Prospect Theory and Currency Returns: Empirical Evidence

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Abstract

We empirically investigate the role of prospect theory in the foreign exchange market. A currency-level measure of prospect-theory value, constructed from the historical distribution of exchange rate returns, negatively forecasts future currency excess returns. A long–short strategy based on this measure yields approximately 5% per annum. Predictability is stronger when arbitrage is limited. Bank order flow is positively associated with prospect-theory value, with inter-dealer and proprietary trading primarily driving this relation. Funds trade against prospect-theory value, acting as arbitrageurs. Overall, our findings suggest that investors evaluate currencies based on historical return distributions, consistent with prospect theory.

Keywords: Foreign exchange, currency returns, prospect theory, limits to arbitrage, order flow
JEL classification: F31, G12, G15, G40

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I. Introduction

The classical present-value relation suggests that asset prices should reflect discounted expected future cash flows. However, it is well recognized that investor trading behavior may also influence asset prices for reasons beyond fundamental news, such as "animal spirits" (Keynes, 1936) or "noise trading" (De Long et al., 1990). The foreign exchange (FX) market offers an ideal venue to investigate non-fundamental determinants of asset prices. As the largest financial market, the FX market is known for its unique institutional features, including high trading volume, the dominance of sophisticated investors, and the absence of short-selling constraints.[1] Prima facie, these institutional features imply that mispricing should be eliminated rapidly given the ease of arbitrage, and hence that the effects of investor behavior on exchange rates should be limited.

Several studies highlight the constraints faced by institutional traders and provide direct evidence that even sophisticated institutional investors or professional traders are subject to behavioral biases. Haigh and List (2005) provide experimental evidence that professional traders exhibit myopic loss aversion. Locke and Mann (2005) and Coval and Shumway (2005) show empirically that professional traders display strong disposition effects and loss aversion. Using proprietary data, O'Connell and Teo (2009) find that institutional currency investors exhibit dynamic loss aversion, consistent with Barberis et al. (2001). This body of evidence indicates that institutional investors may present behavioral bias consistent with prospect theory. Prospect theory, introduced by Kahneman and Tversky (1979), offers a more realistic framework for evaluating risk than the conventional expected-utility framework, and it is arguably the most

[1]According to the triennial global FX market survey of the Bank for International Settlements (Bank for International Settlements, 2025), aggregate daily turnover in the global foreign exchange market reached 9.6 trillion US dollars in April 2025. Financial institutions other than reporting dealers dominate other market participants, representing roughly 50% of total turnover. Inter-dealer trading and non-financial customers account for 46% and 5% of total turnover, respectively.

prevalent framework to accommodate multiple behavioral bias within a unified framework. It is therefore natural to investigate whether prospect theory explains currency returns in a market dominated by institutional investors.

A recent empirical study by Barberis et al. (2016) shows that prospect-theory values predict the cross-section of stock returns. In this paper, we empirically investigate prospect theory in currency markets, which, together with the distinctive institutional features mentioned above, provide a unique setting in which to understand the role of prospect theory in explaining asset returns under more stringent conditions. The intuition for why prospect theory may explain cross-sectional variation in future currency returns is straightforward. Assume the currency market consists of two types of investors: rational investors who evaluate risk within the expected-utility framework, and irrational investors who evaluate risk as described by prospect theory. The latter are more willing to hold high-prospect-theory-value (more appealing) currencies and more inclined to sell low-prospect-theory-value (unattractive) currencies. If these investors account for a non-trivial proportion of the total currency investor population, their trading activity shifts the demand for currencies and therefore affects expected currency returns in equilibrium. Specifically, they bid up high-prospect-theory-value currencies, causing them to become temporarily overvalued, while limits to arbitrage prevent this mispricing from being instantly corrected. This leads to lower expected returns for these currencies in subsequent periods. A similar logic applies to low-prospect-theory-value currencies. In summary, we expect prospect-theory value to be negatively associated with expected currency returns in the subsequent period.

Our findings lend strong empirical support to this prediction. We find that prospect-theory value, derived from the historical distribution of exchange rate changes, negatively and significantly forecasts the cross-section of future currency excess returns. The predictive relation is not only statistically significant but also economically meaningful: a one-standard-deviation increase in prospect-theory value is associated with a 5.4% per annum decline in currency returns in the following month. The predictive power remains strong when controlling for other currency characteristics. Moreover, sorting currencies into five portfolios based on prospect-theory values, we find that currencies with high prospect-theory values significantly underperform their low-value counterparts by approximately 5% per annum. A long–short strategy that buys (sells) low (high) prospect-theory-value currencies—the prospect-theory premium (PTP)—has only moderate correlations with other risk factors in the literature. Abnormal returns (alphas) after controlling for these factors remain statistically significant at the 1% level. After controlling for currency, equity, hedge fund, or tradable macroeconomic factors, alphas are 3.96%, 4.48%, 4.93%, and 5.04% per annum, respectively, comparable in magnitude to the long–short return spread.

Previous studies document that betas with respect to traditional FX risk factors significantly explain the cross-section of currency returns (see, e.g., Lustig and Verdelhan, 2007; Lustig et al., 2011; Menkhoff et al., 2012). Our results, however, show that systematic exposures (betas) to PTP returns do not adequately explain cross-sectional variation in individual currency returns, whereas the prospect-theory-value characteristic remains negatively and significantly correlated with future currency returns. Therefore, the profitability of the PTP strategy can hardly be attributed to systematic risk premia, whether arising from noise-trader risk (De Long et al., 1990) or any other omitted risk factors. Instead, our findings support the existence of mispricing at the individual currency level (characteristic) rather than systematic risk exposure (covariance).

To further test the mispricing hypothesis, we interact the prospect-theory-value variable with proxies for limits to arbitrage. The predictive power is strengthened for currencies with high illiquidity and volatility, and in countries with high sovereign risk. These features impede the ability of rational arbitrageurs to correct mispricing, and hence the predictive relation is stronger. We further observe heterogeneous effects of various FX market participants on the prospect-theory-value–currency return relation. Using currency futures trading positions data from the Commodity Futures Trading Commission (CFTC) Traders in Financial Futures (TFF) reports, we show that dealers amplify the predictive relation, while fund managers and leveraged money weaken it, acting as arbitrageurs. The predictive relation remains strong after controlling for central bank intervention, cross-border portfolio flows, and cross-country sentiment spreads.

We then turn to detailed order flow information to develop a deeper understanding of FX market trading behavior in response to prospect-theory value. Using the CLS FX spot order flow data, we document substantial trading heterogeneity among different participants. Bank order flows amplify prospect-theory-driven mispricing, with inter-dealer trading and bank proprietary trading primarily driving this positive relation. We offer supporting evidence through bank order flow decomposition and analysis of the impact of two historical events: the Volcker Rule and the Global FX Code of Conduct (GFXC). Funds serve as arbitrageurs, correcting mispricing. Order flows of non-financial corporations and non-bank financial institutions do not significantly affect the prospect-theory-value–return relation. These order flow results are broadly consistent with the CFTC trading activity findings mentioned above. This order flow analysis not only contributes to a better understanding of the mechanisms underlying the prospect-theory–currency return relation but also helps explain why, even in FX markets dominated by institutions, prospect-theory-type return patterns can be a well-defined feature.

We conduct additional tests to further clarify the source of predictability. We show that all three prospect-theory components—loss aversion, convexity/concavity, and probability weighting—are individually significant. Second, we rule out a broad set of alternative explanations: the prospect-theory premium remains significant after controlling for technical trading profitability, time-series and factor momentum, alternative behavioral indicators, and volatility risk premia (VRP). In line with Baele et al. (2019), we also find that prospect-theory value is positively correlated with currency VRP, suggesting that prospect theory partially explains the predictive content of VRP.

Finally, we confirm that our findings are robust to an extensive battery of checks. Our results are not driven by parameter choices in constructing prospect-theory value or by a particular sample period. The prospect-theory strategy delivers economically meaningful returns net of bid–ask spreads. The results are unchanged when varying the number of currencies or the quote currency, or when controlling for additional currency return predictors.

The overall contribution of this paper is threefold. First, our paper enriches the growing literature on cross-sectional return predictability in currency markets by introducing a new predictor and a new currency portfolio strategy. Previous studies document that carry trade (Lustig and Verdelhan, 2007; Lustig et al., 2011), momentum (Burnside et al., 2011a; Menkhoff et al., 2012), and value (Asness et al., 2013; Menkhoff et al., 2017) are important currency portfolio strategies.[2] We contribute to this field by introducing a new currency predictor formally motivated by behavioral finance theory—arguably the first in the literature. Our prospect-theory-value-sorted currency portfolios expand the investment opportunity set for

[2] An incomplete list of other currency portfolios includes those based on volatility risk premia (Della Corte et al., 2016a), global imbalances (Della Corte et al., 2016b), economic momentum (Dahlquist and Hasseltoft, 2020), and the output gap (Colacito et al., 2020).

currency portfolio managers and present a new challenge to existing asset pricing models.

Second, this paper adds to the literature on the asset pricing implications of prospect theory by providing novel empirical evidence beyond equity markets. Barberis and Huang (2008) propose a theoretical model linking prospect theory with asset prices and predict that expected skewness is priced in the cross-section of stock returns. Barberis et al. (2016) examine the cross-sectional return predictability of prospect-theory value in US and international stock returns. Zhong and Wang (2018) study prospect theory in the cross-section of corporate bonds. To the best of our knowledge, our paper is the first to analyze the cross-sectional return predictability implications of prospect theory in currency markets, an important asset class beyond equities. Echoing existing prospect-theory studies in equity markets, our analysis of currency markets provides out-of-sample evidence from a different asset class concerning the role of prospect theory in explaining asset returns. Although currency markets differ from stock markets in various respects, our empirical evidence implies that the irrational trading behavior described by prospect theory may exist across different asset classes and may have a common source. Given the unique over-the-counter (OTC) nature of currency markets, our results also provide new evidence from OTC markets, whereas existing studies have concentrated primarily on exchange-traded markets. This evidence is important, as it suggests that the role of prospect theory in explaining asset returns may be pervasive across different market structures.

Third, our paper contributes to the growing literature on the rationality of institutional investors and their role in affecting market efficiency. The conventional view holds that institutional investors are rational and that their trading improves market efficiency. Campbell et al. (2009) and Boehmer and Kelley (2009) show that institutional investors exploit mispricing and improve informational efficiency. Barberis et al. (2016) document that the predictive power of prospect-theory value is stronger for stocks with lower institutional ownership. However, Stein (2009) highlights that institutional ownership may adversely influence price efficiency. Goetzmann et al. (2015) show that both the perception of mispricing and the trading decisions of institutional investors are affected by investor mood.

The strong predictability we document in currency markets—markets dominated by sophisticated institutional investors—suggests that the conventional view of irrational trading being confined to small retail traders may be oversimplified. As Barberis et al. (2021) notes, prospect-theory behavior in asset prices may arise either because institutional investors cannot fully absorb retail demand or because some institutional investors themselves exhibit prospect-theory preferences. Our results reinforce this view. The strength of the prospect-theory portfolio in highly liquid currency markets, including those of developed economies and the G10, challenges the notion that arbitrage should be most effective in liquid environments.

Our findings are consistent with a prior study by O'Connell and Teo (2009), who use proprietary fund manager data to show that institutional currency investors exhibit dynamic loss aversion, providing valuable micro-level evidence on trader behavior. Our study complements theirs by taking a broader market-level perspective using publicly available data. We examine the asset pricing implications of prospect theory across the cross-section of currencies and identify predictable return patterns. We also investigate the economic mechanisms through analysis of both CFTC futures positions and CLS spot order flow data. We further show that, while loss aversion contributes to the observed patterns, probability weighting and value function curvature also play important roles. Our paper thus differs from theirs in focus, scope, and methodology. While both papers highlight the importance of prospect theory in FX markets, they contribute to the literature in complementary but distinct ways.

A closely related study is Chabi-Yo and Song (2012), who investigate the role of probability weighting of rare events in predicting aggregate currency market returns and in pricing carry trade and momentum returns. Our paper differs from theirs in several respects. First, while prospect theory and rank-dependent utility (Quiggin, 1993), on which they rely, are closely related, our paper conducts arguably the first formal empirical investigation of prospect theory in currency markets, whereas their paper focuses on probability weighting. Second, our paper focuses on cross-sectional return predictability, whereas they focus on aggregate time-series predictability. Third, our measure is based on historical information, while their currency-option-based measure is forward-looking. These two measures therefore contain different information sets.

This paper is related to existing behavioral studies in FX markets.[3] This literature either focuses primarily on theoretical perspectives or uses time-series regressions to predict currency returns. In contrast, our paper emphasizes cross-sectional currency return predictability using a new predictor motivated by prospect theory. In addition, our paper is related to the literature on order flow and exchange rates. Since the seminal work of Lyons (1997) and Evans and Lyons (2002), numerous studies over the past two decades have employed the microstructure approach to examine the role of order flow in FX markets.[4] A few recent studies, such as Menkhoff et al. (2016), Burnside et al. (2020), and Ranaldo and Somogyi (2021), consider the role of order flow in explaining the cross-section of currency returns. Using CLS order flow data, we show that the heterogeneous trading behavior of different FX market participants is critical to understanding the influence of prospect theory in the FX market.

[3] This paper is related to existing behavioral studies (Frankel and Froot, 1990; Kozhan and Salmon, 2009; Beber et al., 2010; Burnside et al., 2011b; Ilut, 2012; Yu, 2013).

[4] See Evans and Lyons (2005), Froot and Ramadorai (2005), Evans and Lyons (2008), Love and Payne (2008), Sager and Taylor (2008), Rime et al. (2010), Evans (2010), and Chinn and Moore (2011).

Our paper is also related to the literature on technical trading in the FX markets. Existing studies document the "obstinate passion" of FX professionals for technical trading rules, together with the profitability of these strategies (e.g., Allen and Taylor, 1990; Menkhoff and Taylor, 2007; Neely et al., 2009; Hsu et al., 2016), indicates that investor behavior plays a critical role in shaping exchange rate movements.[5] Indeed, the survey evidence of Taylor and Allen (1992)—that a large proportion of FX traders use technical analysis in some form when trading currencies, especially at shorter horizons—has since been confirmed by surveys across geographies and over time.[6] Our prospect theory findings imply that FX market investors mentally present risk using historical distribution, consistent with the prevalent technical trading in the FX market. We also show that our findings are not simply due to the technical trading.[7]

II. Prospect Theory in Currency Markets

Investing in currency markets is inherently risky due to exchange rate fluctuations, and investors must evaluate this risk when making decisions. The conventional framework for doing so is expected utility theory, which underlies many classical models in financial economics. However, extensive experimental evidence shows that real-world behavior frequently violates its assumptions. Prospect theory, introduced by Kahneman and Tversky (1979) and later extended into cumulative prospect theory by Tversky and Kahneman (1992), provides a more realistic

[5]The "exchange rate–fundamental disconnect puzzle" (Meese and Rogoff, 1983; Mark, 1995; Engel and West, 2005; Rossi, 2013) similarly demonstrates that economic fundamentals fail to describe exchange rate dynamics.

[6]These surveys include the U.S. (Cheung and Chinn, 2001), London (Cheung et al., 2004), Hong Kong (Lui and Mole, 1998), Germany (Gehrig and Menkhoff, 2006), and multiple European centers (Oberlechner, 2001).

[7]To notice, although technical trading and prospect theory are conceptually linked (Grinblatt and Han, 2005), they differ in focus: technical trading evaluates rule profitability, while prospect theory models investor perceptions. The prominence of technical trading in FX markets suggests that investors rely on historical price patterns in ways consistent with prospect-theory framing, providing behavioral motivation for our study. As we show later, prospect-theory-based returns are not fully captured by technical trading.

description of decision-making under risk. Since Benartzi and Thaler (1995), a large literature has applied prospect theory to asset pricing questions, showing that its core elements can explain phenomena such as the equity premium, excess volatility, return predictability, and the pricing of skewness.

Prospect theory differs from expected utility theory in two key respects. First, while expected utility assumes a smooth, concave utility function defined over terminal wealth, prospect theory evaluates gains and losses relative to a reference point. Its value function is kinked at zero—concave for gains and convex for losses—capturing loss aversion and investors' focus on changes in wealth rather than final wealth levels. Second, expected utility treats probabilities linearly, whereas prospect theory uses a non-linear probability-weighting function. This function reflects investors' tendency to overweight small probabilities and to treat gain and loss probabilities asymmetrically. Together, these features make prospect theory a richer and more realistic framework for modeling how investors perceive and evaluate risk.

A. Hypothesis Development

What does prospect theory tell us about currency returns? Our first research question concerns the predictive relation between prospect-theory value and subsequent currency excess returns. Barberis et al. (2016) develop an equilibrium model in which prospect-theory value is negatively associated with future stock excess returns. Currency markets differ from equity markets in their trading mechanisms and market participants. However, if a fraction of currency investors deviates from expected utility preferences and assesses currency risk in accordance with prospect theory, then their trading activity should affect expected currency returns in equilibrium.

To establish the relation between prospect-theory value and currency returns, we construct a measure of prospect-theory value at the currency level. The empirical application of prospect theory requires two steps. First, investors need to form a mental *representation* of a risk. Analogous to Barberis et al. (2016) in equity markets, we posit that a subset of currency investors deviates from fully rational expected utility maximization and instead evaluates risk in accordance with prospect theory. These investors mentally represent the risk of a currency using the past distribution of exchange rate returns. The historical exchange rate price chart is perhaps the first piece of information that investors encounter when seeking information about a currency. Hence, investors are likely to use price charts (and therefore the past distribution of exchange rate returns) to form a mental representation of how risky a currency is. This mental representation is particularly relevant in the FX market, given the prevalent use of technical trading rules.[8]

The second step is that investors need to *value* whether such a representation is appealing. We apply the Tversky and Kahneman (1992) formula to the past distribution of exchange rate changes and construct a currency-level prospect-theory value, which reflects how appealing a currency is to a prospect-theory investor. We provide a formal description of the construction of prospect-theory value in Section III below.

The intuition for the negative relationship between currency-level prospect-theory value and future currency returns is straightforward: prospect-theory investors tend to buy more appealing (high-prospect-theory-value) currencies and sell unattractive (low-prospect-theory-value) currencies on average, even in the absence of macroeconomic signals or rational risk-based reasons. If these investors account for a non-trivial proportion of total

[8] Taylor and Allen (1992) provide direct evidence that over 90% of their survey respondents among FX traders used technical analysis.

currency investors, their trading activity will push appealing currencies to become temporarily overvalued; as a result, these currencies will earn lower expected returns on average. Our first hypothesis is therefore:

Hypothesis 1 (Predictability): *The prospect-theory value of a currency's past return distribution negatively predicts subsequent currency returns in the cross-section.*

The next research question concerns the potential economic mechanisms driving this predictive pattern. We consider two plausible explanations. The first is that the predictive relation may reflect systematic exposures to common factors, including, perhaps, systematic behavioral factors. Although our main predictor is motivated by a behavioral theory, the return predictability pattern may still be partially explained by systematic exposures to common factors for several reasons. Previous studies (Lustig et al., 2011; Verdelhan, 2018) document that currency returns have a strong factor structure; hence, exposure to global currency risk factors should explain a large proportion of currency return variation. The cross-sectional return pattern predicted by prospect theory may therefore simply represent exposure to global risk factors. The predictive relation may also be explained by noise-trader risk, generated by the unpredictability of irrational investors' sentiments (De Long et al., 1990), or by other behavioral factors (Daniel et al., 2020). We investigate whether the predictive relation can be captured by systematic exposures to common factors. Our second hypothesis is therefore:

Hypothesis 2 (Systematic Exposures to Common Factors): *The negative relation between prospect-theory value and subsequent currency returns is fully explained by systematic exposures to common factors.*

Even without systematic exposure to common factors, the predictive return pattern may exist due to mispricing at the characteristic level. Daniel and Titman (1997), for example, show that firm characteristics predict stock returns even after controlling for systematic risk exposures. In currency markets, previous studies such as Lustig et al. (2011) and Ranaldo and Soderlind (2010) examine whether betas with respect to common factors or safe-haven characteristics better explain currency carry trade returns.

If currency investors were fully rational and arbitrage in currency markets were costless and risk-free, any mispricing should be eliminated instantaneously—that is, we should not observe the predictive relation. In reality, investors are subject to behavioral biases (De Long et al., 1990), while betting against mispricing is costly and risky (Shleifer and Vishny, 1997). Real-world arbitrage is limited by trading frictions and capital constraints (see Gromb and Vayanos (2010) for a survey of the limits-to-arbitrage literature). When arbitrage is risky or arbitrage capital is in short supply, rational arbitrageurs cannot eliminate mispricing immediately. Limits to arbitrage may therefore amplify mispricing. Our third hypothesis is:

Hypothesis 3 (Limits to Arbitrage): *The negative relation between prospect-theory value and subsequent currency returns is strengthened when limits to arbitrage are high.*

III. Data and Variable Construction

A. Data

Spot and one-month forward exchange rates at daily frequency from January 1, 1985 to February 28, 2018 are collected from Barclays and Reuters via Datastream. Our main empirical analysis relies on mid-quote data, but we also use bid and ask quotes to construct transaction-cost-adjusted returns in robustness checks. We focus on end-of-month observations S_t

and F_t in direct quotes—that is, exchange rates are quoted in units of US dollars (USD) per unit of foreign currency. An increase in S_t represents an appreciation of the foreign currency and a depreciation of the USD.[9]

Our main empirical analysis focuses on a sample of fifteen developed-economy currencies against the US dollar: Australia, Belgium, Canada, Denmark, the Euro Area, France, Germany, Italy, Japan, the Netherlands, New Zealand, Norway, Sweden, Switzerland, and the United Kingdom. A similar sample has been used by Lustig et al. (2011) and Menkhoff et al. (2012). We refer to this as the Developed Economies sample.[10] These currencies, or the G10 following the introduction of the euro in 1999, are highly liquid and account for approximately 84% of total trading volume in global FX markets (Bank for International Settlements, 2025). They are also commonly used to construct currency strategies in practice; for example, Deutsche Bank Currency Harvest is an ETF that tracks currency carry trade performance using G10 currencies. Using these liquid, major currencies allows us to conduct sharper tests of our predictions based on prospect theory.

B. Currency Prospect-Theory Value

In the spirit of Barberis et al. (2016), we construct a currency-level empirical measure of prospect-theory value, $tk_{i,t}$, for currency i at time t. To do so, we consider a series of K consecutive spot exchange rate returns Δs_i from time $t - K + 1$ to t. Suppose there are m negative and n positive returns (so that $K = n + m$). Sorting these returns from most negative to

[9]The results are robust to alternative quote currencies (Table A13 in the Internet Appendix).

[10]The results hold for extended lists of countries (Tables A11 and A17–A25 in the Internet Appendix).

most positive, we denote them as:

$$\Delta s_{i,-m}, \frac{1}{K}; ...; \Delta s_{i,-1}, \frac{1}{K}; \Delta s_{i,1}, \frac{1}{K}; ...; \Delta s_{i,n}, \frac{1}{K}.$$

Assuming equal probability for each return, each probability is $\frac{1}{K}$. The prospect-theory value ($tk_{i,t}$, following Tversky and Kahneman (1992)) is defined as:

$$\begin{aligned} tk_{i,t} = \sum_{j=-m}^{n} \pi_j v(\Delta s_{i,j}) = & \sum_{j=-m}^{-1} v(\Delta s_{i,j}) \left[w^- \left(\tfrac{j+m+1}{K} \right) - w^- \left(\tfrac{j+m}{K} \right) \right] \\ & + \sum_{j=1}^{n} v(\Delta s_{i,j}) \left[w^+ \left(\tfrac{n-j+1}{K} \right) - w^+ \left(\tfrac{n-j}{K} \right) \right], \end{aligned} \tag{1}$$

where $v(\cdot)$ is the value function and π_j is the decision weight assigned to return $\Delta s_{i,j}$, constructed from the probability-weighting functions $w^-(\cdot)$ and $w^+(\cdot)$ for losses and gains (defined below).

We use exchange rate returns to compute prospect-theory value, as it is intuitive to assess the attractiveness of a currency based on its historical price chart and hence its past return distribution. Since currency markets permit trading in both directions, the definition of gains and losses requires clarification. We follow the literature and focus on exchange rate returns from a US investor's perspective—that is, assuming the investor borrows US dollars and invests in foreign currencies. Under this convention, appreciation of the foreign currency corresponds to a gain for the investor. Appreciation of the US dollar, commonly observed during periods of market stress due to flight-to-safety effects, is consistent with a loss for the currency investor. This setting is therefore consistent with the conventional definition of gains and losses in equity markets. As shown in the robustness checks, changing the denomination currency does not qualitatively affect our main findings. Following the literature, we set $K = 60$; that is, we use the past five years of monthly exchange rate returns to construct prospect-theory value each month.[11]

[11] We also consider using the distribution of currency excess returns to construct prospect-theory values. Our results are robust to different values of K (see Table A7 in the Internet Appendix).

The functional forms of the value and probability weighting functions are specified as:

$$v(x) = \begin{cases} x^{\alpha},\ x \geq 0 \\ -\lambda(-x)^{\alpha},\ x < 0, \end{cases} \qquad w^{+}(p) = \frac{p^{\gamma}}{(p^{\gamma} + (1-p)^{\gamma})^{1/\gamma}},\ \ w^{-}(p) = \frac{p^{\delta}}{(p^{\delta} + (1-p)^{\delta})^{1/\delta}}.$$

Here, α, λ, γ, and δ are parameters of the value and probability weighting functions. The parameter α governs the curvature of the value function, while λ captures the severity of the kink at zero: the higher the value of λ, the more loss-averse the investor. The parameters γ and δ control the degree of tail overweighting; lower values imply greater overweighting of extreme outcomes. We use the original parameter values from Tversky and Kahneman (1992), estimated from experimental evidence: $\alpha = 0.88$, $\lambda = 2.25$, $\gamma = 0.61$, and $\delta = 0.69$. These parameter values are also used by Barberis et al. (2016) for individual stock returns.[12]

C. Currency Excess Returns and Control Variables

The currency excess return $rx_{i,t+1}$ is defined as the return from buying one unit of foreign currency in the forward market and liquidating the position in the spot market when the forward contract matures one month later: $rx_{i,t+1} = (S_{i,t+1} - F_{i,t})/S_{i,t}$. The currency excess return can be decomposed into two components: the spot exchange rate return, $\Delta s_{i,t+1} = (S_{i,t+1} - S_{i,t})/S_{i,t}$, and the forward discount, $fd_{i,t} = (F_{i,t} - S_{i,t})/S_{i,t}$.[13] The first component, the exchange rate return, is also the input variable used to construct prospect-theory value as described in Section B. If covered interest rate parity (CIP) holds, the second component can be closely approximated by

[12] In a later section, we also consider different components of the total prospect-theory value (Table A4): loss aversion $(1, 2.25, 1, 1)$, convexity/concavity $(0.88, 1, 1, 1)$, and probability weighting $(1, 1, 0.61, 0.69)$.

[13] We follow the literature and use simple returns rather than log returns to avoid imposing a joint normality assumption in the subsequent asset pricing tests. Results are qualitatively unchanged when log returns are used.

the foreign-minus-US interest rate differential.[14] The excess return can therefore be expressed as:

$$rx_{i,t+1} = \frac{S_{i,t+1} - S_{i,t}}{S_{i,t}} - \frac{F_{i,t} - S_{i,t}}{S_{i,t}} \approx \frac{S_{i,t+1} - S_{i,t}}{S_{i,t}} + (ir_{i,t} - ir_{us,t}), \tag{2}$$

where $ir_{i,t}$ and $ir_{us,t}$ denote foreign and US one-month interest rates, respectively.

We also control for past returns that typically enter the construction of momentum and value portfolios. To construct currency momentum portfolios, we calculate the cumulative exchange rate return over the past three months ($mom_{i,t} = \sum_{j=1}^{3} \Delta s_{i,t-j}$), following Menkhoff et al. (2012) and Della Corte et al. (2016a). Following Asness et al. (2013) and Dahlquist and Hasseltoft (2020), we use the negative of the past five years' real exchange rate change ($val_{i,t}$) as the signal for forming currency value portfolios. We collect monthly CPI data from the OECD Main Economic Indicators database to construct the currency value signal:

$$val_{i,t} \quad = \quad \log\left(\frac{\bar{S}_{i,t-5y}}{S_{i,t}}\right) - \left[\log\left(\frac{\bar{cpi}_{i,t-5y}}{cpi_{i,t}}\right) - \log\left(\frac{\bar{cpi}_{us,t-5y}}{cpi_{us,t}}\right)\right],$$

where $cpi_{us,t}$ and $cpi_{i,t}$ are the CPI in the US and the foreign country, respectively. The terms $\bar{S}_{i,t-5y}$, $\bar{cpi}_{i,t-5y}$, and $\bar{cpi}_{us,t-5y}$ denote the lagged five-year (averaged over 4.5 and 5.5 years) exchange rates and CPIs. A detailed description of variables and the construction of currency portfolios and risk factors is provided in Internet Appendix Table A1.

Table 1 presents summary statistics for the main variables of interest. Currencies appreciate on average against the USD in our sample. The average excess return is 0.12% per month with a standard deviation of 3.01%. The forward discount is also positive on average. Despite positive excess returns, the average prospect-theory value is negative, indicating that loss-averse traders perceive exchange rate declines during the sample period as more painful than

[14]CIP holds generally (Taylor, 1987, 1989; Akram et al., 2008). A few recent studies document that CIP was violated during the recent financial crisis (Rime et al., 2017; Du et al., 2018).

the pleasure derived from currency appreciation. Unconditionally, prospect-theory value is positively correlated with contemporaneous excess returns and negatively correlated with the forward discount. Thus, high-prospect-theory-value currencies have high past returns and lower interest rates relative to the US on average. Prospect-theory value is also negatively correlated with subsequent currency excess returns. This negative relation indicates that high-prospect-theory-value currencies tend to depreciate in the future, consistent with Hypothesis 1.

IV. Empirical Findings

A. Currency Return Predictability

In this section, we test the predictive relation between prospect-theory value and future currency returns (Hypothesis 1). We begin by estimating the following panel regression:

$$rx_{i,t+1} = \alpha_i + \gamma_t + \beta_1 tk_{i,t} + \delta X_{i,t} + u_{i,t+1}, \tag{3}$$

where α_i and γ_t are currency fixed effects and time (year-month) fixed effects respectively, to absorb all omitted variables related to specific currencies or time trends. The currency-specific control variables $X_{i,t}$ include the forward discount $fd_{i,t}$, the past three-month cumulative exchange rate return $mom_{i,t}$, and the negative of the past five-year real exchange rate change $val_{i,t}$. These characteristics are typically used to form currency carry, momentum, and value portfolios and are related to future currency excess returns, as documented in the literature. We examine whether prospect-theory value contains incremental predictive power for currency returns after controlling for the predictors. Standard errors are double-clustered by currency and time to correct for estimation errors related to specific currencies or time periods. Table 2 presents the estimation results.

Prospect-theory value is negatively related to future excess returns, and its coefficient is statistically significant at the 1% level. The magnitude is economically large: a one-standard-deviation increase in tk_t decreases future excess returns by approximately 0.45% per month (about 5.42% per annum).[15] The effect is robust to the inclusion of control variables.[16] Hence, our results not only support the negative predictive relation stated in Hypothesis 1 but also confirm that the predictive power is incremental to existing currency-level characteristics.

To assess the economic value of this predictability, we construct currency prospect-theory-value portfolios. At the beginning of each month, we sort all currencies into five portfolios according to tk_t. Currencies in portfolio 1 (P_1) have the lowest values of tk_t—that is, they are less attractive based on prospect theory and the exchange rate return distribution. Currencies in portfolio 5 (P_5) have the highest values of tk_t—that is, they are more appealing. We hold portfolios for one month, record their returns, and then rebalance according to the latest signals.

Table 3 presents the main results for prospect-theory-value-sorted currency portfolios. Currency excess returns (Panel A) decline monotonically from P_1 (low tk_t) to P_5 (high tk_t). The long–short strategy (the prospect-theory premium, or PTP), which buys P_1 and sells P_5, produces a statistically significant return spread of 0.42% per month (5.04% per annum) and a Sharpe ratio of 0.17 per month (0.59 per annum). The strategy also exhibits positive skewness and

[15]Since all variables in the regression analysis are standardised, a one-standard-deviation increase in tk_t decreases future excess returns by 0.15 of a standard deviation, or 0.45%, calculated as 0.15 (coefficient) times 3.01% (standard deviation of the dependent variable).

[16]Results are qualitatively unchanged when the lagged monthly excess return is included. Therefore, the negative relation is not attributable to liquidity provision or short-term reversal. Table A14 in the Internet Appendix provides regression results with additional control variables. Our results remain valid.

moderate kurtosis, suggesting that it is unlikely to be affected by crash risk. For exchange rate returns (Panel B), we observe a similar monotonically decreasing pattern and a significant return spread, indicating that tk_t has predictive power for spot exchange rate returns. That is, spot exchange rate predictability rather than persistent interest rate differentials accounts for the return spread of prospect-theory-sorted portfolios. The positive skewness and the dominance of spot exchange rate predictability also differentiate this strategy from carry trades.

The decreasing patterns for both currency excess returns and exchange rate returns are illustrated in Figure 1. Overall, our results provide strong evidence in support of Hypothesis 1: high-prospect-theory-value currencies significantly underperform their low-value counterparts in future currency excess returns.

In addition to the predictive relation and portfolio performance at time $t+1$, we examine what characterises high-tk currencies and what properties they exhibit. In Table 4, we consider contemporaneous characteristics for tk-sorted portfolios at formation (time t). In contrast to the decreasing predictive pattern observed in Table 3, we document an increasing tk–return relation for contemporaneously sorted portfolios. High-tk currencies have high average returns, low standard deviations, and positive skewness on average at portfolio formation. These results hold for both currency excess returns (Panel A) and exchange rate returns (Panel B). That is, these currencies exhibit appealing characteristics that investors are willing to hold, confirming their status as high-prospect-theory-value currencies.

High-tk currencies on average have low interest rate differentials, high past exchange rate returns, and low long-term real exchange rate changes (Panel C). We report the five currencies most frequently appearing in each portfolio (percentage of time in the portfolio) in Panel D. The low-tk portfolio (P1) consists of traditional high-interest-rate currencies such as the Australian dollar (AUD) and New Zealand dollar (NZD), but also contains low-interest-rate currencies such as the Japanese yen (JPY). The high-tk portfolio (P5) includes traditional low-interest-rate currencies such as the Japanese yen (JPY) and Swiss franc (CHF), but also high-interest-rate currencies such as the British pound (GBP). In short, prospect-theory-value portfolios differ substantially from carry trade portfolios, despite some overlap. High-tk currencies cannot simply be characterised as safe-haven currencies.

Figure 2 illustrates the currency compositions of the extreme portfolios for prospect-theory-value-sorted and carry trade portfolios, respectively. The prospect-theory portfolios differ from carry trade portfolios. We also plot cumulative returns for the PTP strategy alongside the cumulative returns of three other well-known currency portfolio strategies: carry (CAR), momentum (MOM), and value (VAL) in Figure 3.[17] The PTP strategy dominates the value strategy and outperforms the momentum strategy most of the time. It also performs comparably to the carry strategy.[18] These portfolio results, together with the regression results in Table 2, demonstrate that the predictive power of prospect-theory value for currency excess returns is unique and cannot be subsumed by existing currency characteristics.

B. Asset Pricing Tests

Given the strong negative predictive relation documented above, we now explore several potential explanations for this predictability, beginning with risk-based explanations.

We consider whether the documented predictability can be rationalised as compensation for exposure to known systematic risk factors. We empirically examine risk-based explanations

[17] See Internet Appendix Table A1 for the construction of these factor strategies.

[18] In unreported analysis, we show that PTP has low correlations with existing currency factor strategies (0.15 with CAR, -0.13 with MOM, and 0.27 with VAL).

from both time-series and cross-sectional perspectives. Table 5 reports time-series regressions of our strategy on well-known risk factors. We consider four categories of factors: currency, equity, hedge fund, and macroeconomic (factor-mimicking portfolio) factors. The set of currency factors includes the conventional factors: dollar (DOL), carry (CAR), momentum (MOM), and value (VAL). In addition, we include two recent currency factors: the global imbalance factor (GI) of Della Corte et al. (2016b) and the unconditional mean-variance efficient factor ($UMVE$) of Chernov et al. (2023).[19] As equity risk factors, we use the factors from Carhart (1997), including the Fama and French (1992) market (MKT), size (SMB), and value (HML) factors, as well as the momentum factor (WML). The set of hedge fund factors includes the bond (BO), currency (CU), and commodity (CO) trend-following factors, and the equity market (EQ), size spread (SS), bond market (BM), and credit spread (CS) factors of Fung and Hsieh (2004).[20] We consider five macroeconomic factors: FX volatility ($FVOL$), FX illiquidity measured by bid–ask spread ($FBAS$), FX skewness ($FSKEW$), the CBOE VIX index ($FVIX$), and the TED spread ($FTED$).[21] With these four categories of factors, we regress PTP on each set using time-series factor-spanning regressions. If PTP cannot be fully spanned by these risk factors, then the predictive power of tk is unlikely to be attributable to risk-based explanations.

PTP has positive exposure to the currency carry factor and the global imbalance factor, negative exposure to momentum and value factors, but insignificant exposure to the dollar factor and the unconditional MVE factor (Panel A). PTP is also exposed to the equity market and

[19] We thank Steven Riddiough for making the global imbalance factor available. We closely follow Chernov et al. (2023) in constructing the unconditional mean-variance efficient factor.

[20] Descriptions of the factor constructions are presented in Internet Appendix Table A1.

[21] Since the macroeconomic factors are non-tradable, we construct factor-mimicking portfolios. We first regress individual currency returns on a constant and the innovation of the macro variable to obtain macro betas using a rolling window regression of 36 months, then construct beta-sorted portfolios. The long–short return spread of the beta-sorted portfolios serves as the tradable version of the macro factors.

momentum factors (Panel B). Among the hedge fund factors, only the trend-following factor in commodity markets is significantly correlated with PTP returns (Panel C). Moreover, PTP is positively exposed to FX illiquidity, FX skewness, and TED spread factors while negatively exposed to the VIX factor; its exposure to the FX volatility factor is insignificant (Panel D). All four categories of factor models explain only limited fractions of PTP variation. Specifically, currency, equity, hedge fund, and macro factors explain 16.74%, 6.13%, 1.58%, and 22.07% of total PTP return variation, respectively. The abnormal returns (alphas) of PTP, controlling for these factors, are slightly lower but remain comparable in economic magnitude to the return spread in Table 3. Abnormal returns are 0.33% per month (approximately 3.96% per annum), 0.37% (approximately 4.48% per annum), 0.41% (approximately 4.93% per annum), and 0.42% (approximately 5.04% per annum) for currency, equity, hedge fund, and macro factors, respectively. In all cases, alphas remain statistically significant at the 1% level. Therefore, the PTP strategy cannot be fully spanned by the risk factors considered.[22]

More generally, if the excess returns to the PTP strategy serve as compensation for bearing some form of risk—whether due to an omitted risk factor or stemming from the presence of irrational investors in the market (for example, noise-trader risk)—we should observe a risk–return trade-off. The predictive pattern may be interpreted as exposure to common factors. These common factors include not only traditional systematic risk factors but potentially also systematic mispricing factors (Stambaugh and Yuan, 2017; Daniel et al., 2020). If the predictive

[22]In unreported analysis, we also consider reverse-spanning regressions. Specifically, we use the carry factor (CAR) as the dependent variable and the prospect-theory premium (PTP) as an independent variable. The carry alpha is 0.31% per month (3.78% per annum) and is marginally significant (t-statistic of 1.86). The PTP coefficient is positive and significant (t-statistic of 2.29). Including dollar, momentum, and value factors renders the carry alpha insignificant (t-statistic of 1.49), while the PTP coefficient remains positive and significant (t-statistic of 2.55). These results, together with our findings in Table 5, support the conclusion that tk contains distinctive predictive power for currency returns.

relation can be explained by any common factors, we expect PTP to be significantly correlated with those factors. Hence, if exposures to PTP are priced in currency returns, this would support a common-factor pricing explanation. To test this prediction, we apply Fama and MacBeth (1973) two-stage regressions to conduct cross-sectional asset pricing tests. In the first stage, we run time-series regressions of each currency's returns on risk factors to obtain factor loadings. In the second stage, we run cross-sectional regressions of average currency returns on factor loadings to estimate risk prices. We use Newey and West (1987) standard errors to calculate t-statistics. Previous asset pricing studies in currency markets have largely relied on currency portfolios as test assets; we instead focus on individual currency-level asset pricing tests.[23] We use PTP along with the main currency factors—dollar (DOL), carry (CAR), momentum (MOM), and value (VAL)—as our candidate risk factors. If PTP betas explain cross-sectional variation in currency excess returns, then PTP may represent a new source of risk or may capture omitted risk factors.

In addition to factor betas, we include the lagged prospect-theory value $tk_{i,t-1}$ to test whether the cross-sectional predictability of prospect-theory value survives after controlling for exposures to traditional risk factors. Including $tk_{i,t-1}$ also allows us to assess whether risk exposure or currency-specific characteristics (or mispricing) primarily drive currency returns.[24]

Table 6 presents cross-sectional asset pricing results. Two main findings emerge. First, PTP beta is not significantly priced in the cross-section of individual currency returns. The insignificant risk price estimate casts doubt on a risk-based explanation for the profitability of the

[23] Lewellen et al. (2010) and Ang et al. (2020) argue that portfolios create a strong factor structure, destroy information by shrinking betas, cause misleading asset pricing results (small pricing errors and high cross-sectional R^2, even if the factor is not priced), and may lead to significant prices of risk for "useless factors". This concern is particularly severe in currency markets, where the number of portfolios is typically small.

[24] See Daniel and Titman (1997) and Davis et al. (2000) for the covariance versus characteristics debate. We recognise that it is empirically challenging to fully disentangle betas (covariance risks) from characteristics. An analogous example in currency markets is explaining carry trade returns with systematic risk exposures versus characteristics (Lustig et al., 2011; Ranaldo and Soderlind, 2010).

prospect-theory-value portfolio.

Second, and more importantly, the currency-level prospect-theory value $tk_{i,t-1}$ is negatively and significantly related to future currency returns, even when factor betas are included. Our evidence suggests that the prospect-theory-value characteristic (tk) dominates covariance risk (PTP betas) in explaining currency returns. Fully ruling out one explanation in favour of another is difficult in the covariance versus characteristics debate, especially when factor loadings and characteristics may be highly correlated. However, our findings indicate that systematic exposures to common factors are unlikely to be the main source of the predictive power contained in currency prospect-theory value, and hence do not support Hypothesis 2.

C. Limits to Arbitrage and Trading Activities

Our previous results confirm that risk-based explanations cannot explain the predictive power of prospect-theory value. In this section, we explore alternative explanations related to mispricing.

1. Limits to Arbitrage

We first examine whether the predictive power is consistent with a limits-to-arbitrage explanation. Predictive return patterns may arise because market frictions impede the deployment of arbitrage capital, subsequently affecting future returns. Previous studies have linked the profitability of currency momentum (Menkhoff et al., 2012; Filippou et al., 2018) and currency volatility risk premia (Della Corte et al., 2016a) strategies to limits to arbitrage.

Intuitively, rational arbitrageurs are more likely to curtail or delay their arbitrage (mispricing correction) activities when FX market frictions are high. We use panel regressions to examine the role of limits to arbitrage in explaining the predictability:

$$rx_{i,t+1} = \alpha_i + \gamma_t + \beta_1 tk_{i,t} + \beta_2 tk_{i,t} \times lta_{i,t} + \beta_3 lta_{i,t} + \delta X_{i,t} + u_{i,t+1}, \tag{4}$$

where we augment the baseline regression specification with a proxy for limits to arbitrage (lta) and its interaction with prospect-theory value. We consider four time-varying, currency-specific measures of limits to arbitrage: bid–ask spread (bas) as a proxy for currency illiquidity, idiosyncratic volatility ($ivol$), total volatility ($tvol$), and the five-year sovereign CDS spread (cds) as a proxy for country risk.[25] If limits to arbitrage enhance the predictive pattern, we expect the interaction term ($tk_{i,t} \times lta_{i,t}$) to be negative and significant.

Table 7 presents the limits-to-arbitrage results. First, the coefficient on prospect-theory value is consistently negative and significant across all specifications, as in the baseline model. Second, the interaction term ($tk_{i,t} \times lta_{i,t}$) is negative in all four cases, consistent with Hypothesis 3. The interaction coefficients are significant when currency illiquidity, total volatility, and sovereign CDS spreads are used. Our findings suggest that limits to arbitrage play an important role in the tk–return relation, since the predictive power of tk variable is stronger when market frictions are high. It is harder for arbitrageurs to correct mispricing, making the predictive relation stronger.

2. Trading Activities in Currency Futures

We then investigate how different market participants affect the predictive relation. We consider Commodity Futures Trading Commission (CFTC) Traders in Financial Futures (TFF)

[25] bas is the ratio of bid–ask spread to the mid quote. $ivol$ is the within-month standard deviation of daily return residuals from a regression of daily currency returns on the DOL and HML factors (Lustig et al., 2011). $tvol$ is the within-month standard deviation of daily exchange rate returns. cds is the five-year sovereign CDS spread (results are unaffected when one-year and ten-year CDS spreads are used).

reports.[26] This report summarizes trading positions of different market participants in currency futures markets and hence allow us to explore heterogeneous trading behaviors. TFF reports categorise participants into four groups: dealers, fund managers, leveraged money, and other reportables. Dealers or intermediaries are large banks and dealers. They tend to have matched books or offset risk between markets and clients; they represent the sell side of the market, as they design or sell financial products to clients. The other three categories—asset managers, leveraged funds, and other reportables—represent the buy side of the market. Asset managers are institutional investors, including pension funds, endowments, insurance companies, and mutual funds. Leveraged funds include hedge funds and money managers, and they engage in arbitrage strategies within and across markets. Other reportables are reportable traders not included in the first three categories who use markets primarily to hedge business risk; they include corporate treasuries, central banks, and smaller banks. In addition to the four categories, we also define a fifth group termed financier, which aggregates fund managers and leveraged money, following Della Corte and Krecetovs (2017).

To measure their trading activities and examine how their trading affects the predictive power of prospect theory value, we construct net demand pressure variable for each category of participants. Specifically, we define the net demand pressure as the difference between long position and short positions divided by total open interests. This measure captures the net buying pressure of each group of participants. We consider a similar regression model specification as before, except for replacing the limits to arbitrage proxies by demand pressure variables.

Table 8 reports results using TFF data. First, the standalone prospect-theory-value

[26] In the appendix, we also consider CFTC COT reports, which report trading positions of commercial and non-commercial traders. We mainly focus on the TFF reports, as it is more granular. We show in Internet Appendix A that the negative predictive relation between tk_t and currency returns is robust when controlling for COT commercial and non-commercial net demand, capital flows, central bank intervention, and investor sentiment.

coefficient remains negative and significant. Second, different participants contribute to the predictive relation in different ways. Dealers and other reportables amplify the predictive relation, while fund managers and leveraged money weaken it. Financiers, which aggregate fund manager and leveraged money trading flows, also weaken the predictive relation. These findings suggest that bank dealers amplify mispricing while funds actively correct it, serving as arbitrageurs. We find additional corroborating evidence in the following analysis of spot order flows.

In summary, our empirical results support the view that limits to arbitrage play an important role in the prospect-theory-value–currency return relation. Our main findings remain robust after controlling for various measures of trading activity, and the predictive power exhibits cross-sectional heterogeneity across different types of participants.

D. Order Flows of Market Participants

In the previous section, we found that certain market participants' derivatives positions are correlated with tk. In this section, we provide more direct evidence from the spot market, showing how different types of FX participants trade in response to prospect-theory value by examining the relationship between tk and their order flows.[27]

We investigate the trading activities of different market participants using the CLS dataset of spot order flow, which aggregates orders globally. CLS is the largest single source of FX executed data available to the market.[28] CLS data categorises FX market participants into

[27] We refer to Internet Appendix B for details on FX market structure, main participants, and CLS data coverage.

[28] As also noted in Ranaldo and Santucci de Magistris (2022), CLS is the largest payment system for the settlement of foreign exchange transactions, and it covers 18 currencies and 40 currency pairs. This infrastructure supports FX trading by reducing settlement risk and enhancing market efficiency. The trade data is directly collected by CLS from its settlement members, when the FX transaction data is booked in the member's back-office system. The CLS spot order flow data is collected from the CLS website through subscription. https://www.cls-group.com/products/data/.

different groups. Banks serve as market makers. Corporations, funds, non-bank financial institutions are the main price takers.[29] In addition to the market making role, banks also take the buy side positions to reflect the inter-bank trading. Due to the two-tier trading system in the FX market (customer-dealer and inter-dealer), inter-bank order flow partially reflects aggregate customer orders. Any orders not submitted by corporations, funds, or non-bank financial institutions are reflected in bank orders.

Our analysis focuses on G10 currencies for the sample period from September 2012 to February 2018. The starting date is determined by data availability. Following the existing literature (Menkhoff et al., 2016; Ranaldo and Somogyi, 2021), we calculate individual currency-level order flow using signed dollar-based volume (buy minus sell volume), capturing order imbalance. We begin by examining how trading activities respond to prospect-theory value, estimating the following panel regression:

$$of_{i,t} = \alpha_i + \gamma_t + \beta_1 tk_{i,t} + \delta X_{i,t} + u_{i,t}, \tag{5}$$

where $of_{i,t}$ is the order flow at time t for currency i for each group of market participants (banks, corporations, funds, non-bank financial institutions, or total order flow). As in Ranaldo and Somogyi (2021), bank order flow is defined as total buy-side order flows subtracting order flows of corporations, funds, and non-bank financial institutions.

Table 9 reports the panel regression results. Prospect-theory value is positively and significantly associated with total order flow contemporaneously. This finding indicates that currencies that are more appealing from a prospect-theory perspective do indeed attract money inflows on average. This observation is important, as it provides direct evidence of a strong link

[29] Corporations refers to non-financial corporations. Funds includes hedge funds, pension funds, and sovereign wealth funds. Non-bank financial institutions includes insurance companies and clearing houses.

between prospect-theory value and trading activities in the FX market. It suggests the existence of prospect-theory-type preferences in aggregate, even in a market dominated by institutional trading. A closer examination of different market participants reveals clear heterogeneity. The positive and significant association holds for banks, corporations, and non-bank financial institutions. In contrast, the relation is significantly negative for fund order flows. The differential patterns across groups of market participants indicate that not all institutions trade in the same way. Hence, the conventional wisdom that treats institutional traders as rational appears to be oversimplified. Unlike other institutions, funds tend to bet against prospect theory and serve as arbitrageurs.

To understand the relative economic magnitude of trading in prospect-theory-value-sorted portfolios, we calculate the average order flow in the PTP (low minus high) portfolio across different groups of market participants. Specifically, we sort all currencies into five portfolios according to their prospect-theory values (tk) and calculate average order flows for each portfolio. We then construct a long–short (P1 minus P5, i.e., PTP) portfolio and obtain the order flows of this portfolio for each group of market participants as:

$$of_t = \sum_{i \in P_1} of_{i,t} - \sum_{i \in P_5} of_{i,t} \tag{6}$$

A positive (negative) portfolio-level order flow indicates that investors in each group buy (sell) low-prospect-theory-value currencies and sell (buy) high-prospect-theory-value currencies. Figure 4 reports the average order flows of the long–short (low minus high) prospect-theory-value portfolios.

The aggregate PTP portfolio order flow is negative, indicating that, on average, FX market participants trade in accordance with prospect theory—that is, they buy high-prospect-theory-value currencies and sell low-prospect-theory-value currencies. Banks have significantly negative portfolio-level order flows and thus trade in accordance with prospect theory, consistent with our regression results above. Bank order flow therefore tends to amplify mispricing.[30] In contrast, funds trade in the opposite direction to that predicted by prospect theory; given their significantly positive order flow in the long–short portfolio, they act as arbitrageurs by correcting mispricing. Non-bank financial institutions also have positive portfolio-level order flow. However, the magnitude of their order flows is only about half that of fund order flows, and their influence tends to be smaller. Finally, corporation order flow is small and statistically insignificant.[31] In short, the portfolio-level order flow analysis supports the conclusion that the opposing trading directions of banks and funds are key to understanding the prospect-theory effect in FX markets.

Our next test examines whether the trading activities of FX market participants influence the return predictive power of prospect-theory value. We consider the interaction between prospect-theory value and the portfolio order flow of a specific group of market participants (of_t) to estimate the incremental effect of $tk_{i,t}$ on future currency returns during periods of increased trading activity. Specifically, we estimate:

$$rx_{i,t+1} = \alpha_i + \gamma_t + \beta_1 tk_{i,t} + \beta_2 tk_{i,t} \times of_t + \beta_3 of_t + \delta X_{i,t} + u_{i,t+1}, \tag{7}$$

Table 10 reports the panel regression results. Consistent with our prediction, funds serve

[30] This could arise for at least two reasons: either banks themselves trade speculatively, or banks' orders reflect speculative customer orders. Identifying precisely which reason primarily drives the mispricing is challenging and requires more granular data. Given that retail trades are small relative to institutional trades in the FX market, our evidence suggests that banks are likely to trade speculatively. This may be partially driven by the proprietary trading desks of banks, which take directional positions and are not risk-neutral. We provide more evidence on how to understand the positive relation between tk and bank order flow in the next section.

[31] Corporations primarily trade for hedging purposes and predominantly in FX derivatives rather than spot markets, though they may partially deviate from full risk minimisation for speculative purposes (Stulz, 1996). This is consistent with our Appendix results using the commercial trading positions from the CFTC.

as arbitrageurs to correct mispricing: the interaction term is positive and significant, effectively weakening the predictive relation between prospect-theory value and currency returns. The stabilising role of funds is consistent with their nature as “smart money” that profits from mispricing. This finding is also consistent with the weakening effect of fund managers and leveraged money in the CFTC TFF reports, as observed in the previous section. In contrast, the interaction term for banks is negative and significant; hence, bank order flows strengthen mispricing, supporting the conjecture and evidence above. The role of corporations is marginal, given their small order flow magnitude. The effect of non-bank financial institutions’ order flow is insignificant, indicating that this category of institutions, such as clearing houses and insurance companies, does not necessarily trade speculatively, nor does it actively correct mispricing.

Overall, our order flow analysis highlights the clear heterogeneous roles of different financial institutions in understanding predictability. The sophistication and heterogeneous composition of institutions—including both destabilisers and arbitrageurs—contribute to the magnitude of mispricing and the speed of its correction.

E. Understanding Bank Order Flows

Our order flow analysis suggests that banks exhibit prospect-theory-type trading, while funds act as arbitrageurs that help correct mispricing. In this section, we further investigate the positive link between tk and bank order flow. We consider three potential mechanisms that may drive this relation: inter-dealer trading, proprietary trading, and hedging demand.

First, bank order flow reflects inter-dealer trading. The FX market operates through a two-tier trading system consisting of customer-dealer and inter-dealer trading. If customer demand (retail or institutional) reflects prospect-theory-driven behavior, this demand is transmitted through dealers and appears in bank order flow.[32]

Second, bank order flow captures proprietary trading, reflecting banks' own active risk-taking positions. Third, bank order flow may also incorporate hedging demand from non-financial corporations. If a currency's historical return distribution appears unattractive under prospect theory, firms with exposure to that currency may hedge more actively or selectively rather than fully hedging mechanically. Such selective hedging behavior could therefore contribute to the observed tk–bank order flow relation (Stulz, 1996). We explore the tk–bank order flow relation through order flow decomposition and event studies.

1. Bank Order Flow Decomposition

We decompose bank order flow into distinct components to isolate the role of different trading channels. Due to the two-tier structure of the FX market, inter-dealer bank order flow reflects, in part, the aggregation of customer orders. At the same time, bank order flows may be correlated with the flows of other market participants.[33] To isolate these effects, we regress bank order flow on the flows of the other three participant groups—corporations, funds, and non-bank financial institutions—and decompose it into residual and fitted components. By construction, the residual captures variation in bank order flow that is orthogonal to these flows. If customer demand contains speculative components, inter-dealer trading transmits this demand into bank order flow, and such effects are reflected in the residual component. We then re-run regression (5)

[32]The "hot potato" nature of inter-dealer trading is well documented in the literature (Lyons, 1997). Because dealers are generally risk-neutral and maintain zero inventories, they are likely to pass excess order imbalances—including those arising from speculative demand—on to other dealers.

[33]One concern is that bank order flow may reflect the hedging needs of non-financial corporations. We show that controlling for the corporate order flows, the residual bank order flow remains positively correlated with prospect theory value. Therefore hedging demand is unlikely to be the main driver underlying the bank order flow-tk relation.

using each component of bank order flow as the dependent variable.

Table 11 reports the results of the bank order flow decomposition. The residual component of bank order flow is positively and significantly related to prospect-theory value, similar to the raw bank order flow measure. This finding suggests that the relation between prospect-theory value and bank order flow is not driven solely by hedging-related demand. It is also consistent with the amplification effect of dealer demand documented in the CFTC TFF results discussed above.

Proprietary trading may also contribute to this relation. If banks' own risk-taking reflects similar behavioral patterns, this activity may be captured by the residual component or by the fitted component associated with fund order flow, given the role of funds in correcting mispricing. We further examine the role of proprietary trading in the event studies that follow. In contrast, the fitted components of corporate and non-bank financial institution flows are not statistically significant. This suggests that hedging demand is less important than inter-dealer transmission and bank risk-taking in explaining the tk–bank order flow relation.

2. Event Studies: Volcker Rule and Global FX Code of Conduct

We rely on historical events to further understand the role of proprietary trading. The post-financial-crisis regulatory environment allows for testing whether proprietary trading drives the observed relationship. The Dodd-Frank Act's Volcker Rule, which explicitly restricts banks' proprietary trading activities, offers a clean empirical setting for this analysis.[34] If proprietary trading were a primary driver of the tk–bank order flow relationship, we would expect this

[34]Section 619 of the Dodd-Frank Wall Street Reform and Consumer Protection Act, commonly known as the Volcker Rule, was fully implemented on July 21, 2015. This rule prohibits banking institutions from engaging in short-term proprietary trading for their own accounts, subject to certain exemptions. For more details, see: www.federalreserve.gov/newsevents/pressreleases/bcreg20131210b.htm.

relationship to weaken substantially after the rule's implementation. We therefore include an interaction term between prospect-theory value and a post-event dummy in the order flow regression.

Table 12 reports the event-study results. Panel A presents the impact of the Volcker Rule. The interaction between tk and a post-Volcker Rule dummy is significantly negative, confirming our prediction. Proprietary trading declined after the rule's implementation, weakening prospect-theory-type trading in bank order flow.[35] Our results therefore suggest that proprietary trading accounts for a substantial share of the positive relationship. Moreover, the standalone tk effect remains positive, although it falls to roughly half its pre-Volcker magnitude, indicating that other channels—such as inter-dealer trading or hedging—also contribute.

Panel B considers the introduction of the Global FX Code of Conduct (GFXC), which promotes the integrity and effective functioning of the wholesale FX market. Its implementation likely reduced bank proprietary trading by increasing market transparency, thereby weakening the tk–bank order flow relationship.[36] Although we also observe the decline of the tk-bank order flow relation after the event, the effect is weaker than for the Volcker rule.[37]

Overall, these event studies provide strong evidence that proprietary trading is an important channel linking prospect-theory preferences to bank order flows.[38]

[35] We also show that the negative tk–fund order flow relation weakened after the event, consistent with the decline in proprietary-trading-driven mispricing and hence the reduction in fund arbitrage activities.

[36] The Global FX Code of Conduct (GFXC) was published in May 2017 by the Foreign Exchange Working Group, operated under the BIS and 16 central banks. More details about the GFXC can be found on the Global Foreign Exchange Committee website: `www.globalfxc.org/fx-global-code`.

[37] As these two events are close, we consider the Volcker rule event using a window ending before the GFXC (April 2017) to isolate the estimation periods. Therefore, the relatively weak relation for GFXC could partially due to the effect of Volcker rule on the pre-GFXC period, making the pre–post difference small. In the Internet Appendix Table A27, using the full samples, we show that the strong Volcker rule results remain, while the GFXC effect becomes statistically significant.

[38] When we replace order flow with trading volume, bank trading volume also declines after the Volcker Rule, consistent with the reduced proprietary trading activities (Table A28 in the Internet Appendix). When we regress bank order flow on corporate order flow, the residual order flow declines significantly after the Volcker Rule, while the

V. Further Analyses and Robustness Checks

In this section, we briefly summarise our results from further analyses and robustness checks. We first conduct three sets of analyses to deepen our understanding of the predictive power of prospect-theory value. We refer to Section C in the Internet Appendix for more detailed discussion.

First, we conduct decomposition analysis along two dimensions. All three behavioral elements—loss aversion, convexity/concavity, and probability weighting—contribute to the predictive power of prospect-theory value. After decomposing prospect-theory value into cross-time, between-time-and-currency, and cross-currency components, we show that only the between-time-and-currency component generates predictive power.

Second, we consider a set of alternative explanations. The predictive power of prospect-theory value cannot be attributed to the profitability of technical trading rules, time-series and factor momentum, or alternative behavioral indicators.

Third, we investigate the link between prospect-theory value and volatility risk premia (VRP). The predictive power of tk is not subsumed by VRP. Instead, the tk–return relation is strengthened for currencies with higher volatility insurance costs, consistent with limits to arbitrage.

We also conduct comprehensive robustness checks. See Section D in the Internet Appendix for additional details. Our results are robust to alternative measures of prospect-theory value. We find that results are generally consistent across different sub-sample periods. Results are also robust to transaction costs and hold when different sets of currencies are considered.

corporate-fitted component does not. This result confirms that proprietary trading, rather than hedging demand, plays a more important role in explaining prospect-theory-type trading by banks (Table A29 in the Internet Appendix).

Using different denomination currencies does not qualitatively change our main findings. Finally, after controlling for a broader set of currency characteristics, the predictive power of prospect-theory value remains strong. Overall, our main findings are robust across different specifications.

VI. Conclusion

This paper investigates behavior consistent with prospect theory in currency markets and shows that currencies with higher prospect-theory values generate lower expected returns. Using the historical distribution of exchange rate returns, we construct a currency-level measure of prospect-theory value. Our evidence shows that prospect-theory value negatively and significantly predicts next-month currency excess returns, even after controlling for other characteristics. A long–short strategy based on prospect-theory value generates statistically significant and economically meaningful profits, while exhibiting only moderate correlations with existing currency factor strategies.

We explore several explanations for this predictive relation. Exposure to common factors cannot account for the predictability. Instead, our findings support a mispricing explanation: the predictive relation is stronger when arbitrage is more constrained. Trading activities of FX market participants also affect the predictive power, although the negative relation remains robust. Using CFTC currency futures positions, we show that dealers trade in accordance with prospect theory, whereas fund managers and leveraged money trade against it, acting as arbitrageurs. Using spot order flow data, we document strong heterogeneous effects. Bank order flows amplify mispricing, primarily through inter-dealer and proprietary trading, while funds act as arbitrageurs that help correct mispricing. The sophisticated and heterogeneous composition of currency market participants is therefore central to understanding the predictive relation in this institutionally driven market.

Overall, this paper provides novel evidence that prospect-theory preferences play an important and previously underexplored role in explaining currency return variation. Our findings extend the asset pricing implications of prospect theory beyond equity markets and suggest that behavioral biases may be pervasive across asset classes, even in markets dominated by institutional investors.

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TABLE 1

Summary Statistics.

This table reports summary statistics of monthly currency excess returns and characteristics (Panel A) and the correlations among the variables (Panel B). The sample runs from January 1990 to February 2018 and covers 15 currencies of developed economies. rx is the currency excess return, fd is the forward discount, tk is the prospect-theory value, mom_t is the cumulative exchange rate return over the previous three months, val_t is the negative of the past five-year real exchange rate change. The past three-month cumulative exchange rate return (mom_t) has more observations than currency excess return, as it only relies on spot exchange rate data. Currency excess returns and characteristics are reported in percentage points.

Panel A: Currency Returns and Characteristics

	Mean	Std.dev	Min	Max	Nr.obs.
rx_t	0.12	3.01	-15.70	16.90	3,735
fd_t	0.07	0.26	-2.80	2.21	3,740
mom_t	0.18	4.70	-33.80	24.30	5,085
val_t	-0.63	5.82	-18.70	24.80	3,875
tk_t	-2.55	0.91	-5.16	-0.02	3,740

Panel B: Correlations

	rx_t	fd_t	mom_t	val_t	tk_t
fd_t	0.07				
mom_t	0.59	0.12			
val_t	0.00	-0.10	-0.04		
tk_t	0.09	-0.19	0.18	-0.08	
rx_{t+1}	0.07	0.04	0.08	0.02	-0.03

TABLE 2

Multivariate Regression Analysis.

This table presents the estimates of the following panel regression $rx_{i,t+1} = \alpha_i + \gamma_t + \beta_1 tk_{i,t} + \delta X_{i,t} + u_{i,t+1}$, where $rx_{i,t+1}$ is the currency i excess return at month $t+1$, $tk_{i,t}$ is the prospect-theory value for currency i at time t, α_i and γ_t represent currency fixed effects and time (year-month) fixed effects dummies respectively. The set of control variables X consists of the forward discount $fd_{i,t}$, the cumulative exchange rate return over the past three months $mom_{i,t}$, and the negative of the past five-year real exchange rate change $val_{i,t}$. t-statistics (reported in brackets) are based on standard errors double clustered by currency and time. The sample runs from January 1990 to February 2018 and covers 15 currencies for developed economies. All variables are standardized to facilitate interpretation.

	1	2	3	4	5
tk_t	-0.15	-0.15	-0.16	-0.16	-0.17
	[-3.21]	[-3.12]	[-3.38]	[-3.31]	[-3.42]
fd_t		0.05			0.04
		[0.93]			[0.75]
mom_t			0.03		0.03
			[1.23]		[1.15]
val_t				0.04	0.04
				[1.23]	[1.15]
Time FE	Yes	Yes	Yes	Yes	Yes
Curr FE	Yes	Yes	Yes	Yes	Yes
Nr.Obs	3,710	3,709	3,710	3,597	3,597
R^2	59.1%	59.1%	59.2%	58.8%	58.8%

TABLE 3

Prospect-Theory Value Sorted Portfolios.

This table reports excess returns and characteristics of prospect-theory-value-sorted portfolios from January 1990 to February 2018 for the sample of 15 currencies for developed economies. P_1 to P_5 are portfolios sorted by prospect-theory value (tk) from low to high. AVG and PTP report the cross-portfolio average and the low-minus-high portfolio return, respectively. Returns are not adjusted for transaction costs. Monthly average returns and standard deviations are reported in percentage points. Skewness, kurtosis, monthly Sharpe ratio, and first order autocorrelation coefficients are reported. Figures in brackets are t-statistics based on Newey and West (1987) standard errors with optimal lag by Andrews (1991). We consider both currency excess return (Panel A) and the exchange rate return component (Panel B).

	P_1	P_2	P_3	P_4	P_5	AVG	PTP
			Panel A: Currency Excess Returns				
$Mean$	0.37	0.19	0.09	-0.02	-0.05	0.12	0.42
	[2.02]	[1.11]	[0.53]	[-0.14]	[-0.38]	[0.82]	[3.14]
$Std.dev$	3.04	2.86	2.82	2.50	2.15	2.33	2.44
$Skew$	-0.14	-0.05	-0.16	-0.27	-0.26	-0.18	0.23
$Kurt$	5.06	3.33	3.23	4.64	5.77	3.79	4.49
SR	0.12	0.07	0.03	-0.01	-0.02	0.05	0.17
$AR(1)$	0.09	0.03	0.09	0.01	0.11	0.09	0.10
p	(0.14)	(0.59)	(0.09)	(0.90)	(0.09)	(0.11)	(0.12)
			Panel B: Exchange Rate Returns				
$Mean$	0.23	0.12	0.05	-0.03	-0.08	0.06	0.31
	[1.28]	[0.71]	[0.29]	[-0.24]	[-0.60]	[0.41]	[2.29]
$Std.dev$	3.03	2.84	2.82	2.50	2.14	2.32	2.44
$Skew$	-0.18	-0.07	-0.19	-0.37	-0.21	-0.22	0.16
$Kurt$	5.15	3.35	3.32	4.92	5.82	3.86	4.60
SR	0.08	0.04	0.02	-0.01	-0.04	0.02	0.13
$AR(1)$	0.08	0.02	0.09	0.01	0.11	0.09	0.11
p	(0.16)	(0.70)	(0.11)	(0.83)	(0.11)	(0.14)	(0.10)

TABLE 4

Portfolio Characteristics and Compositions: Contemporaneous Sorts.

This table reports excess returns and characteristics of prospect-theory value contemporaneously sorted portfolios from January 1990 to February 2018 for the sample of 15 currencies for developed economies. P_1 to P_5 are prospect-theory-value-sorted portfolios from low to high. AVG and $P_5 - P_1$ report the cross-portfolio average and the high-minus-low portfolio difference, respectively. We record average returns and characteristics values at the time portfolios are formed (contemporaneously). Returns are not adjusted for transaction costs. Monthly average returns and standard deviations are reported in percentage points. Skewness, kurtosis and monthly Sharpe ratio are reported. Figures in brackets are t-statistics based on Newey and West (1987) standard errors with optimal lag by Andrews (1991). We consider both currency excess return (Panel A) and the exchange rate return component (Panel B). We report average values of characteristics for each portfolio (in percentage points) in Panel C. We also report top 5 currencies in terms of the percentage of time they are allocated into a specific portfolio (in parenthesis) of each portfolio in Panel D.

	P_1	P_2	P_3	P_4	P_5	AVG	$P_5 - P_1$
			Panel A: Currency Excess Returns				
$Mean$	0.09	0.08	0.14	0.13	0.24	0.13	0.15
	[0.43]	[0.40]	[0.91]	[0.90]	[2.01]	[0.94]	[0.90]
$Std.dev$	3.18	2.98	2.70	2.55	1.96	2.32	2.70
$Skew$	-0.28	-0.23	-0.23	0.01	0.29	-0.19	0.40
$Kurt$	4.69	3.51	3.96	4.37	4.49	3.80	6.53
SR	0.03	0.03	0.05	0.05	0.12	0.06	0.06
			Panel B: Exchange Rate Returns				
$Mean$	-0.06	0.00	0.10	0.12	0.21	0.07	0.27
	[-0.29]	[0.01]	[0.63]	[0.86]	[1.82]	[0.53]	[1.61]
$Std.dev$	3.17	2.97	2.71	2.53	1.95	2.31	2.69
$Skew$	-0.35	-0.27	-0.23	0.00	0.33	-0.23	0.52
$Kurt$	4.83	3.63	4.02	4.37	4.66	3.87	7.00
SR	-0.02	0.00	0.04	0.05	0.11	0.03	0.10
			Panel C: Other Characteristics				
fd_t	0.14	0.09	0.05	0.08	0.02	0.07	-0.13
	[5.52]	[3.32]	[2.03]	[2.09]	[0.51]	[3.18]	[-4.40]
mom_t	0.04	0.15	0.27	0.19	0.60	0.25	0.56
	[0.07]	[0.29]	[0.62]	[0.48]	[1.84]	[0.62]	[1.15]
val_t	-0.78	-0.64	-0.84	-0.89	-0.20	-0.67	0.58
	[-1.11]	[-0.86]	[-1.23]	[-1.40]	[-0.36]	[-1.10]	[1.03]
tk_t	-3.33	-2.80	-2.57	-2.31	-1.73	-2.55	1.60
	[-30.81]	[-27.77]	[-25.65]	[-25.04]	[-24.05]	[-28.19]	[20.24]

Panel D: Portfolio Compositions

	P_1	P_2	P_3	P_4	P_5
$1st$	AUD (0.54)	NOK (0.52)	DKK (0.29)	DKK (0.35)	CAD (0.52)
$2nd$	NZD (0.41)	SEK (0.33)	GBP (0.22)	CAD (0.28)	JPY (0.44)
$3rd$	JPY (0.27)	NZD (0.21)	FRF (0.22)	CHF (0.22)	CHF (0.32)
$4th$	NOK (0.24)	CHF (0.19)	SEK (0.20)	AUD (0.18)	GBP (0.28)
$5th$	GBP (0.24)	GBP (0.15)	CHF (0.17)	SEK (0.17)	NZD (0.19)

TABLE 5

Asset Pricing: Time Series Tests.

This table reports time series asset pricing tests for long-short strategy returns based on prospect-theory value (or prospect-theory premium PTP) from January 1990 to February 2018 for the sample of 15 currencies for developed economies. The dependent variable is the monthly excess returns on PTP strategy and the independent variables are the returns on the set of existing risk factors. We consider three sets of factors. Currency factors include dollar (DOL), carry (CAR), momentum (MOM), value (VAL), global imbalance (GI), and unconditional mean-variance efficient portfolio (UMVE). Equity factors include market (MKT), book to market value (HML), size (SMB), equity momentum (WML). Hedge fund factors include the bond (BO), currency (CU), and commodity (CO) trend-following factors, and the equity market (EQ), size spread (SS), bond market (BM) and credit spread (CS) factors of Fung and Hsieh (2004). Macro factor mimicking portfolios are long-short beta sorted portfolios based on shocks to FX volatility ($FVOL$), FX illiquidity ($FXBAS$), FX skewness ($FXSKEW$), CBOE VIX ($FVIX$), and ted spread ($FTED$). We report α, βs, and adjusted R^2s. Numbers in brackets are t-statistics based on Newey-West standard errors. Monthly abnormal returns and betas are reported in percentage points.

Panel A: Currency Factors

α	β_{DOL}	β_{CAR}	β_{MOM}	β_{VAL}	β_{GI}	β_{UMVE}	$\bar{R}^2$
0.33	-3.66	14.04	-8.86	-17.09	36.14	0.00	16.74%
[2.65]	[-0.59]	[3.20]	[-1.55]	[-1.82]	[3.44]	[-0.04]	

Panel B: Equity Factors

α	β_{MKT}	β_{HML}	β_{SMB}	β_{WML}	$\bar{R}^2$
0.37	9.35	6.06	7.43	-7.20	6.13%
[2.94]	[2.38]	[1.33]	[1.18]	[-2.43]	

Panel C: Hedge Fund Factors

α	β_{BO}	β_{CU}	β_{CO}	β_{EQ}	β_{SS}	β_{BM}	β_{CS}	$\bar{R}^2$
0.41	-1.14	0.54	-3.07	3.61	-0.63	51.52	46.72	1.58%
[2.99]	[-0.87]	[0.65]	[-2.57]	[0.69]	[-0.13]	[0.54]	[0.26]	

Panel D: Macro Factor Mimicking Portfolios

α	β_{DOL}	β_{FVOL}	β_{FBAS}	β_{FSKEW}	β_{FVIX}	β_{FTED}	$\bar{R}^2$
0.42	-0.83	-1.56	23.84	15.66	-17.34	15.47	22.07%
[3.55]	[-0.15]	[-0.20]	[3.35]	[1.86]	[-2.09]	[2.39]	

TABLE 6

Asset Pricing: Cross-Sectional Tests.

This table reports individual currency-level asset pricing results for the sample of 15 currencies for developed economies. We use Fama and MacBeth (1973) two-stage regression to estimate price of risk. The dependent variable is the monthly unconditional individual currency excess return. The independent variables are the betas of the corresponding currency excess return on the following risk factors: dollar (DOL), carry (CAR), momentum (MOM), value (VAL), and the excess returns on the prospect-theory value (PTP). We also include the lagged prospect-theory value tk_{t-1}. Numbers in brackets are t-statistics based on Newey and West (1987) standard errors. Regression coefficients are reported in percentage points.

	1	2	3	4
β_{PTP}	-0.79	-0.49	0.00	-0.42
	[-1.45]	[-0.83]	[0.00]	[-0.64]
β_{DOL}	0.20	-0.04	0.04	-0.52
	[0.67]	[-0.13]	[0.10]	[-0.80]
β_{CAR}			0.61	0.51
			[0.44]	[0.35]
β_{MOM}			-0.04	-0.08
			[-0.03]	[-0.04]
β_{VAL}			-1.60	-0.05
			[-1.69]	[-0.04]
tk_{t-1}		-20.82		-38.50
		[-2.23]		[-2.01]
$Const$	0.02	-0.38	-0.11	-0.48
	[0.15]	[-1.71]	[-0.67]	[-1.89]
R^2	33.98%	47.45%	70.62%	80.32%

TABLE 7

Limits to Arbitrage.

This table presents the estimates of the following panel regression $rx_{i,t+1} = \alpha_i + \gamma_t + \beta_1 tk_{i,t} + \beta_2 tk_{i,t} \times lta_{i,t} + \beta_3 lta_{i,t} + \delta X_{i,t} + u_{i,t+1}$, where $rx_{i,t+1}$ is the monthly currency i excess return at time $t+1$, $tk_{i,t}$ is the prospect-theory value for currency i at time t, α_i and γ_t represent currency fixed effects and time (year-month) fixed effects dummies respectively. The set of control variables X consists of the forward discount $fd_{i,t}$, the cumulative exchange rate return over the past three months $mom_{i,t}$, and the negative of the past five-year real exchange rate change $val_{i,t}$. The limit to arbitrage variable $lta_{i,t}$ corresponds to one of the following currency-level proxies: currency illiquidity using bid-ask spread (bas), idiosyncratic volatility ($ivol$), total volatility ($tvol$), 5 year CDS spread (cds). t-statistics (reported in brackets) are based on standard errors double clustered by currency and time. The sample runs from January 1990 to February 2018 and covers 15 currencies for developed economies. CDS data starts from 2003, hence the number of observations is smaller. All variables are standardized to facilitate interpretation.

	1	2	3	4
	bas	$ivol$	vol	cds
tk_t	-0.17	-0.17	-0.18	-0.39
	[-3.91]	[-3.91]	[-4.85]	[-3.06]
$tk_t \times lta_t$	-0.03	-0.03	-0.08	-0.44
	[-6.41]	[-0.80]	[-2.24]	[-2.30]
lta_t	0.00	-0.04	-0.09	-0.04
	[0.39]	[-1.71]	[-1.53]	[-0.27]
fd_t	0.04	0.04	0.04	0.10
	[0.69]	[0.71]	[0.78]	[0.80]
mom_t	0.03	0.03	0.03	-0.05
	[1.24]	[1.19]	[1.32]	[-2.02]
val_t	0.04	0.04	0.03	0.00
	[1.13]	[1.05]	[0.88]	[0.02]
Curr FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Nr.Obs	3,593	3,597	3,597	985
R^2	58.9%	58.9%	58.9%	62.2%

TABLE 8

CFTC Traders in Financial Futures (TFF).

This table presents the estimates of the following panel regression $rx_{i,t+1} = \alpha_i + \gamma_t + \beta_1 tk_{i,t} + \beta_2 tk_{i,t} \times flow_{i,t} + \beta_3 flow_{i,t} + \delta X_{i,t} + u_{i,t+1}$, where $rx_{i,t+1}$ is the monthly currency i excess return at time $t+1$, $tk_{i,t}$ is the prospect-theory value for currency i at time t, α_i and γ_t represent currency fixed effects and time (year-month) fixed effects dummies respectively. The set of control variables X consists of the forward discount $fd_{i,t}$, the cumulative exchange rate return over the past three months $mom_{i,t}$, and the negative of the past five-year real exchange rate change $val_{i,t}$. The trading activity variable $flow_{i,t}$ corresponds to one of the following currency-level proxies of net demand pressure (long minus short positions scaled by total open interests) of currency futures from CFTC Traders in Financial Futures (TFF) report: dealer (dem_{dealer}), asset manager (dem_{asset}), leveraged money (dem_{lev}), other reportable (dem_{other}). We also define financier ($dem_{financier}$) as the sum of asset manager and leveraged money. t-statistics (reported in brackets) are based on standard errors double clustered by currency and time. The sample runs from June 2006 to February 2018 and covers G10 currencies of developed economies. All variables are standardized to facilitate interpretation.

	1	2	3	4	5
	dem_{dealer}	dem_{asset}	dem_{lev}	dem_{other}	$dem_{financier}$
tk_t	-0.15	-0.15	-0.14	-0.13	-0.16
	[-2.69]	[-2.78]	[-2.45]	[-2.57]	[-2.69]
$tk_t \times flow_t$	-0.06	0.05	0.08	-0.07	0.08
	[-1.87]	[1.55]	[2.32]	[-1.23]	[2.20]
$flow_t$	0.00	0.04	-0.04	-0.02	-0.01
	[0.12]	[1.29]	[-1.13]	[-0.41]	[-0.45]
fd_t	-0.04	-0.02	-0.05	-0.03	-0.05
	[-0.83]	[-0.54]	[-0.97]	[-0.78]	[-0.95]
mom_t	0.04	0.03	0.05	0.02	0.04
	[0.86]	[0.56]	[1.31]	[0.50]	[1.16]
val_t	0.02	0.01	0.02	0.01	0.02
	[0.47]	[0.22]	[0.42]	[0.30]	[0.42]
Curr FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Nr.Obs	979	979	979	979	979
R^2	55.7%	55.6%	55.9%	55.7%	55.9%

TABLE 9

Heterogeneous Order Flow and Prospect-Theory Value.

This table presents the estimates of the following contemporaneous panel regression $of_{i,t} = \alpha_i + \gamma_t + \beta_1 tk_{i,t} + \delta X_{i,t} + u_{i,t}$, where $tk_{i,t}$ is the prospect-theory value for currency i at time t, α_i and γ_t represent currency fixed effects and time (year-month) fixed effects dummies respectively. The set of control variables X consists of the forward discount $fd_{i,t}$, the cumulative exchange rate return over the past three months $mom_{i,t}$, and the negative of the past five-year real exchange rate change $val_{i,t}$. $of_{i,t}$ is currency-level order flow measured by signed dollar volume (buy volume-sell volume) for currency i at time t for each group of market participants. We include currency and time fixed effects. t-statistics (reported in brackets) are based on standard errors clustered by time. We focus on the sample from Sep 2012 to Feb 2018 for the sample of G10 currencies. All variables are standardized to facilitate interpretation. Besides the total order flow (of_{tot}), we also consider order flows by four categories of price takers: bank (of_{bank}), non-financial corporation (of_{co}), fund (of_{fund}), non-bank financial institutions (of_{nbf}).

	1	2	3	4	5
	of_{bank}	of_{co}	of_{fund}	of_{nbf}	of_{tot}
tk_t	0.40	0.25	-0.20	0.15	0.32
	[7.69]	[4.53]	[-2.87]	[1.82]	[5.93]
fd_t	-0.05	0.09	0.00	-0.04	-0.04
	[-1.00]	[2.06]	[-0.02]	[-1.45]	[-1.11]
mom_t	-0.13	-0.09	-0.08	0.04	-0.15
	[-2.96]	[-2.45]	[-1.73]	[0.75]	[-3.79]
val_t	-0.01	0.05	-0.12	-0.04	-0.05
	[-0.27]	[1.31]	[-2.02]	[-0.59]	[-1.01]
Curr FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Nr.Obs	660	644	660	660	660
R^2	39.2%	39.4%	37.4%	32.5%	48.7%

TABLE 10

Heterogeneous Order Flow and tk-Return Relation: Portfolio-Level Order Flow.

This table presents estimates of the following panel regression $rx_{i,t+1} = \alpha_i + \gamma_t + \beta_1 tk_{i,t} + \beta_2 tk_{i,t} \times of_t + \beta_3 of_t + \delta X_{i,t} + u_{i,t+1}$, where $rx_{i,t+1}$ is the monthly currency i excess return at time $t+1$, $tk_{i,t}$ is the prospect-theory value for currency i at time t, α_i and γ_t represent currency fixed effects and time (year) fixed effects dummies respectively. The set of control variables X consists of the forward discount $fd_{i,t}$, the cumulative exchange rate return over the past three months $mom_{i,t}$, and the negative of the past five-year real exchange rate change $val_{i,t}$. The portfolio-level *TK-specific* order flow variable of_t is constructed as follows. We first calculate currency-specific order flow using the signed dollar volume (buy volume minus sell volume) $of_{i,t}$. Then we sort all currencies according to prospect-theory value tk and calculate the low minus high (p1-p5, PTP) portfolio value of order flow (of_t). This variable reflects tk-specific trading activities. Since it is a time-series variable, we do not include year-month fixed effects; Panel B instead includes year fixed effects. t-statistics (reported in brackets) are based on standard errors double clustered by currency and time. We focus on the sample from Sep 2012 to Feb 2018 for the sample of G10 currencies. All variables are standardized. Besides the total order flow (of_{tot}), we also consider order flows by four categories of price takers: bank (of_{bank}), non-financial corporation (of_{co}), fund (of_{fund}), non-bank financial institutions (of_{nbf}). Panel A reports results without time fixed effect. Panel B reports results with year fixed effect.

	1	2	3	4	5	6
	of_{bank}	of_{co}	of_{fund}	of_{nbf}	$joint$	of_{tot}
			Panel A: Without Time FE			
tk	-0.17 [-1.89]	-0.09 [-1.05]	-0.11 [-1.14]	-0.08 [-0.90]	-0.09 [-0.83]	-0.16 [-1.84]
$tk \times of_{bank}$	-0.16 [-3.23]				-0.13 [-2.60]	
of_{bank}	0.07 [0.82]				0.12 [1.33]	
$tk \times of_{co,t}$		-0.01 [-0.08]			0.02 [0.42]	
of_{co}		-0.13 [-1.22]			-0.17 [-1.46]	
$tk \times of_{fund}$			0.12 [2.00]		0.12 [1.74]	
of_{fund}			-0.09 [-0.94]		-0.06 [-0.59]	
$tk \times of_{nbf}$				0.02 [0.33]	0.00 [0.06]	
of_{nbf}				0.11 [1.31]	0.10 [1.34]	
$tk \times of_{tot}$					-0.07 [-0.80]	-0.13 [-2.30]
of_{tot}						0.03 [0.33]
fd	0.04 [0.55]	0.00 [0.05]	0.01 [0.20]	0.01 [0.07]	0.05 [0.72]	0.02 [0.28]
mom	-0.03 [-0.32]	-0.04 [-0.53]	-0.03 [-0.40]	-0.04 [-0.53]	-0.07 [-0.79]	-0.03 [-0.30]
val	0.03 [0.37]	-0.01 [-0.15]	-0.01 [-0.13]	0.03 [0.35]	-0.03 [-0.34]	0.04 [0.44]
Nr.Obs	640	640	640	640	640	640
R^2	4.4%	3.1%	3.3%	2.5%	8.3%	3.3%
			Panel B: With Year FE			
tk	-0.10 [-1.21]	-0.01 [-0.04]	-0.02 [-0.27]	-0.01 [-0.10]	-0.09 [-1.18]	-0.08 [-0.84]
$tk \times of_{bank}$	-0.16 [-2.67]				-0.15 [-2.70]	
of_{bank}	-0.12 [-0.89]				-0.12 [-0.72]	
$tk \times of_{co,t}$		0.01 [0.21]			0.06 [1.23]	
of_{co}		-0.11 [-1.00]			-0.07 [-0.64]	
$tk \times of_{fund,t}$			0.17 [2.64]		0.12 [1.77]	
of_{fund}			-0.03 [-0.26]		-0.03 [-0.27]	
$tk \times of_{nbf}$				0.00 [-0.01]	-0.03 [-0.62]	
of_{nbf}				0.03 [0.30]	-0.02 [-0.21]	
$tk \times of_{tot}$					-0.09 [-1.05]	-0.12 [-2.21]
of_{tot}						-0.14 [-1.12]
fd	0.10 [1.73]	0.07 [1.27]	0.09 [1.62]	0.07 [1.24]	0.11 [1.96]	0.09 [1.60]
mom	-0.11 [-1.16]	-0.10 [-1.08]	-0.11 [-1.20]	-0.11 [-1.15]	-0.12 [-1.33]	-0.11 [-1.15]
val	-0.05 [-0.50]	-0.04 [-0.38]	-0.06 [-0.58]	-0.03 [-0.22]	-0.09 [-0.83]	-0.04 [-0.42]
Nr.Obs	640	640	640	640	640	640
R^2	12.1%	8.7%	10.3%	7.9%	13.9%	11.1%

TABLE 11

Bank Order Flow Decomposition.

This table presents the estimates of the following contemporaneous panel regression $of_{i,t} = \alpha_i + \gamma_t + \beta_1 tk_{i,t} + \delta X_{i,t} + u_{i,t}$, where $tk_{i,t}$ is the prospect-theory value for currency i at time t, α_i and γ_t represent currency fixed effects and time (year-month) fixed effects dummies respectively. The set of control variables X consists of the forward discount $fd_{i,t}$, the cumulative exchange rate return over the past three months $mom_{i,t}$, and the negative of the past five-year real exchange rate change $val_{i,t}$. $of_{i,t}$ is currency-level order flow measured by signed dollar volume (buy volume-sell volume) for currency i at time t for each group of market participants. We include currency and time fixed effects. t-statistics (reported in brackets) are based on standard errors clustered by time. We focus on the sample from Sep 2012 to Feb 2018 for the sample of G10 currencies. All variables are standardized to facilitate interpretation. We consider bank order flow (of_{bank}), its residual ($of_{bankres}$) when regressing on other three types of order flows, as well as fitted components of other three categories: corporation (of_{bankco}), fund ($of_{bankfund}$), and non-bank financial institutions ($of_{banknbf}$).

	1	2	3	4	5
	of_{bank}	$of_{bankres}$	of_{bankco}	$of_{bankfund}$	$of_{banknbf}$
tk_t	0.40	0.15	-0.09	0.20	-0.02
	[7.69]	[2.06]	[-0.81]	[2.05]	[-0.96]
fd_t	-0.05	-0.01	-0.02	-0.14	0.02
	[-1.00]	[-0.24]	[-1.01]	[-1.58]	[1.02]
mom_t	-0.13	-0.08	-0.04	-0.05	-0.02
	[-2.96]	[-1.41]	[-0.95]	[-1.42]	[-0.62]
val_t	-0.01	0.05	-0.05	-0.05	-0.04
	[-0.27]	[0.87]	[-1.19]	[-1.63]	[-1.22]
Curr FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Nr.Obs	660	660	660	660	660
R^2	39.2%	13.7%	15.4%	38.8%	58.6%

TABLE 12

Event Studies: Volcker Rule and GFXC.

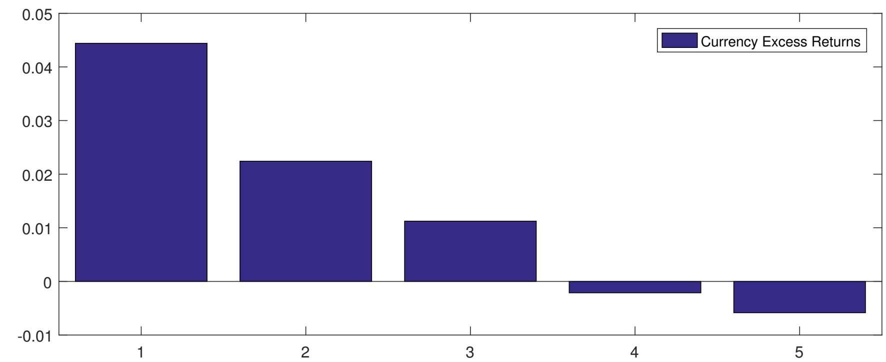
This table presents the estimates of the following contemporaneous panel regression $of_{i,t} = \alpha_i + \gamma_t + \beta_1 tk_{i,t} + \beta_2 tk_{i,t} \times Post + \delta X_{i,t} + u_{i,t}$, where $tk_{i,t}$ is the prospect-theory value for currency i at time t, $tk_{i,t} \times Post$ is an interaction term between prospect-theory value and a post-event dummy. We focus on two events: the Volcker Rule fully implementation in July 2015 and the introduction of global FX market conduct (GFXC) in May 2017. α_i and γ_t represent currency fixed effects and time (year-month) fixed effects dummies respectively. The set of control variables X consists of the forward discount $fd_{i,t}$, the cumulative exchange rate return over the past three months $mom_{i,t}$, and the negative of the past five-year real exchange rate change $val_{i,t}$. $of_{i,t}$ is currency-level order flow measured by signed dollar volume (buy volume-sell volume) for currency i at time j for each group of market participants . We include currency and time fixed effects. t-statistics (reported in brackets) are based on standard errors clustered by time. We focus on the sample from Sep 2012 to Feb 2018 for the sample of G10 currencies. Panel A relies on observations from Sep 2012 to Apr 2017. Panel B relies on observations from Jul 2015 to Feb 2018. All variables are standardized to facilitate interpretation. Besides the total order flow (of_{tot}), we also consider order flows by four categories of price takers: bank (of_{bank}), non-financial corporation (of_{co}), fund (of_{fund}), non-bank financial institutions (of_{nbf}).

	1	2	3	4	5
	of_{bank}	of_{co}	of_{fund}	of_{nbf}	of_{tot}
	Panel A: Volcker Rule (2015-07)				
tk_t	0.51	0.13	-0.39	0.12	0.34
	[6.91]	[2.24]	[-5.04]	[0.98]	[4.64]
$tk_t \times Post$	-0.33	0.01	0.19	-0.02	-0.23
	[-4.32]	[0.21]	[3.00]	[-0.14]	[-2.99]
fd_t	0.00	0.05	-0.02	-0.02	-0.01
	[-0.15]	[1.96]	[-0.87]	[-1.01]	[-0.45]
mom_t	-0.13	-0.10	-0.07	0.07	-0.14
	[-2.65]	[-2.91]	[-1.26]	[1.24]	[-3.18]
val_t	0.04	0.07	-0.14	-0.12	-0.01
	[0.79]	[1.59]	[-2.06]	[-1.84]	[-0.24]
Curr FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Nr.Obs	560	560	560	560	560
R^2	45.0%	47.9%	42.1%	34.7%	54.1%
	Panel B: GFXC (2017-05)				
tk_t	0.06	0.00	0.00	0.09	0.06
	[0.88]	[-0.10]	[-0.04]	[0.54]	[0.78]
$tk_t \times Post$	-0.06	0.42	0.18	0.10	0.04
	[-0.83]	[3.55]	[1.94]	[0.81]	[0.59]
fd_t	-0.01	0.03	-0.01	-0.05	-0.02
	[-0.73]	[2.23]	[-0.55]	[-1.63]	[-1.07]
mom_t	-0.04	-0.09	-0.25	-0.01	-0.12
	[-0.62]	[-1.53]	[-3.75]	[-0.14]	[-2.02]
val_t	-0.01	0.11	-0.16	0.12	-0.05
	[-0.12]	[1.05]	[-1.05]	[0.98]	[-0.60]
Curr FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Nr.Obs	320	320	320	320	320
R^2	24.9%	27.5%	40.9%	34.2%	35.9%

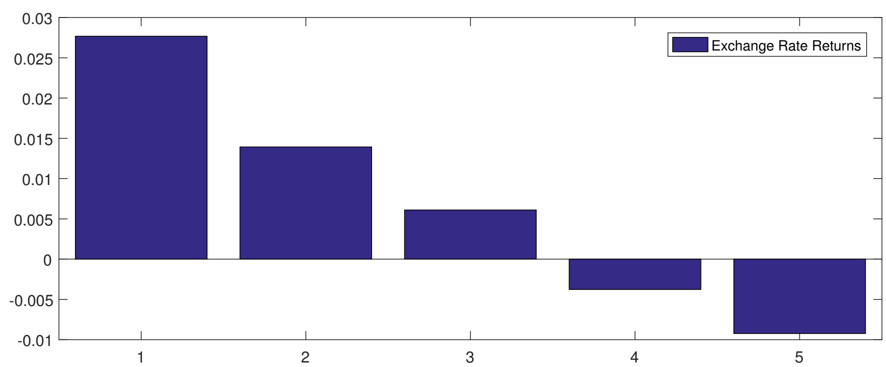
FIGURE 1

Currency Portfolio Returns Sorted by Prospect-Theory Values.

Graph A: Currency excess returns



Graph B: Exchange Rate Returns

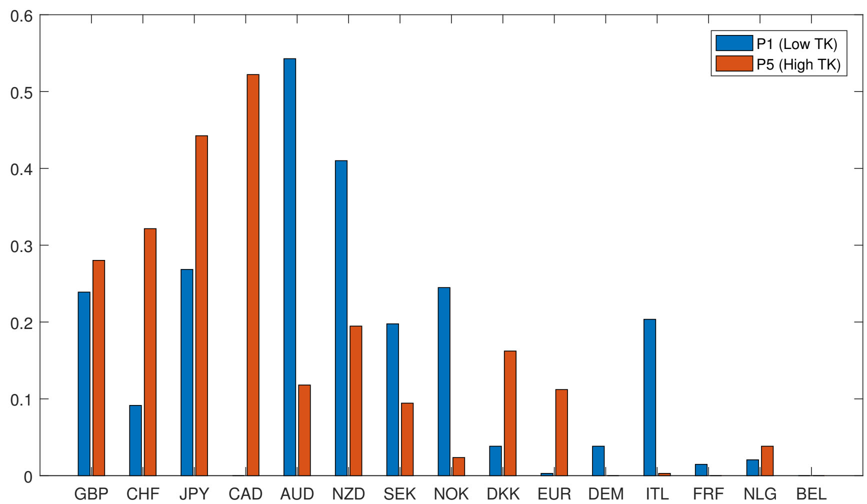


The figure illustrates annualized currency excess returns and exchange rate returns for portfolios sorted by prospect-theory values for the sample of 15 currencies of developed economies from January 1990 to February 2018. Graph A plots the results for currency excess returns $rx_{i,t+1} = (S_{i,t+1} - F_{i,t})/S_{i,t}$ while Graph B plots the results for the exchange rate returns $\Delta s_{i,t+1} = (S_{i,t+1} - S_{i,t})/S_{i,t}$.

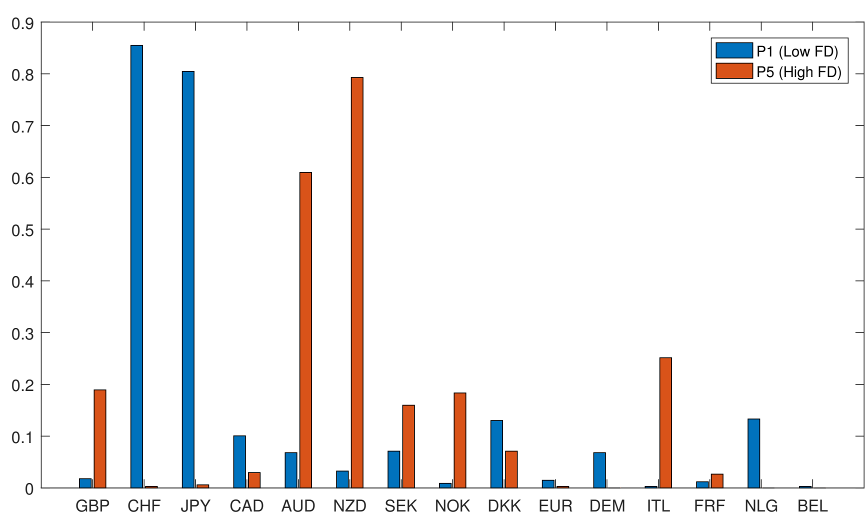
FIGURE 2

Currency Compositions of Prospect-Theory Value and Carry Trade Portfolios.

Graph A: tk-Sorted Portfolios



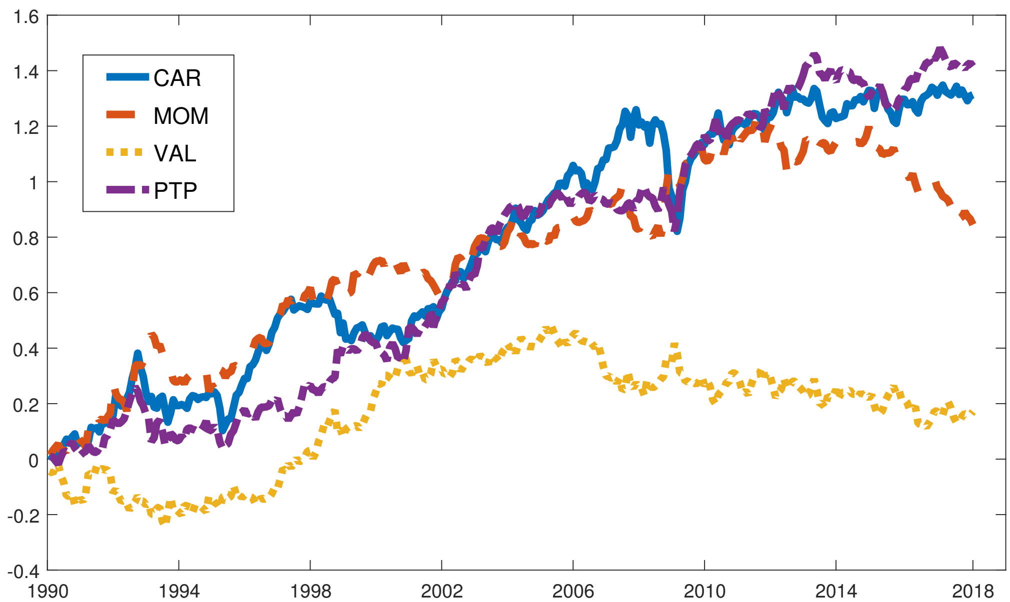
Graph B: Carry Trade Portfolios



The figure plots the frequency of currency within P1 and P5 respectively for prospect theory sorted portfolios (graph A) and for carry trade (forward discount or interest rate differential) sorted portfolios (graph B). The sample covers 15 currencies of developed economies from January 1990 to February 2018.

FIGURE 3

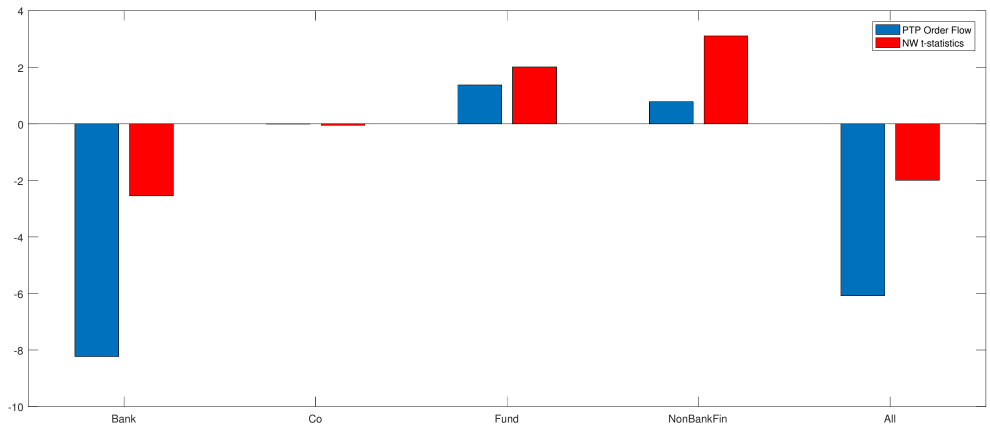
Cumulative Returns for Currency Portfolio Strategies.



The figure illustrates cumulative currency portfolio returns for carry (CAR), momentum (MOM), value (VAL), and prospect-theory value (PTP) strategies. The sample covers 15 currencies of developed economies from January 1990 to February 2018.

FIGURE 4

Heterogeneous Order Flows in the Long-Short Prospect-Theory Value Portfolio.



The figure shows heterogeneous order flow of different FX market participants of the low minus high (PTP) prospect-theory value sorted portfolios. The blue bar is the average value of order flow (in 10^{10} USD) of the PTP strategy, and the red bar is the Newey-West t-statistics. Order flow is defined as the signed dollar volume ($of_{i,t}$) for currency i at time t for each group of market participants. We first sort currencies into five portfolios according to tk_i value and calculate average order flow in each portfolio. Then we calculate the average order flow of the long-short portfolio ($of_t = \sum_{i \in P_1} of_{i,t} - \sum_{i \in P_5} of_{i,t}$). We consider four categories: bank, non-financial corporation (co), fund, non-bank financial institutions (nbf), as well as the aggregate order flow (all). We focus on G10 currencies from Sep 2012 to Feb 2018.

Internet appendix to

"Prospect Theory and Currency Returns: Empirical Evidence "

(not for publication)

This appendix presents supplementary results not included in the main body of the paper.

A Controlling for Trading Activities of Market Participants

In this section, we examine how various FX market participants may affect the predictive relation. We consider how central bank foreign exchange interventions, FX futures trading, cross-border portfolio flows, and sentiment spreads may influence the tk–return relation.

We estimate the following regression specification:

$$rx_{i,t+1} = \alpha_i + \gamma_t + \beta_1 tk_{i,t} + \beta_2 tk_{i,t} \times flow_{i,t} + \beta_3 flow_{i,t} + \delta X_{i,t} + u_{i,t+1}, \tag{A1}$$

where the $flow$ variable measures trading activities of FX participants and sentiment. Specifically, we use the central bank foreign exchange intervention net purchase of currency spot rate to GDP ratio (fxi) from Adler et al. (2021), obtained from the IMF. We use Commodity Futures Trading Commission (CFTC) Commitment of Traders (COT) data on open interest for commercial and non-commercial traders to calculate demand pressure by commercial traders (dem_c) and non-commercial traders (dem_{nc}), as in Della Corte et al. (2016). We use Treasury International Capital (TIC) data from the US Treasury on US bond and equity portfolio flows by foreign investors to calculate net flows for bond, equity, and total portfolios (cap_b, cap_e, and cap_{tot}), as in Hau and Rey (2004) and Hau and Rey (2006). Following Yu (2013), we also use the difference between foreign and US consumer confidence indices (CCI) from the Global Financial Database to measure cross-country sentiment spread ($sent$).

Table A3 reports results on the effects of FX market participants and sentiment. As before, the coefficient on tk remains negative and significant in all specifications. This finding is important, as it indicates that the predictive relation is unlikely to be fully subsumed by these trading activities. The interaction between prospect-theory value and central bank intervention in column (1) is negative and significant.[1] The existing literature on technical trading, such as LeBaron (1999) and Neely (2002), documents that central bank intervention is correlated with technical trading profitability. We show that the return predictive power of prospect-theory value cannot be fully explained by central bank intervention.

The interaction between prospect-theory value and CFTC demand pressure is positive and significant for non-commercial traders (column 2) but negative and significant for commercial traders (column 3). The opposite signs on the interaction coefficients for commercial and non-commercial traders are unsurprising, as these groups mechanically comprise the reportable futures markets. According to the CFTC classification, commercial traders are those who trade primarily for hedging purposes, such as producers, while non-commercial traders are those who trade primarily for speculative purposes, such as money managers. Non-commercial traders therefore serve as arbitrageurs to correct mispricing, consistent with our results using CFTC TFF reports and CLS spot order flow data. The negative interaction coefficient between tk and commercial trader demand admits several alternative explanations. First, some commercial traders engage in selective hedging: when facing high-prospect-theory-value currencies, firms with long exposures are less likely to sell forward, and firms with short exposures are more likely to buy forward. This selective hedging can generate net long positions in high-prospect-theory-value currencies and thereby exert price pressure.[2] Alternatively, a similar effect could arise from

[1] Since the intervention measure is directional, this finding indicates that when intervention is in the same direction as mispricing (buying high-tk currencies), the negative tk–return relation strengthens; when intervention is in the opposite direction to mispricing (selling high-tk currencies), the relation weakens. Moreover, intervention itself may also induce mispricing. Pasquariello (2018) suggests that government intervention in a market could induce deviations from the law of one price in related arbitrage markets, similar to findings in the technical trading literature. Nevertheless, the significant standalone tk coefficient indicates that the predictive power cannot be fully attributed to central bank intervention.

[2] Extant studies, such as Stulz (1996), suggest that commercial traders may hedge with a speculative

selective hedging by dealers. In particular, if bank dealers exhibit prospect-theory-type preferences, this could help explain how they generate asymmetric trading patterns driven by prospect-theory preferences even when non-financial customers fully hedge their future cash flows. Finally, the CFTC COT categorisation may not be sufficiently granular, as the commercial traders category includes swap dealers (banks) hedging OTC exposure.

The coefficients on the interaction terms with capital flows (columns 4 to 6) are insignificant. The coefficient on prospect-theory value, however, remains negative and significant. Hence, the effect of prospect-theory value on currency returns cannot be attributed to the price impact of cross-border equity or bond capital flows, whether arising from portfolio rebalancing or trend-following behavior.[3] The interaction term with sentiment spread (column 7) is also insignificant. Instead, both prospect-theory value and sentiment spread are individually significant. The positive coefficient on sentiment spread is consistent with Yu (2013), who shows that sentiment enters the pricing kernel of a consumption-based model and that sentiment spreads predict currency returns. Our results suggest that prospect-theory value and sentiment spread influence future currency returns through different channels, consistent with their distinct focuses on preferences and beliefs, respectively.

Overall, we show that the predictive relation between prospect-theory value and currency returns is robust to the trading activities of these market participants.

component (i.e., selective hedging); as a result, they exhibit skewness preference.

[3]Table A16 provides additional evidence that, controlling for an MSCI-based equity market prospect-theory value, the original currency tk–return relation remains. Hence, cross-border capital flow is unlikely to explain the predictive relation.

B FX Market Structure and CLS Data

B.1 FX Market Structure and Main Participants

In the spot market, the Bank for International Settlements (BIS), as described in Chaboud et al. (2023), classifies bank-dealers ("reporting dealers") as the main liquidity providers, with the principal liquidity consumers being other bank-dealers, other financial institutions, and non-financial customers. Non-financial customers—mainly corporations engaged in international trade—account for less than 10% of spot turnover. Other financial institutions include institutional investors, asset managers, hedge funds, commodity trading advisors (CTAs), smaller non-dealer banks, and central banks.[4] Given this market structure, speculative trading is most likely to occur within inter-dealer trading and in trading by other financial institutions. Non-financial customers primarily transact for trade-related hedging purposes and are therefore less likely to trade speculatively. Retail traders also tend to trade speculatively, but their volumes are too small to influence market-wide patterns. We therefore view bank-dealers and institutional investors as the most plausible sources of the prospect-theory-preference effects documented in our study.

Two caveats are important. First, the BIS classification differs from that in the CLS data used in our empirical analysis: all non-bank institutional investors are grouped into the "other financial customers" category, which therefore includes both speculators and arbitrageurs. Second, the rise of high-frequency and algorithmic trading since the early 2000s has reduced the share of manual trading by inter-dealer banks, potentially limiting the scope for behavioral biases. For example, Chaboud et al. (2023) report that

[4] Historically, reporting dealers accounted for about two-thirds of FX spot turnover in the late 1990s. This share has since fallen to around 40%, reflecting both a decline in inter-dealer inventory trading and the rise of principal trading firms (PTFs)—often high-frequency traders—as alternative liquidity providers in the early 2000s. Over the same period, the share of other financial institutions has risen sharply to about 50% of turnover. Retail traders represent only a very small fraction of overall activity.

on the EBS platform—one of the major electronic FX trading venues—manual trading accounted for about 80% of activity in 2004, falling to around 40% in 2008 and to roughly 10% by 2022, with bank and non-bank APIs each representing about 40% of activity. Nevertheless, manual trading remains material: according to the latest available data derived from the 2022 BIS Triennial Survey, 23% of FX spot trading is conducted via direct voice channels (e.g., Bloomberg chat) and another 3% through voice brokers (Chaboud et al., 2023). Thus, although algorithmic trading now dominates, there remains scope for speculative behavior and prospect-theory-type preferences in the FX market.

B.2 CLS Data Coverage

Several recent studies, including Cespa et al. (2022), Ranaldo and Somogyi (2021), Hasbrouck and Levich (2021), and Ranaldo and Santucci de Magistris (2022), use CLS data to investigate volume, asymmetric information, trading networks, and liquidity risk in FX markets, respectively. While the dataset does not cover the entire FX market, it is by far the most comprehensive dataset of FX order flow (Ranaldo and Santucci de Magistris, 2022) and covers approximately 50% of global FX trading volume (Cespa et al., 2022).

Ranaldo and Somogyi (2021) note that CLS data cover 29% of BIS coverage. This limited coverage may be attributable to three factors: (i) FX options and non-deliverable forwards are not covered, (ii) some small banks are not settlement members, and (iii) CLS does not settle transactions in every currency. Cespa et al. (2022) suggest that CLS coverage is underestimated relative to BIS figures, as a large fraction of BIS-reported volume relates to interbank trading across desks and double-counts prime-brokered "give-up" trades. After adjustment, CLS covers approximately 50% of BIS-reported trading volume. In Internet Appendix Table B.1 of Cespa et al. (2022), the authors report the percentage share of each currency in CLS data compared with BIS figures. These shares are closely aligned. Hence, CLS provides a reasonably good estimate of overall FX market activity. For instance, G10 currency volume shares from CLS and BIS in April 2016 are as follows: EURUSD (30.61% vs. 28.38%), USDJPY (19.20% vs. 21.82%), GBPUSD (11.08% vs. 11.38%), AUDUSD (6.72% vs. 6.35%), USDCHF (5.34% vs. 4.36%), USDCAD (5.47% vs. 5.28%), NZDUSD (2.10% vs. 1.89%), and USDSEK (2.17% vs. 1.60%). The CLS data therefore provide a reasonably good representation of global FX spot market trading activity.

C Further Analyses

C.1 Dissecting Currency Prospect-Theory Value

In this section, we further explore the source of predictive power through decomposition analysis of prospect-theory value along two distinct dimensions. First, we examine which types of behavioral biases captured by prospect theory matter most in driving the predictive relation. The total prospect-theory value reflects three types of behavioral bias: loss aversion, convexity/concavity, and probability weighting. These are reflected in our baseline parameter specification $(\alpha, \lambda, \gamma, \delta) = (0.88, 2.25, 0.61, 0.69)$. To test the predictive power of each component, we turn off the relevant parameters and test whether the corresponding tk measure still forecasts future returns. We consider the following specifications: loss aversion (la) $(1, 2.25, 1, 1)$, convexity/concavity (cc) $(0.88, 1, 1, 1)$, probability weighting (pw) $(1, 1, 0.61, 0.69)$, loss aversion and convexity/concavity ($lacc$) $(0.88, 2.25, 1, 1)$, loss aversion and probability weighting ($lapw$) $(1, 2.25, 0.61, 0.69)$, and convexity/concavity and probability weighting ($ccpw$) $(0.88, 1, 0.61, 0.69)$. These prospect-theory components are also considered in Barberis et al. (2016).

Panel A of Table A4 reports results using different prospect-theory-value components. We find that the negative and significant relation holds across all components. Complementing Chabi-Yo and Song (2012), we show that components of the prospect-theory function other than probability weighting also affect returns. We also find that the convexity/concavity component—and hence the disposition effect—plays a significant role, although this role is not dominant, consistent with the findings of O'Connell and Teo (2009) that the degree of disposition effect in the foreign exchange market is relatively low. In short, our analysis suggests that all three types of behavioral bias captured by prospect theory contribute to the predictive relation.

Second, we consider a decomposition in the spirit of Hassan and Mano (2019). In particular, we are interested in whether the predictability of prospect-theory value arises from the time-series dimension, the cross-sectional dimension, or both.

We perform this decomposition as follows. The prospect-theory premium strategy, which goes long low-tk currencies and short high-tk currencies in weighted portfolio form, can be written as $-\sum_i \sum_t [rx_{i,t+1}(tk_{i,t} - \bar{tk}_t)]$, where $\bar{tk}_t = \sum_i^N \frac{1}{N} tk_{i,t}$ is the average prospect-theory value of all currencies at time t (the minus sign before the portfolio return reflects the fact that the prospect-theory portfolio strategy goes long low-prospect-theory-value currencies and short high-prospect-theory-value currencies). Following Hassan and Mano (2019), we consider the investor's ex-ante expectation of the variable $\bar{tk}_i^e = E_{i0}[\bar{tk}_i]$ and the unconditional mean $\bar{tk}^e = E_0[\bar{tk}]$, where $\bar{tk}_i$ and $\bar{tk}$ refer to the cross-sectional mean and the mean over both time series and cross-section. Given that $\sum_i (tk_{i,t} - \bar{tk}_t) = 0$, we can decompose the original zero-cost portfolio return into different components:

$$\sum_{i,t}[(rx_{i,t+1}-\bar{rx})(tk_{i,t}-\bar{tk})] = \sum_{i,t}[rx_{i,t+1}\underbrace{(\bar{tk}_i^e-\bar{tk}^e)}_{cs}]$$
$$+\sum_{i,t}[rx_{i,t+1}\underbrace{(tk_{i,t}-\bar{tk}_t-(\bar{tk}_i^e-\bar{tk}^e))}_{btc}]+\sum_{i,t}[rx_{i,t+1}\underbrace{(\bar{tk}_t-\bar{tk}^e)}_{ts}]+\sum_{i,t}[\bar{rx}\underbrace{(\bar{tk}^e-\bar{tk})}_{const}]$$

The first component reflects the "static trade" and focuses on cross-sectional (cs) variation in prospect-theory value. The strategy goes long currencies expected to have low tk value on average and short currencies expected to have high tk value on average. Given the cross-sectional nature of this strategy, it does not involve portfolio rebalancing after formation at time 0.

The second component captures the "dynamic trade" and reflects between-time-and-currency (btc) variation in prospect-theory value. Specifically, the strategy goes long currencies that have low tk value (i) relative to $\bar{tk}_t$ and (ii) relative to their currency-specific mean prospect-theory value. The mean return of this strategy captures the incremental benefit of rebalancing the portfolio each period.

The third component captures cross-time (ts) variation in the average prospect-theory value of all currencies against the US dollar. It goes long all foreign currencies when the average prospect-theory value of all currencies against the US dollar is low relative to its unconditional mean, and short when the average value is high relative to its unconditional mean. The remaining component is a constant.

Panel B of Table A4 presents results using the cross-currency (cs), between-time-and-currency (btc), and cross-time (ts) decompositions of prospect-theory value. We find that only the btc component negatively and significantly predicts future currency returns across all specifications. The pure cs component has a negative coefficient but is statistically insignificant. The pure ts component is not significant and changes sign across specifications. Therefore, the between-time-and-currency component primarily drives the predictive relation documented above. This finding is important, as it differentiates prospect-theory value from other known currency return predictors, such as forward discount, which is mainly driven by cross-sectional variation, and dollar carry (Lustig et al., 2014) as well as momentum (Zhang, 2022), which are mainly attributable to time-series return autocorrelation. The between-time-and-currency nature of our prospect-theory value uncovers a new source of currency return predictability. This component reflects dynamic trading. The profitability mainly stems from going long (short) currencies that have low (high) prospect-theory value relative to the average prospect-theory value of all currencies at the time and relative to their currency-specific mean prospect-theory value.

To summarise, our decomposition analysis suggests that all three types of behavioral bias embedded in prospect-theory value matter, and the between-time-and-currency component dominates the cross-time and cross-currency components in driving the return predictive power of currency prospect-theory value.

C.2 Alternative Explanations

In this section, we consider three sets of alternative explanations: technical trading rules, time-series and factor momentum, and alternative behavioral indicators.

Technical trading is prevalent in the foreign exchange market (see Menkhoff and Taylor (2007) for a review). Since our prospect-theory value relies on the historical distribution of exchange rate changes, it is natural to ask whether the predictability we document mainly reflects the profitability of technical trading rules. We consider two sets of technical trading rules. The first set contains conventional technical signals, including the Bollinger band (BB), the moving average (MA), the moving average convergence divergence (MACD), and the relative strength index (RSI), as in Abbey and Doukas (2012). The second set focuses on moving average rules with different look-back window sizes (MA120, MA150, MA1200), as used in Menkhoff et al. (2012). For each rule, we calculate the monthly return based on the trading signal at the individual currency level and then aggregate to the portfolio level using an equal-weighted average.

Second, we investigate whether our results are driven by different forms of momentum. Since prospect-theory value is constructed using historical price information, we need to confirm that the predictive power extends beyond a simple linear combination of historical returns. In the main analysis, we have already shown that the predictive power of prospect theory is robust when controlling for momentum. In this section, we control for alternative forms of momentum: time-series momentum (Moskowitz et al., 2012) and factor momentum (Ehsani and Linnainmaa, 2022; Zhang, 2022). We construct currency-level time-series momentum and then aggregate to the portfolio level. We also construct currency factor momentum using the average of dollar and carry factor momentum, as in Zhang (2022).

Third, we test whether our findings are driven by other types of behavioral indicators, such as realized skewness, idiosyncratic skewness, co-skewness, extreme returns measured by the maximum and the negative of the minimum daily returns within the month, salience theory value, and the price relative to the 52-week high and low (Boyer et al., 2010; Bali et al., 2011; Cosemans and Frehen, 2021; Li and Yu, 2012). For each indicator, we form long–short strategies based on sorted portfolios.

Table A5 provides results of time-series factor-spanning regressions controlling for alternative explanations. We regress PTP returns on these alternative portfolio returns. Panels A and B report results for technical trading rules. Panels C and D report results controlling for time-series and factor momentum. In all specifications, α remains positive and statistically significant. This suggests that the prospect-theory effect in currency markets extends beyond the profitability of technical trading, time-series and factor momentum, and alternative behavioral indicators.[5] Panel E reports results using alternative behavioral indicators. Across all specifications, we find consistent evidence that the alphas remain positive and statistically significant. The economic magnitude is approximately 45 basis points per month (about 5.4% per annum), comparable to the original long–short portfolio return spread. Controlling for these alternative explanations therefore does not eliminate the majority of the profitability of the prospect-theory-value portfolio. The model fits range from approximately 1% (factor momentum) to around 30% (alternative behavioral indicators). Hence, a large proportion of variation in prospect-theory portfolio returns remains unexplained. Furthermore, Figure A1 demonstrates that the currency compositions of technical-trading-rule-sorted portfolios are substantially different from those of prospect-theory portfolios.

C.3 Relation with Currency Volatility Risk Premia

In this section, we investigate the relation between prospect theory and volatility risk premia (VRP). Baele et al. (2019) develop an equilibrium model with cumulative prospect-theory preferences and show that the model can fit observed option prices and variance premia well in the US index option market. Della Corte et al. (2016) show that volatility risk premia from currency options negatively and significantly predict currency returns, and that this predictive relation is stronger when arbitrage constraints are high.

[5] In addition to controlling for various forms of momentum, we further control for various forms of short-term reversal. Table A14 includes the control for the 1-month past return. Table A15 reports results controlling for 1-day, 1-week, 2-week, and 3-week past returns from the month end, to be consistent with the main monthly empirical specifications. Our main results hold after controlling for these short-term return signals. Hence, the predictive power of prospect-theory value cannot simply be attributed to short-term reversal.

It is therefore important to test whether prospect theory can contribute to understanding the VRP–currency return relation.

We consider two empirical tests. First, we explicitly control for VRP in the predictive regressions. In Table A6, we show that the negative predictive relation between prospect-theory value and currency returns remains when VRP is controlled for. In contrast, the VRP coefficient is insignificant. Therefore, the predictive power of prospect-theory value cannot be attributed to volatility risk premia.[6] We also find a positive and significant interaction term between prospect-theory value and VRP. Hence, the negative prospect-theory–return relation is stronger when VRP is low. This finding is consistent with our limits-to-arbitrage explanation, as low-VRP currencies (where VRP is defined as realized minus implied volatility, so implied volatility is relatively high) have high volatility insurance costs and are therefore more difficult to arbitrage. This finding also indicates that prospect-theory value and VRP are not identical in their predictive information content.

Second, we examine the co-movement between volatility risk premia and prospect-theory value. A correlation check shows that one-year-horizon VRP and prospect-theory value have a contemporaneous correlation of approximately 0.4, while the correlation between one-month-horizon VRP and prospect-theory value is approximately 0.3. The positive correlation supports our conjecture that high-VRP currencies have high prospect-theory value. These currencies have lower volatility insurance costs and are therefore more attractive for speculative trading. As a result, prospect theory helps explain the predictive information content of currency VRP.

[6] This finding suggests that prospect-theory value contains incremental predictive power beyond VRP. We do not claim that prospect-theory value fully subsumes VRP, as the standalone regression coefficient of VRP is not significant in our setting for currencies of developed economies. When emerging-market currencies are included, the VRP coefficient is negative and significant, as in the literature. The predictive power of prospect-theory value remains.

D Robustness Checks

In this section, we discuss the results of comprehensive robustness checks. First, we consider alternative measures of prospect-theory value (Table A7). Using different formation periods or replacing exchange rate changes with currency excess returns when constructing tk does not qualitatively affect our main findings. We show that allowing for exponential decay of returns destroys the predictive relation. Replacing prospect-theory value with expected utility value does not reproduce the predictive pattern. Hence, the functional form of prospect-theory value—that is, the way in which currency investors evaluate mentally represented risks—is critical for generating the documented predictive pattern.

Second, we investigate the performance of our strategy across different sub-sample periods (Table A8). The PTP strategy is significant in non-recession periods, while it is insignificant but still outperforms other currency strategies in recession periods. Furthermore, PTP remains significant both before and after the financial crisis. Our results are therefore generally stable across different sub-sample periods.

Strategy performance remains positive when we control for transaction costs (Table A9). Portfolio results are qualitatively unchanged when we consider alternative numbers of currencies (Table A11), including G10 currencies, 20 developed and emerging currencies, and 37 developed and emerging currencies, as used in Lustig et al. (2011). Using 48 currencies, as in Menkhoff et al. (2012), renders the return spread insignificant. Nevertheless, the negative relation remains. A possible explanation is that currencies of economies with less open capital accounts are less likely to be included in investors' tradable portfolios; hence, investors may be less likely to evaluate their historical distributions in the manner described by prospect theory. To examine this prediction, we use the capital account openness index of Chinn and Ito (2006). The higher the index, the greater the degree of capital account openness of an economy. We remove currencies of less open economies from the 48 developed and emerging currencies when the index is below zero or below one, and then reproduce our main portfolio sorting analysis. Table A12 shows that PTP returns are consistently significant. This finding supports the view that capital account openness plays an important role in understanding our results when considering currencies of emerging economies.

Replacing the USD with different quote currencies does not qualitatively affect our main findings (Table A13). Our main empirical analysis controls for three well-known predictors related to carry, three-month momentum, and value. We also consider several additional currency characteristics used in the literature.[7] Table A14 shows that the coefficient on prospect-theory value remains negative and significant after controlling for these additional predictors. Hence, the predictive relation between prospect-theory value and currency returns cannot be subsumed by existing currency predictors in the literature.

Finally, we reproduce our main empirical results using 37 developed and emerging currencies in Tables A17 to A25. Our main results continue to hold. The predictive power of prospect-theory value is therefore prevalent for currencies in both developed and emerging economies.

[7]The additional characteristics are the one-month lagged return (short-term momentum), the twelve-month lagged return (long-term momentum), the output gap (Colacito et al., 2020), the Taylor rule to capture monetary policy (Taylor, 1993; Molodtsova and Papell, 2009; Filippou and Taylor, 2021), the long- and short-term interest rate spread (Chen and Tsang, 2013), dollar beta (Verdelhan, 2018), and the average forward discount dummy for the dollar carry trade (Lustig et al., 2014). We also control for a synthetic version of the quanto risk premium (Kremens and Martin, 2019; Della Corte et al., 2023), constructed using currency option implied volatility, VIX, and the realized correlation between currency and S&P 500 index returns. We also control for currency volatility risk premia (Della Corte et al., 2016; Londono and Zhou, 2017). Macro variables are collected from the OECD database. Currency option data are obtained from JP Morgan and Bloomberg.

Table A1: Variable Definition

Variable	Definition	Data source
Returns		
rx	Simple excess return of 1-month forward exchange rate	Datastream
Δs	Monthly spot exchange rate changes	Datastream
Prospect Theory		
tk	Currency total prospect-theory (PT) value based on a rolling window of 60 months of spot exchange rate changes	Datastream
la	The loss aversion component of currency PT value	Datastream
pw	The probability weighting component of currency PT value	Datastream
cc	The convexity/concavity component of currency PT value	Datastream
tk_{ts}	The cross-time variation component of currency prospect-theory value following the decomposition method of Hassan and Mano (2019)	Datastream
tk_{btc}	The between-time-and-currency variation component of prospect-theory value following the decomposition method of Hassan and Mano (2019)	Datastream
tk_{cs}	The cross-currency variation component of currency prospect-theory value following the decomposition method of Hassan and Mano (2019)	Datastream
Main characteristics		
fd	Forward discount, defined as the difference between spot and forward exchange rates, divided by the spot exchange rate	Datastream
mom	Momentum signal, defined as the past three-month cumulative exchange rate changes	Datastream
val	Value signal, defined as the negative of the past five-year real exchange rate changes, as in Asness et al. (2013)	Datastream/OECD
Limits to arbitrage and flow		
bas	Bid–ask spread, defined as the ratio of bid–ask quote difference to the mid quote	Datastream
$ivol$	Idiosyncratic volatility, defined as the monthly realized volatility of daily residuals from a factor model with dollar and carry factors	Datastream
$tvol$	Total volatility, the monthly realized volatility of daily spot exchange rate changes	Datastream
cds	The 5-year sovereign CDS spread	Datastream
dem_c	CFTC net demand (the difference between long and short positions) divided by total open interest by commercial traders	CFTC
dem_{nc}	CFTC net demand (the difference between long and short positions) divided by total open interest by non-commercial traders	CFTC
dem_{dealer}	CFTC TFF net demand (the difference between long and short positions) divided by total open interest by dealers	CFTC
dem_{asset}	CFTC TFF net demand (the difference between long and short positions)divided by total open interest by asset managers	CFTC
dem_{lev}	CFTC TFF net demand (the difference between long and short positions) divided by total open interest by leveraged money	CFTC
dem_{other}	CFTC TFF net demand (the difference between long and short positions) divided by total open interest by other reportables	CFTC
$dem_{financier}$	CFTC TFF net demand (the difference between long and short positions) divided by total open interest by financiers (the sum of asset managers and leveraged money)	CFTC
fxi	Central bank intervention of foreign spot net purchase divided by GDP	IMF, Adler et al. (2021)
cap_{tot}	Net foreign-US portfolio flow of all assets from US Treasury (Hau and Rey, 2004; 2006)	TIC
cap_b	Net foreign-US portfolio flow of bonds from US Treasury (Hau and Rey, 2004; 2006)	TIC
cap_e	Net foreign-US portfolio flow of equity from US Treasury (Hau and Rey, 2004; 2006)	TIC
$sent$	Foreign-US sentiment spread, where sentiment is measured using the growth of the country-level consumer confidence index, as in Yu (2013)	Global Financial Database
of_{tot}	Total order flow as the signed dollar volume (buy minus sell)	CLS
of_{bank}	Order flow as the signed dollar volume (buy minus sell) by banks. Bank order flow is total buy side order flow minus order flows of corporation, funds, and non-bank financial institutions.	CLS
of_{fund}	Order flow as the signed dollar volume (buy minus sell) by funds	CLS
of_{co}	Order flow as the signed dollar volume (buy minus sell) by non-financial corporations	CLS
of_{nbf}	Order flow as the signed dollar volume (buy minus sell) by non-bank financial institutions	CLS
$of_{bankres}$	The residual component from regressing bank order flow on corporate, fund, and non-bank financial institution order flows	CLS

Table A1: Variable Definition

Variable	Definition	Data source
of_{bankco}	The corporate fitted component from regressing bank order flow on corporate, fund, and non-bank financial institution order flows	CLS
$of_{bankfund}$	The fund fitted component from regressing bank order flow on corporate, fund, and non-bank financial institution order flows	CLS
$of_{banknbf}$	The non-bank financial fitted component from regressing bank order flow on corporate, fund, and non-bank financial institution order flows	CLS
vol_{tot}	The natural logarithm of spot trading volume in total on buy side	CLS
vol_{bank}	The natural logarithm of spot trading volume by banks	CLS
vol_{co}	The natural logarithm of spot trading volume by corporations	CLS
vol_{fund}	The natural logarithm of spot trading volume by funds	CLS
vol_{nbf}	The natural logarithm of spot trading volume by non-bank financial institutions	CLS
Currency Factors		
PTP	Prospect-theory premium factor. We sort all currencies into five portfolios according to their latest prospect-theory value (tk_t). PTP is the zero-cost return spread of a strategy that goes long low-tk_t currencies and short high-tk_t currencies	Datastream
DOL	Dollar factor, equal to the cross-sectional average of the returns of forward-discount-sorted (fd_t) currency portfolios	Datastream
CAR	Carry trade factor. We sort all currencies into five portfolios according to their latest forward discounts (fd_t). CAR is the zero-cost return spread of a strategy that goes long high-fd_t currencies and short low-fd_t currencies	Datastream
MOM	Momentum factor. We sort all currencies into five portfolios according to their past three-month exchange rate returns ($rx_{t-3,t}$). MOM is the zero-cost return spread of a strategy that goes long high-$rx_{t-3,t}$ currencies and short low-$rx_{t-3,t}$ currencies	Datastream
VAL	Value factor. We sort currencies into five portfolios according to their latest values of the negative of the past five-year real exchange rate changes ($rx_{t-5y,t}$). VAL is the zero-cost return spread of a strategy that goes long the highest $rx_{t-5y,t}$ currencies and short the lowest $rx_{t-5y,t}$ currencies	Datastream
GI	Global imbalance factor. We sort currencies into two baskets based on nfa and then reorder currencies within each basket using ldc. Portfolio 1 (Portfolio 5) contains currencies of countries whose external liabilities are primarily denominated in domestic (foreign) currency. GI is the return of a strategy that goes long portfolio 5 and short portfolio 1	Della Corte, Sarno, and Riddough (2016)
$UMVE$	The return of a tangency portfolio of currencies. Conditional mean is predicted using forward discount, past exchange rate changes, and real exchange rate changes through panel regressions. Conditional covariance matrix is constructed using daily returns within the month, as in Chernov, Dahlquist, and Lochstoer (2023)	Datastream/OECD
Equity Factors		
MKT	The excess return of the US equity market portfolio. The value-weighted returns of all CRSP firms minus one-month Treasury-bill rate	French Data Library
SMB	Equity size factor. The average return on the three small (small capitalisation) portfolios minus the average return on the three big (large capitalisation) portfolios	French Data Library
HML	Equity value factor, defined as the average return on the two high book-to-market ratio portfolios minus the average return on the two low book-to-market ratio portfolios	French Data Library
WML	Equity momentum factor. The average return on two high twelve-month prior return portfolios minus the average return on two low twelve-month prior return portfolios	French Data Library
Hedge Fund Factors		
BO	The trend-following factor in bond markets. See details in Fung and Hsieh (2004)	Fung and Hsieh (2004)
CU	The trend-following factor in currency markets. See details in Fung and Hsieh (2004)	Fung and Hsieh (2004)
CO	The trend-following factor in commodity markets. See details in Fung and Hsieh (2004)	Fung and Hsieh (2004)
EQ	S&P 500 index monthly total return	Datastream
SS	The Russell 2000 index monthly total return minus S&P 500 monthly total return	Datastream
BM	The monthly change in the 10-year Treasury yield	FRED
CS	The monthly change in the Moody's Baa yield less 10-year Treasury yield	FRED
Macro FMP Factors		
$FVOL$	The factor-mimicking portfolio of global foreign exchange volatility risk. The risk measure is the cross-sectional average of daily absolute returns within the month	Datastream
$FBAS$	The factor-mimicking portfolio of global FX illiquidity risk. The risk measure is the cross-sectional average of daily average bid–ask spreads within the month	Datastream

Table A1: Variable Definition

Variable	Definition	Data source
$FSKEW$	The factor-mimicking portfolio of global FX skewness risk—the cross-sectional average of skewness of daily returns within the month (multiplied by a dummy variable of 1 or -1, depending on whether the forward discount is positive or negative)	Datastream
$FVIX$	The factor-mimicking portfolio of the CBOE Volatility Index (VIX)	Datastream/CBOE
$FTED$	The factor-mimicking portfolio of funding illiquidity risk. The risk measure is the TED spread, the spread between 3-Month LIBOR and 3-Month T-Bill	Datastream/Fed St. Louis
Other Control Variables		
mom_1	Short-term momentum, defined as the past one-month exchange rate return	Datastream
mom_{12}	Long-term momentum, defined as the past one-year cumulative exchange rate return	Datastream
og	The output gap as the residual of a regression of industrial production on lagged industrial production	OECD
tr	The Taylor rule based on 1.5 times inflation and 0.5 times output gap	OECD
ts	The term spread based on the difference between long-term and short-term interest rates	OECD
β_{dol}	The beta of the dollar factor estimated using a rolling window of 36 months	Datastream
afd	Average forward discount, defined as a dummy variable indicating whether fd_t is above the cross-sectional average forward discount	Datastream
$mom_{.w}$	The past 1-, 2-, or 3-week exchange rate return from the end-of-month observation	Datastream
mom_{1d}	The past one-day exchange rate return from the end-of-month observation	Datastream
$tkmsci$	PT value based on past 60-month MSCI country equity index local currency total return	Datastream
Technical Factors		
BB	A Bollinger band strategy using daily exchange rate changes within the month	Abbey and Doukas (2012)
MA	A moving average strategy using daily exchange rate changes within the month	Abbey and Doukas (2012)
$MACD$	A strategy based on moving average convergence divergence signal using daily exchange rate changes within the month	Abbey and Doukas (2012)
RSI	A relative strength index strategy using daily exchange rate changes within the month	Abbey and Doukas (2012)
MA_{120}	A strategy using the past 120-day moving average rule	Menkhoff et al. (2012)
MA_{150}	A strategy using the past 150-day moving average rule	Menkhoff et al. (2012)
MA_{1200}	A strategy using the past 1200-day moving average rule	Menkhoff et al. (2012)
Alternative Momentum Factors		
$MOMTS$	The cross-sectional average of past returns over 1, 3, 6, 9, and 12 months	Moskowitz et al. (2012)
$MOMF$	The average of dollar and carry factor momentum over the past 1, 3, 6, 9, 12 months	Zhang (2022)
Other Behavioral Indicators		
$SKEW$	A long–short strategy based on the realized skewness of daily exchange rate changes	Datastream
$IdioSKEW$	A long–short strategy based on realized idiosyncratic skewness of residuals from daily exchange rate changes from a two-factor model of dollar and carry factors	Boyer et al. (2011)
$COSKEW$	A long–short strategy based on monthly co-skewness as the covariance between daily spot exchange rate changes and market volatility	Menkhoff et al. (2012)
MAX	A long–short strategy based on the maximum daily return within the month	Bali et al. (2011)
MIN	A long–short strategy based on the negative of minimum daily return within the month	Bali et al. (2011)
ST	A long–short strategy based on monthly salience theory value using daily spot exchange rate changes within the month and the salience theory value formula	Cosemans and Frehen (2021)
PTH	A long–short strategy based on the 52-week high measure as the ratio of current price to the past 52-week highest price	Li and Yu (2012)
PTL	A long–short strategy based on the ratio of current price to the past 52-week lowest price	Li and Yu (2012)
Options remia		
vrp_{1y}	Currency volatility risk premia based on 1-year maturity option implied volatility and realized volatility using the past 1-year rolling daily return	JPMorgan Bloomberg
vrp_{1m}	Currency volatility risk premia based on 1-month maturity option implied volatility and realized volatility using the past 1-month rolling daily return	JPMorgan Bloomberg
qrp	A synthetic version of the quanto risk premia using currency option implied volatility, square root of VIX, and the realized correlation between currency and stock returns, in the spirit of Kremens and Martin (2019) and Della Corte et al. (2023)	JPMorgan Bloomberg CBOE Datastream

Table A2: Summary Statistics

This table presents summary statistics of all main variables used in the empirical analysis. Panel A reports main variables and prospect-theory value, including currency excess returns (rx), spot exchange rate return (ds), forward discount (fd), past three-month return momentum (mom), past five-year real exchange rate change value (val), prospect-theory value (tk), cross-sectional (tk_{cs}), between-time-and-cross-section (tk_{btc}), and time-series (tk_{ts}) components of prospect-theory value, loss aversion (la), convexity and concavity (cc), and probability weighting (pw). Panel B reports limits-to-arbitrage and trading flow variables, including bid–ask spread (bas), net demand of dealers (dem_{dealer}), asset managers (dem_{asset}), leveraged money (dem_{lev}), other reportables (dem_{other}), financiers (dem_{fin}), non-commercials (dem_{nc}), commercials (dem_c), 5-year CDS spread (cds), foreign exchange intervention (fxi), cross-border bond portfolio flow (cap_b), equity portfolio flow (cap_e), total portfolio flow (cap_t), cross-country sentiment spread ($sent$), total volatility ($tvol$), and idiosyncratic volatility ($ivol$). Panel C reports spot order flow measures, including total order flow (of_{tot}), banks (of_{bank}), non-financial corporations (of_{co}), funds (of_{fund}), non-bank financial institutions (of_{nbf}), the natural logarithm of spot trading volume in total (vol_{tot}), by banks (vol_{bank}), non-financial corporations (vol_{co}), funds (vol_{fund}), and non-bank financial institutions (vol_{nbf}). Panel D reports other control variables, including 1-month past return momentum (mom_1), 12-month past return momentum (mom_{12}), output gap (og), Taylor rule (tr), term spread (ts), dollar beta ($dollarexp$), average forward discount indicator (afd), 1-year volatility risk premia (vrp_{1y}), 1-month volatility risk premia (vrp_{1m}), synthetic quanto risk premia (qrp), Bollinger band (bb), moving average (ma), moving average convergence divergence ($macd$), relative strength (rsi), 120-day moving average (ma_{120}), 150-day moving average (ma_{150}), 1200-day moving average (ma_{1200}), skewness ($skew$), idiosyncratic skewness ($iskew$), maximum daily return of the month (max), the negative of the minimum daily return of the month (min), salience theory value (st), price to the past 52-week high (pth), price to the past 52-week low (ptl), MSCI equity-based prospect-theory value ($tkmsci$), 1-week past return momentum (mom_{w1}), 2-week past return momentum (mom_{w2}), 3-week past return momentum (mom_{w3}), and 1-day past return momentum (mom_{1d}). We report the number of observations (N), mean, standard deviation (sd), maximum (max), and minimum (min) values. All variables except order flows and technical rules are reported in percentage points. Order flow measures are reported in units of 10^{10}. We focus on currencies of 15 developed economies for main variables and G10 currencies for CFTC TFF and CLS order flow data.

Panel A: Main Variables and Prospect-Theory Value

	rx	ds	fd	mom	val	tk	tk_{cs}	tk_{btc}	tk_{ts}	la	cc	pw
mean	0.123	0.059	0.066	0.181	-0.633	-2.550	-0.031	-0.046	0.092	-1.250	0.150	0.020
sd	3.010	3.000	0.257	4.700	5.820	0.903	0.285	0.751	0.692	0.609	0.532	0.396
min	-15.70	-15.80	-2.800	-33.80	-18.70	-5.160	-0.526	-2.560	-1.020	-2.950	-1.250	-0.973
max	16.900	17.300	2.210	24.300	24.800	-0.023	0.645	2.300	1.600	0.347	1.730	1.270
N	3735	3771	3740	5085	3875	3989	5085	3989	5085	3989	3989	3989

Panel B: Limits to Arbitrage and Trading Flows

	bas	dem_{dealer}	dem_{asset}	dem_{lev}	dem_{other}	dem_{fin}	dem_{nc}	dem_c
mean	0.423	-3.130	-2.290	4.990	0.137	2.700	3.800	-5.530
sd	2.240	40.60	13.90	29.20	7.480	32.80	27.00	36.40
min	0.005	-88.10	-61.00	-56.90	-29.00	-70.90	-60.30	-85.50
max	52.10	83.40	41.50	73.20	39.40	79.70	82.50	79.60
N	3774	986	986	986	986	986	1444	1444

	cds	fxi	cap_b	cap_e	cap_t	$sent$	$tvol$	$ivol$
mean	30.27	0.015	-0.732	-0.469	-0.210	-0.386	0.466	0.327
sd	26.64	0.307	36.10	19.80	25.35	2.806	0.196	0.165
min	1.250	-2.170	-139.3	-119.2	-118.0	-11.29	0.061	0.053
max	170.0	7.561	189.5	164.5	170.1	10.12	3.040	2.410
N	1000	1343	4663	4663	4663	4193	3777	3741

Table A2 continued.

Panel C: Order Flow and Trading Volume

	of_{tot}	of_{bank}	of_{co}	of_{fund}	of_{nbf}	vol_{tot}	vol_{bank}
mean	0.025	0.175	-0.006	-0.110	-0.033	25.51	25.37
sd	1.612	1.414	0.113	0.534	0.137	1.627	1.798
min	-6.070	-5.488	-0.658	-3.335	-0.875	21.41	16.08
max	10.04	9.811	0.705	3.407	0.557	28.01	27.85
N	660	660	660	660	660	660	638

	vol_{co}	vol_{fund}	vol_{nbf}	$of_{bankres}$	of_{bankco}	$of_{bankfund}$	$of_{banknbf}$
mean	20.29	23.17	22.35	0.000	-0.012	-0.037	0.091
sd	1.875	1.298	1.839	0.640	0.253	0.272	0.249
min	14.51	20.15	15.06	-3.409	-2.612	-4.100	-0.620
max	24.07	25.81	24.88	3.792	2.932	0.618	2.553
N	644	660	660	660	660	660	660

Panel D: Other Control Variables

	mom_1	mom_{12}	og	tr	ts	$dollarexp$	afd	vrp_{1y}	vrp_{1m}	qrp
mean	0.123	0.680	-0.334	-0.103	-0.563	-0.031	-46.20	-101.6	-45.40	0.062
sd	3.010	9.730	194.7	19.50	1.550	0.801	88.70	14.40	6.030	0.399
min	-15.70	-41.20	-1399	-141.0	-12.46	-8.052	-100.0	-169.1	-76.40	-2.500
max	16.90	36.30	1521	152.2	4.269	41.31	100.0	-61.90	-19.50	2.520
N	3735	5085	4068	4066	4872	3236	3740	2624	2624	2624

	bb	ma	$macd$	rsi	ma_{120}	ma_{150}	ma_{1200}	$skew$	$iskew$	$coskew$
mean	0.439	0.552	-6.211	-0.232	0.439	0.467	0.779	0.894	-4.120	0.955
sd	11.79	11.82	9.834	6.327	11.79	14.79	17.04	66.30	59.50	38.20
min	-23	-23	-23	-23	-23	-23	-23	-327.3	-264.3	-87.40
max	23	23	0	22	23	23	23	291.7	277.6	94.70
N	5085	5085	5085	5085	5085	5085	5085	3777	3741	3777

	max	min	st	pth	ptl	$tkmsci$	mom_{w1}	mom_{w2}	mom_{w3}	mom_{1d}
mean	1.240	1.230	0.002	92.80	108.7	-3.590	0.028	0.049	0.001	0.038
sd	0.676	0.668	0.242	6.330	7.220	1.980	1.260	1.780	2.220	0.663
min	0.117	0.096	-1.820	61.50	100.0	-8.770	-10.50	-14.60	-15.90	-2.980
max	12.70	8.920	1.550	100.0	146.9	1.200	5.780	7.870	14.20	4.020
N	3777	3777	5083	3773	3773	2063	5085	5085	5085	3772

Table A3: Trading Activities and Sentiment

This table presents estimates of the following panel regression: $rx_{i,t+1} = \alpha_i + \gamma_t + \beta_1 tk_{i,t} + \beta_2 tk_{i,t} \times flow_{i,t} + \beta_3 flow_{i,t} + \delta X_{i,t} + u_{i,t+1}$, where $rx_{i,t+1}$ is the monthly currency i excess return at time $t+1$, $tk_{i,t}$ is the prospect-theory value for currency i at time t, α_i and γ_t represent currency fixed effects and and time (year-month) fixed effects dummies respectively. The set of control variables X consists of the forward discount $fd_{i,t}$, the cumulative exchange rate return over the past three months $mom_{i,t}$, and the negative of the past five-year real exchange rate change $val_{i,t}$. The trading activity variable $flow_{i,t}$ corresponds to one of the following currency-level proxies: central bank foreign exchange intervention on spot rate to GDP ratio (fxi), CFTC non-commercial trader demand pressure (dem_{nc}), CFTC commercial trader demand pressure (dem_c), TIC bilateral bond capital net flow (cap_b), equity capital net flow (cap_e), total capital net flow (cap_{tot}), and foreign-US sentiment spread ($sent$). t-statistics (reported in brackets) are based on standard errors double-clustered by currency and time. The sample runs from January 1990 to February 2018 and covers 15 currencies for developed economies. All variables are standardized to facilitate interpretation.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	fxi	dem_{nc}	dem_c	cap_b	cap_e	cap_{tot}	$sent$
tk_t	-0.27	-0.25	-0.25	-0.19	-0.19	-0.19	-0.19
	[-3.77]	[-3.21]	[-3.18]	[-5.25]	[-5.25]	[-5.26]	[-5.01]
$tk_t \times flow_t$	-0.07	0.10	-0.10	0.03	-0.02	0.03	0.01
	[-1.97]	[1.96]	[-1.80]	[0.45]	[-0.60]	[0.53]	[0.26]
$flow_t$	0.01	-0.01	0.02	-0.00	-0.02	-0.01	0.07
	[0.56]	[-0.45]	[0.49]	[-0.09]	[-1.71]	[-0.23]	[2.23]
fd_t	0.08	-0.02	-0.01	0.04	0.03	0.04	0.04
	[0.91]	[-0.13]	[-0.12]	[0.68]	[0.63]	[0.69]	[0.53]
mom_t	-0.03	0.04	0.04	0.03	0.03	0.03	0.03
	[-1.04]	[1.38]	[1.37]	[1.25]	[1.24]	[1.25]	[0.95]
val_t	0.02	0.01	0.01	0.03	0.03	0.03	0.05
	[0.42]	[0.26]	[0.27]	[0.96]	[1.01]	[0.96]	[1.39]
Curr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Nr.Obs	1,519	1,368	1,368	3,441	3,441	3,441	2,957
R^2	71.5%	58.1%	58.1%	59.7%	59.7%	59.7%	56.2%

Table A4: Decomposition Analysis

This table presents results of decomposition analysis. Panel A reports results using different prospect-theory-value components. Different components of prospect-theory value are reflected in our baseline parameter specification $(\alpha, \lambda, \gamma, \delta) = (0.88, 2.25, 0.61, 0.69)$. To test the predictive power of each component, we turn off the relevant parameters and test whether the corresponding tk measure still forecasts future returns. The three components are loss aversion (la) $(1, 2.25, 1, 1)$, convexity and concavity (cc) $(0.88, 1, 1, 1)$, and probability weighting (pw) $(1, 1, 0.61, 0.69)$. We also consider combinations of two components: loss aversion and convexity/concavity ($lacc$) $(0.88, 2.25, 1, 1)$, loss aversion and probability weighting ($lapw$) $(1, 2.25, 0.61, 0.69)$, and convexity/concavity and probability weighting ($ccpw$) $(0.88, 1, 0.61, 0.69)$. Panel B reports results using time-series (ts), between-currency-and-time (btc), and cross-sectional (cs) components of prospect-theory value. For each panel, we present estimates of the following panel regression: $rx_{i,t+1} = \alpha_i + \gamma_t + \beta_1 tk_{i,t} + \delta X_{i,t} + u_{i,t+1}$, where $rx_{i,t+1}$ is the currency i excess return at month $t+1$, $tk_{i,t}$ is the prospect-theory value for currency i at time t, α_i and γ_t represent currency fixed effects and time (year-month) fixed effects dummies respectively. Note that when tk_{ts} (or tk_{cs}) is used, only currency fixed effects (or time fixed effects) are controlled, as adding time fixed effects (or currency fixed effects) would absorb tk_{ts} (or tk_{cs}), respectively. The set of control variables X consists of the forward discount $fd_{i,t}$, the cumulative exchange rate return over the past three months $mom_{i,t}$, and the negative of the past five-year real exchange rate change $val_{i,t}$. t-statistics (reported in brackets) are based on standard errors double-clustered by currency and time. The sample runs from January 1990 to February 2018 and covers 15 currencies for developed economies. All variables are standardized.

Panel A: Behavioral Components

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	tk	la	cc	pw	$lacc$	$lapw$	$ccpw$
tk_t	-0.17	-0.15	-0.13	-0.15	-0.15	-0.16	-0.16
	[-3.94]	[-4.02]	[-3.72]	[-4.18]	[-3.96]	[-3.80]	[-4.47]
fd_t	0.04	0.06	0.07	0.03	0.06	0.03	0.03
	[0.71]	[1.07]	[1.20]	[0.49]	[1.18]	[0.64]	[0.57]
mom_t	0.03	0.03	0.03	0.03	0.03	0.03	0.03
	[1.21]	[1.33]	[1.42]	[1.35]	[1.34]	[1.18]	[1.41]
val_t	0.04	0.03	0.03	0.03	0.03	0.04	0.03
	[1.11]	[1.00]	[0.85]	[0.91]	[1.01]	[1.10]	[0.91]
Curr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Nr.Obs	3,597	3,597	3,597	3,597	3,597	3,597	3,597
R-squared	58.8%	58.9%	58.9%	58.9%	58.9%	58.8%	58.9%

Panel B: cs, btc, and ts Components

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$tk_{cs,t}$	-0.02			-0.02		-0.01	-0.01
	[-0.89]			[-0.92]		[-0.42]	[-0.49]
$tk_{btc,t}$		-0.11		-0.10	-0.09		-0.09
		[-3.94]		[-3.75]	[-2.11]		[-2.06]
$tk_{ts,t}$			0.01		0.00	0.01	0.00
			[0.34]		[-0.09]	[0.32]	[-0.09]
fd_t	0.07	0.04	0.07	0.06	0.05	0.07	0.06
	[1.66]	[0.71]	[0.74]	[1.36]	[0.55]	[0.94]	[0.74]
mom_t	0.02	0.03	0.06	0.03	0.07	0.06	0.07
	[0.99]	[1.21]	[1.72]	[1.29]	[1.87]	[1.74]	[1.88]
val_t	0.03	0.04	0.03	0.03	0.03	0.03	0.03
	[0.81]	[1.11]	[0.72]	[1.02]	[0.77]	[0.70]	[0.75]
Curr FE	No	Yes	Yes	No	Yes	No	No
Time FE	Yes	Yes	No	Yes	No	No	No
Nr.Obs	3,597	3,597	3,597	3,597	3,597	3,597	3,597
R^2	58.5%	58.8%	0.9%	58.8%	1.2%	0.8%	1.1%

Table A5: Alternative Explanations

This table reports results controlling for alternative explanations. Panel A reports results controlling for the profitability of four prevalent technical trading rules: Bollinger band (BB), moving average (MA), moving average convergence divergence ($MACD$), and relative strength index (RSI). Panel B reports results controlling for the profitability of moving average strategies with different window sizes ($MA120$, $MA150$, $MA1200$) corresponding to the past 120, 150, and 1200 days. Panel C reports results controlling for time-series momentum strategies with different look-back windows ($MOMTS1m$, $MOMTS3m$, $MOMTS6m$, $MOMTS9m$, $MOMTS12m$) from the past 1 month to 12 months. Panel D reports results controlling for factor momentum strategies with different look-back windows ($MOMF1m$, $MOMF3m$, $MOMF6m$, $MOMF9m$, $MOMF12m$) from the past 1 month to 12 months, where the average of dollar and carry factor momentum is used. Panel E reports results controlling for skewness-related factors and alternative behavioral factors formed based on skewness ($SKEW$), idiosyncratic skewness ($IdioSKEW$), co-skewness ($CoSKEW$), maximum daily return within the month (MAX), the negative of the minimum daily return within the month (MIN), salience theory value based on the past 1-month daily returns (ST), 52-week high (PTH), and 52-week low (PTL). We conduct time-series asset pricing tests for long–short strategy returns based on prospect-theory value (or prospect-theory premium PTP) from January 1990 to February 2018 for the sample of 15 currencies for developed economies. The dependent variable is the monthly excess return on the PTP strategy and the independent variables are the returns on the set of alternative factors. We report α, βs, and adjusted R^2s. Numbers in brackets are t-statistics based on Newey–West standard errors. Monthly abnormal returns and betas are reported in percentage points.

Panel A: Technical Trading

α	β_{BB}	β_{MA}	β_{MACD}	β_{RSI}	$\bar{R}^2$
0.43	-19.86	0.19	-82.12	-60.07	7.71%
[3.32]	[-1.11]	[0.01]	[-3.42]	[-1.72]	

Panel B: Moving Average

α	β_{MA120}	β_{MA150}	β_{MA1200}	$\bar{R}^2$
0.48	0.32	32.96	-58.06	7.10%
[3.71]	[0.02]	[1.82]	[-3.66]	

Panel C: Time-Series Momentum

α	$\beta_{MOMTS1m}$	$\beta_{MOMTS3m}$	$\beta_{MOMTS6m}$	$\beta_{MOMTS9m}$	$\beta_{MOMTS12m}$	$\bar{R}^2$
0.45	10.37	12.36	-12.24	-40.55	21.96	5.30%
[3.44]	[1.27]	[1.19]	[-1.06]	[-3.02]	[1.47]	

Panel D: Factor Momentum

α	β_{MOMF1m}	β_{MOMF3m}	β_{MOMF6m}	β_{MOMF9m}	$\beta_{MOMF12m}$	$\bar{R}^2$
0.46	-13.14	17.30	-1.03	-21.05	5.94	0.97%
[3.40]	[-1.66]	[1.74]	[-0.11]	[-2.12]	[0.59]	

Panel E: Skewness and Other Behavioral Factors

α	β_{SKEW}	$\beta_{IdioSKEW}$	β_{CoSKEW}	β_{MAX}	β_{MIN}	β_{ST}	β_{PTH}	β_{PTL}	$\bar{R}^2$
0.44	0.90	-7.83	-5.57	14.39	13.89	-2.28	-36.95	5.91	28.49%
[4.01]	[0.12]	[-1.18]	[-0.96]	[1.89]	[1.64]	[-0.33]	[-5.27]	[0.87]	

Table A6: Relation with Volatility Risk Premia

This table presents results on the relation with volatility risk premia. We control for currency volatility risk premia in the main predictive panel regression analysis. We present estimates of the following panel regression: $rx_{i,t+1} = \alpha_i + \gamma_t + \beta_1 tk_{i,t} + \beta_2 vrp1y_{i,t} + \beta_3 tk_{i,t} \times vrp1y_{i,t} + \delta X_{i,t} + u_{i,t+1}$, where $rx_{i,t+1}$ is the currency i excess return at month $t+1$, $tk_{i,t}$ is the prospect-theory value for currency i at time t, and $vrp1y_{i,t}$ is the currency volatility risk premia, defined as the difference between realized volatility and option-implied volatility from options with 1-year maturity, closely following Della Corte et al. (2016). $tk_{i,t} \times vrp1y_{i,t}$ is the interaction term between prospect-theory value and volatility risk premia. α_i and γ_t represent currency fixed effects and time (year-month) fixed effects dummies respectively. The set of control variables X consists of the forward discount $fd_{i,t}$, the cumulative exchange rate return over the past three months $mom_{i,t}$, and the negative of the past five-year real exchange rate change $val_{i,t}$. t-statistics (reported in brackets) are based on standard errors double-clustered by currency and time. All variables are standardized to facilitate interpretation. The sample runs from January 1996 to February 2018 and covers G10 currencies for developed economies. The starting date and sample of currencies are restricted by the available option data.

	(1)	(2)	(3)	(4)
tk_t	-0.20	-0.23	-0.21	-0.24
	[-3.22]	[-3.46]	[-3.13]	[-3.41]
fd_t			0.05	0.04
			[0.81]	[0.70]
mom_t			0.01	0.02
			[0.42]	[0.71]
val_t			0.04	0.05
			[1.30]	[1.45]
$vrp1y_t$	0.05	0.05	0.04	0.04
	[0.59]	[0.60]	[0.46]	[0.45]
$tk_t \times vrp1y_t$		0.19		0.20
		[2.37]		[2.54]
Curr FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Nr.Obs	2,602	2,602	2,548	2,548
R^2	59.2%	59.5%	58.8%	59.1%

Table A7: Portfolio Excess Returns: Alternative Measures of Prospect-Theory Value

This table reports monthly excess returns of prospect-theory-value-sorted portfolios from January 1990 to February 2018 for the sample of 15 currencies for developed economies using alternative measures. Panel A reports results using different formation periods (f). Panel B reports results using different input variables (currency excess return rx and forward discount fd) to calculate prospect-theory value. Panel C reports results using the exponential decay function (parameter ρ) in prospect-theory value, namely $tk(\rho) = \frac{1}{\rho}\sum_{j=-m}^{-1} \rho^{t(j)} v(\Delta s_{i,j}) \left[w^-(\frac{j+m+1}{K}) - w^-(\frac{j+m}{K})\right] + \sum_{j=1}^{n} \rho^{t(j)} v(\Delta s_{i,j}) \left[w^+(\frac{n-j+1}{K}) - w^+(\frac{n-j}{K})\right]$, where $\rho = \rho^1 + ... + \rho^{60}$, and $t(j)$ is the number of months ago the return Δs_j was realized, as in Barberis et al. (2016). Panel D reports results replacing prospect-theory value with expected utility value with different values of risk aversion parameters (θ), namely $EU = \sum_{j=-m}^{n} \frac{1}{60} \frac{(1+\Delta s)^{1-\theta}}{1-\theta}$, as in Barberis et al. (2016). P_1 to P_5 are currency prospect-theory-value-sorted portfolios from low to high. AVG and PTP are average portfolio returns and returns of a strategy that goes short the high-prospect-theory-value portfolio (P_5) and long the low-prospect-theory-value portfolio (P_1). Returns are not adjusted for transaction costs. Monthly average returns are reported in percentage points. Figures in brackets are t-statistics based on Newey and West (1987) standard errors with optimal lag selection following Andrews (1991).

	P_1	P_2	P_3	P_4	P_5	AVG	PTP
			Panel A: Different Formation Periods				
$f = 36$	0.22	0.19	0.13	0.04	0.03	0.12	0.19
	[1.20]	[1.18]	[0.74]	[0.26]	[0.22]	[0.85]	[1.47]
$f = 48$	0.30	0.22	0.10	0.09	-0.08	0.13	0.38
	[1.64]	[1.26]	[0.65]	[0.61]	[-0.63]	[0.89]	[2.98]
$f = 72$	0.29	0.22	0.11	0.05	-0.04	0.12	0.33
	[1.55]	[1.31]	[0.65]	[0.33]	[-0.34]	[0.87]	[2.22]
			Panel B: Different Variables				
rx	0.37	0.07	0.12	0.01	-0.03	0.11	0.41
	[2.29]	[0.37]	[0.71]	[0.05]	[-0.28]	[0.75]	[3.08]
fd	0.02	0.10	0.17	0.03	0.28	0.12	-0.27
	[0.10]	[0.63]	[1.12]	[0.20]	[1.56]	[0.85]	[-1.74]
			Panel C: Different Functions: Exponential Decay				
$\rho = 1$	0.37	0.19	0.09	-0.02	-0.05	0.12	0.42
	[2.02]	[1.11]	[0.53]	[-0.14]	[-0.38]	[0.82]	[3.14]
$\rho = 0.95$	0.25	0.12	0.08	0.08	0.10	0.13	0.15
	[1.48]	[0.63]	[0.50]	[0.57]	[0.78]	[0.89]	[1.18]
$\rho = 0.9$	0.21	0.14	0.11	0.08	0.09	0.13	0.12
	[1.23]	[0.76]	[0.66]	[0.51]	[0.71]	[0.90]	[0.82]
$\rho = 0.85$	0.20	0.09	0.20	0.01	0.13	0.13	0.07
	[1.14]	[0.55]	[1.13]	[0.08]	[1.00]	[0.90]	[0.50]
			Panel D: Different Functions: Expected Utility				
$\theta = 10$	0.19	0.24	0.23	0.03	-0.08	0.12	0.27
	[1.25]	[1.41]	[1.48]	[0.20]	[-0.56]	[0.87]	[1.91]
$\theta = 5$	0.20	0.26	0.09	0.08	-0.02	0.12	0.22
	[1.41]	[1.54]	[0.59]	[0.45]	[-0.15]	[0.86]	[1.60]
$\theta = 3$	0.21	0.22	0.04	0.08	-0.01	0.11	0.22
	[1.58]	[1.33]	[0.25]	[0.49]	[-0.03]	[0.78]	[1.56]

Table A8: Portfolio Excess Returns: Sub-Sample Analysis

This table reports currency portfolio performance for the sample of 15 currencies for developed economies under different sub-sample periods. We consider NBER recession and non-recession periods, and periods before (January 1990 to December 2006) and after (January 2007 to February 2018) the financial crisis. Returns are not adjusted for transaction costs. Monthly returns and standard deviations are reported in percentage points. Skewness, kurtosis, and monthly Sharpe ratios are also reported. Figures in brackets are t-statistics based on Newey and West (1987) standard errors with optimal lag selection following Andrews (1991).

	CAR	MOM	VAL	PTP	CAR	MOM	VAL	PTP
Panel A: NBER Recessions								
	Recession				Non-Recession			
$Mean$	-0.39	0.67	0.27	0.77	0.48	0.20	0.03	0.38
	[-0.40]	[1.02]	[0.56]	[1.18]	[3.29]	[1.47]	[0.21]	[2.88]
Std	4.37	3.53	3.12	3.48	2.59	2.58	2.24	2.29
$Skew$	-0.46	1.23	0.42	0.05	-0.41	0.15	-0.29	0.22
$Kurt$	4.31	5.17	3.21	3.43	3.50	4.22	3.35	4.35
SR	-0.09	0.19	0.09	0.22	0.18	0.08	0.01	0.17
Panel B: Financial Crisis								
	Before Crisis				After Crisis			
$Mean$	0.53	0.45	0.15	0.45	0.17	-0.06	-0.10	0.37
	[2.88]	[2.86]	[0.90]	[2.67]	[0.56]	[-0.24]	[-0.53]	[1.69]
Std	2.44	2.55	2.29	2.35	3.33	2.87	2.40	2.57
$Skew$	-0.52	0.50	-0.14	0.18	-0.50	0.44	-0.03	0.29
$Kurt$	3.85	4.60	3.71	4.90	4.70	5.17	3.43	3.99
SR	0.22	0.18	0.06	0.19	0.05	-0.02	-0.04	0.14

Table A9: Transaction-Cost-Adjusted Portfolio Returns

This table reports returns and characteristics of prospect-theory-value-sorted portfolios adjusted for transaction costs from January 1990 to February 2018 for the sample of 15 currencies for developed economies. P_1 to P_5 are prospect-theory-value-sorted portfolios from low to high. AVG and PTP are average portfolio returns and returns of a strategy that goes short the high-prospect-theory-value portfolio (P_5) and long the low-prospect-theory-value portfolio (P_1). Returns are adjusted for transaction costs. Monthly average returns and standard deviations are reported in percentage points. Skewness, kurtosis, monthly Sharpe ratios, and first-order autocorrelation coefficients (and p-values) are also reported. Figures in brackets are t-statistics based on Newey and West (1987) standard errors with optimal lag selection following Andrews (1991). We consider both currency excess returns (Panel A) and the exchange rate return component (Panel B).

	$P1$	$P2$	$P3$	$P4$	$P5$	AVG	PTP
Panel A: Currency Excess Returns							
$Mean$	0.37	0.17	0.08	-0.04	-0.04	0.11	0.41
	[2.01]	[1.03]	[0.44]	[-0.31]	[-0.29]	[0.76]	[3.05]
Std	3.04	2.86	2.82	2.51	2.14	2.33	2.44
$Skew$	-0.14	-0.06	-0.18	-0.28	-0.26	-0.19	0.22
$Kurt$	5.07	3.33	3.25	4.64	5.74	3.80	4.47
SR	0.12	0.06	0.03	-0.02	-0.02	0.05	0.17
$AR(1)$	0.09	0.04	0.10	0.01	0.12	0.10	0.10
p	(0.12)	(0.51)	(0.07)	(0.86)	(0.08)	(0.09)	(0.12)
Panel B: Exchange Rate Returns							
$Mean$	0.23	0.11	0.04	-0.05	-0.07	0.05	0.30
	[1.28]	[0.66]	[0.24]	[-0.37]	[-0.53]	[0.37]	[2.23]
Std	3.03	2.84	2.82	2.51	2.14	2.32	2.44
$Skew$	-0.19	-0.08	-0.21	-0.37	-0.21	-0.23	0.16
$Kurt$	5.16	3.35	3.35	4.92	5.80	3.87	4.58
SR	0.08	0.04	0.01	-0.02	-0.03	0.02	0.12
$AR(1)$	0.09	0.03	0.10	0.02	0.11	0.09	0.11
p	(0.14)	(0.62)	(0.09)	(0.82)	(0.10)	(0.12)	(0.10)

Table A10: Explanatory Power of Prospect-Theory-Value Components

This table reports returns of prospect-theory-value-component-sorted portfolios from January 1990 to February 2018 for the sample of 15 currencies for developed economies using prospect-theory-value components: loss aversion (la), convexity and concavity (cc), and probability weighting (pw). P_1 to P_5 are currency prospect-theory-value-sorted portfolios from low to high. AVG and PTP are average portfolio returns and returns of a strategy that goes short the high-prospect-theory-value portfolio (P_5) and long the low-prospect-theory-value portfolio (P_1). Returns are not adjusted for transaction costs. Monthly average returns are reported in percentage points. Figures in brackets are t-statistics based on Newey and West (1987) standard errors with optimal lag selection following Andrews (1991).

	$P1$	$P2$	$P3$	$P4$	$P5$	AVG	PTP
			Panel A: Currency Excess Returns				
tk	0.37	0.19	0.09	-0.02	-0.05	0.12	0.42
	[2.02]	[1.11]	[0.53]	[-0.14]	[-0.38]	[0.82]	[3.14]
la	0.26	0.21	0.12	0.06	-0.08	0.11	0.33
	[1.56]	[1.27]	[0.69]	[0.38]	[-0.61]	[0.80]	[2.64]
cc	0.26	0.18	0.09	0.13	-0.09	0.12	0.35
	[1.83]	[1.03]	[0.58]	[0.82]	[-0.52]	[0.82]	[2.43]
pw	0.26	0.26	0.15	0.09	-0.16	0.12	0.41
	[1.68]	[1.52]	[0.89]	[0.60]	[-1.08]	[0.84]	[3.07]
			Panel B: Exchange Rate Returns				
tk	0.23	0.12	0.05	-0.03	-0.08	0.06	0.31
	[1.28]	[0.71]	[0.29]	[-0.24]	[-0.60]	[0.41]	[2.29]
la	0.18	0.16	0.05	-0.01	-0.13	0.05	0.31
	[1.16]	[1.00]	[0.29]	[-0.04]	[-1.03]	[0.38]	[2.47]
cc	0.21	0.10	0.03	0.07	-0.15	0.05	0.35
	[1.48]	[0.60]	[0.19]	[0.46]	[-0.91]	[0.38]	[2.55]
pw	0.15	0.18	0.07	0.01	-0.13	0.06	0.28
	[1.02]	[1.08]	[0.42]	[0.04]	[-0.88]	[0.40]	[2.10]

Table A11: Portfolio Excess Returns: Extended Samples of Currencies

This table reports returns and characteristics of prospect-theory-value-sorted portfolios from January 1990 to February 2018 using different numbers of currencies. We consider extended samples of currencies including 48 developed and emerging currencies as in Menkhoff et al. (2012), 37 developed and emerging currencies as in Lustig et al. (2011), 20 developed and emerging currencies, and G10 currencies. P_1 to P_5 are prospect-theory-value-sorted portfolios from low to high. AVG and PTP are average portfolio returns and returns of a strategy that goes short the high-prospect-theory-value portfolio (P_5) and long the low-prospect-theory-value portfolio (P_1). Returns are not adjusted for transaction costs. Monthly average returns and standard deviations are reported in percentage points. Skewness, kurtosis, and monthly Sharpe ratios are also reported. Figures in brackets are t-statistics based on Newey and West (1987) standard errors with optimal lag selection following Andrews (1991). We consider both currency excess returns and the exchange rate return component.

	$P1$	$P2$	$P3$	$P4$	$P5$	AVG	PTP
				Panel A: 48 Currencies			
$Mean$	0.26	0.33	0.10	0.06	0.06	0.16	0.20
	[1.02]	[2.13]	[0.63]	[0.56]	[1.14]	[1.29]	[0.82]
Std	3.16	2.53	2.64	1.86	0.85	1.93	2.85
$Skew$	0.29	-0.22	-0.35	-0.61	-0.30	-0.37	0.50
$Kurt$	4.54	3.86	4.08	5.90	7.17	4.35	4.91
SR	0.08	0.13	0.04	0.03	0.07	0.08	0.07
				Panel B: 37 Currencies			
$Mean$	0.39	0.29	0.08	0.03	-0.01	0.15	0.39
	[2.16]	[1.87]	[0.51]	[0.25]	[-0.12]	[1.33]	[2.48]
Std	2.96	2.52	2.53	1.86	0.80	1.90	2.62
$Skew$	-0.33	-0.16	-0.29	-0.49	-0.62	-0.43	-0.25
$Kurt$	5.12	3.69	4.02	5.72	9.24	4.38	4.73
SR	0.13	0.11	0.03	0.01	-0.01	0.08	0.15
				Panel C: 20 Currencies			
$Mean$	0.51	0.27	0.03	0.04	-0.05	0.16	0.56
	[1.98]	[1.68]	[0.16]	[0.35]	[-0.77]	[1.18]	[2.40]
Std	3.33	2.76	2.61	2.22	1.23	2.11	2.82
$Skew$	0.15	-0.10	-0.24	-0.14	-0.61	-0.22	0.53
$Kurt$	4.62	3.49	3.44	6.77	6.44	3.97	4.65
SR	0.15	0.10	0.01	0.02	-0.04	0.08	0.20
				Panel D: 10 Currencies			
$Mean$	0.34	0.19	0.03	0.05	-0.06	0.11	0.40
	[1.86]	[1.12]	[0.19]	[0.42]	[-0.46]	[0.78]	[2.91]
Std	3.09	2.81	2.95	2.41	2.19	2.27	2.56
$Skew$	-0.08	-0.05	-0.40	-0.09	-0.20	-0.16	0.32
$Kurt$	5.00	3.32	4.12	4.54	5.69	3.77	4.97
SR	0.11	0.07	0.01	0.02	-0.03	0.05	0.16

Table A12: Portfolio Excess Returns: Removing Currencies of Less Open Economies

This table reports returns and characteristics of prospect-theory-value-sorted portfolios from January 1990 to February 2018 using different numbers of currencies. We consider 48 currencies of developed and emerging economies as in Menkhoff et al. (2012). Panel A reports results after excluding less open currencies with a Chinn and Ito (2006) *kaopen* index (an index measuring a country's capital account openness) below zero. Panel B reports results after excluding less open currencies with a *kaopen* index below one. P_1 to P_5 are prospect-theory-value-sorted portfolios from low to high. AVG and PTP are average portfolio returns and returns of a strategy that goes short the high-prospect-theory-value portfolio (P_5) and long the low-prospect-theory-value portfolio (P_1). Returns are not adjusted for transaction costs. Monthly average returns and standard deviations are reported in percentage points. Skewness, kurtosis, and monthly Sharpe ratios are also reported. Figures in brackets are t-statistics based on Newey and West (1987) standard errors with optimal lag selection following Andrews (1991).

	$P1$	$P2$	$P3$	$P4$	$P5$	AVG	PTP
			Panel A: $kaopen > 0$				
$Mean$	0.31	0.31	0.06	0.15	0.01	0.17	0.30
	[1.83]	[1.76]	[0.43]	[1.26]	[0.11]	[1.45]	[2.02]
Std	2.94	2.73	2.51	2.01	0.71	1.90	2.63
$Skew$	-0.38	-0.12	-0.37	-0.49	-0.86	-0.43	-0.35
$Kurt$	5.62	3.10	4.41	4.62	6.18	4.04	6.32
SR	0.10	0.11	0.03	0.08	0.01	0.09	0.11
			Panel B: $kaopen > 1$				
$Mean$	0.36	0.22	0.08	0.02	-0.05	0.13	0.41
	[1.88]	[1.42]	[0.57]	[0.20]	[-1.49]	[1.12]	[2.27]
Std	3.17	2.69	2.35	2.05	0.50	1.85	3.00
$Skew$	0.01	-0.03	-0.39	-0.58	-2.37	-0.31	0.12
$Kurt$	5.62	3.10	4.41	4.62	6.18	4.04	6.32
SR	0.11	0.08	0.03	0.01	-0.10	0.07	0.14

Table A13: Alternative Quote Currencies

This table reports returns and characteristics of prospect-theory-value-sorted portfolios from January 1990 to February 2018 using different quote currencies for the sample of 15 currencies for developed economies. P_1 to P_5 are prospect-theory-value-sorted portfolios from low to high. AVG and PTP are average portfolio returns and returns of a strategy that goes short the high-prospect-theory-value portfolio (P_5) and long the low-prospect-theory-value portfolio (P_1). Returns are not adjusted for transaction costs. Monthly average returns and standard deviations are reported in percentage points. Skewness, kurtosis, and monthly Sharpe ratios are also reported. Figures in brackets are t-statistics based on Newey and West (1987) standard errors with optimal lag selection following Andrews (1991). We consider GBP, CHF, and JPY as alternative quote currencies (other than USD).

	$P1$	$P2$	$P3$	$P4$	$P5$	AVG	PTP
			Panel A: GBP-Quoted Currencies				
$Mean$	0.25	0.15	-0.09	-0.02	-0.09	0.04	0.33
	[1.46]	[1.09]	[-0.81]	[-0.17]	[-0.98]	[0.34]	[2.23]
Std	2.95	2.47	2.42	2.36	1.50	1.95	2.52
$Skew$	0.63	1.39	0.53	0.93	0.43	1.10	0.16
$Kurt$	5.24	10.24	5.72	6.21	7.54	7.73	4.39
SR	0.08	0.06	-0.04	-0.01	-0.06	0.02	0.13
			Panel B: CHF-Quoted Currencies				
$Mean$	0.21	-0.01	0.12	0.01	-0.05	0.06	0.26
	[1.38]	[-0.07]	[1.05]	[0.11]	[-0.81]	[0.63]	[1.83]
Std	2.89	2.58	2.29	1.90	1.21	1.74	2.59
$Skew$	-0.23	-0.82	-0.95	-0.91	-0.52	-0.99	-0.14
$Kurt$	4.09	5.67	8.98	8.02	9.01	7.70	4.22
SR	0.07	0.00	0.05	0.01	-0.04	0.03	0.10
			Panel C: JPY-Quoted Currencies				
$Mean$	0.36	0.38	0.14	0.17	0.11	0.23	0.25
	[1.70]	[1.84]	[0.65]	[0.91]	[1.08]	[1.36]	[1.62]
Std	3.64	3.63	3.62	3.31	1.97	2.99	2.61
$Skew$	-0.62	-0.55	-0.73	-0.71	-0.84	-0.72	-0.45
$Kurt$	5.92	5.09	4.77	4.98	4.96	5.40	6.33
SR	0.10	0.11	0.04	0.05	0.06	0.08	0.09

Table A14: Additional Controls: Developed Economies

This table presents estimates of the following panel regression: $rx_{i,t+1} = \alpha_i + \gamma_t + \beta_1 tk_{i,t} + \delta X_{i,t} + u_{i,t+1}$, where $rx_{i,t+1}$ is the currency i excess return at time $t+1$, $tk_{i,t}$ is the prospect-theory value for currency i at time t, α_i and γ_t represent currency fixed effects and time (year-month) fixed effects dummies respectively. The set of control variables X consists of the forward discount fd_t, the cumulative exchange rate return over the past three months $mom_{i,t}$, and the negative of the past five-year real exchange rate change $val_{i,t}$, as well as additional control variables including past one-month return mom_1, past twelve-month return mom_{12}, output gap og, Taylor rule tr, term spread ts, dollar exposure β_{DOL}, average forward discount dummy afd, 1-month volatility risk premia ($vrp1m$), and synthetic quanto risk premia using currency implied volatility, VIX, and realized correlation (qrp). t-statistics (reported in brackets) are based on standard errors double-clustered by currency and time. The sample runs from January 1990 to February 2018 and covers 15 currencies of developed economies. All variables are standardized to facilitate interpretation.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
tk_t	-0.17	-0.17	-0.19	-0.19	-0.15	-0.19	-0.16	-0.19	-0.22	-0.20	-0.22
	[-3.95]	[-3.99]	[-4.64]	[-4.64]	[-4.05]	[-4.35]	[-3.75]	[-5.34]	[-3.48]	[-3.71]	[-3.65]
fd_t	0.04	0.04	0.04	0.04	0.01	0.06	-0.01	0.05	0.04	0.05	0.03
	[0.72]	[0.72]	[0.81]	[0.81]	[0.35]	[1.15]	[-0.09]	[1.20]	[0.74]	[0.77]	[1.37]
mom_t	0.03	0.03	0.05	0.05	0.02	0.02	0.03	0.03	0.01	0.01	0.02
	[0.84]	[1.19]	[2.15]	[2.15]	[0.84]	[0.81]	[1.17]	[0.97]	[0.44]	[0.43]	[0.52]
val_t	0.04	0.04	0.02	0.02	0.04	0.05	0.04	0.03	0.04	0.04	0.03
	[1.11]	[1.09]	[1.28]	[1.28]	[1.16]	[1.85]	[1.09]	[1.28]	[1.08]	[1.36]	[0.98]
$mom_{1,t}$	0.01							-0.02			-0.03
	[0.22]							[-0.54]			[-1.00]
$mom_{12,t}$		0.00						0.02			-0.01
		[-0.04]						[0.54]			[-0.26]
og			0.00					-0.40			-0.24
			[0.50]					[-0.55]			[-0.34]
tr				0.01				0.41			0.25
				[0.54]				[0.56]			[0.35]
ts					-0.05			-0.08			-0.09
					[-1.56]			[-1.96]			[-2.18]
β_{dol}						-0.09		-0.13			-0.19
						[-1.23]		[-1.24]			[-1.46]
afd							0.04	-0.02			-0.01
							[1.37]	[-0.87]			[-0.59]
$vrp1m$									0.07		0.07
									[1.20]		[1.04]
qrp										-0.02	-0.08
										[-0.45]	[-1.95]
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Curr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Nr.Obs	3,597	3,597	2,595	2,595	3,433	2,853	3,597	1,930	2,548	2,548	1,677
R^2	58.8%	58.8%	62.8%	62.8%	60.9%	58.7%	58.9%	62.7%	58.8%	58.8%	62.0%

Table A15: Additional Controls: Short-Term Reversal for Developed Economies

This table presents estimates of the following panel regression: $rx_{i,t+1} = \alpha_i + \gamma_t + \beta_1 tk_{i,t} + \delta X_{i,t} + u_{i,t+1}$, where $rx_{i,t+1}$ is the currency i excess return at time $t+1$, $tk_{i,t}$ is the prospect-theory value for currency i at time t, α_i and γ_t represent currency fixed effects and time (year-month) fixed effects dummies respectively. The set of control variables X consists of the forward discount fd_t, the cumulative exchange rate return over the past three months $mom_{i,t}$, and the negative of the past five-year real exchange rate change $val_{i,t}$, as well as additional short-term reversal variables including one-day $mom_{1d,t}$, one-week $mom_{1w,t}$, two-week $mom_{2w,t}$, and three-week $mom_{3w,t}$ lagged past returns from month end. t-statistics (reported in brackets) are based on standard errors double-clustered by currency and time. The sample runs from January 1990 to February 2018 and covers 15 currencies of developed economies. All variables are standardized to facilitate interpretation.

	(1)	(2)	(3)	(4)	(5)
tk_t	-0.17	-0.17	-0.17	-0.16	-0.16
	[-3.93]	[-3.92]	[-3.94]	[-3.91]	[-3.92]
$mom_{1w,t}$	0.00				0.02
	[0.13]				[0.43]
$mom_{2w,t}$		0.00			0.00
		[-0.08]			[-0.04]
$mom_{3w,t}$			-0.01		-0.01
			[-0.19]		[-0.17]
$mom_{1d,t}$				-0.02	-0.03
				[-1.16]	[-1.18]
fd_t	0.04	0.04	0.04	0.04	0.04
	[0.71]	[0.70]	[0.68]	[0.69]	[0.63]
mom_t	0.03	0.03	0.03	0.03	0.03
	[1.23]	[1.13]	[1.06]	[1.31]	[1.07]
val_t	0.04	0.04	0.04	0.04	0.04
	[1.12]	[1.11]	[1.11]	[1.07]	[1.08]
Curr FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Nr.Obs	3,597	3,597	3,597	3,597	3,597
R^2	58.80%	58.80%	58.80%	58.90%	58.90%

Table A16: Equity-Based Prospect-Theory Value for Developed Economies

This table presents estimates of the following panel regression: $rx_{i,t+1} = \alpha_i + \gamma_t + \beta_1 tk_{i,t} + \delta X_{i,t} + u_{i,t+1}$, where $rx_{i,t+1}$ is the currency i excess return at time $t+1$, $tk_{i,t}$ is the prospect-theory value for currency i at time t, α_i and γ_t represent currency fixed effects and time (year-month) fixed effects dummies respectively. The set of control variables X consists of the forward discount fd_t, the cumulative exchange rate return over the past three months $mom_{i,t}$, the negative of the past five-year real exchange rate change $val_{i,t}$, and an additional equity-based prospect-theory value using MSCI country-level equity price indices (in domestic currencies) $tkmsci_{i,t}$. t-statistics (reported in brackets) are based on standard errors double-clustered by currency and time. The sample runs from January 1990 to February 2018 and covers G10 currencies of developed economies. All variables are standardized to facilitate interpretation.

	(1)	(2)	(3)
tk_t	-0.09		-0.10
	[-3.52]		[-3.03]
$tkmsci_t$		0.04	-0.01
		[1.03]	[-0.11]
fd_t	0.02	0.04	0.03
	[0.79]	[1.35]	[1.00]
mom_t	0.03	0.01	0.02
	[1.16]	[0.35]	[0.62]
val_t	0.03	0.02	0.03
	[1.00]	[0.88]	[1.29]
Curr FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Nr.Obs	3,169	2,063	2,063
R^2	56.80%	54.00%	54.40%

Table A17: Multivariate Regression Analysis: Developed and Emerging Economies

This table presents estimates of the following panel regression: $rx_{i,t+1} = \alpha_i + \gamma_t + \beta_1 tk_{i,t} + \delta X_{i,t} + u_{i,t+1}$, where $rx_{i,t+1}$ is the currency i excess return at time $t+1$, $tk_{i,t}$ is the prospect-theory value for currency i at time t, α_i and γ_t represent currency fixed effects and time (year-month) fixed effects dummies respectively. The set of control variables X consists of the forward discount fd_t, the cumulative exchange rate return over the past three months mom_t, and the negative of the past five-year real exchange rate change val_t. t-statistics (reported in brackets) are based on standard errors double-clustered by currency and time. The sample runs from January 1990 to February 2018 and covers 37 currencies of developed and emerging economies. All variables are standardized to facilitate interpretation.

	(1)	(2)	(3)	(4)	(5)
tk_t	-0.14	-0.08	-0.15	-0.13	-0.09
	[-2.46]	[-1.50]	[-2.60]	[-3.00]	[-2.12]
fd_t		0.16			0.16
		[5.63]			[5.72]
mom_t			0.07		0.02
			[1.76]		[0.70]
val_t				0.02	0.01
				[0.90]	[0.51]
Time FE	Yes	Yes	Yes	Yes	Yes
Curr FE	Yes	Yes	Yes	Yes	Yes
Nr.Obs	7,889	7,869	7,889	5,561	5,558
R^2	40.0%	41.7%	40.5%	50.5%	52.5%

Table A18: Time-Series Asset Pricing Tests: Developed and Emerging Economies

This table reports time-series asset pricing tests for long–short strategy returns based on prospect-theory value (or prospect-theory premium PTP) from January 1990 to February 2018 for the 37 currencies of the developed and emerging economies sample. The dependent variable is the monthly excess return on the PTP strategy and the independent variables are the returns on the set of existing risk factors. We consider three sets of factors. Currency factors include dollar (DOL), carry (CAR), momentum (MOM), value (VAL), global imbalance (GI), and the unconditional mean-variance efficient portfolio ($UMVE$). Equity factors include market (MKT), book-to-market value (HML), size (SMB), and equity momentum (WML). Hedge fund factors include the bond (BO), currency (CU), and commodity (CO) trend-following factors, and the equity market (EQ), size spread (SS), bond market (BM), and credit spread (CS) factors of Fung and Hsieh (2004). Macro factor-mimicking portfolios are long–short beta-sorted portfolios based on shocks to FX volatility ($FVOL$), FX illiquidity ($FXBAS$), FX skewness ($FXSKEW$), CBOE VIX ($FVIX$), and TED spread ($FTED$). We report α, βs, and adjusted R^2s. Numbers in brackets are t-statistics based on Newey–West standard errors. Monthly abnormal returns and betas are reported in percentage points.

Panel A: Currency Factors

α	β_{DOL}	β_{CAR}	β_{MOM}	β_{VAL}	β_{GI}	β_{UMVE}	$\bar{R}^2$
0.34	9.94	13.94	-10.48	-6.76	25.03	0.08	10.10%
[2.36]	[1.19]	[2.01]	[-0.74]	[-0.54]	[2.67]	[2.66]	

Panel B: Equity Factors

α	β_{MKT}	β_{HML}	β_{SMB}	β_{WML}	$\bar{R}^2$
0.26	22.90	-1.12	3.64	-4.36	14.37%
[1.63]	[4.39]	[-0.24]	[0.60]	[-1.28]	

Panel C: Hedge Fund Factors

α	β_{BO}	β_{CU}	β_{CO}	β_{EQ}	β_{SS}	β_{BM}	β_{CS}	$\bar{R}^2$
0.42	-2.52	-0.78	-0.78	-3.47	-0.12	32.53	-299.58	7.70%
[2.80]	[-1.94]	[-0.81]	[-0.61]	[-0.73]	[-0.03]	[0.35]	[-3.06]	

Panel D: Macro Factor-Mimicking Portfolios

α	β_{DOL}	β_{FVOL}	β_{FBAS}	β_{FSKEW}	β_{FVIX}	β_{FTED}	$\bar{R}^2$
0.35	6.90	-46.37	26.47	11.54	-9.71	12.16	54.19%
[3.17]	[1.23]	[-4.82]	[3.59]	[1.47]	[-1.11]	[2.13]	

Table A19: Cross-Sectional Asset Pricing Tests: Developed and Emerging Economies

This table reports currency-level asset pricing results from January 1990 to February 2018 for 37 currencies for the developed and emerging economies. We use Fama–MacBeth two-stage regression to estimate the price of risk. The dependent variable is the one-month-ahead monthly unconditional individual currency excess return. The independent variables are the betas of the corresponding currency excess return on the following risk factors: dollar (DOL), carry (CAR), momentum (MOM), value (VAL), and the excess return on prospect-theory value (PTP). We also include prospect-theory value tk_t. Numbers in brackets are t-statistics based on Newey–West standard errors. Regression coefficients are reported in percentage points.

	(1)	(2)	(3)	(4)
β_{PTP}	0.31	-0.20	0.40	-0.02
	[1.55]	[-0.98]	[1.87]	[-0.09]
β_{DOL}	0.10	-0.37	-0.30	-0.74
	[0.25]	[-0.93]	[-0.63]	[-1.76]
β_{CAR}			0.46	0.17
			[0.65]	[0.22]
β_{MOM}			-0.20	-0.09
			[-0.45]	[-0.15]
β_{VAL}			0.27	0.54
			[0.58]	[1.08]
tk_{t-1}		-17.71		-13.95
		[-3.48]		[-2.56]
$Const$	-0.03	-0.16	0.00	-0.06
	[-0.41]	[-2.43]	[0.05]	[-1.47]
R^2	25.10%	33.20%	50.30%	57.80%

Table A20: Limits to Arbitrage: Developed and Emerging Economies

This table presents estimates of the following panel regression: $rx_{i,t+1} = \alpha_i + \gamma_t + \beta_1 tk_{i,t} + \beta_2 tk_{i,t} \times lta_{i,t} + \beta_3 lta_{i,t} + \delta X_{i,t} + u_{i,t+1}$, where $rx_{i,t+1}$ is the monthly currency i excess return at time $t+1$, $tk_{i,t}$ is the prospect-theory value for currency i at time t, α_i and γ_t represent currency fixed effects and time (year-month) fixed effects dummies respectively. The set of control variables X consists of the forward discount $fd_{i,t}$, the cumulative exchange rate return over the past three months $mom_{i,t}$, and the negative of the past five-year real exchange rate change $val_{i,t}$. The limits-to-arbitrage variable $lta_{i,t}$ corresponds to one of the following currency-level proxies: currency illiquidity using bid–ask spread (*bas*), idiosyncratic volatility (*ivol*), total volatility (*tvol*), and 5-year CDS spread (*cds*). We use levels of these variables. t-statistics (reported in brackets) are based on standard errors clustered by currency. The sample runs from January 1990 to February 2018 and covers 37 currencies for the developed and emerging economies. CDS data start from 2003; hence, the number of observations is smaller. All variables are standardized to facilitate interpretation.

	bas	*ivol*	*tvol*	*cds*
	(1)	(2)	(3)	(4)
tk_t	-0.09	-0.08	-0.06	-0.23
	[-2.07]	[-1.69]	[-1.28]	[-4.15]
$tk_t \times lta_t$	-0.03	-0.02	-0.07	-0.16
	[-7.51]	[-1.28]	[-1.74]	[-4.03]
lta_t	0.00	-0.02	-0.07	-0.26
	[0.39]	[-1.13]	[-1.56]	[-4.09]
fd_t	0.16	0.16	0.16	0.19
	[9.18]	[8.53]	[8.73]	[5.50]
mom_t	0.02	0.02	0.02	-0.01
	[0.62]	[0.59]	[0.61]	[-0.40]
val_t	0.01	0.01	0.01	-0.03
	[0.55]	[0.52]	[0.53]	[-0.80]
Curr FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Nr.Obs	5,554	5,558	5,558	2,011
R^2	52.5%	52.5%	52.6%	59.3%

Table A21: Trading Activities and Sentiment: Developed and Emerging Economies

This table presents estimates of the following panel regression: $rx_{i,t+1} = \alpha_i + \gamma_t + \beta_1 tk_{i,t} + \beta_2 tk_{i,t} \times flow_{i,t} + \beta_3 flow_{i,t} + \delta X_{i,t} + u_{i,t+1}$, where $rx_{i,t+1}$ is the monthly currency i excess return at time $t+1$, $tk_{i,t}$ is the prospect-theory value for currency i at time t, α_i and γ_t represent currency fixed effects and time (year-month) fixed effects dummies respectively. The set of control variables X consists of the forward discount $fd_{i,t}$, the cumulative exchange rate return over the past three months $mom_{i,t}$, and the negative of the past five-year real exchange rate change $val_{i,t}$. The trading activity variable $flow_{i,t}$ corresponds to one of the following currency-level proxies: central bank foreign exchange intervention on spot rate to GDP ratio (fxi), CFTC non-commercial trader demand pressure (dem_{nc}), CFTC commercial trader demand pressure (dem_c), TIC bilateral bond capital net flow (cap_b), equity capital net flow (cap_e), total capital net flow (cap_{tot}), and foreign-US sentiment spread ($sent$). t-statistics (reported in brackets) are based on standard errors double-clustered by currency and time. The sample runs from January 1990 to February 2018 and covers 37 currencies for developed and emerging economies. All variables are standardized to facilitate interpretation.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	fxi	dem_{nc}	dem_c	cap_b	cap_e	cap_{tot}	$sent$
tk_t	-0.10	-0.26	-0.25	-0.10	-0.10	-0.10	-0.17
	[-1.35]	[-3.51]	[-3.45]	[-1.93]	[-1.96]	[-1.91]	[-4.21]
$tk_t \times flow_t$	-0.00	0.03	-0.03	-0.03	-0.01	-0.05	0.02
	[-0.31]	[0.73]	[-0.67]	[-1.05]	[-0.27]	[-1.92]	[1.10]
$flow_t$	0.00	0.03	-0.02	-0.00	0.00	-0.00	0.05
	[0.28]	[1.09]	[-0.93]	[-0.39]	[0.26]	[-0.38]	[2.11]
fd_t	0.17	0.04	0.04	0.16	0.16	0.16	0.15
	[9.71]	[0.41]	[0.44]	[8.95]	[9.09]	[8.93]	[9.23]
mom_t	0.01	0.03	0.03	0.01	0.01	0.01	0.03
	[0.39]	[0.93]	[0.94]	[0.41]	[0.39]	[0.34]	[1.48]
val_t	0.00	-0.01	-0.01	0.01	0.01	0.01	0.02
	[0.19]	[-0.18]	[-0.17]	[0.42]	[0.40]	[0.45]	[0.63]
Curr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Nr.Obs	3,208	1,608	1,608	5,173	5,191	5,191	4,370
R^2	57.6%	54.2%	54.1%	55.0%	54.9%	55.0%	55.6%

Table A22: Decomposition Analysis: Developed and Emerging Economies

This table presents results of decomposition analysis. Panel A reports results using different prospect-theory-value components: loss aversion (la), convexity and concavity (cc), and probability weighting (pw). We also consider combinations of two components ($lacc$, $lapw$, $ccpw$). Panel B reports results using time-series (ts), between-currency-and-time (btc), and cross-sectional (cs) components of prospect-theory value. For each panel, we present estimates of the following panel regression: $rx_{i,t+1} = \alpha_i + \gamma_t + \beta_1 tk_{i,t} + \delta X_{i,t} + u_{i,t+1}$, where $rx_{i,t+1}$ is the currency i excess return at month $t+1$, $tk_{i,t}$ is the prospect-theory value for currency i at time t, α_i and γ_t represent currency fixed effects and time (year-month) fixed effects dummies respectively. The set of control variables X consists of the forward discount $fd_{i,t}$, the cumulative exchange rate return over the past three months $mom_{i,t}$, and the negative of the past five-year real exchange rate change $val_{i,t}$. t-statistics (reported in brackets) are based on standard errors double-clustered by currency and time. The sample runs from January 1990 to February 2018 and covers 37 currencies for developed and emerging economies. All variables are standardized to facilitate interpretation.

Panel A: Behavioral Components

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	tk	la	cc	pw	$lacc$	$lapw$	$ccpw$
tk_t	-0.09	-0.11	-0.11	-0.11	-0.13	-0.07	-0.13
	[-2.00]	[-2.47]	[-3.93]	[-3.32]	[-2.95]	[-1.67]	[-3.59]
fd_t	0.16	0.16	0.16	0.16	0.16	0.16	0.16
	[9.46]	[9.67]	[9.94]	[9.59]	[9.81]	[9.52]	[9.56]
mom_t	0.02	0.02	0.02	0.02	0.02	0.01	0.02
	[0.58]	[0.65]	[0.84]	[0.78]	[0.70]	[0.55]	[0.83]
val_t	0.01	0.01	0.01	0.01	0.01	0.01	0.01
	[0.53]	[0.43]	[0.60]	[0.61]	[0.45]	[0.56]	[0.62]
Curr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Nr.Obs	5,558	5,558	5,558	5,558	5,558	5,558	5,558
R-squared	52.5%	52.6%	52.6%	52.5%	52.6%	52.4%	52.6%

Panel B: cs, btc, and ts Components

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$tk_{cs,t}$	0.02			0.01		0.03	0.02
	[1.08]			[0.53]		[1.33]	[0.86]
$tk_{btc,t}$		-0.06		-0.06	-0.05		-0.05
		[-2.00]		[-2.38]	[-1.37]		[-1.67]
$tk_{ts,t}$			0.01		0.01	0.02	0.01
			[0.36]		[0.22]	[0.42]	[0.26]
fd_t	0.15	0.16	0.16	0.15	0.15	0.15	0.14
	[8.58]	[9.46]	[6.43]	[8.02]	[6.05]	[6.03]	[5.69]
mom_t	0.02	0.02	0.05	0.02	0.05	0.05	0.06
	[0.67]	[0.58]	[1.29]	[0.79]	[1.35]	[1.37]	[1.44]
val_t	0.01	0.01	0.03	0.01	0.03	0.03	0.03
	[0.71]	[0.53]	[0.89]	[0.41]	[0.88]	[0.89]	[0.89]
Curr FE	No	Yes	Yes	No	Yes	No	No
Time FE	Yes	Yes	No	Yes	No	No	No
Nr.Obs	5,558	5,558	5,558	5,558	5,558	5,558	5,558
R-squared	52.2%	52.5%	3.4%	52.3%	3.6%	3.2%	3.4%

Table A23: Alternative Explanations: Developed and Emerging Economies

This table reports results controlling for alternative explanations. Panel A reports results controlling for the profitability of four prevalent technical trading rules: Bollinger band (BB), moving average (MA), moving average convergence divergence ($MACD$), and relative strength index (RSI). Panel B reports results controlling for the profitability of moving average strategies with different window sizes ($MA120$, $MA150$, $MA1200$) corresponding to the past 120, 150, and 1200 days. Panel C reports results controlling for time-series momentum strategies with different look-back windows ($MOMTS1m$, $MOMTS3m$, $MOMTS6m$, $MOMTS9m$, $MOMTS12m$) from the past 1 month to 12 months. Panel D reports results controlling for factor momentum strategies with different look-back windows ($MOMF1m$, $MOMF3m$, $MOMF6m$, $MOMF9m$, $MOMF12m$) from the past 1 month to 12 months, where the average of dollar and carry factor momentum is used. Panel E reports results controlling for skewness-related factors and alternative behavioral factors formed based on skewness ($SKEW$), idiosyncratic skewness ($IdioSKEW$), co-skewness ($CoSKEW$), maximum daily return within the month (MAX), the negative of the minimum daily return within the month (MIN), salience theory value based on the past 1-month daily returns (ST), 52-week high (PTH), and 52-week low (PTL). We conduct time-series asset pricing tests for long–short strategy returns based on prospect-theory value (or prospect-theory premium PTP) from January 1990 to February 2018 for the sample of 37 currencies for developed and emerging economies. The dependent variable is the monthly excess return on the PTP strategy and the independent variables are the returns on the set of alternative factors. We report α, βs, and adjusted R^2s. Numbers in brackets are t-statistics based on Newey–West standard errors. Monthly abnormal returns and betas are reported in percentage points.

Panel A: Technical Trading

α	β_{BB}	β_{MA}	β_{MACD}	β_{RSI}	$\bar{R}^2$
0.51	-72.01	72.08	-388.85	56.08	25.00%
[3.85]	[-1.94]	[2.65]	[-7.34]	[0.99]	

Panel B: Moving Average

α	β_{MA120}	β_{MA150}	β_{MA1200}	$\bar{R}^2$
0.62	-40.95	40.62	-96.19	10.10%
[4.03]	[-1.74]	[1.51]	[-2.73]	

Panel C: Time-Series Momentum

α	$\beta_{MOMTS1m}$	$\beta_{MOMTS3m}$	$\beta_{MOMTS6m}$	$\beta_{MOMTS9m}$	$\beta_{MOMTS12m}$	$\bar{R}^2$
0.50	-9.92	-0.27	21.79	-83.98	54.62	2.60%
[3.39]	[-0.51]	[-0.01]	[0.93]	[-3.05]	[1.63]	

Panel D: Factor Momentum

α	β_{MOMF1m}	β_{MOMF3m}	β_{MOMF6m}	β_{MOMF9m}	$\beta_{MOMF12m}$	$\bar{R}^2$
0.43	5.67	7.30	-4.27	-23.43	25.59	0.48%
[2.47]	[0.33]	[0.47]	[-0.37]	[-1.21]	[1.49]	

Panel E: Skewness and Other Behavioral Factors

α	β_{SKEW}	$\beta_{IdioSKEW}$	β_{CoSKEW}	β_{MAX}	β_{MIN}	β_{ST}	β_{PTH}	β_{PTL}	$\bar{R}^2$
0.28	2.31	5.56	-6.29	27.12	21.58	3.86	-0.33	0.14	76.6%
[3.30]	[0.31]	[0.97]	[-1.13]	[3.05]	[2.33]	[0.67]	[-5.85]	[2.22]	

Table A24: Relation with Volatility Risk Premia: Developed and Emerging Economies

This table presents results on the relation with volatility risk premia. We control for currency volatility risk premia in the main predictive panel regression analysis. We present estimates of the following panel regression: $rx_{i,t+1} = \alpha_i + \gamma_t + \beta_1 tk_{i,t} + \beta_2 vrp1y_{i,t} + \beta_3 tk_{i,t} \times vrp1y_{i,t} + \delta X_{i,t} + u_{i,t+1}$, where $rx_{i,t+1}$ is the currency i excess return at month $t+1$, $tk_{i,t}$ is the prospect-theory value for currency i at time t, and $vrp1y_{i,t}$ is the currency volatility risk premia, defined as the difference between realized volatility and option-implied volatility from options with 1-year maturity, closely following Della Corte et al. (2016). $tk_{i,t} \times vrp1y_{i,t}$ is the interaction term between prospect-theory value and volatility risk premia. α_i and γ_t represent currency fixed effects and time (year-month) fixed effects dummies respectively. The set of control variables X consists of the forward discount $fd_{i,t}$, the cumulative exchange rate return over the past three months $mom_{i,t}$, and the negative of the past five-year real exchange rate change $val_{i,t}$. t-statistics (reported in brackets) are based on standard errors double-clustered by currency and time. All variables are standardized to facilitate interpretation. The sample runs from January 1996 to February 2018 and covers 20 currencies for developed and emerging economies. The starting date and the sample currency coverage are restricted by the available option data.

	(1)	(2)	(3)	(4)
tk_t	-0.12	-0.08	-0.18	-0.15
	[-2.77]	[-1.89]	[-3.15]	[-2.72]
fd_t			0.15	0.15
			[5.21]	[5.07]
mom_t			0.03	0.03
			[1.12]	[1.26]
val_t			0.01	0.01
			[0.54]	[0.21]
$vrp1y_t$	-0.10	-0.07	-0.04	-0.01
	[-1.91]	[-1.40]	[-0.78]	[-0.25]
$tk_t \times vrp1y_t$		0.04		0.06
		[1.84]		[2.08]
Curr FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Nr.Obs	4,053	4,053	3,583	3,583
R-squared	51.9%	52.0%	56.1%	56.2%

Table A25: Additional Controls: Developed and Emerging Economies

This table presents estimates of the following panel regression: $rx_{i,t+1} = \alpha_i + \gamma_t + \beta_1 tk_{i,t} + \delta X_{i,t} + u_{i,t+1}$, where $rx_{i,t+1}$ is the currency i excess return at time t+1, $tk_{i,t}$ is the prospect-theory value for currency i at time t, α_i and γ_t represent currency fixed effects and time (year-month) fixed effects dummies respectively. The set of control variables X consists of the forward discount fd_t, the cumulative exchange rate return over the past three months $mom_{i,t}$, and the negative of the past five-year real exchange rate change $val_{i,t}$, as well as additional control variables including past one-month return $mom_{1,t}$, past twelve-month return $mom_{12,t}$, output gap og, Taylor rule tr, term spread ts, dollar exposure β_{DOL}, average forward discount dummy afd, 1-month volatility risk premia ($vrp1m$), and synthetic quanto risk premia using currency implied volatility, VIX, and realized correlation (qrp). t-statistics (reported in brackets) are based on standard errors double-clustered by currency and time. The sample runs from January 1990 to February 2018 and covers 37 currencies for developed and emerging economies. All variables are standardized to facilitate interpretation.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
tk_t	-0.09	-0.09	-0.14	-0.14	-0.14	-0.10	-0.09	-0.10	-0.18	-0.20	-0.11
	[-2.00]	[-2.01]	[-3.64]	[-3.64]	[-3.38]	[-1.90]	[-1.97]	[-2.23]	[-3.43]	[-3.35]	[-1.85]
fd_t	0.16	0.16	0.0749	0.0748	0.15	0.17	0.16	0.08	0.15	0.16	0.09
	[-9.11]	[-8.55]	[-1.55]	[-1.55]	[-11.06]	[-10.02]	[-9.04]	[-1.71]	[-9.84]	[-10.48]	[-1.44]
mom_t	0.02	0.02	0.03	0.03	0.03	0.01	0.02	0.03	0.03	0.03	0.04
	[-0.53]	[-0.77]	[-1.30]	[-1.30]	[-1.33]	[-0.33]	[-0.60]	[-0.78]	[-1.37]	[-1.31]	[-0.91]
val_t	0.01	0.01	0.00	0.00	0.02	0.02	0.01	0.00	0.02	0.01	0.02
	[-0.53]	[-0.55]	[-0.11]	[-0.11]	[-0.62]	[-0.85]	[-0.53]	[-0.15]	[-0.62]	[-0.50]	[-0.74]
$mom_{1,t}$	0.00							-0.02			-0.04
	[-0.02]							[-0.64]			[-0.92]
$mom_{12,t}$		-0.01						-0.01			-0.01
		[-0.40]						[-0.26]			[-0.34]
og			0.02					-0.44			-0.82
			[-1.67]					[-0.74]			[-1.15]
tr				0.02				0.45			0.84
				[-1.67]				[-0.76]			[-1.16]
ts					-0.01			-0.03			-0.02
					[-0.25]			[-0.90]			[-0.38]
β_{dol}						-0.03		0.00			-0.01
						[-1.07]		[-0.04]			[-0.36]
afd							0.00	0.00			0.00
							[-0.12]	[-0.01]			[-0.16]
$vrp1m$									-0.04		-0.06
									[-1.07]		[-0.79]
qrp										0.01	-0.06
										[-0.21]	[-1.34]
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Curr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Nr.Obs	5,558	5,558	3,708	3,708	4,702	4,741	5,558	2,848	3,583	3,583	2,194
R^2	52.5%	52.5%	61.8%	61.8%	59.5%	51.6%	52.5%	63.6%	56.1%	56.1%	62.6%

Table A26: Short-Term Reversal for Developed and Emerging Economies

This table presents estimates of the following panel regression: $rx_{i,t+1} = \alpha_i + \gamma_t + \beta_1 tk_{i,t} + \delta X_{i,t} + u_{i,t+1}$, where $rx_{i,t+1}$ is the currency i excess return at time $t+1$, $tk_{i,t}$ is the prospect-theory value for currency i at time t, $\alpha_i$and γ_t represent currency fixed effects and time (year-month) fixed effects dummies respectively. The set of control variables X consists of the forward discount fd_t, the cumulative exchange rate return over the past three months mom_t, and the negative of the past five-year real exchange rate change val_t, as well as additional short-term reversal variables including one-day $mom_{1d,t}$, one-week $mom_{1w,t}$, two-week $mom_{2w,t}$, and three-week $mom_{3w,t}$ lagged past returns from month end. t-statistics (reported in brackets) are based on standard errors double-clustered by currency and time. The sample runs from January 1990 to February 2018 and covers 37 currencies for developed and emerging economies. All variables are standardized to facilitate interpretation.

	(1)	(2)	(3)	(4)	(5)
tk_t	-0.09	-0.09	-0.09	-0.09	-0.09
	[-2.05]	[-2.02]	[-2.01]	[-1.99]	[-2.05]
$mom_{1w,t}$	0.02				0.01
	[1.10]				[0.23]
$mom_{2w,t}$		0.02			0.04
		[1.02]			[0.67]
$mom_{3w,t}$			0.01		-0.03
			[0.30]		[-0.52]
$mom_{1d,t}$				0.01	0.00
				[0.62]	[0.19]
fd_t	0.16	0.16	0.16	0.16	0.16
	[9.48]	[9.34]	[9.00]	[9.36]	[8.70]
mom_t	0.01	0.01	0.01	0.01	0.01
	[0.37]	[0.19]	[0.32]	[0.52]	[0.31]
val_t	0.01	0.01	0.01	0.01	0.01
	[0.54]	[0.54]	[0.53]	[0.53]	[0.55]
Curr FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Nr.Obs	5,558	5,558	5,558	5,558	5,558
R^2	52.50%	52.50%	52.50%	52.50%	52.50%

Table A27: Event Studies: Volcker Rule and GFXC

This table presents the estimates of the following contemporaneous panel regression $of_{i,t} = \alpha_i + \gamma_t + \beta_1 tk_{i,t} + \beta_2 tk_{i,t} \times Post + \delta X_{i,t} + u_{i,t}$, where $tk_{i,t}$ is the prospect-theory value for currency i at time t, and $tk_{i,t} \times Post$ is an interaction term between prospect-theory value and a post-event dummy. We focus on two events: the Volcker Rule full implementation in July 2015 and the introduction of the Global FX Committee (GFXC) in May 2017. α_i and γ_t represent currency fixed effects and time (year-month) fixed effects dummies respectively. The set of control variables X consists of the forward discount $fd_{i,t}$, the cumulative exchange rate return over the past three months $mom_{i,t}$, and the negative of the past five-year real exchange rate change $val_{i,t}$. $of_{i,t}$ is currency-level order flow measured by signed dollar volume (buy volume minus sell volume) for currency i at time t for each group of market participants. We include currency and time fixed effects. t-statistics (reported in brackets) are based on standard errors clustered by time. We focus on the sample from Sep 2012 to Feb 2018 for the sample of G10 currencies. All variables are standardized to facilitate interpretation. Besides the total order flow (of_{tot}), we also consider order flows by four categories of price takers: bank (of_{bank}), non-financial corporation (of_{co}), fund (of_{fund}), non-bank financial institutions (of_{nbf}).

	(1)	(2)	(3)	(4)	(5)
	of_{bank}	of_{co}	of_{fund}	of_{nbf}	of_{tot}
Panel A: Volcker Rule (2015-07)					
tk_t	0.56	0.18	-0.31	0.14	0.41
	[7.69]	[3.24]	[-4.26]	[1.13]	[5.48]
$tk_t \times Post$	-0.34	0.15	0.25	0.02	-0.20
	[-4.94]	[2.19]	[4.25]	[0.16]	[-2.95]
fd_t	-0.01	0.08	-0.03	-0.04	-0.02
	[-0.52]	[2.40]	[-1.06]	[-1.83]	[-0.83]
mom_t	-0.14	-0.09	-0.08	0.04	-0.15
	[-3.14]	[-2.32]	[-1.57]	[0.77]	[-3.89]
val_t	0.01	0.05	-0.14	-0.04	-0.04
	[0.12]	[1.14]	[-2.23]	[-0.60]	[-0.75]
Curr FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Nr.Obs	660	660	660	660	660
R^2	40.70%	39.70%	38.20%	32.50%	49.30%
Panel B: GFXC (2017-05)					
tk_t	0.44	0.16	-0.27	0.14	0.32
	[7.81]	[3.43]	[-3.95]	[1.40]	[5.53]
$tk_t \times Post$	-0.18	0.42	0.31	0.06	-0.02
	[-2.73]	[3.78]	[3.56]	[0.49]	[-0.35]
fd_t	-0.03	0.06	-0.03	-0.04	-0.04
	[-0.78]	[1.98]	[-1.11]	[-1.68]	[-1.06]
mom_t	-0.13	-0.09	-0.08	0.04	-0.15
	[-2.96]	[-2.57]	[-1.70]	[0.75]	[-3.79]
val_t	-0.02	0.07	-0.11	-0.04	-0.05
	[-0.35]	[1.69]	[-1.90]	[-0.56]	[-1.01]
Curr FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Nr.Obs	660	660	660	660	660
R^2	39.50%	40.90%	38.20%	32.50%	48.70%

Table A28: Event Studies: Trading Volume

This table presents estimates of the following contemporaneous panel regression: $vol_{i,t} = \alpha_i + \gamma_t + \beta_1 tk_{i,t} + \beta_2 tk_{i,t} \times Post_t + \delta X_{i,t} + u_{i,t+1}$, where $vol_{i,t}$ is trading volume of currency i at time t for each group of market participants, $tk_{i,t}$ is the prospect-theory value for currency i at time t, and $tk_{i,t} \times Post_t$ is an interaction term between prospect-theory value and a post-event dummy. We focus on two events: the Volcker Rule full implementation in July 2015 and the introduction of the Global FX Committee (GFXC) in May 2017. α_i and γ_t represent currency fixed effects and time (year-month) fixed effects dummies respectively. The set of control variables $X_{i,t}$ consists of the forward discount $fd_{i,t}$, the cumulative exchange rate return over the past three months $mom_{i,t}$, and the negative of the past five-year real exchange rate change $val_{i,t}$. We include currency and time fixed effects. t-statistics (reported in brackets) are based on standard errors clustered by time. We focus on the sample from September 2012 to February 2018 for the sample of G10 currencies. All variables are standardized to facilitate interpretation. Besides the total trading volume (vol_{tot}), we also consider trading volumes by four categories of price takers: bank (vol_{bank}), non-financial corporation (vol_{co}), fund (vol_{fund}), and non-bank financial institutions (vol_{nbf}).

Panel A: Volcker Rule (2015-07)

	(1)	(2)	(3)	(4)	(5)
	vol_{bank}	vol_{co}	vol_{fund}	vol_{nbf}	vol_{tot}
tk_t	0.01	0.00	-0.08	-0.05	0.01
	[0.47]	[0.10]	[-4.69]	[-3.95]	[0.76]
$tk_t \times Post$	-0.04	-0.16	0.03	0.01	-0.04
	[-3.99]	[-3.64]	[1.42]	[0.92]	[-3.78]
fd_t	0.01	0.01	-0.07	0.00	0.02
	[1.40]	[0.55]	[-2.01]	[0.36]	[3.38]
mom_t	0.02	-0.05	-0.02	0.04	0.01
	[1.57]	[-1.61]	[-0.78]	[3.23]	[1.07]
val_t	-0.03	-0.03	-0.05	-0.04	-0.03
	[-2.57]	[-0.83]	[-3.46]	[-3.11]	[-5.44]
Curr FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Nr.Obs	638	563	660	660	660
R^2	96.50%	67.70%	94.70%	94.40%	99.10%

Panel B: GFXC (2017-05)

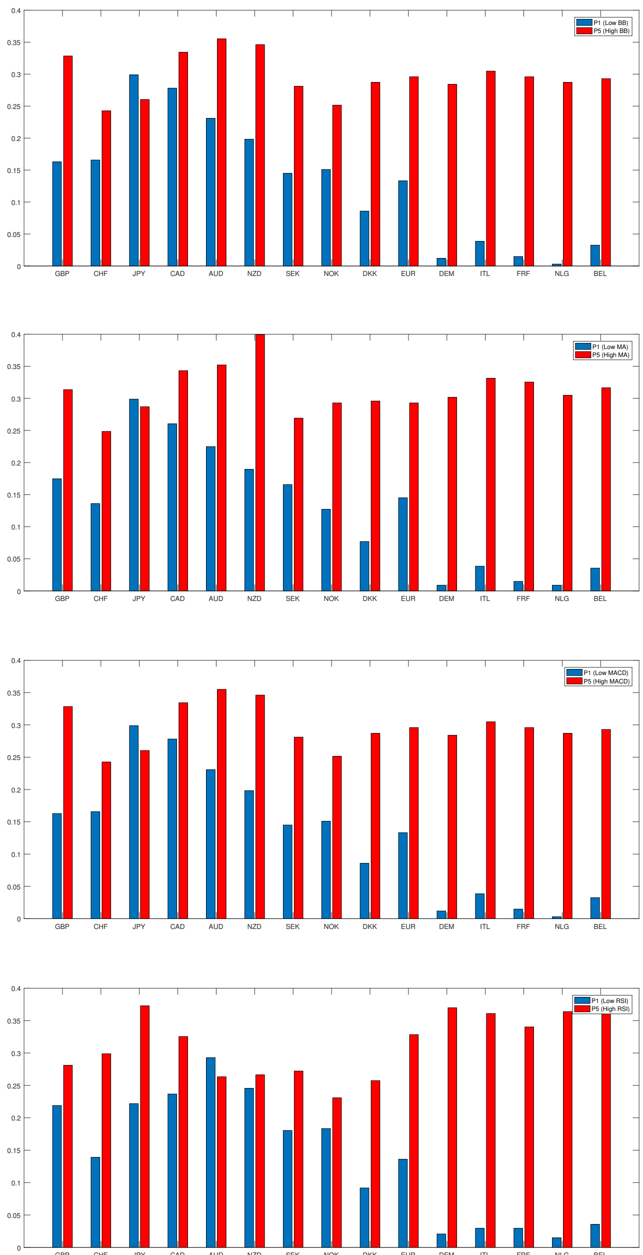
	(1)	(2)	(3)	(4)	(5)
	vol_{bank}	vol_{co}	vol_{fund}	vol_{nbf}	vol_{tot}
tk_t	-0.01	-0.05	-0.07	-0.05	-0.01
	[-0.61]	[-1.50]	[-4.50]	[-4.04]	[-0.85]
$tk_t \times Post$	-0.04	-0.03	0.03	0.03	-0.02
	[-2.59]	[-0.70]	[1.07]	[1.26]	[-1.34]
fd_t	0.01	-0.01	-0.07	0.00	0.02
	[1.54]	[-0.39]	[-2.07]	[0.29]	[3.82]
mom_t	0.02	-0.05	-0.02	0.04	0.01
	[1.68]	[-1.67]	[-0.83]	[3.20]	[1.25]
val_t	-0.03	-0.03	-0.05	-0.03	-0.03
	[-2.90]	[-0.95]	[-3.30]	[-2.96]	[-5.91]
Curr FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Nr.Obs	638	563	660	660	660
R^2	96.50%	67.30%	94.70%	94.40%	99.10%

Table A29: Bank and Corporate Order Flow: Decomposition and Event Studies

This table presents estimates of the following contemporaneous panel regression: $of_{i,t} = \alpha_i + \gamma_t + \beta_1 tk_{i,t} + \beta_2 tk_{i,t} \times Post_t + \delta X_{i,t} + u_{i,t+1}$, where $tk_{i,t}$ is the prospect-theory value for currency i at time t, and $tk_{i,t} \times Post_t$ is an interaction term between prospect-theory value and a post-event dummy. We focus on two events: the Volcker Rule full implementation in July 2015 and the introduction of the Global FX Committee (GFXC) in May 2017. α_i and γ_t represent currency fixed effects and time (year-month) fixed effects dummies respectively. The set of control variables $X_{i,t}$ consists of the forward discount $fd_{i,t}$, the cumulative exchange rate return over the past three months $mom_{i,t}$, and the negative of the past five-year real exchange rate change $val_{i,t}$. $of_{i,t}$ is currency-level order flow measured by signed dollar volume (buy volume minus sell volume) for currency i at time t for each group of market participants. We include currency and time fixed effects. t-statistics (reported in brackets) are based on standard errors clustered by time. We focus on the sample from September 2012 to February 2018 for the sample of G10 currencies. All variables are standardized to facilitate interpretation. We consider bank order flow (of_{bank}), its residual ($of_{bankres}$) when regressing on corporate order flow, as well as the fitted component of corporation (of_{bankco}). Panel A reports results of baseline regression using bank order flow, residual, and corporate fitted component. Panels B and C include $tk_{i,t} \times Post_t$, an interaction term between prospect-theory value and a post-event dummy. We focus on two events: the Volcker Rule full implementation in July 2015 and the introduction of the Global FX Committee (GFXC) in May 2017.

	Panel A: Baseline			Panel B: Volcker Rule			Panel C: GFXC		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
	of_{bank}	$of_{bankres}$	of_{bankco}	of_{bank}	$of_{bankres}$	of_{bankco}	of_{bank}	$of_{bankres}$	of_{bankco}
tk_t	0.40	0.26	-0.06	0.56	0.34	-0.03	0.44	0.28	-0.05
	[7.69]	[3.59]	[-0.44]	[7.69]	[3.85]	[-0.19]	[7.81]	[3.75]	[-0.40]
$tk_t \times Post$				-0.34	-0.18	-0.06	-0.18	-0.11	-0.04
				[-4.94]	[-2.38]	[-0.75]	[-2.73]	[-1.18]	[-0.21]
fd_t	-0.05	0.01	-0.04	-0.01	0.02	-0.03	-0.03	0.02	-0.03
	[-1.00]	[0.20]	[-1.39]	[-0.52]	[1.04]	[-1.19]	[-0.78]	[0.51]	[-1.46]
mom_t	-0.13	-0.12	-0.04	-0.14	-0.13	-0.05	-0.13	-0.12	-0.04
	[-2.96]	[-2.13]	[-1.02]	[-3.14]	[-2.19]	[-1.03]	[-2.96]	[-2.12]	[-1.02]
val_t	-0.01	0.02	-0.02	0.01	0.03	-0.02	-0.02	0.02	-0.02
	[-0.27]	[0.44]	[-0.41]	[0.12]	[0.63]	[-0.34]	[-0.35]	[0.38]	[-0.43]
Curr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Nr.Obs	660	660	660	660	660	660	660	660	660
R^2	39.20%	20.10%	2.20%	40.70%	20.50%	2.20%	39.50%	20.20%	2.20%

Figure A1: Currency Compositions of Technical Trading Rule Portfolios



The figure plots the frequency of each currency within P_1 (low) and P_5 (high) respectively for technical-trading-rule-sorted portfolios. We consider four technical trading rules: Bollinger band (BB), moving average (MA), moving average convergence divergence (MACD), and relative strength index (RSI), and present these figures from top (BB) to bottom (RSI). The sample covers 15 currencies of developed economies from January 1990 to February 2018.

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