Time-Varying Global Dollar Risk in Currency Markets

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ABSTRACT

This paper documents that the price of dollar risk exhibits significant time variation, switching sign after large realized dollar fluctuations, when global dollar demand is high and funding constraints are tight. To exploit this feature of dollar risk, I propose a novel currency investment strategy which is effectively short the dollar in normal states, but long the dollar after large dollar movements. The proposed strategy is not exposed to standard risk factors, yields an annualized return exceeding 4%, and has an annualized Sharpe ratio of 0.34, significantly higher than that of well-known currency strategies. Furthermore, I show that currencies other than the dollar do not exhibit the same sign-switching pattern in their price of risk, consistent with the view that the dollar is special.

Keywords: foreign-exchange, U.S. dollar, systematic FX risk, trading strategies, currency betas, FX options, derivative markets.

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I. Introduction

Conventional wisdom places a special role to the U.S. economy and to its currency in international financial and foreign exchange (FX) markets.[1] Indeed, the U.S. dollar is on one side of over 88% of all foreign exchange transactions, it is the dominant invoicing currency, and it is the numeraire of the world's largest equity market.[2] However, the literature disagrees on whether the dollar is a unique currency in the sense that it is a risk factor driving risk premia in the cross-section of all other currencies. On the one hand, Lustig, Roussanov, and Verdelhan (2011) show that the dollar factor – an equally-weighted basket of dollar denominated currencies – is one of two global factors that explains risk premia in foreign exchange markets. On the other hand, recent studies question if global base currency risk is unique to the dollar (Boudoukh, Richardson, Thapar, and Wang (2018), Aloosh and Bekaert (2019), Panayotov (2019)).[3]

In this paper, I contribute to this debate by showing that the price of dollar risk exhibits significant time variation and that its price pattern is more complex than previously documented. Introducing a new proxy for the price of dollar risk – the Dollar Portfolio Line (DPL), which captures the relationship between currencies' excess returns and their exposure to dollar risk – I show that the price of risk switches its sign after large return realizations of the dollar. In these periods funding constraints are tight, global dollar demand is high, and currencies with large (small) exposure to the dollar systematically depreciate (appreciate). Exploiting the time-variation of dollar risk, I propose a novel currency trading strategy that generates more than 4% annualized average excess returns (Sharpe ratio: 0.34). Lastly, I show that the state-dependent price pattern of base currency risk is a unique feature of the dollar and cannot be replicated using other currencies.

To motivate my approach, Figure 1 highlights the importance of the time-variation in the slope of the DPL. I consider dollar risk exposure as defined in Verdelhan (2018) and form equally-weighted portfolios based on currencies' risk exposures.[4] Then, I construct the DPL based on estimated exposure to dollar risk and portfolio excess returns, to capture the gradient between the

[1] The financial press regularly highlights how the U.S. dollar had become the most important indicator of risk perception in financial markets (e.g. Bloomberg (2017)) and how return movements of the U.S. dollar affect the global economy and international investors (e.g. The Economist (2019)).

[2] For further information see BIS (2019), Gopinath (2015), and WFE (2017).

[3] The dollar factor is used as a primary risk factor in various FX studies following Lustig, Roussanov, and Verdelhan (2011), and Lustig, Roussanov, and Verdelhan (2014) and Verdelhan (2018) provide further evidence that exposure to dollar risk is priced in the cross-section of currencies. In contrast, Boudoukh, Richardson, Thapar, and Wang (2018) and others question whether global risk is a unique feature of the dollar and whether exposure to dollar risk is significantly priced in recent years and across currencies of developed countries.

[4] Following Verdelhan (2018), exposure to dollar risk is measured by dollar betas that are defined as the ratio of the covariance between currency returns and the dollar portfolio and the variance of the dollar portfolio. Portfolio 1 (Portfolio 3) contains the three currencies with the lowest (highest) exposure to dollar risk.

low and high dollar risk portfolios.

INSERT FIGURE 1 HERE

Figure 1a plots the unconditional average of the DPL between January 1999 and December 2017 and shows that the DPL has been only slightly upward sloping over the last twenty years, reminiscent of the flat security market line (SML) of the CAPM in equity markets.[5] In contrast to the SML, however, the gradient of the DPL is highly sample-period dependent. Figure 1b shows that while the DPL is conditionally upward sloping (black line) most of the time, it switches its sign following large fluctuations of the dollar (red line).

Disregarding the state-dependent slope dynamics leads to an unconditional flat DPL, where differences between high and low dollar risk portfolios are not priced in the cross-section.[6] Therefore, I conjecture, it is crucial to account for the sign-switching price pattern of dollar risk when assessing the role of the dollar as a global risk factor in currency markets.

To capture the time-varying dynamics of the DPL, I build upon a recently growing literature that derives risk measures from derivative markets instead of using rolling-window regressions. These forward-looking estimates offer an attractive alternative to quantify risk as they can be derived in an almost model-free setting. Their application in currency markets is particularly appealing. For one, FX option markets are very liquid, and updated quotes are reflective of traders' perceptions of recent and expected market dynamics.[7] This allows to estimate dollar risk practically in real-time. Further, for a portfolio of bilateral currencies one can derive the entire risk-neutral variance-covariance matrix using currency cross-pairs (Mueller, Stathopoulos, and Vedolin (2017)), and without imposing any assumptions on assets' correlation, which is in stark contrast to other asset classes (Buss and Vilkov (2012), Christoffersen, Fournier, and Jacobs (2017)).

Next, inspired by Lettau, Maggiori, and Weber (2014), who analyse the role of downside risk in currency markets, I investigate how large fluctuations of the dollar portfolio have an impact on the return dynamics of foreign currencies. Since the dollar is perceived as an indicator of financial market risk (Shin (2016)), I analyse how the DPL is affected by its return movements. Furthermore, I assess the relation between dollar risk and country-specific characteristics, and link the slope of the DPL to funding liquidity, equity market dynamics, FX order flow and global

[5] See e.g. Black (1972), Frazzini and Pedersen (2014), and Hong and Sraer (2016).

[6] Verdelhan (2018) introduces a global dollar trade where investors buy (short) currencies with large dollar risk exposure and short (buy) currencies with low exposure if the average interest rate differential of foreign countries vis-à-vis the U.S. is positive (negative). Aven after accounting for the average interest rate differential as an investment signal, the trading strategy generates 1.58% annualized average excess return (t-stat: 0.86) when the cross-section is limited to G10 currencies.

[7] For example, daily average trading volume of FX options increased from US$ 119 billion in 2004 to US$ 294 billion in 2019 (BIS (2019)).

capital flows (Avdjiev, Du, Koch, and Shin (2019), Cenedese, Payne, Sarno, and Valente (2015), Evans and Lyons (2002), Avdjiev, Bruno, Koch, and Shin (2018)). Lastly, I assess if the unveiled pattern of the DPL is unique to the dollar or if other base currency portfolio lines behave similarly.

Taking this persistent heterogeneous pricing pattern between low and high dollar risk portfolios into account proves to be important when considering the dollar's role as a global risk factor. Investigating further I revisit the global dollar trade by Verdelhan (2018) and propose large return fluctuations of the dollar as a new investment signal. I show that an investor who buys currencies with large dollar risk exposure and shorts assets with low exposure, and reverses the trade after large return movements of the dollar portfolio, earns positive and significant annualized average excess returns of over 4%. In line with a risk-based explanation, portfolio returns are increasing monotonically with exposure to dollar risk. Further, the positive and significant high-minus-low portfolio returns based on dollar risk exposure indicate investors bear the risk of dollar appreciation most of the time as they are effectively short the U.S. dollar, but after large return fluctuations they bear the risk of dollar depreciation when they are effectively long the dollar. I argue the uncovered pattern of the DPL reflects investors' concern about future market turmoil. Expecting worsening market conditions after large fluctuations of the dollar drive flight-to-safety liquidity dynamics, and cause safe-haven currencies to appreciate and riskier currencies to depreciate.

Further, I analyse the return generating process of the revisited global dollar strategy and document its independence from existing factors. Notably, the global dollar trade with the new investment signal is the only approach that generates positive and significant returns over the last twenty years. Even after accounting for transaction costs the Sharpe ratio is 0.34. To put this in perspective, the well-known carry trade and currency momentum strategies generate Sharpe ratios of 0.18 and -0.30, respectively. The comparably high risk-adjusted returns of the revisited global dollar trade highlight the importance of the new investment signal that captures the slope of the DPL. Furthermore, detaching the global dollar trade from the average interest rate differential, which has been originally used as an investment signal, makes its return process largely independent from the carry trade and other existing FX trading strategies. Similarly, risk factors from equity markets (Fama and French (1993)), the hedge fund literature (Fung and Hsieh (2001)) and the mutual fund industry (Fung and Hsieh (2015)) are not able to fully span the return dynamics of the global dollar trade, leaving significant abnormal returns unexplained.

I proceed exploring macroeconomic determinants that are related to the slope of the DPL and help to understand the returns of the revisited global dollar trade. I find a close link between funding liquidity constraints (Du, Tepper, and Verdelhan (2018)), financial market uncertainty, the relative performance of equity markets (Cenedese, Payne, Sarno, and Valente (2015)), capital flows (Della Corte, Riddiough, and Sarno (2016)), FX order flow (Evans and Lyons (2002)) and the sign of the DPL's slope. For example, a rise in financial market uncertainty and worsening funding

conditions, coincide with periods when the slope of the DPL is negative. During these months, capital flows and FX order flow point towards positive net demand for the dollar, indicative of investors' objective to buy safe haven assets. In contrast, investors have net demand for foreign currencies when the DPL is positive. This suggests investors chase returns during most of the sample period and allocate capital to riskier currencies, while flight-to-safety dynamics prevail in months following large fluctuations of the dollar.

Lastly, I employ alternative numeraire portfolios as global risk factors addressing the question if my results are unique to the dollar. I repeat the same strategy outlined above for alternative base currencies (e.g. Japanese yen portfolio), identify months with large return swings, and allocate currencies into baskets according to their level of base currency risk. Irrelevant of the (non-dollar) numeraire currency, this leads to insignificant portfolio excess returns. Large return swings of alternative base currencies cause less cross-sectional co-movement in currency markets compared to the common cross-sectional return pattern caused by return swings of the dollar portfolio. Relatedly, factor slopes of non-dollar base portfolios do not show the same systematic change as it can be found for the DPL. In fact, only the gradient of the DPL can be related to funding costs and equity return differentials, while these are not significant explanatory factors of the gradients of other base currency portfolio lines. Overall, the findings in this paper highlight the special role of the dollar in currency markets and document how its return movements affect the cross-section of G10 currencies.

Literature Review. In addition to studies mentioned above, the paper contributes to various strands in the literature. First, I add to a recently growing line of papers that exploits the forward-looking signal-processing nature of option-derived betas. While the majority of studies focus on equity markets (Buss and Vilkov (2012), Christoffersen, Fournier, and Jacobs (2017), evidence from option-derived measures in FX markets is still limited (Bang-Nielsen (2018)).

Second, I build upon the seminal work by Lustig, Roussanov, and Verdelhan (2014) and Verdelhan (2018) and investigate the unique role of the U.S. dollar as a global risk factor in currency markets. I propose an alternative trading strategy that exploits the slope of the DPL and that is based on large return fluctuations of the dollar. This approach relates my study to earlier papers examining the role of downside risk in currency markets (Atanasov and Nitschka (2014), Dobrynskaya (2014), Lettau, Maggiori, and Weber (2014)). In contrast to previous studies, I focus on large return realizations of the dollar portfolio instead of considering downside risk in equity markets. Further, following Levi and Welch (2018) who argue that previous findings regarding time-varying risk in currency markets suffer from in-sample biases, I ensure that portfolio returns are generated completely out-of-sample.

Third, revisiting the global dollar trade I take into account recent criticism regarding the U.S. dollar's role as a risk factor (Boudoukh, Richardson, Thapar, and Wang (2018)) and I show how

portfolio returns based on the new investment signal differ from the original global dollar trade by Verdelhan (2018) that conditions portfolio allocations on the sign of the average forward discount. Conducting a return decomposition, I show how the two investment signals are complementary to each other and argue that they capture different sets of information. Further, while a large number of studies explore return processes of the carry (e.g. Menkhoff, Sarno, Schmeling, and Schrimpf (2012a)) and momentum trade (e.g. Menkhoff, Sarno, Schmeling, and Schrimpf (2012b)), dynamics of portfolio returns based on dollar risk exposure are comparably less understood. This paper aims to fill this gap.

Fourth, introducing a novel currency investment strategy this paper is also related to studies exploring currency risk factors and FX strategies based on interest rate differentials (Lustig and Verdelhan (2011), Lustig, Roussanov, and Verdelhan (2014)), momentum (Menkhoff, Sarno, Schmeling, and Schrimpf (2012b), Moskowitz, Ooi, and Pedersen (2012)), and implied volatilities from option markets (Mueller, Stathopoulos, and Vedolin (2017), Della Corte, Ramadorai, and Sarno (2016), Della Corte, Kozhan, and Neuberger (2018)). In contrast to these papers, I propose a new investment signal that captures the price of dollar risk and I allocate currencies into portfolios based on dollar risk exposure. As part of the empirical analysis, I show that returns of the proposed novel trading approach are unrelated to well-known FX strategies and not exposed to risk factors from various asset classes.

Fifth, I discuss the special role of the U.S. dollar in currency markets (Maggiori (2013), Hassan (2013), Maggiori (2017)), and I show that exposure to dollar risk is related to funding liquidity (Du, Tepper, and Verdelhan (2018), equity market returns (Djeutem and Dunbar (2018)), capital flows (Hau and Rey (2005)), and FX order flow (Evans and Lyons (2002)). I document that these factors are significantly linked to the gradient of the DPL, relating the paper to an early strand of literature that addresses the flat SML in equity markets (Black (1972)).

The paper proceeds as follows. Section II outlines the data. Section III describes the methodology to derive dollar risk from FX option markets and illustrates the time-varying dynamics of dollar risk. Section IV revisits the global dollar trade and analyses its return dynamics. Section V assesses the special role of the dollar compared to other base currencies. Section VI outlines further tests and robustness checks and Section VII concludes the discussion.

II. Data

I employ foreign exchange rate data from two different data sources. First, I obtain end-of-month spot and forward rates from WM/Reuters through Datastream to construct monthly currency excess returns. This data is standard in the literature. The sample period comprises all months between January 1999 to December 2017. As outlined below, the sample period is determined

by the availability of option data. The cross-section of currencies includes the Australian dollar (AUD), Canadian dollar (CAD), Swiss franc (CHF), euro (EUR), British pound (GBP), Japanese yen (JPY), Norwegian krone (NOK), New Zealand dollar (NZD), and Swedish krona (SEK) vis-à-vis the U.S. dollar. The sample of currencies largely resembles the set of developed countries in previous studies (e.g. Verdelhan (2018), Lustig, Roussanov, and Verdelhan (2011))[8]. In aggregate these currencies cover approximately 71% of total daily trading volume in the foreign exchange market (BIS (2019)). Exchange rates are expressed as U.S. dollar per foreign currency, such that an increase in currency prices implies an appreciation of the foreign currency vis-à-vis the U.S. dollar.

Following Mueller, Tahbaz-Salehi, and Vedolin (2017), excess returns are defined as $xret_{t+1} = f_t - s_{t+1}$ where f_t refers to the one-month log forward rate and s_{t+1} is the log spot rate in period $t+1$.[9] To account accurately for the costs of portfolio rebalancing in the context of FX trading strategies, I construct net excess returns considering the bid- and ask prices of the forward and spot rates. In line with Menkhoff, Sarno, Schmeling, and Schrimpf (2012b), I define net excess returns of a long position as $xret^l_{t+1} = f^b_t - s^a_{t+1}$ and those of a short positions as $xret^s_{t+1} = -f^a_t - s^b_{t+1}$. The superscript a (b) denotes the ask (bid) price of the spot and forward rate at the end of the month when investors' positions are open and closed, respectively.

Second, I obtain information on end-of-month FX options from two different sources. For the period January 1999 to February 2013, I use data from JP Morgan. The options are plain-vanilla European calls and puts with one month maturity. Importantly, the sample includes the G-9 currency pairs vis-à-vis the U.S. dollar and all 36 cross-pairs. Hence, the sample comprises 45 currency pairs in total. I obtain implied volatilities for at-the-money (ATM), 10-delta, 25-delta calls, and 10-delta and 25-delta puts. To extend the sample period until December 2017, I supplement the database with quotes from Bloomberg for the period from March 2013 onward. In contrast to the data from JP Morgan, FX implied volatilities on Bloomberg are quoted as at-the-money straddles, risk-reversals and butterflies. I focus on the same 10-delta and 25-delta strikes of these instruments. Following Carr and Wu (2009) and Castagna and Mercurio (2007), I exploit linear combinations of these instruments to back-out plain vanilla implied volatilities that are comparable to those obtained from JP Morgan.

In addition to the datasets on currency prices compiled from spot and derivative segments of the foreign exchange market, I obtain the following variables from different data vendors. First,

[8] In contrast to these studies I do not include the Danish krone due to the lack of available option data and because of its peg with the euro (Mueller, Stathopoulos, and Vedolin (2017)).

[9] I implicitly assume covered interest rate parity holds at the monthly frequency and that the synthetic interest rate differential equals the interest rate differential between foreign (r^*) and domestic (r) country, such that $f_t - s_t \approx r^*_t - r_t$. While there has been recent evidence of deviations from CIP during crises (Baba and Packer (2008)) and in the post-financial crisis periods (e.g. Du, Tepper, and Verdelhan (2018)), Akram, Rime, and Sarno (2008) argue that CIP generally holds at daily and lower frequencies.

to relate dynamics of dollar risk to international developments in equity markets, I obtain MSCI country indices from Datastream. The equity indices track the performance of local equity markets and are comparable across countries. They have been used in previous studies that assess the link between currency prices and the relative performance of domestic and foreign equity markets (e.g. Djeutem and Dunbar (2018), Cenedese, Payne, Sarno, and Valente (2015)). In line with these papers, I construct equity excess return differentials between U.S. and foreign equity markets as $\tilde{rx}_t^{EQ,i} = rx_t^{EQ,i} - rx_t^{EQ,US}$, where $rx_t^{EQ,i}$ and $rx_t^{EQ,US}$ denote excess returns of foreign and U.S. equity markets, respectively. Taking an U.S. investors point of view, well performing domestic equity markets are associated with low or negative values of $\tilde{rx}_t^{EQ,i}$.

Second, I obtain data on transactions of long-term securities between foreigners and U.S. residents from the U.S. Department of Treasuries. The Treasury International Capital Systems database provides information at the individual country level on gross purchases ($purch_t^i$) and sales ($sales_t^i$) between U.S. residents and foreigners of long-term security i in month t. Taking the difference between gross sales and gross purchases of U.S. Treasuries, Government bonds, corporate bonds, and corporate stocks, I construct a capital flow measure that captures demand for U.S. securities. It is defined as $flow_t = \sum_i sales_t^i - \sum_i purch_t^i$ where the superscript i refers to each of the four different U.S. securities, and $sales_t^i$ ($purch_t^i$) denotes gross sales (purchases) from (by) foreigners to (from) U.S. residents in month t. A positive value means more U.S. securities were sold by foreigners than bought from U.S. residents.[10]

Third, I employ information on trading activity in the foreign exchange market sourced from Thomson Reuters Tick History Database. The database records tick-by-tick stamped information on trading volume, direction of trades, and currency prices from Thomson Reuters Matching interdealer trading platform. While data for major currency pairs is available from April 2006 onwards, information for the entire currency cross-section is only available since 2011. To match high-frequency data with monthly FX returns, I aggregate information on trading volume and the direction of trades to the monthly level. Based on the direction of trades, I follow Evans and Lyons (2002) and construct order flow as the difference between buyer- and seller-initiated traded volume. The variable captures net demand for the base currency and has been extensively used in the market microstructure literature.[11]

Lastly, I obtain short-term interest rates for all countries from Datastream, equity risk factors from Kenneth French's and fund risk factors from David Hsieh's website.[12]

[10] A detailed description of the database is provided in Warnock and Warnock (2009).

[11] Extensive surveys on the use of order flow in FX markets are provided in Osler (2008) and King, Osler, and Rime (2013).

[12] The data libraries can be accessed via `https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html` and `https://faculty.fuqua.duke.edu/~dah7/HFData.htm`, respectively.

III. Time-Varying Dollar Risk

This section describes the methodology to measure dollar risk in currency markets and it outlines how dollar betas are derived from foreign exchange (FX) option implied volatilities. Subsequently, I provide summary statistics of dollar betas and show how currencies' exposure to dollar risk is varying over the course of my sample period.

A. Methodology: Time-Varying Dollar Betas

Following the approach in Verdelhan (2018), I measure dollar risk in FX markets as currencies' contemporaneous exposure to the dollar factor, which is defined as an equally-weighted basket of U.S. dollar denominated currency returns. In line with a single factor model in equity markets - i.e. capital asset pricing model - dollar betas capture systematic U.S. dollar risk. They measure the covariation between the returns of an individual asset and the dollar portfolio, normalized by the variance of the dollar portfolio. It is defined as

$$\beta_t^i = \frac{Cov(\Delta s_t^i, Dol_t^i)}{Var(Dol_t^i)} \tag{1}$$

where Δs_t^i refers to the return of currency i in period t and Dol_t is the dollar factor, defined as the cross-sectional average of currency returns ($Dol_t^i = \frac{1}{N-1}\sum_{k=1}^{N-1} \Delta s_t^k$) excluding currency i. Importantly, an assets' exposure to dollar risk is time-varying and can be calculated at every point in time t. It captures the changing exposure of currency i to market conditions and allows to assess the asset's reaction to global shocks, changing trading environments or macroeconomic risk. A high β_t^i-estimate implies currency i has large exposure to dollar risk, while the opposite is true for low values of β_t^i.

To capture empirically time-varying exposure to dollar risk different approaches have been brought forward by the literature. Originally, Verdelhan (2018) employs monthly data and obtains time-varying beta coefficients using backward-looking rolling-window regressions. Alternatively, Bang-Nielsen (2018) suggests exploiting option prices to estimate covariances and variances in Equation (1). These estimates are forward-looking, not biased by past shocks, and account for markets' expectations about price developments (Buss and Vilkov (2012)). They are particularly attractive for the analysis of currency risk as FX option markets are very liquid. Further, currency cross-pairs can be employed to estimate the entire variance-covariance matrix without imposing assumptions on the correlation structure. In fact, Bang-Nielsen (2018) shows that option-implied betas outperform historical estimates and predict dollar risk more accurately. Based on these findings, I employ forward-looking beta estimates in my main analysis and assess as part of the robustness tests section that my findings are robust when realized betas are used.

To derive dollar betas from option markets I follow the approach in Mueller, Stathopoulos, and Vedolin (2017) and extract risk-neutral expectations of currency variance and covariance measures from implied volatilities. The approach is standard in the literature and outlined in detail in the Appendix. Important to note is that for the construction of covariances, access to the entire set of cross-pairs is required. This limits the currency cross-section in my analysis to the most frequently traded G10 currencies, even though option data for U.S. denominated emerging market currencies has been widely used in previous studies (e.g. Della Corte, Kozhan, and Neuberger (2018)). Equipped with information on non-U.S. dollar cross-rates, I construct FX implied moments and Equation (1) can be re-written as

$$\mathbb{E}_t^j\left[\beta_{t+\tau}^i\right] = \frac{Cov_t(\Delta s_{t+\tau}^i, Dol_{t+\tau}^i)}{Var_t(Dol_{t+\tau}^i)} = \frac{\frac{1}{N-1}Cov_t(\Delta s_{t+\tau}^i, \Delta s_{t+\tau}^k)}{Var_t(Dol_{t+\tau}^i)} \tag{2}$$

where $j = \{Q; P, K\}$ denotes option-implied risk neutral estimates or realized measures constructed with a rolling window of length K, respectively. The numerator $\frac{1}{N-1}Cov_t(\Delta s_{t+\tau}^i, \Delta s_{t+\tau}^k)$ captures the covariation of currency returns i with the dollar portfolio and the denominator $Var_t(Dol_{t+\tau}^i)$ measures the variance of the market as the sum of entries of all variance and covariance matrices.[13] While both, risk-neutral and realized measures, capture time-variation of beta estimates, the latter one does not incorporate market expectations about future price developments that might be already priced into currency rates. Further, historical estimates are more likely to be exposed to shocks and are affected by events that took place during the length of the rolling window. While a larger window may increase the number of observations and produces more precise estimates, it also increases the likelihood of including a shock which then impacts the calculation of dollar betas. Option-implied betas are not affected by these issues and, therefore, I use them as the main measure of dollar risk in the analysis.

B. Descriptive Statistics: Option-Implied Dollar Betas

As shown in Figure 1, portfolios' exposure to dollar risk is highly time-varying, with implications for asset pricing models, hedging approaches and trading strategies. Assuming constant dollar risk or not accounting for its changing price of risk, implies one averages slopes of the dollar portfolio line (DPL) across different states of the world. This results in the flat unconditional DPL discussed in the Introduction.

As dollar risk is time-varying, it is important to timely capture potential return reversals related to changes in currency's risk profile and the changing exposure should be reflected by

[13] Following Verdelhan (2018) I exclude currency i from the right-hand side to avoid a mechanical relationship between dollar betas and covariances.

currencies' dollar betas. Indeed, one would expect measures of dollar risk to move substantially over the course of the sample period. This is confirmed by Figure 2.

INSERT FIGURE 2 HERE

The black line shows the time series dynamics of forward-looking dollar betas derived from option markets ($\mathbb{E}_t[\beta^Q_{t+1}]$) for every U.S. dollar bilateral exchange rate. As shown, currencies' dollar risk exposure varies strongly over the course of the sample period. While Scandinavian currencies (NOK, SEK) and the British pound (GBP) have a fairly constant level of dollar risk, for most other currencies it is changing significantly over time. Further, for almost all currencies dollar risk changes abruptly in times of financial turmoil, such as the crises periods at the beginning of the sample period and during the years 2008 and 2009.

The volatile risk dynamics are also confirmed by the summary statistics of dollar betas in Table 1. While the average level of dollar risk is reasonably close to one for most currencies (except for JPY and CAD), their standard deviation lies between 0.13 and 0.30. The comparably large level of volatility implies that currencies' exposure to systematic U.S. risk is changing substantially and frequently over time. Further, the range between minimum and maximum observations exceeds the value of one for almost all currencies and it even reaches 2.15 for the Japanese yen (JPY). For JPY the minimum value is even negative, emphasizing the currency's importance as a hedging instrument. Overall, the wide range of beta realizations for each currency pair is evidence that dollar risk has been notably fluctuating even over the relatively short sample period of 228 months. The next section discusses the implications of these dynamics for the slope of the DPL.

INSERT TABLE 1 HERE

IV. Global Dollar Risk

This section introduces a new investment signal, based on large fluctuations of the dollar portfolio, that captures systematic changes of the price of dollar risk. Subsequently, I revisit the global dollar trade strategy, provide a decomposition of its returns based on the average forward discount, and compare the returns of the new strategy with existing currency trading aprroaches and various risk factors. Lastly, I show how dollar risk relates to macroeconomic variables and developments in financial markets.

A. The Market Price of Dollar Risk

As shown in Lustig, Roussanov, and Verdelhan (2014) and Verdelhan (2018) the market price of dollar risk is time-varying and switches its sign dependent on the average forward discount (AFD)

of foreign countries vis-á-vis the United States.[14] It serves as a signal for the expected future value of the dollar. When the AFD is positive investors earn a risk premium for holding foreign currencies (and have positive loadings on the risk factor) and short foreign currencies when the AFD is negative (and have negative loadings on the risk factor). Put differently, investors are compensated for the risk that the dollar appreciates when the AFD is positive, and depreciates when the AFD is negative. Hence, despite its strong persistence, previous studies relied on the AFD as an investment signal that determines the portfolio allocation and affects investor's perception of dollar risk.

Motivated by the time-varying dynamics of the dollar portfolio line (DPL, Figure 1), in this section I propose an alternative investment signal that is based on large fluctuations of the dollar portfolio and captures the changing sign of the DPL - as a proxy for dollar risk - in the short-run. This approach builds upon Lettau, Maggiori, and Weber (2014) who assess the role of equity downside risk for the cross-sectional pricing pattern in currency markets. My decision to focus on large fluctuations of the U.S. dollar instead of equity markets is threefold. First, the signal accounts for the fact that extreme return movements of the dollar portfolio constitute swings of U.S. specific systematic risk. Given the dominant role of the U.S. dollar in international financial markets, one would expect that this has an immediate effect on other currencies. Second, accounting for large appreciations and depreciations of the dollar considers that currencies with different degrees of dollar risk exposure respond asymmetrically to strong up- and downswings of the dollar. Third the signal circumvents the potential issue that downside risk of US equity markets is not directly informative about the economic conditions of other equity markets, while the dollar portfolio takes the relative value of foreign currencies into account.

To classify return realizations of the dollar portfolio as large fluctuations, I benchmark returns in every period t against a pre-sample period. It covers monthly observations between January 1994 to December 1998. A month is characterised by large return fluctuations, if the realization of the dollar portfolio in period t is more than one-and-a-half standard deviations away from the pre-sample mean. Between January 1999 and December 2017, I classify 62 months as periods with large return swings.

It is worth noting that my definition of large return realizations resembles a stricter benchmark compared to previous studies. For example, Lettau, Maggiori, and Weber (2014) define months of downside risk as periods when equity market returns are more than one standard deviation away from an in-sample mean. Further, as I make the classification of return realizations before allocating currencies into portfolios, I circumvent criticism brought forward in Levi and Welch (2018). The authors argue that in-sample benchmarks and definitions of extreme realizations lead

[14] Assuming covered interest rate parity holds, the average forward discount is a proxy of the average interest rate differential.

to biased results and, therefore, they emphasize the importance of using cut-off points, which are defined ex-ante. While Levi and Welch (2018) use a 36-month window as benchmark in their study, the pre-sample period in my analysis is slightly longer to ensure the benchmark is more resilient to possible outliers. Overall it is worth emphasizing that my main findings are not driven by the exact definition of periods of large fluctuations. In fact, I show that my findings are robust to a broad set of alternative definitions.[15]

To illustrate the role of large dollar fluctuations on currency returns, I form portfolios based on currencies' dollar exposure. The approach is as follows. At the end of each month t, I allocate currencies into three portfolios according to their expected exposure to dollar risk in month $t+1$. Currencies in portfolio 3 have the highest expected exposure to dollar risk, while those in portfolio 1 have the smallest exposure. Investors go long portfolio 3 and short portfolio 1 during normal times, and revert the portfolio allocation after large swings of the dollar portfolio. Portfolios are held for one month, and currencies are re-allocated based on their respective dollar exposure in the next period.

INSERT FIGURE 3 HERE

Figure 3 shows the link between annualized average portfolio excess returns and dollar betas separately for normal times (black) and in months after large return fluctuations of the dollar (red). The x-axis shows the average level of dollar risk measured by option-implied betas while the y-axis refers to annualized average excess returns. The black- (red-) shaded areas indicate the 10% error bands based on high (P3) and low (P1) portfolio excess returns. The following observations are worth noting.

First, the DPL is positive and upward sloping most of the sample (165 months). Portfolio excess returns are increasing with the magnitude of the beta estimates (β_{P1}: 0.58 to β_{P3}: 1.17). While average annualized portfolio excess returns of low dollar risk currencies are negative (-0.99%), the high dollar risk portfolio (P3) generates 2.90% excess returns. The 10% error bands suggest that returns are negative (positive) for portfolio 1 (portfolio 3) for the majority of months.

Second, I document that the DPL is flipped following large return realizations of the dollar portfolio. In these months, excess returns of low dollar risk currencies (P1) are positive, while those exposed to high-dollar risk generate negative returns. Again, the error bands indicate that this is true for the majority of observations even though the return dispersion appears to be higher for currencies allocated to portfolio 3. The conditional DPLs suggest that the price of dollar risk changes its sign in different states of the world. Return movements of the dollar portfolio, therefore, are crucial for the assessment of the dollar as a global risk factor.

[15] As part of the robustness checks, I consider different lengths of the pre-sample periods, the use of rolling- and extending windows of various lengths, and varying distances from the mean as alternative definitions.

Further, I document in Figure 3b that extreme return realizations on both sides of the return distribution matter. As before, I display the conditional DPL during normal periods (black), but explicitly distinguish between months after large dollar depreciations (light red, diamonds) and appreciations (dark red, squares).

As shown, excess returns of low and high dollar risk portfolios respond similarly to large dollar movements independent of their direction. In both states, large dollar appreciations and depreciations, currencies with low dollar risk exposure appreciate while high dollar risk currencies depreciate. For example, after months of large dollar appreciations P3 returns decline (-4.25%), exemplifying that investors holding these assets are exposed to the risk of large return declines when demand for safe haven currencies increases. At the same time, returns of P1 currencies is 1.54%. Similarly, when the dollar depreciated, returns to low dollar risk currencies increase (3.11%) relatively more than P3 currencies lose in value (-1.63%). Overall, Figure 3b suggests one needs to account for return dynamics on both sides of the distribution, instead of focusing only on downside risk.

B. Revisiting the Global Dollar Trade

As fluctuations of the dollar are relevant for the gradient of the DPL, this section revisits the global dollar trade strategy when large return reversals of the dollar portfolio are employed as an investment signal. After allocating currencies into portfolios according to their exposure to dollar risk, an investor goes long (short) portfolio 3 (portfolio 1) in normal times but reverses the trade after extreme fluctuations of the dollar portfolio. Within each portfolio, currencies are equally-weighted as it is standard in the literature. Results to alternative weighting schemes are discussed below. The benchmark results for the return dynamics of the revisited dollar strategy are reported in Table 2.

INSERT TABLE 2 HERE

The high-minus-low portfolio of the revisited global dollar trade strategy generates 4.26% annualized average excess returns once dollar portfolio swings are taken into account. Returns are significantly different from zero at the 5% level. Two thirds of these returns come from currencies with the largest betas (2.90%), while the remaining part stems from low dollar risk currencies (-1.36%). Individual portfolio excess returns are monotonically increasing from P1 to P3 which is in line with their unconditional dollar exposure of 0.57 (P1), 0.95 (P2), and 1.28 (P3), respectively. Even though portfolio returns are individually not significantly different from zero, they are significantly different from each other and the difference grows with portfolios' dollar exposure. To test for this relationship formally, I use the monotonicity relationship (MR) test by Patton and Timmermann (2010). I calculate the return differential between two adjacent portfolios $\Delta = \mu_i - \mu_{i-1}$

where $i = 2, 3$ and test the null hypothesis $H_0 : \boldsymbol{\Delta_i} \leq 0$ against the alternative $H_A : \boldsymbol{\Delta_i} > 0$, where $\boldsymbol{\Delta} = [\Delta_2, \Delta_3]$. P-values are obtained using stationary bootstrapping and are reported in column (MR). In addition, I report the p-values for the test-statistics that the return pattern is strictly positive. It is labelled (Up). For both tests, the p-value is smaller than 1%, rejecting the null hypothesis in favour of a monotonically increasing relationship across portfolios.

Overall, 96% of the revisited global dollar trade stem from changes in the spot rate. For one, this is an intuitive finding as the strategy should compensate investors for movements of the spot rate. On the other hand, it is already indicative that return dynamics are (unconditionally) unrelated to trading strategies whose profitability largely depends on interest rate differentials.

Alternative portfolio sorting approaches strengthen a risk-based interpretation of these results and underscore that returns to the high-minus-low portfolio are not driven by individual outliers or beta estimates of specific currency pairs. I use the linear-weighting scheme by Hassan and Mano (2018) where the weight in each period t allocated to currency i is defined by its distance from the cross-sectional average across the total number of currencies N. It is defined as

$$w_{it}^{\beta,lin} = c_t \left[\beta_{it} - \sum_i \beta_{it}/N \right]$$

where c_t is a scaling factor that ensures that the absolute weights sum up to unity, β_{it} refers to expected dollar risk of currency i in period t and N is the number of currencies. Further, I use the rank-weighted portfolio approach as in Asness, Moskowitz, and Pedersen (2013) where I weight currency i according to their cross-sectional rank in period t. The weighting scheme is defined as

$$w_{it}^{\beta,port} = c_t \left[\text{rank}(\beta_{it}) - \sum_i \text{rank}(\beta_{it})/N \right]$$

where c_t again refers to a scaling factor such that portfolio weights $(w_{it}^{\beta,port})$ sum up to one. The linear- and rank-weighted portfolio excess returns are then defined as

$$xret_t^{lin} = \sum_i w_{it}^{\beta,lin} xret_{it} \qquad\qquad xret_t^{port} = \sum_i w_{it}^{\beta,port} xret_{it}$$

Using linear- and portfolio rank weighting schemes, the strategy generates 4.32% (P_{LIN}) and 3.91% (P_{RANK}) annualized excess returns, respectively. In both cases, returns are significantly different from zero at the 5% level. These results confirm the assertion that results are not driven by a particular currency pair and alleviates concerns that outliers or specific months are driving my findings.

Lastly, returning to Table 2, I report the average transition probability matrix that shows the

changes of portfolio allocations. While portfolio allocations on the diagonal are more persistent, the off-diagonal entries indicate that currencies are frequently allocated to different portfolios. This suggests that returns to the strategy are not purely driven by a small subset of currencies that have persistent dollar-risk exposure but that frequent portfolio allocation is necessary. Given the short sample period, I assess this aspect more formally as part of the robustness checks.

INSERT TABLE 2 HERE

C. Understanding return dynamics: Comparison of Investment Signals

To understand the return dynamics of the revisited global dollar trade, I start the analysis by differentiating between returns in different states and then compare returns based on the new investment signal with the average forward discount (AFD), which has been employed as an investment signal in previous studies. The results are reported in Table 3. In Panel A, I document returns to individual portfolios in 'normal' months and periods following large dollar fluctuations. Differentiating the portfolio allocation between these two states shows, that returns are monotonically increasing from P1 (-0.99%) to P3 (2.89%) during normal periods, but they decrease monotonically from P1 (2.35%) to P3 (-2.90) following large movements of the dollar. In both cases, the HML is large in magnitude but has opposite signs (Normal: 3.89% and Large Fluctuations: -5.26%).

Panel B shows annualized average returns when the AFD is used as a sole conditioning variable. Following previous studies, I distinguish between periods when the AFD is positive (average foreign interest rates are higher than domestic interest rates), and when the AFD is negative (average foreign interest rates are lower than domestic interest rates). As documented, HML portfolio returns are positive when the AFD is larger than zero (2.33%) and they turn negative (-0.25%) during periods when U.S. interest rates are higher than in the rest of the world ($AFD \leq 0$). Even though the combination of the two HML portfolios is not significantly different from zero, the changing signs across states confirm a linear relationship between compensation for dollar risk and the AFD.

Next, I combine the AFD with the new investment signal and investigate how return realizations differ between the four different states. Panel C shows results for months when the AFD is larger than zero and when one explicitly distinguishes between periods following large fluctuations of the dollar ($AFD > 0$ & Large Fluctuations) and the remaining months ($AFD > 0$ & Normal). Interestingly, Table 3 reports that average HML portfolio returns have opposite signs, even though the AFD is positive during the entire 144 months. In normal periods the HML portfolio generates 5.58% (t-stat: 2.33) while returns are negative (-5.28%) following large fluctuations of the dollar. A similar diverging return pattern for the HML portfolios can be found when the AFD is smaller

than zero (Panel D). Returns are positive during normal periods (1.22%), but turn negative after large fluctuations of the dollar (-5.20%).

Furthermore, it is worth noting that different portfolios are the driving forces in the two states. When the AFD is positive, risky currencies contribute relatively more to the HML portfolio during normal periods (P3: 5.58%), while currencies with low dollar risk exposure have the highest returns after large fluctuations of the dollar (P1: 4.50%). The opposite is true when the AFD is negative. In these states low dollar risk currencies generate the highest returns (in magnitude) during normal periods (P1: -2.56%), while comparably risky currencies depreciate the most after large fluctuations of the dollar (P3: -7.70%).

Overall, I note that even if the AFD does not change its sign, there exist systematic return differences between normal periods and months following large fluctuations of the dollar portfolio. The decomposition of HML portfolio returns into the four different states in Table 3 highlights that large dollar fluctuations play an important role for the dollar trade as currencies strongly depreciate during these periods. Given the findings in Table 3, the new investment signal can be considered as a complement to the AFD that contains more refined information of dollar movements in the short-run. As further discussed in the next section, this additional information is important for investors' portfolio allocation and for the profitability of the global dollar trade.

INSERT TABLE 3 HERE

D. Understanding return dynamics: Comparison with standard FX strategies

To investigate the relation of the revisited global dollar trade with other well-established trading strategies, I provide an overview of strategies' performances and their correlation in Table 4. This step serves two objectives.

First, it is of interest if the excess returns of the trading strategy remain positive and significant once transaction costs are taken into account. To this end, the following results refer to net returns that proxy transaction costs by the prevalent bid-ask spread reported on WMR/Reuters. I assume short and long positions are closed and opened every month so that transaction costs accrue every period even though currencies may be allocated to the same portfolio twice in a row. Since it is well-known that bid-ask spreads of indicative quotes on Reuters are overestimating transaction costs (Gilmore and Hayashi (2011), Gargano, Riddiough, and Sarno (2017)), reported net returns of all strategies can be considered as conservative and as a lower bound.

Second, assessing the co-movement of returns with other strategies is a crucial aspect when considering the dollar as separate global risk factor in currency market. I address this concern by calculating conditional and unconditional correlations in Table 4.

INSERT TABLE 4 HERE

In Table 4, HML refers to high-minus-low portfolio returns of the revisited global dollar trade, Dol refers to the classic dollar trade using the AFD as an investment signal (Verdelhan (2018)), $Carry$ is the high-minus-low portfolio from the classic carry trade (Lustig and Verdelhan (2011)), $Dol - Carry$ is the dollar-carry trade (Lustig, Roussanov, and Verdelhan (2014)), MOM_{1M}^{CS} refers to cross-sectional momentum with 1-month formation period (Menkhoff, Sarno, Schmeling, and Schrimpf (2012b)), MOM_{1M}^{TS} is time-series momentum with 1-month formation period (Moskowitz, Ooi, and Pedersen (2012)), Dol^{Q} refers to the global dollar-trade based on forward-looking betas (Bang-Nielsen (2018)), and VRP refers to the high-minus-low portfolio of the volatility risk premium strategy (Della Corte, Ramadorai, and Sarno (2016)).

As reported in Panel A, excess returns of the revisited global dollar trade are not consumed by transaction costs. After taking into account the bid-ask spread net returns of the revisited global dollar trade are 3.84%, indicating that investors earn a significant risk premium (t-stat: 2.12). The strategy is the only trading approach generating significant and positive returns over the last 20 years. It produces a positive Sharpe ratio of 0.34. This is worth to emphasize as conventional FX trading strategies have been performing poorly during these years (Arnold and Wong (2017)). For example, while Carry and Dollar-Carry generate positive returns they are not significantly different from zero. Momentum remains unprofitable when only G10 currencies are considered.

Further, Table 4 indicates that net excess returns of HML are not more volatile than returns of other strategies and minimum (maximum) monthly observations do not imply that returns are driven by one particular month. With regard to skewness, the return distribution is barely shifted to one side, suggesting that returns to the high-minus-low portfolio are no compensation for crash risk. This is an important difference to the carry trade (Brunnermeier, Nagel, and Pedersen (2009)).

Panel B shows the unconditional correlations between the strategies. As reported, the revisited dollar trade is weakly negatively correlated with strategies that rely on the AFD (Carry, Dollar-Carry, classic dollar trade) and positively correlated with momentum-based trading and VRP. The former observation is important as it underlines the independent return generating process of the revisited dollar trade from carry. The latter result is interesting. It points towards the fact that the revisited dollar trade shares a common feature with momentum trading with a formation period of one month.

In Panel C and D, I proxy for tail correlations by considering the co-movement of strategies' returns in months of extreme return realizations of the value-weighted S&P500 index. I calculate the correlation between strategies in the top 5% percentile (Panel C) and the bottom 5% percentile (Panel D) of the equity index. As reported, the signs of the correlations are positive (negative) with carry (momentum) on both sides of the return distribution. While strategies' comovements increase during these months compared to the unconditional correlation, they are

far from indicating the same return generating process.

E. Understanding return dynamics: FX strategies and Factor Models

To test the relationship between well-established currency strategies and the revisited dollar trade more formally, I regress the high-minus-low portfolio excess returns (net of transaction costs) on risk factors from different asset classes. The results are presented in Table 5.

INSERT TABLE 5 HERE

In Panel A, I employ different combinations of risk factors identified in the foreign exchange literature to explain return dynamics of the revisited dollar trade. Independent of the set of risk factors, however, I find that significant abnormal returns remain unspanned. For example, using the dollar and carry factor as explanatory variables, annualized abnormal returns of 4.64% remain unexplained.

Similarly, return dynamics are not fully spanned by risk factors commonly used in other asset classes. Panel B of Table 5 explores return correlations between the revisited dollar trade and three- and five-factor models as well as equity momentum returns. While the latter factor is weakly significant at the 10% level, the remaining information from equity markets are not spanning portfolio returns and leave abnormal returns of at least 3.68% unexplained.

Further, I assess the link between the revisited global dollar trade and factors from the hedge fund or mutual fund literature. In Panel C, I use the factor model by Fung and Hsieh (2001). It consists of the five portfolio-straddle factors ($PTFS$) in bond (BD), foreign exchange (FX), commodities (COM), interest rates (IR), and stock markets (STK), returns on the S&P500 total return index (Mkt^{EQ}), the size spread factor that measures the difference between Russell 2000 index monthly total return and S&P500 monthly total return index (SS^{EQ}), the change in the 10-year Treasury yield (Mkt^{BD}), the credit spread as the difference between Moody's Baa yield minus the 10-year Treasury yield (CS^{BD}), and returns on the MSCI emerging market index (Mkt^{EM}).

In Panel D, I use returns on MSCI US Equities, (MKT_{US}), MSCI non-US (MkT_{World}), US Government Bond returns (BD_{US}), Non-US Government Bond returns (BD_{World}), one-month eurodollar deposit returns (ED_{1M}), spot gold ($Gold$), Emerging market equities (Mkt^{EMkt}), and US dollar index (DOL). All variations of these factor models leave significant abnormal returns unexplained and most factors are not significant. One notable exception are the returns on U.S. equity markets whose coefficients are negative and significant at the 5% level (-0.11 in Panel C, -0.15 Panel D). In contrast, coefficients of international equity markets (i.e. MkT_{World} or Mkt^{EM}) remain insignificant. While I explore the link between equity markets and dollar risk in the next section, the overall evidence suggest that return dynamics of the dollar trade are independent of existing risk factors.

INSERT TABLE 5 HERE

F. Understanding dollar risk exposure: Macroeconomic conditions

While the return dynamics of the revisited dollar trade appear to be unrelated to existing factors and strategies, in this section I explore how macroeconomic conditions vary between states when the slope of the DPL is positive or negative, and how they impact currencies' exposure to dollar risk.

To begin with, Table 6 shows the difference between various indicators that measure funding costs, uncertainty, and trading dynamics in both states of the DPL. The first row (Normal) refers to average values during months classified as 'normal', while the second row (Large Fluct.) documents average values in months subsequent to large fluctuations of the dollar portfolio. The row 'Diff' reports differences in means and 't-stat' denotes the test statistics of a conventional t-test assessing if the difference of averages is zero. The following observations are worth noting.

First, large fluctuations of the dollar portfolio are associated with an increase in uncertainty in financial markets. This is documented in the first three columns of Table 6. They show the average values of the VIX (VIX), St.Louis Fed Financial Stress Index (FSI), and volatility in FX markets (Vol). All three indicators increase in value following large fluctuations of the dollar portfolio and are significantly larger compared to the remaining months of the sample. For example, the VIX increases from 18.99 to 23.11 and FX volatility doubles from 0.22 to 0.45. As denoted in the last row, the difference between the two averages is significant at the 1% level. These results are in line with an on-going discourse that movements in the value of the U.S. dollar are indicative of risk perception in financial markets (Shin (2016)). Table 6 suggests that standard indicators of financial risk increase following large return movements of the dollar.

Second, coinciding with large fluctuations of the dollar portfolio global funding conditions worsen. This is reflected by a larger TED spread which increases from 0.42 to 0.55 (t-stat: 2.12), but also by larger absolute deviations from covered interest rate parity ($|CIPdev|$).[16] As shown, the CIP basis increases from 19.61 to 30.96 basis points during months following large return movements of the dollar. The difference between the two states is significant at the 1% level.

The impact of funding conditions on the slope of the DPL is of interest for at least two reasons. For one, Frazzini and Pedersen (2014) show that funding constraints lead to a decline in the slope of the SML in equity markets and most other major asset classes. As the dollar portfolio serves as a measure of dollar specific systematic risk one would expect that funding conditions also affect the price of dollar risk and the gradient of the DPL. This is confirmed by Table 6. Further, volatile

[16]Following previous studies (e.g. Borio, Iqbal, McCauley, McGuire, and Sushko (2018)), I calculate deviations from CIP as the difference between interest rate differentials and the synthetic borrowing costs from FX swap markets.

funding costs, increasing dollar demand, and tighter funding constraints have been playing an important role in the foreign exchange market during (Baba and Packer (2008)) and after the financial crisis (Borio, Iqbal, McCauley, McGuire, and Sushko (2018), Du, Tepper, and Verdelhan (2018)). The significant difference between the two states in Table 6 indicates that deviations from CIP also have an impact on the price of dollar risk, as larger funding costs coincide with periods in which the slope of the DPL is negative.

Third, I investigate the impact of the DPL on economic activity and flow dynamics. Motivated by the role of equity returns reported in Table 5 and the link between currency and equity markets (Cenedese, Payne, Sarno, and Valente (2015), Djeutem and Dunbar (2018)), I analyse how equity return differentials between foreign and domestic markets differ between the two states of the DPL. As previous results suggest that large fluctuations of the dollar are associated with higher uncertainty, flight-to-safety liquidity dynamics may result in larger capital inflows into the U.S. and lead to relatively stronger performing domestic equity markets. This conjecture is largely confirmed by the last three columns of Table 5. First, following large fluctuations of the dollar foreign equity markets perform relatively poorly compared to U.S. equity markets. Even though the difference in means is not significant (-0.36bps vs. -52.32bps), it increases substantially during these months.

While the flight-to-safety dynamics are only marginally observable from equity markets, they are confirmed by flow measures and suggestive of portfolio rebalancing by international investors. I use capital flow of U.S. securities and order flow data from FX interdealer markets to investigate the relation between global dollar demand and exposure to dollar risk. As argued by Hau and Rey (2005), international movements in capital flows should be ultimately reflected in the foreign exchange interdealer market as banks act as intermediaries and rebalance their inventories. Therefore, one would expect to find a consistent pattern in both flow measures.

In column 4, I document that capital flows show an increase in net demand for U.S. dollar during periods of heightened uncertainty and high funding costs. As capital flows are defined as the difference between sales and purchases of U.S. denominated assets from (of) foreigners to (from) U.S. residents, a negative number implies a relatively larger amount of assets were bought by foreigners from U.S. residents (positive dollar demand). Conversely, a positive number implies a higher demand for foreign currencies. During months when the DPL is positive, sales exceed purchases by almost 80 million U.S. dollar, while more U.S. denominated assets are purchased when the slope of the DPL is negative (-201.65 million). The difference between the two states is significant at the 5% level (t-stat: 2.00) and the findings are in line with previous studies (e.g. Della Corte, Sarno, and Sestieri (2012), Della Corte, Riddiough, and Sarno (2016)) showing that global capital imbalances and portfolio flows affect the price of bilateral exchange rates due to changing net demand of investors.

Lastly, the portfolio rebalancing channel and flight-to-safety dynamics are also reflected by order flow measures in the foreign exchange interdealer market. Column 6 shows that there is net demand for foreign currencies during normal periods (positive order flow). In these months buyer-initiated volume exceeds seller-initiated volume by 53.63 billion U.S. dollar. In contrast, following large fluctuations of the dollar portfolio, almost thrice the amount of seller-initiated volume is driving demand for the U.S. dollar on FX interdealer platforms (-145.22 billion U.S. dollar). The difference between the two states is significant at the 5% level (t-stat: -2.05). Overall, equity return differentials, capital flows, and FX order flow suggest that investors' demand for U.S. dollar as a safe haven currency increases in periods of higher uncertainty and tight funding conditions, and when the slope of the DPL is negative.

INSERT TABLE 6 HERE

In Table 7 I confirm the previous findings and show that currencies' dollar risk exposure is related to measures of financial uncertainty and funding constraints. The table reports results of the following predictive regression

$$\beta_{i,t+1} = \alpha + \beta F_t + \epsilon_{t+1}$$

where dollar risk exposure of portfolio 1 (top panel, β_{P1}) or portfolio 3 (bottom panel, β_{P3}) serves as the dependent variable and lagged factors (F) that capture economic conditions, such as log VIX (VIX), TED spread (TED), global FX volatility (Vol), and FSI (FSI), are used as explanatory variables.

The regression coefficients indicate a close relationship between dollar risk exposure, financial market uncertainty, and funding conditions. Interestingly, I find that coefficients in Panel A and B almost always have opposite signs. For example, an increase in uncertainty (VIX) lead to a decline in risk exposure for portfolio 1 (β_{P1}), but an increase in risk exposure for portfolio 3 (β_{P3}). Currency portfolios response asymmetrically to the changing environment of financial risk. One possible interpretation of these results is the following. As currencies in portfolios 3 are more likely to experience sudden depreciation when levels of uncertainty and funding costs rise, their level of risk exposure is increasing. This implies that investors demand a comparably larger compensation for holding high dollar risk currencies, as they bear a comparably larger risk of dollar appreciation during these periods. Overall, Table 6 and 7 highlight how changes in systematic risk factors in financial markets (i.e. uncertainty and funding conditions) are reflected by dollar betas and incorporated by the slope of the DPL.

INSERT TABLE 7 HERE

V. The Special Role of the U.S. Dollar

While the U.S. dollar is the dominant currency in the foreign exchange market and on one side of each trade for more than 88% of all transactions, an important remaining question is if similar return dynamics are observed when any of the other G10 currencies is employed as numeraire currency. I address this in two ways. For one, I check if the same trading strategy outlined before leads to similar trading profits when non-U.S. dollar currencies are used as base currencies. Further, I assess the link between measures of financial market uncertainty, funding costs, equity return differentials, and the gradient of different base portfolio lines.

To this end, I construct 72 additional bilateral exchange rates denominated in one of the G10 currencies other than the U.S. dollar and I calculate an associated set of option implied-betas ($\mathbb{E}_t[\beta^Q_{j,t+1}]$) that measure base currency risk for non-U.S. dollar exchange rates. Then, as in the original strategy outlined above, I identify large return movements for each of the nine unconditional base portfolios (i.e. euro portfolio or Japanese yen portfolio) separately. As these can potentially capture different degrees of global risk, market movements of other base currencies can be associated with other periods than those documented for the dollar. The rationale of this approach is the following. If the dollar does not have a special role in currency markets, then using other base currencies should not significantly affect the profitability of the trading strategy. The results are reported in Panel A of Table 8.

INSERT TABLE 8 HERE

As documented, employing different base currencies than the U.S. dollar results in very different outcomes. Across non-dollar base portfolios, the returns to the high-minus-low portfolio are not different from zero for all nine base currencies. Also, there is no clear pattern between the magnitude of risk exposure (e.g. yen betas) and excess returns.

This result is supported by Figure 4 which displays base portfolio lines for non U.S. dollar base currencies. For example, in Figure 4a I construct the Australian dollar portfolio as the average of foreign currencies vis-à-vis the Australian dollar, identify its large return realizations, and form long and short positions based on currencies expected exposure to Australian dollar risk. In contrast to Figure 3a which documented a clear change in the slope of the DPL, comparable dynamics cannot be found for any of the other base currency lines.

INSERT FIGURE 4 HERE

I interpret Panel A of Table 8 and Figure 3a as first evidence that dynamics of the U.S. dollar have a special role for the cross-section of currencies and that its large return fluctuations lead to common spillovers across G10 currencies.

To provide further evidence for this conjecture, in Panel B of Table 8 I repeat the same portfolio allocation for each base currency as before but instead of using large fluctuations of each base currency as an investment signal, I use the dollar portfolio as decision-making indicator to buy (sell) portfolio 3 and sell (buy) portfolio 1. In this case, a clearer pattern emerges though results are not as strong as for dollar denominated currencies.

First, the high-minus-low portfolios for the AUD and JPY are statistically significant (with opposite signs) and generate -3.83% and 3.74% annualized average excess returns respectively. The other two typical carry trade currencies, CHF and NZD, show similarly strong returns (2.91% and -2.66%), though both are not significant. Second, for six out of nine currency pairs returns are increasing (decreasing) with the magnitude of betas supporting a risk-based explanation. Third, country-characteristic patterns emerge. Currencies with exposure to commodity markets (AUD, CAD, NOK, NZD) generate negative returns, while other currencies produce positive returns. These patterns are in line with previous papers that emphasize the importance of commodities for currency prices (e.g. Ready, Roussanov, and Ward (2017)).

Differences in the pattern of high-minus-low returns between Panel A and B indicate that price movements of the U.S. dollar play an important role for all exchange rates even if the dollar is neither directly nor indirectly quoted. It appears that currencies co-move more strongly with each other after large fluctuations of the dollar, compared to return swings of non-U.S. dollar currencies. Further, as only the slope of the DPL is systematically changing its sign, it appears that investor price other base currencies more persistently. Even though returns can be partly mirrored using alternative base currencies, large return movements of the dollar appear to have a special role in foreign exchange markets.

Lastly, I address economic channels that attribute a special role to the dollar and, therefore, have an impact on the gradient of the slope of the DPL. I construct the gradient of the slope as the difference between realized excess returns of portfolio 3 and portfolio 1, and normalize it by the spread of portfolio betas. This allows me to obtain a monthly time series of slope gradients for each base portfolio line. Then, I run the following contemporaneous regression

$$i_t^{\nabla} = \alpha + \beta_1 F_t + \varepsilon_t$$

where i_t^{∇} refers to the gradient of the base portfolio line of currency i and F_t denotes economic factors that capture various conditions in financial markets. As explanatory variables, I use funding costs as proxied by the cross-sectional average of absolute deviations from covered interest parity ($|CIPdev|$), changes in financial market risk aversion as proxied by changes in the VIX (ΔVIX), funding costs measured by the TED spread (TED), changes in the Financial Stress Index (ΔFSI) published by the St. Louis, global FX volatility (Vol), and equity return differentials between

foreign and domestic countries ($\bar{rx}^{EQ}$). If the U.S. dollar owns a unique role in currency markets, then one would expect these factors only explain the gradient of the DPL (USD^{∇}) and that the slope turns negative when conditions in financial market worsen. Regression results are reported in Table 9.

INSERT TABLE 9 HERE

First, I find that only the gradient of the DPL is significantly associated with all six factors, while factors are largely not distinguishable from zero for all other base currencies. One exception is the gradient of the Australian dollar, where almost all variables are significant. As established in Figure 4, however, the slope of the Australian dollar portfolio does not show a distinct conditional state-dependence as the DPL.

Second, signs of obtained coefficients of the DPL are in line with expectations. For example, an increase in funding costs measured by absolute deviations from CIP ($|CIPdev|$) or the TED spread (TED) are associated with a flatter or a negative slope of the DPL. Further, the negative coefficients of ΔVIX, ΔFSI, and Vol imply that similar dynamics can be observed for an increase in risk and uncertainty in financial markets. Lastly, when world equity markets outperform the U.S. the slope is positive, but it turns negative when domestic markets are relatively stronger. This is in line with earlier results that indicate flight-to-safety and larger investments in U.S. denominated assets are associated with a negative slope of the DPL.[17]

VI. Further tests

To corroborate the robustness of my results, I conduct a series of additional tests and robustness checks. In the interest of space, I describe the tests and refer the reader to the appendix, where results are fully displayed.

A. Additional Results

A.1. Persistence of Cross-sectional Dollar Risk Exposure

To begin with, I follow Della Corte, Ramadorai, and Sarno (2016) and assess to what extent the results of the revisited global dollar trade strategy are driven by persistent cross-sectional differences in exposure to dollar risk. This is a particular concern as the availability of option data only allows to investigate return dynamics since January 1999.

[17]The results are confirmed by a simple non-parametric exercise shown in the Appendix (Figure 5). I split the sample into two groups and allocate slope gradients into a low and high portfolio if observations of funding conditions, uncertainty, and equity market differentials are below or above their respective medians. Then I calculate the average gradient for each group separately. The bar plots show how the sign of the DPL's slope changes across different realizations of the state variables.

To control for persistent cross-sectional differences, I calculate the level of dollar risk for each currency pair as the sample average over the entire period January 1999 to December 2017. While this approach inherently introduces a look-ahead bias, it is line with Hassan and Mano (2018) and allows decomposing strategy returns into a static and dynamic component. In fact, as shown in Table 10, 2.65% (equivalent to 63%) of generated portfolio excess returns of the high-minus-low portfolio stem from currencies which have the lowest and highest dollar risk on average. The remaining proportion (37%) arise from monthly portfolio rebalancing in response to changes in dollar exposure. This substantial component of portfolio returns adds notion to the initial stylized fact that currencies' exposure to dollar risk is not only changing over time but also in the cross-section of currencies.

A.2. Extended Sample Period

One potential concern arising from the analysis is that large outliers during the financial crisis are driving the results and that the strategies' profitability are driven by the limited span of the sample period. To alleviate this concern, I re-run the analysis for a longer sample period, using all monthly observations between 1985 to 2017. As data on option prices is not available for this period, I measure currencies' dollar exposure by 60-month rolling regression windows. Large return fluctuations are based on an extending window, whereby the first benchmark is constructed for the period January 1985 to December 1989. In total, 41 months are characterised by large return fluctuations.

I document that the revisited dollar trade strategy is highly profitable, even when a longer sample period. The average annualized high-minus-low portfolio based on equally-weighted portfolios generates 3.84% returns. It is statistically significant at the 5% level (t-stat: 2.30). The linearly-weighted and portfolio-ranked portfolio returns are 4.12% (t-stat: 2.41) and 3.53% (t-stat: 2.21), respectively. Notably, for the same sample period the original dollar trade that uses the AFD as an investment signal for the price of dollar risk only generates 2.71% (not significantly different from zero). These results suggest that my findings are not limited to the most recent years, but that they are a constant feature of the foreign exchange market.

A.3. Diversification Benefits

The low correlation of the revisited global dollar trade with other trading strategies suggests that investors can benefit from unexplored diversification benefits by combining the revisited global dollar trade with other trading strategies. To address this conjecture, I follow Della Corte, Ramadorai, and Sarno (2016) and Gargano, Riddiough, and Sarno (2017) and investigate the role of the trading approach from a portfolio manager's perspective. I consider four strategies as part

of one FX portfolio - revisited global dollar trade, carry, dollar-carry, and volatility risk premia trade - and investigate how the Sharpe ratio of a hypothetical investment strategy changes, if one naively forms *(i)* an equally-weighted portfolio of strategies, *(ii)* maximises the minimum-variance portfolio (MV), or *(iii)* aims to maximize the Sharpe ratio by investing into the tangency portfolio. While the equally-weighted portfolio approach attaches a weight of 25% to each of the individual currencies, the weights of the global minimum portfolio are chosen to achieve the lowest achievable level of risk. In line with standard finance theory I solve the following minimization problem ($\omega\Sigma\omega$ s.t. $\omega\mathbf{1} = 1$), where ω refers to a $(N \times 1)$ vector of portfolio weights, Σ is the variance-covariance matrix $(N \times N)$, and $\mathbf{1}$ refers to a $(N \times 1)$ vector of ones. For the MV-portfolio, weights are calculated as $\omega_{MVP} = \frac{\Sigma^{-1}\mathbf{1}}{\mathbf{1}'\Sigma\mathbf{1}}$ and weights for the tangency portfolio are defined as $\omega_{TP} = \frac{\Sigma^{-1}\mathbf{1}}{\mathbf{1}'\Sigma\mu}$, where μ refers to a $(N \times 1)$ vector of expect returns for each of the strategy. To highlight the diversification benefits of the new strategy compared to the classic dollar trade, the Sharpe ratios of the latter (based on AFD as an investment signal) are denoted in parentheses.

As expected, I find that the equally-weighted portfolio performs poorly as traditional strategies do not generate significant positive returns. The Sharpe ratio is only 0.14 (0.12). It increases slightly to 0.21 (0.14) for the minimum variance portfolio, but in both cases the risk-adjusted returns of the hypothetical FX portfolio are lower than the Sharpe ratio of the revisited global dollar trade individually. In contrast, using weights of the tangency portfolio the Sharpe ratio increases to 0.57 (0.35), as investors can leverage investments in the global dollar trade with short-positions in VRP and dollar carry. In sum, the strategy uncovers unexplored diversification benefits that potentially leads to higher risk-adjusted returns to investors.

A.4. Hedge Fund Industry and Currency Returns

The previous section suggests that the revisited global dollar trade strategy entails unexplored benefits that can be exploited by investors if they are able to leverage some of their positions. A natural question to ask is whether the strategy might be already implemented by market participants. In the spirit of Gargano, Riddiough, and Sarno (2017), I address this question by investigating the correlation between the HML portfolio and hedge fund returns. As this group of market participants is able to take short-positions across asset classes and can leverage their investment positions, they might potentially benefit largely from the additional diversification properties (as suggested in the previous subsection). Monthly data on hedge fund returns are obtained from the Lipper-TASS database which also reports funds' asset under management and funds classification of their trading style and investment approach.[18] I focus on funds classified as Global-Macro and Managed Futures as these investment styles are known for their trend-following strategies based

[18]Following Patton, Ramadorai, and Michael (2015), I clean the database for well-known databases that exist in commercially available hedge fund databases.

on short- and long-positions. Within this group, I also specifically consider funds whose primary investment approach lies on currency markets. For each fund classification I construct monthly value-weighted (VW) return series and employ these as the main dependent variable. The VW-returns are then regressed on the returns of the revisited global dollar strategy and a set of control variables such as the high-minus-low portfolios of carry or momentum, all five portfolio straddle factors (Fung and Hsieh (2001)) and the average bid-ask spread to control for liquidity conditions. The results are reported in Table 11.

INSERT TABLE 11 HERE

As shown, returns to the revisited dollar strategy appear to be uncorrelated to hedge fund returns across almost all fund classifications. For Managed Futures, the coefficient is weakly significant though the time series is shorter as no observations are available for the first half of the sample period. The link between the two series is not surprising as these funds take short and long positions and generate profits from exploiting trends in asset prices. As the revisited dollar trade is essentially based on return reversals of the dollar portfolio, it captures price trends between market reversals. In contrast to the revisited global dollar trade, it is worth noting that carry and momentum are strongly and positively correlated with hedge fund returns. This suggests that adding the global dollar trade to the FX portfolio could possibly improve the risk-return profile of funds.

A.5. Dollar Portfolio and Global Volatility

While I use fluctuations of the dollar portfolio as an investment signal of the dollar trade, it might be that other statistical signals capture similar risk-characteristics and lead to comparable profitable return. For example, it is well-known that large market participants reverse their carry positions following volatile market environments,[19] exploiting the close link between the forward discount and global volatility in foreign exchange markets (Menkhoff, Sarno, Schmeling, and Schrimpf (2012a)). To assess the impact of high volatility regimes on the dollar trade, I measure monthly global FX volatility as the daily realized volatilities within a month, averaged across countries: $\sigma_t^{FX} = \frac{1}{T_t}\sum_{\tau \in T_t}\sum_{k \in K}(\frac{|r_\tau^k|}{N_\tau})$, where N_τ is the number of currencies on day τ and T_τ refers to the number of observations within a month t. Second, I construct an alternative investment signal which reverses the carry or dollar trade when global volatility σ_t^{FX} is larger than the average $t-j$ months, whereby j varies between 3 months and 12 months.

I find that using global volatility as an investment signal improves returns for the carry trade significantly. Gross returns increase from weakly significant 3.40% to highly significant 4.70%

[19] One example of such an approach is UBS V10 Currency Index with Volatility Cap(`https://www.sec.gov/Archives/edgar/data/1114446/000139340109000609/c167020_69544-424b2.htm#tRF`).

annualized average returns. Accounting for volatility regimes plays an important role for the carry trade. For the global dollar trade similar inferences can be drawn, though results depend heavily on the benchmark that is used to calculate past volatility regimes. Hence, the strategy's performance varies drastically with the definition of the exact investment signal. The dollar trade produces low or insignificant returns if volatility regimes are defined relative to long-term averages of 6-month or more. In contrast, the strategy produces positive returns when short-term volatility dynamics are considered. On average, the global dollar strategy conditioned on volatility regimes produces 3.80% annualized returns. This is slightly lower than in the main analysis. Yet, it points towards the fact that return reversals of the dollar portfolio used in the main analysis coincide with periods of high global volatility. It also underscores that large fluctuations of the dollar portfolio on both side of the return distribution affect the market price of dollar risk.

A.6. Alternative Holding Periods

Next, I investigate the persistence of excess returns following the portfolio allocation. In the main text, the holding period is limited to one month even though persistent exposure to dollar risk could allow to hold positions for longer periods of time. As reported in Panel A of Table 12, I find that average portfolio returns are profitable and significantly different from zero for holding periods of one and two months. They are positive, but not statistically different from zero afterwards. These findings point towards the changing risk dynamics in currency markets. It again suggests that the pricing pattern of dollar risk is changing frequently, and that the impact of large dollar fluctuations on portfolio returns are comparably short-lived. The results are also in line with Menkhoff, Sarno, Schmeling, and Schrimpf (2012b) which show that cross-sectional momentum currency trading is only profitable for short holding periods.

A.7. Maturities of Options

Further, I analyse whether options with maturities longer than one-month can be used to exploit short-term dollar risk. To this end, I calculate high-minus-low portfolio returns of the revisited global dollar trade with holding periods of one month when currency betas are derived from option prices with maturities ranging from one month to twelve months. It is important to note that the sample period for this exercise is limited to January 2013 to December 2017, as these are the only years for which I can obtain option prices with maturities for more than one month for all nine currency pairs and their cross-rates. Despite this short coming, Panel B in Table 12 documents that returns are very similar in magnitude, positive, and largely significant independent of the maturity of the options. While further research is required, this indicates that a large proportion of information about short-term dynamics is shared across the term structure of options.

B. Robustness Tests

With regard to the robustness of my results, I assess different perturbations of the methodology employed in the main analysis to alleviate concerns that results are driven by sample-specific characteristics or modelling decisions.

B.1. Sub-Sample Analysis

First, I conduct a sub-sample analysis and assess to what extent returns to the revisited dollar trade differ before and after the financial crisis (cut-off date is October 2009) and during recession and non-recession periods.[20] Results are reported in Table 13.

Overall, I find that results are stable across sub-sample periods. For example, while pre-crisis returns are 4.33% the strategy generates 4.18% annualized average excess returns in the post-crisis period. During non-recession months, the returns to the strategy are significant at the 5% level (3.71%), while during the 28 recession months returns are high 8.40% though not significant. Further, in 74% of all years the strategy generates positive returns, pointing towards the fact that returns are not driven by specific years of the sample.

B.2. Currency Cross-Section

Furthermore, I investigate if the return process of the revisited dollar trade is driven by one particular currency pair. To this end, I exclude sequentially individual currency pairs from the portfolio construction and calculate returns to the strategy when the cross-section is limited to eight currency pairs. The results are reported in Table 14.

Independent of the cross-section of currencies, average annualized excess returns to the revisited global dollar trade vary between 3.14% (excluding JPY) to 5.58% (excluding CAD). In all cases returns are significantly different from zero at least at the 5% level.

B.3. Definition of Large Return Movements

As a further robustness check, I revisit the results for different threshold definitions that define periods of large fluctuations of the dollar portfolio. While the benchmark results are based on a comparison of returns in month t and a pre-sample average of returns between January 1994 to December 1999, I consider various alternative specifications. Instead of using a fixed window, I repeat the analysis with extending or rolling windows to alleviate concerns that results are driven by specific return characteristics in the pre-sample period. Then, I consider different pre-sample

[20] Recessions are defined based on the NBER classification of business cycle expansions and recessions: `$https://www.nber.org/cycles.html$`.

means that do not cover the entire five years of the pre-sample period, but only include two, three or four years starting from January 1997, January 1996, January 1995 onward, respectively. Also, I use wider and smaller distances from the mean as cut-off points, considering definitions between one and two-and-a-half standard deviations. The results are documented in Table 15.

While these alternative specifications do not cover all possible perturbations, it is worth noting that similar return profiles can be found irrelevant of the benchmark specifications. Returns to the HML portfolio range between 3.26% (t-stat: 1.78) and 4.54% (t-stat: 2.50). This indicates that my findings are not driven by the definition of the threshold and that return fluctuations of the dollar portfolio are priced by investors.

B.4. Realized Measures of Dollar Risk

In contrast to the original global dollar trade that relies on historical betas, the main results in this study are derived from option-implied betas. This is motivated by results in Bang-Nielsen (2018) which show that forward-looking betas are more accurate predictors of dollar risk than historical betas. To alleviate concerns that findings are a result of the choice of dollar risk measures and not by the signal of dollar risk, I employ the same trading approach but use historical betas based on 60-months rolling window regressions. As expected, employing historical measures of dollar risk, I find that the strategy generates slightly lower returns. Yet, the high-minus-low portfolio generates 3.2% annualized average returns, significant at the 10% level, while linearly- and rank-based weighting lead to 3.66% (t-stat: 1.95) and 3.87% (t-stat: 2.26), respectively.

One implication of the slightly smaller returns is the lower predictive performance of historical betas compared to option-implied betas. In fact, forming portfolios and using high-frequency data that only includes data of the forecasting horizon, I show that option-implied betas tend to consistently overpredict dollar risk, while the forecasting error of historical betas is less predictable and larger in magnitude (Figure 6). Also, the mean square error (MSE) of historical betas is larger compared to the prediction error produced by option-implied betas. The difference is significant as indicated by the Diebold-Marino statistics (Table 16). Further, option-implied betas tend to capture return reversals more accurately than historical measures. Panel B of Table 16 shows that ex-ante option-implied betas tend to be higher (lower) more frequently than historical betas, when ex-post returns are larger (smaller). Overall, the comparison of the predictive power of different measures builds upon earlier findings and confirms that forward-looking betas are more accurate predictors of dollar risk than realized measures.

VII. Conclusion

This paper provides empirical evidence that the dollar is priced in the cross-section of G10 currencies, contributing to an on-going debate whether base currency risk explains risk premia in foreign exchange markets. I propose a novel method to assess time-variation of global dollar risk and introduce the dollar portfolio line (DPL), which captures the link between dollar betas and excess returns. While the DPL is unconditionally flat, I document that its slope varies substantially over the sample period and it turns negative in months of high global dollar demand and tight funding constraints.

Investigating the dynamics of the slope, I suggest a new investment signal based on large fluctuations of the dollar portfolio and revisit its implications for the global dollar trade. Returns to a strategy that buys currencies with high exposure to dollar risk, shorts currencies with low exposure, and reverses these positions after large fluctuations of the dollar portfolio exceed more than 4% (Sharpe Ratio: 0.34) per annum. The returns are uncorrelated with standard risk factors and significantly exceed profits from well-known currency strategies during my sample. I document that the slope of the DPL is negative during months of high uncertainty, tight funding constraints, and global net demand for the U.S. dollar. Furthermore, these factors are only significantly explaining the slope of the DPL and are largely unrelated to alternative currency base portfolio lines. In fact, base currency portfolio lines of other numéraire currencies do not show the same systematic change in their slope as it is documented for the DPL, consistent with the view that the dollar has a special role in currency and international financial markets.

Overall, my findings highlight the importance of variations in the value of the dollar for currency markets since large return movements cause systematic spillover effects. The results add to an on-going debate on whether movements of the dollar can be considered as a proxy of market participants' perceptions of systematic risk in financial markets. While the focus of this paper is the empirical analysis of dollar risk dynamics, the development of a theory that captures the uncovered non-linear price pattern of dollar risk is an important avenue for future research.

VIII. Tables

Table 1. Summary Statistics: Dollar Risk Measures

This table reports summary statistics of currencies' exposure to dollar risk measured by forward-looking option-implied dollar betas ($E_t[\beta^Q_{t+1}]$). The following descriptive statistics are reported: mean (Avg), standard deviation (Std), maximum value (Max), minimum value (Min), skewness ($Skew$), kurtosis ($Kurt$), autoregressive coefficient ($AR(1)$), and number of observations (N). The sample period is January 1999 to December 2017.

	AUD	CAD	CHF	EUR	GBP	JPY	NOK	NZD	SEK
Avg	0.98	0.57	0.96	1.06	0.73	0.53	1.15	1.00	1.13
Std	0.19	0.24	0.21	0.18	0.13	0.30	0.12	0.22	0.13
Max	1.43	1.03	1.48	1.72	1.40	1.89	1.49	1.59	1.49
Min	0.40	0.05	0.39	0.67	0.42	−0.26	0.79	0.36	0.80
Skew	−0.45	−0.58	−0.14	1.12	0.71	0.42	0.01	−0.75	0.09
Kurt	3.44	2.49	2.47	5.44	5.71	5.37	3.17	3.93	2.79
AR(1)	0.80	0.92	0.79	0.85	0.69	0.83	0.67	0.83	0.68
N	228	228	228	228	228	228	228	228	228

Table 2. Revisited Global Dollar Trade

This table reports annualized average returns to the revisited global dollar trade. At the end of every month currencies are allocated into portfolios according to their exposure to dollar risk. Exposure to dollar risk is derived from option-implied betas. P3 (P1) contains currencies with the largest (smallest) dollar beta. During normal times investors buy currencies allocated to P3 and short currencies in P1. Following large return realizations of the dollar portfolio, investors reverse their portfolio allocation and buy currencies in P1 and short currencies in P3. Portfolios are held for one month. P_{HML} refers to a dollar-neutral high-minus-low portfolio. P_{LIN} and P_{RANK} refer to linearly- and rank-based weighted portfolios, respectively. In Panel B and C, I decompose excess returns into the change of the spot rate and the forward discount. The columns MR and UP report p-values of a monotonicity relationship tests accounting for magnitude and direction of return differences, respectively. Panel D reports the average transition probability matrix. Transition probabilities should be read from rows to columns. For example, the average probability that a currency moves from P1 in period t to P2 in period $t+1$ is 20.51%. Numbers in parentheses refer to t-statistics. The sample period is January 1999 to December 2017.

Panel A: Excess Returns

	P_1	P_2	P_3	P_{HML}	P_{LIN}	P_{RANK}	MR	UP
Mean	-1.36	1.47	2.90	4.26	4.32	3.91	0.01	0.01
T-Stat	(-0.87)	(0.66)	(1.18)	(2.35)	(2.11)	(2.33)		

Panel B: Spot Rate Changes

	P_1	P_2	P_3	P_{HML}	P_{LIN}	P_{RANK}	MR	UP
Mean	-1.23	1.17	2.89	4.12	4.01	3.73	0.01	0.01
T-Stat	(-0.79)	(0.53)	(1.18)	(2.27)	(1.89)	(1.97)		

Panel C: Forward Discount

	P_1	P_2	P_3	P_{HML}	P_{LIN}	P_{RANK}	MR	UP
Mean	-0.14	0.31	0.00	0.14	0.31	0.19	0.47	0.59
T-Stat	(-1.82)	(2.80)	(0.02)	(1.15)	(2.38)	(1.49)		

Panel D: Average Transition Probability Matrix

	$P1$	$P2$	$P3$
P_1	54.47	20.51	25.02
P_2	24.90	58.48	16.62
P_3	17.55	17.56	53.78

Table 3. Combined Investment Signals: AFD and Large Dollar Fluctuations

This table reports annualized average excess returns and corresponding t-statistics. At the end of every month currencies are allocated into portfolios according to their exposure to dollar risk. Exposure to dollar risk is derived from option-implied betas. P3 (P1) contains currencies with the largest (smallest) dollar beta. The column "HML" refers to returns of a high-minus-low portfolio that buys currencies in P3 and sells currencies in P1. Panel A reports results to this strategy when large dollar fluctuations (Normal vs. Large Fluctuations) are used as a conditioning variable (investment signal). Panel B reports results to this strategy when the average forward discount (AFD) is used as a conditioning variable (investment signal). Panel C and D report results to this strategy when the AFD ($AFD \leq$ vs. $AFD > 0$) and large fluctuations of the dollar portfolio (Normal vs. Large Fluctuations) are used as combined conditioning variables (combined investment signal). The column N refers to the number of observations where the conditions of the combined investment signals are met. Numbers in parentheses report corresponding t-statistics. The sample period is January 1999 to December 2017.

Panel A: Investment Signal: Dollar Fluctuations

	Normal						Large Fluctuations				
	P1	P2	P3	HML	N		P1	P2	P3	HML	N
Avg	-0.99	2.09	2.89	3.89	165	Avg	2.35	0.17	-2.90	-5.26	62
T-Stat	(-0.54)	(0.82)	(1.06)	(2.00)		T-Stat	(0.79)	(0.04)	(-0.54)	(-1.26)	

Panel B: Investment Signal: AFD

	AFD > 0						AFD ≤ 0				
	P1	P2	P3	HML	N		P1	P2	P3	HML	N
Avg	1.34	3.58	3.68	2.33	144	Avg	-2.54	-1.93	-2.79	-0.25	83
T-Stat	(0.65)	(1.18)	(1.09)	(0.97)		T-Stat	(-1.08)	(-0.64)	(-0.85)	(-0.09)	

Panel C: Combined Investment Signals: AFD > 0

	AFD > 0 & Normal						AFD > 0 & Large Fluctuations				
	P1	P2	P3	HML	N		P1	P2	P3	HML	N
Avg	0.00	3.61	5.58	5.58	101	Avg	4.50	3.50	-0.79	-5.28	43
T-Stat	(0.00)	(1.03)	(1.53)	(2.33)		T-Stat	(1.23)	(0.58)	(-0.11)	(-0.94)	

Panel D: Combined Investment Signals: AFD ≤ 0

	AFD ≤ 0 & Normal						AFD ≤ 0 & Large Fluctuations				
	P1	P2	P3	HML	N		P1	P2	P3	HML	N
Avg	-2.56	-0.31	-1.34	1.22	64	Avg	-2.50	-7.36	-7.70	-5.20	19
T-Stat	(-0.97)	(-0.09)	(-0.34)	(0.37)		T-Stat	(-0.48)	(-1.57)	(-1.51)	(-1.00)	

Table 4. Net Return Analysis: Comparison of FX strategies

This table reports summary statistics of the revisited global dollar trade strategy (HML) and compares its return dynamics with other FX trading strategies. Panel A reports net excess returns (using reported bid-ask spreads as a proxy for transaction costs) for the revisited global dollar trade (HML), classic dollar trade (Dol, Verdelhan (2018)), Carry (Lustig, Roussanov, and Verdelhan (2011)), dollar-carry (Dol-Carry, Lustig, Roussanov, and Verdelhan (2014)), cross-sectional momentum (Mom_{1M}^{CS}), Menkhoff, Sarno, Schmeling, and Schrimpf (2012b)), time-series momentum (Mom_{1M}^{TS}, Moskowitz, Ooi, and Pedersen (2012)), classic dollar trade with Q-betas (Dol^Q, Bang-Nielsen (2018)), and volatility risk premium trade (VRP, Della Corte, Ramadorai, and Sarno (2016)). Panel B reports unconditional correlations between all strategies. Panel C and D show tail correlations between the revisited global dollar trade and other FX strategies in the top and bottom 5% of realized returns of the S&P500 value-weighted index. The sample period is January 1999 to December 2017.

Panel A: Summary Statistics

	HML	Dol	Carry	Dol-Carry	Mom_{1M}^{CS}	Mom_{1M}^{TS}	Dol^Q	VRP
Mean	3.84	1.41	2.63	2.45	-1.27	0.85	1.31	1.56
T-Stat	(2.12)	(0.72)	(1.42)	(1.29)	(-0.69)	(0.44)	(0.71)	(0.00)
SR	0.34	0.03	0.18	0.16	−0.30	−0.04	0.02	0.06
std	7.89	8.47	8.06	8.31	7.97	8.36	7.96	6.78
max	9.67	9.33	8.03	7.12	11.34	14.24	8.03	7.44
min	−8.03	−9.13	−11.53	−9.46	−8.22	−7.53	−9.67	−6.06
skew	−0.06	−0.07	−0.84	−0.41	0.08	0.55	−0.33	0.02
kurt	4.73	4.46	5.84	4.09	6.07	8.10	4.70	3.79
AR(1)	0.06	−0.07	0.12	0.01	−0.02	0.09	−0.06	−0.06
N	227	227	227	227	227	227	227	227

Panel B: Unconditional Correlations

	HML	Dol	Carry	Dol-Carry	Mom_{1M}^{CS}	Mom_{1M}^{TS}	Dol^Q	VRP
HML	1.00							
Dol	−0.21	1.00						
Carry	−0.07	0.37	1.00					
Dol-Carry	−0.08	0.52	0.35	1.00				
Mom_{1M}^{CS}	0.30	−0.07	0.15	0.02	1.00			
Mom_{1M}^{TS}	0.30	−0.08	−0.10	0.05	0.67	1.00		
Dol^Q	−0.20	0.90	0.44	0.52	−0.06	−0.09	1.00	
VRP	0.13	0.28	0.55	0.26	0.04	−0.08	0.34	1.00

Panel C: Tail Correlations - worst 5% of S&P500 months

HML	1.00	−0.37	−0.58	−0.28	0.46	0.70	−0.46	−0.45

Panel D: Tail Correlations - best 5% of S&P500 months

HML	1.00	−0.43	−0.56	−0.03	0.40	0.24	−0.47	−0.40

Table 5. Revisited Global Dollar Trade and Risk Factors

This table reports results from contemporaneous regressions between HML portfolio returns of the revisited global dollar trade and risk factors from different asset classes. Panel A shows results using standard FX factors, such as the unconditional dollar factor (DOL), carry ($Carry$), cross-sectional momentum (MOM), and global volatility (Vol) as explanatory variables. Panel B shows results for equity factor models (three factors and momentum or five factor models). Panel C reports results using risk factors employed in the hedge fund literature, i.e. portfolio straddle factors ($PTFS$) in bond (BD), foreign exchange (FX), commodity (COM), interest rates (IR) and stock markets (STK) by Fung and Hsieh (2001), or the eight-factor model that complements a subset of these factors with equity market (Mkt^{EQ}), size spread (SS^{EQ}), bond market index (Mkt^{BD}), credit spread (CD^{BD}) and emerging market returns (Mkt^{EM}). In Panel D, I use factors from the mutual fund literature that capture U.S. and world equity market returns (Mkt^{US}, MkT^{World}), U.S. and world bond market dynamics (BD^{US}, BD^{World}), the euro-dollar deposit rate (ED_{1M}), gold index ($Gold$), emerging market returns (Mkt^{EMmkt}), and the dollar index (DOL). Numbers in parentheses refer to t-statistics adjusted for Newey-West standard errors. The sample period is January 1999 to December 2017.

Panel A: FX Factors

α	DOL	$Carry$	Mom	Vol							$\bar{R}^2$	N
4.64	0.19	-0.15									0.03	227
(2.42)	(2.57)	(-1.03)										
4.38	0.20	-0.13	0.10	0.10							0.03	227
(2.76)	(2.96)	(-1.01)	(0.91)	(0.91)								

Panel B: Equity Factors

α	Mkt	SMB	HML	MOM^{EQ}	CMA	RMW					$\bar{R}^2$	N
3.73	-0.01	-0.00	0.01	0.00							0.00	227
(1.93)	(-0.21)	(-0.08)	(0.18)	(2.19)								
3.65	-0.00	0.00	-0.00		0.00	0.00					0.00	227
(1.74)	(-0.33)	(0.42)	(-0.77)		(0.65)	(0.65)						

Panel C: Hedge Fund Factors

α	$PTFS_{BD}$	$PTFS_{FX}$	$PTFS_{COM}$	$PTFS_{IR}$	$PTFS_{STK}$	Mkt^{EQ}	SS^{EQ}	Mkt^{BD}	CD^{BD}	Mkt^{EM}	$\bar{R}^2$	N
4.40	-0.01	0.01	0.01	-0.00	0.01						0.00	227
(1.80)	(-1.08)	(1.05)	(1.13)	(-0.02)	(0.76)							
3.98	-0.01	0.01	0.01			-0.10	-0.00	0.08	0.08	0.08	0.01	227
(2.07)	(-0.99)	(0.79)	(1.18)			(-1.98)	(-0.09)	(0.66)	(0.74)	(0.74)		

Panel D: Mutual Fund Factors

α	Mkt_{US}	Mkt_{World}	BD_{US}	BD_{World}	ED_{1M}	$Gold$	MKt^{EMkt}	DOL			$\bar{R}^2$	N
7.18	-0.14	0.03	-0.21	-0.20	-0.53	0.00	-0.03	0.24			0.04	227
(2.74)	(-2.04)	(0.31)	(-0.71)	(-1.03)	(-0.64)	(0.12)	(-0.55)	(1.99)				
5.49	-0.14	0.03	-0.21	-0.20		0.00	-0.03				0.04	227
(2.60)	(-2.04)	(0.31)	(-0.71)	(-1.03)		(0.12)	(-0.55)					

Table 6. Time-Varying Global Dollar Risk and Macroeconomic Conditions

This table reports sample averages of different macroeconomic variables in months classified as 'Normal' and in months following large fluctuations of the dollar portfolio ('Large Fluct.'). The first two rows show average values for both regimes. The row 'Diff' denotes the difference between the averages, and the last row ('t-stat') reports the statistics of a standard t-test assessing if the means between the two regimes are the same. The columns refer to the following variables: VIX (VIX), Financial Stress Index (FSI), global FX volatility (Vol), TED spread (TED), absolute deviations from covered interest rate parity ($|CIPdev|$), cross-sectional average of return differentials between foreign equity markets and the U.S. equity market ($\bar{rx}_t^{EQ}$), capital flows of U.S. long term securities ($Flow$), and FX order flow (OF). The sample period is January 1999 to December 2017.

Panel A: Dollar Fluctuations

	VIX	FSI	Vol	TED	$\|CIPdev\|$	$\bar{rx}_t^{EQ}$	$Flow$	OF
Normal	18.99	-0.21	0.22	0.42	19.61	-0.36	79.67	53.63
Large Fluct.	23.11	0.19	0.45	0.55	30.96	-52.32	-201.65	-145.22
Diff	4.12	0.41	0.23	0.13	11.35	-51.96	-281.31	-198.86
t-stat	(3.54)	(2.62)	(4.87)	(2.12)	(3.70)	(-1.23)	(-2.00)	(-2.05)

Table 7. Dollar Risk Exposure: Predictive Regressions

This tables reports coefficients from the linear regression $\beta_{i,t+1} = \alpha + \beta F_t + \epsilon_{t+1}$, where $\beta_{i,t+1}$ refers to the cross-sectional average of currencies' dollar risk exposure in portfolio 1 (top panel, $\beta_{P1,t+1}$) or in portfolio 3 (bottom panel, $\beta_{P3,t+1}$). F_t refers to the following different macroeconomic variables: log of VIX (VIX), TED spread (TED), global FX volatility (Vol), and the Financial Stress Index (FSI). Numbers in parentheses refer to Newey-West adjusted standard errors. The sample period is January 1999 to December 2017.

Panel A: Low dollar risk currencies

	β^{P1}	β^{P1}	β^{P1}	β^{P1}	β^{P1}	β^{P1}
VIX	-0.27				-0.21	0.01
	(-2.37)				(-1.76)	(0.05)
TED		-0.18			-0.08	-0.08
		(-1.69)			(-0.65)	(-0.95)
Vol			-0.19		-0.06	
			(-2.13)		(-0.65)	
FSI				-0.27		-0.24
				(-1.87)		(-1.34)
$\bar{R}^2$	0.07	0.03	0.03	0.07	0.07	0.06
N	227	227	227	227	227	227

Panel B: High dollar risk currencies

	β^{P3}	β^{P3}	β^{P3}	β^{P3}	β^{P3}	β^{P3}
VIX	0.54				0.51	-0.12
	(6.63)				(5.61)	(-1.24)
TED		0.25			0.05	0.09
		(3.29)			(0.55)	(1.32)
Vol			0.29		0.02	
			(4.86)		(0.34)	
FSI				0.47		0.51
				(4.53)		(4.41)
$\bar{R}^2$	0.29	0.06	0.08	0.22	0.29	0.23
N	227	227	227	227	227	227

Table 8. Revisited Global Risk Trade: Alternative Base Currencies

This table reports annualized average excess returns for the revisited global dollar trade when non-U.S. dollar base currencies are employed (indicated by columns). In Panel A non-U.S. dollar denominated currencies are sorted into portfolios according to their risk exposure to the respective base currency (e.g. exposure to yen risk). Currencies in portfolio 3 (P3) have a high exposure to base currency risk while portfolio 1 (P1) contains currencies with low base currency risk exposure. P_{HML} refers to a high-minus-low portfolio. Months of large return swings are defined by benchmarking return realizations of the base factor in every period against a pre-sample mean (e.g. large return realizations of the yen portfolio). In Panel B, currencies are sorted into portfolios according to their risk exposure to different base currencies, but months of large returns movements are defined by large return swings of the dollar portfolio. Thus, the investment signal in Panel B is the same as in the main analysis. Numbers in parentheses refer to t-statistics. The sample period is January 1999 to December 2017.

Panel A: Alternative Base Currencies

	AUD	CAD	CHF	EUR	GBP	JPY	NOK	NZD	SEK
P_1	-2.95	0.18	-2.41	-0.27	-0.16	1.08	1.24	-5.29	-0.15
	(-1.85)	(0.10)	(-1.61)	(-0.26)	(-0.09)	(0.48)	(0.80)	(-2.68)	(-0.11)
P_2	-2.80	0.90	-1.75	1.72	-1.19	2.12	2.01	-4.77	0.63
	(-1.40)	(0.51)	(-0.88)	(1.04)	(-0.67)	(0.77)	(1.17)	(-2.02)	(0.36)
P_3	-5.20	0.89	-0.29	1.30	2.33	1.27	0.93	-4.43	0.70
	(-2.06)	(0.42)	(-0.13)	(0.69)	(1.12)	(0.40)	(0.41)	(-1.69)	(0.40)
P_{HML}	-2.25	0.72	2.12	1.57	2.50	0.19	-0.31	0.86	0.85
	(-1.23)	(0.44)	(1.09)	(0.89)	(1.50)	(0.10)	(-0.16)	(0.47)	(0.51)

Panel B: Alternative Base Currencies & Large Dollar Fluctuations

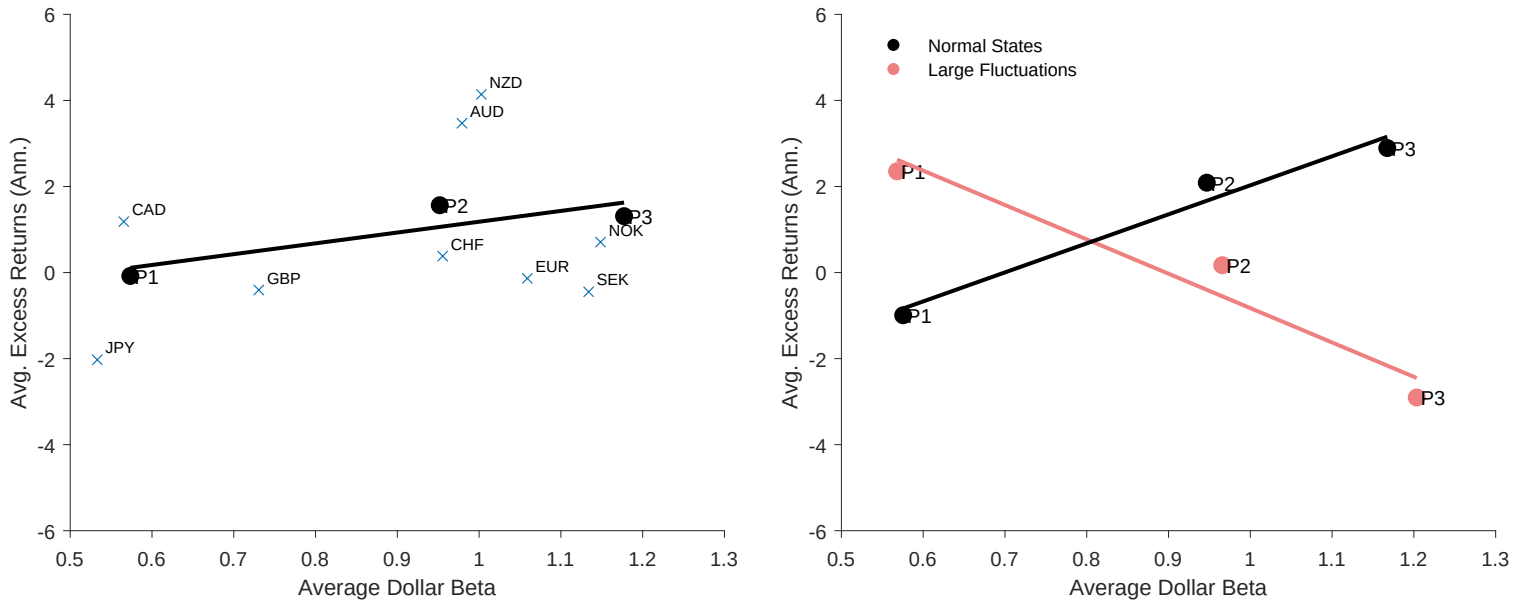
	AUD	CAD	CHF	EUR	GBP	JPY	NOK	NZD	SEK
P_1	0.76	-1.94	1.60	-0.08	0.78	4.06	-2.29	-2.82	-2.53
	(0.47)	(-1.15)	(1.07)	(-0.08)	(0.44)	(1.80)	(-1.50)	(-1.41)	(-1.86)
P_2	-0.23	-1.90	2.98	0.29	1.93	5.49	-1.84	-3.77	-0.45
	(-0.11)	(-1.07)	(1.51)	(0.17)	(1.09)	(2.01)	(-1.07)	(-1.59)	(-0.26)
P_3	-3.07	-3.14	4.51	0.78	1.99	7.80	-4.48	-5.49	-1.13
	(-1.21)	(-1.49)	(2.06)	(0.41)	(0.95)	(2.53)	(-2.01)	(-2.10)	(-0.64)
P_{HML}	-3.83	-1.21	2.91	0.86	1.21	3.74	-2.19	-2.66	1.40
	(-2.11)	(-0.74)	(1.50)	(0.48)	(0.72)	(2.14)	(-1.16)	(-1.47)	(0.85)

Table 9. Base Factor Slopes: Univariate Regressions

This table reports results from univariate regressions with the gradient of the base portfolio line of each currency as dependent variable on the left hand side. In each month t the gradient is calculated as the spread between excess returns of P3 and P1 currencies, normalized by the spread of base currency risk exposure (i.e. β_{P3} and β_{P1}). The following variables are used as explanatory variables: funding costs - proxied by absolute deviations from covered interest rate parity ($|CIPdev|$), change in the VIX (ΔVIX), TED spread (TED), changes in the Financial Stress Index (ΔFSI), global FX volatility (Vol), and return differentials in equity markets ($\overline{\tilde{rx}_t^{EQ}}$). Numbers in parentheses refer to Newey-West adjusted t-statistics. The sample period is January 1999 to December 2017.

	AUD^{∇}	CAD^{∇}	CHF^{∇}	EUR^{∇}	GBP^{∇}	JPY^{∇}	NOK^{∇}	NZD^{∇}	SEK^{∇}	USD^{∇}
$\lvert CIPdev \rvert$	0.06	-0.10	-0.02	0.02	0.08	0.02	0.05	0.10	-0.00	-0.18
	(1.26)	(-1.35)	(-0.57)	(0.40)	(1.12)	(0.53)	(1.46)	(1.19)	(-0.10)	(-2.32)
$\bar{R}^2$	-0.00	0.01	-0.00	-0.00	0.00	-0.00	-0.00	0.01	-0.00	0.03
ΔVIX	0.44	-0.17	-0.02	0.05	-0.03	-0.04	-0.10	-0.11	-0.04	-0.31
	(7.27)	(-1.56)	(-0.54)	(0.27)	(-0.40)	(-1.77)	(-0.61)	(-1.55)	(-0.88)	(-3.56)
$\bar{R}^2$	0.19	0.02	-0.00	-0.00	-0.00	-0.00	0.01	0.01	-0.00	0.09
TED	0.22	-0.01	-0.05	0.13	0.27	0.01	0.09	-0.13	0.05	-0.22
	(2.17)	(-0.21)	(-1.12)	(1.63)	(1.33)	(0.29)	(1.36)	(-2.00)	(1.43)	(-1.89)
$\bar{R}^2$	0.04	-0.00	-0.00	0.01	0.07	-0.00	0.00	0.01	-0.00	0.04
ΔFSI	0.46	-0.12	-0.08	0.10	-0.07	0.01	0.06	-0.16	0.01	-0.35
	(6.90)	(-1.24)	(-1.39)	(0.62)	(-1.28)	(0.34)	(0.62)	(-2.13)	(0.94)	(-5.24)
$\bar{R}^2$	0.21	0.01	0.00	0.01	0.00	-0.00	-0.00	0.02	-0.00	0.12
Vol	0.23	-0.20	-0.01	-0.01	0.03	-0.06	0.04	-0.02	0.02	-0.17
	(3.24)	(-1.07)	(-1.06)	(-0.14)	(1.05)	(-1.15)	(0.84)	(-0.63)	(0.68)	(-1.93)
$\bar{R}^2$	0.05	0.03	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	0.02
$\bar{rx}^{EQ}$	0.24	0.15	0.05	0.04	0.00	0.02	-0.00	-0.20	-0.04	0.31
	(3.35)	(1.48)	(1.19)	(0.82)	(0.00)	(0.41)	(-0.01)	(-0.92)	(-0.96)	(4.33)
$\bar{R}^2$	0.05	0.02	-0.00	-0.00	-0.00	-0.00	-0.00	0.03	-0.00	0.09

IX. Figures



(a) Dollar Portfolio Line: Unconditional Average

(b) Dollar Portfolio Line: Conditional Averages

Figure 1. Dollar Portfolio Line

These figures show the unconditional average dollar portfolio line (DPL) for the full sample period January 1999 to December 2017 (Figure 1a) and conditional DPLs for months classified as 'Normal States' (black line) and for months following large fluctuations of the dollar portfolio (red line, Figure 1b). Currencies are allocated to three portfolios based on their exposure to dollar risk which is measured by dollar betas (Verdelhan (2018)). Following Bang-Nielsen (2018) betas are derived from FX option implied volatilities. The set of G10 currencies includes the Australian dollar (AUD), Canadian dollar (CAD), Swiss franc (CHF), euro (EUR), British pound (GBP), Japanese yen (JPY), Norwegian krone (NOK), New Zealand dollar (NZD), and Swedish krona (SEK).

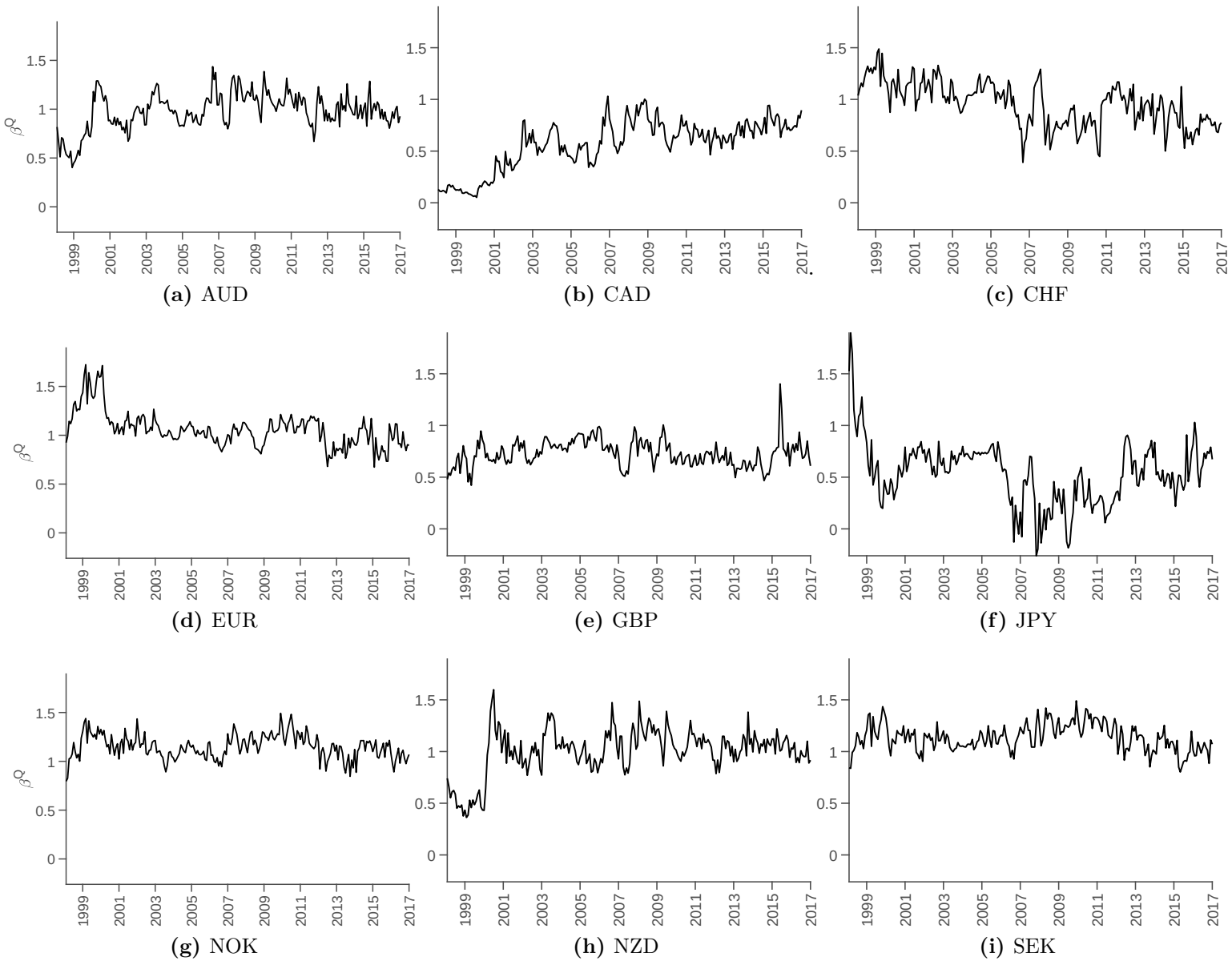
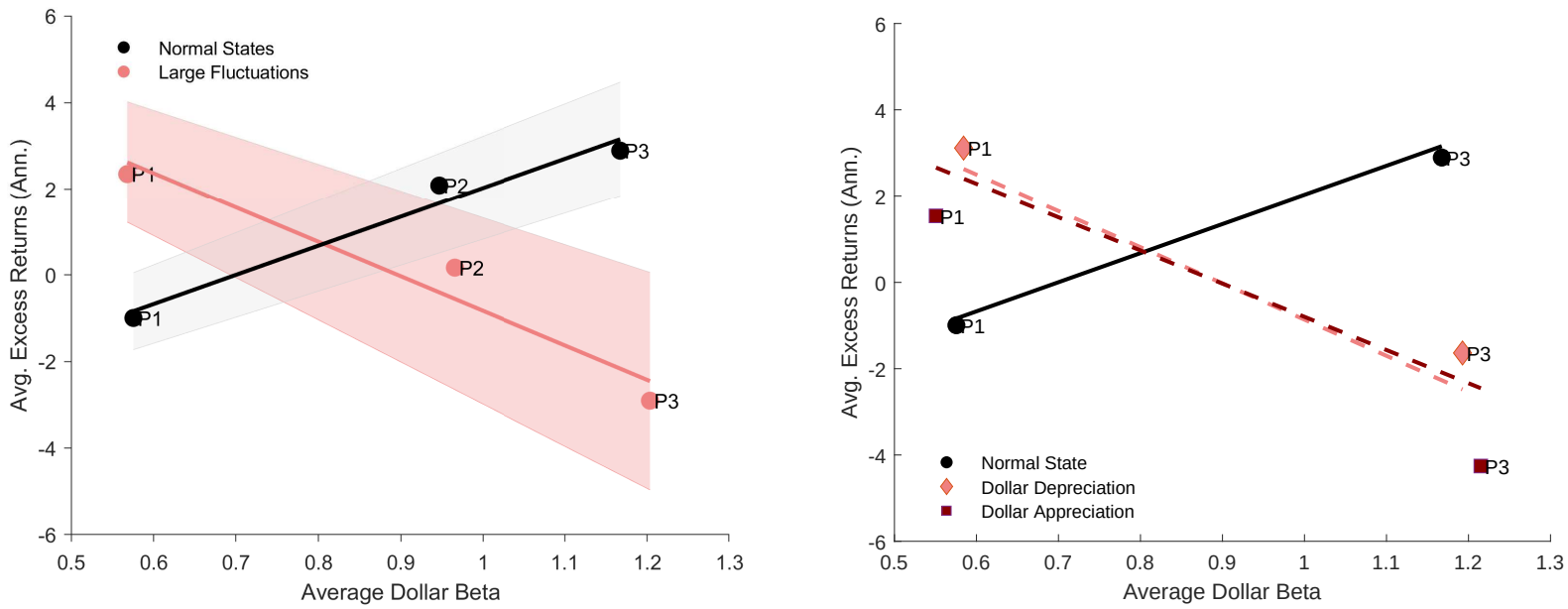


Figure 2. Time-Varying Dollar Risk

These figures show time-series dynamics of forward-looking dollar betas (β^Q) which are derived from FX option markets. The sample period is January 1999 to December 2017.

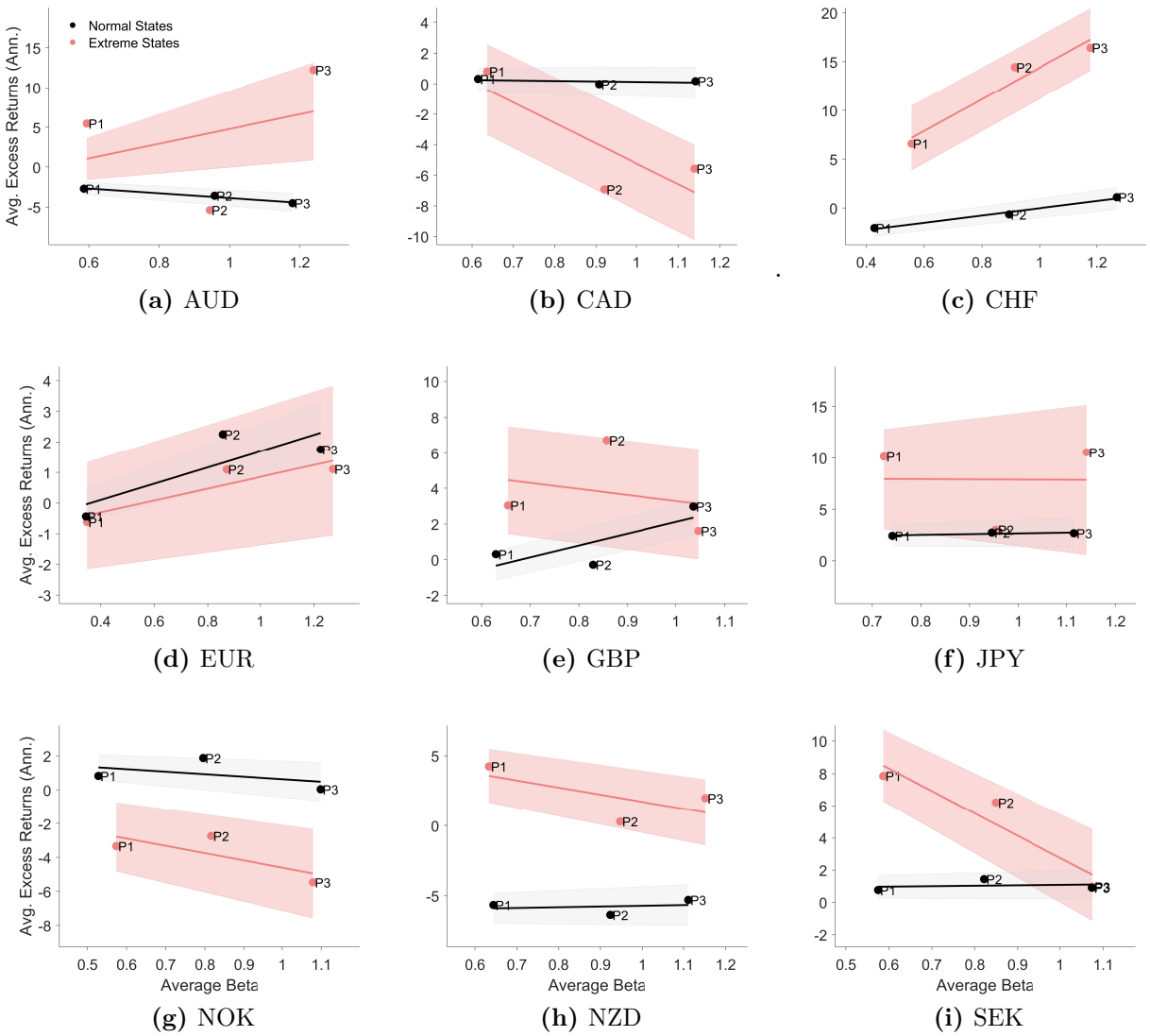


(a) DPL incl. Error Bands

(b) Dollar Appreciation and Depreciation

Figure 3. Revisited Dollar Trade: Time-varying Dollar Portfolio Line

These figures show the dollar portfolio line (DPL) accounting for state-dependent return dynamics. In Figure 3a the black line refers to portfolio excess returns and dollar risk during normal times, while the red line refers to months following large return realizations of the dollar portfolio. These months are defined out-of-sample by comparing realized returns in every month t against a pre-sample period. Figure 3b additionally distinguishes between months following large appreciations (dark red, squares) and depreciations (light red, diamonds) of the dollar portfolio. The sample period is January 1999 to December 2017.



(a) AUD (b) CAD (c) CHF

(d) EUR (e) GBP (f) JPY

(g) NOK (h) NZD (i) SEK

Figure 4. Base Portfolio Lines: Non-U.S. Dollar Base Currencies

These figures show base portfolio lines for each of the nine non-U.S. dollar base portfolios. For each base portfolio, I define large return fluctuations by comparing base portfolio returns with a pre-sample period (January 1994 to December 1999). In months with normal return realizations of the base portfolio investors go long currencies with high base currency risk (e.g. high yen risk betas) and short currencies with low base currency risk (e.g. low yen risk betas). After large return fluctuations, investors reverse the portfolio allocation. The y-axis refers to annualized portfolio excess returns realized during normal states (black) and during months after large fluctuations of the base factor (red). The red and black shaded areas refer to 10% standard errors based on excess returns of low and high base currency risk portfolios, respectively. The sample period is January 1999 to December 2017.

X. Appendix: Methodology and FX Option Data

A. *Option-implied FX Moments*

In order to construct option-implied estimates of dollar risk, I follow Britten-Jones and Neuberger (2000) and equipped with a set of call and put option prices I obtain risk-neutral expectations of asset prices' higher moments and covariate processes. In fact, Jiang and Tian (2005) show that inferences based on these measures are robust in the presence of jumps, which is of importance for currency markets where sudden price movements are common (e.g. Barndorff-Nielsen and Shephard (2006)). The expected risk neutral-variance ($E_t^Q\left[RV_{t+\tau}^2\right]$) at time t over period $t+\tau$ is then defined as,

$$E_t^Q\left[RV_{t+\tau}^2\right] = \kappa\left(\int_0^{F_{t,\tau}} \frac{1}{K^2} P_{t,\tau} K d(K) + \int_{F_{t,\tau}}^{\infty} \frac{1}{K^2} C_{t,\tau} K d(K)\right) \tag{3}$$

where $P_{t,\tau}$ and $C_{t,\tau}$ are the put and call prices at time t with strike price K, maturity date $t+\tau$, and $F\tau, t$ is the forward rate with time to maturity $t+\tau$ and $\kappa = 2e^{(i_{t,\tau}\tau)}$, where $i_{t,\tau}$ denotes the domestic risk-free interest rate with maturity τ.

As FX options are conventionally quoted in terms of implied volatilities at fixed deltas, I use the evaluation formula in Garman and Kohlhagen (1983) to extract all the required information in Equation (3). I obtain option strike prices associated with each of the quoted implied volatilities. Then, I calculate put and call prices for all quoted option-deltas. Notably, information on FX options is limited to the most liquid products and only five implied volatilities at different deltas are available to construct a volatility smile for each currency pair. Since Equation (3) assumes an infinite number of strike prices, I use a cubic spline around the available strike prices and for a fixed level of moneyness to smooth out the curvature of the volatility smile between the originally quoted levels of implied volatility. This is a standard approach in the literature (e.g. Della Corte, Ramadorai, and Sarno (2016)). Subsequently, the integral in Equation (3) is approximated by a trapezoidal integration scheme. While this approach introduces two types of errors - truncation errors and discretization errors (Jiang and Tian (2005)), previous studies argue that the impact of implementation errors are small (Della Corte, Ramadorai, and Sarno (2016), Mueller, Tahbaz-Salehi, and Vedolin (2017)).

Next, I assume absence of triangular arbitrage so that the link between two U.S. dollar based exchange rates and their cross-currency pairs is given by $S_t^{mj} = \frac{S_t^m}{S_t^j}$. Expressed in logs one can write the change of the exchange rate between period t and $t+\tau$ as,

$$\Delta s_{t+\tau}^{mj} = \Delta s_{t+\tau}^{m} - \Delta s_{t+\tau}^{j} \tag{4}$$

Taking variances on both sides, I re-write Equation (4) as

$$\int_t^{t+\tau} (\sigma_u^{mj})^2 du = \int_t^{t+\tau} (\sigma_u^m)^2 du + \int_t^{t+\tau} (\sigma_u^j)^2 du - 2 \times \int_t^{t+\tau} (\zeta_u^{mj}) du \tag{5}$$

where ζ_u^{mj} denotes the risk-neutral covariance between exchange rate m and j. It can be precisely calculated by re-arranging Equation (5) as

$$\int_t^{t+\tau} (\zeta_u^{mj}) du = \frac{1}{2} \times \left[\int_t^{t+\tau} (\sigma_u^m)^2 du + \int_t^{t+\tau} (\sigma_u^j)^2 du - \int_t^{t+\tau} (\sigma_u^{mj})^2 du \right] \tag{6}$$

Equations (5) and (6) are used to construct the entire variance-covariance matrix for a set of currencies versus a common base currency and their cross-rates.

B. FX Option Data

In the empirical analysis I employ foreign exchange implied volatilities data from two different data sources. For the period January 1999 to February 2013 FX option data is obtained from JP Morgan's Dataquery database. For the period March 2014 to December 2017 I use FX option data from Bloomberg. Both sources provide data for at-the-money (ATM), at 15-delta and 25-delta instruments. While the data from JP Morgan is quoted in terms of plain vanilla options that refer to either call and put options with a specific strike price, implied volatility data from Bloomberg is quoted in terms of at-the-money straddles, risk reversals, and butterfly spreads. Hence, before calculating risk-neutral variances and covariances, I back out the plain vanilla implied volatilities from these instruments.

To this end, I follow the steps in Carr and Wu (2009) and Castagna and Mercurio (2007) which are outlined below and exemplify the linear relationship between FX options quoted on Bloomberg and plain-vanilla implied volatilities as quoted on JP Morgan's Dataquery database. Further details on these steps are provided in the two mentioned studies, while Wystup (2006) provides a more general overview of quoting conventions in FX option markets.

To obtain implied-volatilities of plain vanilla options for 10-delta and 25-delta puts, at-the-money, 10-delta and 25-delta calls, I use at-the-money straddles, risk-reversal and butterfly spreads from Bloomberg. A straddle refers to the sum of call and put options that share the same strike price, risk reversals contain information about the skewness of the underlying's return distribution, while butterfly spreads capture information about its kurtosis. I obtain one time series for the straddle and two (10-delta and 25-delta) time series for risk reversals and butterfly spreads from Bloomberg. The maturity of all instruments is one month to match the maturity of options in the earlier period of the sample. Then, the link between a straddle and at-the-money implied

volatility is straight forward

$$\sigma_{0\delta} = \sigma_{ATM} \tag{7}$$

where $\sigma_{0\delta}$ refers to the implied volatility of the straddle and σ_{ATM} denotes the implied volatility of an at-the-money option. For put ($\sigma_{j\delta,p}$) and call options ($\sigma_{j\delta,c}$) with delta $j = 10, 25$ the following linear relationships can be used to obtain the required information

$$\sigma_{j\delta,c} = \sigma_{ATM} + \frac{\sigma_{j\delta,RR}}{2} + \sigma_{j\delta,BS} \tag{8}$$

$$\sigma_{j\delta,p} = \sigma_{ATM} - \frac{\sigma_{j\delta,RR}}{2} + \sigma_{j\delta,BS} \tag{9}$$

where $\sigma_{j\delta,RR}$ and $\sigma_{j\delta,BS}$ refer to risk reversals and butterfly spreads with delta j, respectively. Using data sourced from Bloomberg in Equations (7) – (9) returns implied volatilities that are associated with specific strike prices for 10–, 25–delta put, call and at-the-money options, and that are comparable to the data in the earlier sample period.

XI. Appendix: Additional Tables and Figures

Table 10. Static Dollar Trade

This table reports annualized average excess returns (Panel A) and spot rate changes (Panel B) to the revisited global dollar trade. At the beginning of the sample period currencies are allocated to portfolios based on their average dollar risk exposure over the entire sample period January 1999 to December 2017. Currencies with large (small) dollar betas are allocated to Portfolio 3 (Portfolio 1). Portfolios are held for the entire sample period and are not re-balanced. P_{HML} refers to a high-minus-low portfolio. Numbers in parentheses show respective t-statistics.

Panel A: Static Trade - Excess Returns

	P_1	P_2	P_3	P_{HML}
Mean	-0.56	1.47	2.09	2.65
T-Stat	(-0.39)	(0.59)	(0.89)	(1.59)

Panel B: Static Trade - Spot Rate Changes

	P_1	P_2	P_3	P_{HML}
Mean	-0.31	1.05	2.08	2.40
T-Stat	(-0.22)	(0.42)	(0.89)	(1.44)

Table 11. Dollar Trade and Hedge Fund Returns

This table reports results from the regression

$$ret_{j,t}^{VW} = \alpha + \beta_1 HML_t + \beta_2 HML_t^{Carry} + \beta_3 HML_t^{MOM} + \boldsymbol{\gamma}\mathbf{X}_t + \varepsilon_t$$

where $ret_{t,j}^{VW}$ refers to the value-weighted index of hedge fund group j in period t, HML are net returns of the revisited global dollar trade, HML^{Carry} refers to the carry trade, HML^{MOM} are momentum returns, and the matrix $\mathbf{X}$ contains control variables such as the five portfolio straddle factors by Fung and Hsieh (2001), and the average bid-ask spread as a proxy for liquidity conditions. Numbers in parentheses show Newey-West adjusted t-statistics. The sample period is January 1999 to December 2017.

	All	Global Macro	Managed Futures	Currencies	Primary Currencies
α	0.27	0.27	-0.89	-0.21	-0.21
	(0.39)	(0.39)	(-0.91)	(-0.37)	(-0.37)
HML	4.83	4.79	10.87	1.25	1.25
	(0.84)	(0.83)	(1.71)	(0.20)	(0.20)
HML^{Carry}	4.83	4.79	10.87	1.25	1.25
	(0.84)	(0.83)	(1.71)	(0.20)	(0.20)
HML^{Mom}	4.83	4.79	10.87	1.25	1.25
	(0.84)	(0.83)	(1.71)	(0.20)	(0.20)
Controls	YES	YES	YES	YES	YES
$\bar{R}^2$	0.08	0.08	0.12	0.08	0.08
N	227	227	141	227	227

Table 12. Holding Period and Option Maturities

This table reports annualized average returns to the revisited global dollar trade strategy. In Panel A, currencies are allocated to portfolios based on option-implied betas with a maturity of one month and which are held for periods of 1-month, 2-month, 3-month, 6-month, 9-month, and 12-month. Numbers in parentheses present t-statistics. The sample period is January 1999 to December 2017. In Panel B, option-implied betas with different maturities are used to allocate currencies into portfolios. Independent of the maturity of the option, the holding period is one month. Data on FX options is obtained from Bloomberg and, due to data limitations, the sample is limited to January 2013 to December 2017.

Panel A: Holding period - Revisited Global Dollar Trade						
	$1M$	$2M$	$3M$	$6M$	$9M$	$12M$
Mean	4.24	2.70	1.43	0.65	0.21	0.25
T-stat	(2.33)	(2.10)	(1.44)	(0.98)	(0.40)	(0.55)
Panel B: Option Maturity						
	$1M$	$2M$	$3M$	$6M$	$9M$	$12M$
Mean	3.44	3.95	3.24	3.93	3.93	3.77
T-stat	(1.50)	(1.74)	(1.60)	(1.95)	(1.93)	(1.83)

Table 13. Robustness: Sub-sample Analysis

This table reports annualized average excess returns to the revisited global dollar trade in different sub-sample periods. At the end of each month currencies are allocated to portfolios according to their dollar betas. Currencies with large (small) beta are allocated to Portfolio 3 (Portfolio 1). In normal times, an investor goes long currencis in Portfolio 3 and shorts currencies in Portfolio 1; following large return fluctuations of the dollar the portfolio allocation is reversed. Panel A and B split the sample in two sub-periods (cut-off point: October 2009) to capture return dynamics before (129 months) and after (98 months) the financial crisis. Panel C and D distinguish between NBER recession (26 months) and non-recession periods (201 months). Numbers in parentheses refer to t-statistics. The sample period is January 1999 to December 2017.

Panel A: Pre-crisis period				
	P_1	P_2	P_3	P_{HML}
Mean	-3.83	-2.63	0.50	4.33
T-Stat	(-1.55)	(-0.80)	(0.14)	(1.68)
Panel B: Post-crisis period				
	P_1	P_2	P_3	P_{HML}
Mean	0.34	4.97	4.52	4.18
T-Stat	(0.17)	(1.64)	(1.35)	(1.65)
Panel C: NBER recession periods				
	P_1	P_2	P_3	P_{HML}
Mean	1.50	14.52	9.89	8.40
T-Stat	(0.28)	(1.48)	(0.94)	(1.10)
Panel D: NBER non-recession periods				
	P_1	P_2	P_3	P_{HML}
Mean	-1.84	0.03	1.87	3.71
T-Stat	(-1.13)	(0.01)	(0.77)	(2.05)

Table 14. Robustness: Currency Cross-section

This table reports annualized average excess returns to the revisited global dollar trade when individual currencies (indicated by column) are excluded from the cross-section. At the end of each month currencies are allocated to portfolios according to their dollar betas. Currencies with large (small) dollar betas are allocated to Portfolio 3 (Portfolio 1). Numbers in parentheses refer to t-statistics. The sample period is January 1999 to December 2017.

	AUD	CAD	CHF	EUR	GBP	JPY	NOK	NZD	SEK
P_{HML}	3.83	5.58	4.42	4.77	4.10	3.14	3.72	3.78	4.62
	(2.19)	(2.97)	(2.46)	(2.68)	(2.15)	(2.05)	(2.07)	(2.13)	(2.58)

Table 15. Robustness: Threshold Definition

This table reports annualized average excess returns to the revisited global dollar trade when different definitions of large return fluctuations are used. The benchmark specification defines large return movements as realizations that are more than one and a half standard deviations away from the mean in the five year pre-sample period January 1994 to December 1998. The perturbations shown in this table change different specifications of this definition: HML^{ext} uses an extending window, HML^{roll} is based on a rolling-window approach, HML^{4yrs}, HML^{3yrs} and HML^{2yrs} denote different pre-sample periods of 4-, 3-, or 2-years. In the bottom panel, I use different bands around the pre-sample means covering cut-off points between 1 to 2.5 standard deviations. For each alternative specification, the trading approach is the same as described in the main text. At the end of each month currencies are allocated to portfolios according to their dollar betas. Currencies with large (small) betas are allocated to Portfolio 3 (Portfolio 1). In normal times, an investor goes long Portfolio 3 and shorts Portfolio 1; following large return realizations of the dollar the strategy is reversed. Numbers in parentheses refer to t-statistics. The sample period is January 1999 to December 2017.

	HML^{ext}	HML^{roll}	HML^{4yrs}	HML^{3yrs}	HML^{2yrs}
Mean	4.54	3.52	3.76	4.31	3.77
T-Stat	(2.50)	(1.93)	(2.06)	(2.37)	(2.07)
	$HML^{1\sigma}$	$HML^{1.75\sigma}$	$HML^{2\sigma}$	$HML^{2.25\sigma}$	$HML^{2.5\sigma}$
Mean	3.60	3.52	3.96	3.96	3.26
T-Stat	(1.97)	(1.93)	(2.18)	(2.18)	(1.78)

Table 16. Robustness: Forecasting Performance of Dollar Risk Measures

This table documents the forecasting performance of option-implied ($\mathbb{E}_t[\beta^Q_{t+1}]$) and historical dollar risk measures ($\mathbb{E}_t[\beta^{P,60M}_{t+1}]$) constructed with a 60-month window and backward-looking rolling regressions. Panel A reports the ex-post mean square error $MSE = \frac{1}{T}\sum_{i=t+1}^{T} err^{\beta}_i$, where

$$err^{\beta}_{t+1} = R\beta^P_{t+1} - \mathbb{E}_t[\beta^j_{t+1}]$$

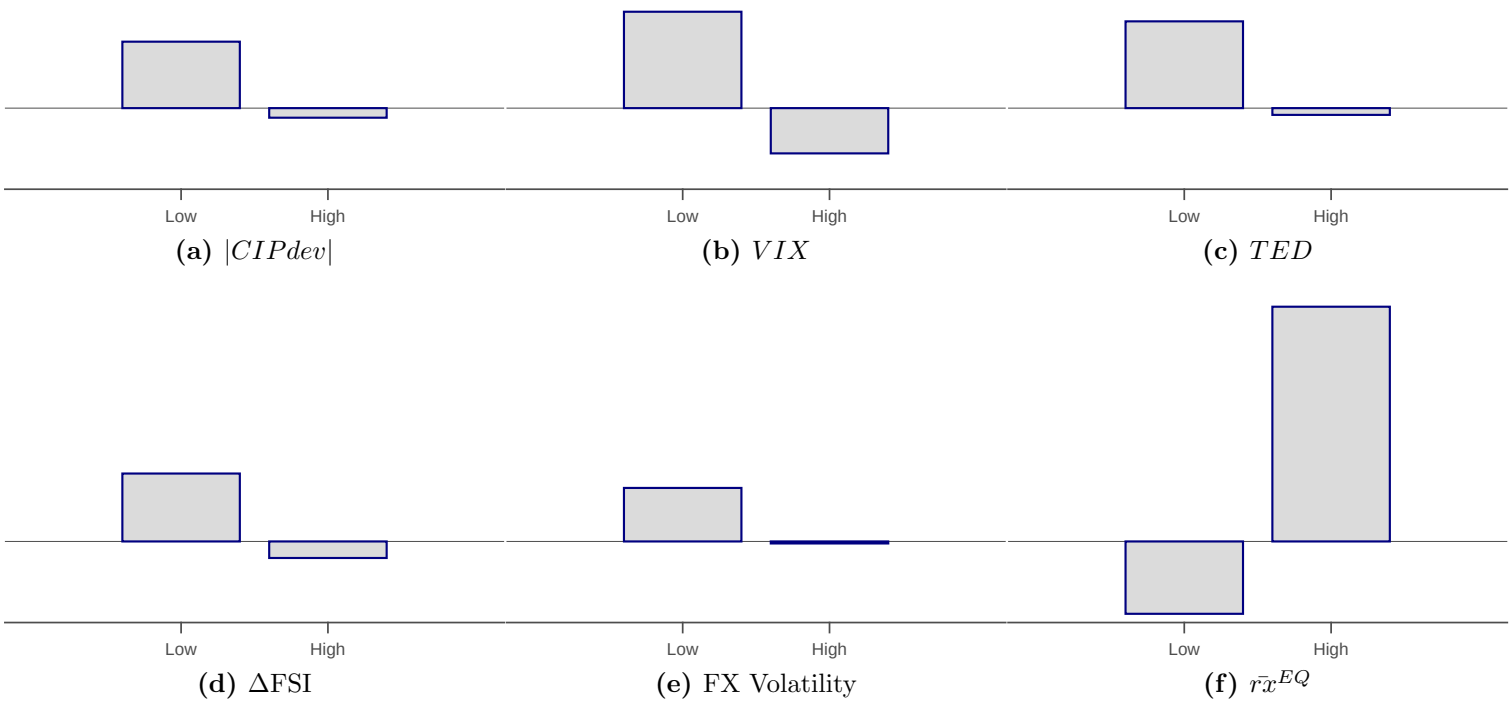
and $R\beta^P_{t+1}$ refers to realized dollar risk measured using high-frequency data observed during the forecasting horizon between period t and $t+1$, and the ex-ante expected dollar risk estimates $\mathbb{E}_t[\beta^j_{t+1}]$, where $j = \{Q; P, 60M\}$. The row '$DM^{Q;P,60M}$' reports the Diebold-Marino test-statistic that the prediction errors of $\mathbb{E}_t[\beta^Q_{t+1}]$ and $\mathbb{E}_t[\beta^{P,60M}_{t+1}]$ are identical. Panel B reports the number of correct directional forecasts (in percent) defined as the number of times an increase (decrease) in ex-ante beta estimates is associated with an increase (decline) in ex-post returns. $Direct^Q$ and $Direc^P_{60M}$ refer to the directional forecasts of option-implied and 60-month backward looking betas, respectively. The sample period is January 1999 to December 2017.

Panel A: Mean Square Error

	AUD	CAD	CHF	EUR	GBP	JPY	NOK	NZD	SEK
MSE^Q	0.05	0.03	0.02	0.01	0.02	0.09	0.02	0.09	0.02
$MSE^{P,60M}$	0.08	0.03	0.08	0.07	0.04	0.29	0.05	0.10	0.07
$DM^{Q;P,60M}$	-4.80	-2.73	-8.19	-7.82	-5.55	-6.71	-6.84	-2.01	-8.93

Panel B: Direction Forecasts

	AUD	CAD	CHF	EUR	GBP	JPY	NOK	NZD	SEK
$Direc^Q$	59.47	60.35	55.95	63.44	59.47	61.23	61.23	65.64	59.47
$Direc^P_{60M}$	53.74	58.59	56.83	60.35	53.74	59.03	56.83	55.51	60.35

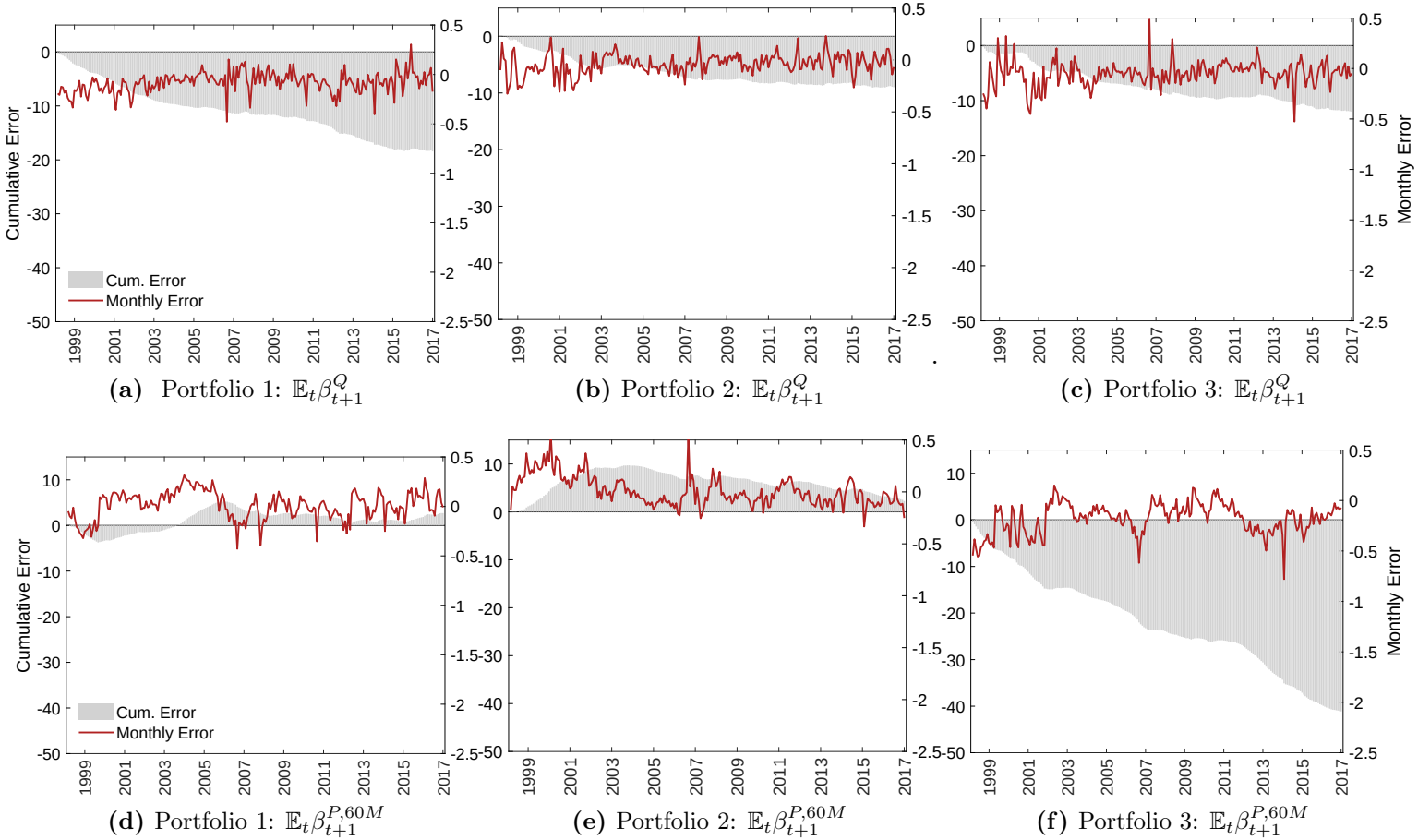


(a) $|CIPdev|$ **(b)** VIX **(c)** TED

(d) ΔFSI **(e)** FX Volatility **(f)** $\bar{rx}^{EQ}$

Figure 5. State-Dependent Slope of DPL

These figures show the slope of the DPL when observations are ranked by country-specific and macroeconomic variables, such as average funding costs ($|CIPdev|$), VIX (VIX), TED Spread (TED), Financial Stress Index (FSI), global FX volatility (Vol), and equity return differentials between foreign countries and the US ($\bar{rx}^{EQ}$). Based on each of the six variables I rank observations and split the sample in the top 50% and bottom 50% percentiles. The bars show the average direction of the slope of the DPL in low and high states. The sample period is January 1999 to December 2017.



(a) Portfolio 1: $\mathbb{E}_t\beta^Q_{t+1}$ **(b)** Portfolio 2: $\mathbb{E}_t\beta^Q_{t+1}$ **(c)** Portfolio 3: $\mathbb{E}_t\beta^Q_{t+1}$

(d) Portfolio 1: $\mathbb{E}_t\beta^{P,60M}_{t+1}$ **(e)** Portfolio 2: $\mathbb{E}_t\beta^{P,60M}_{t+1}$ **(f)** Portfolio 3: $\mathbb{E}_t\beta^{P,60M}_{t+1}$

Figure 6. Cumulative and Monthly Forecasting Error

These figures show the monthly forecasting error (red line) and the cumulative forecasting error (grey bar) for three different portfolios. Portfolio 1 (Portfolio 3) contains low (high) dollar risk currencies. The top panel refers to forecasting errors from option-implied betas (err^{β^Q}) while forecasting errors of historical betas based on 60-month rolling-window regressions are presented in the bottom panel ($err^{\beta^{P,60M}}$). In each month, the forecasting error is defined as

$$err^{\beta}_{t+1} = R\beta^P_{t+1} - \mathbb{E}_t[\beta^j_{t+1}]$$

where $R\beta^P_{t+1}$ refers to realized betas measured using high-frequency data during the forecasting horizon t to $t+1$, and $\mathbb{E}_t[\beta^j_{t+1}]$ are ex-ante dollar risk estimates, where $j = \{Q; P, 60M\}$ denotes option-implied and historical betas, respectively. The sample period is January 1999 to December 2017.

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