefficient should equal unity. A negative β_r implies a violation of the UIP, i.e., that a currency with a higher interest rate compared to the U.S. appreciates.

In Tab. 4 we report the results of the regression Eq. (5.2). For the entire sample and every currency, the slope coefficient β is negative, indicating the forward premium puzzle as the empirical evidence suggests. The negative slope coefficient implies that currency with a higher interest rate, appreciates, contradicting the theory. However, the coefficient is statistically insignificant with the only exception of EUR. When taking a closer look at the currency regimes, it appears that the negative slope coefficient largely stems from the first regime when the currency is considered as a funding currency. In Regime 1, the uncovered interest rate parity does not hold for AUD, CHF, and MXN. For MXN, the forward premium explains 5% of the total variation in the exchange rate changes. At the same time, it flips the sign in Regime 3 and although UIP still does not hold, β is positive for the majority of currencies and insignificant. Although the results suggest that interest rate differential can explain currency changes in Regime 1, it does so with a wrong sign, contradicting the theory. Furthermore, the violation of UIP in Regime 1 may lead to the occurrence of carry traders who want to exploit this inefficiency. We thus conclude that the currency carry trade has major implications for exchange rate markets and may explain existing FX anomalies.

6 Trading Strategy based on Central Bank Announcements

Until now, we have shown that a monetary policy tightening surprise accompanied by a decrease in the stock market leads to the U.S. dollar appreciation against foreign currencies. In contrast, in the case of an information shock (i.e., when U.S. stock market increases after a monetary policy tightening), the U.S. dollar depreciates. Using this evidence, we develop an FX trading strategy in which the investor makes her investment decision on the day of the announcement and takes into consideration the joint behavior of bond yields and stock prices.

In order to gain from the U.S. dollar appreciation following central bank announcements, the investor buys the U.S. dollar when she observes an increase in the bond yield and simultaneously a decrease in the stock market prices on the day of the Fed meeting. Otherwise, she implements a conventional FX strategy. She holds the portfolio until the next scheduled meeting. To create the strategy, the investor uses the closing price on the day of the announcement. As a conventional strategy, we consider a strategy based on the Dollar factor (DOLL) and a carry trade strategy (HML) as proposed in Lustig *et al.* (2011). According to the former, the investor buys all available currencies at time t and sells the U.S. dollar. As a result, the excess return of the strategy at time $t+1$ can be expressed as

$$\mathrm{DOLL}_{t+1} = \frac{1}{N}\sum_{i=1}^{N} rx^{i}_{t+1}, \tag{6.1}$$

where $rx^{i}_{t+1} = f_t - s_{t+1}$ denotes the log excess return for buying the foreign currency i and selling the U.S. dollar. It is expressed as the difference between the log forward at time t and the log spot rate in foreign currency i at time $t+1$, and N is the number of currencies available at time t.

The carry trade strategy, *HML*, is based on taking the advantage of the interest rate differential between two currencies.[9] To profit from this strategy, the investor borrows in low-yielding currencies and invests in high-yielding currencies. By assuming that the covered interest rate parity holds, under no-arbitrage, the forward discount, i.e., the difference between the log forward and the log spot rate should be equal to the interest rate differential $f_t - s_t = i^*_t - i_t$. As a result, in each period t, all currencies are sorted into three portfolios in ascending order based on their forward discounts. One-third of all available currencies with the highest forward discount are assigned to Portfolio 3, whereas one-third of currencies with the lowest forward discount are allocated into Portfolio 1. Portfolio 2 contains the remaining currencies, which are not traded. All currencies are equally-weighted within each portfolio. Given that, a carry trade investor buys currencies featuring high interest rates (Portfolio 3) and sells currencies with low interest rates (Portfolio 1) with respect to the U.S. Thus, the excess return of the carry trade strategy is defined as

$$\mathrm{HML}_{t+1} = R^{P3_{Carry}}_{t+1} - R^{P1_{Carry}}_{t+1}, \tag{6.2}$$

[9] Here, we stick to the standard abbreviation, HML, for carry trade in the literature standing for "high minus low" strategy, where investor buys a portfolio containing currencies with high interest rate differentials and sells a portfolio containing currencies with low interest rate differentials.

Table 5: Summary Statistics of Currency Portfolios

	P1	P2	P3	HML	DOLL
Panel A: Strategy created end-of-month					
Mean	-0.700	0.792	2.762	3.462	0.966
SD	7.285	8.864	11.545	6.772	8.957
Skewness	-0.113	-0.673	-0.949	-0.679	-0.675
Kurtosis	0.475	1.735	2.761	1.278	2.039
Sharpe Ratio	-0.096	0.089	0.239	0.511	0.108
Panel B: Strategy created on the announcement day					
Mean	-1.556	-0.498	1.933	3.488	1.350
SD	5.626	6.990	8.555	5.866	8.238
Skewness	-0.071	-1.199	-1.184	-0.551	-0.771
Kurtosis	0.670	5.095	3.458	0.765	3.181
Sharpe Ratio	-0.277	-0.071	0.226	0.595	0.164
Panel C: Strategy created on the announcement day based on the shock					
Mean	-1.043	0.231	3.021	4.465	2.152
SD	4.174	4.440	6.054	4.882	4.709
Skewness	0.113	-0.500	-0.345	0.399	0.569
Kurtosis	3.729	5.934	3.933	6.580	5.750
Sharpe Ratio	-0.250	0.052	0.499	0.915	0.457

Notes: This table shows the summary statistics of portfolio monthly excess returns. The returns and the standard deviation are annualized and in percent. In Panel A, portfolios are constructed at the end of the month and held for one month, thus not taking Fed announcements into account. In Panel B portfolios are constructed on the day of the central bank announcement and held until the next scheduled Fed meeting. Panel C shows summary statistics of portfolios created on the day of the central bank announcement by taking into consideration the nature of the shock. The sample covers the period from June 2004 until June 2019 including the whole sample of currencies.

where $R_{t+1}^{P1_{Carry}}$ and $R_{t+1}^{P3_{Carry}}$ denote the average excess return at time $t+1$ of the Portfolio 1 and Portfolio 3, respectively.

The consideration of monetary policy surprises together with the carry trade strategy is of particular interest, as this strategy may be exposed to sudden losses when an exogenous and thus unanticipated shock occurs. Typically, the distribution of returns of the carry trade strategy features a negative skewness, such that positive returns may be more frequent but smaller, while losses are less frequent, they might be much larger in size. Based on this, the carry trade strategy can be deemed as "picking nickels in front of a steamroller" (The Economist, 2007).

Since the investor expects the U.S. dollar to appreciate if the rise in interest rates is accompanied by a fall in S&P 500 stock prices on the day of the Fed meeting, she buys the U.S. dollar and sells all available currencies at t when observing this signal. This results in an inverse Dollar strategy, where the total log excess return of this procedure is expressed as $-\frac{1}{N}\sum_{i=1}^{N} rx_{t+1}^{i}$. [10] Otherwise, she implements either the Dollar (DOLL) or the Carry trade strategy (HML). As a result, the return of the new strategy, $FX^{\text{Anncmt, Shock}}$, that is created on the day of the Fed announcement and takes into consideration the shock, has the following formal expression:

$$FX^{\text{Anncmt, Shock}} = \begin{cases} -\frac{1}{N}\sum_{i=1}^{N} rx_{t+1}^{i}, & \text{if } m_t^{\text{ff}} > 0 \;\; \& \;\; m_t^{\text{SP500}} < 0 \\ \text{DOLL}_{t+1} \;\; \text{or} \;\; \text{HML}_{t+1}, & \text{otherwise,} \end{cases} \tag{6.3}$$

where m_t^{ff} and m_t^{SP500} correspond to surprises in the policy indicator and in the S&P 500, respectively. In what follows, we analyze the strategy performance for the whole sample, as well as the emerging and developed markets separately.[11]

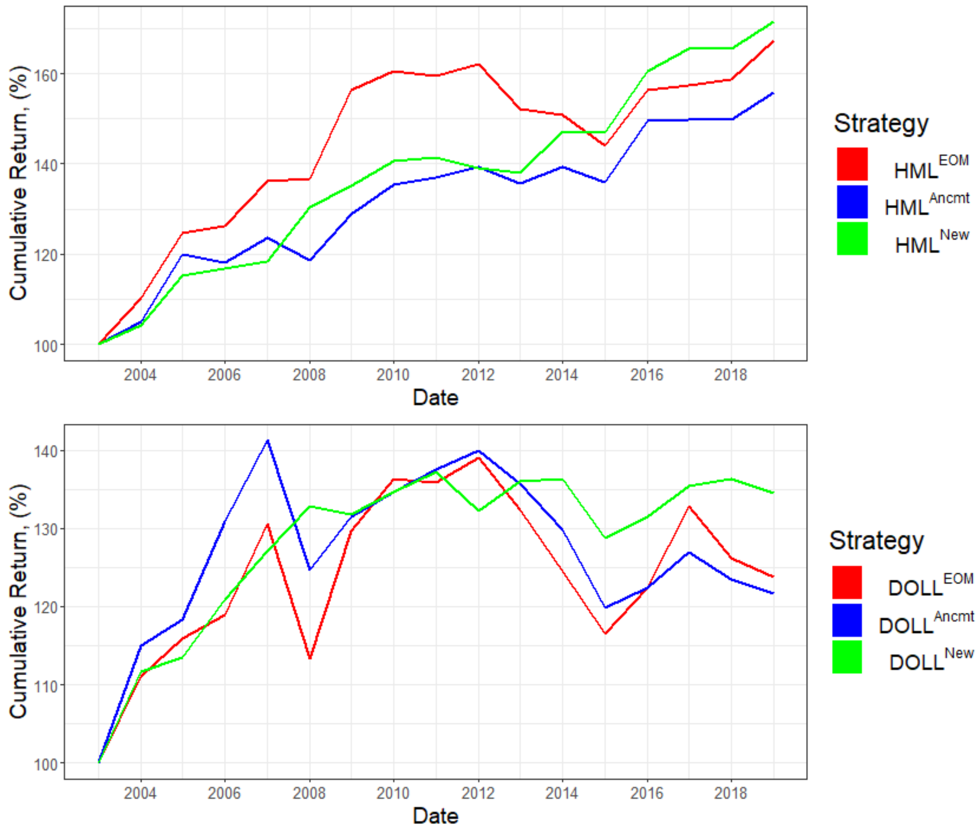
In Tab. 5 we provide the summary statistics of the three carry trade portfolios (P1, P2, P3), the carry trade strategy (HML), and the Dollar strategy (DOLL) depending on the day and the signal when the portfolios are created. Panel A represents the results, when portfolios are constructed at the end of the month *without* taking the Fed's announcements into consideration. For the carry trade portfolios, returns are monotonically increasing from Portfolio 1 to Portfolio 3, resulting in an HML return of 3.5% p.a. However, the carry trade strategy exhibits high volatility, leading to a Sharpe ratio of 0.511. Furthermore, the HML returns are negatively skewed, which confirms the evidence in the literature (Brunnermeier *et al.*, 2008; Menkhoff *et al.*, 2012; Dobrynskaya, 2014). The strategy based on the Dollar factor earns significantly lower returns and yields only about 1% p.a. If the investment strategy is created not at the end of the month but on the day of the central bank announcement and held until the next scheduled meeting, a slight improvement in performance can be seen in Panel B. However, significant improvement is observed when the strategy is created on the day of the announcement *and* is based on the nature of the shock (Panel C). As the additional signal that comes from the central bank's announcements allows to avoid periods of foreign currency depreciation, the volatility of the carry trade portfolio decreases by 1.9 percentage points p.a. that leads to a Sharpe Ratio of 0.915, which is 1.8 times higher compared to the original strategy (Panel A). The portfolio furthermore exhibits positive skewness, drastically reducing the probability of high losses. The same evidence is observed for the DOLL strategy, where the Sharpe ratio is 4 times higher and equals 0.457. These features are also seen in the cumulative return plot, Fig. 6. It shows that the new strategy overcomes big losses, especially during times of high economic volatility. By taking the advantage of currency movements on the day of FOMC meetings, investors can reduce the volatility of an overall portfolio and avoid large losses.

The results remain robust for both developed and emerging market currencies (Tab. F6 and Tab. F7). However, importantly, the carry trade strategy, which takes into account shocks following central bank announcements, remains highly profitable after the global financial crisis (GFC). As depicted in App. F, it features a Sharpe ratio of 0.84 and outperforms the original carry trade strategy, which proved to be unprofitable after the GFC by far (see, e.g., Falconio, 2021).

[10] Note that rx_{t+1}^{i} is the log excess return for *buying* the foreign currency i and selling the U.S. dollar. As a result, the negative of the return, i.e., $-rx_{t+1}^{i}$, presents the case, where the investor *sells* the foreign currency.

[11] In order not to start in times of crisis, our portfolio analysis starts in June 2004. Moreover, most currencies in our sample are available only from 2004 onwards.

Figure 6: Cumulative Returns of Carry Trade and Dollar Strategies



Notes: The top panel shows the cumulative returns of the carry trade strategy created at the end of the month (HML^{EOM}), on the day of the central bank announcement (HML^{Ancmt}), and the carry trade strategy created on the day of the announcement that takes into consideration the co-movement between bond yields and S&P 500 prices (HML^{New}). The bottom panel shows the cumulative returns of the Dollar strategies, created similarly. Strategies are created for the period from June 2004 to June 2019 using all available currencies.

7 Concluding Remarks

In this study, we examine the impact of U.S. monetary policy shocks on exchange rates relative to the U.S. dollar. According to recent advances in the literature, we separate these shocks into conventional monetary policy and information shocks. Moreover, we deviate from standard economic exchange rate models and utilize a model that takes the global importance of the U.S. dollar into account. For this, the convenience yield is a central concept stating that the safe and highly liquid U.S. Treasuries are key for exchange rate developments, ultimately adding a cash-flow component to the modelling stance. Within a linear vector autoregressive framework (VAR), we demonstrate that the nature of monetary policy shocks is a critical factor in determining how exchange rates respond. By simulating a restrictive monetary policy surprise, we conduct an impulse response analysis for 10 developed and 21 emerging market currencies vis-à-vis the U.S. dollar.

Specifically, we find that currencies react to both shocks with a reverse sign. Namely, the monetary policy shock leads to a U.S. dollar appreciation, while an information shock lets the U.S. dollar depreciate. This evidence suggests that information shocks are also transmitted through the exchange rate channel.

In addition to this, the second part of our paper employs a nonlinear model stance to check for the importance of a specific currency trading strategy for the transmission of monetary policy. Within a threshold VAR framework, we discriminate between three regimes of carry trade activity, where a currency is used either as an investment (Regime 3) or funding currency (Regime 1) or falls in an indeterminacy region (Regime 2). As a regime indicator variable we employ the net open interest on the currency futures positions of the U.S. Commodity Futures Trading Commission (CFTC).

With this setup, we show that the impact of both types of shocks is strongly influenced by the prevailing carry trade regime, i.e., whether a currency is being used as a funding or investment currency in a carry trade. We observe that when a currency is subjected to pronounced carry trade activity, its reactions to both types of shocks are amplified. Our findings therefore provide insights into the causes of currency crashes. Moreover, we find that the unique characteristics of the respective currencies appear to play a crucial role in determining the specific reactions.

Equipped with information about the regime allocation, we proceed to put two exchange rate anomalies under scrutiny, the exchange rate disconnect and the forward premium puzzle. Our results indicate that if a currency belongs to one of the high carry trade regimes, i.e., Regime 1 and 3, both puzzles are more pronounced. Again, we conclude that the currency carry trade indeed has major implications for exchange rate markets and may explain existing FX anomalies quite well.

Finally, based on these insights, we develop a trading strategy to assess whether we can outperform the carry trade and a strategy based on the dollar risk factor by including the insights about the nature of the monetary policy shocks. We find that using the shocks as signals to create the portfolio leads not only to improved performance in terms of the Sharpe ratio and downside risks but also in excess returns.

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A Estimation of β^* to Derive the Convenience Yield

To estimate the impact of the convenience yield on the U.S. dollar, we follow a similar approach to Jiang *et al.* (2021). We consider an expression, where innovations in the exchange rate are regressed on these of the Treasury basis and simultaneously controlling for news about future interest rate differences, a currency risk premium, and a constant. The equation reads as follows:

$$(\mathbb{E}_t - \mathbb{E}_{t-1})s_t = -\frac{(\mathbb{E}_t - \mathbb{E}_{t-1})x_t}{(1-\phi_a)(1-\beta^*)} + \mathbb{E}_t \sum_{\tau=0}^{\infty}(y^{\$}_{t+\tau} - y^*_{t+\tau}) - \mathbb{E}_t \sum_{\tau=0}^{\infty} rp^*_{t+\tau} + \bar{s}. \tag{A.1}$$

For estimating the innovations in the Treasury basis, $\Delta\bar{x}^{Treas}_{t+1}$, we implement the following regression:

$$\bar{x}^{Treas}_{t+1} - \bar{x}^{Treas}_t = \alpha + \beta_1\bar{x}^{Treas}_t + \beta_2(y^{\$}_t - \bar{y}^*_t) + \varepsilon_{t+1}, \tag{A.2}$$

where $\bar{x}^{Treas}_t$ is the average Treasury basis of all available currencies at t, $(y^{\$}_t - \bar{y}^*_t)$ is the difference between the U.S. 1-year government interest rate and the average of all foreign 1-year government interest rates available at t. Therefore, we interpret the residuals of the regression, ε_{t+1}, as innovations in the Treasury basis, $\Delta\bar{x}^{Treas}_{t+1}$.

Now, to estimate the impact of the Treasury basis innovations on the exchange rates, we run the following regression:

$$\Delta\bar{s}_{t+1} = \alpha_0 + \alpha_1\Delta\bar{x}^{Treas}_{t+1} + \epsilon_{t+1}, \tag{A.3}$$

where $\Delta\bar{s}_{t+1}$ is the monthly change in the log exchange rate vis-à-vis the U.S. dollar and $\Delta\bar{x}^{Treas}_{t+1}$ are the innovations in the Treasury basis.

Tab. A1 reports results of Eq. (A.3) for monthly data, which shows that a decrease in the Treasury basis by 1% leads to the 3.08% appreciation of the U.S. dollar.

Table A1: Impact of Treasury Basis on the Nominal Exchange Rate

	Dependent variable:
	$\Delta\bar{s}_{t+1}$
$\Delta\bar{x}^{Treas}_{t+1}$	-3.08^{***}
	(0.67)
Constant	−0.001
	(0.001)
Observations	419
Adjusted R^2	0.05
Note:	*p<0.1; **p<0.05; ***p<0.01

Following Jiang *et al.* (2020) and assuming that the average Treasury basis $\bar{x}^{Treas}_t$ follows an AR(1) process, we obtain (an annualized) autoregressive coefficient $\phi_a = 0.52$ from $\bar{x}^{Treas}_{t+1} = \alpha + \phi_a\bar{x}^{Treas}_t + \eta_{t+1}$.

Finally, this allows us to implicitly infer β^*. For the fundamental equation to hold, we need to find a β^* that satisfies:

$$(E_t - E_{t-1})s_t = -\frac{(E_t - E_{t-1})x_t}{(1-\phi_a)(1-\beta^*)}, \tag{A.4}$$

We stick to Jiang *et al.*'s (2021) approach adjusted for monthly frequency and simulate a 10 bp decrease in the Treasury basis $a = 10 \times \frac{1}{1-\phi_a^{12}} = 10.00387$. Since the USD appreciates by $\hat{\alpha}_1 = 0.308\%$ in response to the decrease in Treasury basis by 10bp (as seen in Tab. A1), the β^* that satisfies $1 - \dfrac{10.00387}{30.8}$ equals 0.68. We hold β^* constant for all currencies. Since emerging market currencies exhibit large deviations from the covered interest rate parity, we use the developed market currencies to estimate β^*.

B Full Conditional Posterior Simulation

We obtain the joint posterior density by multiplying the likelihood with the prior. First, we define $\boldsymbol{Y}$ and $\boldsymbol{S}$ as the full history of $\boldsymbol{Y}_t$ and S_t $(t = 1, \ldots, T)$. By the use of Bayes theorem we obtain

$$\begin{aligned} p(\boldsymbol{\theta}, \boldsymbol{\gamma} \mid \boldsymbol{Y}) &\propto p(\boldsymbol{Y} \mid \boldsymbol{\theta}, \boldsymbol{\gamma}) p(\boldsymbol{\theta}, \boldsymbol{\gamma}) \\ &\propto \prod_{r=1}^{R} p(\boldsymbol{Y} \mid \boldsymbol{\theta}_r) p(\boldsymbol{\theta}_r \mid \boldsymbol{S}) p(\boldsymbol{S} \mid \boldsymbol{\gamma}) p(\boldsymbol{\gamma}). \end{aligned} \tag{B.1}$$

As we rely on data augmentation, we iterate between the following two steps. First, we classify the observations into one of the regimes, and second, we draw the parameters of the model conditional on the classification. For the classification step, we sample the group indicator $\boldsymbol{S}$ according to

$$p(\boldsymbol{S} \mid \boldsymbol{Y}, \boldsymbol{\theta}, \gamma, d) \propto p(\boldsymbol{Y} \mid \boldsymbol{S}, \boldsymbol{\theta}, \boldsymbol{\gamma}) p(\boldsymbol{S} \mid \boldsymbol{\gamma}). \tag{B.2}$$

The regime-dependent coefficients in $\boldsymbol{\theta}$ are assumed to be fixed and the indicator depends on the threshold parameter γ and delay parameter d. The posterior density of those parameters is given by

$$p(\boldsymbol{\gamma} \mid \boldsymbol{Y}, \boldsymbol{\theta}) \propto p(\boldsymbol{Y} \mid \boldsymbol{\theta}, \boldsymbol{\gamma}) p(\boldsymbol{\gamma}). \tag{B.3}$$

Conditional on the regime indicator $\boldsymbol{S}$, sampling the regime-specific parameters $\boldsymbol{\theta}_r = (\boldsymbol{A}_r, \boldsymbol{\Sigma}_r)$ is particularly easy because we can rely on well-known conditional posterior densities of linear time series models. This results in applying Bayes theorem

$$p(\boldsymbol{\theta}_r \mid \boldsymbol{Y}, \boldsymbol{S}) \propto p(\boldsymbol{Y} \mid \boldsymbol{S}, \boldsymbol{\theta}_r) p(\boldsymbol{\theta}_r \mid \boldsymbol{S}), \quad r = 1, \ldots, R, \tag{B.4}$$

and retrieving the posterior distribution of the regime-specific coefficients $\boldsymbol{\theta}_r$.

We employ a Gibbs sampler to draw iteratively from the joint posterior density. The resulting Markov chain is then used to inspect and analyze the posterior quantities. In the following, we will outline the individual Gibbs steps and how to draw from the conditional posterior distributions.

(i) Conditional on the regime indicator S_r, we start by sampling the regime-specific coefficients. These consist of three group of coefficients: the VAR coefficients, the associated shrinkage prior coefficients, and the variance covariance matrix. First, we gather all right-hand side variables in $\boldsymbol{X}_t = (1, \boldsymbol{m}'_{t-1}, \boldsymbol{y}'_{t-1}, \ldots, \boldsymbol{m}'_{t-p}, \boldsymbol{y}'_{t-p})'$ and stack them into matrix form $\boldsymbol{X} = (\boldsymbol{X}_1, \ldots, \boldsymbol{X}_T)'$. Similarly, we stack $\boldsymbol{m} = (\boldsymbol{m}_1, \ldots, \boldsymbol{m}_T)'$, and $\boldsymbol{y} = (\boldsymbol{y}_1, \ldots, \boldsymbol{y}_T)'$, and $\boldsymbol{\varepsilon} = (\boldsymbol{\varepsilon}_1, \ldots, \boldsymbol{\varepsilon}_T)'$. Then, it is convenient to define $\tilde{\boldsymbol{X}}_r = \boldsymbol{D}_r \boldsymbol{X}$, $\tilde{\boldsymbol{y}}_r = \boldsymbol{D}_r \boldsymbol{y}$, $\tilde{\boldsymbol{m}}_r = \boldsymbol{D}_r \boldsymbol{m}$, and $\tilde{\boldsymbol{\varepsilon}}_r = \boldsymbol{D}_r \boldsymbol{\varepsilon}$. $\boldsymbol{D}_r$ is a selection matrix of size $T_r \times T$ and T_r denotes the number of observations per regime r. Hence, $\tilde{\boldsymbol{X}}_r$, $\tilde{\boldsymbol{y}}_r$, and $\tilde{\boldsymbol{m}}_r$ denote all observations in the respective regime r. The VAR in matrix notation thus reads

$$\begin{pmatrix} \tilde{\boldsymbol{m}}_r & \tilde{\boldsymbol{y}}_r \end{pmatrix} = \tilde{\boldsymbol{X}}_r \begin{pmatrix} \boldsymbol{0} & \boldsymbol{A}_r \end{pmatrix} + \tilde{\boldsymbol{\varepsilon}}_r, \tag{B.5}$$

where $\boldsymbol{A}_r = \left(\boldsymbol{c}_r^y, \boldsymbol{A}_{r1}^{my}, \boldsymbol{A}_{r1}^{yy}, \dots, \boldsymbol{A}_{rp}^{my}, \boldsymbol{A}_{rp}^{yy}\right)'$ gathers all coefficients, which have to be estimated in the VAR equation. As a last step, we denote with $\boldsymbol{\alpha}_r = \text{vec}(\boldsymbol{A}_r)$ the vectorized version of $\boldsymbol{A}_r$.

(a) We sample the VAR coefficients following Jarociński and Karadi (2020). First, we construct a diagonal $(n_y(n_y p+1)) \times (n_y(n_y p+1))$ prior covariance matrix $\underline{\boldsymbol{V}_i}$, where we specify the elements in step (b). This yields the following conditional posterior distribution

$$\boldsymbol{\alpha}_r \mid \Sigma_r, \tilde{\boldsymbol{y}}_r, \tilde{\boldsymbol{m}}_r \sim \mathcal{N}\left(\overline{\boldsymbol{\alpha}}_r, \overline{\boldsymbol{V}}_r\right), \tag{B.6}$$

with the posterior quantities defined as follows:

$$\overline{\boldsymbol{\alpha}_r} = \overline{\boldsymbol{V}_r}\left(\underline{\boldsymbol{V}_r^{-1}\boldsymbol{\alpha}}_r + \left(\left(\boldsymbol{\Sigma}_r^{YY.1}\right)^{-1} \otimes \tilde{\boldsymbol{X}}_r'\right)\left(\tilde{\boldsymbol{y}}_r + \tilde{\boldsymbol{m}}_r\left(\boldsymbol{\Sigma}_r^{MM}\right)^{-1}\boldsymbol{\Sigma}_r^{MY}\right)\right) \tag{B.7}$$

and

$$\overline{\boldsymbol{V}_r} = \left(\underline{\boldsymbol{V}_r^{-1}} + \left(\boldsymbol{\Sigma}_r^{YY.1}\right)^{-1} \otimes \tilde{\boldsymbol{X}}_r'\tilde{\boldsymbol{X}}_r\right). \tag{B.8}$$

Here we use the notation $\boldsymbol{\Sigma}_r = \begin{pmatrix} \boldsymbol{\Sigma}_r^{MM} & \boldsymbol{\Sigma}_r^{MY} \\ \boldsymbol{\Sigma}_r^{YM} & \boldsymbol{\Sigma}_r^{YY} \end{pmatrix}$ and $\boldsymbol{\Sigma}_r^{YY.1} = \boldsymbol{\Sigma}_r^{YY} - \boldsymbol{\Sigma}_r^{YM}\left(\boldsymbol{\Sigma}_r^{MM}\right)^{-1}\boldsymbol{\Sigma}_r^{MY}$.

(b) Now we proceed to sample the parameters of the Horseshoe (HS) prior to construct the $k \times k$ prior variance-covariance matrix $\boldsymbol{V}_r = \text{diag}\left(\lambda_{r1}^2\tau_r^2, \dots, \lambda_{rk}^2\tau_r^2\right)$. Makalic and Schmidt (2015) provide a simple and efficient sampling scheme based on auxiliary variables that lead to conjugate conditional posterior distributions of all parameters. Hence, we re-write the HS prior as follows. We assume that

$$\begin{aligned} \alpha_{rj} \mid \lambda_{rj}^2, \tau_i &\sim \mathcal{N}(\underline{\alpha_{rj}}, \lambda_{rj}^2\tau_r^2), \\ \lambda_{rj} &\sim C^+(0,1), \\ \tau_r &\sim C^+(0,1), \end{aligned} \tag{B.9}$$

which can be re-written by making use of the scale mixture representation of the half-Cauchy distribution. We introduce two auxiliary parameters, ν_{rj} $(j = 1, \dots, k)$ and ξ_r and write the HS prior with the following hierarchy

$$\begin{aligned} \alpha_{rj} \mid \lambda_{rj}^2, \tau_i &\sim \mathcal{N}(\underline{\alpha_{rj}}, \lambda_{rj}^2\tau_r^2), \\ \lambda_{rj}^2 \mid \nu_{rj} &\sim \mathcal{IG}(1/2, 1/\nu_{rj}), \\ \tau_r^2 &\sim \mathcal{IG}(1/2, 1/\xi_r), \\ \nu_{r1}, \dots, \nu_{rk}, \xi_r &\sim \mathcal{IG}(1/2, 1). \end{aligned} \tag{B.10}$$

The conditional posterior distributions for the local and global hypervariances are also inverse-Gamma distributed and look as follows

$$\lambda_{rj}^2 \mid \alpha_{rj}, \tau_r^2, \nu_{rj} \sim \mathcal{IG}\left(1, \frac{1}{\nu_{rj}} + \frac{\alpha_{rj}^2}{2\tau_r^2}\right), \qquad j = 1, \dots, k \tag{B.11}$$

$$\tau_r^2 \mid \boldsymbol{\alpha}_r, \boldsymbol{\lambda}^2, \xi_r \sim \mathcal{IG}\left(\frac{k+1}{2}, \frac{1}{\xi_r} + \frac{1}{2}\sum_{j=1}^{k} \frac{\alpha_{rj}^2}{\lambda_{rj}^2}\right). \tag{B.12}$$

Finally, the conditional posterior distributions for the auxiliary variables are

$$\nu_{rj} \mid \lambda_j^2 \sim \mathcal{IG}\left(1, 1 + \frac{1}{\lambda_{rj}^2}\right), \qquad j = 1, \dots, k \tag{B.13}$$

$$\xi_r \mid \tau_r^2 \sim \mathcal{IG}\left(1, 1 + \frac{1}{\tau_r^2}\right). \tag{B.14}$$

(c) Draw $\boldsymbol{\Sigma}_r$ from its conditional distribution

$$\boldsymbol{\Sigma}_r \mid \boldsymbol{A}_r, \tilde{\boldsymbol{y}}_r, \tilde{\boldsymbol{m}}_r \sim iW\left(\overline{\nu}_r, \overline{S}_r\right), \tag{B.15}$$

where $\overline{\nu}_r = \nu + T_r$ and $\overline{\boldsymbol{S}}_r = \boldsymbol{S} + \left(\begin{pmatrix}\tilde{\boldsymbol{m}}_r & \tilde{\boldsymbol{y}}_r\end{pmatrix} - \tilde{\boldsymbol{X}}_r \begin{pmatrix}\boldsymbol{0} & \boldsymbol{A}_r\end{pmatrix}\right)' \left(\begin{pmatrix}\tilde{\boldsymbol{m}}_r & \tilde{\boldsymbol{y}}_r\end{pmatrix} - \tilde{\boldsymbol{X}}_r \begin{pmatrix}\boldsymbol{0} & \boldsymbol{A}_r\end{pmatrix}\right)$.

(ii) The regime-independent parameters $\boldsymbol{\gamma}$ have a Gaussian prior and we sample them using a Griddy Gibbs sampler (Ritter and Tanner, 1992) following Huber and Zörner (2019). The Griddy Gibbs sampler evaluates the conditional posterior $p(\gamma_r \mid \boldsymbol{\gamma}_{-r}, \boldsymbol{\Sigma}, \boldsymbol{A})$, with $\boldsymbol{\gamma}_{-r}$ being the vector $\boldsymbol{\gamma}$ with the r-th element excluded, at a set of candidate points $\tilde{\gamma}_r^{(1)}, \dots, \tilde{\gamma}_r^{(Q)}$, and computes

$$w_{ir} = \frac{p(\tilde{\gamma}_r^{(i)} \mid \boldsymbol{\gamma}_{-r}, \boldsymbol{\Sigma}, \boldsymbol{A})}{\sum_{i=1}^{Q} p(\tilde{\gamma}_r^{(i)} \mid \boldsymbol{\gamma}_{-r}, \boldsymbol{\Sigma}, \boldsymbol{A})}. \tag{B.16}$$

These weights are then used to perform inverse transform sampling in order to obtain draws from $p(\gamma_r \mid \boldsymbol{\gamma}_{-r}, \boldsymbol{\Sigma}, \boldsymbol{A})$. $\boldsymbol{\Sigma} = (\boldsymbol{\Sigma}_1, \dots, \boldsymbol{\Sigma}_R)$ and $\boldsymbol{A} = (\boldsymbol{A}_1, \dots, \boldsymbol{A}_R$. In the empirical application, we set $Q = 50$ and apply linear interpolation to obtain a sequence of weights that approximate the actual CDF accurately. Note that the likelihood function of the model is flat with respect to specific values of γ_r if no change in the corresponding regime allocation is induced. Finally, it is worth emphasisizing that we also introduce the restriction that a certain fraction of observations (unless otherwise noted, 5% of T) has to remain within each regime.

C Convergence Diagnostics

To assess convergence of the Markov chain, we summarize three convergence diagnostics for the models presented in Sec. 3. Markov chain sampler should return identically and independent distributed draws. If this condition is not fulfilled, resulting samples are correlated and more draws are needed. Therefore, we estimate three different statistics to assess the degree of autocorrelation in the MCMC chain. The inefficiency factor indicates how many draws are required to draw one identically and independently distributed draw. Dependence factor measures autocorrelation (Raftery and Lewis (1991)). A dependence factor greater than 5 indicates strong autocorrelation. Geweke's convergence diagnostic (Geweke (1992)) compares means of the first 10% and last 50% of the Markov chain. Tab. C1 reports the share of Z-scores that exceed the critical value of 1.96. The last column corresponds to the fraction of stable draws.

For the VAR model convergence is achieved for all currencies. The dependence factors do not exceed 5, the share of Z-scores exceeding the critical value of 1.96 is small. The number of stable draws is low for TWD and TRY. For the remaining currencies, it exceeds 20%.

For the TVAR model, convergence is similarly achieved. Inefficiency factors and dependence factors are on average higher than in the linear model but that is expected. Geweke's Z-scores exceed in no single instance the critical value of 1.96. The number of stable draws drops to somewhat low level in several instances but in those cases we ensured to sample more draws such that posterior analysis is possible.

Table C1: Convergence statistics - VAR

	Inefficiency Factor	Dependence factor	Geweke's Z-scores	% draws retained
AUD	4.52	1.30	0.00	44.66
BRL	1.67	1.19	0.01	43.35
CAD	3.30	1.47	0.02	66.71
HRK	5.17	4.49	0.00	33.48
CHF	3.17	1.51	0.04	77.90
CLP	1.82	1.32	0.02	27.74
COP	10.03	1.38	0.04	40.96
CZK	3.29	1.96	0.00	88.23
DKK	8.70	1.71	0.03	55.10
EUR	2.93	2.46	0.03	89.56
GBP	3.43	2.05	0.09	85.17
HUF	2.05	1.24	0.08	32.35
IDR	1.55	1.17	0.03	32.87
ILS	2.64	1.63	0.02	74.57
INR	3.34	1.40	0.00	58.13
JPY	7.21	1.70	0.07	55.31
KRW	6.03	2.34	0.07	55.98
KWD	6.41	1.88	0.03	68.77
MXN	2.30	1.17	0.07	33.72
MYR	2.97	1.63	0.01	68.56
NOK	6.12	1.22	0.03	40.35
NZD	4.67	1.54	0.06	83.95
PHP	2.95	1.26	0.05	45.16
PLN	1.97	1.29	0.04	56.13
RUB	13.18	1.32	0.01	30.51
SEK	2.31	1.36	0.04	48.51
SGD	3.38	1.60	0.00	74.53
THB	10.12	1.64	0.08	69.82
TWD	1.25	1.12	0.01	3.81
TRY	1.18	1.05	0.03	3.45
ZAR	4.64	1.14	0.04	20.34

Table C2: Convergence statistics - TVAR

	Inefficiency Factor	Dependence factor	Geweke's Z-scores	% draws retained
		AUD		
Regime 1	7.29	1.92	0.00	9.93
Regime 2	4.32	1.77	0.02	3.47
Regime 3	9.03	3.05	0.00	21.69
		CAD		
Regime 1	5.50	4.55	0.00	38.91
Regime 2	3.53	3.42	0.00	7.51
Regime 3	4.67	3.22	0.00	30.89
		CHF		
Regime 1	9.98	9.15	0.00	57.48
Regime 2	1.52	1.48	0.49	2.42
Regime 3	4.04	4.73	0.00	27.14
		EUR		
Regime 1	11.93	6.34	0.00	62.97
Regime 2	7.61	2.93	0.00	41.08
Regime 3	3.03	1.44	0.00	11.42
		GBP		
Regime 1	18.49	8.20	0.00	63.48
Regime 2	5.73	2.59	0.00	15.05
Regime 3	5.62	2.70	0.00	38.75
		JPY		
Regime 1	2.40	2.01	0.00	15.63
Regime 2	3.09	3.06	0.00	16.08
Regime 3	2.32	1.35	0.00	12.00
		MXN		
Regime 1	3.67	3.95	0.00	15.58
Regime 2	3.81	6.48	0.00	26.95
Regime 3	1.12	1.18	0.00	0.71
		NZD		
Regime 1	6.06	3.93	0.00	33.11
Regime 2	1.40	1.43	0.00	4.70
Regime 3	3.38	3.11	0.00	13.63

D Regime Allocation

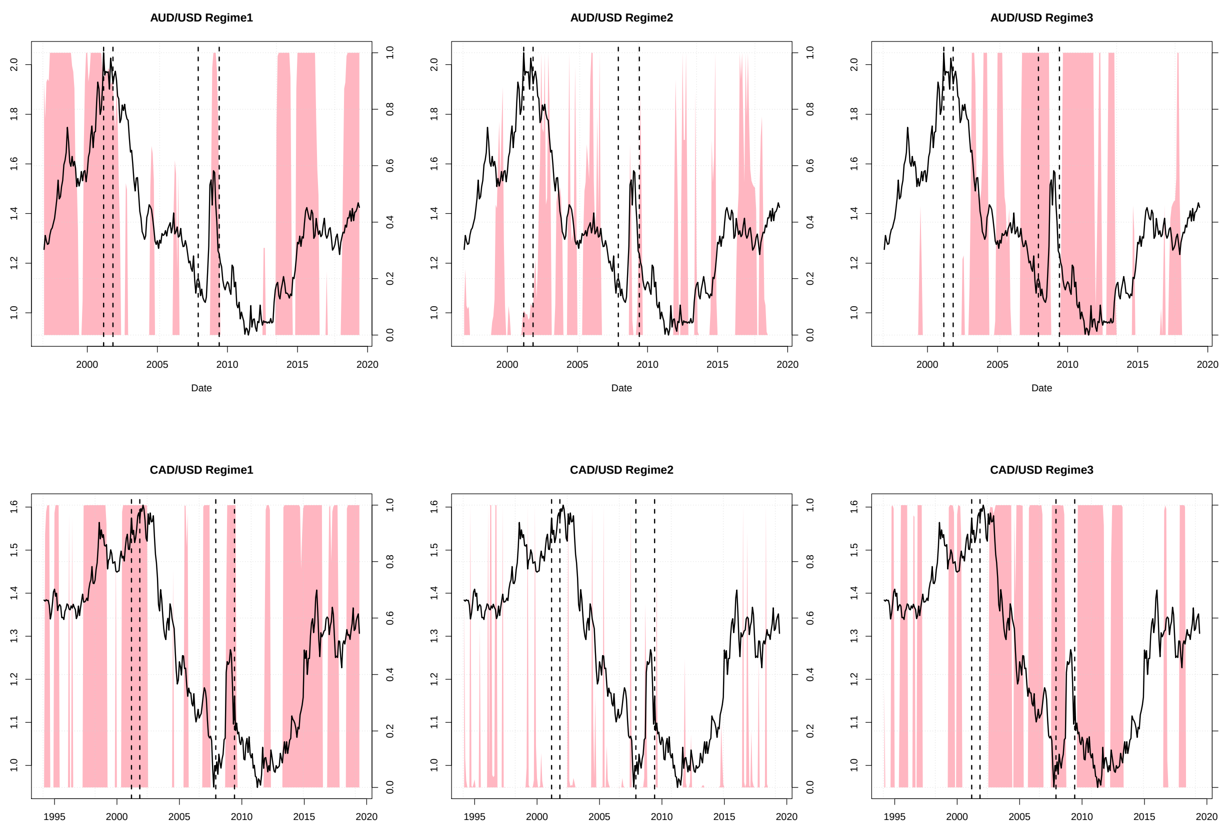
Table D3: Threshold Parameters

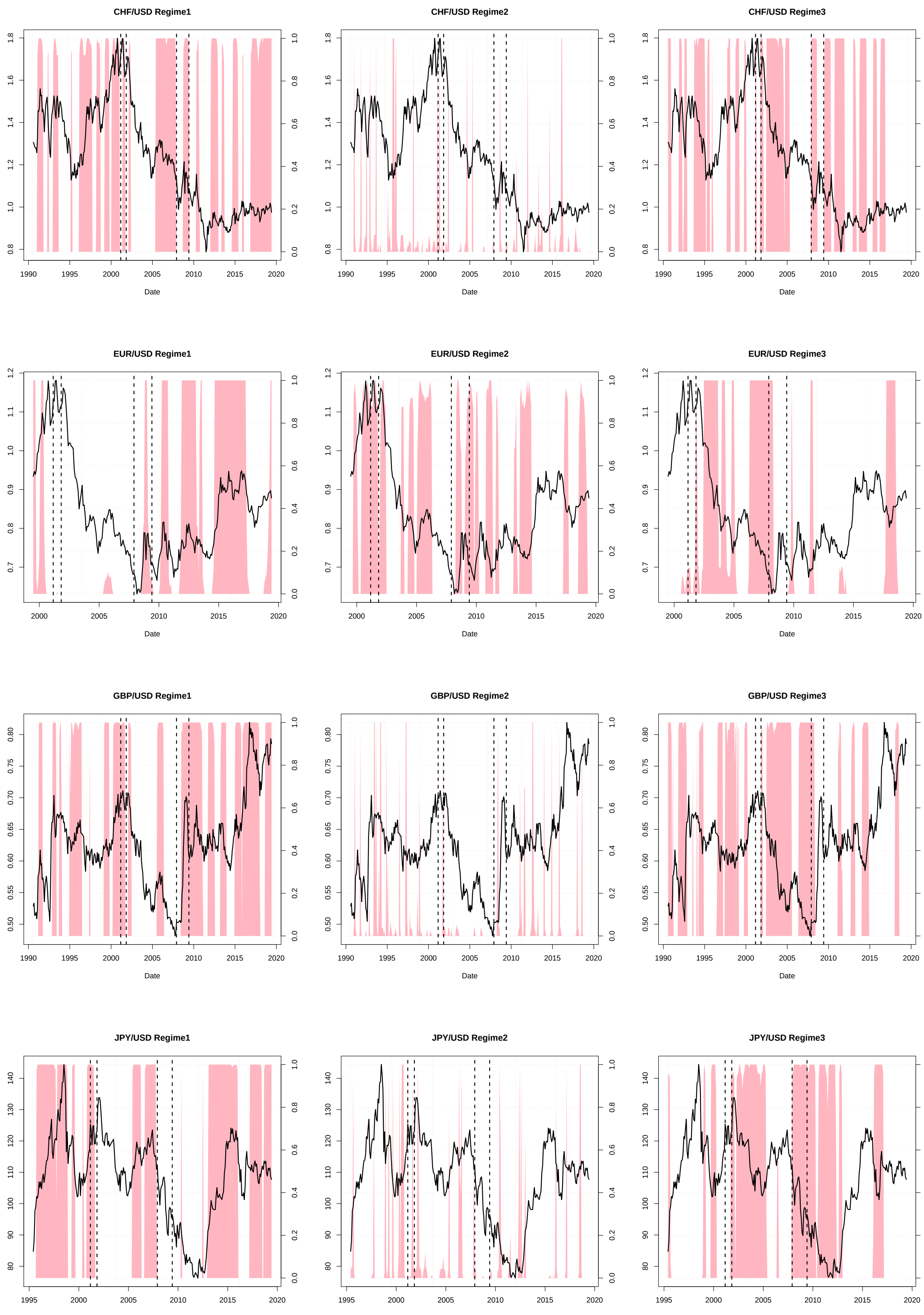
	AUD	CAD	CHF	EUR	GBP	JPY	MXN	NZD
γ_1	0.089	-0.001	-0.104	-0.096	-0.026	-0.154	0.083	0.162
γ_2	0.277	0.058	-0.047	0.161	0.027	-0.079	0.356	0.385

Notes: This table shows the average threshold parameters used to identify the regime. The parameter estimation is described in Sec. 3.

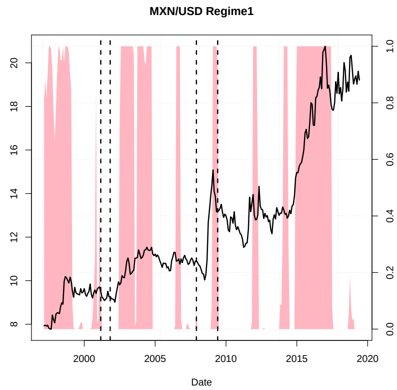
The following graphs show the exchange rate dynamics expressed in foreign currency per USD (left axis) and the probability of being in the particular regime (right axis).

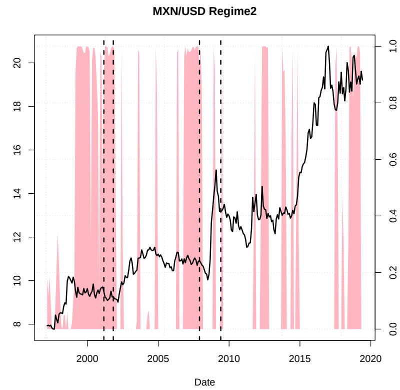
Figure D1

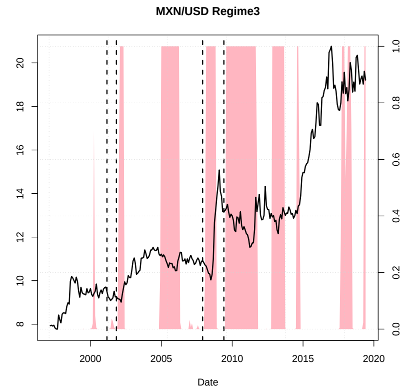




CHF/USD Regime1
CHF/USD Regime2
CHF/USD Regime3
EUR/USD Regime1
EUR/USD Regime2
EUR/USD Regime3
GBP/USD Regime1
GBP/USD Regime2
GBP/USD Regime3
JPY/USD Regime1
JPY/USD Regime2
JPY/USD Regime3
Date


MXN/USD Regime1
8 10 12 14 16 18 20
0.0 0.2 0.4 0.6 0.8 1.0
2000 2005 2010 2015 2020
Date


MXN/USD Regime2
8 10 12 14 16 18 20
0.0 0.2 0.4 0.6 0.8 1.0
2000 2005 2010 2015 2020
Date


MXN/USD Regime3
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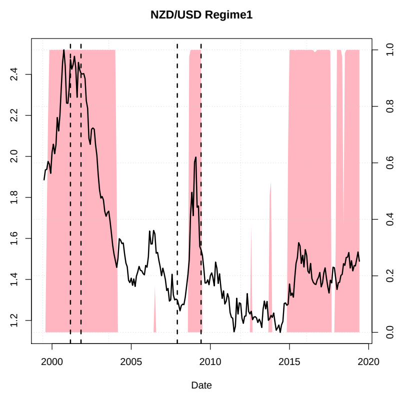
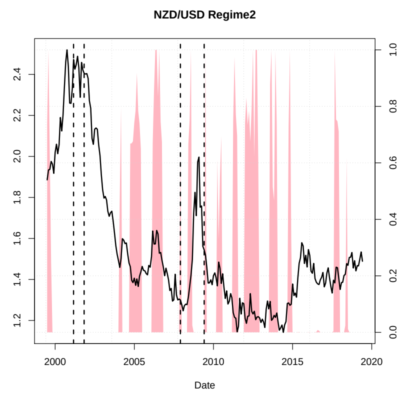
0.0 0.2 0.4 0.6 0.8 1.0
2000 2005 2010 2015 2020
Date


NZD/USD Regime1
1.2 1.4 1.6 1.8 2.0 2.2 2.4
0.0 0.2 0.4 0.6 0.8 1.0
2000 2005 2010 2015 2020
Date


NZD/USD Regime2
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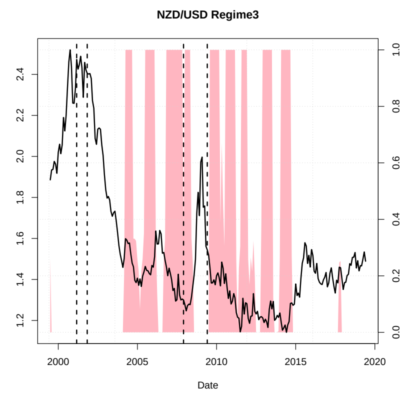
0.0 0.2 0.4 0.6 0.8 1.0
2000 2005 2010 2015 2020
Date


NZD/USD Regime3
1.2 1.4 1.6 1.8 2.0 2.2 2.4
0.0 0.2 0.4 0.6 0.8 1.0
2000 2005 2010 2015 2020
Date

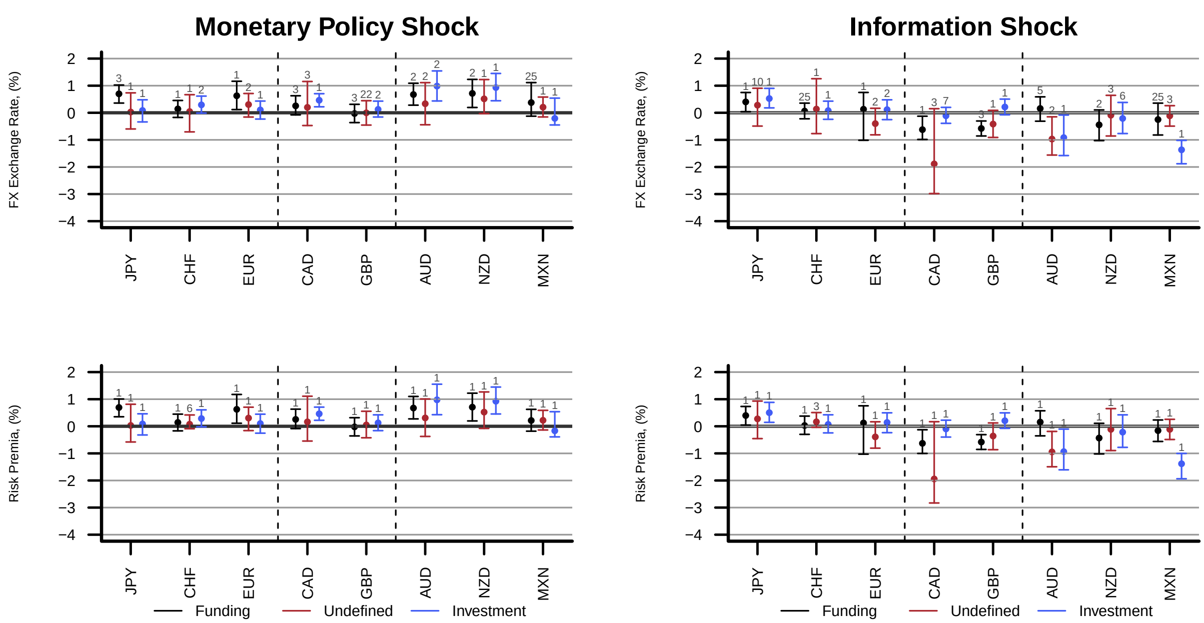
E Maximum Impulse Responses Across Regimes

Table E4: Summary Statistics of Currency Returns

	Total					*Regime 1*				*Regime 2*				*Regime 3*			
	Starting Date	Mean	SD	Skewness	Kurtosis	Mean	SD	Skewness	Kurtosis	Mean	SD	Skewness	Kurtosis	Mean	SD	Skewness	Kurtosis
AUD	1990-01-01	1.835	11.324	-0.465	5.458	0.051	11.428	0.164	3.048	-3.446	8.462	0.115	1.835	3.469	13.760	-0.966	6.203
CAD	1990-01-01	0.064	7.831	-0.575	7.096	-0.400	8.219	0.143	4.675	-3.787	11.830	-3.267	13.435	1.455	7.742	-0.076	3.025
CHF	1990-01-01	0.126	10.591	0.009	4.316	2.106	10.760	0.202	4.387	0.058	10.885	0.125	2.188	-3.582	10.840	-0.151	4.215
EUR	1999-01-01	-0.284	9.568	-0.147	4.150	-4.674	10.690	-0.160	4.240	7.553	10.998	-0.072	2.570	3.074	8.251	-0.052	3.499
GBP	1990-01-01	-0.581	8.626	-0.375	4.312	-2.063	9.743	-0.479	4.337	-6.606	7.960	-0.010	2.118	1.041	7.101	-0.183	3.174
JPY	1990-01-01	-1.237	10.391	0.299	5.194	-4.157	10.265	1.183	7.766	-9.138	8.314	-0.164	2.452	-2.157	11.302	-0.427	3.551
MXN	1995-05-01	2.981	11.163	-1.115	6.785	1.637	11.999	-0.294	3.596	-10.268	6.089	0.493	1.656	-2.528	13.144	-1.123	4.919
NZD	1999-01-01	2.931	11.628	-0.342	5.009	2.589	14.296	-0.230	4.776	4.473	11.241	0.383	2.829	4.576	12.622	-0.639	3.478

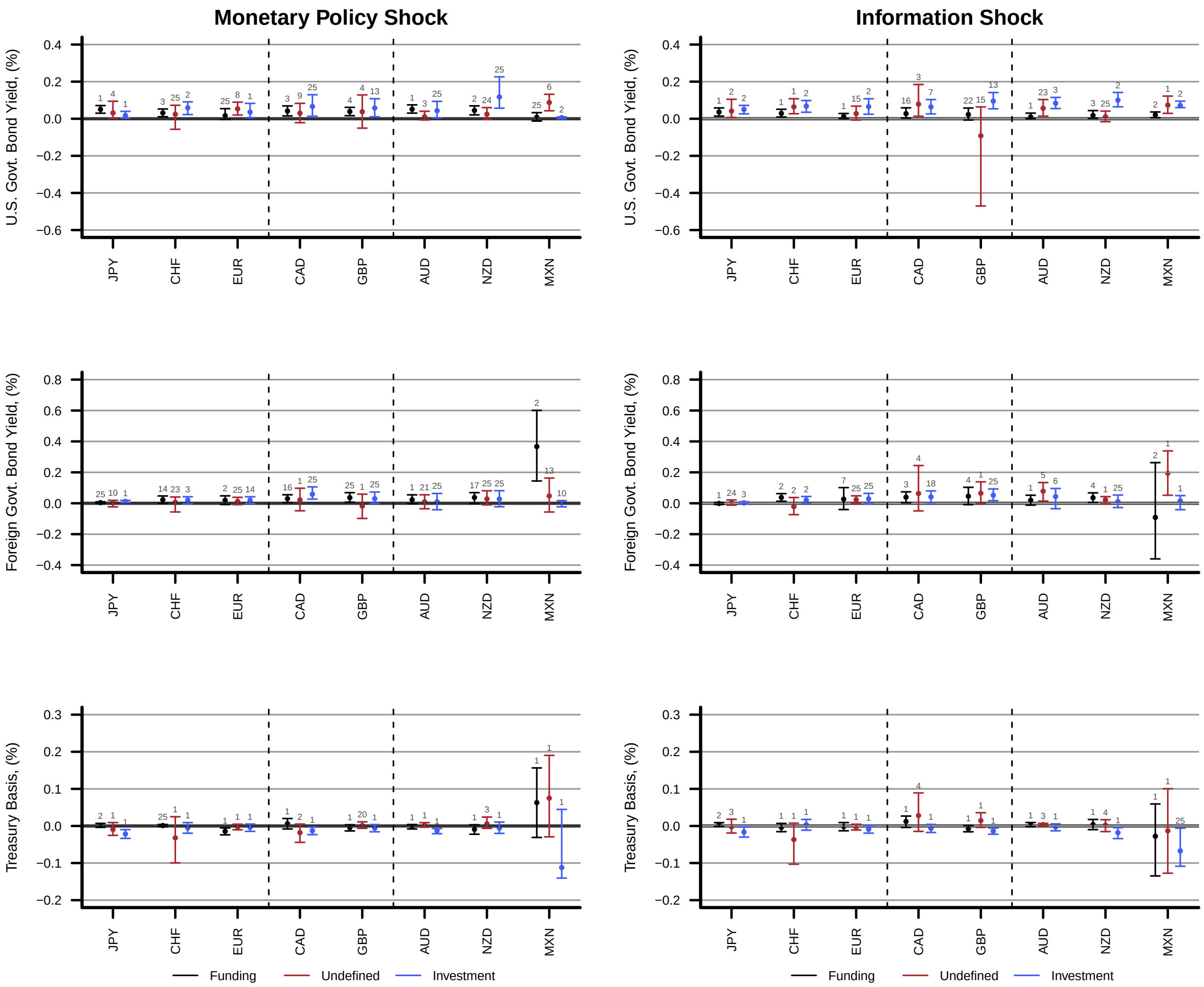
Notes: This table shows the mean, the standard deviation, the skewness, and the kurtosis for monthly log excess returns, rx_{t+1}, for the *Total* sample as well as for *Regime 1*, *Regime 2*, and *Regime 3*. Mean and standard deviation are annualized and in percent. The base currency is the U.S. dollar. The results for the second regime should be interpreted with caution, as a currency can be in both the "Investment" and "Funding" regimes, but not as pronounced.

Figure E4: Maximum Impulse Responses of FX Exchange Rates and Risk Premia



Notes: The upper panel shows the percentage change of the exchange rate vis-à-vis the U.S. dollar, while the lower panel the respective risk premium after a restrictive one standard deviation monetary policy shock (left column) or information shock (right column). Maximum responses are shown with their corresponding 80% credible set. The results for the second regime should be interpreted with caution, as a currency can be in both the "Investment" and "Funding" regimes, but not as pronounced. For the abbreviations, we refer to Sec. 3.1.

Figure E5: Maximum Impulse Responses of U.S. and foreign Interest Rates and Treasury Basis to a Monetary Policy and Information Shock



Notes: The upper panel shows the percentage change of the exchange rate vis-à-vis the U.S. dollar, while the lower panel the respective risk premium after a restrictive one standard deviation monetary policy shock (left column) or information shock (right column). Maximum responses are shown with their corresponding 80% credible set. The results for the second regime should be interpreted with caution, as a currency can be in both the "Investment" and "Funding" regimes, but not as pronounced. For the abbreviations, we refer to Sec. 3.1.

F Robustness Regarding the Trading Strategies

Table F5: Summary Statistics of Currency Portfolios After Global Financial Crisis Starting 2013-01-01

	P1	P2	P3	HML	DOLL
Panel A: Strategy created end-of-month					
Mean	-3.148	-2.484	-2.130	1.019	-2.572
SD	7.117	5.936	9.538	6.176	7.242
Skewness	0.384	0.286	-0.022	-0.163	0.243
Kurtosis	-0.168	-0.390	0.233	0.949	-0.134
Sharpe Ratio	-0.442	-0.418	-0.223	0.165	-0.355
Panel B: Strategy created on the announcement day					
Mean	-3.648	-3.050	-1.283	2.365	-2.616
SD	4.799	3.863	7.697	6.023	4.985
Skewness	0.417	0.044	-0.124	-0.433	0.364
Kurtosis	0.242	-0.130	-0.080	0.206	0.076
Sharpe Ratio	-0.760	-0.789	-0.167	0.393	-0.525
Panel C: Strategy created on the announcement day based on the shock					
Mean	-2.564	-1.680	0.607	4.633	0.309
SD	4.071	3.682	6.867	5.503	4.069
Skewness	0.287	-0.084	-0.145	-0.647	0.267
Kurtosis	4.061	3.560	3.405	3.954	2.770
Sharpe Ratio	-0.630	-0.456	0.088	0.842	0.076

Notes: This table shows summary statistics of portfolio monthly excess returns. The returns and the standard deviation are annualized and in percent. In Panel A portfolios are constructed at the end of month and held for one month. In Panel B portfolios are constructed on the day of the central bank announcement and held until the next scheduled Fed meeting. Panel C shows summary statistics of portfolios created on the day of the central bank announcement by taking into consideration the nature of the shocks. The sample covers the period after the Global Financial Crisis from January 2013 until June 2019 including the whole sample of currencies.

Table F6: Summary Statistics of Currency Portfolios, Developed Market Currencies

	P1	P2	P3	HML	DOLL
Panel A: Strategy created end-of-month					
Mean	-1.224	-1.090	0.900	2.124	-0.334
SD	7.364	8.880	12.108	8.100	9.152
Skewness	0.112	-0.207	-0.551	-0.698	-0.261
Kurtosis	-0.397	1.013	2.396	1.966	1.355
Sharpe Ratio	-0.166	-0.123	0.074	0.262	-0.037
Panel B: Strategy created on the announcement day					
Mean	-1.681	-3.130	-0.545	1.136	-1.661
SD	5.308	8.578	9.601	8.239	7.194
Skewness	0.010	-0.574	-0.818	-1.276	-0.233
Kurtosis	-0.108	2.474	4.365	4.746	1.647
Sharpe Ratio	-0.317	-0.365	-0.057	0.138	-0.231
Panel C: Strategy created on the announcement day based on the shock					
Mean	0.579	0.486	-0.346	2.801	-0.181
SD	5.396	5.412	5.651	5.584	5.233
Skewness	0.029	-0.818	-1.109	0.099	0.451
Kurtosis	2.934	6.780	8.270	5.294	4.717
Sharpe Ratio	0.107	0.090	-0.061	0.502	-0.035

Notes: This table shows summary statistics of portfolio monthly excess returns created using only developed market currencies. The returns and the standard deviation are annualized and in percent. In Panel A portfolios are constructed at the end of month and held for one month. In Panel B portfolios are constructed on the day of the central bank announcement and held until the next scheduled Fed meeting. Panel C shows summary statistics of portfolios created on the day of the central bank announcement by taking into consideration the nature of the shocks. The sample covers the period from June 2004 until June 2019 including the whole sample of currencies.

Table F7: Summary Statistics of Currency Portfolios, Emerging Market Currencies

	P1	P2	P3	HML	DOLL
Panel A: Strategy created end-of-month					
Mean	-0.020	0.908	3.849	3.869	1.600
SD	7.234	8.184	12.924	7.739	9.031
Skewness	-0.424	-0.850	-0.967	-0.826	-0.818
Kurtosis	1.232	2.329	2.438	1.836	2.159
Sharpe Ratio	-0.003	0.111	0.298	0.500	0.177
Panel B: Strategy created on the announcement day					
Mean	-0.869	0.269	3.050	3.919	0.836
SD	4.902	6.879	9.368	6.837	6.620
Skewness	-0.464	-1.249	-1.175	-0.764	-1.198
Kurtosis	2.026	4.270	3.311	1.660	4.139
Sharpe Ratio	-0.177	0.039	0.326	0.573	0.126
Panel C: Strategy created on the announcement day based on the shock					
Mean	-2.479	-2.222	-2.642	4.889	2.451
SD	3.703	3.975	5.430	5.154	4.178
Skewness	-0.048	-0.681	-1.401	0.524	0.745
Kurtosis	4.202	6.538	9.630	7.006	6.645
Sharpe Ratio	-0.669	-0.559	-0.486	0.949	0.587

Notes: This table shows summary statistics of portfolio monthly excess returns created using only emerging market currencies. The returns and the standard deviation are annualized and in percent. In Panel A portfolios are constructed at the end of month and held for one month. In Panel B portfolios are constructed on the day of the central bank announcement and held until the next scheduled Fed meeting. Panel C shows summary statistics of portfolios created on the day of the central bank announcement by taking into consideration the nature of the shocks. The sample covers the period from June 2004 until June 2019 including the whole sample of currencies.